Multiseasonal Remote Sensing of Vegetation with One-Class Classification – Possibilities and Limitations in Detecting Habitats of Nature Conservation Value

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To Daniel and my parents.

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Acronyms and Abbreviations

ACC$_{Prod}$ Producers Accuracy

ACC$_{User}$ Users Accuracy

ATCOR-3 Atmospheric/Topographic Correction for Mountainous Terrain

AUC Area Under Curve

BMWi German Federal Ministry of Economics and Technology

BSVM Biased Support Vector Machine

CAP Common Agricultural Policy

CORINE Coordination of Information on the Environment

DEM Digital Elevation Model

DLR German Aerospace Center

EFA European Environment Agency

EnMAP Environmental Mapping and Analysis Program

EO Earth Observation

EU European Union

FN False Negative

FNR False Negative Rate

FP False Positive

FPR False Positive Rate

GPS Global Positioning System

HNV High Nature Value

HT Habitat Type

Km Kilometer

LUCAS Land Use/Cover Area Frame Statistical Survey

m Meter

Max Maximum

MNF Minimum Noise Fraction

NIR Near Infrared

OAC Overall-Accuracy

OCC One-class Classifier

OCSVM One-class Support Vector Machine

P Positives

PLS Partial Least Square

PU Positive Unlabeled

SDM Species Distribution Modeling

SPOT Satellite Pour l'Observation de la Terre

SRTM Shuttle Radar Topography Mission

SVM Support Vector Machine

TN True Negative

TNR True Negative Rate

TP True Positive

TPR True Positive Rate

Summary

Due to growing impacts on biodiversity caused by global change and on-going intensification of land use, monitoring of vegetation becomes increasingly important. National and international programs for nature conservation and management aim to organize these efforts. Mapping of habitats relevant for nature conservation often involves the identification of patches of target habitats in a complex mosaic of vegetation types extraneous for conservation planning. In field surveys, this is often a time-consuming and work-intensive task. Limiting the necessary ground reference to a small sample of target habitats and combining it with area-wide remote sensing data could greatly reduce and therefore support the field mapping effort. But conventional supervised classification methods need to be trained with a representative set of samples covering an exhaustive set of all classes. Acquiring such data is work intensive and hence inefficient in cases where only one or few classes are of interest. The usage of one-class classifiers (OCC) seems to be more suitable for this task – but has up until now neither been tested nor applied for large scale mapping and monitoring in programs such as those requested for the Natura 2000 European Habitat Directive or the High Nature Value (HNV) farmland Indicator. It is important to uncover the possibilities and mark the obstacles of this new approach since the usage of remote sensing for conservation purposes is currently controversially discussed in the ecology community as well as in the remote sensing community. Thus, the focal and innovative point of this thesis is to explore possibilities and limitations in the application of one-class classifiers for detecting habitats of nature conservation value with the help of multi-seasonal remote sensing and limited field data.

The first study is a pioneering work that ascertains the usage of an OCC is suitable for mapping Natura 2000 habitat types (Chapter 2). Applying the Maxent algorithm in combination with a low number of ground reference points of four habitat types and easily available multi-seasonal satellite imagery resulted in a combined habitat map with reasonable accuracy. There is potential in one-class classification for detecting rare habitats – however, differentiating habitats with very similar species composition remains challenging. Habitat types with a wide characterization are difficult to delineate even with an OCC. Nevertheless, this rather simple and affordable approach has to be recommended for further studies and could be used for pre-surveys of previously unmapped areas, as a tool for identifying potential gaps in existing habitat inventories as well as a first way of checking the changes in the distribution of habitats.

Motivated by these positive results, the topic of the second study of this thesis is whether low and High Nature Value grasslands can be differentiated with remotely-sensed reflectance data, field data and one-class classification. This approach could supplement existing field survey-based monitoring approaches such as for the High Nature Value farmland Indicator (Chapter 3). Three one-class classifiers together with multi-seasonal, multispectral remote sensing data in combination with sparse field data were analysed for their usage A) to classify HNV grassland against other areas and B) to differentiate between three quality classes of HNV grassland according to the current German HNV monitoring approach. Results indicated reasonable performances of the OCC to identify HNV grassland areas, but clearly showed that a separation into several HNV quality classes is not possible. This can be explained by the definition of the different HNV classes in the field which bases on the presence of HNV character species. Thus the difference between two quality classes can depend on the presence or absence of one single species. The spectral signal related to this differences is too narrow to be detectable by the tested classifiers or current remote sensing systems. Hence, with the presented approach only HNV grasslands as a whole can be identified from the rest of the landscape matrix based on its spectral signal. This could be of practical use in monitoring systems for pre-classifying the landscape, e.g. in terms of a HNV grassland mask. Further studies should focus on combining the presented approach with an object oriented classifier or with land registry data for improving the results. Future developments in sensor techniques may help to differentiate grasslands of high ecological value.

The first and second study show that usage of an OCC for detecting vegetation of conservation value is feasible. But they demonstrate as well that the validation of OCC results is complex and crucial. Among other things, the validation of OCC may be affected by the landscape itself and the sampling design. Due to this, in the third study (Chapter 4) the robustness and weak spots of an OCC were tested considering the effect of landscape composition and sample size on accuracy measurements. For this purpose artificial landscapes were generated to avoid the common problem of case-studies which usually can only make locally valid statements on the suitability of a tested approach. On the contrary, with simulated distribution data complete knowledge is given about the properties of the target class and the landscape. Thereby, assessing and discussing the robustness of OCC for usage with remote sensing data is possible in a more objective way. In the presented study, the performance of the OCC increases with an increasing number of target samples for training, as well as with an increasing number of background samples for training – in the latter case with a saturation and decrease at a certain number of

background samples. In respect to the prevalence of the target class in the artificial landscape results are inconclusive. OCC performance increases with decreasing number of pixels from similar classes in the artificial landscape. Whereas results concerning target sample size and the amount of similar classes in the background confirm conclusions of earlier studies from the field of species distribution modelling, results for background sample size and prevalence of target class give new insights and a basis for further studies and discussions. The OCC Maxent proves to be a robust and reliable classifier for mapping vegetation types in combination with remote sensing data. These results can inform and facilitate both conservation and classification efforts.

In conclusion the utilisation of an OCC together with reflectance and sparse field data for addressing rare vegetation types of conservation interest proves to be useful in all presented studies of this thesis. It is demonstrated that certain important habitats can be classified without requiring additional information about the rest of the landscape. This reduces sampling effort and thus provides the opportunity to support monitoring in a more efficient and cost-effective way in the future. However, there are obstacles that should be of concern in further studies. Due to their similar plant functional traits and hence similar spectral properties some vegetation types, especially in grassland, remain difficult or are impossible to distinguish even with this new method. Vegetation types with a wide characterization concerning their plant composition, e.g. vegetation types with a high inherent variability, are also with an OCC difficult to identify. It will always be challenging and sometimes impossible to translate the vegetation continuum into discrete classes. It is to hope that researchers from both the ecologists and the remote sensing community will work together in a collaborative way to further improve their respective capabilities for the common goal.

Zusammenfassung

Aufgrund des durch Klima- und Landnutzungswandel bedingten Verlustes der biologischen Vielfalt gewinnt die Suche nach effizienten Methoden des Vegetationsmonitorings an Brisanz. Es ist Aufgabe der nationalen und internationalen Naturschutzprogramme Monitoringkonzepte zu entwickeln und zu etablieren, die diesen Anforderungen gewachsen sind. Naturschutzfachlich relevante Vegetationstypen kommen oft nicht großflächig, sondern nur kleinteilig vor. Dabei sind sie in der Regel innerhalb einer Landschaftsmatrix von nicht relevanten Vegetationstypen verteilt. Mit flächendeckenden Fernerkundungsdaten und einem geringen Satz an Felddaten könnte ein naturschutzfachliches Monitoring sinnvoll unterstützt und kosteneffizient gestaltet werden. Herkömmlich verwendet man für diese Aufgabe Multiclass-Klassifikationsmethoden. Diese müssen jedoch mit einem großen Satz an Trainingsdaten unterstützt werden, wobei jede in der Landschaft vorhandene Klasse abgedeckt werden muss. In Fällen, in denen nur eine oder nur wenige Klassen von Interesse sind, ist eine derartige Herangehensweise nicht effizient. Die Nutzung von Einklassen-Klassifikatoren (one-class classifier: OCC) erscheint vielversprechender und anwendungsorientierter für solche Aufgaben, wurde aber bisher für ein naturschutzfachliches Vegetationsmonitoring, etwa im Rahmen des Natura 2000 Monitorings oder des High Nature Value (HNV) Farmland Monitorings, nicht getestet und analysiert. Da zwischen Fernerkundlern und naturschutzfachlichen Anwendern teils große Uneinigkeit über die Chancen und Grenzen des fernerkundlichen Monitorings für die oben genannte Aufgabe besteht, ist es notwendig, die Diskussion hierzu transparent und offen zu halten. Im Zentrum dieser Arbeit steht daher die Analyse des Potentials von OCC für ein naturschutzfachliches Fernerkundungsmonitoring.

In der ersten Studie der vorliegenden Arbeit werden erstmalig die Möglichkeiten der Erfassung naturschutzfachlicher Vegetationstypen mit Hilfe eines OCC, multisaisonalen Fernerkundungsdaten sowie einem kleinen Satz an Felddaten behandelt. Am Beispiel von vier Lebensraumtypen des Natura 2000 Programms ließ sich mit diesem Ansatz eine Verbreitungskarte mit ausreichender Genauigkeit erstellen. Klassen, welche eine sehr ähnliche Artenzusammensetzung aufweisen bzw. eine weitgefasste Charakterisierung haben, waren dabei besonders schwer zu trennen. Das grundlegende Potential eines OCC für ein naturschutzfachliches Monitoring konnte in dieser ersten Studie jedoch klar unter

Beweis gestellt werden. Ein einfacher und kostengünstiger Ansatz wie dieser könnte in Zukunft bei der Vorauswahl zu kartierender Gebiete und der Erkennung mutmaßlicher Veränderungen herangezogen werden.

Nachdem sich die Verwendung eines OCC als generell möglich und sinnvoll herausgestellt hat, wurde in der zweiten Studie untersucht, inwiefern naturschutzfachlich relevantes Grünland nach dem Beispiel von HNV Farmland mit der beschriebenen Methode identifiziert und qualitativ unterschieden werden kann. Es wurden multisaisonale Fernerkundungsdaten sowie ein kleiner Satz Felddaten verwendet und dabei drei OCC auf ihre Verwendbarkeit getestet: A) zur Identifikation von HNV Grünland in der Gesamtlandschaft; B) zur Identifikation von drei HNV Grünland Wertstufen in der Gesamtlandschaft. Es zeigte sich, dass mit der gewählten Methode hochwertiges Grünland zwar identifiziert werden kann, eine weitere Unterteilung in die drei Wertstufen jedoch nicht möglich ist. Die drei HNV Wertstufen werden anhand der Präsenz/Absenz von Indikatorarten im Feld definiert. In der gesamten Artenzusammensetzung der verschiedenen Stufen zeigen sich allerdings nicht genügend Unterschiede, die sich in den fernerkundlichen Daten widerspiegeln und es konnte kein signifikanter Zusammenhang zwischen HNV Wertstufen und Reflektanz nachgewiesen werden. Mittels des gewählten Ansatzes dieser Arbeit lässt sich daher allein HNV Grünland klassifizieren. Für weitere Verwendungen könnte die Verschneidung einer daraus generierten HNV Grünland Maske mit Daten zu Feldschlägen oder mit objektbasierten Klassifikationsansätzen in Erwägung gezogen werden. Zukünftige technische Entwicklungen mit höherer spektraler Auflösung könnten eine weitere Differenzierung der Grünland Wertstufen ermöglichen.

Die ersten beiden Studien ergaben, dass die Verwendung eines OCC unter bestimmten Limitationen als sinnvoll erachtet werden kann. Es zeigt sich aber auch, dass die Validierung eines solchen Ansatzes schwierig, aber maßgeblich ist und daher eine ausreichende Robustheit des Klassifikators gegeben sein muss. Aufgrund dessen wurde in der dritten Studie die Stabilität eines OCC in Bezug auf die Landschaftszusammensetzung, sowie das Stichprobendesign untersucht. Dazu wurden keine regionalen Erhebungen durchgeführt, sondern künstliche Landschaften erzeugt, die einen vollständigen Überblick ermöglichen und es gestatten, das Samplingdesign sowie die Landschaftszusammensetzung vollständig zu kontrollieren. Während die Analyse zur Trainingsgröße und dem Anteil ähnlicher Klassen in der Landschaft die Ergebnisse früherer Studien aus dem Feld des species distribution modelling bestätigten, konnten neue Erkenntnisse bezüglich der Themen Prävalenz und Umfang der Background Trainingsdaten gewonnen werden. Der OCC Maxent erwies sich für die relevante Aufgabe als robuster und geeigneter Klassifikator.

Mit dieser Arbeit konnte gezeigt werden, dass ein OCC zusammen mit Fernerkundungs- sowie Felddaten für ein naturschutzfachliches Monitoring gewinnbringend eingesetzt werden kann. Es ist möglich, die relevanten Klassen ohne genaueres Wissen über den Rest der Landschaft zu extrahieren und identifizieren. Dies reduziert den notwendigen Kartieraufwand und könnte Monitoringprogramme zukünftig effizient und kostengünstig unterstützen. Eine Herausforderung bleibt die Differenzierung sehr ähnlich definierter Klassen. Gerade im Bereich des Grünlandes werden die Grenzen der in dieser Arbeit aufgezeigten Methode, bzw. des aktuellen Standes der Technik, sichtbar. Vegetationstypen mit ähnlicher Artenzusammensetzung, und damit ähnlichen Pflanzenmerkmalen, sind auch mit dieser Methode nicht vollständig abzugrenzen und zu identifizieren. Auch Vegetationstypen, die aufgrund ihrer vorgegebenen Definition nur unscharf charakterisiert sind, sind schwer erfassbar. Diese Einteilung der natürlicherweise kontinuierlich vorkommenden Vegetation in diskrete Klassen wird immer eine Herausforderung darstellen. Abschließend kann festgestellt werden, dass die Einklassen-Klassifikation für ein naturschutzfachliches Fernerkundungsmonitoring als anwendungsorientiert, sinnvoll und zukunftsträchtig erachtet werden kann und weiterführende Arbeiten hierzu vorangetrieben werden sollten. Eine enge Zusammenarbeit von Fernerkundlern und Ökologen auf diesem Gebiet wäre wünschenswert und vielversprechend.

1. Introduction

1.1. Preface

"*Remote sensing is the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation*" (Vanden Borre et al. 2011). Since the launch of the first multispectral sensor Landsat 1 in 1972, the technology for Earth observation from space has played an increasingly important role in understanding and monitoring the surface of the world (Rose et al. 2015). Today more than 100 Earth observation satellites are orbiting around Earth, carrying a wide variety of sensors (CEOS 2015). Remote sensing is widely studied and used in various fields of investigations, such as ecology, meteorology, hydrology, geology, geography and more. Remote sensing is also applied in the field of nature conservation to gain information on human-induced and natural land cover changes, which are widely considered as one of the primary drivers of species and habitat endangerment and biodiversity decline and therefore should be monitored over broad areas (Hansen et al. 2001). This thesis focuses in particular on the application of remote sensing for monitoring in a conservation context.

1.2. Remote sensing in a nutshell

Remote sensing is the process of obtaining information about an area or object without being in direct contact with it. Two major benefits of using remote sensing to monitor and map land surface areas are the possibility to retrieve information in otherwise inaccessible or distant areas and its cost-efficiency in many cases (compared to wall-to-wall inventories on the ground). Data acquisition is performed by sensors and operated from unmanned airborne vehicles (UAV), airborne (airplanes) or spaceborne platforms (satellites). Two forms of sensors exist, passive and active sensors (Figure 1.1). Images of passive sensors are the result of measurements of electromagnetic energy emitted and reflected by the Earth's surface in sensor specific wavelength-regions (covered by the sensors bands) (Pettorelli et al. 2014, Vanden Borre et al. 2011). These kind of data can be divided into panchromatic, multispectral and hyperspectral remote sensing data, depending on the number and spectral continuity of the sensors bands. Panchromatic sensors have only one band, which gathers information about the total radiance reaching each pixel. Multispectral sensors have up to 10 usually rather broad bands (band width of 10 nm and more), which provide aggregated information about reflectance of several parts of the electromagnetic spectrum. Contrarily, hyperspectral sensors can have more than 200 narrow bands which provide very detailed information over a broad and continuous range of the electromagnetic spectrum (usually from 400 to 2500 nm). Active sensors emit electromagnet radiation signals that are then partially reflected by the Earth's surface. The reflected part of the transmitted signal is recorded by the sensor. Radar data as well as LIDAR data belong to this group of active sensors.

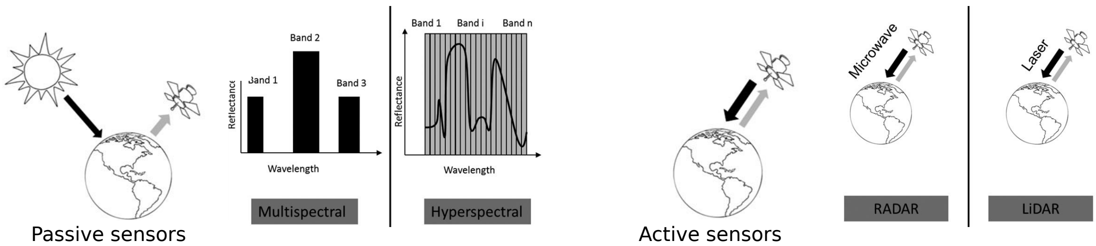

Figure 1.1.: Different types of remote sensing sensors (adapted from Petorelli et al. 2014).

In former times, images taken out of airplanes were recorded on film and converted into analogue photographs, but digital sensors have replaced these early analogue cameras. Progress in technical development has led to images with not only higher spectral but also higher spatial and temporal resolution (Schmidtlein et al. 2014, Vanden Borre et al. 2011). In contrast to airborne data sensors on satellites have wider swath, providing data with a larger spatial extend and therefore reducing the tedious and error prone mosaicking of multiple small pictures. The focus of this thesis lay on the application of spaceborne passive optical data.

1.3. Broad fields of application

Due to the technical limitation of the former available sensors, up to twenty years ago remote sensing data was mainly applied on very broad spatial scale or vague thematic issues. Early studies combining remote sensing and nature conservation assessed land-use and land-cover changes such as deforestation in the Amazon basin (Skole & Tucker 1993) or global changes in the distribution of cropland (Ramankutty & Foley 1999). Thanks to the development of sensors with higher spatial, temporal and spectral resolutions and more advanced methods in recent approaches remote sensing is nowadays used on very fine scales, right up to mapping the floristic composition as a continuum (Schmidtlein et al. 2012) or for measuring pigment content of different tree species (Fassnacht et al. 2015). Today there are numerous possibilities for the application of remote sensing: in urban area change detection (Yang et al. 2003), for damage assessment in crisis areas (Klonus et al. 2012), to identify critical bird breeding habitats (Goetz et al. 2010) and to assess the effects of anthropogenic light on seabirds (Rodrigues et al. 2012), for monitoring glacier movement (Schneevoigt et al. 2011), for landslide mass movement assessment (Strozzi et al. 2005) or mining monitoring (Sen et al. 2012), for fire (Vogelmann et al. 2011) or flood detection (Gianinetto & Villa 2007) as well as for volcano activity documentation (Agustan et al. 2012).

Current and past advantage of the use of remote sensing data when working on vegetation is the possibility to map in otherwise inaccessible or distant areas in a rapid and cost saving way. In former days the interpretation of aerial photographs was standard in some fields of application. Today, (semi-) automated, computer based methods are available, but visual interpretation is still a standard in many operational processes. There are two main types of remote sensing approaches for addressing vegetation: direct approaches addressing observations of species and species composition, whereas indirect remote sensing approaches aiming to identify environmental parameters as proxies (Turner et al. 2003). In this case remote sensing is used or studied for various subjects, in fundamental as well as in applied research: in precision agriculture to map crop and herb distribution across agricultural stands (Lopez-Granados et al. 2006), for detection of agricultural expansion (Arvor et al. 2012), for identifying cropland and grassland on parcel level (Esch et al. 2014) as well as for classifying crops on a subcontinental scale (Conrad et al. 2011). Remote sensing is also used for retrieval of forest-inventory variables (Kennedy et al. 2010, Fassnacht et al. 2016). There are studies on wetland monitoring (Landmann et al. 2013) as well as studies that took place in savannah regions (Ferner et al. 2015), some aimed to assess the composition and quality of grasslands (Kawamura et al. 2008) or the structure of heathland (Schmidt et al. 2017). Ecological parameters were addressed, such as identifying carbon stocks in the Amazon basin (Asner et al. 2010) or different pollination types (Feilhauer et al. 2016). Such possibilities of remote sensing based data for assessing ecological properties of vegetation have been reviewed widely (Gillespie et al. 2008, Kerr & Ostrovsky 2003, Nagendra et al. 2001, Schimel et al. 2013, Turner et al. 2003, Ustin & Gamon 2010, Vanden Borre 2011, Wang et al. 2010).

1.4. Remote sensing and nature conservation

While there is a large number of case-studies investigating the general potential of remote sensing to assess vegetation properties the number of studies focusing on the development of methods to directly support monitoring and reporting commitments of governmental organizations and administrations is still limited. This contrasts the demand of these organizations: International and national laws require information about the extent and condition of areas of conservation interest. Thus, detailed monitoring programs are needed; conserving biodiversity needs data. The ability to monitor the state and condition of vegetation, landscapes and habitats is fundamental for developing appropriate and optimized management strategies and for controlling their success. Long-term and reliable information about changes of the target of conservation interest is essential. This includes information about the distribution, structure, composition and functionality of this target – may it be small areas or entire countries and beyond. In the context of this need, the use of remote sensing is a matter to controversial discussions (Pettorelli et al. 2014) and some studies on this subject implemented first applications. Buchanan et al. 2005 for instance used remote sensing data to identify moorland vegetation and its structure, while Veitch et al. 1995 monitored heathland. Moorland vegetation and heathland are examples for vegetation types of ecological and conservation value (Figure 1.2). Moreover, both types are very often addressed by remote sensing approaches due to their noticeable structures. Other studies tested whether coarse-scale field characteristics can provide information on fine-scale indicators for Natura 2000 heathland (Spanhove et al. 2012) or produced continuous fraction maps of grass encroachment in Natura 2000 heathland (Mücher et al. 2013). Schuster et al. 2011 provided an approach to detect Natura 2000 grasslands by detecting the mowing dates via remote sensing, while Förster et al. 2008 studied the possibilities of combining GIS data and remote sensing data in an object based approach to classify Natura 2000 forest and heathland types. Approaches to identify the species composition of some Natura 2000 habitat types with hyperspectral remote sensing and field data (Feilhauer et al. 2014) have recently been presented. Apart from many studies that refer to Natura 2000, remote sensing is also used to detect invasive species (Andrew & Ustin 2008, Hestir et al. 2008). For all the aforementioned studies, if working on a fine spatial or thematic scale, combining the data of remote sensing with reference field work data was either obligatory or at least strongly improved the results. Although only a few standardized remote sensing based applications are used by nature conservation agencies or organisations, the above mentioned studies and many others show the potential usefulness of remote sensing methods for nature conservation, so research must be driven forward. The monitoring of vegetation becomes increasingly important due to the impacts of global change and the on-going intensification of land use. National and international programs for nature management and conservation aim to organize this monitoring effort. In this context, two international programs of nature conservation concern are going to be presented in detail.

Figure 1.2.: Murnauer Moos, Bavaria – Conservation area and Natura 2000 site: A highly structured complex of bogs, fens and wet grasslands, surrounded by more intensively used grasslands. Picture: Stenzel.

1.5. Natura 2000

In 1992, the European Union (EU) agreed upon the Natura 2000 Habitat Directive, a large program dedicated to the conservation of target species and habitat types, the aim of which is to create a network of protected areas. All EU member states are required to designate Natura 2000 sites where special habitats or species occur and to report about the state and condition of these species and habitat types on a six-year basis. The Habitat Directive on the conservation of habitat types and of wild fauna and flora (92/43/EEC), known as Fauna-Flora-Habitats (FFH) Directive, was adopted in 1992 as an implementation instrument of the 1979 Bern Convention on the Conservation of European

Wildlife and Natural Habitats. Together with the Birds Directive (79/409/EEC, amended version 2009/147/EC), it constitutes the main legal framework for nature conservation in the European Union (Vanden Borre et al. 2011). The Natura 2000 network was established to guarantee an adequately large survival space for European species that are threatened, endangered or have their main prevalence in Europe and thus giving Europe a special responsibility. Therefore the program aims to ensure long-term survival for European endangered and valuable species and habitats. All habitats protected by the Habitats Directive are listed in its Annex 1, which currently consists of 231 habitat types (HT). The definition of the habitat types is very heterogeneous, the majority is defined by vegetation, whereas some are defined by physiographic features (Ssymank et al. 1998). These habitat types may occur at different scales, from point locations to landscapes. Such heterogeneity of the habitats poses a number of challenges. Most challenging is that they can differ in their inherent variability a lot (Figure 1.3). Guidance on the definition of habitat types is given in the European Interpretation Manual (European Commission 2007), which was subsequently translated by the EU member states into national interpretation guides, as well as into federal state interpretations. Today, about 18% of the European terrestrial area is designated as Natura 2000 site. It is important to know that not all Natura 2000 sites are strictly preserved areas. There are core protected zones as well as agricultural or forestal managed zones, since often the main part of the site is still in private hand. For all sites there is a prohibition on deterioration. Other restrictions exist as well, such as the ban on ploughing up grasslands. All European member states must ensure that the sites are managed both ecologically and economically, as one of the Natura 2000 guidelines says that there has to be a management plan for every single site. This criterion is not fulfilled yet in many states. Another objective of the program is that monitoring has to be implemented. Since the Habitat Directive requires information about condition and change of habitat types on a six-year regular base, the need for an extensive, reliable and cost efficient monitoring is immense. Every country develops its own method to monitor and report. In Germany, for all species and habitat types, there is a stratified random sample, considering the different biogeographical regions (alpine, continental, atlantic). For each reporting period information about state and change are collected according to a complex system of evaluation (e.g. species: population size, reproduction rate; habitats: structure, characteristic species). For very rare species there is no stratified sample but a complete census of all remaining occurrences.

When thinking about monitoring one has to keep in mind that every EU member state is requested to designate at least 10% of its terrestrial surface as a Natura 2000 site. So the idea to use remote sensing data for direct monitoring as well as using remote sensing products as parameters came up in several studies and is implemented in some countries.

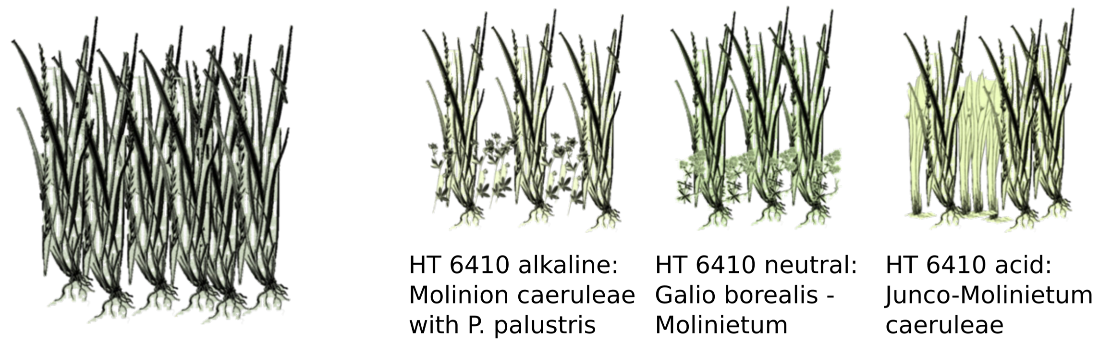

Figure 1.3.: Variation possibilities in one single Natura 2000 habitat type.

But until now, the operational use of at least semi-automated remote sensing analysis, instead of aerial photograph interpretation (a more hand work-intensive type of remote sensing) seems to be limited to pilot projects and exemplary cases (e.g. Bock et al. 2005, Corbane et al. 2013, Diaz Varela et al. 2008, Feilhauer et al. 2014, Förster et al. 2008, Mack et al. 2016, Schuster et al. 2011). Especially in its beginnings remote sensing techniques failed or were imprecise in mapping very detailed habitats like Natura 2000 habitat types.

Nowadays, since new methods and technologies are evolving rapidly, the opportunities for novel and operational applications of remote sensing data in monitoring are increasing. However, there is still a need for valuable studies that focus on understanding and identifying the right signals to differentiate and monitor, as well as creating new methods or fostering promising ideas.

1.6. High Nature Value farmland

Another European program that requires broad monitoring of state and changes occurring in selected landscapes is the High Nature Value farmland (HNV farmland) Indicator. In the last 50 years intensification of agricultural land use systems drastically reduced extensively used grassland areas as well as extensive crop fields, vineyards or structural elements like hedges. But these areas are of high ecological value due to their high species richness and occurrence of rare or endangered species. HNV farmland refers to farming systems that support more extensively land uses, with low inputs of pesticides or fertilizers. Cultivation as well as low stocking rates are beneficial to higher biodiversity (Veen et al. 2009). Historically, many of the important habitats for rare and endangered species have developed from a number of pre-industrial extensive agricultural practices which are now increasingly abandoned (Brunbjerg et al. 2015). HNV farmland is categorized into three types: as farmland that supports 1) semi-natural habitats and vegetation, 2) low intensity farming and diverse, small-scale mosaics of land use types, 3) rare species or a high proportion of European or world populations (Andersen et al. 2003). Common agricultural areas as well as agricultural sites in Natura 2000 or other conservation sites could be HNV farmland. HNV farmlands have recently become part of the nature conservation strategy within the EU, dictating the member states to develop a HNV farmland indicator for monitoring areas still holding high nature values. As part of a nature conservation strategy the European Union implemented an indicator as one of many baseline indicators to identify and monitor changes in High Nature Value farmland areas. This indicator is also part of the common agricultural policy (CAP) of the EU, as a baseline indicator as well as an impact indicator of the success of conservation actions. The HNV farmland indicator should represent the variation in biodiversity and natural structures in the agricultural landscape while being easy to understand. The details of how to implement such an indicator was at the discretion of each EU member state (2009/147/EC). Since no rules have been specified on how to identify and monitor HNV farmland areas, all EU member states address the national HNV farmland indicator in different ways (Lomba et al. 2014 & 2015, Brunbjerg et al. 2015). Current approaches are based on highly work intensive field-work and rough spatial extrapolation, or they take place on very pragmatic, theoretical or superficial levels. HNV farmland in Germany is monitored at a high spatial resolution; beside HNV farmland against no HNV farmland three HNV farmland quality classes are established (Figure 1.4). The monitoring is implemented on plots of Germany's National Biodiversity Monitoring program in which surveys of breeding birds were also carried out (Sudfeldt et al. 2012). The nationwide representative sampling design consists of 2637 sample sites and is representative for the whole of Germany. Its stratified sampling design is the result of 6 land use classes (e.g. grassland, forest, urban) and 21 landscape types (defined by temperature, precipitation, soil type etc.). Each sample site is 1 km^2 in size. On these sites the German breeding bird monitoring is implemented since 2004. Since 2009 the HNV farmland monitoring is conducted on all sites that have at least 5% of arable land. On each sample plot all semi-natural landscape elements are defined as HNV farmland (hedges, ditches, field margins). Croplands, vineyards and grasslands that contain a certain amount of characteristic HNV farmland vascular plant species are of high nature value as well (Benzler et al. 2015). The monitoring is done on a four-year routine. From 2009 to 2013 the HNV farmland indicator dropped from 13.1% to 11.7% and the trend is still decreasing. Especially in the grassland areas a high decrease was noted, alerting policy makers as well as ecologists, since up to two third off all plant species, rare as well as more common ones, depend on grassland. Therefore, loss in HNV grassland could lead to immense loss in biodiversity.

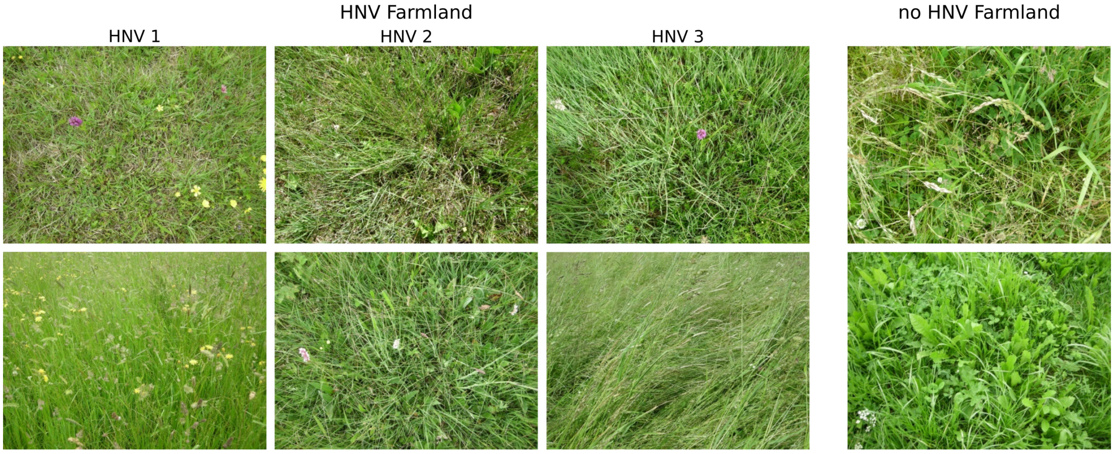

Figure 1.4.: Different stands of HNV grasslands and regular grassland, showing high variability throughout the classes (Pictures: Stenzel, field campaign 2011 and 2012).

Some earlier studies aimed to assess the composition and quality of grasslands with remote sensing data (Kawamura et al. 2008, Lauver 1997, Yamano et al. 2003, Franke et al. 2012). For identifying HNV farmland with remote sensing data there a few approaches, mostly working on a very rough scale (Belenyesi et al. 2008, Jackson et al. 2009, Parr et al. 2006, Pointereau et al. 2007, Samoy et al. 2007, Weissteiner et al. 2011). Since the definition of HNV farmland varies in each EU member state approaches on detecting it with remote sensing have to be numerous and to vary a lot.

1.7. Remote sensing – A controversy discussed issue in ecology

As seen before remote sensing is recognised as a powerful tool to acquire data on vegetation, but up to date its use for operational monitoring and reporting applications is still limited. One reason appears to be the knowledge gap between users like ecologists or nature conservation agencies and producers or providers like the remote sensing community (Vanden Borre et al. 2011). In the context of certain monitoring needs of international, but also national and regional monitoring programs the usage and added value of remote sensing is discussed controversially (Graef et al. 2009, Kerr & Ostrovsky 2003, Pettorelli et al. 2014, Roughgarden et al. 1991).

Users have long recognised the potential of remote sensing data in the visual interpretation of aerial photographs since it is well known as an important tool for several applications. Nevertheless the adoption of more advanced (semi-)automated analysis techniques is lagging behind (Gross et al. 2009, Mehner et al. 2004). Some producers even call ecologists to be reluctant to adopt new approaches (Aplin 2005). On the other hand there is a huge mistrust in the user community, since some providers promised heaven and Earth but could not fulfill their promises. As Vanden Borre et al. 2011 points out, many users are inexperienced with remote sensing data and products and do not know what to expect from it. On the other hand, producers are sunken into technological developments and details without knowing exactly what kind of application the user needs or how exactly they intend to use it, have no knowledge of what are basic requirements and what is incidental. Interdisciplinary studies aiming to develop products specifically matching the scientific interests of both communities are not very common. Mutual misunderstandings lead to unreasonable expectations, developments not suited for the planned purpose, disappointment and general disbelief in the added value of remote sensing (Kennedy et al. 2009, Turner et al. 2003). On the other hand there is a strong interest among researchers, users and providers to better understand how conservation and biodiversity research can benefit from remote sensing. Users, producers and their corresponding research communities have lately begun to coordinate their works, and precisely this synchronization is the key to improve the potential for remote sensing data effectively supporting environmental operational applications (Petorelli et al. 2014). Today it is not unusual to discover a session on the applications of satellite data to ecology in meetings such as the International Association on Vegetation Science IAVS Symposium in Brno, Czech Republic, in 2015, a conference with more than 700 participants. Its remote sensing session, chaired by a geoecologist and a biogeographer, was well attended and had fruitful discussions.

1.8. Observing from above – Added value and obstacles

The observation of Earth's surface from above could have a huge added value for conservation monitoring: Optical remote sensing is based on physical measurements of the reflectance of discrete wave lengths. From a technical point of view, the monitoring of vegetation with remote sensing is the repeated measurement of an area with remote sensing sensors with the intention to capture changes. It is based on the assumption that what can be seen as a change on the ground is usually closely related to processes that change the electromagnetic properties of the vegetation areas and are hence detectable with remote sensing. These changes can be measured in terms of spatial and temporal extent, spatial and temporal stability as well as intensity and frequency. However, this detection of changes is just the second step. The first step should always be to ensure that it is possible to identify the target. If this is confirmed one can test if changes are to be detected too and if no-change situations are also captured correctly. Changes can only be detected by remote sensing if a change on the ground causes changes in the spectral signal (Singh 1989). Measuring changes with remote sensing data typically requires knowledge of the study site and the target class so that the features of the changed image can be related to processes.

A big advantage for the application of remote sensing techniques is that vegetation has a very characteristic electromagnetic spectrum which enables its detection (Figure 1.5). It has low reflectance in the blue and visible red, and a peak in green and infrared. Since the human eye cannot gain information about the infrared region, but green is part of our visible range, plants appear green to us. Several insects (pollinators), however, can see in the infrared wavelengths and can be attracted by certain infrared impressions (Koch et al. 2009). With this green, infrared and near-infrared peaks and its small variations due to species composition there is a region in the electromagnetic spectrum that could be helpful for identifying and distinguishing vegetation types. The decision whether to use hyper- or multispectral data depends on the objectives, as well as on costs and available data (Aplin et al. 2005). Furthermore, remote sensing data can cover large areas within short intervals and high spectral resolution, which is advantageous when working in hard-to-access areas, and for areas that have various land cover classes. Such a large geographic expansion of data cannot be achieved only by field work, at least not exhaustively, and therefore remote sensing data could support studies or projects in case of spatial extension.

But what are the obstacles in using remote sensing data for vegetation conservation purpose? Even today with evolved spectral and spatial resolution of remote sensing sensors and advanced methodical techniques, detecting and monitoring vegetation types (semi-)automated with remote sensing seems to be a challenging task. One of the main obstacles is that the target vegetation sticks not to the pixel boundaries, resulting in mixed pixels. This is of course due to continuous vegetation occurrence as well as due to the wide range of plant species composition and vegetation layering. Also other components like open soil or litter could influence the reflectance signal. It will always be challenging and sometimes impossible to put vegetation continuum into discrete classes (Lewis 1998). One solution for this task is gradient mapping (Schmidtlein & Sassin 2004, Feilhauer et al. 2014), but for some application where discrete classes are necessary a method like this is not feasible. Another challenge is that the general spectral signature of plant

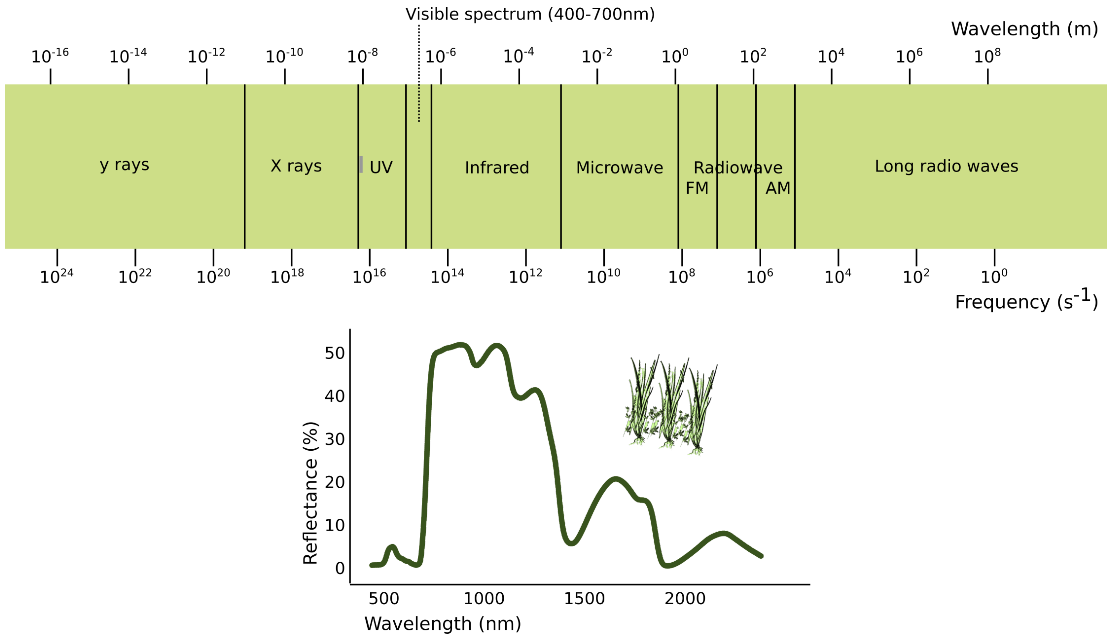

Figure 1.5.: Electromagnetic spectrum and model reflectance curve of photosynthetic active vegetation (curve after Feilhauer 2011).

compositions is usually very similar. Often there are just a few differences, which might be due to structure, stress induced by nutrient availability or diseases, or aging.

Because of this one vegetation type can show differing spectral signals under different environmental conditions. In this respect intraspecies variability can be higher than interspecies variability. This leads to another challenge, the spatio-temporal variability (Bruzzone & Persello 2009, Feilhauer & Schmidtlein 2011, Foody et al. 2006, Propastin 2009). Due to climatic reasons one type of vegetation may appear different at the same time of one year but at different places, e.g. in higher and lower altitudes. In addition, one type could appear rather different at the same place but at different times in the year, due to phenology. Plants develop over time, plant communities as well. So one single vegetation type could appear in many different shapes, i.e. could have rather varying spectral signals throughout the year, at different sites, at different circumstances (Feilhauer 2011). This can also be utilized: When working with multiseasonal data, the combination of images of the same area taken at different times of the year, the phenological curve of species or vegetation types could be recognised because even if it is shifted slightly, e.g. after cold and long winter to later in the year, the form of the curve stays more or less the same. Nowadays, this use of multiseasonal data is standard when working with vegetation (Franke et al. 2012, Hunt et al. 2003, Toivonen & Luoto 2003, Vogelmann et al. 2011).

The mapping of vegetation types, i.e. of habitats with relevance for nature conservation sometimes requires the complete mapping of an area, at times with dozens of different land use or land cover types to differentiate, as well as the need to give information about condition. In more specific approaches it could involve the identification of patches of detailed target habitats in a complex mosaic of vegetation types not relevant for conservation planning. Whereas in the former mentioned case several supervised and unsupervised multiclass classification approaches are already conventional, far advanced and used in applications, for the latter case implementation is more tricky and objective of recent research.

1.9. Looking for the needle in the haystack: one-class classification

When working with remote sensing data for detecting vegetation types sometimes one has to look for the needle in the haystack. The problem is to map one or few classes of interest in a large area that is mainly covered by numerous classes which do not need to be identified nor separated.

Conventional supervised classification methods need to be trained with a representative set of samples covering an exhaustive set of all classes and are in this case inefficient for classifying one or few classes of interest (Mack et al. 2014). For classifying an area on coarse scale, e.g. simple land cover classes forests, croplands, grasslands, detecting some impressive events like fire losses or deforestation, or working in an area with only few and very different vegetation types, multi-class classifiers are the method of choice. The aforementioned examples can be well distinguished and are easy to sample. But if not all occurring classes are defined in the training data a vital condition is not fulfilled and significant classification errors can occur since all pixels of the not defined classes will be mapped to one of the known classes (Boyd et al. 2006, Foody et al. 2006, Mack et al. 2014). For some conservation purposes it is necessary to identify one single target habitat from the vegetation matrix without needing any information about the rest of the landscape. One of the Natura 2000 habitat types, to give an example, are Molinion meadows, which are rare in most parts of Germany as well as in Europe, and could be accompanied with vegetation types not of interest for conservation purposes. Molinion meadows are a result of extensive farming practices and therefore endangered. Information about condition and change of this one specific habitat type is important, since it represents one of the species richest habitats in Central Europe. If one would use a multiclass classifier for this purpose, one has to take into account that the target class, here the Molinion meadows, is defined on fine scale by species composition, and at this level one has to define all other occurring classes and sample them. For conservation purposes this would be a way to a cost intensive approach and would not at all help to reduce field work but enlarge it, and therefore helps not to reduce sceptical positions. The usage of one-class classifiers (OCC) seems to be more suitable for this task, but their advancement and adjustment for monitoring vegetation with remote sensing has just recently been started, including the work of this thesis.

OCC are classifiers that can deal with available presence while lacking absence data. Particularly in remote sensing, OCC are used to map one specific class of interest. Training these classifiers requires only reference data for the class of interest, while data for other classes is not needed. This reduces the field sampling effort substantial. Among these classifiers are three groups: the ones that actually used presence-only data like climate envelope models (P: positives), one that adds pseudo-absences to the presence data (PU: positive-unlabelled) and the third group which works with background data (PB: positives-background) (Mack et al. 2016). Pseudo-absences are a spatial random sample with additional constraints such as a minimum distance to observed presences or other information about the target species (Zhang et al. 2015). Background data is a mere random sample representing the distribution of environmental variables in the study area and could also be called background distribution (Lahoz-Montfort et al. 2014). In remote sensing the background is represented not by environmental layers, like in species distribution modelling, but by different bands of a sensor ergo the reflectance of the area. Binary classifiers, e.g. logistic regression, treat pseudo-absences or background as if they were observed absences (Ferrier et al. 2002, Mack et al. 2016). In species distribution modelling (SDM), as long as the occurrence rate of the target species in the landscape is unknown, no occurrence probabilities can be calculated but only the relative likelihood of occurrence (Phillips and Elith 2013) and these unscaled occurrence probabilities are interpreted as relative site suitability (Hanewinkel et al. 2014). In remote sensing, since one does not calculate environmental niche of a species but the combination of reflectance that represents the target the best, one should not speak of suitability but of probability or relative likelihood. OCC are well established in the field of SDM, where occurrence records about one species together with environmental (or other) variables are used to model the probable distribution. In remote sensing, where OCC are used to classify satellite images, the presence of one class in a pixel leads naturally to the absence of all other classes, whereas in SDM several species can occur at the same location. Interestingly, OCC for vegetation mapping of conservation purposes are rather unknown.

The usage of OCC, remote sensing and field data for the task of mapping one class of interest in a large area that is mainly covered by numerous classes which do not need to be identified nor separated seems to be promising, but has barely been studied. In the context of conservation monitoring programs robust and reliable methods are needed and both fundamental and applied research on this has to be pushed forward. At the same time analyses of possibilities and limitations and their ecological reasons are necessary, keeping the fruitful but sensitive teamwork on this topic alive.

1.10. Aims and Structure of this thesis

Even though remote sensing is studied and applied in numerous and diverse contexts (chapter 1.3) it is not a common tool in nature conservation monitoring (chapter 1.4). Mapping of habitats with relevance for conservation purposes often involves the identification of patches of habitats in a complex mosaic of vegetation not relevant for conservation planning. Conventional supervised classification methods need to be trained with a representative set of samples covering all existing classes and are therefore inefficient for classifying only few classes of interest (chapter 1.9). Limiting the necessary ground reference to a small sample of target habitats and combining it with area wide remote sensing data would greatly reduce and therefore support the field mapping effort. The usage of one-class classifiers (OCC) seems to be suitable for this task, but has barely been tested or applied in the context of large scale conservation mapping.

Therefore the focal and innovative point of this thesis is the exploration of the possibilities and limitations of one-class classifiers for detecting habitats of conservation value with the help of remote sensing and limited field data. The key issues of the thesis are:

- Can semi-automated one-class classification methods with remote sensing data and limited field data map efficiently disperse habitat patches in a huge area – i.e. can it support large scale monitoring programs such as Natura 2000 or High Nature Value farmland?
- Can semi-automated one-class classification methods with remote sensing data and limited field data differentiate between similar habitat types occurring in mosaic like structures as well as differentiate between grasslands of different use-intensities and therewith different nature values?
- How can success and failure of the above mentioned tasks be explained in an ecological context?
- Do some one-class classifiers perform better than others in this respect?
- In which way are success and failure concerning the above mentioned tasks influenced by landscape composition and sampling design?

The thesis consists of three independent studies (chapter 2 to 4). Up to this point two studies are published in peer-reviewed international journals while the third is in preparation for submission:
The first study is a pioneering work that ascertains whether the usage of an OCC could be suitable for mapping vegetation types of conservation value, taking the example of Natura 2000 habitats (chapter 2). Since Natura 2000 is one of the most important conservation programs in Europe and there is still a lack in satisfying European wide monitoring it is of international interest to find new approaches supporting this issue. Since the Natura 2000 habitat types are often rare but widespread, it is possible that an OCC can solve this problem better than conventional methods. Applying and tuning the Maxent algorithm (an OCC commonly known from species distribution modelling) with low number of ground reference points along with multi-seasonal satellite imagery should produce convincing habitat maps. Results should help to draw first conclusions in regard to the aim of this thesis.

The second study consists of an examination of the potential of several OCC for mapping and differentiating grassland of ecological value with remote sensing data (chapter 3). The European High Nature Value (HNV) farmland indicator describes the amount of non-intensive farmland. The expanse of more extensively used HNV grasslands is constantly decreasing and their high biodiversity and uniqueness as habitats make them of conservation value. Due to their almost identical plant functional traits the classification of grasslands into several subclasses is known to be rather challenging. The results of three OCC, each classifier with its individual technical focus, are compared regarding the mere identification of HNV grassland in the landscape as well as the detailed differentiation of three HNV grassland value classes. Success and failure are discussed in respect to the ecological background.

Although there seems to be huge advantages of OCC for mapping vegetation types it is important to point out some problematic instances concerning the accuracy assessment: some errors do not appear in an accuracy assessment if the test set does not include the unknown classes. Also results could be questioned to be trustworthy if validation data are biased. If not all classes are known no information on true negatives and false negatives are available (for instance if no information about the background is available or it is not known if a given class belongs to the class of interest). Therefore it is of major interest to evaluate if the performance of the OCC is stable and robust under changing conditions. In the third study (chapter 4) robustness and weak spots of an OCC are tested in respect to the effect of landscape composition and sampling design on accuracy measurements.

In sum this thesis introduces the utilisation of OCC for addressing rare vegetation types with remote sensing data and gives impulses for future research that can be built upon it. Current possibilities and obstacles in identifying habitats of conservation value with remote sensing data, field data and OCC are presented. These results should provide a solid base for further work on applications, but also reveal the limitations of these techniques.

2. Remote sensing of scattered Natura 2000 habitats using a one-class classifier

2.1. Abstract

Mapping of habitats with relevance for nature conservation involves the identification of patches of target habitats in a complex mosaic of vegetation types not relevant for conservation planning. Limiting the necessary ground reference to a small sample of target habitats would greatly reduce and there for support the field mapping effort. We thus aim to answer in this study the question: can semi-automated remote sensing methods help to map such patches without the need of ground references from sites not relevant for nature conservation? Approaches able to fulfil this task may help to improve the efficiency of large scale mapping and monitoring programs such as requested for the European Habitat Directive. In the present study, we used the maximum-entropy based classification approach Maxent to map four habitat types across a patchy landscape of 1000 km^2 near Munich, Germany. This task was conducted using the low number of 125 ground reference points only along with easily available multi-seasonal RapidEye satellite imagery. Encountered problems include the non-stationarity of habitat reflectance due to different phenological development across space, continuous transitions between the habitats and the need for improved methods for detailed validation. The result of the tested approach is a habitat map with an overall accuracy of 70%. The rather simple and affordable approach can thus be recommended for a first survey of previously unmapped areas, as a tool for identifying potential gaps in existing habitat inventories and as a first check for changes in the distribution of habitats.

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2.2. Introduction

Monitoring of vegetation becomes increasingly important due to impacts of global change and on-going intensification of land use. National and international programs for nature management and conservation aim to organize this monitoring effort. In 1992 the European Union agreed upon the Natura 2000 habitat directive, a large monitoring program dedicated to the conservation of certain habitats types in a network of protected areas (Council Directive: 79/409/EEC, 92/43/EEC). Member states are required to report about the state of the habitat types on a six-year basis. Across Europe, the respective protected areas cover 13.7% of terrestrial surface (07/13; http://ec.europa.eu) including 231 defined habitat types, which are usually corresponding to distinct vegetation types. The reporting commitment hence demands a huge effort of mapping vegetation. Most member states address this demand with field surveys, but there is still a lack of knowledge on the distribution and state of habitats in large portions of area (Evans 2006). Here, remote sensing techniques that enable a (semi-) automatic assessment may help. Current literature documents the potential of remote sensing for conservation monitoring (see i.e. Nagendra et al. 2013, Turner et al. 2003, Vanden Borre et al. 2011, for reviews). However, the implementation of advanced analysis techniques stays far behind this potential (Fassnacht et al. 2006). For example, only 18 out of 25 European member states are currently using remote sensing for the monitoring of Natura 2000 areas. Most of them, however, rely on visual image interpretation (Vanden Borre et al. 2011). The studies that are trying to take advantage of semi-automated classification methods show a clear tendency toward applications in areas with an almost seamless mosaic of relevant habitats (Alexandridis et al. 2009, Corbane et al. 2013). However, in reality, few areas are entirely covered by target habitats. This means that most current studies avoid to address an urgent problem. There is a strong demand toward classification techniques that are able to identify isolated habitat islands in a matrix of non-relevant surface classes (Boyd et al. 2006, Foody et al. 2006). Article 17 of the Habitat Directive claims the monitoring of Natura 2000 habitat types is not restricted to revealed sites. Therefore data need to be collected both in and outside the Natura 2000 sites to get a full overview of conservation status of the habitat types (92/43/EEC). There are, however, to our knowledge no studies addressing this problem using a realistic habitat mapping scenario. Accordingly, we address the question if semi-automated remote sensing methods can help to map disperse(and sometimes difficult to differentiate) habitat patches without ground reference from non-relevant sites. We propose to use a small sample of ground reference data from relevant habitats, multiseasonal, multispectral satellite imagery and a one-class classifier (OCC) to address the problem. Limiting the required ground reference to a small sample of target habitats optimizes the field mapping effort. This may improve the efficiency of large scale mapping and monitoring programs such as requested for the European Habitat Directive.

2.3. Data and methods

The current study combines point based field data with areawide multiseasonal remote sensing data (Figure 2.1). We use a maximum entropy-based OCC approach to generate a set of habitat maps featuring logistic probabilities of habitat occurrences for each pixel. Several OCC-maps of different habitat types are subsequently combined to build one joined habitat map.

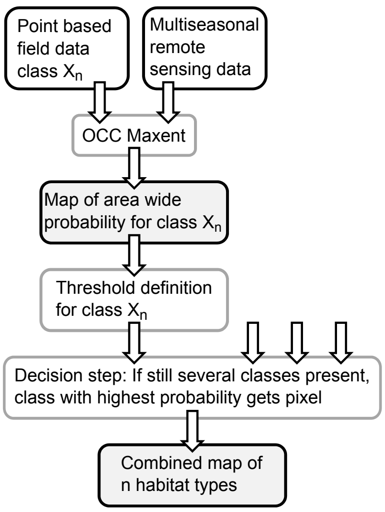

Figure 2.1.: Workflow.

2.3.1. Field based data

The study took place south of Munich, Germany, the study site covers an area of 20 $km \times 50$ km (Figure 2.2). This area is mainly characterized by grasslands, mires and forest. The landscape was shaped by Pleistocene glaciers and features a rich variety of mires and bogs. The moraine bedrock is calcareous; therefore most minerotrophic plant communities are calciphil. In spring of 2012 four different types of Natura 2000 habitat types (HT) were sampled on ground. We focused on four grassland and open wetland types, because they are common in the area and co-occur in mosaic structures with partly continuous transitions. These four habitat types are the following (Natura 2000 classification key, LfU and LWF 2010): HT 6410: Molinia meadows on calcareous, peaty or clayey-silt-laden soils. HT 7120: Degraded raised bogs still capable of natural regeneration. HT 7140: Transition mires and quaking bogs. HT 7230: Alkaline fens. Ground reference data of habitat occurrences were collected in the area of investigation using plots positioned in predefined areas from a habitat inventory. An initial seed of reference plots was placed randomly within these areas and plots that did not pass a homogeneity check or could not be assigned to one of the tar-get habitat types were removed. Due to the spatial resolution of the RapidEye imagery (5 m) we selected a plot size of 9 $m \times 9$ m to avoid mixed pixels. All dominant and characteristic plant species and some structural parameters (height, density, cover fractions of litter and open soil) were recorded and the habitat type was assigned. We collected in total $n = 125$ Plots (50 for HT 6410, 39 for HT 7120, 10 for HT 7140, 26 for HT 7230). The location of the plots was determined in the field with the GPS receiver Magellan(TM) Mobile Mapper 6 (error < 2 m).

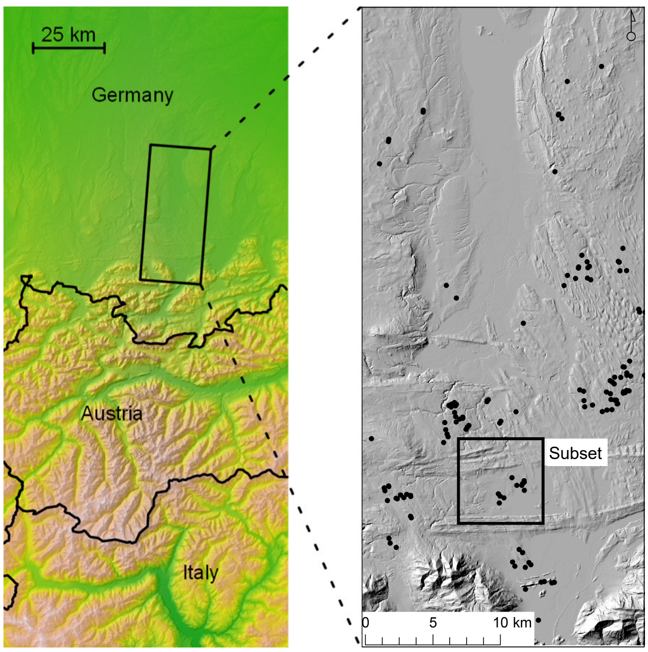

Figure 2.2.: Study site in Southern Germany (1,000 km^2, $n = 125$).

2.3.2. Remote sensing data

For this study, we used Earth observation (EO) data of the RapidEye sensors, which feature a high spatial (5 m) as well as temporal (about 10 days) resolution and provide spectral information in the blue ($440-510$ nm), green ($520-590$ nm), red ($630-685$ nm), Red-Edge ($690-730$ nm) and NIR ($760-850$ nm) region. The RedEdge band has been developed especially for analyses targeting vegetation (Blackbridge 2013). When EO data are used for vegetation analyses of small habitat patches, a high spatial resolution of the imagery is desirable (Gillespie et al. 2008, Turner et al. 2003). Five images were acquired uniformly distributed during the vegetation period in May, June, July, August and September of 2011. 40.128.627 pixels covered the area of investigation. The RapidEye data have been delivered as Level-1b imagery. The images have thus been radiometrically as well as sensor corrected and were band aligned. The data were subsequently further pre-processed with the operational, fully automatic processing system CATENA (Krauss et al. 2013). In this processing chain, the satellite imagery was firstly automatically orthorectified by physically correcting the sensor model of the Level-1 data and applying it to the images (Krauss et al. 2013). The imagery was then projected onto a reference digital elevation model (DEM), which was generated as best-of-DEM from SRTM C- and X-band, Mona-Pro and GTOPO data with a 30 m spatial resolution (Krauss et al.2013). This allows for the generation of the ortho images, which are finally atmospherically corrected with ATCOR-3 to eliminate atmospheric and topographic effects using an accurate spectral and radiometric sensor calibration as well as the DEM for mountainous terrain (Richter 2009).

2.3.3. Maximum entropy modelling

The one-class classifier used in this study is based on the maximum entropy approach (Sethna 2006, Shannon 1948). This method is particularly known for modelling potential species distributions based on environmental parameters and has been implemented in a software called Maxent (Phillips et al. 2004). As a general-purpose machine learning method it is also suitable to map real distributions based on remote sensing data (Bradley et al. 2012 for a critical discussion of the use of remote sensing data for modeling potential and actual species distribution). Until now it is not well established in remote sensing (but see Amici 2011 Cord 2012, Evangelista et al. 2009, Li & Guo 2010, Zimmermann et al. 2011, for some applications). Since the maximum entropy approach is able to model the spatial distribution of the response variable based on presence-only data, it is able to deal with our topic of mapping diffuse habitat patches without ground reference from non-relevant sites. The approach can be described from two perspectives, the statistical (Elith et al. 2011) and the machine learning perspective (Dudík et al. 2004, Phillips et al. 2004). In terms of statistics, the idea of the maximum entropy approach is to minimize the relative entropy between two probability densities, one estimated from the presence data of habitat types and one from the landscape, defined in covariate space (Elith et al. 2011). The algorithm estimates a ratio of the $f1(z)/f(z)$, where z is a vector of predictors (in our case the reflectance in a specific pixel), $f1(z)$ is the conditional probability density, i.e. the probability density of z given the target is present, and $f(z)$ is the unconditional probability density. The occurrence records are required for the estimation of $f1(z)$ and the background samples for $f(z)$. The mathematical estimation of the density is based on the maximum entropy principle and is described in detail in Phillips et al. (2006) and Phillips & Dudik (2008). Maxent software allows a large basis expansion of the original predictors z. These basis expansions are quadratic terms, interactions step functions and hinge features calculated from the original covariates. If chosen, the probability densities are estimated in this expanded feature space which allows for an improved discrimination between the class of interest and the rest of the imagery. To avoid over-fitting, a l1-regularization is used (Dudík et al. 2004). The regularization parameter beta can be specified to regulate the amount of regularization. The data-output of the Maxent modelling software is a map of predicted suitability (relative probability for each pixel) ranging from 0 to 1 (Elith et al. 2011). Maxent is available free for educational and non-commercial use as a multi-platform Java based software.

2.3.4. Our classification procedure

We built Maxent models that relate point-based information on each of the target habitat types to area wide, multiseasonal surface reflectance. With five dates and five spectral bands we had a set of 25 spatial predictor variables. No mask was applied to the image and no derived indices were used, to keep the approach as simple as possible. A sample of 10,000 background points was randomly taken from the imagery. For habitat presence data we used 50 for HT 6410, 39 for HT 7120, 10 for HT 7140, 26 for HT 7230, all divided into test and training data (1:1). The derived model provides a value of logistic probability of occurrence for habitat types. The separate modelling of the four habitat types resulted in four individual, pixel-based predictions. These predictions were joined into one habitat map featuring distributions of the four classes. The logistic, relative probability values of the output of different models depend on properties of background and sampling and can-not be kept constant in different investigations. We approached the problem by using consistent sets of predictor layers and an almost similar ratio of presence-to background-data. We tested the influence of sampling by adopting Maxent models with variable subsamples and found only minor effects on the results. To delineate habitats from the landscape matrix we had to define an appropriate threshold of probability. This task proved to be rather challenging. The optimal threshold with minimized scatter and a minimum of missed habitats highly depends on the class of interest. The 'sensitivity equals specificity' approach to deter-mine this threshold is a viable solution to this challenge

(R package SDMTools, VanDerWal et al. 2012). The function is based on the sampled ground reference data of one class as presence data, ground truth of the other three classes as absence data, and this for all four cases. While this is not specificity in a common sense it is well suited for defining a threshold. Values above this threshold, one for each class, were set to zero. Conclusively, the final prediction was based on a maximum rule of the individual OCC results. Accordingly, every pixel was allocated to the class with the highest probability value, resulting in a combined map where every pixel was associated either to one of the four habitat types or to no class. Maxent model building and model prediction was done with the Maxent Wrapper (Oldenburg et al. 2012) within the EnMAP-Box (Held et al. 2012). Threshold definition, threshold setting and merging of the four predictions were done in the R statistical environment (R Core Team 2013) using the packages raster (Hijmans, 2013) and SDMTools (VanDerWal et al. 2012).

2.3.5. Validation

The Maxent software provides information on the fit of the generated models using measures such as the area under the curve (AUC). However, we have no information about the absence of habitats in the landscape. Therefore, conventional validation measures are not applicable. The habitat presence data were randomly divided into test and training data (1:1). Based on these data, overall-accuracy (OAC), users-accuracy (AccUser) and producers-accuracy (AccProd) were calculated for the classification and confusion of the four habitat types (Table 2.1). It is important to note that these measures quantify in our case merely the con-fusion between habitats, but not the accuracy that was achieved in the detection of habitats within the landscape. For the latter, additional absence data would be required. In addition, the miss rate is given by dividing the number of falsely negative classified plots by the total number of plots. For further comparison, Cohens Kappa is provided (Cohen 1968). As a second validation approach we computed three values for each pixel (Figure 2.5). (a) We calculated how many classes were considered in the majority voting. This served as an assessment of how many of the four different classes had values larger than zero after setting the threshold and provides an overview about ambiguous or unambiguous decisions. (b) We computed the probability value of the most likely class in order to provide a general view of the strength of the decision. (c) We assessed the Shannon index as an expression of how certain the decision for the class with the maximum probability value was. Here an index of 0 indicates unambiguous conditions, high values indicate similar probabilities for different classes, resulting in uncertainty regarding the assignment to a single class. These three values provide complementary information about the certainty or uncertainty of classification in each pixel. In all three figures unstable conditions are shown in red, stable conditions in blue.

2.4. Results

As a first result, probability maps of occurrence were derived for each of the four habitats (Figure 2.3). These maps also illustrate that the frequency of habitats as well as the sharpness of their delineation varies from class to class. Merging the four individual habitat distribution maps results in the multi-class classification.

Table 2.1.: Confusion matrix of four habitat types: HT separability (training- and test-data (bold)).

		Observed				No. classified pixel	Acc_{User}
		6410	7120	7140	7230		
Predicted	6410	14 **16**	0 **0**	0 **1**	3 **5**	17 **22**	0.82 **0.73**
	7120	0 **0**	15 **16**	0 **0**	0 **0**	15 **16**	1.00 **1.00**
	7140	2 **1**	3 **3**	4 **2**	1 **1**	10 **7**	0.40 **0.29**
	7230	4 **4**	0 **0**	1 **2**	5 **6**	10 **12**	0.50 **0.50**
No. Ground truth		20 **21**	18 **19**	5 **5**	9 **12**		
Acc_{Prod}		0.70 **0.76**	0.83 **0.84**	0.80 **0.40**	0.56 **0.50**		
						OAC	0.73 **0.70**

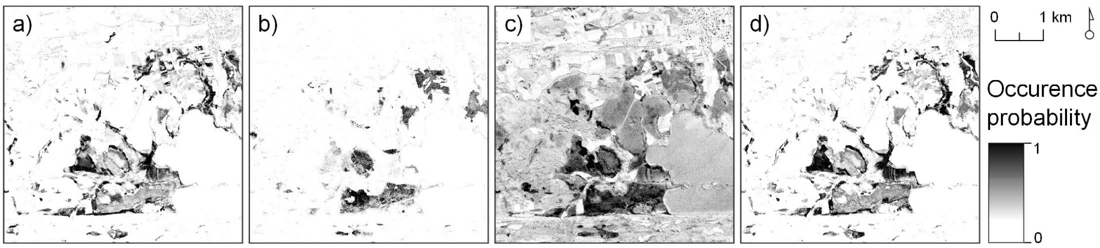

Figure 2.3.: Maxent classification output: occurrence probability of four different habitat type classes (a) HT 6410, (b) HT 7120, (c) HT 7140, (d) HT 7230.

The validation of this classification resulted in an OAC of 73% for training data and 70% for test data. The validation error was unevenly distributed across the classes. Degraded raised bogs (HT 7120) were very well predicted, but also the distinction between Molinia meadows (HT 6410), degraded raised bogs (HT 7120) and alkaline fens (HT 7230) was reasonable. Transition mires and quaking bogs (HT 1740) mixed up with other classes: AccProd varied between 40% and 84% (training 56% and 83%), AccUser ranged from

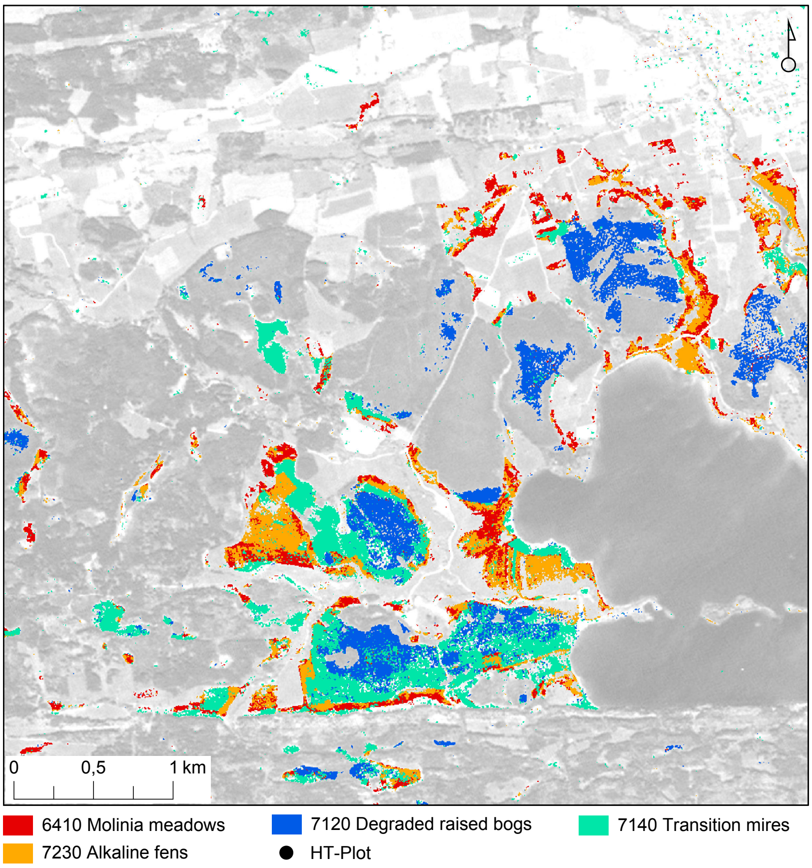

Figure 2.4.: Subset of the combined map of four habitat types.

29 to 100% (training 40% to 100%) (Table 2.1). Cohens Kappa was 0.58 for test data (training 0.63). The identification of habitat types in the unknown landscape matrix was possible with an underestimation of habitat occurrence of 8% (falsely negative classified divided by total number of plots). Figure 2.4 shows a subset of the map with the four habitat classes.

Figure 2.5 provides information on how many classes were involved in the pixel-wise decision process. 95.1% of all pixels were not assigned to any habitat type after the threshold setting. Of the classified pixels, 73% were assigned unambiguously. In 24%, 3% and 1% of the classified pixels there were two, three and more candidate classes (Figure 2.5a). Concerning the habitat types separability we were able to reach an unexpected classification depth (we are not aware of other work approaching this level of detail in similar applications). 58% of the probability values of classified pixels were in the range of 0.6–0.79, 25% of all probability values were above 0.8 (Figure 2.5b). The calculated Shannon index for each classified pixel is between 0 and 1.4, most of the pixels have

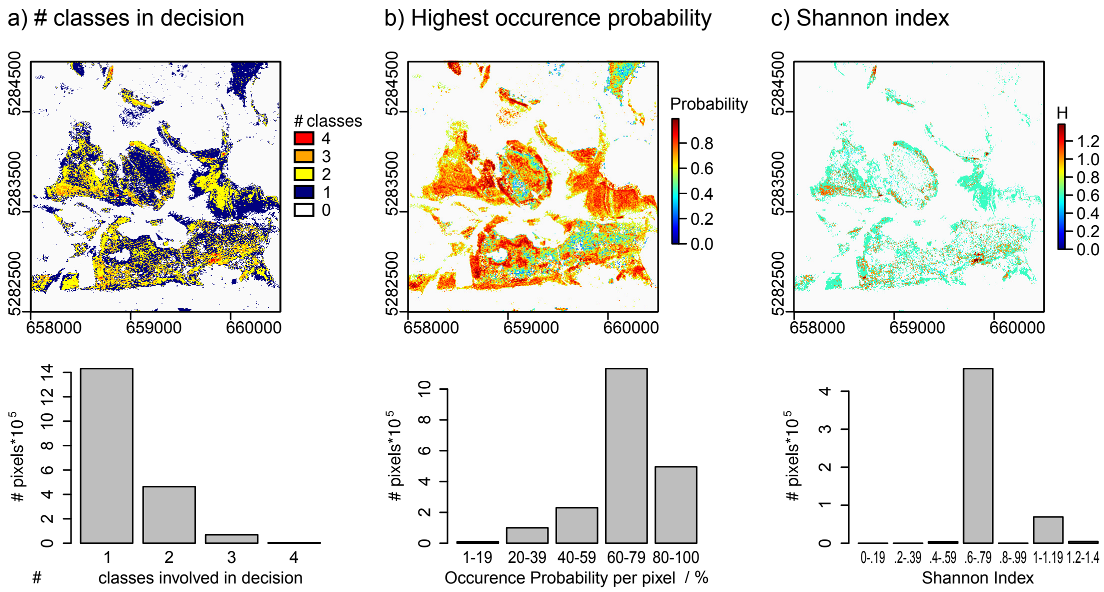

Figure 2.5.: *a)* Number of classes involved in decision process for each pixel. *b)* Highest occurrence probability value for each pixel. *c)* Shannon Index for each pixel.

an index of 0.6 to 0.8 or 1 to 1.2 (Figure 2.5c). Moreover, it could be observed that misclassified plots frequently feature a higher Shannon value than correctly classified plots (Figure 2.6). This relationship is comprehensible since high Shannon values indicate similar occurrence probabilities for all classes under consideration and thus a higher ambiguity of the decision. The same applies to the maximum probability values. Here, misclassified plots generally feature a lower maximum probability, indicating an increased likelihood of confusion.

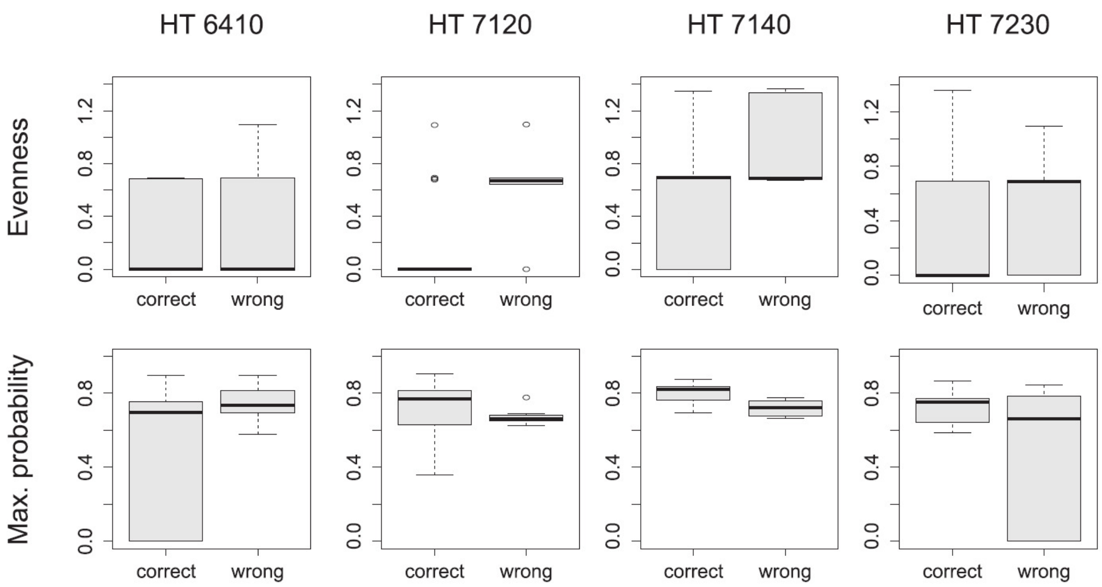

Figure 2.6.: Relationship between correct/wrong classification results four all 125 plots and Shannon Index together with maximum probability. The actual plots for each habitat type were separately divided into correct/wrong classified plots and whiskers-boxplots for their Shannon Index and maximum probability value are given.

2.5. Discussion

The task of identifying disperse patches of habitats can be hardly resolved using multi-class approaches (such as the maximum likelihood or support vector machines). These classifiers require a training set comprising all classes of the area to be represented in the reference data, which involves an extreme mapping effort. As an alternative, a mask can be used to exclude all areas which do not belong to one of the classes of interest. However, this requires a priori decisions or a pre-classification of the area. Methodological alternatives to conventional classifiers are known under the terms classification with reject option (Dubuisson & Masson 1993), partially supervised classification (Mantero et al. 2005, Marconcini et al. 2014) or one-class classifiers (Minter 1975, Phillips et al. 2004, Sanchez-Hernandez et al. 2007a).

We decided to use Maxent particularly due to the reported strength of solving complex classification problems with limited training data. An advantage of Maxent is its ability to deal with presence-only data and small survey sample sizes (Phillips & Dudik 2008). There is hence no need for ground reference information about the rest of the landscape. Non-linear relations and multi-dimensional feature spaces can be described (Elith et al.2011). Further, continuous output about the spectral properties that are used for habitat detection is given (Saatchi et al. 2008). However, as with all OCC a challenge is a satisfactory validation of the resulting models if just presence-only data is available.

Apart from the problem of finding the targets in a non-relevant matrix, the discrimination of similar habitats tends to be difficult. For example, the discrimination of types of grasslands that differ in shades of species composition has been rarely accomplished (Franke et al. 2012). Unfortunately, this level of discrimination is frequently key to the accomplishment of many habitat inventories. It has been proposed before to use multiseasonal remote sensing data to resolve this problem (Franke et al. 2012, Hunt et al. 2003, Toivonen & Luoto 2003, Vogelmann et al. 2011). The varying phenological development of individual species contributes to the overall reflectance. Accordingly, using several scenes from different times of the year could improve the detection of slight differences in species composition. The RapidEye sensor, which has a good trade-off of spatial, temporal and spectral resolution (Tyc et al. 2005), is well suited for tasks of multi-season remote sensing of vegetation targets.

The potential to discriminate vegetation types with a distinct phenological development may, however, be affected by an increased level of accumulated noise and inferences in multi-seasonal data. To take full advantage of a unique phenological development, it is inevitable that this development shows a synchronous trend across the area of investigation. This synchrony is sometimes affected by influences of phenology. Unfortunately, climatic effects may lead to a considerable asynchrony and cause a dissimilar spectral appearance of otherwise similar vegetation stands. The impact of such climatic effects on vegetation mapping is well known since the early days of remote sensing (e.g. Spurr 1948). In multiseasonal data, these effects may accumulate and severely impair the mapping accuracy (Feilhauer & Schmidtlein 2011, Feilhauer et al. 2013). Furthermore, disturbance events or differences in land use may hamper the use of phenological differences by adding local noise. In the present study, the benefits of multiseasonal data prevailed and enabled an accurate detection of habitat types.

Our results indicate that the chosen method is capable to accurately predict Natura 2000 habitat types. Concerning the habitat type separability we were able to reach a required classification depth with an OAC of 70%; identifying habitat types in the landscape matrix was possible with an underestimation of 8%. Also the second validation approach shows that the results of our classification approach are reliable. This validation results in a map indicating where the classification is more and less reliable. For 73% of all pixels classified as habitats, the classification was unambiguous. It has been shown that mistakes are more frequent where probability values of different classes for each pixel were more similar or in case of small maximum probability value of the winning class. These positive results were not granted since Maxent models are affected by a range of problems. For example, individual Maxent models result in probabilities that are influenced by sampling (Elith et al. 2011). Joining such results, as has been done here, needs some care. We used the same background data for all models, a representative sample of occurrences with no apparent sampling bias and a similar ratio between presence- and background-data. Validation shows that these measures reduce the error to a bearable minimum.

We can see that both AccProd and AccUser vary between the different habitat types (Table 2.1). Especially results for HT 7140 lacked robustness. This type consists of transition mires and is thus by definition a mixed class. Classes like this will continue to be a big challenge (Evans 2006, Schmidtlein & Sassin 2004).

Comparing our results with existing studies is difficult, since the problem of huge, unknown and non-relevant classes is commonly avoided by using masks or by working in areas without non-relevant sites. Hence, a well-established method of validation does not exist. We have to point out that most often validation examines the distinction of class of interest from the rest, whereas here separability of very similar classes from one another is measured. There are studies with similar goals and partially similar methods but the results are difficult to compare since confusion matrices are lacking or treating each class separately (Amici 2011, Li & Guo 2010). Other related studies are limited to one class of interest (Sanchez-Hernandez et al. 2007a, 2007b), in contrast to our study, where four habitat types are classified. Considering our results we like to recommend this simple and affordable approach for further studies on surveys of previously unmapped areas, identifying potential gaps in existing habitat inventories and checking for changes in the distribution of habitats. Open challenges identified in this study include the following points: (1) More adequate validation methods are urgently required. Such validation should take into account confusions with the landscape matrix instead of focusing solely on the confusion between habitats. Accordingly, some sort of efficient sampling still has to take place in the entire landscape. (2) Another task is to find a meaningful and reproducible solution for the definition of the threshold for the transformation of probabilities into binary information on habitat occurrence. Here, more research is needed. (3) For principal reasons, some problems may never be completely resolved: the influence of spatial non-stationarity on vegetation and spectral pattern is crucial, a problem which is attended just lately (Bruzzone and Persello 2009, Foody et al. 2006, Propastin 2009). Spatial non-stationarity in the relation between vegetation types and reflectance is induced by different phenological stages in different places at the same time of a year (Feilhauer & Schmidtlein 2011). For example, meadows in an area can feature similar species composition but different flowering aspects depending on their altitudinal position. To know about and deal with this variation requires more attention.

Compared to spectral libraries (Clark et al. 2007) we found no ill-posed problems (Hadamard 1902, Garabedian 1964) meaning that the relation between vegetation traits and reflectance was unambiguous. Given phenology, stress and stochasticity of species composition, the assumption that vegetation reflectance can be re-constructed from primary "pure" reflectance spectra is over-optimistic. We therefore think and support that field data will remain crucial for successful mapping of vegetation.

2.6. Conclusions and outlook

We successfully identified dispersed patches of four habitat types scattered across a complex background matrix of vegetation not relevant for nature conservation. With our parsimonious approach, it was possible to accurately delineate and to distinguish very similar habitat types, which is crucial for applications in conservation and management. In addition, the discrimination between habitats and non-relevant sites was rather satisfying. The chosen methodological approach has thus a promising potential for monitoring Natura 2000 habitats that tend to be rare in the landscape. It was possible to provide a consistent classification of a large area using a small ground reference sample. Still, it has to be kept in mind that the performance of any approach may depend on the vegetation types under investigation. Further work will thus be necessary to test the transferability of the method concerning time, area and target classes. Further research is also necessary in the field of threshold definition to reduce underestimation and scatter. The establishing of a conventional method of validation for approaches like this is of crucial importance.

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3. Identification of High Nature Value farmland with remote sensing and minimal field data

3.1. Abstract

In the last 50 years intensification of agricultural land use systems drastically reduced extensively used grassland areas. These areas are of high ecological value due to high species richness and occurring rare species. Therefore, recent European Union (EU) laws stipulate the conservation and monitoring of this farmland, also called “High Nature Value” (HNV) farmland. As a consequence of these new laws, a so called HNV indicator system was implemented that requires all EU member states to establish a nationwide monitoring system for HNV areas. These monitoring systems are challenged among other by the difficult differentiation between grassland types which today at fine scale is only possible with time and cost intensive field work. Due to this high work-load and financial limitations, nationwide field campaigns have to be sample-based and hence will not deliver a spatially consistent result. In this study, we examine whether low and High Nature Value grasslands can be differentiated with remotely-sensed reflectance data, which could support existing field survey-based monitoring approaches. We used multi-seasonal, multispectral remote sensing data (RapidEye) in combination with sparse field data (collected in southern Germany) and three one-class classifiers to classify A) HNV grassland against other areas and to differentiate between B) three quality classes of HNV grassland according to the current German HNV monitoring approach. The results for A) indicated high performances of the tested approaches to identify HNV grassland areas. Biased support vector machine delivered best overall results (high detection rate and low false positive rates). However, the results also showed a consistent underestimation of HNV grasslands. Results for B) showed that a separation into several HNV quality classes is not possible with any of the tested approaches. We conclude that with the presented approach HNV grasslands can be identified from the landscape matrix based on its spectral signal. Combining the presented approach with an object oriented classifier

or with land registry data could further improve the results.

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3.2. Introduction

Due to their high species richness and as habitats of numerous endangered species, non-intensively used grassland regions are primary targets of nature conservation in Europe (Dierschke & Peppler-Lisbach 2009, Rennwald 2000). In the European Common Agricultural Policy (CAP) (Council Directive: 1974/2006/EC) these kinds of grasslands are considered as an important part of High Nature Value (HNV) farmland. The concept of HNV farming was developed in the 1990s from a growing understanding that the conservation of biodiversity in Europe is linked to the persistence of low-intensity farming systems (Baldock et al. 1993). The HNV farmland definition differentiates three HNV types: i) farmland with a high proportion of semi natural features, ii) dominated by low intensity farming or a mosaic of semi-natural and cultivated land and large-scale features, and iii) as farmland supporting rare species or a high proportion of European or world populations of species (Andersen et al. 2003).

HNV grasslands are often leftovers from traditional land use and are hence found at low nutrient sites featuring habitats for specialist species (plants and animals) with narrow niches (Henle et al. 2008, Sukopp et al. 2006). HNV grasslands have therefore been assigned with a high conservation value (Critchley et al. 2003, Sullivan et al. 2010). Since the 1970s, due to the intensification of agricultural land use systems, the area of grasslands in general and of species rich HNV grasslands in particular is decreasing dramatically (Haber 2014, Korneck et al. 1998, Meisel 1983, Veen et al. 2009). Currently, permanent grassland covers 15% of the European Union (EU) and 34% of the European agricultural area (European Union 2010, Eurostat 2015). According to the European environmental agency (EEA 2010), today only one quarter of these grasslands can still be considered as non-intensive, meaning that most areas are already depleted of species. Since grasslands contribute an essential part of species richness (Veen et al. 2009) such a decrease is a major threat to the conservation of biodiversity (Stoate et al. 2009).

To limit further losses of semi-natural or extensive grasslands, several conservation programs were established. The aim of these programs is to ensure that high species richness will coexist alongside productive agricultural areas (Armsworth et al. 2012, Scherr & McNeely 2008). For an evaluation of the applied measures, some indicators have been proposed and put forward by the EU Rural Development policy framework (Benzler 2009, 2012). This also includes the HNV farmland indicator which aims on quantifying the proportion of ecological valuable farmland in Europe.

Since every EU state independently decides about the way to derive the HNV farmland indicator, a variety of differing approaches exists (Oppermann et al. 2012). In many cases available land use-, land cover-, remote sensing- or species-data have been used, while in some other cases specific field surveys have been conducted (Evaluation Expert Network 2009). However, no European wide standardized framework exists and some of the conducted approaches have either been highly work-intensive of were lacking accuracy. For example, the German Federal Agency for Nature Conservation found CORINE data as well as evaluations on farm-level too coarse for monitoring HNV farmland areas, since they often appear as small patches in a matrix of intensively managed areas (Begemann et al. 2007). Integration of the HNV farmland monitoring into other national programs was not achievable because of misfits in spatial resolution, temporal resolution or thematic content.

The current monitoring method in Germany for identifying HNV grassland areas uses a list of HNV character species for the identification of HNV grasslands (Benzler et al. 2015) (in this study, the focus lays on grassland areas, hence we refrain from presenting the additionally existing approaches to identify HNV crop fields or HNV agricultural landscape elements). Every four years, a number of fixed $1\,km^2$ sample areas are checked for the appearance of HNV character species to evaluate a trend in changes of grassland. In a hierarchic approach, every seemingly species-rich and homogeneous area is examined for character species by using transects. According to the number of character species the plot is assigned to one of three HNV quality classes (not to be confused with the three HNV types of Andersen et al. 2003 described above). The results of this sample based approach are then extrapolated at the national scale. Although this approach is already highly optimized in terms of workload, the regular monitoring is labour-intensive due to the relatively large amount of monitoring sites, which have to adequately represent approximately 5 million hectare of grasslands in Germany.

In this context, the application of (high temporal and spatial) resolution remote sensing data have been discussed in the scientific literature as an efficient supplement to field-based monitoring systems that are used to identify and monitor natural vegetation areas (e.g. Feilhauer et al. 2014, Förster et al. 2008, Rocchini et al. 2013, Schmidtlein & Sassin 2004, Schuster et al. 2015, Stenzel et al. 2014 and many more). Several more studies had a specific focus on HNV areas but mainly used comparably coarse remote sensing and other spatial data to identify areas of HNV farmland on broad scales (e.g., Weissteiner et al. 2011, Belenyesi et al. 2008, Pointereau et al. 2007, Samoy et al. 2007, Parr et al. 2006, Jackson et al. 2009). On the other hand, the number of studies on finer scales is very sparse. One exception is the study of Hazeu et al. 2014 who used fraction of vegetation cover and land cover/use data products derived from multi-seasonal SPOT4/5 and Rapid Eye data to map HNV farmland types. Additionally, multi-seasonal remote sensing data was used in a step-wise classification approach based on object-based image analyses to highlight changes in the HNV farmland landscape. Another relevant study stems from Sullivan et al. 2011 who studied the possibilities of using fine-scale spatial data to map semi-natural habitat cover on farms for the identification of HNV farmland in Ireland. Although not directly pointing on remote sensing data, the authors clearly state that the more commonly used broad scale mapping methods for HNV farmland have a high risk of overseeing farmland biodiversity on the individual farm level.

In our study, we addressed this knowledge gap by attempting to match the current German practice for surveying HNV areas in the field with remote sensing data. The current HNV grassland mapping procedure in Germany consists of (1) an identification of the HNV grasslands themselves and (2) a differentiation between three HNV quality classes. A differentiation of other (intensively used) agricultural areas is not relevant. With typical supervised classification methods in remote sensing, all classes need to be covered by the training data to ensure classification success. However, collecting sufficient and accurate training data (especially in non-relevant patches) is connected to financial challenges. This raises the question, whether alternative methods exist to differentiate HNV grassland from other grassland with remote sensing data. Potential approaches include the integration of a mask that can be used to exclude all areas which do not belong to the classes of interest, but this requires a priori information or a pre-classification of the area which again requires reliable reference information. Suitable methodological alternatives to conventional multi-class supervised classifiers include classification with reject option (Dubuisson & Masson 1993), partially supervised classification (Mantero et al. 2005) or one-class classifiers (Mack et al. 2016, Minter 1975, Phillips et al. 2004). These methods have in common that they focus on few or only one target class and thereby minimize the required reference information.

Here, we combine a small sample of ground reference data from relevant grassland classes with multi-seasonal, multispectral RapidEye data and recent one-class classifiers (OCC) from the field of machine learning. The big advantage of using an OCC is that it can deal with presence only data, so no sampling in non-relevant areas is needed. This can increase the efficiency of large scale mapping and monitoring as needed for HNV farmland monitoring. The proposed approach can only work (1) if the HNV grassland areas are spectrally separable from all intensively used grasslands (including various intensity levels and species compositions) and (2) if the three defined HNV quality classes differ in their spectral properties.

Based on earlier research, we hypothesize that a spectral separation of intensively and non-intensively used grassland might be possible due to differing functional traits of the two grassland types affecting the spectral properties of the plants. While in highly intensive grassland areas, plants are typically not facing shortage of environmental factors such as nutrient or water supply, non-intensively used grasslands can often be found to be short on at least one of these factors. In non-limited environments, competitive species featuring for example tall-growing, productive grasses, or herbs with large leaves both with high chlorophyll content typically prevail, while in limited environments, other species featuring properties adapted to survive under non-optimal conditions (e.g., smaller or shorter leaves, thicker wax layers, etc.) occur (Cingolani et al. 2005, Pierce et al. 2013). In addition the effect of intensive or extensive mowing or grazing has a huge impact on occurring plant functional traits. Such differences in traits were found to influence the spectral properties of plants and hence support their differentiation (Kattenborn et al. 2016 (submitted), Schmidtlein et al. 2012). On the other hand, we assume that the distinction of multiple HNV quality classes will be more challenging as their species composition largely overlaps (see also Section 3.3.1).

Accordingly, the main objectives of the present study are to (i) investigate if HNV grassland can be accurately discriminated against all other landscape elements using remote sensing and plot based field data of HNV grassland only, (ii) to analyse if it is possible to use the same method to differentiate between HNV quality classes, and finally (iii) to compare different OCC algorithms for their practicality to address objectives (i) and (ii).

3.3. Data and methods

3.3.1. Field based data

We defined HNV grassland based on the current German approach of HNV monitoring (Benzler et al. 2015) and also sampled our plots accordingly. The core element of the approach is a list of HNV character species which contains species that are not necessarily rare or endangered, but are characteristic for extensively used grasslands of a region. Examples of such indicator species are *Achillea ptarmica L.*, *Knautia arvensis (L.) Coult.*, *Succisa pratensis Moench*, *Tragopogon pratensis L.* During the field survey, each homogeneous area (in terms of species composition) is screened from outside the field for occurrences of HNV character species. Then, every seemingly species-rich plot is examined for HNV character species by using a $2\,m \times 30\,m$ transect. In the current

German approach, each transect is then assigned to one of three quality classes based on the number of occurring HNV character species (not to be confused with the three HNV types of Andersen et al. 2003):

- HNV 1: Exceptionally High Nature Value farmland (8 or more HNV character species).
- HNV 2: Very High Nature Value farmland (6 or 7 HNV character species).
- HNV 3: Moderately High Nature Value farmland (4 or 5 HNV character species).

The different classes of HNV grasslands in the study area have been inventoried during field surveys in the growing seasons of 2011 and 2012.

The study site is located in southern Germany, in the foothills of the Bavarian Alps, and covers an area of $20\,km \times 50\,km$ (Figure 3.1). It is characterised by grasslands, extensive peatlands, mires and forest. The moraine bedrock in the study site is calcareous and therefore most minerotrophic plant communities are calciphil. The grassland in the area of investigation had been shaped by a variety of land use systems, from intensive to extensive and small to medium parcel sizes. Peatland has been under severe anthropogenic pressure through drainage, cultivation and peat removal (Franke et al. 2012).

Seventy-five grassland sites were surveyed in the field. The location of the plots was determined with a differential GPS receiver of type Magellan (TM) Mobile Mapper 6 (positional error $< 2\,m$). An initial set of reference plots was placed randomly within the study area. Plots occurring outside of grasslands or that did not pass a homogeneity check (we visually checked that the corresponding RapidEye pixel lay in a spectrally homogeneous area and not at a border between two spectrally differing areas) were removed before the field survey. Following the official guidelines of the German HNV monitoring system, all HNV character species and additionally the dominant species (in terms of coverage) were recorded along the transects. The HNV quality class was then assigned based on the number of occurring HNV character species, while the dominant species were not directly used in the study but gave some ecological information about each plot.

From the 75 surveyed grassland sites, 43 were assigned to the non-HNV grassland class, 12 to HNV-3, 14 to HNV-2 and 6 to HNV-1 (a total of 32 HNV grassland sites). For extended validation, 28 additional non-grassland plots were obtained from the LUCAS (Land Use/Cover Area Frame Statistical Survey) database. Implemented by Eurostat, this survey produces harmonized land cover/use statistics (`http://www.ec.europa.eu/eurostat/web/lucas`) and gave in our case information about presence or absence of grasslands. All non-grassland plots extracted from the LUCAS data were additionally verified by visual comparison with the RapidEye data and by considering field photographs provided by LUCAS. Additionally, we excluded plots located at the edges of grassland.

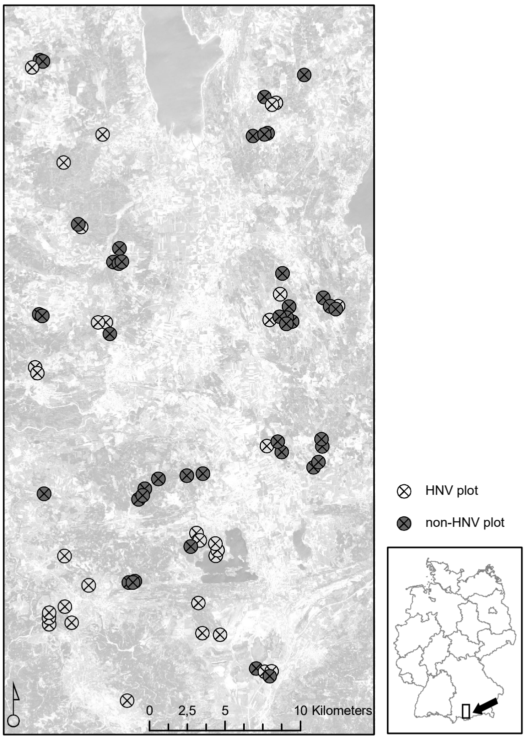

Figure 3.1.: Location of surveyed grassland sites within the study area in Bavaria, Germany.

3.3.2. Remote sensing data

We used data from RapidEye, a system that features a high spatial ($5\,m$) and temporal (about 10 days) resolution and provides spectral information in the blue ($440-510\,nm$), green ($520-590\,nm$), red ($630-685\,nm$), RedEdge ($690-730\,nm$) and NIR ($760-850\,nm$) region of the radiometric spectrum. When remote sensing data are used for vegetation analyses of small habitat patches, high spatial resolution of the imagery is desirable (Gillespie et al. 2008, Turner et al. 2003). Furthermore, the availability of spectral information in the near infrared (NIR), and the RedEdge is supposed to be valuable as the NIR carries valuable information to separate plant species (Fassnacht et al. 2014, Feilhauer et al. 2015). We used five images per year, unevenly distributed over the vegetation period from April to September 2011 and 2012 (see Table 3.1). The uneven distribution is a consequence of limited data availability due to cloud cover. The decision to use five images was based on earlier research that showed that less than 5 images led to notably worse results, while using more than 5 scenes resulted in only marginally improved results (Stenzel et al. 2015). The RapidEye data were delivered as Level-1b imagery and were further pre-processed with the automatic processing system CATENA (Krauss et al. 2013). For further information see Stenzel (2014). With five images each consisting of five spectral bands we built an image stack of 25 bands for each year, which served as input to the subsequent classification procedure. While free RapidEye data is available in limited amounts for scientific purposes, the current cost of such high-resolution imagery (RapidEye, Ikonos, Geoeye) is around 1-14€$/km^2$ depending on sensor and acquisition mode (Ørka & Hauglin 2016).

Table 3.1.: Dates of RapidEye data.

2011		09.05.	25.05.			23.08.		06.09.		26.09.
2012	26.04.			26.05.	13.08.		29.08.		08.09.	

3.3.3. Classifiers

As outlined in the introduction, there is an increasing demand toward classification techniques that are able to identify habitat patches in a matrix of non-relevant landscape classes (Boyd et al. 2006, Foody et al. 2006). One-class classifiers (OCC), based on presence-only data, are able to map patches of specific target classes without ground reference from all other non-relevant classes. In our study, we compare the usage of the three OCC-algorithms: Maxent, One-class support vector machine (OCSVM) and Biased support vector machine (BSVM). In addition, we compare the OCC results for the differentiation of several HNV quality classes with results obtained from a supervised support vector machine (SVM) classification (multi-class classifier).

The Maxent classifier is based on the maximum entropy approach (Shannon 1948, Sethna 2006). This method has earlier been applied for modelling potential species distributions based on environmental parameters (Elith et al. 2011, Dudik et al. 2004, Phillips et al. 2004). The algorithm is able to perform efficiently even with few occurrence records (Pearson et al. 2007, Wisz et al. 2008). We used Maxent version 3.3.3k with default settings and have chosen the logistic output format. The algorithm has been implemented in a multi-platform Java based software called Maxent (Phillips et al. 2004).

The semi-supervised one-class SVM (OCSVM) is one of the most common positive-samples-only classifiers in remote sensing. It was formerly used for anomaly detection (Banerjee et al. 2006) or studies about incomplete and unreliable training data (Munoz-Mari et al. 2007) and has recently been engineered for change detection (Camps-Valls 2008). When few or less precise training samples are available, the OCSVM can produce unreliable results (Munoz-Mari et al. 2010). Therefore, as with other pattern recognition and machine learning algorithms, it is crucial to parameterize the OCSVM with care.

The biased SVM (BSVM) is a special form of a binary SVM and is adapted to solve an OCC problem with a positive and unlabelled data training set. It maximises sample size while minimizing numbers of unlabelled samples classified as positive. It also constrains positives to be correctly classified including noise error. Therefore the two main parameters on positive and negative errors are weighted separately (Liu et al. 2003). We used the R-package 'one-class' which provides extensive possibilities for parameter tuning and easy data handling for Maxent, OCSVM and BSVM (Mack 2015).

For the attempts to classify multiple HNV quality classes, we additionally tested a multi-class SVM algorithm. This algorithm can be considered standard in the supervised classification of remote sensing data. Here, we first applied a minimum noise fraction (MNF) transformation (Green et al. 1988) to the RapidEye raster stack. Earlier studies have shown that using the first few MNF components as input to a supervised SVM leads to generally high classification performances for separating vegetation species (Fassnacht et al. 2014) if highly correlated data (e.g., hyperspectral or multi-temporal) are used. Subsequently, the SVM classification was based on the available reference data from the three HNV quality classes and a workflow that was earlier described by Fassnacht et al. (2015). In short, we used a SVM algorithm implemented in the "e1071" package of R and applied a radial basis function kernel. Based on the reference data, the classifier was tuned for the two kernel parameters gamma and cost with an automated grid search. This automated grid search allows to optimally adapt the classifier to the data while at the same time prevents over-fitting (see Kuhn & Johnson 2014 for more detailed information).

3.3.4. Classification scenarios

For monitoring HNV grasslands it is interesting to not only differentiate between HNV grassland and the rest of the landscape, but also between the three different HNV quality classes. Therefore, we applied the classifiers to two scenarios: A: HNV grassland vs rest ('finding HNV grassland') and B: 3 classes HNV-1, -2, -3 vs rest ('differentiating HNV grassland') (Figure 3.2).

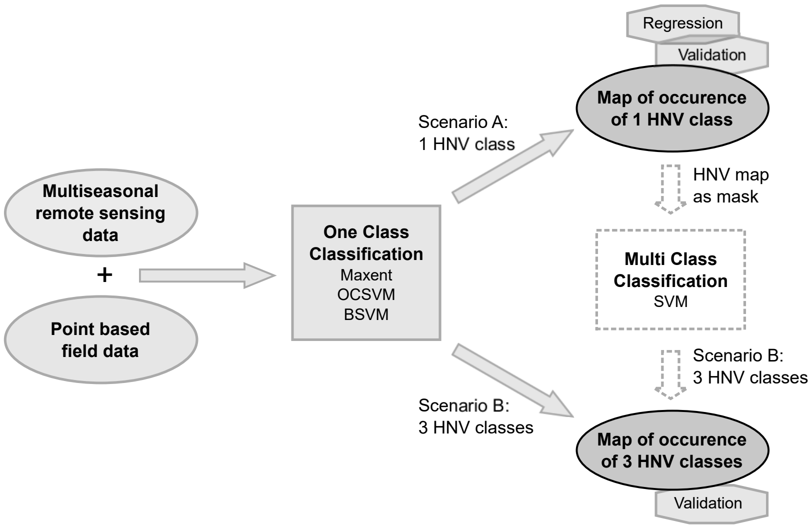

Figure 3.2.: Workflow.

3.3.5. Classification process

First, the OCC models were trained with the extracted reflectance information from the positions of the surveyed sites and the corresponding information on the categorical classes from the field survey. Afterwards the trained OCC models were applied to the full RapidEye scene.

The derived OCC results provide a pixel-based value of probability of occurrence for each class. All results were rescaled from zero to one. To delineate HNV grassland from the rest of the landscape, we had to define an appropriate threshold of probability. Earlier studies described an optimal threshold as the threshold that minimises scatter and simultaneously minimises missed habitats. This translates into a threshold where sensitivity equals specificity. This threshold can be automatically retrieved with available tools (R package 'SDMTools': VanDerWal et al. 2012) and was shown to be successful in former OCC studies (e.g., Stenzel et al. 2014). For Scenario B, the three predictions for the three HNV quality classes were joined into a single map. Every pixel was allocated to the class with the highest probability value of the three individual OCC runs. This resulted in a map where every pixel was associated either to one of the three HNV quality classes or to none.

Being aware that in Scenario B alternative approaches to OCC exist and are more commonly used, we wanted to compare the OCC approach against a multiclass approach. That is we calculated a SVM classification for the HNV-1, -2, -3 classes. Because we have no class information about the rest of the landscape, we used the result of Maxent for 2011 in Scenario A as a HNV grassland mask which we applied to the RapidEye image stacks. Within the remaining pixels the 3 different HNV quality classes were differentiated. The decision to use the Maxent result of 2011 as mask was somewhat arbitrary but based on the good classification results of the corresponding model runs in combination with the visual impression of the classification maps.

All classifications were conducted for two data sets stemming from 2011 and 2012 which allowed us to draw some conclusions on the robustness of the applied methods. Field data for each class was divided randomly into training and test data (2:1), 20 model iterations were run and mean results are reported. All processing was done in the statistical environment R (Raster package: Hijmans 2013, R Core Team 2013).

3.3.6. Validation

The major benefit of the OCC approach - the ability to deal with presence only data - is challenging for validation. For OCC approaches, conventional validation measures are difficult or impossible to apply or are only partly suitable to assess reliable classification accuracy. As a consequence, we calculated several statistical measures of classification performance that could be obtained based on the available reference data. To get information about classifier performance concerning absences of HNV grassland areas we applied two dataset: (1) absences from LUCAS data (LUCAS-no-grassland plot: bareland, water, urban area, woodland, wetland, cropland), (2) absences from own field work (grassland plots that are non-HNV-grassland).

Sensitivity (true positive rate or producer's accuracy): This measure describes how many of the areas classified as HNV grassland indeed are HNV grassland areas. With the HNV grassland presence data (test data) we calculated sensitivity or true positive rate (TPR) defined as:

$$TPR = \frac{\sum TP}{\sum (TP + FN)} \tag{3.1}$$

where TP are true positives and FN are false negatives. Hence, the TPR describes the proportion of HNV grassland reference areas that are correctly classified as such.

Specificity (true negative rate): For the two datasets of absences (non-HNV-grassland, LUCAS-no-grassland) we calculated the specificity or true negative rate (TNR) defined as:

$$TNR = \frac{\sum TN}{\sum(TN + FP)} \tag{3.2}$$

where TN are true negatives and FP are false positives. Hence the TNR describes the proportion of non HNV grassland areas that are correctly identified as such. As we calculated TNR separately for the non-HNV-grassland plots of our own reference data and for the LUCAS-no-grassland plots we can also make distinct statements concerning the separability of (1) HNV grassland areas from non-grassland areas and (2) HNV grassland areas from other intensive grassland areas.

Overall accuracy: Last, we calculated with all test data (presence test data, non-HNV-grassland data and LUCAS-no-grassland data) the overall accuracy (OAC) defined as:

$$OAC = \frac{\sum TP + \sum TN}{\sum(TP + TN + FP + FN)} \tag{3.3}$$

As the quantitative validation of the OCC maps is challenging, we additionally judged the quality of the obtained classification map based on a visual comparison between the classification maps and the remote sensing data. Such a visual assessment can serve as a supplement of the numeric validation procedure and is also important to judge the suitability of the produced maps for supporting practical field work. The location of the presented subsets of the classifications maps were selected so that they contain samples of all three HNV quality classes and are representative for the study area.

Comparable validation for the multi-class SVM approach was challenging. Applying the Maxent 2011 mask was a necessary restriction, to exclude all non-HNV-grassland areas, but leads to change in available validation samples. Moreover it leads to the situation that one could not include LUCAS-no-grassland or non-HNV-grassland plots into validation, since the mask predefines that all remaining area is one of the three HNV grassland classes. Therefore just overall accuracy concerning the confusion matrix of the three classes against each other is calculated for the multi-class SVM, so the comparison of the OCC results with the premasked SVM classification result is limited and focuses on visual comparison.

Additional insights were obtained by regressing reflectance values against numbers of HNV character species per plot. This was done using partial least squares regression (Wold et al. 2001) as implemented in the autoPLS package (Schmidtlein et al. 2012) and served as a test of linear relation between spectral information and HNV character species numbers.

3.4. Results

For Scenario A, that is classification of HNV grassland area against the rest of the landscape matrix, we observed reasonable sensitivity values (true positive rate) of 72%, 75% and 81% for Maxent 2011, Maxent 2012 and OCSVM 2011, respectively, but a low value of only 53% for OCSVM 2012. The BSVM resulted in a perfect sensitivity (100%). Specificity (true negative rate) for LUCAS-samples (non-grassland areas) is almost always up to 100%. Specificity values obtained with non-HNV-grassland field samples are reasonable for both Maxent and OCSVM 2011 (86%, 74%, 77% respectively) but only fair for OCSVM 2012 (65%) and almost perfect for BSVM (98%, 95%). Overall accuracy is reasonable for Maxent and OCSVM 2011 (85%, 82%, 83%) and fair for OCSVM 2012 (71%) and again almost 100% for BSVM.

For Scenario B, that is the differentiation of the three HNV quality classes against each other and the landscape matrix, the sensitivity values drop for all approaches. Sensitivity does not reach reasonable values for Maxent (59%, 59%), is even worse for OCSVM (44%, 28%) but shows reasonable values for BSVM (94%, 81%). In the case of the no-grassland areas from the LUCAS data, specificity is almost perfect for Maxent (93%, 100%), reasonable for OCSVM (89%, 89%), and perfect for BSVM. Specificity for non-HNV grassland samples is varying a lot between the different approaches (Maxent: 44%, 65%, OCSVM: 51%, 65%, BSVM: 84%, 79%). Overall accuracy is reasonable for Maxent (62%, 73%) and fair for OCSVM (59%, 60%), and reaching reasonable values of 91% and 89% for BSVM. The overall accuracy for the premasked multi-class SVM reaches 58% and 55%, but keep in mind that comparison is limited due to reduction of validation data set (Table A.4; Figure 3.5).

Based on the accuracy measurements, BSVM resulted as the most suitable classifier to identify HNV grassland in our test area and to differentiate between the three HNV quality classes. Maxent and OCSVM both reached moderate accuracies, with the OCSVM being slightly worse in most cases. The BSVM reaches high OAC values in both scenarios but these values are somewhat relativized by an examination of the actual classification maps (see subsets in Figure 3.3 and Figure 3.4). BSVM produced results in which classes were accurately differentiated on the reference plot scale, but the HNV grasslands areas in general seem to be notably underestimated. This can for example be observed by focusing on the shape of the agricultural field (in the false colour composite panel) in which the HNV grassland sample plot of Figure 3.3 is located. Supposedly, the whole field would be

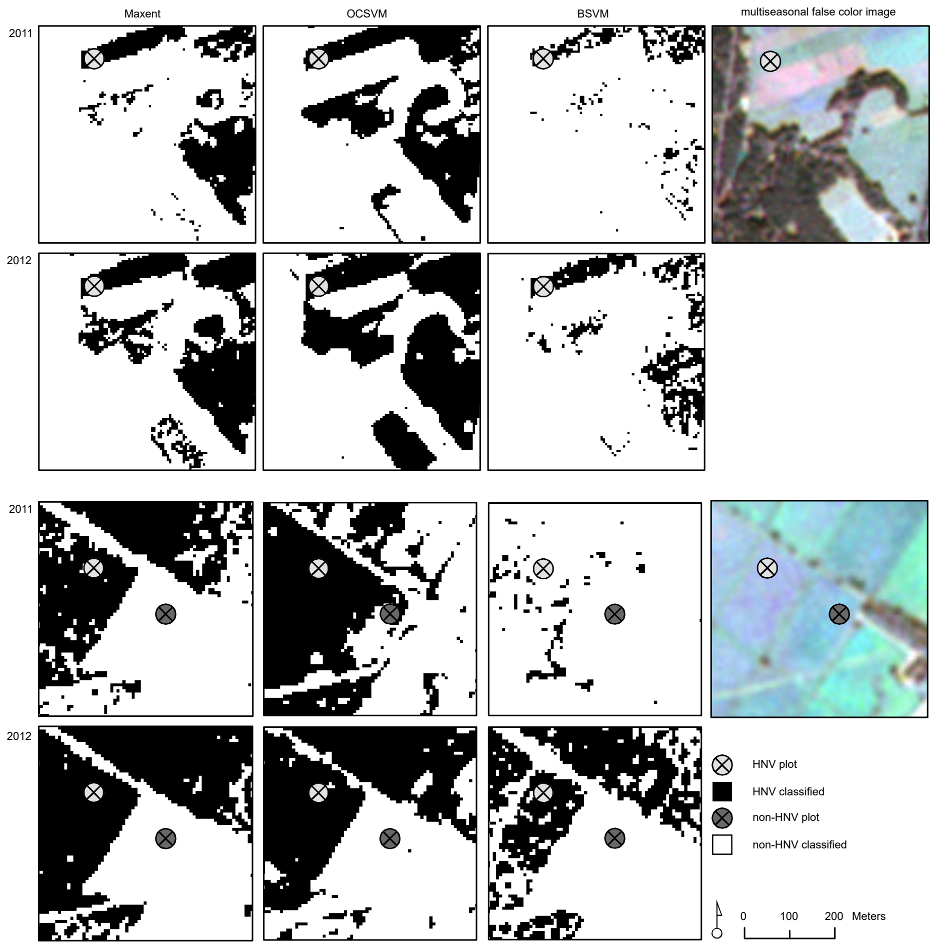

Figure 3.3.: Subset of the classification maps (Maxent, OCSVM, BSVM) for HNV grassland vs rest at two actual plot-sites, plus multiseasonal false colour image (May11_band4, Aug11_band4, Sep11_band4) of the site.

classified into the HNV grassland area when applying field methods, while the BSVM only classified a small fraction of the field into the target class. Furthermore, for Scenario A, the classification maps of the BSVM show increased variability across the two examined years when compared to Maxent and OCSVM (Figure 3.3), which gave relatively stable classification patterns across the years. Examining the classification maps of scenario B a high instability both for classified area as well as for the different HNV quality classes can be seen for every classifier and for the different years. The most stable results can be recognised for the premasked multi-class SVM approach (Figure 3.4).

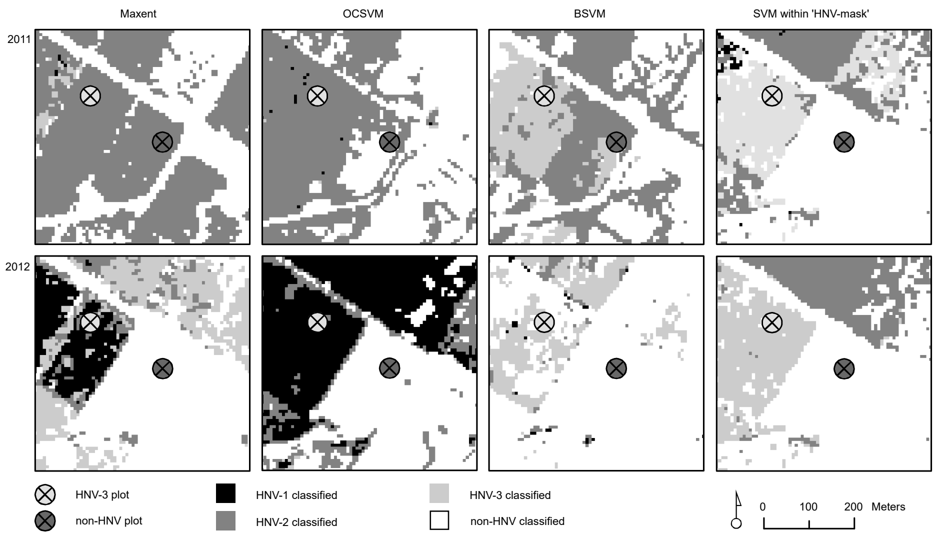

Figure 3.4.: Subset of the classification maps (Maxent, OCSVM, BSVM) for HNV-1, -2, -3 vs rest at an actual plot-site, plus results of the multi-class SVM (within the masked area that was defined as HNV grassland by Maxent 2011 classification result (see Figure 3.3).

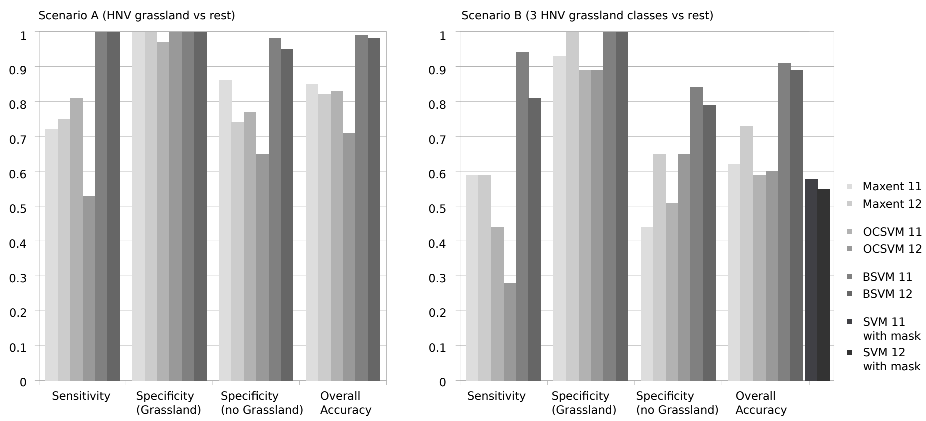

Figure 3.5.: Accuracy measurements for Scenario A and B for the different classifiers for 2011 and 2012. Sensitivity, specificity, Overall accuracy.

3.5. Discussion

Up to now, the potential of remote sensing for the detection of high ecological value grassland areas (such as High Nature Value (HNV) grassland) has barely been studied on fine scales. However, spatially explicit data from remote sensing could provide important information for applications such as biodiversity conservation or monitoring of land use intensification and is also needed for reports to the EU Rural Development policy framework. Here, we tested the application of recent implementations of one-class classifiers (OCC) to map HNV grassland against all other landscape elements from multi-temporal RapidEye data (Scenario A). Furthermore, we extended the approach with an additional subdivision of the HNV grassland areas into three sub-categories defined by the German Federal Agency for Nature Conservation (Scenario B).

From the tested approaches, BSVM provides the best accuracy measures in all cases, followed by Maxent and OCSM with OCSM reaching notably lower accuracies. These three OCC can be distinguished into two groups depending on the data used for training: P-classifiers are only trained on presence samples of the target class (P for positives), PU-classifiers additionally learn from unlabelled (U) samples (such as background samples). While OCSVM is a P-classifier Maxent and BSVM belong to the PU-classifiers. The better and more stable performance of Maxent and BSVM (Baldeck & Asner 2015, Li & Guo 2010, Liu et al. 2003, Mack et al. 2016) is likely to be based on the additional information from the background data, thereby making PU-classifiers usually more expensive in respect of processing time (Munoz Mari et al. 2010).

Separating HNV areas from the landscape matrix worked almost perfect for BSVM and fine for Maxent and OCSVM, but the separation of the three HNV quality classes was not possible with Maxent and OCSVM. Given the small size of training and test samples and the high variability in species composition of the examined HNV quality classes a high underestimation of the target class, especially regarding Scenario B, could be expected and was confirmed by the medium sensitivity values. Specificity showed in all cases that HNV grassland could be well separated from other landcover classes (specificity LUCAS data) with high accuracy. The differentiation between HNV grassland and other grasslands (specificity of non-HNV-grassland) was more complicated as indicated by dropping accuracy measures. Nevertheless, accuracies were still reasonable for Scenario A (all classifiers) while for Scenario B only BSVM provides reasonable results. The observed results vary between the years, but we could not identify a clear trend concerning this variation. Only BSVM performed consistently better for the year 2011. However, the differences to 2012 are minimal. There are obvious reasons for variations of the results between the years including slightly varying farmland management, phenology and different dates for data recording. Varying classification results due to phenology have been reported frequently in earlier studies attempting vegetation classification from remote sensing data (Blackburn & Milton 1995, Key et al. 2001). However, based on our results, we can only confirm earlier findings (Stenzel et al. 2015) that the applied number of five annual RapidEye scenes seems to deliver comparably stable results in terms of accuracy.

While the numerical validation of the classifications indicated high performances for Scenario A, visual interpretation of the resulting maps slightly lowered the expectations. The maps of Maxent and OCSVM which both produced less accurate results according to the obtained performance measures, showed an overestimation of the actual HNV grassland areas. Contrary, the maps of BSVM showed a consistent underestimation of HNV grassland when assuming a spatial consistency of the assigned class within an individual field. This also indicates a slight over-adaptation of the BSVM to the data.

Putting these findings into the view of a practitioner, the BSVM could be a valuable tool to reliably identify HNV grassland areas without including too many false positives. This would help to avoid wasting resources by sending field crews to areas wrongly classified as HNV grassland. At the same time, the BSVM is less suitable for mapping the actual extent of HNV grassland areas, as it most probably will underestimate the areas according to the field guidelines. For operational application, a combination of BSVM results with land-registry data could be a suitable approach to identify fields with potential HNV grasslands. On the other hand, the Maxent classifier might be a better application oriented choice for mapping the actual HNV grassland area. Maxent showed reasonable accuracies and high temporal stability (the differences between the mappings results of the two years were relatively low). Judged on expert knowledge of the area, the presumable borders of the HNV grassland areas are mapped reasonably well. Therefore it could support a preselection for the actual field work.

For making any of these approaches interesting for operational approaches a cost-efficiency analysis would be required. Such an analysis would have to compare the additional cost caused by the remote sensing data against the savings obtained by a potentially more efficient field campaign and the additional information provided based on the spatial consistency of the remote sensing product. Such cost-efficiency studies are still very sparse in the remote sensing community but have been presented for example in a forestry context (see Fassnacht et al. 2016 for a short summary). Newly available free remote sensing data for example from the recent Sentinel-2 mission could further foster remote-sensing based approaches for monitoring HNV areas. The lower spatial-resolution of Sentinel-2 could be an obstacle for the approach in the presented study but this could be partly compensated by the increased spectral information. Further research is required to draw final conclusions on this matter.

From an ecological perspective, the good results for Scenario A match our hypothesis that the functional traits shaping the reflectance properties of species in intensively used grassland areas differ from those of species in extensively used HNV grassland areas and conforms with earlier studies (e.g., Schmidtlein et al. 2012). A notable correlation between grassland usage intensity and optical remote sensing data has already been identified in earlier studies (e.g., Franke et al. 2012). Franke et al. 2012 also pointed out that spatially explicit data on grassland use intensity could provide valuable information for biodiversity conservation as well as for monitoring land use intensification in areas with high nature value which agrees with our findings.

For Scenario B, our results showed that with the given approach there is no relevant signal in the reflectance of grasslands to divide it into the defined HNV quality classes. This again matches our hypothesis. The definition of the HNV quality classes based on character species leads to a situation in which a single occurrence of one HNV character species makes the differences between classes HNV 1 and 2 (or 2 and 3). As none of these individual character species is likely to make up for a notable portion of a 5 by 5 m RapidEye pixel, it seems obvious that a differentiation of the HNV quality classes based on their spectral properties will be challenging in most cases. This is also mirrored in earlier studies on remote-sensing based estimations of alpha-diversity in grasslands which typically reported notably higher error rates than a single species (e.g., Hall et al. 2010). As a consequence, the results for Scenario B are all notably worse than those of Scenario A (Figure 3.5, Table A.4). Highest OAC values were produced by the BSVM, followed by Maxent. OCSVM was outperformed in nearly every case of Scenario B. Focusing on the classification maps for Scenario B, huge differences in the classification patterns between the classifiers as well as between the two years can be observed (Figure 3.4). More or less the same areas are addressed as HNV grassland, but the variability of the HNV quality class allocated to each pixel is high. This applies to all of the tested classifiers and therefore, the still very high accuracies reported for the BSVM (in all validation cases) may be seen as a good example for the existing problem of validation when reference data is as sparse as in the current case: The reported accuracies are correct for what they are testing (i.e. the quality of the model based on the available samples), but they do not necessarily agree with the wall-to-wall mapping accuracy or reliability. The difficulty to separate the three classes of HNV grassland with the applied remote sensing data is further confirmed by the multi-class SVM approach. Even so the visual impression of the SVM maps gives the most stable results (Figure 3.4), there is still a lot of fuzziness in the maps, and confusion matrix of the three different classes gave only fair results.

These results indicate that a separation of the three current HNV quality classes, defined by occurrence of special HNV character species, cannot be accomplished at least with this kind of multispectral data and with a pixel resolution of $5\,m$. To further examine this assumption that the separability of the three HNV quality classes is not possible due to their spectral similarity, the RapidEye reflectance values were regressed against plot HNV character species number by partial least squares regression (Wold et al. 2001) using the autoPLS package (Schmidtlein et al. 2012). This resulted in a R^2 value of 0.17 for the calibration and 0.07 for the validation set. This further underlines that there is not much detectable variability within the spectral information that relates to the number of HNV character species and therefore the defined HNV quality classes.

The results of our study are closely related to the addressed HNV farmland type (extensive grassland) and its quality classes. Earlier studies focusing on HNV farmland mostly addressed other HNV farmland types which focuses on structural diversity of agricultural areas (Weissteiner et al. 2011) which in most cases also led to the application of spatial data with coarser grain (Parr et al. 2006, Pointereau et al. 2007). Furthermore, as Hazeu et al. 2014 have already pointed out: all classification methods to identify HNV farmland with remote sensing data must be adapted to regional characteristics such as field size, type of landscape in regard to the complexity of the HNV farmland definitions, as well as temporal variability and bioclimatological characteristics.

3.6. Conclusions and outlook

An accurate pre-identification of potential High Nature Value (HNV) grasslands from satellite data could be of help for nature conservation administration when planning obligatory field surveys. Here, we tested the suitability of multi-temporal, multispectral RapidEye data in combination with recent one-class classifiers to differentiate three HNV quality classes of farmland areas in a diverse agricultural landscape in South Germany.

Our results showed that the differentiation of the three HNV quality classes (defined based on the number of characteristic HNV species) was impossible with multitemporal RapidEye data, due to lack of spectral variability between the three classes. However, the differentiation between HNV grassland and the rest of the landscape was successful.

Further improvements of these results could be achieved by integrating more spectral information (e.g., from new systems such as Sentinel-2 or upcoming hyperspectral missions) and by further optimizing existing one-class classifier algorithms (e.g., more sophisticated parameter tuning). Embedding the presented classification scenarios into an object-based approach could be beneficial to improve on the mapping omissions which were observed for the BSVM - the most successful algorithm in the sample-based evaluation.

Generating a HNV grassland mask by excluding a huge amount of the rest of the landscape in which with a very high probability no HNV grassland is occurring could reduce the amount of fieldwork to a more manageable extent. This could be valuable to support field campaigns and reduce related costs by reducing the frequency of erroneous field visits to non-HNV areas. Also the possibility of using a multi-class classifier approach with an OCC HNV grassland mask has to be studied further.

Although HNV farmland detection methods are in general to some point promising, remote sensing does not provide the appropriate solution for adequate monitoring alone. Especially the differentiation of several grassland usage intensity classes due to their similar plant functional traits - and hence similar spectral properties - is challenging.

Acknowledgement

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4. How do landscape patterns affect the mapping of rare target classes? – Remote sensing based classification of habitats with Maxent

4.1. Abstract

For conservation purposes robust and standardised monitoring methods are needed. If remote sensing based mapping of rare habitats is attempted in a landscape with many other land-cover classes, one-class classifiers (OCC) are a promising option. The validation of OCC results is complex yet crucial and it may be affected by the landscape composition and the sample size. Due to this, the robustness and weak spots of an OCC were tested in this study with regard to their effects on the accuracy measurements and therefore on the reliability of the results. For this purpose artificial landscapes were generated to avoid the typical problem of case-studies, typically only making locally valid statements about the suitability of a tested approach. On the contrary, simulated distribution data provides complete knowledge about the properties of the target class and the landscape. Therefore, assessing and discussing the robustness of OCC for usage with remote sensing data is possible in a more objective way. In the presented study, the performance of the OCC improved with an increasing number of target samples for training, as well as with an increasing number of background samples for training. In the latter case the study revealed a saturation and decrease at a certain number of background samples. Results were inconclusive with respect to the prevalence of the target class in the artificial landscape. OCC performance increased with a decreasing number of pixels from similar classes in the artificial landscape. Whereas results concerning target sample size and the amount of similar classes in the background confirmed conclusions of earlier studies from the field of species distribution modelling, results for background sample size and prevalence of target class gave new insights and a basis for further studies and discussions. The tested OCC Maxent proved to be a robust and reliable classifier for mapping vegetation types

in combination with remote sensing data.

This chapter is submitted as: Stenzel, S., Dolos, K., Fassnacht, F.E., Schmidtlein, S., 201X. How do landscape patterns affect the mapping of rare target classes? – Remote sensing based classification of habitats with Maxent (Ecological Informatics).

4.2. Introduction

Several national and international attempts and programs to stop the loss of biodiversity have increased the demand for effective vegetation monitoring approaches to support nature conservation. It is challenging to obtain information over large areas for the purpose of landscape management particularly when some of the target classes are rare. As an example serve Natura 2000 habitat types (HT) (Council Directive 79/409/EEC, 92/43/EEC), which are defined based on a very fine semantic scale (typically on the level of species composition, meaning on one or more plant communities), additionally complicating their detection and separation. In this context remote sensing is recognized as a possible support technique, especially in combination with field data (Corbane et al. 2013, Feilhauer et al. 2014, Mücher et al. 2013, Schuster et al. 2011, Vanden Borre et al. 2011). However, special remote sensing approaches need to be developed. Standard methods such as conventionally supervised classifications are not well-suited for efficiently identifying a rare target habitat type in a complex landscape as they require extensive and expensive reference data for all occurring classes. If a remote sensing-assisted mapping of rare target classes is attempted in a given landscape with many other land-cover classes, one-class classifiers (OCC) are a promising option (Amici et al. 2011, Cord 2011, Liu & Guo 2010, Mack et al. 2016, Stenzel et al. 2014, 2017).

OCC are also used in the field of species distribution modelling (SDM), which has a similar objective (identifying the distribution of a single species). Most current species distribution models are based on statistical correlations between species occurrence and spatial environmental data. Some OCC require environmental information as well as reference information on both, target species presence and absence for a sample location (presence-absence data; therefore also called binary classifiers). Other OCC methods require only presence records and environmental information (Boyd et al. 2006, Foody et al. 2006). The latter group can be further subdivided into models that only use presence records and other approaches that additionally draw samples from the environmental information at random locations (Mack et al. 2016). This so called background data is meant to represent the distribution of environmental variables in the study area (presence-background data) (Lahoz-Montfort et al. 2014). This background data is likely to contain both, presence and absence samples. One of the best established and frequently applied OCC in species distribution modelling is Maxent (Phillips et al. 2004), an algorithm and a software package developed for modelling species distributions with species occurrence records along with a large random sample of the background environment (Phillips & Dudık 2008). Maxent applies the maximum entropy principle (Sethna 2006, Shannon 1948) for fitting the model so that the estimated distribution deviates from a uniform distribution only to the lowest degree required to explain observations. The good performance of Maxent in modelling rare species with low sample sizes (Elith et al. 2006) raises the question of whether this could also be true for the task to model rare habitat types in remote sensing, in particular in the presence of similar classes.

Although Maxent has shown its potential to efficiently map target classes from remote sensing data (Cord & Rödder 2011, Li & Guo 2010, Mack et al. 2014, Stenzel et al. 2014), there are still some challenges to face. Model performance for identifying a target class is known to be affected by landscape patterns, its environmental properties and by the sampling design (Elith et al. 2011). From a remote sensing perspective this relates to the landscape composition, its corresponding spectral properties and the sampling design. There are two sampling design driven data properties: 1) the number of positive field observations for the target class, and 2) the number of background points used in model fitting. Regarding landscape patterns, there are two additional data properties: 3) the prevalence of the target class in the landscape (here: number of target class pixels divided by the total number of pixels), and 4) the similarity of the target class spectra to the spectra of other land-cover classes in the landscape.

So far, all conducted studies using remote sensing for monitoring nature conservation areas via Maxent are case studies conducted over limited geographical extents. Therefore, the reported performance of Maxent in these studies is valid for a single study area with the given landscape composition that is used to sample the background data. A generalization of these local findings to judge Maxent's ability to map a given target habitat is limited as landscapes in central Europe are heterogeneous and changes in the size and composition of the background might have a notable influence on the obtained results. This subject is broadly discussed in the species distribution modelling community (Bean et al. 2012, Halvorsen et al. 2016, Hernandez et al. 2006, Wisz et al. 2008) with focus on environmental variables but has hardly been addressed in remote sensing.

This has some practical implications, as illustrated by the following examples. For the development of operational remote sensing supported monitoring systems, it is important to have reliable estimates of how much reference data has to be collected during the field surveys to reach an optimal balance between cost of the data acquisition and obtained accuracy. Amongst other factors, the minimum amount of reference data in an OCC based approach will depend on the landscape composition, which varies across study sites and hence cannot be determined in a general way based on case studies. One way to progress towards more general conclusions is to apply simulated distribution data. This data allows for controlling how factors are combined, how species are distributed and enables a complete validation (Miller 2014, Lahoz-Montfort 2014) as complete knowledge about the properties of the target class and the landscape is given.

The application of simulated data where the class membership of each pixel is known exactly is a common approach in the field of algorithm testing, but has rarely been applied to address more application-oriented objectives. We argue that by examining artificial remote sensing datasets with varying amounts of land cover classes and background information, as well as with differing proportions of pixels belonging to the class of interest and co-occurring similar habitats, we are able to assess and discuss the robustness of Maxent for the usage with remote sensing data in a more objective way. This makes it possible to retrieve generalizable information about strength and weakness of Maxent. Generalization is needed to assess the potential of the method for a broader application in nature conservation and monitoring activities based on remote sensing data and to ultimately find an optimized balance between field work and classification accuracy.

To support monitoring for nature conservation with remote sensing and field data it is of particular importance to get information about the needed extent of field surveys and to estimate the potential of this approach for reliable habitat distribution maps. Therefore, in this study we investigate how (1) the sample size of the target class and 2) the number of background points, 3) the prevalence of the target class and (4) the similarity of classes in the background to the target class affect the performance of Maxent based classification and thereby the variation in validation results. It is of importance for further works to know about the robustness of an OCC for the aforementioned purpose. The tests have been conducted using simulated data sets constructed from true reflectance assessed by remote sensing data (Figure 4.1).

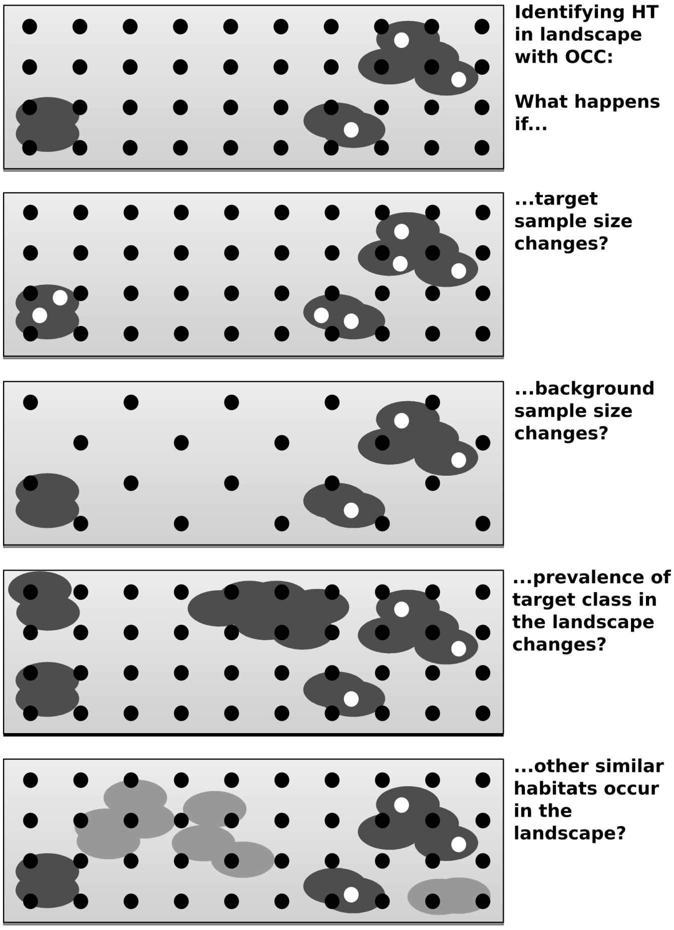

Figure 4.1.: Objectives.

4.3. Methods

4.3.1. Field data

Four Natura 2000 habitat types (HT) were examined in this study: HT 6410 Molinion meadows on calcareous, peaty or clayey-silt-laden soils; HT 7120 Degraded raised bogs still capable of natural regeneration; HT 7140 Transition mires; HT 7230 Alkaline fens (LfU & LWF 2010). Since all four habitat types were nutrient-limited wetland habitats, occurring together in mosaic-like structures and building a natural gradient, they share many species and trait characteristics. Ground truth data originates from a field campaign in southern Germany in 2011 and 2012. In this area, the four habitat types often occurred together in big mosaic structures with other non-protected land-cover types (grasslands, forests, crop fields). Especially the similarity of the four habitat types and their co-occurrence, often with continuous transitions, made this data set suitable for our experiment. Based on expert knowledge of the area we extended the sample points gathered in the field by visual interpretation, but only for sites where we reliably knew that one of the habitat types occurred. The assignment followed the Natura 2000 classification key (LfU and LWF 2010).

4.3.2. Remote sensing data

We used reflectance data from multi-temporal RapidEye imagery of 2011. We used five scenes and all five spectral bands of the sensor at a pixel size of $5\,m$. The individual bands were standardized resulting in 25 predictors with value ranges from 0 to 1 (see Stenzel et al. 2014 for more details).

4.3.3. Artificial landscape

To test the influence of variation in the reference sample and landscape (background) composition, several artificial datasets were created. From the pool of habitat type reflectance (extracted from the imagery at the field sampling sites) as well as from the background reflectance pool (a random sample representing the overall matrix), a defined quantity of pixels was drawn to create multi-seasonal artificial landscapes (AL) for which the class (one of the habitat types or background) of every pixel was known. We created 12 different artificial landscapes for each of the four different habitat types, each consisting of 50,000 pixels. The number of pixels belonging to the target class (prevalence) varied for each artificial landscape respectively and so did the number of pixels belonging to one of the other three habitat types, which were relatively similar to the target class (similarity of background). For each of these 48 artificial landscapes we ran Maxent models with varying training sample sizes for the target class and background points (27 different combinations). For each combination of landscape and sampling design 200 replicates were calculated resulting in 259,200 models in total (Table 4.1).

4.3.4. OCC

We trained Maxent (Phillips et al. 2004) with default settings, but changed the parameter addsamplestobackground=F to be in full control of background samples and sample sizes. This is not recommended for studies aiming at the best model for a particular dataset, since this default setting is known to improve results. Each model was then applied to the corresponding artificial landscape. We used Maxent's logistic output, which represents an index of suitability rather than probability, if one is dealing with species (Elith et al.

Table 4.1.: Overview over all possible variation in landscape and sampling design.

Parameter	No. of levels	Levels
Habitat type (HT)	4	HT 6410; HT 7120; HT 7140; HT 7230
Prevalence HT	3	100; 500; 1,000
Prevalence similar classes	4	0; 100; 500; 5,000
HT training data	3	10; 30; 50
Background data	9	0; 100; 500; 1,000; 5,000; 10,000; 20,000; 30,000; 40,000; 50,000
Case	**No. of cases**	**Tuning parameter**
Artificial landscape (AL)	48	HT, prevalence HT, prevalence similar classes
Sampling design	27	HT training data, background data
Total number of cases	1296	(each 200 iterations)

2006, Lahoz-Montfort et al. 2014) and which presents a relative likelihood for target class membership in case of predicting an object using its reflectance. In the context of remote sensing data and habitats, one has to keep in mind that each pixel, having a specific reflectance value, can only be classified as one class, rejecting all other classes. Hence, it is reasonable to convert likelihoods into binary classes. Here, we calculated a threshold that was optimized for a maximum sum of sensitivity and specificity (also used e.g., by Bean et al. 2012 and Liu et al. 2005 (R Dismo package; Hijmans & Elith 2016). For details on the software and the principles underlying see for example Elith et al. (2011).

4.3.5. Accuracy assessment

Validation was performed for each habitat type with a random sample set extracted from the AL with 50 samples for the target class (positives) and 50 samples not belonging to target class (negatives). Mean of AUC (threshold independent), Kappa, sensitivity and specificity (all threshold dependent) were calculated for the 200 iterations of every parameter combination (R package SDMTools; VanDerWal et al. 2012). For all models the accuracy measures of the 200 iterations were aggregated and depicted in illustrative heat maps.

4.3.6. Spectral similarity

Furthermore, to display the similarity of the 4 habitat types and the background we calculated Euclidean distances between (i) the sample pixels of each habitat type; (ii) between samples of each habitat type to the other habitat types; and (iii) between samples of each habitat type and samples of the background. In addition, a rank-based, non-metric multidimensional scaling (NMDS; Kruskal 1964) was applied. Since we had no null values in our dataset we used the Euclidean distance and random starting configuration. NMDS is a widely applied standard, which is able to maximize rank order correlation, cope with non-linear features and linearises the fit between species data and environmental or spectral variation (Schmidtlein et al. 2010). The NMDS aims at reducing the difference between the distances of the original matrix and its counterparts found in ordination space. This difference is expressed as stress. In the past, ordination methods have often been applied in ecological studies to depict structures of communities as well as for finding the ecological relation between vegetation structure and environmental variables (Jongman et al. 1995). Nowadays, their application has been broadened to remote sensing data (Schmidtlein & Sassin 2004, Feilhauer et al. 2011).

All calculations were performed in the R statistical environment (R Core Team 2015).

4.4. Results

Euclidean distances among target class pixels and similar class pixels were smaller than between each target class and the background (Figure 4.3). This underlined the validity of the experimental approach. Within class similarity was highest for HT 7140, lowest for HT 7120, probably the latter induced by highest structure variability caused by varying amounts of woody parts of dwarf shrubs, resulting in fuzzy results for this class. Dissimilarity of habitat types to the background was low for HT 7120 and HT 7140 and higher for HT 7230 and HT 6410. Within class dissimilarity was smaller than between class dissimilarity for all four habitat types individually. Dissimilarity of all four habitat types to the others was smaller than to the landscape. Results show, that the interpretation of each of the habitat types as target class and the remaining habitat types as similar class pixels was valid.

The NMDS on the reflectance data of the habitat types and on a random subset of the background (each class n=500, stress value = 0.08) explained 92% of total variance (Figure 4.2). Data points belonging to the background sample had high loadings on the first axis indicating low similarity to the other classes. Data points belonging to one of the 4 habitat types overlapped. HT 7120 data points had also higher loadings on the first axis and also on the second axis, and thus were less similar to the other habitat types. The other three habitat types strongly overlapped indicating high similarity. This is in accordance with results of figure 4.3 and our basic assumption of similarity of classes and dissimilarity with background.

Figure 4.4 to 4.7 show different measures for model quality (AUC, Kappa, specificity, sensitivity) for all four habitat types. Values for these measures depended on the artificial landscape (Figure 4.4 to 4.7, a)) and on the sampling design (Figure 4.4 to 4.7, b)).

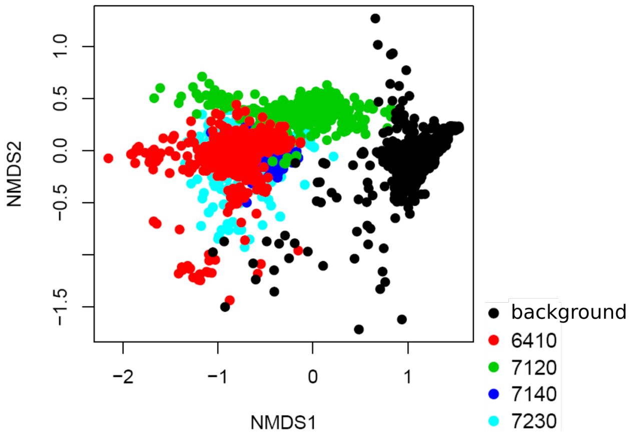

Figure 4.2.: NMDS, results for the four different target classes and background (=0) from reflectance pool (Distance: Euclidian, stress: 0.08).

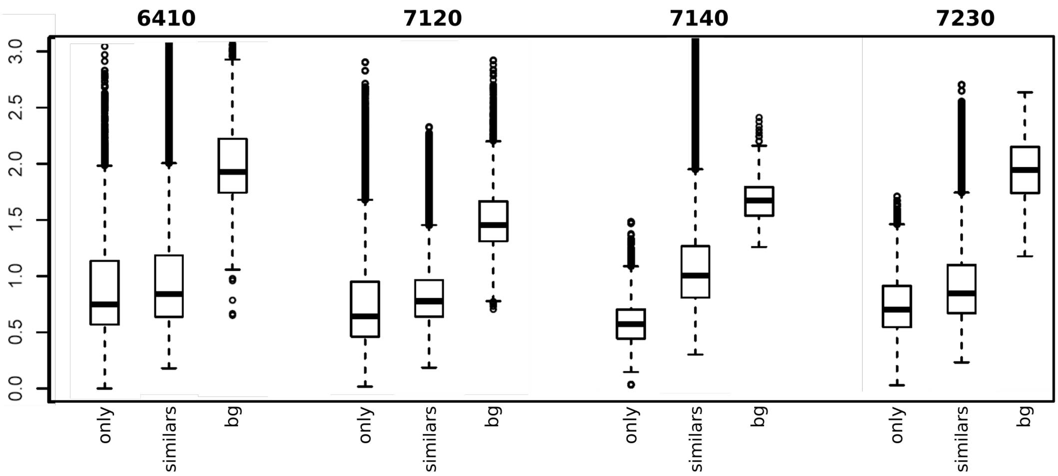

Figure 4.3.: Boxplot of euclidean distances of rescaled reflectance, results for the four different target classes (only = distances within classes; similars = distances of target class and similar classes; bg = distances of target class and background).

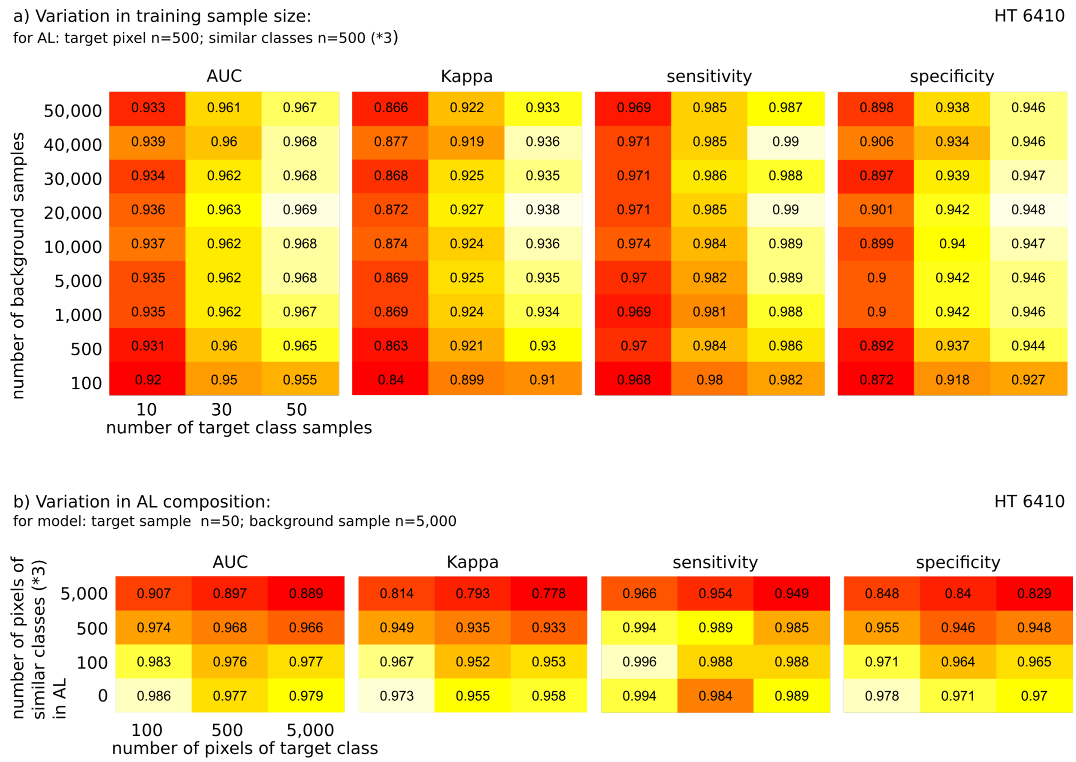

Figure 4.4.: HT 6410: a): Influence of the number of target class samples and background sample size on model performance (AUC, Kappa, sensitivity, specificity). Here, the composition of the AL was kept constant. Model quality increased with increasing sample size for the target. Regarding the background, maximum values were reached at 1,000-30,000. b): Influence of artificial landscape (AL) composition. The graph shows how model performance (AUC, Kappa, sensitivity, specificity) depends on the number of pixels from similar habitats and from the target class. Training sample size and background sample size are kept constant. Model quality decreased with increasing similarity of the background and increasing share of target class.

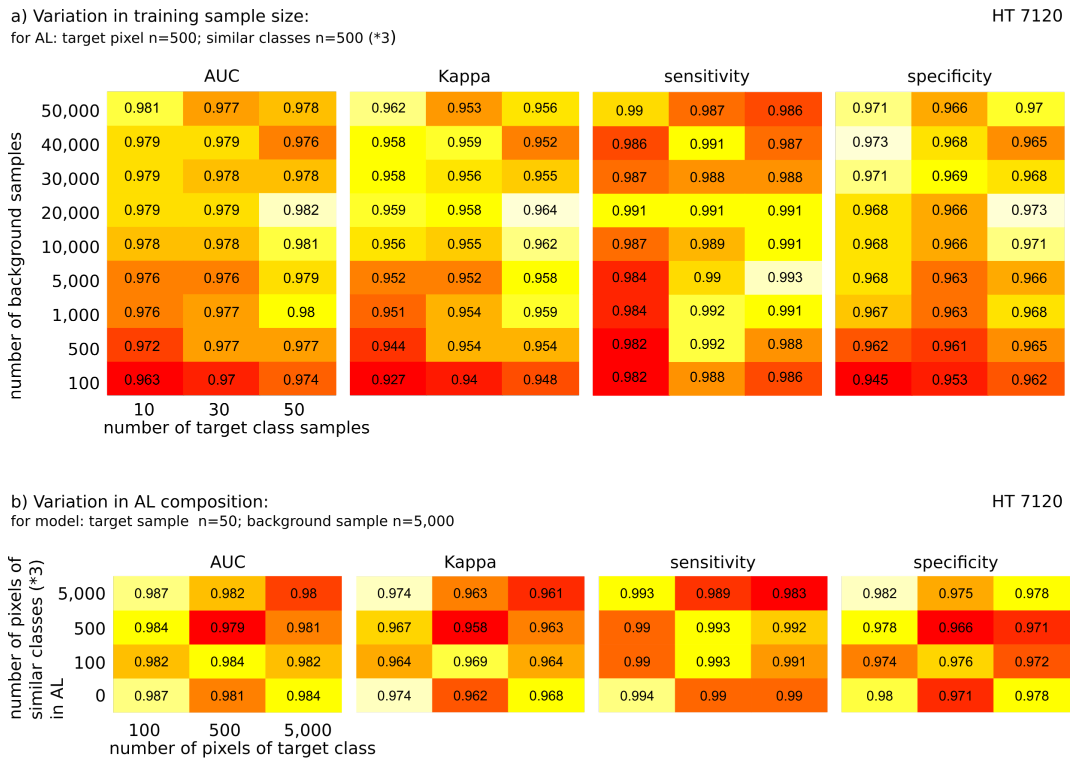

Figure 4.5.: HT 7120: a): Influence of the number of target class samples and background sample size on model performance (AUC, Kappa, sensitivity, specificity). Here, the composition of the AL was kept constant. Model quality increased with increasing sample size for the target. Regarding the background, maximum values were reached at 1,000-30,000. b): Influence of artificial landscape (AL) composition. The graph shows how model performance (AUC, Kappa, sensitivity, specificity) depends on the number of pixels from similar habitats and from the target class. Training sample size and background sample size are kept constant. Model quality decreased with increasing similarity of the background and increasing share of target class.

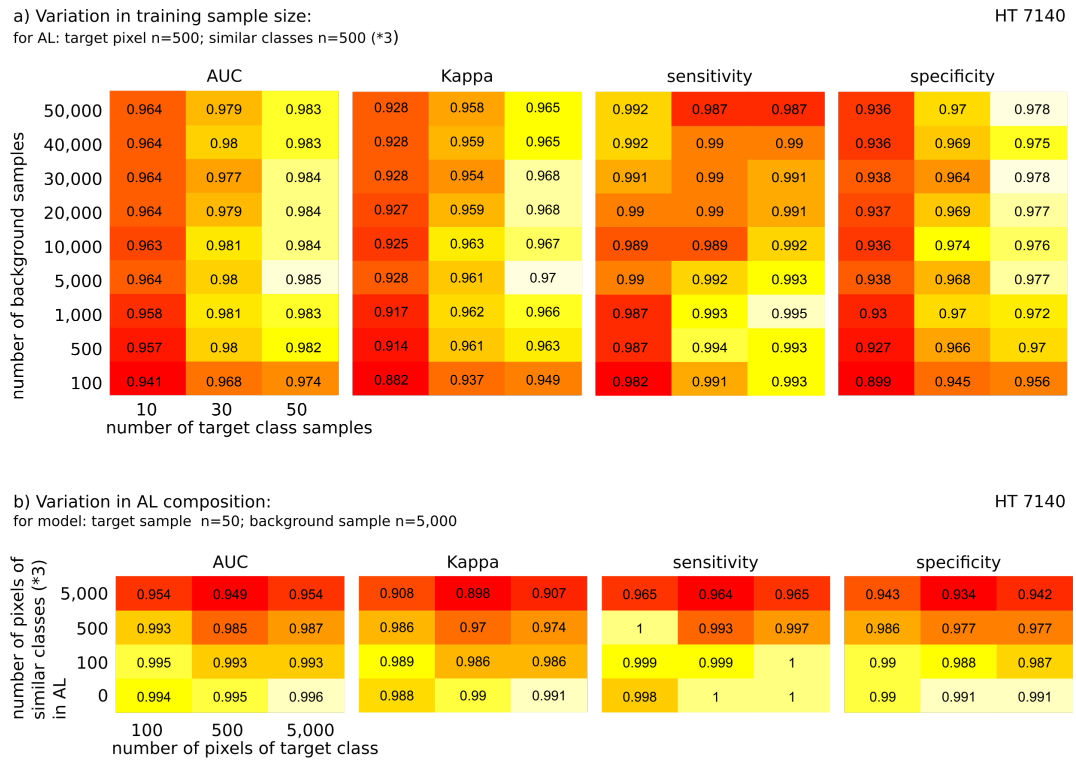

Figure 4.6.: HT 7140: a): Influence of the number of target class samples and background sample size on model performance (AUC, Kappa, sensitivity, specificity). Here, the composition of the AL was kept constant. Model quality increased with increasing sample size for the target. Regarding the background, maximum values were reached at 1,000-30,000. b): Influence of artificial landscape (AL) composition. The graph shows how model performance (AUC, Kappa, sensitivity, specificity) depends on the number of pixels from similar habitats and from the target class. Training sample size and background sample size are kept constant. Model quality decreased with increasing similarity of the background and increasing share of target class.

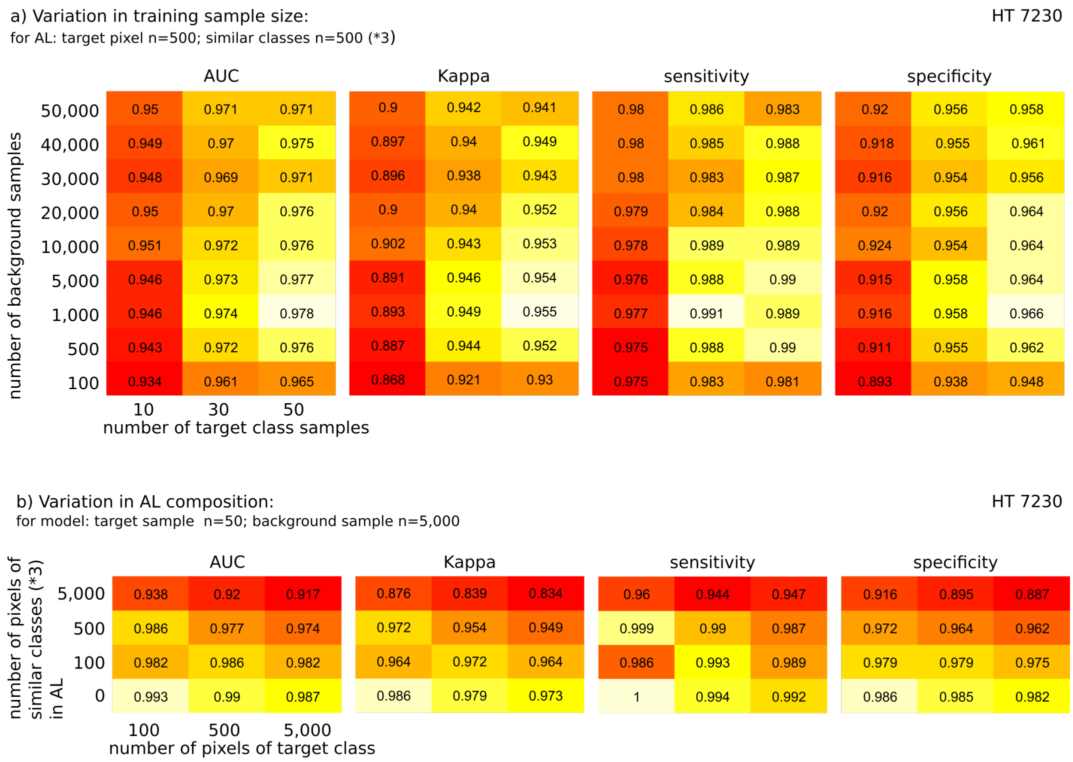

Figure 4.7.: HT 7230: a): Influence of the number of target class samples and background sample size on model performance (AUC, Kappa, sensitivity, specificity). Here, the composition of the AL was kept constant. Model quality increased with increasing sample size for the target. Regarding the background, maximum values were reached at 1,000-30,000. b): Influence of artificial landscape (AL) composition. The graph shows how model performance (AUC, Kappa, sensitivity, specificity) depends on the number of pixels from similar habitats and from the target class. Training sample size and background sample size are kept constant. Model quality decreased with increasing similarity of the background and increasing share of target class.

Overall performance was very high, resulting in accuracies ranging between 0.83 and 1 and the different accuracy measures showed similar trends. Outcomes for HT 7120 were fuzzier than for the other habitat types or even inconclusive. This is a result of the aforementioned within high dissimilarity in this class.

(1) The performance of Maxent increased with increasing number of target samples during the training stage for all HT.

(2) The performance of Maxent increased with increasing number of background samples during training stage clearly until 1,000 samples, with a saturation or decrease when passing 10,000 – 30,000 samples (the results for each individual HT show that the tipping point is reached at different levels, and depending on training sample size, but there is always such a stagnation or tipping point).

(3) Results were inconclusive with respect to the number of pixels of the target class in artificial landscape. Decrease of model quality with high prevalence was observed for HT 6410 and HT 7230, the contrary was observed for HT 7140 and no clear pattern emerged for HT 7120.

(4) The performance of Maxent increased with decreasing number of pixels from similar classes in the AL for all but HT 7120. Here results were inconclusive.

4.5. Discussion

The aim of this study was to analyse the effect of landscape composition and sampling design on the classification accuracy of rare target classes. Maxent, we hoped, would be a promising tool for addressing this task because it has been applied successfully in species distribution modelling. Four Natura 2000 habitat types, which need to be monitored and for which status reports must be delivered to the European Union, served as examples. Our results were meant to improve the basis of knowledge on which effective monitoring tools and sampling designs for remote sensing and OCC based monitoring of rare habitat types can be developed.

In the SDM community there are several previous studies that evaluated the influence of factors such as sample size relationships or parameter tuning on model performance of different SDM, including Maxent, but not with the parameter combination of our study. Some of them should be mentioned to give a small overview about recent work. Bean et al. 2012 tested distribution data for one species across multiple years and presented negative effects of temporally or spatially biased sample size on threshold selection. Bradley 2016 worked with 15 plant species from the US regarding the question of whether presence-only SDM based on locations of high species abundance predict abundance more effectively than models based on occurrences. High abundance models consistently showed greater separation between intermediate and high abundance ranks than any occurrence models. Also, high abundance models had the greatest separation between intermediate ranks of abundance. Velásquez-Tibatá et al. 2016 tested the effects of small sample sizes and large georeferencing error and emphasized the high importance of species environmental tolerances. Stockwell et al. 2002 studied the effects of composition of training sample and sample size with different sizes of training data and sampling with replacement. Only few studies tested the effect of variation in parameters and jointly analysed their relative effects. Dorman et al. 2008 tested variable selection alongside correction method, modelling technique, uncertainty and collinearity. They conducted an analysis quantifying uncertainty in each step during the model-building sequence to variation in model validity and climate change projection uncertainty, leading to 81 different model approaches and over 700 projections. They discovered that model type and data quality dominated the results for climate projections. Since comparison of different model types is conducted frequently and comparison of model types has received good results they appeal to study effects of data quality more detailed. Thibaud et al. 2014 introduced a new virtual framework to study the relative importance of factors involved in the construction of SDM, including the tuning parameters' missing covariate, spatial autocorrelation, sample size, sampling design and modelling technique. Most studies used real occurrence data, a few studies, however, used simulated data and described it as a powerful evaluation framework that allows for a profound quality assessment (Zurell et al. 2010, Miller 2014). The complexity of a final model in general is determined by the choices of model selection, regularization method, and strictness of criteria (Reineking 2006, Halvorsen et al. 2016). Maxent stable performance in many studies may be explained by the way it uses regularization to avoid over-fitting. The amount of regularization varies flexibly with each given sample size to ensure stable performance. L-1-regularization omits irrelevant variables from the model by using shrinkage parameter (Phillips 2006). This procedure is regarded as one of the main reasons for its good performance (e.g., Elith 2006, Phillips 2008, Wisz 2008, Hernandez et al. 2006). Maxent has been assessed as robust concerning small sample sizes, and it had, among other, the best predictive power across all sample sizes, and since it performed well in our work it can be recommended for further studies.

Variation in target class sample size (1): Our study shows that an increased number of target class samples improved the classification accuracy for all habitat types. Results of models with a sample size of 10 were very poor, whereas at a sample size of 30 model predictions were already stable and reasonable. This increase in model quality was caused by a better description of the predictor distributions of the target class and, thereby, an enhanced separability from the background distribution. The minimum number of positive samples is thus influenced by the number and complexity of predictor variables. These findings were very much in line with former studies on the effects of positive sample size: Wisz et al. 2008 tested 12 SDM for 46 species on varying target sample sizes (n = 10, 30, 100) and found that no algorithm predicted consistently well with sample size below n=30). Guisan et al. 2007 proved with 10 SDM, 50 species and up to 13 predictors that increasing number of occurrences (classes of $n = 0 - 40, 41 - 130, 131270, > 271$) used for model training result in better models, which tended to be more sensitive to grain. Hernandez et al. 2006 found the same when testing four SDM on 17 animals species for six different sample size treatments ($n = 5, 10, 25, 50, 75, 100$) with up to 10 predictors. Maxent performed most capably, and they point out that results are better for species with small geographic ranges and limited environmental tolerance (see our discussion of target prevalence). At some point the distributions are well described and a further increase does not add much information to the model, thus maximum model accuracy is approached. Knowing the right number of positive records at which the increase in model accuracy levels off can be considered as the most time and cost effective field sampling strategy. When positive sample size increases, accuracy should also increase until achieving its maximum, reaching an asymptote. The maximum accuracy and the sample size at which it is reached depends on the study area, particularly on the number of classes, the overlap among their predictor distributions, data quality and spatial resolution (Hernandez et al. 2006). This was also confirmed by our results, which show that maximum qualities were lower for landscapes with a high proportion of similar classes in the landscape. Accordingly, insufficient occurrence data is of big concern because classification quality is influenced by the number of records used in model building. When sample sizes are small, outliers have more influence than when more data is available to buffer their effects (Wisz et al. 2008).

Variation in background sample size (2): With increasing number of background samples model accuracy increased until saturation. In some cases, model accuracy even dropped at higher numbers of background points suggesting that there is a case specific optimal number of background points. In this study, the optimal number of background points varied between 10,000 and 30,000 for the four habitat types. These values are confirmed by other studies (Elith et al. 2006, Phillips & Dudik 2008) and match more or less the default Maxent value for background sample size of 10,000. That there should be an optimal number of background points undermines the assumption that more data on the background improve the description of the background distribution of predictors and hence improve the model. However, the pattern of an optimal background sample size is related to target class sample size (number of positive samples) and its ability to adequately describe the target class distribution. If the target class does not have a well defined predictor distribution compared to the background distribution, adding a lot of of background data could decrease the signal to noise ratio until the algorithm cannot detect the systematic pattern any more. Accordingly, for fuzzy classes like HT 7120 the optimal number of background data was lower than for the others. However, we cannot provide the reason here but we would like to open this topic for discussion in the field of presence-background modelling, since, interestingly, there a practically no studies on this until now. So far, we conclude that it is useful to increase the number of background data systematically until model quality saturates or decreases again. We suggest treating background sample size as another tuning parameter during model development.

Influence of prevalence of target class (3): Here prevalence is defined as number of target class pixels divided by the total number of pixels. The results from other studies, where models for species with broad geographic and environmental ranges seem to be less accurate than those for species with smaller ranges (Manel et al. 2001, Kadmon et al. 2003, Thuiller 2004, Luoto et al. 2005, Elith et al. 2006), were neither confirmed nor rejected. While many studies have tested the effect of sample size on accuracy, not a single study has manipulated the target range while controlling all other factors. This prevents evaluating the effects of prevalence versus e.g. sample size on model accuracy (Hernandez et al. 2006). Indeed, in the case of species distribution models based on environmental data, it is reasonable to assume that prevalence is negatively correlated with model accuracy. First, prevalence in the study region is often correlated with niche marginality of the species, i.e. overlap of target class distribution and background distribution. Therefore low niche marginality and high prevalence often leads to low separability of predictor distributions. Second, if a target has a small range it is likely that more of its environmental space is covered with fewer samples than a target with a large range (Breiner et al. 2015, Kadmon et al. 2003). For spectral data there is in our opinion no reason to expect such correlation among prevalence, sample size and overlap among target class and background distribution and therefore no reason why rare habitats should yield higher model accuracies. Spatially rare habitats as well as common habitats could both have low or high variance in their spectral signal; e.g. predictions for rare habitats with a narrow variance in spectral signal based on few records are likely to be as good as those based on a large number of samples, which is not valid for rare habitats with a wider variance in reflectance. However, to make a clear statement, a larger gradient of prevalence is needed and additionally explicit assessment of how spectral distributions overlap among target class and background.

Influence of similar classes in the background (4): The more similar class samples occur in the AL the worse were the models. A higher proportion of similar classes in the landscape and thereby in the background sample reduced the dissimilarity among distributions. This can be seen easily in the ordination (Figure 4.2). The overlap of background and target class is considerably larger if background is including some samples of the 3 similar habitat types. Overlapping distributions in predictor space naturally reduce model accuracy in classification models. This insight can be a starting point for determining minimum sample sizes for habitat modelling, e.g. by determining the optimal distance between target class spectra and landscape spectra to improve model quality. This is comparable to the effect of niche marginality (see e.g. Dolos et al. in prep., Hernandez et al. 2006, Heino 2005).

Implication for habitat mapping: OCC such as Maxent proved useful to support mapping of rare habitat types because less field sampling is required. Based on our study we suggest assessing the required sample size for ground reference data for Natura 2000 habitat types based on a small data set (maybe sites known already from previous mappings) in advance of the main field campaign. Such a study can be based on remote sensing data and added information on the presence of habitat types in the landscape. Overlap of target class spectra with background can be used together with within class and between class similarity (see Figure 4.3, 4.2) to estimate the required presence sample size or training data set. Sample size estimation based on the effect size is very common in ecological field studies but less common in remote sensing.

4.6. Conclusion and outlook

Landscape properties and sampling design influenced maximum and actual model accuracy. The influence of target class prevalence in the landscape was inconclusive while the presence of similar classes clearly impaired classification accuracy. For monitoring of rare habitat types which occur in a mosaic with similar habitat types, a higher number of positive samples for model fitting is required and can counteract the effect of stronger overlap of target class and background distributions. We recommend assessing the sample size of positive observations to approach the maximum model accuracy in pre-studies based on former studies usually available for protected habitat types or a new but small dataset. This will help to decide in advance if the respective habitat type can be mapped with the required accuracy based on remote sensing data and OCC and how much sampling effort will be necessary.

Additionally, maximum model accuracy can be approached by an optimal number of background points. Background data are gratis because they are unlabeled samples from the predictor data. In any study using background data it seems reasonable to systematically assess the effect of different background sample sizes and to choose the optimal one at the turning point or when model accuracy values saturate. This is just another step in model tuning similar to adjusting e.g. the number of trees when using random forests or boosted regression trees, or adding a kernel function when using support vector machines. Finally, we showed that already quite small sample sizes of $n = 30$ were sufficient to create Maxent models for four rare habitat types with acceptable accuracy. All these results encourage to further assess the potential of Maxent (and other OCC) together with remote sensing data as large scale monitoring support for protected vegetation such as Natura2000 habitat types.

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5. Synopsis

The focal and innovative point of this thesis is the exploration of the possibilities and limitations in the application of one-class classifier (OCC) for detecting habitats of conservation value with the help of remote sensing and limited field data.

The results of the first study prove that the application of the OCC Maxent together with remote sensing data is suitable for mapping rare vegetation types of high conservation value. With such an approach it is possible to identify Natura 2000 habitat types scattered within a complex background matrix of vegetation not relevant for nature conservation. It was achieved to delineate and to distinguish similar habitat types, which is crucial for applications in conservation and management. The discrimination between habitats and non-relevant sites was satisfactory. Also, it was possible to provide a consistent classification of a large area using a small amount of ground reference sample. In conclusion, there seems to be an undrawn potential in one-class classification for detecting habitats of low prevalence. However, the differentiation of related habitats with very similar species composition remains a challenge. Habitat types with a wide definition and heterogeneous species composition are difficult to delineate even with OCC. The procedure applied in this study seems to be promising, but further work will be needed to test the transferability of the method at different points in time, areas and for other target classes. Further research is also necessary in the field of threshold definition to reduce underestimation and scatter. Establishing a standard method of validation for approaches like this is crucial. Still, this rather simple and affordable approach is highly recommended for application in further studies (accordingly, the number of studies working on one-class classification for monitoring vegetation is already increasing). OCC could be used for pre-surveys of previously unmapped areas as a tool for identifying potential gaps in existing habitat inventories or as a first check for changes in the distribution of habitats. The first study confirms the initial assumption of this thesis that the application of OCC is promising for vegetation conservation monitoring.

The results of the second study show that there are further possibilities but also some limitations when working with OCC and reflectance data for mapping vegetation of conservation concern. While the differentiation between High Nature Value (HNV) grassland and the rest of the landscape was successful, the differentiation of three HNV quality classes was not possible using OCC and multi-temporal remote sensing data due to a lack of spectral variability between the quality classes. The assignation of different HNV classes is performed by presence or absence of HNV character species in the field. However, this did not lead to a sufficiently different spectral signal for being assigned to the right class and no clear correlation between HNV quality classes and reflection was found. Identifying grassland with high ecological values is possible by means of remote sensing. Nonetheless, the classification of grassland into several quality subclasses is still challenging since different grassland plant communities have almost identical plant functional traits. Further improvements of results could probably be achieved by integrating more spectral information (e.g. from new systems such as Sentinel-2 or upcoming hyperspectral missions) and by further optimizing existing OCC algorithms (e.g. flexible parameter tuning). Also, generating a HNV grassland mask by excluding the major part of the landscape in which with a very high probability no HNV grassland is occurring could reduce the amount of fieldwork to a more manageable extent. This could be helpful to support field campaigns and lessen related costs by reducing the frequency of erroneous field visits to non-HNV areas. Furthermore, the possibility of using a multi-class classifier approach in combination with this OCC based HNV grassland mask has to be tested in further studies. The investigated OCC performed different. Maxent, as in many other studies of species distribution modelling, proved again to be robust and reliable, due to its nature and settings it overestimated the area. The biased support vector machine (BSVM) has to be emphasised as well and performed equivalently, but due to its nature and standards it underestimated the area. Embedding the presented classification scenario into an object-based approach could be beneficial to improve mapping omissions especially for BSVM. It can be concluded that this method of grassland quality detection is promising, but remote sensing and one-class classification alone are not sufficient for adequate monitoring. In particular the differentiation of several grassland usage intensity classes is and will be challenging due to their similar plant functional traits – and hence similar spectral properties – and should be the topic of further research.

While it was shown that usage of OCC together with reflectance data for detecting vegetation of conservation value is feasible it became apparent that validation of OCC results is crucial and thus their robustness is of great importance. The third study therefore tested the robustness and weakness of the OCC Maxent regarding the effect of landscape composition and sample size on accuracy measurements. For this purpose, artificial landscapes with simulated distribution data were generated. This allowed for complete knowledge of the properties of the landscape and the target class and thus for assessing and discussing the robustness of the OCC for usage with remote sensing data in a more objective way. The investigation of the importance of the target sample size and the amount of similar classes in the background confirms the results of earlier studies concerning species distribution modelling (SDM): The performance of the OCC improves with increasing number of training samples and also with a decreasing number of pixels from similar classes in the artificial landscape. Further analysis of the role of background sample size and the prevalence of the target class give new insights and a basis for further studies and discussions: The performance of the OCC improves with an increasing number of background samples for training, exhibiting saturation and even a decrease of performance at a certain number of background samples. It can be concluded that an intermediate amount of background pixels is needed, contradicting the common belief of 'the more the better'. The reasons for this turning point seem to be very important and should be subject of further research. Results are inconclusive with respect to the prevalence of the target class in the artificial landscape. However, some presumption could be made, i.e. that rare habitats as well as common habitats could both have low or high variance in their spectral signal. This is different from SDM, where a target with a small range is likely to have more of its environmental space covered with fewer samples than a target with a large range. For further studies, a larger gradient of prevalence should be covered and additionally, a more explicit assessment of how spectral distribution overlap among target class and background is needed. It is recommended to use a simulated region with controlled complexity to evaluate the effects of several parameters on model performance. In summary, this study proves the OCC Maxent to be a robust and reliable classifier for mapping vegetation types for conservation purposes in combination with remote sensing data. Data availability is always of importance because model quality is obviously influenced to some degree by the number and choice of samples used in model training. Additionally, the landscape composition plays an important role and has an influence on model performance and sample choice.

In this thesis the application of OCC in combination with reflectance data for mapping rare vegetation types of conservation interest was tested and proved to be useful. It could be clearly shown that these habitats could be classified without having information about the rest of the landscape, thus reducing sampling effort and supporting a more efficient and cost-effective monitoring. Here, OCC prove to be advantageous compared to multiclass approaches. The OCC Maxent is found to be a robust and reliable classifier. Ideas for future research can and should be built upon the results of this thesis. However, there are still obstacles that should be of concern in further studies. Some targets, especially certain grassland vegetation types, are difficult or impossible to separate by means of OCC due to their similar plant functional traits leading to non-separable spectral properties. Vegetation types with a wide characterization concerning their plant composition, e.g. vegetation types with a high inherent variability, are also with an OCC difficult to identify. One has to keep in mind that it will always be challenging and sometimes impossible to force vegetation into discrete classes that is naturally occurring as a continuum. Since monitoring programs are in need of these discrete classes, this forced separation is sometimes inevitable. It remains necessary that researchers from both sides, the ecology and the remote sensing community, will work together in a collaborative way to further improve their respective capabilities for the common goal.

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Appendix A.

Data

Table A.1.: Natura 2000 LRT – plot coordinates (UTM WGS84 Zone 32N).

HT 6410	
UTM 32 X	UTM 32 Y
651245	5281070
651224	5284901
650886	5284784
652549	5284315
652888	5282590
661138	5285112
659424	5289592
658590	5291332
655487	5299781
665901	5301526
666085	5301194
666182	5300195
665052	5300296
665263	5301068
665281	5301141
665522	5302021
650550	5308776
670251	5293015
669055	5294180
665655	5291954
665743	5290802
665684	5291256
666308	5290925
667347	5291901
668124	5291014
667666	5291345
661459	5289942
660570	5278999
661605	5279279
654194	5275322
663770	5312395
668817	5292006
662302	5275009
662506	5277831
661348	5277293
655373	5289638
655852	5290792
653751	5312602
656223	5298842
667946	5292993
668584	5291807
668716	5291859
656698	5289955
656937	5289136
657038	5289299
657153	5289424
659508	5289730
659460	5284197
661742	5279112
661325	5278920

HT 7120	
UTM 32 X	UTM 32 Y
651332	5280703
650945	5284590
651214	5284942
650886	5284809
651770	5284031
660351	5285552
660655	5290433
658517	5291253
669721	5298014
665961	5301091
665937	5300322
668556	5302524
668206	5301563
668336	5300857
665374	5292052
668170	5291025
667736	5290585
667034	5290451
667907	5292491
668564	5293761
668832	5293303
661132	5280017
660873	5280244
666979	5315987
669003	5291985
663473	5277806
663293	5277767
662739	5277862
655353	5284183
656090	5291119
656224	5290987
656158	5290873
655680	5290902
655625	5288581
655697	5283543
655296	5288163
656702	5290031
659399	5283683
659748	5284071

HT 7140	
UTM 32 X	UTM 32 Y
651128	5283870
651849	5283993
652850	5284161
652829	5282694
668278	5301507
670169	5293129
667947	5291298
668074	5291300
667620	5292727
668395	5292980

HT 7230	
UTM 32 X	UTM 32 Y
661259	5284613
661081	5284994
661247	5285336
660713	5284989
658488	5291179
661196	5296989
670209	5297804
664438	5300527
664183	5299767
668828	5300871
667625	5291765
667370	5290559
668646	5293743
668837	5293132
669119	5293078
664025	5312121
668591	5291905
649953	5288438
655531	5283764
655213	5284562
656176	5290076
656100	5290372
656471	5289887
655868	5290995
653767	5312740
669788	5297809

Table A.2.: HNV – plot coordinates (UTM WGS84 Zone 32N).

Non-HNV	
UTM 32 X	UTM 32 Y
651270	5284849
659376	5289712
660416	5289857
651173	5291645
658753	5285233
649602	5300396
652794	5306054
654987	5303859
654929	5303869
655321	5304748
655496	5303882
654267	5298885
655583	5299803
669540	5299071
666123	5300912
666322	5300142
665321	5300072
649637	5317206
668318	5291661
667513	5290267
663953	5312194
664493	5314770
649903	5288516
655522	5282655
655954	5287943
652173	5306344
666102	5303306
667124	5316236
664488	5312290
665643	5291275
665357	5291979
668263	5291933
667633	5290420
668381	5301483
668621	5300917
668980	5300751
656163	5288431
657262	5289506
666412	5300403
665916	5300247
664176	5276973
664631	5276688
659842	5285461

HNV 3	
UTM 32 X	UTM 32 Y
650249	5279906
652866	5282479
659992	5285915
660218	5285445
653998	5300082
653913	5300068
665045	5300232
664647	5291687
656074	5290594
655958	5283420
653788	5312496
664513	5276763

HNV 2	
UTM 32 X	UTM 32 Y
651281	5281057
650269	5280674
651739	5280003
661290	5284649
665744	5301711
661564	5279192
660129	5281313
664993	5314252
656529	5285299
654912	5277260
656007	5280152
655265	5280801
649569	5317163
649336	5296888

HNV 1	
UTM 32 X	UTM 32 Y
651475	5284401
661261	5285234
651205	5310433
660393	5279315
655403	5274854
656120	5274587

Table A.3.: List of species (Wisskirchen & Haeupler).

Family	Species
Alliaceae	Allium suaveolens Jacq.
Apiaceae	Angelica sylvestris L.
	Astrantia major L.
	Carum carvi L.
	Heracleum sphondylium L.
	Ligusticum mutellina (L.) Crantz
Asteraceae	Achillea millefolium L.
	Arnika montana L.
	Bellis perennis L.
	Centaurea jacea L.
	Centaurea scabiosa L.
	Cirsium arvense (L.) Scop.
	Cirsium oleraceum (L.) Scop.
	Cirsium palustre (L.) Scop.
	Cirsium rivulare (Jacq.) All.
	Crepis biennis L:
	Crepis capillaris (L.) Wallr.
	Eupatoria cannabinium L.
	Hieracium aurantiacum L.
	Hypochaeris radicata L.
	Leontodon autumnalis L.
	Leontodon hispidus L.
	Leucanthemum vulgare Lam.
	Senecio aquaticus Hill
	Taraxacum sect. Ruderalia Kirschner
	Tragopogon pratensis L.
Betulaceae	Alnus glutinosa (L.) J. Gaertn.
	Betula pubescens Ehrh.
Boraginaceae	Myosotis scorpioides
Brassicaceae	Capsella bursa pastoris (L.) Med.
Campanulaceae	Campanula patula L.
	Campanula rotundifolia L.
	Campanula glomerata L.
	Phyteuma orbiculare L.
Caryophyllaceae	Cerastium holosteoides Fr.
	Dianthus carthusianorum L.
	Lychnis flos cuculi L.
	Silene latifolia Poir.
	Stellaria media (L.) Vill.
Colchicaceae	Colchicum autumnale L.
Cyperaceae	Carex davalliana Sm.
	Carex echinata Murray
	Carex flacca Schreb.
	Carex flava L.
	Carex hostiana DC.

Family	Species
Cyperaceae	Carex panicea L.
	Carex paniculata L.
	Carex rostrata Stokes
	Eriophorum angustifolium Honck.
	Eriophorum latifolium Hoppe
	Eriophorum vaginatum L.
	Schoenus ferrugineus L.
	Scirpus sylvaticus L.
	Trichophorum cespitosum (L.) Hartm
Dennstaedtiaceae	Pteridum aquilinum (L.) Kuhn
Dipsacaceae	Knautia arvensis Coult.
	Scabiosa columbaria L.
	Succisa pratensis Moench
Droseraceae	Drosera longifolia L.
	Drosera rotundifolia L.
Equisetaceae	Equisetum arvense L.
	Equisetum sylvaticum L.
Ericaceae	Andromeda polifolia L.
	Calluna vulgaris (L.) Hull
	Erica tetralix L.
	Vaccinium myrtillis L.
	Vaccinium oxycoccos L.
	Vaccinium uligunosum L.
	Vaccinium vitis-idaea L.
Euphorbiaceae	Euphorbia cyparissias L.
Fabaceae	Lathyrus pratensis L.
	Lotus corniculatus L.
	Lotus pedunculatus Cav.
	Medicago lupolina L.
	Trifolium dubium Sibth.
	Trifolium montanum L.
	Trifolium pratense L.
	Trifolium repens L.
	Vicia angustifolia L
	Vicia sepium L.
Gentianaceae	Gentiana pneumonanthe L.
	Gentiana utriculosa L.
	Gentiana verna L.
Geraniaceae	Geranium pratense L.
Iridaceae	Gladiolus palustris Gaudin
	Iris sibirica L.
Juncaceae	Juncus alpinus Vill.
	Juncus effusus L.
	Juncus tenuis Willd.
	Luzula campestris (L.) DC.

Family	Species
Juncaceae	Luzula sylvatica (Huds.) Gaudin
Lamiaceae	Betonica officinalis L.
	Glechoma hederacea L.
	Menta aquatica L.
	Prunella vulgaris L.
	Teucrium chamaedrys L.
	Thymus pulegioides L.
Lentibulariaceae	Pinguicula vulgaris L.
Lycopodiaceae	Lycopodiella inundata (L.) Holub
Melanthiaceae	Tofielda calyculata (L.) Wahlenb.
	Veratrum album L.
Menyanthaceae	Menyanthes trifoliata L.
Orchidaceae	Dactylorhiza incarnata (L.) Soó
	Dactylorhiza maculata (L.) Soó
	Epipactis palustris (L.) Crantz
	Gymnadenia conopsea (L.) R. Br.
	Orchis palustris Jacq.
	Platanthera bifolia (L.) Rich.
Parnassiaceae	Parnassia palustris L.
Pinaceae	Picea abies (L.) H. Karst.
	Pinus mugo Turra
	Pinus sylvestris L:
Plantaginaceae	Plantago lanceolata L.
	Plantago major L.
Poaceae	Agrostis stolonifera L.
	Alopecurus geniculatus L.
	Alopecurus pratensis L.
	Anthoxanthum odoratum L.
	Arrhenatherum elatius (L.) P. Beauv.
	Briza media L.
	Bromus erectus Huds.
	Cynosorus cristatus L.
	Dactylis glomerata L.
	Elymus repens (L.) Gould
	Festuca pratensis Huds.
	Festuca rubra L.
	Glyceria fluitans (L.) R. Br.
	Holcus lanatus L.
	Lolium perenne L.
	Molinia arundinacea Schrank
	Molinia caerulea (L.) Moench
	Phleum pratense L.
	Phragmites australis (Cav.) Trin.
	Poa pratensis L.
Polygalaceae	Polygala amarella Crantz

Family	Species
Polygalaceae	Polygala chamaebuxus L.
Polygonaceae	Bistorta officinalis Delarbre
	Bistorta vivipara (L.) Delarbre
	Rumex acetosa L.
	Rumex acetosella L.
	Rumex obtusifolius L.
Primulaceae	Lysimachia vulgaris L.
	Primula farinosa L.
	Primula veris L.
Ranunculaceae	Caltha palustris L.
	Pulsatilla pratensis (L.) Mill.
	Ranunculus acris L.
	Ranunculus flammula L.
	Trollius europaeus L.
Rhamnaceae	Frangula alnus Mill.
Rosaceae	Alchemilla vulgaris agg.
	Filipendula ulmaria (L.) Maxim.
	Geum rivale L.
	Potentilla erecta (L.) Raeusch.
	Potentilla palustris (L.) Scop.
	Sanguisorba minor Scop.
	Sanguisorba officinalis L.
Rubiaceae	Galium album Mill.
	Galium boreale L.
	Galium mollugo L.
	Galium palustre L.
	Galium verum L.
Salicaceae	Salix pendandra L.
	Salix alba L.
Scrophulariaceae	Bartsia alpina L.
	Digitalis purpurea L.
	Euphrasia officinalis L.
	Euphrasia stricta D. Wolff
	Melampyrum pratense L.
	Melampyrum sylvaticum L.
	Pedicularis palustris L.
	Pedicularis sceptrum-carolinum L.
	Rhnianthus serotinus (Schönh.) Schinz
	Rhnianthus minor L.
	Veronica chamaedrys L.
Sphagnaceae	Sphagnum spec
Violaceae	Viola palustris L.

Table A.4.: Accuracy measures chapter 3

		Maxent		OCSVM		BSVM	
		2011	2012	2011	2012	2011	2012
Scenario A	Sensitivity	0.72	0.75	0.81	0.53	1	1
	Specificity (Grassland)	1	1	0.97	1	1	1
	Specificity (no Grassland)	0.86	0.74	0.77	0.65	0.98	0.95
	Overall Accuracy	0.85	0.82	0.83	0.71	0.99	0.98
Scenario B	Sensitivity	0.59	0.59	0.44	0.28	0.94	0.81
	Specificity (Grassland)	0.93	1	0.89	0.89	1	1
	Specificity (no Grassland)	0.44	0.65	0.51	0.65	0.84	0.79
	Overall Accuracy	0.62	0.73	0.59	0.6	0.91	0.89