Remote sensing in support of conservation and management of heathland vegetation

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Dipl.-Geogr. Johannes Matthias Schmidt

aus Köln

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Referent: Prof. Dr. Sebastian Schmidtlein

Korreferent: Prof. Dr. Stefan Hinz

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Abstract

Assessing and monitoring the state of vegetation from stand level to the continental scale are major tasks related to environmental changes and a rapid decrease of biodiversity. Remote sensing with its possibility to deliver objective and reliable wall-to-wall data is regarded as a valuable tool that can potentially deliver that kind of information. To tap this potential of earth observation it has to be combined with knowledge about species, relevant processes and how changes occur in space and time.

In an ideal case, the demanded spatial representations of vegetation are acquired in multidisciplinary procedures and, moreover, are assessable by different stakeholders; from the site manager to the global-thinking decision maker. Even though few appropriate monitoring concepts are in preparation, feasibility remains to be confirmed. Established systems, however, often rely on approved strategies and traditional attitudes which sometimes hamper the inclusion of novel techniques, such as remote sensing.

This thesis comprises four studies that seek to combine mapping procedures from field ecology and benefits from remote sensing information in order to setup modules for an integrated vegetation monitoring concept. Appropriate procedures are developed by the example of a heathland landscape and in the context of an established European nature conservation scheme.

The first study approaches the question of how to map patch-wise habitat quality classes of dwarf shrubland by remote sensing from several perspectives. The major aim is to present a product that directly meets the demands of European conservation authorities. It is assessed what patch sizes are meaningful, if multi-seasonal information provides an additional value, whether the mapping benefits from including SAR imagery and if sufficient accuracies can be reached.

The second study is presenting a new remote sensing-based method for quality assessment of dwarf shrub heathland. Inspired by field mapping procedures the aim is to integrate an established assessment guideline into a procedure that makes use of earth observation. Proxies obtained from UAV and airborne data provide the basis for a continuous representation of varying habitat states. Operationalizing field experts' decision making is represented by rule sets that enable the derivation of quality classes. Therefore, the final product represents a pixel-wise mapping of what is demand by European conservation authorities.

In order to enhance transferability the method was applied in a similar way in study three, but this time based on free and generally accessible spaceborne data. The innovative point was the inclusion of SAR imagery that allows for a better derivation of structural vegetation attributes. Classification results were satisfactory; also for testing the transferability, which is realized by using an independent remote sensing dataset.

The fourth study represents another, innovative form of remote sensing-based vegetation monitoring. By considering general plant functional types it is detached from conventional classification approaches. The approach enables comparisons across regions and time, which is an important feature of a consistent monitoring system. A functional signature of heathland landscapes is depicted that makes use of continuous information about plant strategies obtained from airborne remote sensing. It is demonstrated that successional changes can be monitored by means of this signature.

Even though, it is possible to obtain remote sensing-based products that are strictly oriented towards meeting the requirements of conservation authorities integrated procedures that are oriented towards the advantages of earth observation allow for obtaining more accurate and rather appropriate results. For example, discrete quality classes that ought to be obtained per patch can be mapped more accurate when pixel-wise remote sensing information is exploited. Moreover, results suggest that an integration of structural vegetation properties is advantageous for habitat quality assessments (at least for dwarf shrub heathland), particularly when SAR data is considered. For future monitoring schemes it is advised to involve vegetation classification approaches that consider generalization to facilitate comparisons in time and space.

Hence, is can be concluded that targeted remote sensing proxies which reveal information about, for example, species populations, species traits, community composition, and ecosystem structure, are useful products for a coherent and detailed vegetation monitoring on the landscape scale. Obtaining such spatial representations in interdisciplinary approaches on various scales, assessable for different stakeholders, is probably the key to keep track of shifts and impacts in a changing environment and to support the management of fragile and endangered systems.

Zusammenfassung

Die Abschätzung und das Monitoring von Zuständen der Vegetation sind wichtige Aufgaben angesichts des globalen Umweltwandels und des drastischen Rückgangs der Biodiversität. Die Fernerkundung kann diese Art von Information prinzipiell liefern, da sie flächendeckend objektive und belastbare Daten bereitstellt. Um das vorhandene Potential auszuschöpfen, ist es jedoch notwendig, fernerkundliche Daten mit Informationen über Pflanzen und relevante Prozesse zu verknüpfen sowie dem Wissen über Veränderungen in Raum und Zeit.

Im Idealfall werden diese räumlichen Darstellungen in multidisziplinären Verfahren gewonnen und so aufbereitet, dass sie vom lokal agierenden Landespfleger bis hin zum global denkenden Entscheidungsträger von Interesse sind. Obwohl solche Monitoringkonzepte bereits in Vorbereitung sind, muss deren Machbarkeit erst noch unter Beweis gestellt werden. Etablierte Systeme hingegen neigen dazu, allzu oft an bewährten Methoden und traditionellen Sichtweisen festzuhalten, was der Einbindung neuer Technologien, so etwa der Fernerkundung, manchmal im Wege steht.

Die vorliegende Arbeit besteht aus vier Einzelstudien, die versuchen, Kartierverfahren aus der Feldökologie mit den Vorteilen fernerkundlicher Verfahren zu verbinden, um so Module für ein ganzheitliches und fachübergreifendes Vegetationsmonitoring zu entwickeln. Geeignete Ansätze werden anhand einer Heidelandschaft und im Kontext eines bewährten europäischen Naturschutzprogramms entwickelt.

Die erste Studie nähert sich von mehreren Perspektiven der Frage, wie der Erhaltungszustand von Zwergstrauchheiden objektbasiert mittels Fernerkundung kartiert werden kann. Es geht darum, herauszufinden, welche Objektgrößen sinnvoll sind, ob multi-saisonale Informationen einen Mehrwert liefern, ob die Berücksichtigung von SAR-Daten Vorteile mit sich bringt und ob der Ansatz mit ausreichender Genauigkeit umsetzbar ist.

Die zweite Studie präsentiert eine neuartige, fernerkundungsbasierte Methode für die Abschätzung des Vegetationszustands von Zwergstrauchheiden. Inspiriert von Kartierverfahren aus der Feldarbeit ist das Ziel des Vorhabens, einen etablierten Leitfaden zur Einschätzung der Habitatqualität in ein Verfahren zu integrieren, das auf Erdbeobachtung beruht. Indikatoren, die aus Daten von Drohnen- und Flugzeugbefliegungen gewonnen werden, ermöglichen kontinuierliche Darstellungen von variierenden Habitatzuständen. Die Ableitung diskreter Klassen wurde durch ein regelbasiertes Verfahren ermöglicht, das auf der Operationalisierung von fachlichen Entscheidungsfindungen beruht. Das Endergebnis stellt somit eine pixelweise Kartierung von dem dar, was von Naturschutzbehörden in Europa gefordert wird.

Um die Übertragbarkeit der Methode zu erhöhen, wurde sie in ähnlicher Weise in Studie drei angewendet. Dieses Mal jedoch wurden Satellitendaten berücksichtigt, die kostenlos und frei zugänglich sind. Der Ansatz war insofern innovativ, als dass SAR-Daten miteinbezogen wurden, die eine bessere Ableitung von Strukturparametern der Vegetation ermöglichen. Die Klassifikationsergebnisse waren zufriedenstellend; auch in Bezug auf die Übertragbarkeit, die anhand eines zweiten Fernerkundungsdatensatzes getestet wurde.

Studie vier repräsentiert eine andere, innovative Form des fernerkundungsbasierten Vegetationsmonitorings. Durch die Einbeziehung generalisierter, funktioneller Pflanzentypen ist der Ansatz losgelöst von konventionellen Klassifikationsverfahren. Der Ansatz erlaubt Vergleiche in räumlicher und zeitlicher Hinsicht - eine wichtige Eigenschaft eines einheitlichen

Monitoringsystems. Weiterhin wird eine funktionale Signatur von Heidelandschaften dargestellt, die sich flächendeckende Information über Pflanzenstrategien zu Nutzen macht, welche mittels flugzeuggestützter Fernerkundungsdaten gewonnen wurden. Es wird zudem veranschaulicht, dass unterschiedliche Sukzessionsstadien mit Hilfe dieser Signatur nachverfolgt werden können.

Es lassen sich fernerkundungsgestützte Produkte erzeugen, die stark an dem ausgerichtet sind, was Naturschutzbehörden in regelmäßigen Abständen verlangen. Doch ermöglichen integrative Verfahren, die die Vorteile der Fernerkundung miteinbeziehen, die Ableitung genauerer und besser geeigneter Resultate. So können etwa Klassifikationen des Erhaltungszustands, die eigentlich auf räumlichen Aggregationen basieren, genauer kartiert werden, wenn die Information einzelner Pixel ausgeschöpft wird. Die Ergebnisse legen darüber hinaus nahe, dass die Einbindung struktureller Vegetationsparameter vorteilhaft ist, um Habitatqualität abschätzen zu können (zumindest jene von Heidelebensräumen), insbesondere wenn SAR-Daten dafür verwendet werden. Bei der Entwicklung zukunftsgerichteter Monitoringvorhaben sollte zudem die Einbindung von generalisierten Vegetationsklassifikationen angedacht werden, um so Vergleiche in Zeit und Raum zu erleichtern.

Als Schlussfolgerung kann angemerkt werden, dass zielgerichtete, fernerkundungsgestützte Stellvertretervariablen sinnvolle Ergänzungen für ein ganzheitliches und detailliertes Vegetationsmonitoring sein können, indem sie beispielsweise über Artvorkommen, Pflanzeneigenschaften, Zusammensetzungen von Gemeinschaften und Ökosystemstrukturen Auskunft geben können. Die Gewinnung solcher räumlicher Darstellungen in interdisziplinären Verfahren, nutzbar auf mehreren Skalen und zugänglich für unterschiedliche Interessengruppen, ist wahrscheinlich der Schlüssel, um Veränderungen und Auswirkungen in einer sich verändernden Umwelt zu überblicken und um das Management von fragilen und gefährdeten Systemen unterstützen zu können.

Contents

1 Introduction

Since centuries, people do have a fascination for heathlands; their open and sparse character makes them both interesting and repulsive at once. William Shakespeare used a heath scenery as the setting of a supernatural encounter in the beginning of his tragedy *Macbeth*, Alexander von Humboldt was keen on the adaptability and resilience of heathland vegetation in his *Aspects of Nature*, and these harsh landscapes were also recurring motifs in the works of Caspar David Friedrich and William Turner.

In Europe, the evolution and existence of heathlands as mostly cultural landscapes is closely linked to the history of human settlements, which is expressed by similar local names throughout the continent (e.g., German *Heide*; Scots *hedder*; Danish *hede*; Swedish *hed*; from Germanic *haiþī*) that share the meaning as common pasture, untilled land, or wasteland. They are characterized by dwarf shrub formations and sparse grassland with varying forms, and most of them have the same background of existing as a consequence of land use histories. Heathlands were established when traditional practices such as wood cutting and wood pasture led to the clearance of places with an underlying impoverished soil. Since they provide a variety of ecological niches, they support a specialized biota, some of which is not found elsewhere. The lack of nutrients and land use pressure often led to an absence of trees, resulting in landscapes with an open character. In summary, these characteristics make heathlands interesting places for observations, inspirations and investigations.

1.1 The ecology of European heathlands

Heathlands characterized by dominance of the dwarf shrub *Calluna vulgaris* Hull. (hereafter simply *Calluna*, common name: heather) are major cultural landscapes in Europe. They mainly occur in Atlantic regions, but also scattered in isolated areas outside the main distribution range (Diemont et al., 2013). These landscapes are products of several millennia enduring human activity, thus creating and maintaining mosaics of resilient dwarf shrub vegetation and undemanding grassland (Rose et al., 2000). Constant exploitation due to grazing and wood pasture prevented natural succession and thus preserved open habitats. The intense land use led to nutrient-poor and relatively acid environments (Webb, 1986). The focus of this thesis is on a rather dry heathland landscape (Fig. 1.1.1). In the following it is referred to this type.

The rough conditions offer a broad range of niches, partly promoting high species diversity (Piessens et al., 2004). Dry heathland supports a majority of the reptile fauna of north-west Europe and a particularly rich variety of warmth-loving invertebrates (Kirby, 2001). However, the extreme form of *Calluna*-heathland, represented by very high coverages the shrub layer, is species-poor for vascular plants (Ausden, 2007). More open areas can support a wider variety of mosses, lichens, and species-rich grass and herb communities adapted to the dry and nutrient-poor conditions. Besides a (partially) high biodiversity, heathland landscape provide important ecosystem services like carbon storage and recreational value (Cordingley et al., 2015).

The ecology of heathlands is characterized by the life cycle of the key species *Calluna* (Watt, 1947). This successional cycle is represented by four growth phases of the dwarf shrub (Gimingham, 1975): pioneer (0-5 years old), building (5-15), mature (15-25) and degeneration phase (25-40). Every stage within this cycle is characterized by the age and the height of *Calluna*, starting with a seedling and ending with the dying off (see Fig. 1.1.1). Moreover, species composition changes throughout the cyclic succession as many species are linked to particular developmental stages. At the beginning, sparse vegetation of vascular plants is observable with a large amount of open soil and lichens. When *Calluna* becomes older and more dominant it can form dense layers that exclude almost all other species. As the dwarf shrub slowly collapse while degenerating, new open patches appear that provide the basis for a restart of the successional cycle. Moderate disturbance decelerates the succession. The cycle can be disrupted when tree species develop and start to form pioneer forests. By means of nature conservation it is desired to have mosaics of the four heather phases and to prevent the development of woody species (Ausden, 2007).

Due to the abandonment of traditional agricultural practices and changes in land use, total heathland area has decreased strongly and the related habitats became more and more fragmented. The absence of disturbance leads to an overaging of the *Calluna* plants and supports the encroachment of grasses and pioneer tree species. Moreover, atmospheric nutrient input exacerbates the situation (Heil and Diemont, 1983).

Fig. 1.1.1 *Heathland vegetation in the Oranienbaum Heath, the study site of this thesis. It is characterized by areas dominated by Calluna. This dwarf shrub is often occurring in patchy stands, partly interspersed by grassland communities (here: sparse pioneer grassland) and open sandy soil (top). Mosaics with species-rich calcareous grassland where Calluna forms lower coverages is considered as a desired state in terms of nature conservation (bottom left). Here, different successional phases of heather occur and open soil promotes seedling recruitment. The grazing management promotes heterogeneous stands of Calluna dominated heathland and counteracts heathland degradation, for example, grass encroachment (bottom right). Species richness is particularly low in these areas due to suppression by dominant grasses.*

1.2 Conservation and management of heathlands

The importance of heathlands, in combination with the threats they are facing, made them subject to a wide range of conservation designations. Most Central European heathlands are under protection within the Natura 2000 network. This network was designed to protect Europe's most threatened species and habitats and established based on a set of legislation focusing on biodiversity conservation in Europe: the Birds Directive and the Habitats Directive (Council of the European Communities, 1992). Established in 1992, the network nearly covers 20% of terrestrial area of the European Union (ca. 790,000 km), distributed among 9 coherent biogeographic regions all over Europe, and provides a high level of protection to about 1000 threatened species and 230 habitat types. Implementing this nature legislation was also highlighted in the *EU Biodiversity strategy to 2020*, installed in 2011 (EU Commission, 2011). This policy aims at halting the loss of biodiversity and the degradation of ecosystem services in the EU. The first of six targets within the strategy document demands the full implementation of the Birds and Habitats Directive, including the improvement of monitoring and reports.

European member states are demanded to generate regular reports every six years that include thematic and spatial information about the state and the perspective of the listed species and habitats. These periodic reports should base on a standardized monitoring system that allows for repeatable and comparable assessments. The mapping and quality assessment of habitat types is supported by superior guidelines (European Interpretation Manual; EC, 2007) that were subsequently adapted to small-scale applications by the member states and the federal states within. However, in many cases neither the monitoring system is based on common standards nor effective management plans have been elaborated (Ledoux et al., 2000). This is mainly due to economic factors and the presence of a variety of mapping guidelines.

In conclusion, there is a need for more standardized and cost-effective methods that allow for obtaining information about the state of vegetation in Natura 2000 areas. Repeatable and comparable results would then enable the setup of a consistent and comprehensive monitoring system.

Managing heathlands

The abandonment of land use for agricultural purposes is associated with the absence of disturbance and a reduction of nutrient discharge. Moreover, heathlands are nowadays subject to deposition of anthropogenic atmospheric nitrogen. This encourages the growth of competitive grasses (e.g., bushgrass, Calamagrostis epigejos; purple moor-grass, Molinia caerulea) and pioneer tree species (birch, *Betula pendula*; pine, *Pinus sylvestris*) at the expense of *Calluna* and less competitive grass species (Heil and Diemont, 1983). Military training areas represent a certain form of land use that provide disturbance regimes (fires, tank movements) and thus lead to open landscapes which often feature large amounts of heathland vegetation (Härdtle et al., 2009).

Most management actions represent former land use practices of heathlands as they aim at deporting nutrients from the area to prevent the loss of specialized heathland vegetation adapted to sparse environments (Härdtle et al., 2009). Thus, conservation-related management of heathland usually seeks to prevent the expansion of competitive grasses, bracken (*Pteridium* *aquilinum*) and pioneer trees in order to maintain patchy vegetation of dwarf shrubs comprising mixtures of different successional phases, interspersed by bare ground and grassland. As large areas that feature very high coverages of *Calluna* are rather poor in species, this shall be limited to small patches.

A key aim in managing heathlands is to provide varied structure of the shrub layer comprising mixture stands interspersed with bare ground in order to maximize the range of suitable conditions for a variety of species. The conditions for these heathland species vary primarily in relation to the stage of re-growth following disturbance. Therefore, interventions are conducted specifically on the patch level, for example, by guidance of herbivores (fences, licking stones) or selective mowing (Lorenz et al., 2013). Over time, the herbaceous vegetation is usually out-competed by *Calluna* dwarf shrubs, unless their dominance is suppressed. Hence, heathlands' structure and species composition can be modified by management.

The most common forms of heathland management involve burning, cutting, mowing and grazing systems, each associated with positive and negative aspects (Ausden, 2007). When large herbivores are introduced, the trampling leads to open, disturbed soil locations; the grazing reduces litter material and browsing suppresses the succession of *Calluna* plants and pioneer trees. In a study that was carried out in the same study area, Henning et al. (2017) recommend to set up systems of low-intensity grazing in combination with one-time mowing. A main advantage of this system is trampling that leads to open and disturbed soil promoting the seedling recruitment of *Calluna*.

Appropriate management actions are often cost and time intensive, and there is current research and a lively discussion about "right" or "best" practices (Härdtle et al., 2009). Possible interventions should be effective in terms of personnel and financial effort and compatible with other interests, primarily recreation. Here, best practice examples could demonstrate a path forward. Furthermore, an appropriate and, ideally, transferable monitoring system would be needed in order to check whether conducted actions produced desired outcomes.

1.3 Background of the thesis: research project and study area

This thesis was supported by the German Federal Environmental Foundation (DBU, www.dbu.de), which is one of Europe's largest foundations with a yearly budget of around 50 million Euros dedicated to project funding. The DBU mainly promotes projects of environmental relevance focusing on environmental technology and research, nature conservation, environmental communication and cultural assets (DBU, 2015). Moreover, the conservation efforts of the DBU are expressed in the administration of 70 sites of the National Heritage in Germany. Many of these sites, which cover around 70,000 ha in total, have previously been used as military training areas. The focus is on implementing long-term systems under sustainable management that support biodiversity and provide important ecosystem services (Wahmhoff, 2010).

The study area of this thesis, the Oranienbaum Heath, has been selected as representative site for setting up an exemplary management project mainly based on large herbivores (Lorenz et al., 2013). The aim is to develop a sustainable grazing management system that is thought to be adapted in similar DBU sites. The Oranienbaum Heath is located near Dessau, Saxony-Anhalt, Germany, and represents a rather dry form of Central European heathland.

Furthermore, an interdisciplinary scheme bringing several PhD projects together was set up by the DBU in 2011 (Schaefer and Schlegel-Starmann, 2017). The main purpose was to examine successional processes in the Oranienbaum Heath, partially influenced by management efforts, such as grazing by large herbivores, tree cutting and mowing of dwarf shrub heathland. One main aspect of the research initiative was the relation to monitoring initiatives of the DBU considering repeatability and transferability to other sites. The current thesis represents the remote sensing aspect within this research consortium. Due to this background, the thesis was designed to meet the requirements of developing an application-oriented and cost-effective approach for mapping heathland habitats related to Natura 2000 monitoring and in support of site management.

1.4 Surveying from above: remote sensing for capturing vegetation

Field mappings by experts that are based on plot-wise surveys mostly provide required information about the state and change of vegetation. Permanent sampling plots represent a relatively objective approach for the observation of changes, resulting in stationary knowledge. However, spatial changes of the vegetation between the plots, such as the shift of vegetation types, cannot be tracked that way (Sachteleben and Behrens, 2010; Whittaker et al., 2005). Gaining field-based continuous information about an area is hardly possible as it is labor- and cost-intensive. Consulting remote sensing techniques potentially enables for capturing wall-to-wall information and therefore for interpolating between the stationary knowledge. Remote sensing provides this helpful information by making use of images of the Earth's surface formed by sensors that detect reflected electromagnetic energy. These sensors are characterized by using distinct technologies to capture varying regions of the electromagnetic spectrum. Typical platforms that carry the remote sensing devices include airplanes, satellites, and UAVs.

Optical remote sensing

Optical remote sensing targets energy that is reflected and emitted by the Earth (Fig. 1.4.1a), therefore it is referred to as passive remote sensing (here, LiDAR as active optical system is disregarded). These sensors typically capture relatively short wavelengths between 400 and 14,000 nm (0.4 – 14 µm), represented by the visible and infrared regions of the electromagnetic spectrum (Fig. 1.4.1d). Respective sensors operate during the day as visible and near-infrared radiation can only be measured by daylight and they are also hampered by clouds.

As optical remote sensing data is sensitive to chemical and partly biophysical plant traits it provides an appropriate basis for describing and discriminating vegetation (Hill et al., 2005). Concerning capturing vegetation, reflectance is regarded an expression of several aspects, such as species composition, short-term dynamics, and site properties not related to plant species composition (Jones and Vaughan, 2010). Together, these factors affect biochemical and structural properties of the vegetation canopy, such as pigmentation, orientation, and water content, as well as leaf area and leaf structure. Additionally, reflectance is a result of the amount of open soil and dead plant material. The typical spectral curve representing healthy green vegetation is characterized by a significant minimum in the visible region (resulting from the pigments) and a drastic increase of reflectance in the near infrared (Fig. 1.4.1c). High reflectance between 0.7 and 1.3 µm is mainly a result of the internal structure of plant leaves, which is largely varying among different plant species (Fig. 1.4.1d). That is why reflectance within this spectral region is important for the description and discrimination of plant species and communities. Retaining water in the leaves leads to absorption minima in higher wavelengths. Remote sensing does not sense species diversity directly, but enables the identification of spectral-spatial-temporal signatures of vegetation communities (Jones and Vaughan, 2010).

SAR remote sensing

Microwave remote sensing detects much longer wavelengths (between ~1mm and 1m; Fig. 1.4.1d). Here, a sensors actively emit series of electromagnetic beams and record those which have been reflected (Campbell, 2002); see Fig. 1.4.1a. Here, it is only referred to synthetic aperture radar (SAR; radar = radio detection and ranging) as active system, which usually uses wavelengths between approximately 4 and 8 cm. Broadly speaking, SAR sensors record the microwaves reflected by objects, which allows for visualizations of backscatter intensities (microwave imaging). In general, objects with a rough textured reflect more energy than smooth objects. Rough surfaces, such as forests, tend to scatter the pulse in many directions, increasing the chance

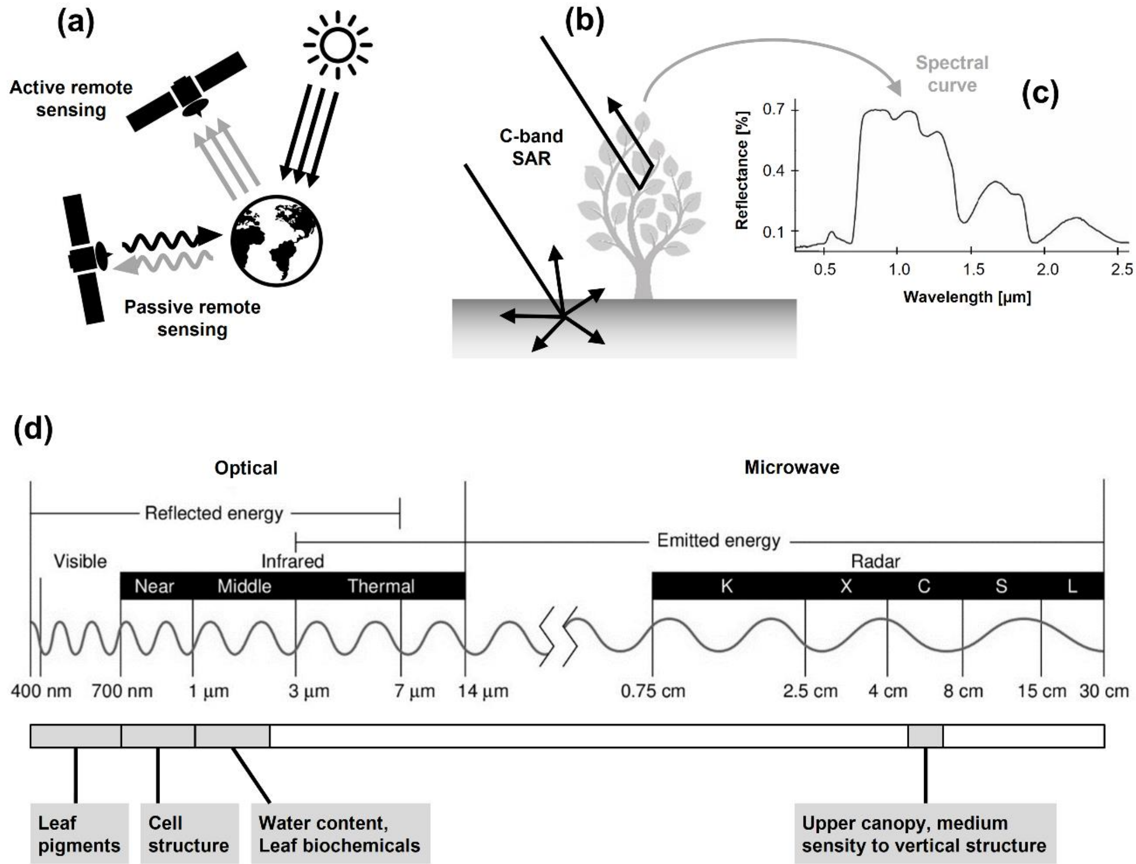

Fig. 1.4.1 *Simplified vizualization of remote sensing from space: While passive sensors measure naturally occurring energy, active systems emit radiation in the direction of a target and then detect the reflected radiation (a). SAR-backscatter mainly provides information about vegetation structure (b), whereas optical properties of vegetation (c) are captured by passive systems. These different technologies can be used to detect distinct regions of the electromegnetic spectrum (c; Adapted from Turner et al., 2003:307): Energy that is reflected and emitted by the Earth at wavelengths between 0.4 and 14 µm is captured via optical remote sensing, whereas longer wavelengths are recoreded by radar technologies (microwave imaging).*

that some beams will return to the sensor (Richards, 2009). Water bodies, for example, represent smooth objects that are highly reflective. However, when they are perpendicular to the direction of the incoming pulse, most of (or even all) energy is reflected away and never returns to the sensor.

Microwave backscattering from land surfaces is sensitive to vegetation features. Structure that is represented by size, orientation, and distribution of scattering surfaces as well as dielectric constant, such as moisture content, are crucial surface parameters (Richards, 2009). The dielectric characteristics of vegetation material are influenced by moisture content over a wide range of the microwave spectrum. In addition, geometrical features of plants affect scattering in a different fashion according to frequency and polarization. Active remote sensing information is complementary to optical sensors, as it can penetrate into the vegetation canopy and thus its backscatter is mostly related to structural-morphological parameters of the vegetation (Fig. 1.4.1b) which is only partly described by the optical signal. Moreover, the abilities of active sensors to penetrate clouds and to operate day and night makes them interesting when high repetition rates are desired (Schuster et al., 2015).

The SAR signal of vegetation is generally build up by 1) surface scattering from the top of the canopy, 2) volume scattering (interaction of inner parts of the vegetation), and 3) surface scattering from the ground (Fernandez-Ordonez et al., 2009). In general, elements that are smaller than the wavelength produce little backscatter, and longer wavelengths are more sensitive to the vertical structure of vegetation. In addition to vegetation, the basic reflectivity of the soil can play a major role. Dry soil is characterized by low radar reflectivity (Fig. 1.4.1b), whereas saturated soil is a strong reflector (Richards, 2009). Moist soils represent intermediate backscatter values. Relief may also affect the SAR signal, but can be ignored due to the flat terrain of the study area.

C-band SAR that is used in this thesis mainly provides information about the upper part of the vegetation canopy and about surface characteristics (Fig. 1.4.1b). SAR backscatter could be relevant for characterizing heathland vegetation, which is predominantly build up by herbaceous vegetation and dwarf shrubs. The *Calluna* shrubs affect SAR backscatter by many small stems and branches with varying orientations as well as by small scale-like leaves (Duguay et al., 2015).

Remote sensing resolutions

Three definitions of resolution are important in the field of remote sensing: 1) spatial, 2) temporal, and 3) spectral resolution (Campbell, 2002). The spatial resolution refers to the pixel size of a remote sensing product, describing how detailed the observed area was recorded (Fig. 1.4.2). Concerning ecological applications this would be related to the smallest object that can be detected, considering that an “object” could vary from a single plant species over certain plant communities and to whole landscapes. If an area is repeatedly captured, the time lag between the recordings is defined by the temporal resolution. This may be of interest, when, for instance, vegetation phenology has to be captured over a year (Jones and Vaughan, 2010). Spectral resolution is only relevant for optical systems. The term describes which spectral range was captured, and how detailed (i.e., into how many bands the spectrum was sliced). Remote sensing data with a high spectral resolution, e.g., hyperspectral data, does allow for nuanced recordings of reflectance patterns, whereas only rough estimations could be made based on ‘simple’ imagery using much less bands (Fernandez-Ordonez et al., 2009).

Broadly speaking, the radar equivalent to the spectral resolution of optical sensors would be frequency and wavelength, expressed by SAR bands (Curlander and MacDonough, 1991; Fig. 1.4.2). For ecological applications, characterization of these bands depends on their ability to penetrate ice, the top soil layer, the vegetation canopy and which layers of the canopy.

When a mapping should be conducted based on remote sensing data, these factors have to be considered: Which type of remote sensing (optical, passive, or in combination) does allow for detecting respective vegetation characteristics? Would simple RGB-data be sufficient or do certain vegetation phenomena only become observable by using data that covers a larger spectral range, such as multispectral or hyperspectral imagery. What size do the “objects” have that I want to capture and which pixel size would be appropriate for the result? Does the mapping task demand for repeated observations, and, if so, within which period? However, in practice, one important question should be added: Which data is accessible or affordable?

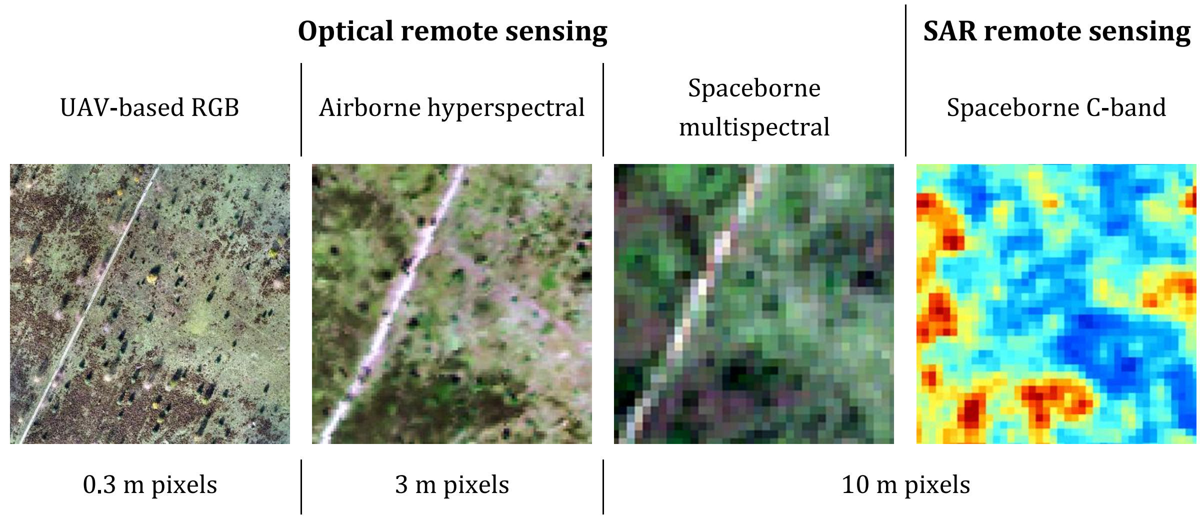

Fig. 1.4.2. *Exemplary presentation of different remote sensing data used in this thesis. Each time, the same area is shown which is located in the south of the study area. Images are depicted featuring varying spatial resolution that were captured by various sensors on different platforms. Optical imagery is displayed in RGB colors, whereas SAR backscatter is expressed by intensity (red = high, dark blue = low).*

1.5 How to use the remotely sensed information?

Finding appropriate methods of exploiting the earth observation information is of similar importance to the question of which data to use. Basically, a distinction is made between two categories of remote sensing approaches. Either direct observations are possible, e.g., identification of single species and species assemblages, or indirect measures are obtained that rely on environmental parameters as proxies (Turner et al., 2003). In conservation-related tasks that would basically mean: either relevant information is captured manually, or by the help of statistical methods. The first possibility represents very basic procedures, such as visual interpretation and manual digitization, that are very common in the field of conservation mapping (Gross et al., 2009; Vanden Borre et al., 2011a). However, these approaches rely on subjective decisions; a fact that makes them scarcely transferable (Cherrill and Mcclean, 1999). In general, semi-automatic approaches are considered as more robust and repeatable (Kampouraki et al., 2008).

Semi-automatic procedures mostly combine field measurements ("ground truth") and remote sensing data in statistical models. Here, field-based training samples are associated with a set of remote sensing predictors (from pixels that correspond to the location of the samples), and rules for predicting new observations are derived (Franklin, 1995). This way of obtaining area-wide information can be thought of as a kind of interpolation, where forms of statistical learning are used to predict wall-to-wall information (Hastie et al., 2009), for instance, about vegetation patterns. The thematic accuracy of such a mapping product can then be assessed, for example, based on the percentage of correctly assigned of vegetation types.

In predictive vegetation mapping, the obtained product depends on the response variable, which can either be continuous (e.g., abundance of species) or categorical (e.g., presence/absence of species). Consequently, different methods are used to predict the dependent variable based on values of the independent variables represented by remote sensing features (Franklin, 1995). Classification techniques can be used to produce discrete maps, for instance, of vegetation types that of interest for conservation authorities. Natural vegetation, however, does not appear in discrete classes, but rather as a continuum (McIntosh, 1967). Here, regression models that base on continuous training data can be used for predicting continuous information over a larger extent. Species composition, for example, can be mapped via regressing species-based ordination scores against remote sensing imagery for obtaining continuous information (Feilhauer et al., 2011; Schmidtlein and Sassin, 2004). It should be noted that a link between the variable derived in the field and the remote sensing imagery is an essential prerequisite for the success of a spatial prediction (see section 1.4).

Using remote sensing for obtaining information about richness in animal species is far more complicated given their mobility and lower coverages. Hence, the remote sensing signal is mostly not affected by fauna; exceptions are large animals (Fretwell et al., 2014; Vermeulen et al., 2013) or large groupings of animals (Guinet et al., 1995; LaRue et al., 2014). Therefore, remotely sensed imagery does not directly quantify animal species but estimations can be derived based on relations between plant species richness and animal species richness, e.g., by measurements of functional diversity (Petchey and Gaston, 2002). A study that is of interest with regard to this thesis was presented by Luft et al. (2016). They predicted occurrence probabilities of an endangered butterfly species via mapping habitat characteristics based on hyperspectral remote sensing in a similar landscape containing heathland vegetation.

1.6 Remote sensing for nature conservation

Nature conservation with its needs for spatial information could benefit from the techniques and procedures described above. In Europe, for instance, the mandatory monitoring standards related to the habitats directive require mappings of habitat types and assessments of habitat quality. These repeated mappings are conducted in the field. However, they require a great effort and the results are difficult to reproduce. An effective monitoring which bases on robust and reproducible methods is demanded. Here, the combination of standardized field information and remote sensing could provide an appropriate basis when linked in semi-automatic procedures. The development of methods for monitoring purposes includes both discrete and continuous information. The latter allows for detecting ecotone shifts or precise observations of spatial processes which are essential for the management. However, discrete classes are demanded by conservation authorities with regards to the Habitats Directive.

Several studies demonstrated that remote sensing can be useful to support the mappings related to European monitoring purposes (e.g., Bock et al., 2005; Förster et al., 2008; Vanden Borre et al., 2011b). Heathlands represent a major subject of research related to remote sensing-based applications. First studies dealt with the distinction of heathland types. Spaceborne multispectral remote sensing (Lucas et al., 2007) as well as high resolution RGB aerial imagery (Mac Arthur and Malthus, 2008) provided appropriate basis for the classifications. Applications that base on hyperspectral data allow for more precise applications. Fine-scale vegetation characteristics that are of interest for conservation, such as detailed separation of heather age classes, were captured by Delalieux et al. (2012). Focusing on coarse-scale parameters, like the occurrence of dwarf shrubs or grass encroachment, Spanhove et al. (2012) were able to derive small-scale information on habitat quality. Besides producing continuous maps of grass encroachment, Mücher et al. (2013) also addressed the target of finding mapping units that pool pixel-wise representations. Luft et al. (2014) suggested to reconcile the US-American monitoring standards with the European monitoring demands to set up a new feasible method. By linking species ordination and hyperspectral imagery, Neumann et al. (2015) were able to map continuous probabilities of both habitat type affiliations and habitat quality.

Although many possible remote sensing applications have been demonstrated, there are struggles to operationally implement them in monitoring systems. Different points of view of both communities, remote sensing and nature conservation, and, as a consequence, communication problems are often instanced in this context (Skidmore et al., 2015). The remote sensing community has a tendency to focus on target variables that can be detected via available sensors, whereas the conservationists have variables in mind that are directly connected to conservation issues and it seems that they are not aware of what is detectible via remote sensing. A reformulation of monitoring guidelines for improving their compatibility with remotely-sensed data would presumably be connected to a rather long-term process. Alternatively, remote sensing approaches are adapted to better match existing field guidelines (Corbane et al., 2015). Ideally, integrated approaches on the basis of interdisciplinary work between remote sensing experts and ecologists are arranged to accomplish future monitoring schemes (Pettorelli et al., 2014).

Harmonized variables for biodiversity monitoring

The development of essential biodiversity variables (EVBs; Pereira et al., 2013) is a prominent example for a concept that has been developed in cooperative effort between ecologists and remote sensors in order to define a set of standards. The EBV concept shall provide guidance to observation systems as to what and how to measure key aspects of biodiversity (genetic diversity, species diversity, ecosystem diversity) that suit remote sensing specific needs as well.

Recently, Skidmore et al. (2015) emphasized the remote sensing of EVBs, and Pettorelli et al. (2016) presented possible implementations, mainly focusing on capturing relevant parameters from space. The selected (and proposed; see Pettorelli et al., 2016) variables are considered as key parameters that foster understanding and global monitoring of changes in the Earth's biodiversity (CBD, 2010). These metrics are related to, for example, species traits, community compositions as well as ecosystem structure and functioning and therefore can be linked to biodiversity (Pereira et al., 2013). Moreover, they share characteristics like sensitivity to change, describing state variables (contrary to drivers or results), and are represented at intermediate levels between primary observations and high-level indicators. They are meant to serve as proxies, e.g., for indicating global problems such as deforestation, or monitoring the restoration of degraded ecosystems, and should support decision makers and assessments related to biodiversity change. They are meant to reflect the complexity and multidimensionality of biodiversity based on few meaningful and traceable variables (Pettorelli et al., 2016).

Although the EVBs were defined for monitoring systems with a global scope, regional aspects should also be taken into account. Paganini et al. (2016) point out that during the prioritization process for selecting certain variables it would important to consider how a variable will be used in practical cases, for example, in regional biodiversity assessments. Moreover, it is remarkable that, although agreements are arranged on the global scale (e.g., Convention on Biological Diversity; CBD, 2010), conservation action mostly takes place at the national or regional level. Vihervaara et al. (2017) linked existing national biodiversity state indicators to the EBV scheme and conclude that national remote-sensing assessments could consider to include certain variables, such as ecosystem function and structure, community composition and species traits, due to a particular benefit.

According to Maes et al. (2012) Natura 2000 assessments could also be relevant in that regard. They report that habitats attributed with a “favorable” conservation status provided higher values of both biodiversity and ecosystem services than those in an “unfavorable" status. This possible link between the European monitoring scheme and the EBV concept was then emphasized by Zlinszky et al. (2016) who stated that the conservation status assessment could, when mapped at a coarser scale, qualify as an EBV as basic characteristics (focus on state variables, sensitivity to change over time, scalability, and usefulness for informing progress toward the CBD targets) are met.

1.7 Synthesis of research needs

Although there is a growing number of remote sensing-based applications aiming to support conservation mapping, they have not yet found their way to operational monitoring schemes. A lack of acceptance of remote sensing-based procedures by applied nature conservation can still be observed. For example, regarding Natura 2000-related studies it is frequently pointed out by nature conservationists that remote sensing-based products do not directly meet the demands of the regular reports. Amongst other reasons this may have caused struggles to operationally implement remote sensing technologies into existing monitoring systems.

The underlying cause may be communication problems that are attributed to different points of view the communities typically have (Skidmore et al., 2015). Although there are recent efforts to agree upon common standards within the remote sensing and the nature conservation communities (for example, essential biodiversity variables; Pereira et al., 2013) this must be seen rather as a long-term process concerning the establishment of operational implementations of remote sensing methods into monitoring systems. Short-term solutions might be found in transferring established methods from one field to the other by adjusting these methods with regards to the respective demands (Corbane et al., 2015). Some studies pointed in this direction, however, few well suited results were presented up to now. Remote sensing-based products that meet the demands of decision makers with respect to the Habitats Directive are still rare. Reviewing remote sensing studies in the context of Natura 2000, Corbane et al. (2015) conclude that further efforts are necessary to overcome barriers in communication, including the development of common standards concerning terminology, data formats, and products.

Indeed, the gap between nature conservation and the remote sensing community has been narrowed by several studies in the last years. However, remote sensing-based approaches often lack transparency and deliver results that are not directly related to the demands of applied nature conservation (Vanden Borre et al., 2011b). More efforts should be put in developing methodologies that use the benefits of remote sensing for producing comprehensible results that are directly related to what is required by ecologists and conservation authorities.

One important requirement for procedures using Earth observation for long term monitoring tasks is the consistency and transferability of the approaches which also depends on the consistent delivery of Earth Observation data. Recently, the European Space Agency (ESA) started their Copernicus program that provides freely available spaceborne SAR and multispectral data. Supporting the monitoring of Natura 2000 areas was one major aim of the Copernicus mission (Kuntz et al., 2014). In relation to that, habitat quality assessments could be tested by using these satellite data. In this context it is mentionable that the potential of actively-derived SAR information has not been explored sufficiently in the context of habitat mapping related to European nature conservation.

Commonly, both optical and structural vegetation properties are considered when habitat quality is assessed in the field. While passive optical information is frequently used in remote sensing-based approaches for monitoring habitat quality, active sensors that directly capture structural aspects have rarely been implemented (Schuster et al., 2015). SAR information is regarded as complementary to passive optical data, yet it was mainly used for exploring broader vegetation types. Concerning dwarf shrub heathland, the use of optical data alone does not fully cope with the demands of a comprehensive assessment as the structural aspect is not directly captured (Spanhove et al., 2012). Approaches that consider active remote sensing data for assessing the specific vertical structural characteristics of shrub heathland remain to be realized.

Conventional vegetation mapping has a tendency to focus on discrete classification (Feoli, 1984). Regarding the Habitats Directive this focus is expressed by the definition of discrete habitat types. However, some monitoring demands are hardly compatible with conventional vegetation classification approaches (Chiarucci et al., 2008). As the Natura 2000 network consists of a multitude of habitats that stretch across broad geographic regions, a system that allows comparisons of a variety of these habitats on equal footing is desirable. One potential solution might be found in considering general plant strategies that allow to describe communities (Allen and Starr, 1982). Among several approaches the CSR-concept (involving C - competitiveness, S - stress tolerance, and R - ruderality) proposed by Grime (1974) seems to be particularly promising. It is regarded to combine generality with flexibility to adapt local conditions (Hunt et al., 2004). Moreover, it is compatible with remote sensing, which allows for gaining wall-to-wall information (Schmidtlein et al., 2012). However, there is a lack of examples illustrating the benefit of such a generalized system with regards to an operational monitoring scheme.

1.8 Research questions & thesis outline

Motivated by these research needs, the objective of this thesis is to promote the operational use of remote sensing in conservation mappings schemes. The potential implementation of Earth observation data should be illustrated towards an effective and transferable monitoring of conservation areas. The main research questions of this thesis are:

- What are the benefits and limitations of a patch-wise conservation status mapping using remote sensing imagery?
- How to integrate existing field guidelines for habitat quality assessment into a remote sensing-based procedure?
- Can information about vegetation structure derived from remote sensing provide an additional value for assessing the quality of dwarf shrub shrubland?
- How can a generalized concept of plant strategies contribute to enhanced comparability and transferability of a remote sensing-based vegetation monitoring?
- What kind of remote sensing resolutions are appropriate regarding the needs of conservation-related mappings and which remote sensing technologies are beneficial for assessing the habitat quality of heathland vegetation?

The research questions are addressed by the example of a Central European heathland landscape and in the light of an existing European monitoring scheme for conservation areas. Four research studies, each prepared as an individual research paper, were carried out as core of this thesis.

Heathlands offer appropriate test sites for the development of remote sensing-based mapping procedures. First of all, the open landscapes can be surveyed from above. Moreover, the key species *Calluna* features remote sensing friendly properties: the dense patches can be well detected by optical sensors. Due to the complex structure, *Calluna* stands are characterized by relatively high SAR backscatter, despite of low to medium vegetation heights. These two aspects are closely related to the quality assessment of respective habitat types. For example, dense and tall *Calluna* patches are mostly assigned to a "bad" conservation status, whereas mosaics of *Calluna* and dry grassland is often considered as "good"; both vegetation states most likely feature specific reflectance characteristics.

The research papers were jointly developed in open teamwork, which means that more than the thesis' author is responsible for the content. All manuscripts were originally written by the first author and then subsequently revised by the co-authors. The research studies 2.2 and 2.4 have already been published and remain unchanged in this thesis. The manuscripts of study 2.1 (in preparation) and study 2.3 (under review) might be changed during the review process. Fig. 1.8.1 provides a schematic overview of the research studies included in this thesis.

The first study approaches the question of how to map patch-wise habitat quality classes of dwarf shrubland by remote sensing from several perspectives. The major aim is to present a remote sensing-based product that directly meets the demands of European conservation authorities. It is assessed what patch sizes are meaningful, if multi-seasonal information provides an additional value, whether the mapping benefits from including SAR imagery and if sufficient accuracies can be reached.

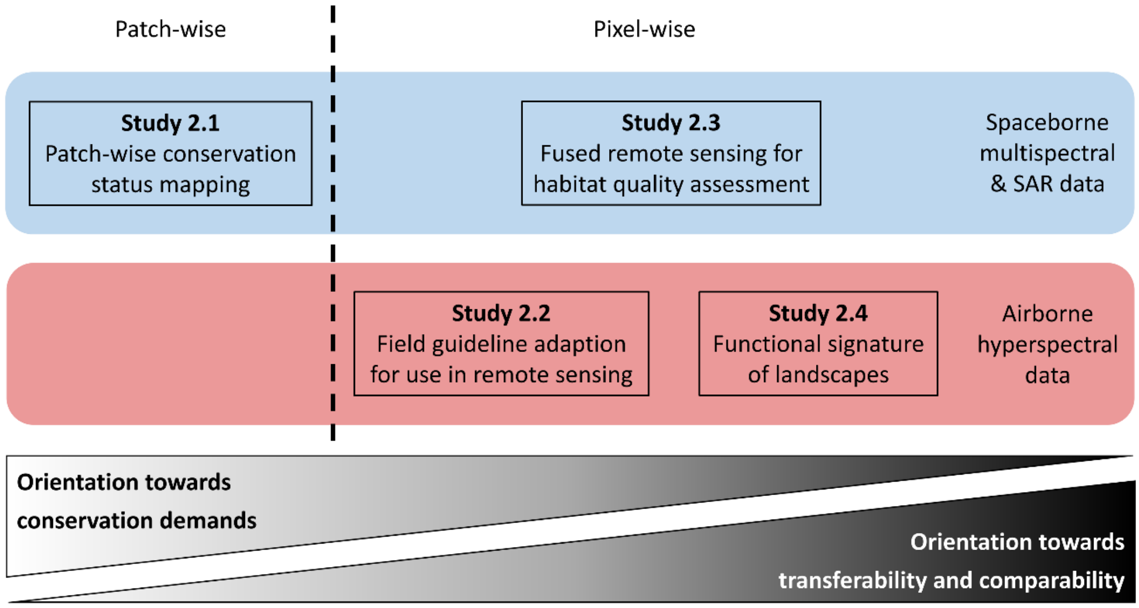

Fig. 1.8.1 *Overview of the four research studies embedded in this thesis and a schematic picture of their contribution. The studies share the methodic principle of predictive vegetation mapping by linking field samples and remote sensing (RS) data that was either spaceborne multispectral or airborne hyperspectral. Thematic orientation of the studies evolves from a strong orientation towards conservation-related demands, over integrated approaches based on transferring field assessment to remote sensing, to a generalized framework complementary to conventional vegetation maps that rather allows comparisons across regions and time.*

In the second study, a new method for a quality assessment of dwarf shrub heathland is proposed. The underlying motivation was to integrate a field mapping guideline into a remote sensing-based procedure. Therefore, assessment parameters are transferred to remote sensing proxies. Combining these proxies in an RGB composite enables a continuous visualization of a variety of stand attributes. The step from a gradient map to discrete quality classes is achieved by applying thresholds derived from expert knowledge.

A similar approach is chosen for the third study, exploring the synergetic use of spaceborne imagery. Here, the inclusion of SAR data allows for deriving structural parameters. The operationalization of experts' decision making process into a rule-based methodology is used to derive the conservation status of *Calluna*-heathland. Transferability of the approach is tested based on a second, independent remote sensing dataset.

In the fourth study, the functional signature of a heath landscape is assessed based on plant strategies. Therefore, continuous maps of plant functional strategies were obtained by the use of airborne imagery. Within a transferable ecological feature space, this signature provides a detailed overview of how the vegetation in the examined area adapted to environmental conditions. Discrete classes of plant functional types representing habitat types are be mapped in order to relate the functional concept to conventional vegetation classifications.

Summarized, this thesis aims to present modules for an integrated concept to support the management and nature conservation of heathland areas and inform policy makers by delivering objective information on habitat status based on remote sensing products. The single procedures are closely related to established field mapping schemes. In combination, they could be used for both management of heathlands (revealing necessary management actions, evaluation of interventions) and the quality assessment demanded by conservation authorities. A wide range of remote sensing technologies is tested and evaluated in order to derive recommendations for future mappings. By closely combining concepts and methods of both communities remote sensing and nature conservation, the aim is to initiate an operational use of Earth observation in future vegetation monitoring.

2 Research studies

2.1 How to map the patch-wise conservation status of shrublands with remote sensing?

Johannes Schmidt, Pete Bunting

Abstract

Conservation authorities in Europe require spatial information about the conservation status of rare and threatened habitat. Moreover, it is demanded to obtain such maps based on consistent mapping units derived in field-based procedures. However, these mappings rely on objective decisions and are therefore difficult to reproduce – a fact that hampers the setup of a consistent vegetation monitoring. Remote sensing offers the possibility to deliver the demanded information about vegetation properties and, moreover, allows for reliable derivations of vegetation patches that base on reproducible methods. However, there is still a lack of appropriate remote sensing-based methods with respect to this task.

Here, we combine field-based conservation status assessments with freely available spaceborne data including multispectral imagery and SAR backscatter from four different seasonal dates. We seek to assess what patch sizes are meaningful, if multi-seasonal information provides an additional value, whether the mapping benefits from including SAR imagery and if sufficient accuracies can be reached. These questions are answered by the example of dwarf shrub heathland.

We received low to moderate accuracies for the patch-wise classification of heathlands conservation status. Results confirm that neither including multi-seasonal information nor using multi-sensor synergies enable for precise mapping of patch-wise quality classes. Two general trends were observed: SAR data seems to be more informative, when the information is pooled in patches and large patches rather benefit from multi-sensor synergies. Finally, we would advise to focus on other (rather pixel-wise) procedures for deriving spatial information about vegetation states related to predefined quality classes.

This study is in preparation for submission to Remote Sensing in Ecology and Conservation as:
Schmidt, J., Bunting, P.: How to map the patch-wise conservation status of dwarf shrublands using multi-sensor spaceborne remote sensing?

2.1.1 Introduction

It is widely accepted that nature conservation mappings can benefit from remote sensing, such as those related to the European Habitats Directive. Many studies have already demonstrated the potential of remote sensing information to fulfil monitoring demands (e.g., Förster et al., 2008; Stenzel et al., 2014; Vanden Borre et al., 2011b and many more). Recently, Corbane et al. (2015) provided a review about studies that use remote sensing for conservation mapping in Natura 2000 sites. They underlined the statement of Vanden Borre et al. (2011b) that a complete (in terms of the Natura 2000 context) remote sensing-based conservation status assessment has not yet been presented.

Two aspects are relevant concerning Natura 2000 monitoring: spatial information about the occurrence of habitat types is demanded as well as about the state of vegetation, which is expressed in quality classes. While the first task has been targeted in several studies, for example, via one-class-classification (Stenzel et al., 2014) or based on species ordination (Neumann et al., 2015), rather little attention has been given to the second aspect. Several studies in heathlands addressed the assessment of parameters closely related to the demanded procedure (Delalieux et al., 2012; Frick, 2007; Mücher et al., 2013; Spanhove et al., 2012). Even though, Neumann et al. (2015) mapped continuous conservation status probabilities of heathland habitats based on species ordination, no map depicting discrete conservation status classes was obtained. The latter was mapped by Schmidt et al. (2017b) utilizing a rule-based approach in order to transfer a field guideline to a remote sensing approach. However, both studies presented pixel-wise maps, which are considered as rather inappropriate for conservation authorities (Spanhove et al., 2012). According to the field guidelines, the habitat quality assessment should base on mapping units built up by homogeneous vegetation. Thus, pixel-based results do not directly match what is required by conservation authorities, even if they depict quality classes. Here, object-based remote sensing approaches offer a solution for the designation of appropriate mapping units.

A few studies presented object-based remote sensing approaches for mapping European heathlands. Lucas et al. (2007) used segmented multi-seasonal Landsat data to separate heathland types in a rule-based classification approach. Objects of high resolution RGB imagery enabled Mac Arthur and Malthus (2008) to characterize and classify heathland. Förster et al. (2008) were able to obtain habitat extents and quality based on objects derived from high resolution multispectral QuickBird images. Detailed habitat patch maps were presented by Haest et al. (2010) who re-classified land cover types obtained from hyperspectral airborne imagery. In a more detailed approach Thoonen et al. (2013) used kernel-based reclassification to derive homogeneous mapping units based on hyperspectral remote sensing. They were able to separate heathland types as well as heather age classes. After obtaining continuous fraction maps of grass encroachment, Mücher et al. (2013) used a posteriori segmentation for the quality assessment of a heathland site. Haest et al. (2017) present a patch-wise mapping of conservation status indicators, such as cover of encroaching grasses and trees, which enabled them to distinguish between two status classes (“favorable” or “unfavorable”) per indicator. However, they do not deliver a final map depicting the three status classes.

Diverse remote sensing applications make use of fused optical and SAR (synthetic aperture radar) data describing vegetation, mostly on broader scales, e.g., forests (Montesano et al., 2013; Reiche et al., 2015), wetlands (Hong et al., 2015; Rodrigues and Souza-Filho, 2011), agricultural areas (Hill et al., 2005; Peters et al., 2011), or land cover classes (Ullmann et al., 2014). Object-based multi-sensor synergies are typically exploited for broad land cover mapping (Carvalho et al., 2010; Furtado et al., 2015; Gianinetto et al., 2015; Peters et al., 2011). Combining actively and passively derived remote sensing information within objects enables to assess the spectral behavior and texture of vegetation patches. However, there are no conservation-related approaches that used SAR-optical synergies for detailed vegetation mapping up to now.

Conservation-related mappings mainly used optical remote sensing. As it is sensitive to chemical and partly biophysical plant traits it provides an appropriate basis for describing and discriminating vegetation (Hill et al., 2005). However, the inclusion of structural-morphological information would be desirable as it is crucial for an adequate conservation status assessment (Delalieux et al., 2012; Schuster et al., 2015). Active sensors like LiDAR and SAR could potentially deliver this complementary information on vegetation structure (Saatchi and Rignot, 1997). Unlike optical sensors, active remote sensing can penetrate into the vegetation canopy and thus returns a signal derived mainly from its physical structure, providing structural-morphological information. Moreover, the ability to penetrate clouds is advantageous when time series are required. However, there are only few studies exploring this advantage for heathland mapping. Millin-Chalabi et al. (2013) used C-band SAR backscatter and InSAR coherence from ERS-2 to detect a burn scar in a UK peatland via comparing pre- and post-fire imagery. For mapping purposes on scales finer than forest stand level active sensors alone have been proven to be less successful (Li et al., 2013; Ranson and Sun, 1994; Saatchi and Rignot, 1997). However, they can offer benefits when fused with optical data.

Here, we aim to set up a demand-oriented conservation status assessment based on mapping units. By the example of *Calluna* heathland we use spaceborne data for object-based products depicting quality classes. We approach the question of how to map the patch-wise conservation status of dwarf shrublands with remote sensing from different perspectives. Spatial representations that comprise patches of varying size are compared with respect to classification accuracy and mapping suitability. Moreover, we seek to assess if multi-sensor synergies and the inclusion of multi-seasonal data is beneficial for the mapping task.

2.1.2 Material and methods

Study area & habitat mapping

The study was carried out in the Oranienbaum Heath, a Natura 2000 site which is located near Dessau in in Saxony-Anhalt, Germany (N 51.77350°, E 12.36120°). This heathland represents an abandoned former military training ground with an open landscape of around 550 ha. Habitats characterized by the dwarf shrub *Calluna vulgaris* (henceforth just *Calluna*) occur frequently (codes H 2310 and H 4030 according to the European Natura 2000 habitat classification), often interspersed with grasses and herbs. Moreover, pioneer grassland appears on inland dunes (H 2330) and in the southern part species-rich calcareous grassland (H 6120) can be found. Heathland degradation in terms of grass encroachment can be observed in the northern and central parts of the OH, which is often associated with a decrease in species richness (Heil and Diemont, 1983). More detailed descriptions of the study site can be found, e.g., in Felinks et al. (2012b) and Schmidt et al. (2017a).

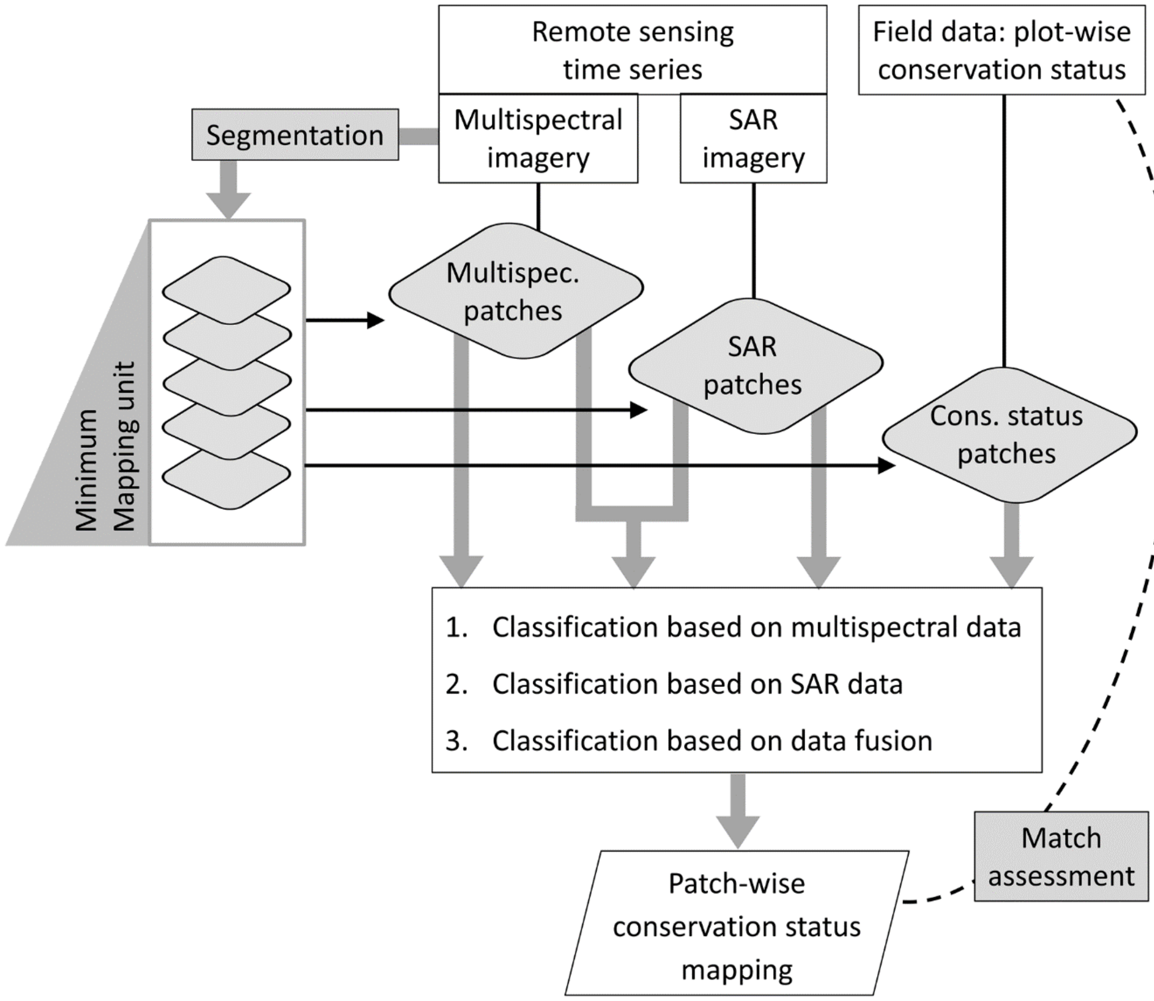

Fig. 1. *Workflow of the study. The aim of the study was to provide a meaningful mapping of Calluna-heathland's conservation per patch. As no remote sensing-related specification is provided in the field guidelines we approached the task from different positions. Different patch representations were tested that based on varying MMU-parameters (minimum mapping unit) for segmenting multispectral imagery. As vegetation structure is considered as an important factor for field mapping, we also wanted to test the potential of including SAR data into the procedure, because this signal is mainly build up by structural properties. Moreover, we also wanted to provide a statement about the use of multi-seasonal data, which could be relevant for future mappings similar to the presented procedure.*

The target habitat of this study is *Calluna* heathland. The dwarf shrub associations are widely distributed in Europe on low-nutrient soils and regarded as major cultural landscapes of conservation interest (Ascoli et al., 2009; Diemont et al., 2013). The cyclic succession of *Calluna* is an important feature of the habitat type, represented by four different phases (pioneer, build-up, mature, and degeneration), where each phase is associated with a certain species composition. Hence, structural aspects are a key factor for the quality evaluation. Parameters for field-based assessment are defined in the Natura 2000 mapping scheme and further specified in regional guidelines (LAU, 2010). The mapping should base on units assigned on a scale of 1:10,000, and the given parameters for deriving quality classes should be applied to units of similar vegetation. The designation of these units is at the mapper's discretion. Hence, it is not specified how to define the smallest feature that is to resolve, i.e., a minimum mapping unit (MMU).

The three parameters Habitat structure, co-occurring species, and impairments are crucial for the assessment of a patch. Habitat structure expressed by horizontal and vertical variation, composed by the coverage of *Calluna* (minimum of 30 % for the designation of the habitat type) and the occurrence of different successional stages, i.e. the growth phases (Gimingham, 1972). Moreover, the amount of open soil and lichens is considered. Thresholds for the co-occurrence of certain plant species are defined, mainly represented by sparse grassland. Grass and tree encroachment, the occurrence neophytes, and species indicating eutrophication are regarded as impairments. The final assessment of a vegetation patch is expressed by quality classes. The conservation status is generated as a result of the three parameters; it is either "favorable" ('A'), "inadequate" ('B'), or "bad" ('C').

In terms of nature conservation, a "favorable" habitat condition is represented by *Calluna* heathland featuring open patches of sparse grassland. Here, all *Calluna* growth phases potentially appear and the shrub layer is not dominated by old, tall plants. A lack of one parameter leads to the devaluation towards 'B'. A "bad" conservation status is given when *Calluna* forms large zones of dense, degenerated heathland excluding most other species. Heathland that is heavily encroached by dominant grasses represents the other frequent variety of class 'C'.

In summary, zones that feature high coverages of the dwarf shrub vegetation tend to be assigned to class 'C' as they often represent old, degenerated *Calluna*-stands with only minor to none occurrence of species-rich grassland (Schmidt et al., 2017b). High amounts of the latter often occur in areas where about half of the area is covered by *Calluna*; therefore leading to an 'A'-assignment. Transitional zones between these extremes are often mapped as class 'B'. We assume that it is possible to identify appropriate vegetation units in the segmentation process and that these objects can be classified due to different optical and backscatter properties.

Field data

The conservation status was documented for 350 field plots measuring 10 x 10 m in July 2015. The samples were chosen according to random sampling based on a mask presented in Schmidt et al. (2017b) to ensure that appropriate locations representing *Calluna* habitats were chosen. A plot was established if the random point represented the surrounding vegetation of 25 m (also in terms of mosaicked vegetation), else it was dismissed. The habitat quality was assessed according to the assessment parameters described above.

Remote sensing data

Spaceborne remote sensing used in this study included both multispectral and SAR data. Datasets of four dates were considered, where the acquisition date of the multispectral sensor served as reference date: spring (day of year: 113), summer (180), autumn (253), and winter (358).

Multispectral data

Spaceborne multispectral images from Sentinel-2 (S2) (ESA, 2016b) consist of ten bands covering a spectral range from 490 to 2190 nm. Four bands have a pixel size of 10 m (490, 560, 664, and 842 nm), whereas six feature a ground resolution of 20 m: the vegetation red edge (705, 740, 783, and 865 nm) as well as the water content bands (1610, and 2190 nm). There is an overlap of two bands at 842 nm (bandwith of 115 nm) and 865 nm (bandwith of 20 nm), respectively. The narrow band was designed to represent the NIR plateau of vegetation without being contaminated from water vapour. For processing we sampled those bands with 20 m pixels down to 10 m. Finally, we received a stack containing multispectral imagery for four dates (see Table 1).

SAR data

Spaceborne Sentinel-1 (S1) SAR provided the actively derived information that is potentially valuable for deriving structural information. S1 is a dual polarization radar that measures surface backscattering using a C band SAR with ca. 6 cm wavelength (ESA, 2016a). We used level-1 GRDH (Ground Range Detected with high resolution) products. The processing of the SAR images included the application of an orbit file, geometric calibration, and terrain correction. We intentionally used unfiltered SAR data for the patch-wise products as we considered the pooling of pixels within patches as filtering process. For the pixel-wise representations, we used SAR imagery where speckle has been filtered. These steps were performed in the software SNAP (ESA, 2016c).

We fused ascending and descending SAR images for every date, because previous studies showed that this could improve the results (i.a., Goering et al., 1995 for noise removal, Niu and Ban, 2013 for land cover mapping, and Deo et al., 2015 for DEM generation) due to the minimization of geometric distortions, such as layover, shadow, and foreshortening. Therefore, we included SAR data acquired in two different passes (opposite viewing angles) for each of the four dates (see Table 1), and calculated a mean layer was calculated for each polarization (VH, VV), respectively. This weighted average fusion approach was also applied in other studies with respect to different applications (Carrasco et al., 1997; Crosetto, 2002; Sansosti et al., 1999). Thus, we ended up with a stack of two SAR-bands (averaged VH and VV, respectively) per season.

As forest can easily be identified by means of SAR backscatter, it served as basis for manually creating a threshold-based mask. This forest mask was applied to all remote sensing bands of both types.

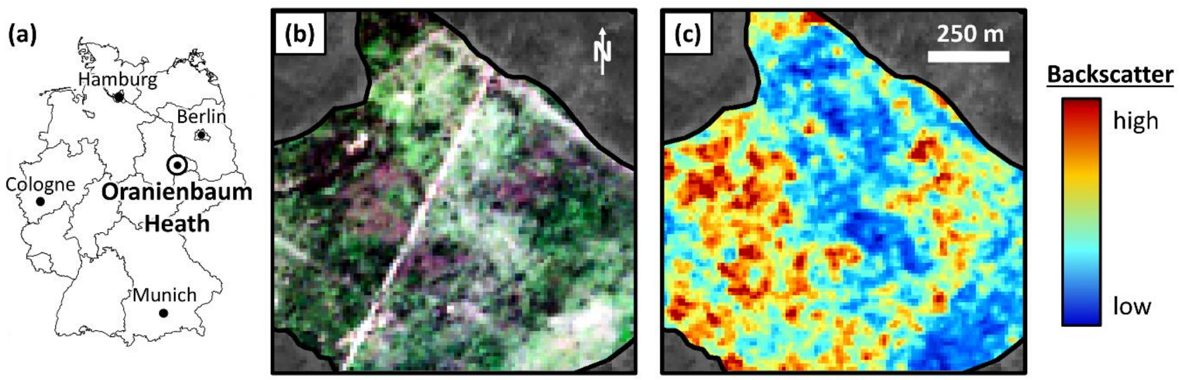

Fig. 2. *The study area Oranienbaum Heath is located near Dessau, Saxony-Anhalt, Germany (a). Multispectral Sentinel-2 (b; RGB-bands 4, 3, 2) and Sentinel-1 SAR (c; mean of ascending and descending VH) data was considered for mapping the conservation status of dwarf shrubland. Here, a subarea located in the south of the study area is presented. Recently mown areas appear in violet colors in the optical image (b).*

Table 1. *Remote sensing data.*

			S1 fusion	
Season	**DOY**	**S2**	**ascending**	**descending**
Spring	113	22/04/2016	19/04/2016	21/04/2016
Summer	180	28/06/2016	30/06/2016	09/07/2016
Autumn	253	09/09/2016	10/09/2016	07/09/2016
Winter	358	24/12/2015	21/12/2015	23/12/2015

Segmentation process

We applied the segmentation procedure proposed by Shepherd et al. (2014), which is further described in Clewley et al. (2014), using *RSGISLib* (Bunting et al., 2014) in Python. It bases on a K-means clustering, which is used for the generation of seeds for the segmentation (and optionally sub-sampling the data). The pixels are then assigned to the associated cluster centre. If these clumps are below the minimum object threshold to the neighbouring clump that is closest in terms of the Euclidian distance ('colour'), they are eliminated. For faster processing, the imagery was converted to the 'KEA' image format (Bunting and Gillingham, 2013), which is able to store image objects and associated attributes. As input for the segmentation we took the multispectral imagery of all four dates into account, where forest had already been already masked. SAR data was not included in the segmentation as it was reported to be inappropriate for deriving sharp boundaries (Carvalho et al., 2010).

Crucial parameters for the segmentation process are 1) the image sampling parameter, 2) the number of clusters, and 3) the minimum object size. The first setting defines the sampling of the input image. Moreover, the number of clusters (k) for the kmeans-computation has to be specified as well as the minimum size of the resulting objects, which is considered as the MMU. As we focussed on the assessing the MMU-parameter both other parameters were kept constant. For all segmentations the image sampling parameter was set to 10 and 120 clusters were considered. Five different parameters were tested for the MMU: 5 pixels (0.05 ha), 10 pixels (0.1 ha), 25 pixels (0.25 ha), 50 pixels (0.5), and 100 pixels (1 ha). We refer to the segmentation results as 'patch products', specified by respective the MMU-parameter.

The patch products are attributed with contextual (from the field survey) and remote sensing information, providing the basis for supervised classification of conservation status classes. In order to define objects representing the target habitat, the patch products were intersected with a continuous representation of *Calluna* coverages from Schmidt et al. (2017b), receiving mean coverages of the key species *Calluna* per patch. As specified in the field guidelines, we proceeded with patches featuring more than 30% of *Calluna* coverage, those with coverage scores below were dropped. The remaining patches served as basis for the classification process. Consequently, they were intersected with the field samples (representing either 'A', 'B', or 'C'), resulting in conservation status objects. If a segment contained more than one plot, it was assigned to the dominant class via majority voting. Consequently we checked for the match between the field-based classifications of habitat quality and the conservation status that was assigned by majority voting. The representativity of this assignment is assessed via confusion matrices calculate the agreement between the field-based classification of the single plots and the respective patch-wise classification that was assigned by the majority voting.

We finally received 86,108, 157, 230, and 279 conservation status patches for the different MMU-products, respectively. Pixel information of the single remote sensing bands (multispectral and SAR) was averaged within the patches. For the SAR-bands standard deviation was calculated additionally. Hence, for each of the four seasonal dates we ended up with a stack of ten bands containing multispectral objects (representing ten bands) and a stack of four bands containing SAR objects (representing mean and standard deviation for both fused polarization bands). The segmentation results are referred to as “patch products” and are further specified with respect to the corresponding MMU-parameter; for instance, the patch product 25 represents the result from the segmentation with a MMU-parameter of 25 m.

The mean correlation between the original pixel information and the averaged information within the patches was calculated based on Spearman's rho statistic (rs). This step was carried out for each patch product and for both remote sensing data types, respectively. Thereby, we wanted to assess the representativity of the patch products. We consider this estimation as one information about meaningful segmentation-parameters and as an adaption of the demonstrations of Legendre and Fortin (1989), which has been done before (Salas et al., 2016; van der Meer and Bakker, 1997).

Classification

Support Vector Machines (SVM) classification was used to separate the observation status objects and to obtain wall-to-wall information on the three status classes. Nowadays, SVM is considered as conventional method for treating higher-dimensional remote sensing data (i.a. Fassnacht et al., 2014; Mack et al., 2016; Schuster et al., 2015). Mountrakis et al. (2011) provide a description of SVM in the context of remote sensing. The influence of the single input remote sensing bands on the performance of the classification model can be assessed via a variable importance evaluation. The SVM applications were performed in R (R Development Core Team, 2013) using *caret* (Kuhn, 2016) and *kernlab* (Karatzoglou et al., 2004).

In order to enhance comparability of the classifications, we used 78 samples each time (minimum number given by patch product 100) based with varying input data, where 18 samples (23 %) were holdout for an independent validation. Besides this measure of overall accuracy, we assessed the mapping suitability based on the match between the spatial prediction of the model and the original field samples. Each time, three classifications were performed based on 1) multispectral data, 2) SAR data, and 3) both in combination, considering multi-seasonal information each time. The validation based on a bootstrap procedure with 100 iterations. Each time, classification accuracy and mapping suitability are estimated.

As class imbalances could cause problems in classification tasks (e.g., Chen et al., 2004; Waske et al., 2009; Breidenbach et al., 2010) we resampled the data; a step that is seen as a common practice in the context of developing predictive models on imbalanced data as it frequently improves models’ predictive performance (Kuhn and Johnson, 2016). We found that models trained without resampling did not produce results competitive with those trained on the resampled data.

The classification procedure was also applied to the pixel-wise imagery (which we refer to as patch product 1) in order to allow conclusions about benefits and drawbacks of patch-wise mappings. The best performing models from the 100 iterations were selected based on a sound relation between a high classification accuracy (based on validation dataset) and a high match with the field data, i.e., the mapping suitability (as this rather represents the goal that we want to achieve).

2.1.3 Results

Segmentation and representativity of the patch products

The varying MMU-parameter during the segmentation process influenced the mean patch size, the number of patches per product as well as the representativity. Fig. 3 reveals what we expected; smaller patches feature higher correlations between the single pixel and the averaged patch-wise information, which means that heterogeneity increases with the size of a patch. This applies for both data types, however, correlations for SAR data were much lower. The same tendency can be observed for the representativity with respect to the field-based conservation status assessments.

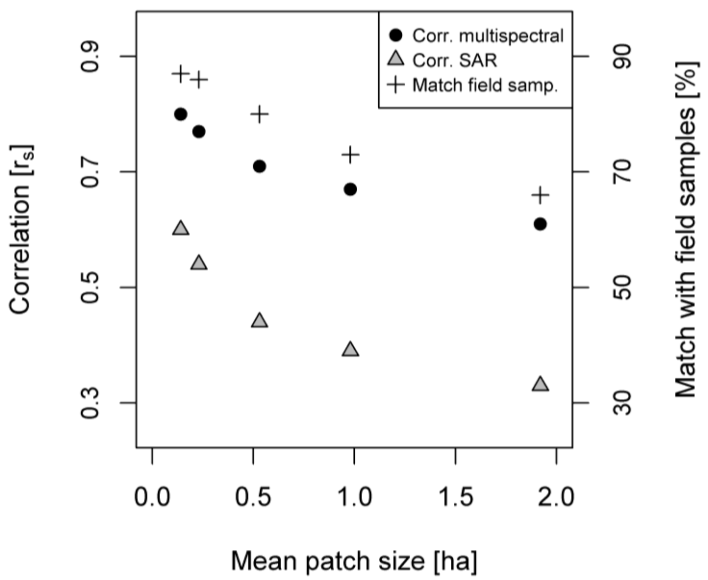

Fig. 3. *Mean correlations between the pixel values and the corresponding mean within the patches for both multispectral (dots) and SAR (triangles) data a shown. Very low variability within the small patches can be observed for both data types, which increases with the patch size. Moreover, the mean match between the conservation status classification of the samples within a patch and the class of the respective patch is assigned to the plot (crosses), where the classification of a patch based on majority voting. Here, the smaller patches also feature a higher representativity.*

Classification results

Mostly, high variations of overall accuracy measures were observed (Fig. 4a). For the multispectral data, variability is high only for patch products 1 and 5. Moreover, higher accuracies were reached for the optical data and fusion of both data types did not provide a remarkable benefit. It can be observed that on average low to moderate overall accuracies were reached.

On average, low to moderate matches between the mapping results and the field plots can be seen (Fig. 4b). Here, some slight trends are visible with respect to the match between the obtained map and the field samples ("mapping suitability"). SAR data alone is characterized by particularly low matches at the pixel level, which constantly increase for the respective patch sizes. A reverse trend applies for the multispectral imagery. Here, information on the pixel level and for smaller patches seems to be more suitable for the classification procedure. However, a remarkable peak can be observed for the patch product 100 (mean patch size of 1.92 ha). Here, the classification benefits from the synergetic use of multispectral and SAR data.

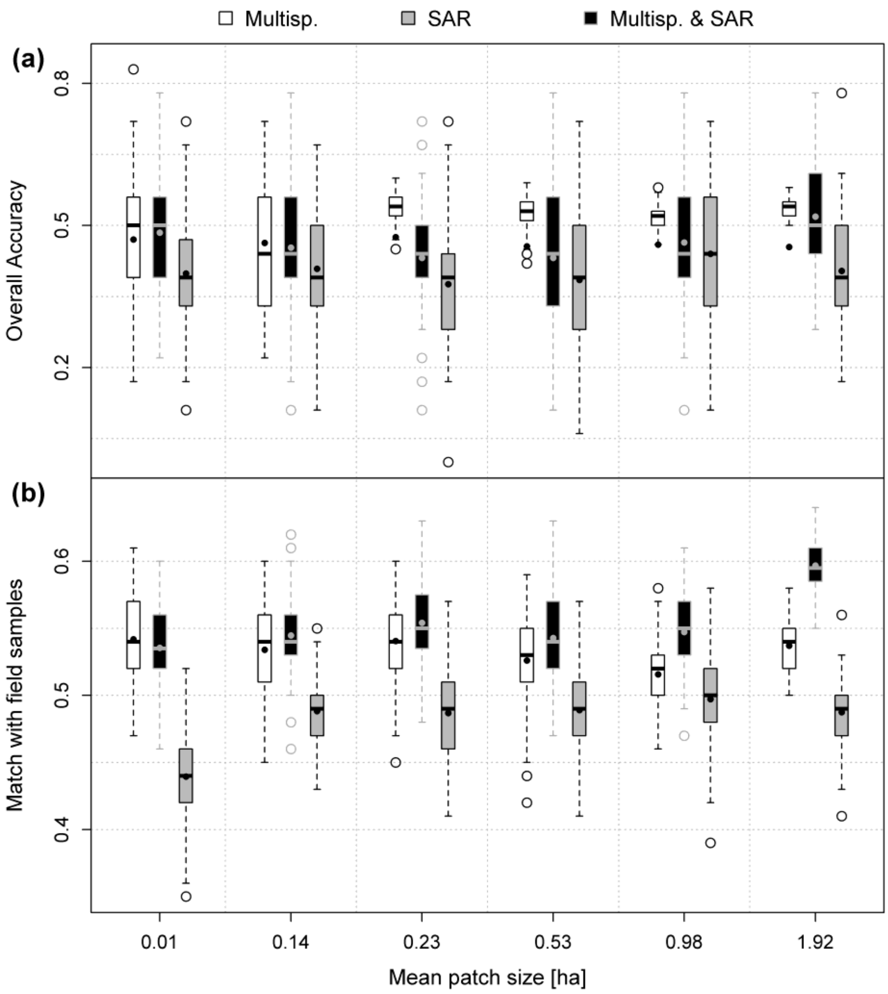

Fig. 4. *Model accuracies (a) and mapping suitabilities (b; assessed as match with the field samples) for the different patch products visualized by boxplots. Pixel-wise classification can be seen far left, followed by the patch products 5 to 100 (from left to right). No real trend is visible for (a), whereas (b) reveals that SAR-information is rather less informative on the pixel level, and that for patch product 100 (mean patch size of 1.92 ha) the fused imagery is particularly beneficial.*

Variable importances

Variable importances are reported as averaged scores based on the 100 bootstrap iterations. An overall mean was calculated for the single seasons. Considering the use of multi-seasonal data it is obvious that imagery acquired in spring (22/04/2016) and winter (24/12/2015) was of particular importance for the classification models (Fig. 5). Especially those bands representing the vegetation red edge and near infrared region (S-2 bands 6, 7, 8, 8a) are highlighted. For the SAR-bands, a rather balanced situation can be seen. VH-band is slightly more important than the VV-band. Standard deviation of SAR backscatter played rather minor roles with moderate increases for summer (28/06/2016) and winter. Optical data acquired in autumn (09/09/2016) was only useful for the model performance with respect to the patch product 100.

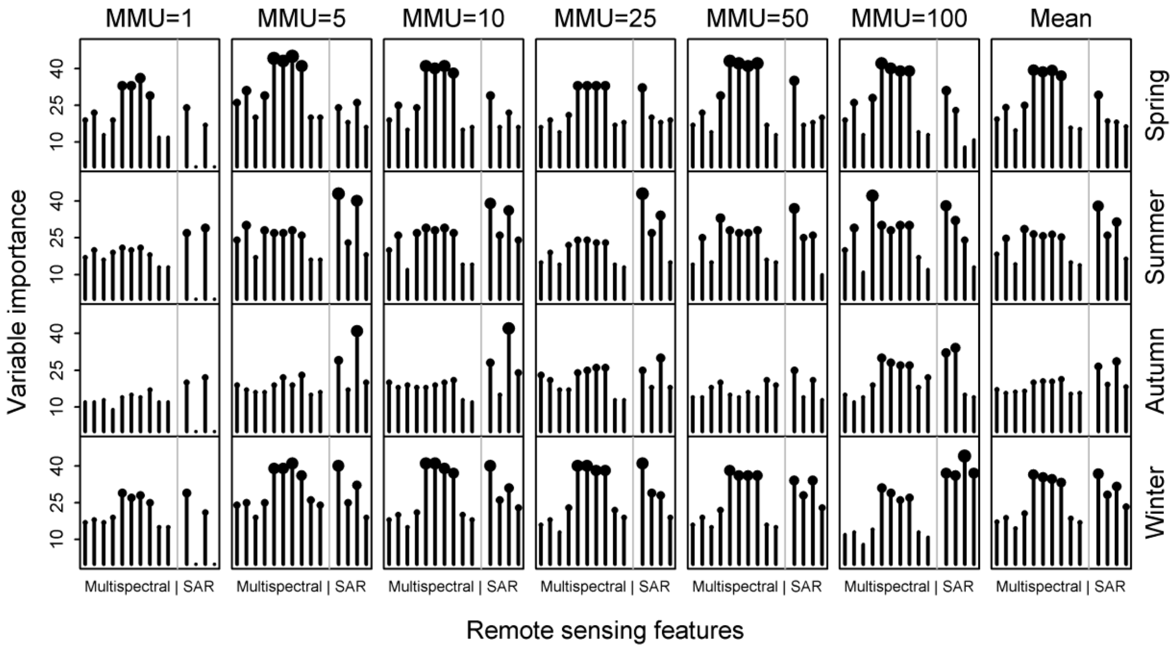

Fig. 5. *Mean variable importances of the classification models that based on the fused data (dot sizes are in direct relation to the heights of the lines and are used for better visualization). Results are presented for the different patch products, divided into the four seasonal dates. Multispectral bands for spring and winter representing the red edge and near infrared spectrum were particularly important for the classification process. The fused SAR bands (VH and VV of ascending and descending orbits, respectively) are of similar importance. Standard deviation of SAR backscatter features highest scores for the winter.*

Patch-wise conservation status mapping

Each time, the best model (given a sound relation between model accuracy and mapping suitability) from the 100 iterations that based on fused data was considered: patch product 1 (61% mapping suitability / 61% overall Accuracy); patch product 5 (60% / 72%); patch product 10 (62% / 69%); patch product 25 (63% / 64 %); patch product 50 (61% / 72%); patch product 100 (64% / 78%). The respective patch-wise mappings of conservation status classifications are shown in Fig. 6 for visual examination, along with a map depicting the spatial deviation between the single products. An area that has recently been mown (see Fig. 2 for comparison) is consistently classified as ‘C’, but for the pixel-wise representation. Here, the classification as ‘C’ is more accurate as a combination of homogeneous vegetation structure and absence of characteristic species can be observed . Other patches that are classified similarly throughout the products are predominantly representations of class ‘A’.

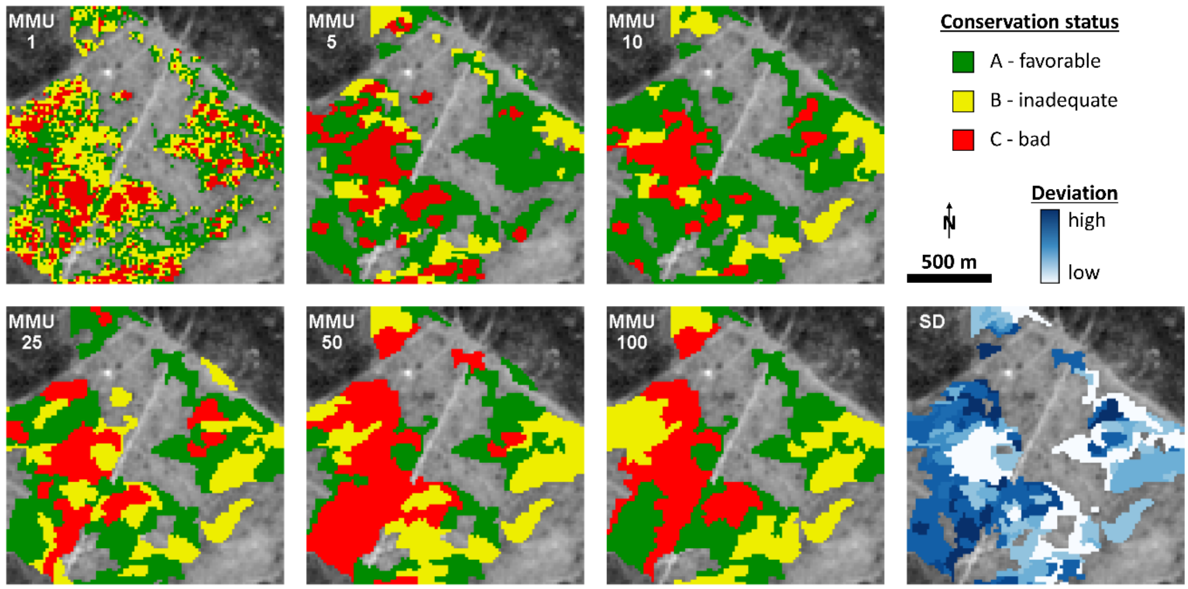

Fig. 6. *Representations of the patch-wise mappings depicting the conservation status based on varying patch sizes in the south of the study area. The general pattern seems to be similar at a first glance, however, the map depicting deviations reveals that major differences occur (the pixel-wise map is not considered). No deviation can be seen for a large patch in the center that has recently been mown (constantly 'C'; however, this does not apply to MMU 1) and for some smaller areas that were predominantly classified as 'A'.*

2.1.4 Discussion

In this study we wanted to obtain patch-wise maps depicting the conservation status of dwarf shrub heathland - a product that is highly demanded by conservation authorities - by multi-seasonal spaceborne remote sensing. As only one specification (the mapping scale) is given in the mapping guidelines, we approached the task from several positions.

Even though we considered comprehensive remote sensing datasets (comprising multi-seasonal information of distinct earth observation technologies) we only achieved low to moderate classification accuracies. Even if the results showed rather low accuracies on average, we would have expected more upwards outliers towards higher mapping accuracies. This is in agreement with other studies that reported difficult spectral separability of heathland subtypes (Barrett et al., 2016; Diaz Varela et al., 2008). Fusing multispectral and SAR data slightly improved the results only for large patches. Hence, we would not make a recommendation about a most appropriate patch product based on these findings. More detailed information about small-scale vegetation structure (Delalieux et al., 2012; Zlinszky et al., 2015) is eventually more promising for such mapping tasks. According to Carvalho et al. (2010), the inclusion of object-based texture measures is maybe interesting for future research as they could improve the results. We did not consider objects' shapes in the classification as it was reported that heathland patches are not characterized by typical shapes (Mücher et al., 2013).

Although object-based mappings for identifying dominant heather areas have been proven successful (Förster et al., 2008; Mac Arthur and Malthus, 2008), it seems that the patch-wise derivation of conservation status classes is more challenging. This could be attributed to the inability of earth observation to detect the full range of indicators used to determine heathland types in adequate detail (Corbane et al., 2015). Here, the assignment of the target habitat (*Calluna* heathland) is very basic as it only bases on the modeled distribution of the key species *Calluna*. To complete such a remote sensing based mapping the proposed segmentation approach could be combined with studies rather focusing on the identification of habitat types (for example, Feilhauer et al., 2014; Haest et al., 2017; Stenzel et al., 2014). However, we consider our approach to be in agreement with the field guidelines.

Concerning the correlations between single pixels and patches (Fig. 4) , the segmentation with MMU 25 seems to be most appropriate concerning the compromise between the degree of aggregation and the remaining information(Drăguţ and Eisank, 2011). Objects resulting from MMU-parameters of 5 and 10 show higher correlations, however, at the expense of a "patchy" mapping result which is rather inappropriate in terms of the guidelines. The trend was also reflected when comparing the modelling result with the field plots: a steady decline of agreement can be observed for larger mapping units; the segmentations with MMU 50 and 100 tend to deliver rather mixed objects in terms of habitat conditions (and, of course, larger heterogeneity in reflectance). In relation to the previous field mapping of Felinks et al. (2012b) who assigned mapping units with a mean size of 0.74 ha, the closest results are of MMU = 25 (0.53) and 50 (0.98).

Usually, applying a model to different scenes results in lower accuracies due to the potential effect of spatial autocorrelation (Legendre, 1993; Wei and Chow-Fraser, 2008). It is important to consider that a model is more likely to be transferable as long as the model response it rather fitting to a general signal, instead to local characteristics which cannot be transferred to other sites (Juel et al., 2015). Therefore, reducing the features could increase model transferability based on a low dimensional feature space providing effective information and reduced noise (Landgrebe, 2005). According to our findings we would recommend to consider multispectral data acquired in winter, spring, and - with constraints – summer, and to focus on the spectral region of the vegetation red edge and near infrared. SAR backscatter could provide complementary information, however, it seems that patch-wise fusion of optical and SAR data is more promising with regard to large-scale applications.

With respect to that, approach transferability is more important than transferability of complex models (Wenger and Olden, 2012). Object-based approaches can be transferred as shown for a rule-based classification of land cover classes and broader vegetation types (Rokitnicki-Wojcik et al., 2011) and also for finer vegetation classes based on random forest classification (Juel et al., 2015). However, we assume that the transferability of a classification model related to habitat conditions of a single vegetation type is probably more difficult. Here, application of rule sets could be considered (Schmidt et al., 2017b; Zlinszky et al., 2015), when adapted to an object-based procedure. The approach of Nieland et al. (2015) to use kernel-based spatial reclassifications of habitat objects was specifically designed for being transferable to similar areas.

While our output could meet the expectations of Natura 2000 mapping tasks, the procedure does not allow for deeper insights into the ecology of an area. To achieve that, it could be combined with pixel-wise approaches that focus, e.g., on floristic gradients (Feilhauer et al., 2011; Neumann et al., 2015), plant functional traits (Schmidt et al., 2017a; Schmidtlein et al., 2012) or other fine-scale indicators (Schmidt et al., 2017b; Spanhove et al., 2012). Potentially, these combinations allow for more sufficient classification accuracies; for instance, via considering knowledge about indicator species (Förster et al., 2008).

However, Spanhove et al. (2012) regard most pixel-based approaches as sub-optimal for Natura 2000 applications, although they have been proven successful for heathland applications. As object-based image analysis (OBIA) try to model how humans interpret remote sensing images (Blaschke, 2010) they could provide designations of appropriate mapping units (i.e., vegetation patches) required by the Natura 2000 guidelines. Automatic image segmentation is generally seen as more robust and repeatable in terms of objectivity and precision than manual digitization (Kampouraki et al., 2008), although confusions cannot be ruled out. According to our findings, the supervised classification procedure for field-based habitat quality assessments is hardly transferable in direct manner to a patch-wise remote sensing approach.

We belief, that there is an uncertain future for patch-wise mappings related to vegetation monitoring. Maybe there will be specific standards defining MMU-parameters for remote sensing-based approaches in Natura 2000 areas (Förster et al., 2008), or re-orientations of monitoring guidelines towards remote sensing needs (Corbane et al., 2015; Schmidt et al., 2017b). At the moment most remote sensing procedures should rather be seen as reactions to the monitoring recommendations that were designed for field surveys (but see the EBV concept; Pereira et al., 2013; Pettorelli et al., 2016).

2.1.5 Conclusion

In this study, we mapped the conservation status of dwarf shrub heathland based on several segmentation products reflecting varying sizes of shrubland patches. Results confirm that neither including multi-seasonal information nor using multi-sensor synergies enable for precise mapping of patch-wise quality classes; we received low to medium accuracies each time.

Multispectral data acquired in spring and winter (especially red edge and near infrared) is apparently most appropriate for patch-wise quality assessments of dwarf shrubland. VH and VV backscatter was relatively meaningful throughout the year. SAR data seems to be more informative when the information is pooled in patches, and large patches rather benefit from multi-sensor synergies. This could be considered for future applications and deserves more attention with regards to conservation mapping.

Instead of proposing certain segmentation parameters for the designation of appropriate mapping units, we would rather recommend to focus on alternative, mainly pixel-wise methods for deriving information about states of vegetation that are related to predefined quality classes. Finally, pixel-wise representations can still be aggregated in units. However, more precise definitions are needed for designating these units via earth observation. Probably, the reformulation of obsolete standards is inevitable; alternatively, new monitoring schemes could be defined. Integrated procedures that make use of established methods from different communities potentially represent adequate solutions.

Acknowledgements

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2.2 Adapting a Natura 2000 field guideline for use in remote sensing

Johannes Schmidt, Fabian E. Faßnacht, Christophe Neff, Angela Lausch,
Birgit Kleinschmit, Michael Förster, Sebastian Schmidtlein

Abstract

Remote sensing can be a valuable tool for supporting nature conservation monitoring systems. However, for many areas of conservation interest, there is still a considerable gap between field-based operational monitoring guidelines and the current remote sensing-based approaches. This hampers application in practice of the latter. Here, we propose a remote sensing approach for mapping the conservation status of *Calluna*-dominated Natura 2000 dwarf shrub habitats that is closely related to field mapping schemes. We transferred the evaluation criteria of the field guidelines to three related variables that can be captured by remote sensing: (1) coverage of the key species, (2) stand structural diversity, and (3) co-occurring species. Continuous information on these variables was obtained by regressing ground reference data from field surveys and UAV flights against airborne hyperspectral imagery. Merging the three resulting quality layers in an RGB representation allowed for illustrating the habitat quality in a continuous way. User-defined thresholds can be applied to this stack of quality layers to derive an overall assessment of habitat quality in terms of nature conservation, i.e. the conservation status.

In our study, we found good accordance of the remotely sensed data with field-based information for the three variables key species, stand structural diversity and co-occurring vegetation (R^2 of 0.79, 0.69, and 0.71, respectively) and it was possible to derive meaningful habitat quality maps. The conservation status could be derived with an accuracy of 65%. In interpreting these results it should be considered that the remote sensing based layers are independent estimates of habitat quality in their own right and not a mere replacement of the criteria used in the field guidelines. The approach is thought to be transferable to similar regions with minor adaptions.

Our results refer to *Calluna* heathland which we consider a comparably easy target for remote sensing. Hence, the transfer of field guidelines to remote sensing indicators was rather successful in this case but needs further evaluation for other habitats.

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2.2.1 Introduction

There is little doubt that remote sensing has potential to support nature conservation administrations with periodic reporting commitments such as those related to the Habitats Directive of the European Union. Recently, many applications demonstrated the large potential of remote sensing information for monitoring vegetation status (e.g., Bock et al., 2005; Förster et al., 2008; Stenzel et al., 2017; Vanden Borre et al., 2011b). Luft et al. (2014) and Corbane et al. (2015) provide a good overview about studies that developed remote sensing approaches to fulfill monitoring demands.

Heathland ecosystems have been targeted by several earlier remote sensing studies, mostly applying multispectral and hyperspectral data (e.g., Lucas et al., 2007; Neumann et al., 2015; Spanhove et al., 2012). Segmentation of multi-seasonal Landsat imagery enabled Lucas et al. (2007) to separate heathland types in a rule-based classification approach. An object-based approach using RGB aerial images with a high spatial resolution provided an appropriate basis for the characterization and discrimination of heathland classes in a study of Mac Arthur and Malthus (2008). Delalieux et al. (2012) used airborne hyperspectral data to estimate structural attributes of heathlands which are relevant to assess their conservation status. They applied a decision tree classification to allocate each pixel to a certain age class. Spanhove et al. (2012) also focused on capturing fine-scale indicators (e.g., the age structure of *Calluna* and cover of mosses) by airborne hyperspectral imagery. Applying boosted regression trees they used coarse-scale parameters (e.g., occurrence of dwarf shrubs or grass encroachment) for gaining information on the habitat quality. Mücher et al. (2013) produced continuous fraction maps of grass encroachment by spectral mixture analysis. Via segmentation they were able to define appropriate mapping units for nature conservation. Luft et al. (2014) proposed measuring priority indicators following the idea of applying the US-American monitoring standards in Europe. These efforts underlined the benefit of remote sensing for assessing the quality of dwarf shrub heathland habitats; however, they did not exactly deliver what is required by the Habitats Directive. For the first time, Neumann et al. (2015) explicitly mapped the conservation status of heathlands. They derived the conservation status based on floristic gradients in an ordination space.

In the recent past, UAV derived data also proved to be helpful for detecting precise land-cover information by serving as a reference data source for coarser remote sensing data (e.g., Fassnacht et al., 2015). UAV data have also been suggested as base data for monitoring the restoration of a bog complex (Knoth et al., 2013). The authors conclude that UAV missions could help to support field surveys and could play a major role in future monitoring tasks. In further related UAV applications, Dufour et al. (2013) tested RGB-mosaics and digital surface models (DSMs) derived from UAV flights for mapping riparian vegetation and Gonçalves et al. (2016) used high resolution color orthophotography and DSMs derived from UAV for assessing habitat extent and condition by applying a Random Forest classifier in a heathland ecosystem. Both studies confirmed the potential of UAV systems to supplement field-work by providing spatially continuous data.

Despite these numerous case studies, there have been few attempts to operationally integrate remote sensing approaches in existing monitoring systems. Communication problems between remote sensing experts and nature conservationists have often been blamed in this regard (Skidmore et al., 2015). The problems originate from the differing perspectives of the two communities: Remote sensing needs to focus on target variables that sensors can "see". However, these variables often do not match the variables assessed in the field. Conservation experts often base their typifications and evaluations of habitats on the occurrence and abundance of certain individual species that often can be hardly traced with remote sensing because they are small or under the canopy of co-occurring vegetation. There are two theoretic approaches how these two perspectives can be brought together: (1) Existing monitoring guidelines are re-formulated in a cooperative effort between conservation and remote sensing experts to improve their compatibility with remotely-sensed data, e.g., the development of essential biodiversity variables (EBVs) such as community composition (Xi et al., 2015) and ecosystem structure (Hansen et al., 2014), and (2) remote sensing approaches are adapted to better match existing field guidelines (Corbane et al., 2015). These two cases are extreme cases of a continuum of options and, in real life, combinations of both cases may often provide the best solutions. In the current study we use an existing monitoring approach based on field surveys as a starting point for adapting remote sensing methods. Here, we suggest a comprehensible approach closely related to traditional in situ field mapping procedures. This has been lacking so far. In our opinion, the present study is the first that is explicitly oriented towards a field approach for a classification of heathland habitat qualities. It is clear that field-based quality criteria can hardly ever been matched by remote sensing but we tried to define remotely-traceable quality criteria as close as possible to the original ones used for habitat assessment and quality evaluation.

To reach this objective, we combined hyperspectral remote sensing, small scale UAV data and field samples to create a remote-sensing based layer for each of the quality criteria which were then merged into a final map depicting the conservation status of the *Calluna* heathland habitats. One advantage of this approach is that not only a map depicting the habitat quality is available after the assessment but also the individual layers of the quality criteria. This can enable an after-the-fact revision of thresholds used to define the conservation status of a habitat which is hardly possible with field-based assessments.

2.2.2 Material and methods

In order to obtain a map illustrating the conservation status of *Calluna* heathland habitats we combined three quality layers: (1) coverage of *Calluna vulgaris*, (2) stand structural diversity, and (3) co-occurring vegetation. The quality layers were computed by combining remote sensing data and field samples and then combined into two final products. First, we used the three layers as an input to an RGB-visualization that depicts the habitat state in a continuous way. Second, optimized thresholds from expert evaluation are applied to the quality layers to classify the conservation status, expressed in three discrete classes (see workflow of the study in Fig. 1).

Study site

The study area Oranienbaum Heath (OH) is located near Dessau in the Elbe-Mulde-lowland in Saxony-Anhalt, Germany (N 51.77350°, E 12.36120°; see Fig. 2a). The northern part of the study area is dominated by cover sands while the south features ground moraines and shows a more diverse topography (Felinks et al., 2012a). The average precipitation of the region is around 500 mm per year. Forests were partly replaced by more or less open pasture since centuries. Heavy forest fires in the first half of the 20th century and the use as a military training ground by the soviet army after 1945 maintained an open landscape and parts of the ancient inventory of pasture plant communities (John et al., 2010). Today the open area has a size of 550 ha. After being

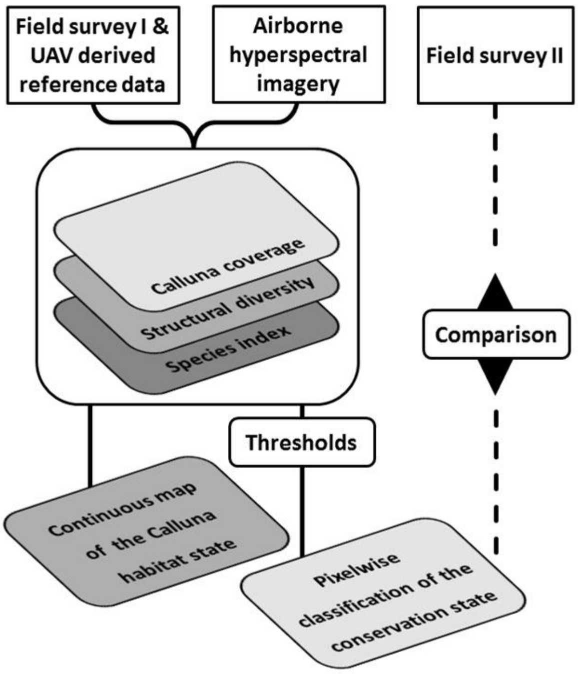

Fig. 1. *Workflow of the study*

abandoned as military training area, the heath and grassland ecosystems are threatened by the increase of bushgrass (*Calamagrostis epigejos*) and the encroachment of pioneer tree species (birch, aspen and pine). As part of a landscape management project (Lorenz et al., 2013), grazers like Konik horses and Heck cattle maintain the habitats of plant species bound to open landscapes.

Typical communities of the non-forested areas in the OH include dwarf shrub associations (codes H 2310, 4030 according to the Natura 2000 European habitat classification system) on dry, lime-deficient soils characterized by *Calluna vulgaris* (L.) Hull (henceforth just *Calluna*) (Schmidt et al., 2017a). *Calluna* heathland represents the target habitat of this study. These heathlands are widely distributed in Western and Central Europe on sandy, low-nutrient soils and regarded as one of the major cultural landscapes in Europe (Ascoli et al., 2009; Diemont et al., 2013). However, the *Calluna* habitats mostly occur scattered (e.g., on recent or former military training areas) and are often threatened by eutrophication and habitat fragmentation (Cordingley et al., 2015; Rose et al., 2000). As they have a high biodiversity value and provide important ecosystem services, they are subject to a wide range of international and national conservation designations (Kirkpatrick and Blust, 2013). These dwarf shrub habitats are characterized by the aging-cycle of the dominant dwarf shrub *Calluna* (Watt, 1947). The plants undergo a cyclic succession of different phases (pioneer, buildup, mature, and degeneration) each with a characteristic species composition. In an optimal state in terms of conservation, *Calluna* heaths feature mosaics of these four phases being interspersed by Cryptogams and xeric grassland (Aerts and Heil, 1993).

Inland dunes with open *Corynephorus* and *Agrostis* grasslands (H 2330) feature open grassland vegetation. Between the single tufts, cryptogams appear frequently. As pioneer vegetation, cryptogams need open sandy patches and a low nutrient level. *Xeric sand calcareous grasslands* (H 6120) mainly grow on alkaline sandy soils and often co-occur with other low-nutrient grasslands and *Calluna* heath. Species richness peaks in these grasslands characterized by *Koeleria macrantha*, *Festuca ovina*, and *Peucedanum oreoselium*. Mosaics of calcareous grassland and *Calluna*-heather occur frequently in the south. Larger zones of degraded heathland that are encroached by *Calamagrostis epigejos* can be found in the northern and central parts of the OH. Favored by nutrient enrichment (due to the abandonment and atmospheric input), the appearance of this dominant species often leads to a decrease in species diversity due to shading and litter (Heil and Diemont, 1983; Tilman, 1993).

Vegetation assessment in the field

In July and August 2014, 70 plots were recorded in a vegetation survey (Fig. 2). To ensure that all habitats were represented, the vegetation samples were chosen by stratified random sampling based on a map of an earlier habitat survey by Felinks et al. (2012a). Vegetation assessments were done in 3 m x 3 m - plots. The coverages of individual vascular plant species as well as the fractions of bare soil, cryptogams, and dead material (litter and wood) were recorded.

During a second field survey in August 2014, 300 squares (100 m²) representing *Calluna* habitats were assessed. The locations of the plots were selected randomly throughout the study area, however, only areas with *Calluna* coverage of more than 25% were considered. For each plot we documented the conservation status based on the decision parameters from the field guidelines described in Table 1. The original mapping guidelines refer to larger units, while we conducted the estimate of habitat quality in the 100 m² squares. The criteria were adapted accordingly: smaller amounts of open soil were considered as adequate when deciding whether a sample was in a "favorable" or "inadequate" status. Lichens only have a small impact on assigning the conservation status in the study area (pers. comm. K. Henning).

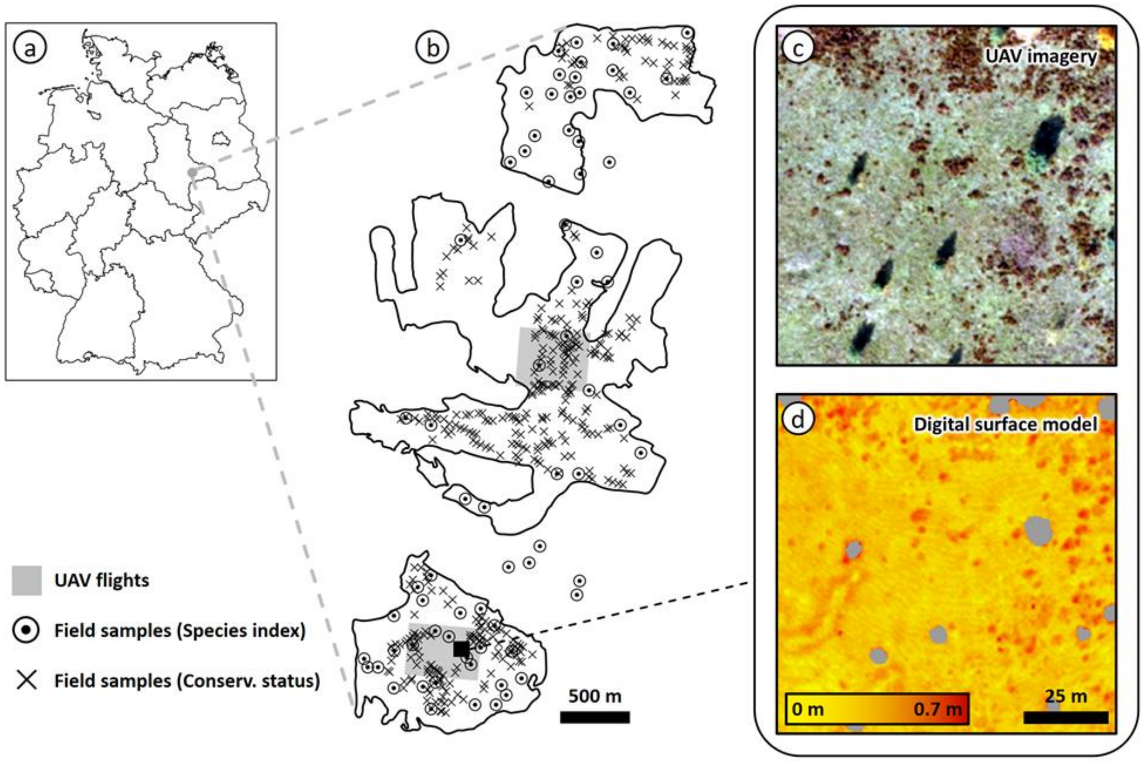

Fig. 2. *The study site Oranienbaum Heath (b) is located near Dessau, Saxony-Anhalt, Germany (a). Circles indicate locations where co-occurring species were mapped. The conservation status according to the field guidelines was assessed at locations marked with crosses. In panels c and d, an exemplary zoom-in to UAV based RGB imagery and the digital surface model (trees were masked and are colored in gray) derived from the UAV data with 'Structure-from-Motion' photogrammetry are depicted.*

Remote sensing data

On 18 July 2014, hyperspectral images with a pixel size of 3 x 3 m were acquired with an AISA dual sensor which covers the spectral range from 0.48 - 2.29 µm with 200 bands (Lausch et al., 2013). In the pre-processing of the acquired images, the water absorption features around 1.4 and 1.9 µm were excluded. Geometric accuracy was enhanced on the basis of high-resolution orthophotos (MLU Sachsen-Anhalt, 2012). To remove illumination effects within the stripes, cross-track illumination correction was applied. Remaining noise in the mosaicked image (4 stripes) was removed with a Minimum Noise Fraction Transformation. For the inverse transformation, we corrected for one component. All forested areas were masked out.

An UAV-flight campaign (50 m flight altitude, stripes overlap of 60%) in October 2014 produced RGB aerial images of two subareas of the OH (Fig. 2b, c). The sub areas were selected to represent a wide range of open vegetation conditions in the study area. The aerial images of each flight were georeferenced and composed to a single mosaic in VisualSFM (Changchang Wu, 2013). The mosaics of the northern and the southern subarea both covered around 25 ha with a pixel size of 0.3 m. The UAV-data was also used to calculate vegetation height from a three-dimensional point cloud in VisualSFM. In the software Treesvis (Weinacker et al., 2004), a Normalized Digital Surface Model (= canopy height model) with a resolution of 0.3 m was created on the basis of the point cloud (Fig. 2d).

Transfer of field guidelines to remote sensing

To keep the study as close to the regular monitoring procedure as possible we designed our approach taking into consideration the regional guidelines for field mapping (LAU, 2010). According to these instructions, surveys should be conducted on a map scale of 1:10,000. The field guidelines refer to mapping units which are defined as sites with a homogeneous vegetation. No information is provided about the size of these units (e.g., a minimum mapping unit); the designation is at the mapper's discretion. Three parameters are crucial for the evaluation of a habitat: (1) habitat structure, (2) co-occurring key species, and (3) degradation in terms to what is desired from a conservation perspective (see Table 1). The first parameter combines coverage of *Calluna*, the (co-) occurrence of *Calluna* growth phases, as well as the amount of open soil and lichens. Sparse grassland is the desired vegetation to co-occur with *Calluna*. Typical species of sparse grassland include, for example, *Anthoxanthum odoratum*, *Festuca ovina*, *Koeleria macrantha*, *Rumex acetosella*, and *Thymus pulegioides* (mainly H 6120). Degradation is indicated by encroaching grasses or bushes as well as the appearance of neophytes, or species indicating eutrophication.

The field guidelines comprise proxies that represent certain vegetation types of mainly early regeneration. As a result of these three parameters, one 'joint quality indicator' (hereafter JQI) has to be generated, which provides the basis for defining the conservation status of a mapping unit. The status can either be "favorable" ('A'), "inadequate" ('B'), or "bad" ('C') and should base on the median of the three parameters (exception: if a partial value is considered as 'C' the evaluation cannot be 'A'). This classification is predefined by conservation authorities. It is derived from a range of stand attributes describing habitat states that are subjected to supervised classification.

Table 1. *Parameters for conservation status assessment of Calluna heathland according to the regional field guidelines and the 'translation' to the presented remote sensing-based approach.*

Criteria	A (favorable)	B (inadequate)	C (bad)	Remote sensing proxy
1) Habitat structure	**Excellent**	**Good**	**Medium-bad**	
Structural diversity	All growth phases are present, degeneration < 50%	Not all growth phases are present, degeneration 50-70%	Degeneration > 70%	*Calluna* cover, stand structural diversity
Cover open soil	> 10%	5-10%	< 5%	Stand structural diversity, species index
Cover lichen	> 10%	5-10%	< 5%	Stand structural diversity, species index
2) Co-occurring key species (vasc. plants)	**Present**	**Mostly present**	**Partly present**	
Amount	≥ 8	≥ 5	≥ 1	Species index
3) Degradation	**None - low**	**Medium**	**Severe**	
Cover grass or bush encroachment	< 10%	10-30%	> 30-70%	Stand structural diversity, species index
Cover pressure indicators, Neophytes	None	< 10%	> 10%	Species index

The three parameters habitat structure, co-occurring key species, and degradation were translated to three proxies measurable with remote sensing data: (1) coverage of *Calluna*, (2) stand structural diversity as the coefficient of variation calculated as the ratio of the standard deviation and the mean vegetation height, and (3) a species index that reflects co-occurring vegetation (see section 'Calculation of the decision layers').

Coverage of *Calluna* (minimum of 30%) is decisive for the assignment of the habitat type which is the first step in the field guidelines. In addition, the *Calluna* coverage layer also relates to the 'structural diversity' parameter of the guidelines. Interpreted together with the vegetation height layers (standard deviation and mean) it allows for deriving knowledge on the four growth phases. The factor open soil is captured by information provided by the mean vegetation height (very low) and especially the species index layer (strong soil signal for sparse vegetation). The same was assumed for the appearance of lichens which depend on open soil and low disturbance. The occurrence of typical vegetation according to the guidelines is addressed by the species index (high values indicating many co-occurring key species). Degradation is taken into account in the same way (few or no co-occurring key species and high coverage of pressure indicators).

Calculation of the decision layers

For modeling the distribution and coverage of *Calluna*, the UAV data (RGB, pixel size of 0.3 m) was used as ground reference. They were separated into two classes ('*Calluna*' and 'rest') via supervised SVM Classification. Corresponding training samples were collected based on visual interpretation. In the two UAV images the fraction of pixels classified as *Calluna* were calculated within 10 by 10 pixel grid cells to match the 3 by 3 m pixel size of the hyperspectral imagery. Then, coverage of *Calluna* was extracted for 700 random points to train a SVM Regression between the *Calluna* coverage reference values and the hyperspectral image. The regression model was applied to the full image to derive *Calluna* coverage values for the whole study area.

We followed the same approach to estimate vegetation heights: the mean UAV vegetation heights were calculated for 10 by 10 pixel grid cells and then a SVM regression between 500 random points and the hyperspectral data was used to estimate the vegetation height for the whole study area. Plant height was proven to be detectable via remote sensing as vegetation characteristics related to a certain height are also linked to spectral attributes of, e.g., soil signal, green leaf area, senescence, wood, or shadow (Xavier et al., 2006; Yang and Chen, 2004).

Species inventory is seen as indicator of the conservation status (Neumann et al., 2015). We developed an index that on the one hand considers indicators of good conservation status such as *Agrostis capillaris*, *Anthoxanthum odoratum*, *Danthonia decumbens*, *Euphorbia cyparissias*, *Festuca ovina*, *Hieracium pilosella*, *Koeleria macrantha*, *Rumex acetosella*, and *Thymus pulegioides* but on the other hand also reflects habitat degradation in terms of encroachment of grasses or pioneer trees, or eutrophication. The later processes were represented by *Betula pendula*, *Pinus sylvestris*, *Populus tremula*, *Brachypodium pinnatum*, *Calamagrostis epigejos*, *Oenothera spec.*, *Pteridium aquilinum*, *Tanacetum vulgare*, and *Verbascum lychnitis*. Although *Calluna* is named as key species in the field guidelines, we did not consider it here because this information is already included in the *Calluna*-layer. This key species index was computed for each of the 70 field plots based on the occurrence and coverage of the mentioned species. We applied the following equation to receive the species index 'i': $i = n_s \log(c_s) - n_u \log(c_u)$; where n_s and c_s are the number and the cover of the characteristic species, while n_u and c_u are the corresponding values of species indicating negative pressure. By dividing the index 'i' by the maximum value we achieved standardization. The index finally ranged between -0.24 and 1. These values were regressed against the hyperspectral data with PLSR to derive wall-to-wall estimates of the key species index.

Modeling

For each of the three remote sensing proxies a spatially continuous map was calculated by combining field samples and remote sensing information. To derive the maps (called 'quality layers' in the following) we tried both, support vector machines (SVM; in classification and regression mode), and partial least square regression (PLSR) and proceeded with the best performing approach.

PLSR (Wold et al., 2001) is known to be able to deal with high-dimensional and collinear data (e.g., hyperspectral data: Wold et al., 2001; Smith et al., 2003; Yu et al., 2014). On the basis of the covariance between the predictor and response variables it computes new predictor components which are then used to build a linear regression model. Here, we used the PLSR algorithm implemented in the package 'autopls' (Schmidtlein et al., 2012) in R (R Development Core Team,

2013) which includes a backward selection of predictors. The model fit was assessed by using R^2 (leave-one-out validation) and RMSE.

Similarly to PLSR, SVM deal comparatively well with high dimensional feature spaces like hyperspectral data (i.a., Chan et al., 2012; Fassnacht et al., 2014; Feilhauer et al., 2015). It can be used for classification (SVM-C) and regression (SVM-R). Here, the model fits were assessed by 10-fold cross-validation. Model performance is reported as R^2 and RMSE. Classification accuracy was assessed using the Kappa index K and the overall accuracy derived from a confusion matrix. Both SVM applications were carried out in R using the 'caret' package (Kuhn, 2016). Technical details on SVM can be found in Burges (1998) while Mountrakis et al. (2011) review SVM in the field of remote sensing.

The modeled quality layers had a pixel size of 3 m. According to the field guidelines the required scale for the mapping is 1:10,000. Following the suggestions of Hengl (2006) the recommended pixel size for the mapping would be 5 m (finest: 1 m, coarsest: 25 m). Hengl (2006) also points out that the operator has to decide whether a fine spatial resolution is required or not. Based on our knowledge of the study area, we think that a pixel of approximately 10 m provides an appropriate basis for the mapping task. Hence, mean and standard deviation of 3 x 3 pixel neighborhoods were calculated for each of the quality layers which resulted in maps with a resolution of 9 m.

RGB visualization

To allow for a continuous illustration of the three derived quality layers we combined them in a Red-Green-Blue (RGB) color composite map. This illustration represents the habitat state and enables the identification of comparably fine gradients that are not apparent in the final discrete habitat suitability map. *Calluna* coverage was assigned to red, stand structural diversity (coefficient of variation between the standard deviation and the mean vegetation height) to green, and the species index to blue. Areas with *Calluna* coverage of less than 30% were masked out. The mask was smoothed (slightly expanded) to include the fringes of the potential *Calluna* habitats as well. This ensured that these transition zones are, like in field mapping, included in the evaluation. We name this product the 'JQI-map' as it represents the joint quality indicator (i.e., the state of *Calluna* habitats) by continuous colors rather than by fixed classes.

Deriving the conservation status

To derive the final habitat quality class, the single quality layers were classified via a decision tree classification (status classes 'A', 'B', and 'C', respectively; see Fig. 3). The applied thresholds in the decision tree were based on field-knowledge. Subsequently, we equated the classes with numbers: 'A'=3, 'B'=2 and 'C'=1. By merging the classified layers we received three values per pixel. Summing these values led to sums between 3 and 9 which could be seen as a map of affiliations to the conservation status. The overall conservation status (A/B/C) was then derived referring to the field guidelines: the median of the three criteria was taken for the assignment (see Table 2). Finally, this result was related to the second field mapping: An accuracy assessment was conducted based on the 300 field reference samples. The amount of correctly classified pixels is described by the overall classification accuracy. We also tried to improve the classification result

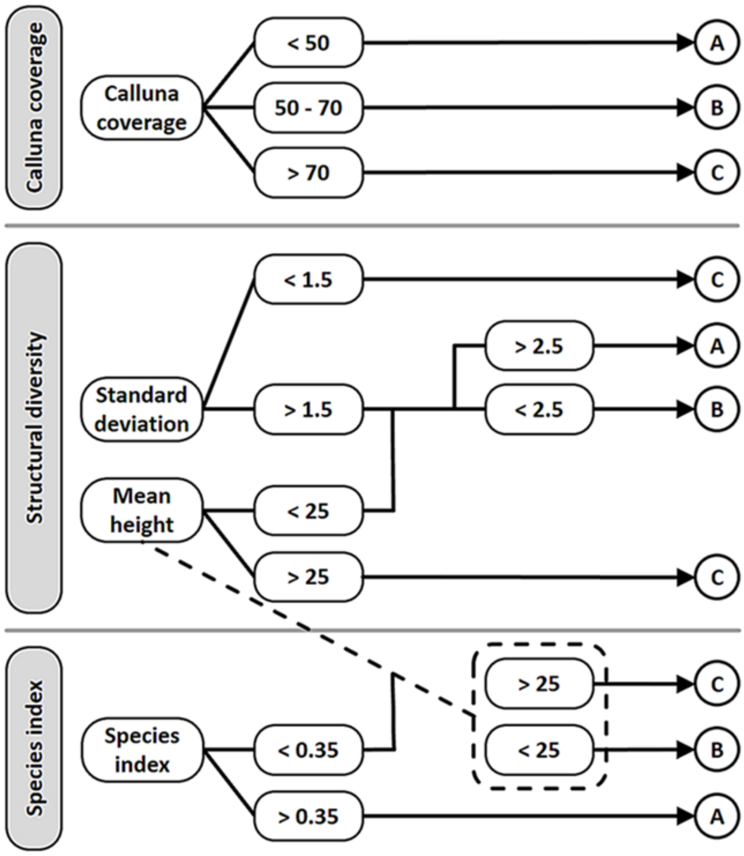

Fig. 3. *Decision tree for deriving the three discrete habitat quality classes from the quality layers. The dotted line indicates that a second criterion (here: mean height) is consulted for separating the classes 'B' and 'C' for the species index.*

by optimizing the thresholds in an iterative process. Therefore, we tested different parameters for every threshold value and layer and also assessed the classification accuracy for every step.

For *Calluna* coverage, two thresholds were used: 50% and 70%. Areas that featured less than 50% *Calluna* coverage were considered as 'A', those with more than 70% as 'C'. The cells between were assigned to 'B'. The criterion stand structural diversity is represented by both mean height and the standard deviation. Pixels with a mean height of more than 25 were assigned to 'C', same applied to areas with a low standard deviation (< 1.5). The remaining cells were considered as 'A' or 'B'. Here, one standard deviation-threshold was determining: values below 2.5 were considered as 'B', the ones above as 'A'. For the species index two decision steps were made. First, a threshold was set to separate 'A' (high index > 0.35) from both remaining classes. Second, mean height was consulted to separate 'B' and 'C'. Thus areas with a low species index (< 0.35) and higher values for the vegetation height (> 25) are seen as 'C', whereas a low species index in combination with low vegetation leads to 'B'.

2.2.3 Results

Modeling results

Table 2 summarizes the results for the calculation of the quality layers as well as for the validation of the JQI-map. The SVM models for classifying the UAV data of the two subareas into '*Calluna*' and a 'rest class' performed with accuracies of 95% (K = 0.93) and 98% (K = 0.96). These classification results were used as reference data to estimate wall-to-wall *Calluna* coverage from the hyperspectral image. The SVM regression for *Calluna* coverage resulted in an R^2 of 0.79 with an RMSE of 15.72%. The obtained cover ratios varied between 0% and 96%. The SVM regression between the UAV derived reference heights and the hyperspectral data showed a correlation of R^2 = 0.69 (RMSE = 3.53 cm). The obtained heights ranged between 0 m and 0.4 m. Standard deviation was low for sand and sparse calcareous grassland (around 0) and particularly high at edges of high and low vegetation like the mosaics of *Calluna* and grassland (up to 6.1). The PLSR regression model to obtain estimates for the key species index resulted in an R^2 of 0.71 (RMSE = 0.16). Using the backward selection autoPLS, the model was trained on 12 predicting bands which resulted in 11 latent vectors. The highest resulting index values can be observed for the calcareous meadows in the south (1.20), the lowest in areas dominated by *Calamagrostis epigejos* (-0.61). An index below 0 was only found for grass encroached areas.

Table 2. *Results of the models for calculating the single decision layers and for the validation.*

Product	Method	Reference	Predictor	Input (n)	Result (K, R^2)	OA (%)	RMSE
Calluna (UAV subareas)	SVM-C	Training samples	RGB UAV data	430 / 370	0.93 / 0.96	95 / 98	-
Calluna coverage	SVM-R	*Calluna* mask	Hyperspectral	700	0.79	-	15.72
Vegetation height	SVM-R	NDSMs	Hyperspectral	500	0.69	-	3.53
Species index	PLSR	Field data	Hyperspectral	70	0.71	-	0.16
Validation JQI map	CM	Field data	JQI map	300	0.47	65	-

SVM-C / -R: Support vector machines classification / - regression, PLSR: Partial least square regression; NDSM: Normalized digital surface model; CM: Confusion matrix; Classification results are assessed as Kappa (K) and overall accuracy (OA), regression results as R^2 and RMSE.

RGB representation

In the JQI-map of Fig. 5a the colors of the pixels correspond to the RGB color space spanned by the three quality layers *Calluna* coverage (red), stand structural Diversity (green) and key-species index (blue; see color wheel) and thus show the *Calluna* habitat state. Field impressions representing these states are shown in Fig. 4. The mono *Calluna* stands are displayed in reddish colors indicating that besides a high cover of *Calluna* the other parameters are low (4a). This is the case for a few dense stands in the central OH and in the south, which are neighbored by zones in orange or violet. Orange indicates a more diverse structure as yellowish colors represent higher stand structural diversity (4b). This can be observed for a relatively large area in the center. Here, *Calluna* stands have recently been mown, but small single patches of *Calluna* remained and only few species found their way to this area till now. Areas with high structural richness in combination with low values for the species index and for *Calluna* coverage appear in green (4c). This situation applies to the co-occurrence of high *Calluna* stands and species poor meadows, a state that mostly occurs patchy outside of the dense *Calluna* heathland. Cells that contain a certain

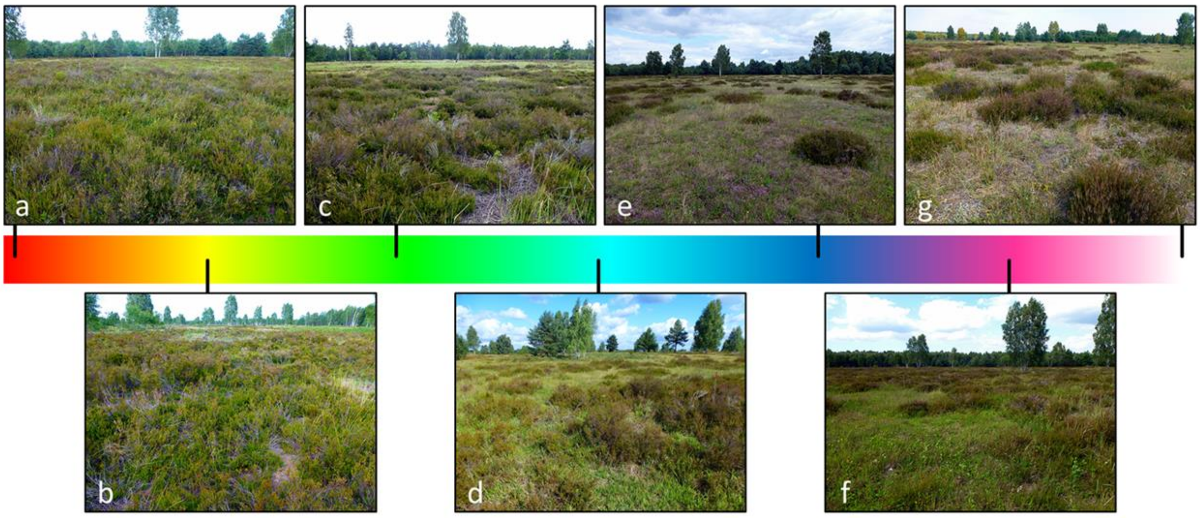

Fig. 4. *Different Calluna habitat states corresponding to the colors of the RGB-legend in Fig. 5a. Here, the three-dimensional color space is shown as a simple one-dimensional gradient. This gradient ranges from dense, homogeneous Calluna-stands (a, red) over areas with a high stand structural diversity (c, green) to zones with a high species index (e, blue). Gradual changes between these extremes appear in yellow, cyan, and violet, respectively (b, d, f). Balanced situations of the three criteria appear in rather faint colors (g) in the map.*

amount of *Calluna* (rather close to the minimum of 30%), feature medium species index values and are well structured are colored in cyan (4d). Transitional zones between dense heather stands and sparse, species rich meadows in the southern OH are predestined for that designation. Less structured meadows that are home to many characteristic species but lack sufficient heather plants (in terms of the field guidelines) are displayed in blue (4e) and remain in the map due to the smoothed masking mentioned above. This mainly applies to calcareous grassland in the south at the edge areas of *Calluna* heathland. Violet cells show a higher *Calluna* coverage, appearing in a rather homogeneous stand structure and with co-occurring vegetation represented by a lower species index (4f). This state can be observed frequently where homogeneous *Calluna* patches are interspersed by grasses and herbs indicating degradation. Brighter colors are found for areas with a more balanced situation of the three parameters (4g). *Calluna* habitat state that is desirable in terms of conservation appears in blue and bluish-green colors indicating rather low coverages of *Calluna*, a sufficient species index and a balanced stand structural diversity.

Table 3. *Confusion matrix for comparing the remote sensing-derived product and the field mapping of the conservation status classes.*

	Reference Data				
Classified Data	A	B	C	Total	User's Accuracy
A	**41**	10	1	52	0,79
B	25	**70**	33	128	0,55
C	12	23	**85**	120	0,71
Total	78	103	119	300	
Producer's Accuracy	0,53	0,68	0,71		

Overall classification accuracy = 65%, Kappa = 0.47 ($p < 0.001$). Bold values indicate the correct classifications.

Deriving the conservation status

Defining thresholds for the three quality layers delivered two results. Firstly, a map depicting habitat states by the sums of the three input maps (3 to 9, Fig. 5b), and, secondly, a map that illustrates the derived conservation status in discrete classes (Fig. 5c). The latter was compared to field mapping results (n = 300; with 'A' = 78, 'B' = 103, 'C' = 119) via a confusion matrix which resulted in an overall classification accuracy of 65% and Kappa of 0.47 that was found to be statistically significant ($p < 0.001$, assessed via McNemar's test; McNemar, 1947) (see Table 3).

Most cells with a high cover of *Calluna* also tend to feature a low stand structural diversity and a low species index. Thus, the low sums (3 and 4) lead to the assignment of class 'C' ("bad", red), which applies to 18% of the target habitat. The peripheral zones of the *Calluna* dominated areas are often classified as "favorable" ('A', green). These areas show a good habitat state with a maximum of one "inadequate" parameter (sums of 8 or 9). They mostly occur scattered and sum up to 38% of the pixels. Transitional zones between these two extremes are accounted as 'B' ("inadequate", yellow). These areas lack at least two evaluation parameters (sums of 5 to 7) and cover 44% of the map.

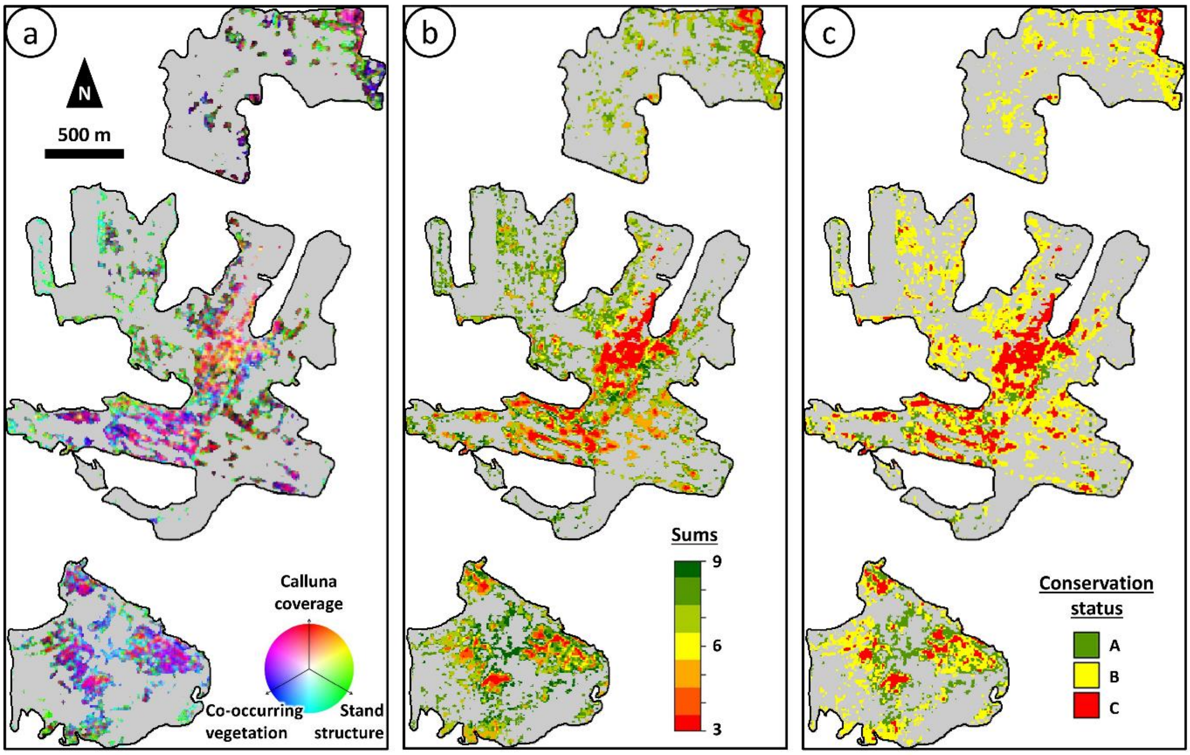

Fig. 5. *The state of Calluna habitats is visualized via an RGB-representation (a). Pixel colors correspond to their values resulting from the three remote sensing-derived quality layers Calluna coverage (red), stand structural diversity (green) and co-occurring vegetation (blue). This map is meant as a visualization of the 'joint quality indicator', which then allows for deriving the conservation status. A smoothed mask was applied to delete cells with less than 30% of Calluna, but to preserve fringes of the potential habitats. Field impressions that correspond to the RGB colors are shown in Fig. 4. Thresholds from expert evaluation were applied to the three single decision layers for discriminating the status classes (A = 3, B = 2, C = 1). The three values were summed up to receive a single value per pixel illustrating an approximation of the habitat quality (b). The conservation status (c) is assigned based on the sums (8/9 = A, 5/6/7 = B, 3/4 = C).*

2.2.4 Discussion

We aimed to transfer existing field guidelines for mapping *Calluna* habitats to a remote sensing approach. To do so, we translated a field guideline into a mapping scheme that can be used in remote sensing. After individually modeling *Calluna* coverage, stand structural diversity, and co-occurring vegetation from a combination of remote sensing and field data, we applied expert-based thresholds to create maps depicting the conservation status in a spatially explicit way.

Models for the criteria layers

Results confirmed that *Calluna* could be distinguished well from other vegetation. This provides an appropriate basis for the designation of the habitat type. Problems in the estimation of *Calluna* coverage partially occurred where *Calluna* had been mown in the recent past. Here, *Calluna* often covers more than 50% but other vegetation is absent and mostly open soil occurs along with *Calluna*. The influence of open soil is likely to have caused the observed underestimation of *Calluna* coverage in these areas due to its strong influence on the spectral signal. Our approach also has limitations in capturing understory stands of *Calluna*. This applies for example to pioneer forests which in some cases could be considered as habitat type H4030 in a minimal conservation status (bush or tree encroachment up to 70%). However, here, these zones were excluded by applying a forest mask.

An accuracy of $R^2 = 0.69$ for modeling the mean height was considered a satisfying result. The main aim to gain continuous information on stand structural diversity was achieved. Using photogrammetrically derived fine scale vegetation heights from UAV flights as reference was a low cost approach (Lausch et al., 2016; Westoby et al., 2012). However, using ‘real’ structural information, which is directly linked to remote sensing data (e.g., LiDAR-derived, see Kepfer-Rojas et al., 2015, or SAR-derived, see Neumann et al., 2010) possibly enables more accurate results.

Our way of considering co-occurring vegetation is simple but efficient. We included both, the quantity of characteristic species as well as the coverages in a key species index. An R^2 of 0.71 showed that the proposed index can be mapped by remote sensing with good accuracies. Here, the selection of species in the proposed index mainly represents sparse grassland. This is reasonable in our study region but should be adapted when the approach is transferred to other areas. The index covers several species groups in a gradient that also seems to show up in the hyperspectral signal. These species groups include grassland vegetation associated to a good conservation status as well as degraded heathland, which is characterized by plant senescence or large leaf areas and high chlorophyll content, respectively, due to grass encroachment and ruderality.

As open soil is important for the germination of *Calluna* (Henning et al., 2015), it is a crucial factor when evaluating the habitat quality during field mapping. We consider that the combination of the quality layers stand structural diversity and species index addresses this problem and that no further model for the amount of open soil is required. The same applies to the coverage of lichens. A high species index (indicating sparse grassland vegetation) in combination with a low canopy or a canopy with a high gap-fraction favors the appearance of lichens and thus could be seen as indicator for a good conservation status. Integrating an additional model could be taken into consideration as some studies have already made progress using remote sensing approaches for detecting lichen cover (e.g., Nordberg and Allard, 2002; Somers et al., 2010). However, as mentioned above, lichens are not considered as being important for the mapping decisions in the study area.

Applicability of the approach

Our approach is in accordance with the recommendations of Corbane et al. (2015) who stated that the development of remote sensing based indicators correlating well with field-based species-related parameters (and the conservation status) are desirable. The applied thresholds are based on expertise evaluation and can be handled flexible. When the approach is transferred to another area the thresholds could need adaption. The application of thresholds enables the step from gradient maps to discrete units. We think that this approach could help in improving the transparency of the quality assessment process as it is comprehensible in every step of the decision process. Even the single remote sensing-based quality layers of *Calluna* coverage, stand structural diversity and co-occurring species on their own can be a useful template for field mapping and for managing heathlands. In combination - as the proposed JQI-map - they provide an overview of the decision space in a spatially and thematically continuous way.

The differentiation of the mainly addressed habitat type *European dry heaths* (H4030) from similar habitats in the study area (H2030 *Dry sand heaths with Calluna and Genista*) could be accomplished by adapting the species index and by an additional information layer representing the amount of sand. However, these two habitats are difficult to distinguish via remote sensing and were merged in other studies as well (e.g., Nieland et al., 2015). Moreover, the latter habitat is of minor importance in the study area. According to the guidelines, mapping units which contain more than 25% of calcareous grassland (H6120) have to be assigned to the latter due to its priority status. Thus, areas that were classified as *Calluna* habitats in a “favorable” status in our study might actually belong to habitat H6120. Some further adaptation could be tested to capture calcareous grassland; primarily via the key species index as several positive indicator species occur in both habitats. Furthermore, considering structural information could help in identifying areas of these sparse meadows.

According to the field guidelines the coverage of *Calluna* (> 30%) is only decisive as a first step when an area is assigned to the habitat type. However, we decided to include this parameter when applying the thresholds. It has to be considered that the field guidelines apply to mapping units, whereas, here, they are adapted to a pixel based approach. Our findings in the field indicate that plots that feature less than 50% *Calluna* cover tend to represent a good habitat state. The opposite was found for samples with more than around two thirds of *Calluna* cover: with only few exceptions they contained overaged heath and hardly any characteristic species hence leading to a “bad” conservation status. The combination of the two height layers (mean height and standard deviation) enabled us to separate areas that have a similar mean height but differ in their stand structure as well as the other way around. For example, a dense patch of high, overaged *Calluna* could have a similar low stand structural diversity like low meadows. On the other hand, *Calluna* stands with different textures could occur, that are very similar with regard to mean height. The thresholds concerning the species index were chosen based on our field estimates. In some areas it correlates with the *Calluna* coverage: the less *Calluna* occurs, the higher the probability of co-occurring species indicating a good conservation status. However, as the index includes species that indicate degradation as well, it provides additional information. Areas that are affected by grass encroachment or ruderality show a very low index as they feature high coverages of species representing an undesirable conservation status.

Comparing the remote sensing result and field-derived classification

The conservation status (A, B, or C) was assigned based on the expert-defined thresholds applied to the three quality layers mapped with remote sensing. The patterns that are displayed in the maps correspond well to what we expected from field knowledge.

The overall accuracy of 65% (relating the remote sensing-derived map to the field data) should rather be seen as a comparison than a validation result. Two types of error that may occur are represented in the confusion matrix, omission and commission. An accuracy assessment via this matrix should be interpreted as a comparison between two maps (a field-derived and a remote sensing-derived) which both contain a level of uncertainty, rather than a comparison between the remote sensing map and a true reference (Foody, 2008). The later method can either produce smoothing effects by using too coarse resolution or result in intra-class variations if the spatial resolution of the data is very high (Nieland et al., 2015). In this context Hearn et al. (2011) reported inconsistencies in repeated vegetation mapping efforts. They stated that up to 65% of ‘change’ could potentially be caused by observer error. This error is even enhanced within NATURA 2000 areas, because local experts tend to overestimate locally relevant species and underestimate locally abundant species (Förster et al., 2008; and further discussed by Nieland et al., 2015). Foody (2008) concludes that the reliability of a map should always be judged within its context in order to reduce inappropriate criticism and false perceptions of remote sensing-based results. According to this, the accuracy derived from the confusion matrix should be interpreted with caution. Overall, the classification of classes ‘B’ and ‘C’ is generally sound as indicated by a producer’s accuracy of around 70%. The result for class ‘A’ is notably worse (53%). Finally, it can be emphasized that there is a good discriminatory power for separating the extreme classes ‘A’ and ‘C’.

We stress that our approach is not meant to replace field derived maps that serve as basis for the monitoring reports. Both methods (field mapping and the proposed remote sensing approach) try to put a desirable vegetation state in concrete terms by the help of single proxies. We tried to walk well-trodden paths and add a remote sensing perspective. Our approach should be seen as a transparent and transferable method for supporting conservation mapping. The transferability of rule-based approaches in the context of conservation status mapping was also emphasized by Zlinszky et al. (2015).

However, especially when it comes to a strict reading of the guidelines, our approach is problematic as it is based on pixels. Some parameters for the evaluation, e.g., coverage of open soil or lichens, should rather be considered based on mapping units. Here, object-based analysis (Mücher et al., 2013) or a kernel-based approach (Nieland et al., 2015) could be solutions for finding units of homogeneous vegetation. An alternative could be an adaptation of the guidelines to take account of the capabilities of remote sensing.

2.2.5 Conclusion

In this study, we transferred existing field guidelines for mapping *Calluna* habitats to a remote sensing-aided monitoring approach. Three quality parameters were mapped with remote sensing and summarized in an RGB-visualization: *Calluna* coverage, stand structural diversity and an index reflecting co-occurring vegetation. In a second step the results were translated into discrete habitat quality classes which are in close agreement with the mapping guidelines applied in the field surveys.

The remote sensing derived map of the study area was mostly in agreement with what we saw in the field. Areas with high coverage of *Calluna* tend to represent an undesirable conservation status as they often feature overaged heather with a homogeneous structure and lack co-occurring species. The optimal state is given in transitional zones between *Calluna* heath and calcareous grassland. Here, *Calluna* occurs to a certain extent (not more than 50%) and is interspersed by sparse grassland, which leads to a high stand structural diversity. As the open vegetation favors the rejuvenation of *Calluna*, several age classes coexist.

The three quality layers could be mapped with good accuracies. UAV data provided appropriate reference data and could play an important role for conservation mapping. An overall agreement of 65% between the remote sensing result and field mapping shows that the approach works. Furthermore, we argue that by deriving maps of the individual variables used as indicator for habitat quality assessments, it is possible to derive a more objective habitat quality map. Thresholds for the definition of quality states can be readily changed after-the-fact and evaluated with respect to their spatial consequences. This enables to evaluate the best thresholds instead of relying on expert guesses in the field, which have a low repeatability and often diverge.

The approach is thought to be transferable to similar regions with minor adaptions. We believe that our method can be a valuable supplement to field mappings by improving efficiency and by improving transparency of the quality assessment process. Future research could be (1) to transfer the approach to other areas with similar habitats and (2) to test it based on different types of remote sensing data (e.g., the Sentinel satellites). Moreover, the designation of appropriate, homogeneous mapping units could be addressed as required by existing mapping guidelines. Adaptation of the mapping guidelines in the field to the capabilities of remote sensing instead of vice versa, however remains an important topic that should be explored to further improve habitat quality assessments using remote sensing.

Acknowledgements

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2.3 Synergetic use of Sentinel data for quality assessments of heathland

Johannes Schmidt, Fabian E. Fassnacht, Michael Förster, Sebastian Schmidtlein:

Abstract

Habitat quality assessments often demand wall-to-wall information about the state of vegetation. Remote sensing could provide this information by capturing optical and structural attributes of plant communities. Although active and passive remote sensing approaches are considered as complementary techniques they are rarely combined regarding conservation mapping.

Here, we combined spaceborne multispectral and SAR data for a remote sensing-based quality assessment of dwarf shrub heathland, which was inspired by nature conservation field guidelines. Therefore, three earlier proposed quality layers including (1) coverage of the key dwarf shrub species, (2) stand structural diversity and (3) an index reflecting co-occurring vegetation were mapped via linking in situ data and remote sensing imagery. These layers were combined in an RGB representation depicting varying stand attributes, which afterwards allowed for deriving pixel-wise habitat quality classes.

The links between field observations and remote sensing data reached correlations between 0.66 and 0.9 for modelling the single quality layers. The patterns of both continuous map and discrete quality classes were in line with the field observations. Finally, the remote sensing-based mapping of heathland conservation status showed an overall fit of 79% compared to field data. Transferring the approach in time, using imagery with a different acquisition date, caused a decrease in accuracy. Although the model results were still sound, the derived habitat qualities showed a comparably low fit.

Our findings suggest that Sentinel-1 SAR contains information about vegetation structure that is complimentary to optical data and therefore considered as relevant for nature conservation. While we think that rule-based approaches for quality assessments offer the possibility for gaining acceptance in both communities (applied conservation and remote sensing) there is still need for developing more robust and transferable methods. It is likely that the potential of the Sentinel-satellites for monitoring heathlands can be increased by including multi-temporal or multi-seasonal information.

This study is in review at Remote Sensing in Ecology and Conservation as:

Schmidt, J., Fassnacht, F.E., Förster, M., Schmidtlein, S.: Synergetic use of Sentinel-1 and Sentinel-2 for assessments of heathland conservation status.

2.3.1 Introduction

Shrublands are ecologically important vegetation formations characterized by low woody vegetation (Ausden, 2007). They occur worldwide but predominantly in areas lacking sufficient water or warmth for the growth of trees (semi-arid areas, high mountains, and high latitudes). They are found in, e.g., North America (sagebush steppe/chaparral; Dalgleish et al., 2011), Australia (bluebush shrubland; Dawson and Ellis, 1996), South Africa (Karoo shrubland; Mucina and Rutherford, 2006), and circumpolar within the Low Arctic (Boreal shrublands) in Siberia (Frost et al., 2013), Canada (Douglas and Bliss, 1977) and Northern Europe (Muller, 1952) as well as in higher mountains worldwide (Körner and Ohsawa, 2005).

In Western and Central European lowlands and montane areas, shrublands occur largely as a replacement-vegetation of forests caused by past land-use and current conservation management. The drier variety of these anthropogenic shrublands is characterized by a low woody layer that is typically formed by a single ericaceous species, *Calluna vulgaris* (L.) Hull (henceforth just *Calluna*), interspersed by open soil and sparse vegetation (low growing grasses, mosses and lichens). We consider these shrublands as representative for other habitats with similar characteristics, that is, a low shrub layer with understory grasses and herbs. European *Calluna* shrublands are strongly declining due to land-use change and are therefore a target of conservation efforts (Kirkpatrick and Blust, 2013). Most *Calluna* shrublands are protected within the Natura 2000 network of conservation areas, which requires periodic monitoring reports about the habitats' state in terms of conservation.

To support these monitoring tasks, several previous studies assessed the benefits of remote sensing and demonstrated good potential of using airborne and spaceborne data (e.g., Bock et al., 2005; Förster et al., 2008; Vanden Borre et al., 2011b). Most of these studies used passively recorded optical remote sensing data. However, passively recorded optical remote sensing data can be supplemented with data from active sensors like LiDAR (e.g., Kepfer-Rojas et al., 2015; Leutner et al., 2012; Zlinszky et al., 2015) and synthetic aperture radar (SAR). For monitoring purposes, SAR seems especially interesting as its ability to penetrate clouds supports the straightforward collection of time series data (Schuster et al., 2015). Furthermore, SAR data is complementary to optical sensors, as it can penetrate into the vegetation canopy and thus its backscatter is mostly related to the physical structure of the vegetation which is only partly described by the optical signal.

Only few studies examined SAR data for mapping purposes in dwarf shrub heathlands or herbaceous vegetation. In these studies, time series of TerraSAR-X backscatter information provided the basis for detecting swath events in grasslands (Schuster et al., 2011) as well as for the differentiation of grassland types (Schuster et al., 2015). Very accurate classifications between grassland and crops were conducted by Dusseux et al. (2014) when using multi-temporal optical imagery and polarimetric SAR products in combination. Bargiel (2013) achieved high accuracies for classifying vegetation types, such as shrub patches and grassland based on a multi-channel TerraSAR-X time series. SAR time series from ERS-2 and ASAR enabled Millin-Chalabi et al. (2013) to detect a fire scar in a upland moorland characterized by peat bog when jointly analyzing pre and post-fire acquisition of SAR data. To obtain information on shrub growth in the Sub-Artic Duguay et al. (2015) applied SAR (TerraSAR-X, Radarsat-2) in combination with in situ data. They compared the backscatter signal of both sensors concerning their sensibility for detecting shrub density and height.

Fusing actively and passively sensed data provides information about both the structure and the material content of the depicted objects. The synergistic use of both, SAR and optical remote sensing was applied in several studies for describing vegetation in diverse applications, e.g., forests (Montesano et al., 2013; Reiche et al., 2015), wetlands (Hong et al., 2015; Rodrigues and Souza-Filho, 2011), agricultural areas (Hill et al., 2005; Peters et al., 2011), upland vegetation types (Barrett et al., 2016) or broad land cover classes (Ullmann et al., 2014). However, up to now, there are no studies related to mappings of conservation areas that used SAR-optical synergies.

Although several studies have been dealing with remote sensing-based approaches concerning the European monitoring procedures (e.g., Franke et al., 2012; Spanhove et al., 2012; Stenzel et al., 2017; and see Corbane et al., 2015 for a synthesis), there is still no valid and wide applicability of Earth observation methods in this branch of nature conservation. Hence, Sentinel-1 (S1) and Sentinel-2 (S2) might help to increase the applicability of remote sensing-based procedures in practical monitoring tasks. There are already vegetation-focused studies using Sentinel data (e.g., Delgado-Aguilar et al., 2017; Immitzer et al., 2016), but there is no directly related work dealing with conservation mapping so far. However, Feilhauer et al. (2014) tested the ability of simulated S2 data for monitoring purposes of Natura 2000 areas. They showed that this imagery could be useful when mapping discrete classes of habitat types. They achieved similar accuracies compared to remote sensing imagery with higher spatial and spectral resolution.

In our study we jointly analyze multispectral Sentinel-2 and Sentinel-1 SAR data of EU's Copernicus mission for habitat mapping and monitoring purposes. For an example of dwarf shrub heathland habitats we use this combination of sensors to create a map that suits the monitoring demands of the European Habitat Directive. To achieve that, we adapt an approach proposed by Schmidt et al. (2017b) who transferred field mapping guidelines to a remote sensing methodology using rule-based classification. This earlier approach bases on remote sensing proxies from airborne data reflecting wall-to-wall information on (1) the key species, (2) stand structural diversity and (3) co-occurring vegetation. Here, we combine spaceborne remote sensing data and field samples to obtain the same three variables and finally derive spatial representations of continuous habitat states and the conservation status.

2.3.2 Material and methods

We aimed at combining SAR and multispectral imagery for quality assessment of dwarf shrub habitats in accordance with the required monitoring procedure of the European Natura 2000 conservation network. Inspired by field guidelines, we mapped three continuous quality layers: (1) coverage of the key dwarf shrub species, (2) stand structural diversity, and (3) an index reflecting co-occurring vegetation, which enabled us to derive conservation status classes.

Study area and occurring habitats

The study was conducted in the open landscape of the Oranienbaum Heath that is located near Dessau, Saxony-Anhalt, Germany (N 51.77350°, E 12.36120°; see Fig. 1a). Formerly used as military training ground, the open landscape still holds parts of ancient pasture plant communities (John et al., 2010). Today, the heathland ecosystems are threatened by the increase of

Calamagrostis epigejos and the encroachment by pioneer tree species. For a detailed description of the study area see Schmidt et al. (2017a).

The dominant communities of the non-forested areas in the study include dwarf shrub associations characterized by high coverages by *Calluna vulgaris* (habitat types H-2310 and H-4030 according to the Natura 2000 guidelines). These habitats are characterized by the aging-cycle of *Calluna* where the plants undergo a cyclic succession of different phases (pioneer, buildup, mature, and degeneration), each with a characteristic species composition (Gimingham, 1972; Watt, 1947). In an optimal state, in terms of conservation, heathland patches feature mosaics of these four phases being interspersed by cryptogams and sparse grassland (Ausden, 2007).

Besides the dwarf shrub habitats, grassland occurs in varying forms. Open pioneer grasslands (H-2330 with *Corynephorus* and *Agrostis*) appear on inland dunes. Calcareous sandy grasslands (H-6120) mainly occur in the south of the study area featuring a high species diversity; typical plant species include *Koeleria macrantha*, *Festuca ovina*, and *Peucedanum oreoselium*. They are often neighboring other low-nutrient grasslands or *Calluna* heath forming a mosaicked vegetation. Heathland degraded by grass encroachment of *Calamagrostis epigejos* can mainly be found in the northern and central part. Favored by nutrient enrichment, the appearance of this dominant species often leads to a decrease in species diversity due to shading by large amounts of live plant material and litter (Heil and Diemont, 1983).

Since these heathlands have a large geographic distribution and adaptation capacity to different climatic ranges, we think that they represent appropriate test sites for developing monitoring techniques that can be transferred to similar habitats. Compared to other habitats, *Calluna* heathland can be explored by Earth observation with relatively high accuracies as the most relevant parameters for monitoring directly relate to structurally or spectrally detectable variables. We assume our concept to be transferable to shrublands that that have similar characteristics concerning a dominant shrub layer of few (or even one) species.

Data

Vegetation assessments in the field

We used four field datasets in this study; three for calculating quality layers used for an integrated assessment of habitat quality (see explanation below) and another one for validation of the derived conservation status classification. Two field surveys were conducted in 2014 and 2015 for collecting these datasets.

Coverage ratios of vascular plants were recorded in 85 plots measuring 10 x 10 m in August 2014. The samples were located in the field with a stratified random approach using an earlier mapping by Felinks et al. (2012a) to ensure that all occurring heathland habitats were considered. Accordingly, this collection was named ‘heathland dataset’. Homogeneity in terms of vegetation composition had to be given in a 20 m radius around the random point, else it was dismissed. These plot observations served as basis for calculating a species index described below. Moreover, the validation of the habitat mask based on this dataset (see section 2c below).

Coverage values of *Calluna* were documented for 400 plots of 10 x 10 m in July 2015 (‘*Calluna* dataset’). In 160 of these samples, we additionally sampled mean height and standard deviation of the height from 15 measurements of the vegetation height within the sample plot (‘structure dataset'). The plot locations were chosen by stratified random samplings based on the habitat map from Schmidt et al. (2017b) to ensure that the target habitat is captured in all its specificities.

Independent from that, another field survey was conducted in July 2015 where plots measuring 10 by 10 m that represent *Calluna* habitats were checked for their conservation state. The locations were randomly selected all over the study area. If *Calluna* covered less than 25%, the plot was dropped. We documented the conservation status for 350 samples based on the mapping instructions from LAU (2010). This data served as reference for testing the remote sensing-based conservation status map ('test dataset').

SAR data

Sentinel-1 (S1; Fig. 1c) is a dual polarization radar that measures two-dimensional surface backscattering using a C-band SAR with 6 cm wavelength (ESA, 2016a). Each scene in this study comprises two polarization types, VV and VH. For VV data sending and receiving are vertical, whereas VH represents a cross-polarized signal that bases on vertical polarized sending and horizontal polarized receiving. The signal includes scattering components from the ground surface, the vegetation (canopy and branches) and their interactions (Burgin et al., 2011). Both surface geometry and its physical properties affect the information within the backscattered signal. Being a short wavelength SAR, the signal of Sentinel-1 interacts with the upper part of vegetation canopies allowing for retrieving biophysical vegetation parameters.

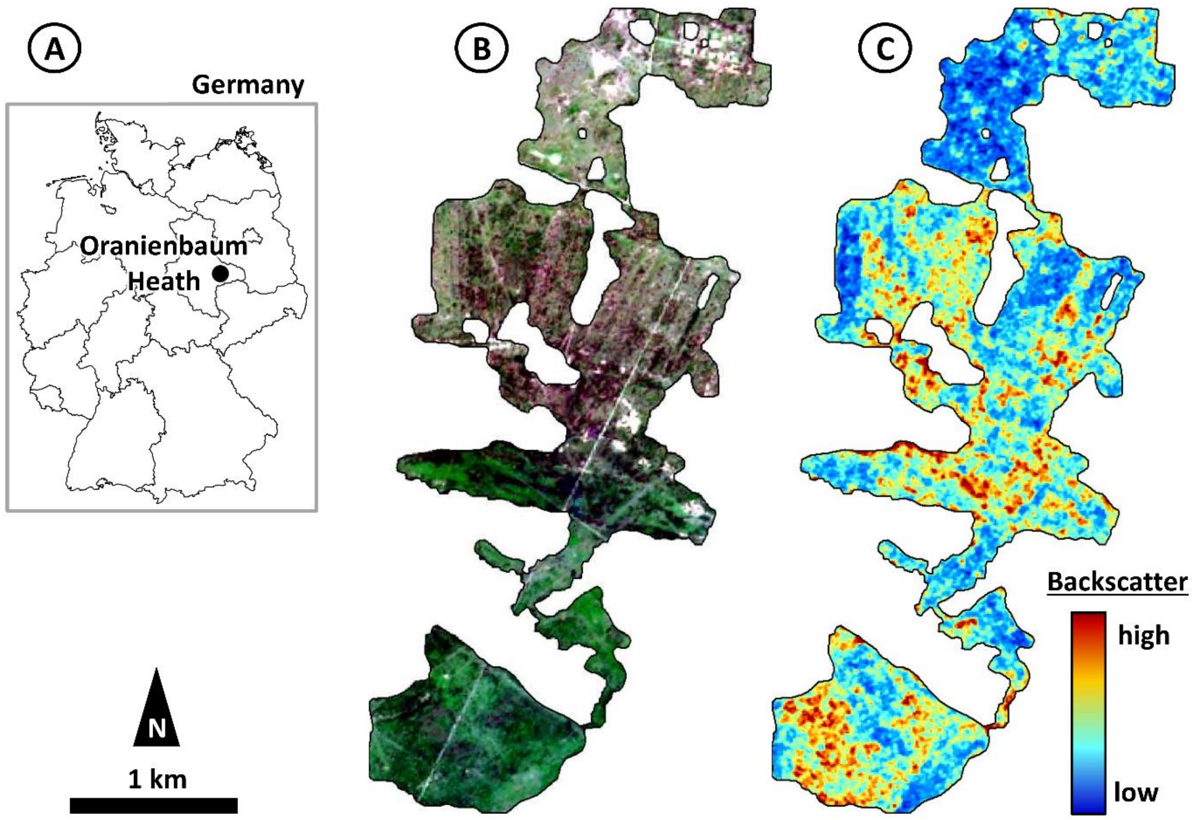

Fig. 1. *The study site Oranienbaum Heath is located near Dessau, Saxony-Anhalt, Germany (A). Panel B gives an impression of the multispectral data used in this study (Sentinel-2; RGB-bands: 4, 3, 2). Forests are masked. SAR backscatter information from Sentinel-1 provided information on the vegetation structure (C; mean of ascending and descending VH backscatter). As the target habitat Calluna heathland is mainly found in the central and southern part of the study we focus on these areas when mapping the habitat quality (D).*

We used level-1 GRDH (Ground Range Detected with high resolution) products, which were recorded in IW (interferometric wide swath) mode. The processing of the SAR imagery contained 1) the application of an orbit file, 2) geometric calibration, 3) terrain correction, and 4) speckle filtering. These steps were performed in the software SNAP (ESA, 2016c).

It has been shown in other applications that a fusion of ascending and descending SAR data can improve the results (e.g., Goering et al., 1995 for noise removal; Gernhardt and Bamler, 2012 for detecting building deformation; Deo et al., 2015 for DEM generation) because geometric distortions, such as layover, shadow and foreshortening are minimized. Thus, we considered scenes that were acquired in two different orbits (opposite viewing angles). The first image was acquired on 30 June 2016 (descending mode), the second on 9 July 2016 (ascending mode) (see Table 1). Additionally, we calculated a mean layer for each polarization, respectively. Therefore, backscatter values were rescaled from 0 to 1. This simple weighted average approach for fusing SAR images of ascending and descending pass was also applied by others (Carrasco et al., 1997; Crosetto, 2002; Sansosti et al., 1999).

The six bands (VV and VH for two dates plus the respective means) were merged in a stack featuring a spatial resolution of 10 m. Moreover, we calculated the textural features *variance* and *entropy* in R (package gclm; Zvoleff, 2015) based on 3 x 3 grey-level co-occurrence matrices (Haralick et al., 1973) for each band but the mean layers as they proved to enhance the models. *Entropy* describes the uniformity of the grey-level distribution in an image, i.e. the disorder, whereas variance is helpful to capture boundaries and edges as it bases on the dispersion of values around the mean of a kernel (Ouma, 2006). The SAR imagery served as basis for creating a threshold-based forest mask based on visual interpretation.

In order to check for transferability, the classification procedure is tested based on a second, independent remote sensing dataset. Therefore, we considered two more SAR images that were acquired around 25 days before (see Table 1). The processing described above was applied in the same way.

Table 1. *Satellite data used in this study.*

Dataset	Sensor	Date	DOY	Pass
Calibration	S2	2016-06-28	180	D
	S1	2016-06-30	182	A
		2016-07-09	191	D
Transfer	S2	2016-06-08	160	D
	S1	2016-06-08	160	D
		2016-06-11	163	A

S2: Sentinel 2; S1: Sentinel 1; D: descending orbit; A: ascending orbit

Multispectral imagery

Additionally, we applied a Sentinel-2 (S2, Fig. 1b) (Drusch et al., 2012; ESA, 2016b) image acquired on 28th of June 2016. Four bands (red, green, blue and near infrared) around the central wavelengths of 490, 560, 665, and 842 nm have a pixel size of 10 m. The red edge is represented by four bands with a spatial resolution of 20 m (705, 740, 783, and 865 nm). Two other bands (around 1610 and 2190 nm) that are registered for the discrimination of clouds, snow, and ice have a pixel size of 20 m, too. We used these ten bands that covered the spectrum from 490 nm to 2190 nm, scaling those with 20 m pixels down to 10 m. The original S2 data was re-projected and processed using ESA's software SNAP (ESA, 2016c). The textural feature *contrast*, which bases on the grey-level difference of neighboring pixels (Ouma, 2006), was calculated additionally. The SAR-based forest mark was applied as well.

According to Hengl (2006) the pixel size of both Sentinel products would be appropriate for the mapping task: a mapping scale of 1:10,000 demanded by the conservation guidelines would require cells between 1 m and 25 m (recommended: 5 m). This was supported by Schmidt et al. (2017b) who used a spatial resolution of 9 m in a study similar to the presented approach.
A second multispectral image, which was acquired 20 days before the calibration image, was included into the second remote sensing dataset for testing the methodology (see Table 1).

Methods

We created three independent models representing the quality layers named (1) *Calluna* coverage (using both multispectral and SAR data), (2) stand structural diversity (using SAR) and (3) a species index (using multispectral imagery). The three spatial layers were used for a continuous graphical representation of what determines the habitat conservation status. Afterwards, the actual conservation status classes were derived by a decision tree classification on pixels (see Fig. 2). Our procedure is following the principle proposed by Regan et al. (2004): we aim at formalizing experts' decision making process, illustrated through the conservation status assessment under the Habitats Directive, in order to transfer the rules to remote sensing products.

Transfer of the field guidelines to remote sensing

The requirement of an area to qualify as Calluna habitat is a minimum coverage of the key species *Calluna* of 30% (LAU, 2010). The amount of the growth phases of *Calluna* are of major importance for structural aspects by means of the field assessment. The properties of open soil and lichens should be included, too. As sparse grassland is the desired co-occurring vegetation, associated species are listed in the field guidelines as indicators of "favorable" habitat conditions. They include, for example, *Anthoxanthum odoratum*, *Festuca ovina*, *Koeleria macrantha*, *Rumex acetosella*, and *Thymus pulegioides*. Negative habitat pressure is represented by bush or grass

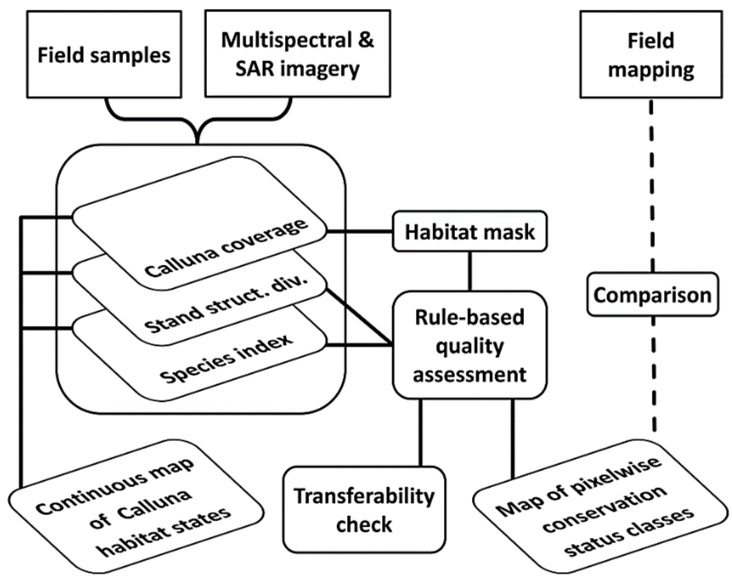

Fig. 2. *Workflow of the study*

encroachment as well as the occurrence of neophytes or species indicating eutrophication. The conservation status of a mapping unit should summarize the situation of these assessment parameters. Thus, one “joint quality indicator” has to be generated that expresses the median of the features by a single value. It is either “favorable” (A), “inadequate” (B), or “bad” (C).

These guidelines for mapping *Calluna* habitats in the field were transferred to a remote sensing approach by Schmidt et al. (2017b) who proposed to approximate the field mapping parameters by three remote sensing proxies: (1) coverage of the key species *Calluna*, (2) stand structural diversity and (3) a species index reflecting co-occurring vegetation. All information that is needed for assigning the conservation status is potentially captured either by a single quality layer or a combination of several of them (see section ‘Model building’).

In a first step, a continuous layer representing cover ratios of *Calluna* enabled us to create a mask of the target habitat by excluding areas that do not have an appropriate fraction of *Calluna* cover (less than 30%) and therefore do not qualify as target habitat, independent from the quality of the two other criteria. Afterwards wall-to-wall information about stand structure and vegetation co-occurring with *Calluna* were used for discriminating the quality classes within the remaining areas. Stand structure is captured by combining mean canopy height with the standard deviation in order to jointly represent stand structural diversity. A species index was used to describe the vegetation that co-occurs with *Calluna*. The index was calculated as a simple ratio between the coverage of indicator species for “favorable” and “bad” conservation status: $i = n_f \log (c_f) - n_b \log (c_b)$; where n_f and c_f are the number and the cover species indicating a “favorable” status, while n_b and c_b are the corresponding values of species indicating a “bad” status. Standardization was achieved by dividing the index by its maximum value. The considered indicator species are pre-defined by the field guidelines (LAU, 2010).

By applying thresholds based on expert judgment to the modeled quality layers we aimed at deriving status classes (see section ‘Deriving the conservation status’). This map depicting the pixelwise conservation status was then compared to field mapping results from a second, independent field dataset (‘test dataset’).

Model building

We applied Support Vector Machines (SVM) in regression mode to obtain wall-to-wall information on the three quality layers. We selected SVM as a nowadays conventional method for treating higher-dimensional remote sensing data (i.a. Fassnacht et al., 2014; Mack et al., 2016; Schuster et al., 2015). A good description of SVM in the context of remote sensing is given by Mountrakis et al. (2011). The model fit of SVM are reported in R^2 and normalized RMSE (nRMSE) as obtained by 10-fold cross-validation with 30 repeats. Normalizing the RMSE allows for comparisons between the models as the result is dimensionless (expressed in percentage). It is calculated by dividing the RMSE by the range of observed values. Influence of the different input variables on model performance was assessed via variable importance evaluation. The SVM applications were performed in R (R Development Core Team, 2013) using the ‘caret’ package (Kuhn, 2016).

For creating the habitat mask *Calluna* coverages were calculated by regressing coverage values of the *Calluna* dataset (n = 400) against fused SAR and multispectral data. As stand structure is represented by both canopy height and its diversity, we calculated two SVM models based on the 160 field samples of the structure dataset. The mean of 15 values per field sample was considered for modeling the mean canopy height, whereas standard deviation was considered for modeling the height diversity. Combining these two spatial representations helped to separate areas that feature a similar canopy height but differ in their structural diversity as well as the other way around. For example, a dense patch of high-growing old *Calluna* plants could have a similar low structural diversity like a plane layer of mown *Calluna* heathland. On the other hand, *Calluna* stands with completely different texture, but similar mean height could occur. Furthermore, the key species index reference values calculated from the heathland dataset with n = 85 was regressed against the S2 multispectral imagery by SVM to achieve a continuous information about the co-occurring vegetation for the whole study area.

Creating the habitat mask

For the designation of the target habitat we proceeded as described in the field guidelines (LAU, 2010): Only pixels with more than 30% *Calluna* coverage were considered. The areas of interest were slightly smoothed by applying a mean filter (3x3) to include the fringes of the *Calluna* heathland habitats as well. This ensured that these transition zones are, like in field mapping, included in the evaluation.

For validating this remote sensing-derived habitat mask, we compared it with field-based vegetation clusters from the heathland dataset. The isopam algorithm (Schmidtlein et al., 2010) was used to differentiate vegetation into four types: *Calluna* heathland, calcareous sandy grassland, open sandy grassland, and degraded heathland dominated by *Calamagrostis epigejos*. The three clusters that are not associated with *Calluna* heathland were merged. Here, 76 out of 85 plots were considered; 9 were masked due to the application of the forest mask.

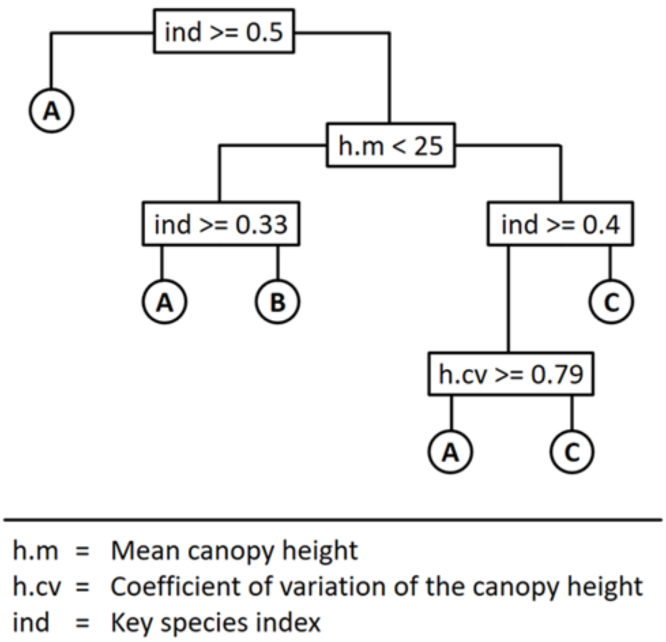

Fig. 3. *Decision tree for separating the three conservation status classes based on the mean vegetation height, coefficient of variation of the height, and the species index. The latter was particularly important for separating quality class 'A' from both 'B' and 'C'. Classes 'B' and 'C' could be well distinguished based on the mean height. The coefficient of variation of the vegetation height was useful for minor adaptions.*

Visualizing Calluna habitat states and deriving the conservation status

We combined the single quality layers in a Red-Green-Blue (RGB) color composite map. Coverage of *Calluna* is represented in red, stand structural diversity in green, and the species index in blue. Stand structural diversity is represented by the coefficient of variation between the standard deviation and the mean vegetation height. This map illustrates the variety of habitat states as gradients in the landscape.

The quality classes were derived in a procedure very similar to the assessment in the field. The coverage of *Calluna* was only crucial for identifying the habitat type, not for assessing the habitat quality. Co-occurring vegetation (species index) and stand structure (mean height and coefficient of variation) served as quality parameters in a decision tree approach (see Fig. 3). The thresholds were approached by gradually changing the values in order to achieve the highest possible agreement between the field data and the remote sensing result; the fit was assessed by a confusion matrix. We intentionally name that step “comparison” (resulting in a “fit” instead of “accuracy”) as we assume that it is rather a matching test than validating a dataset by reference to another, true dataset (Foody, 2008; and further discussed in Schmidt et al., 2017b).

Transferability check

In order to test the transferability of the proposed method and to assess the influence of short-term variation in image attributes and weather on the results we transferred the workflow to another remote sensing dataset acquired around three weeks before. The analysis of the transfer dataset followed the procedure described above (except for the RGB visualization), where we tested the transfer of the initial decision tree calibrated with reference to the reference remote sensing dataset.

2.3.3 Results

Modeling results

Modeling the *Calluna* coverage resulted in an R^2 of 0.90 and an nRMSE of 10.2% (Fig. 4a, Table 2). The obtained cover ratios varied between -4% and 97%. Values below 0 occurred in large sandy areas with high reflectance values. Multispectral bands (especially of the visible region as well as the beginning of red edge and SWIR) were notably important for the SVM regression, whereas the

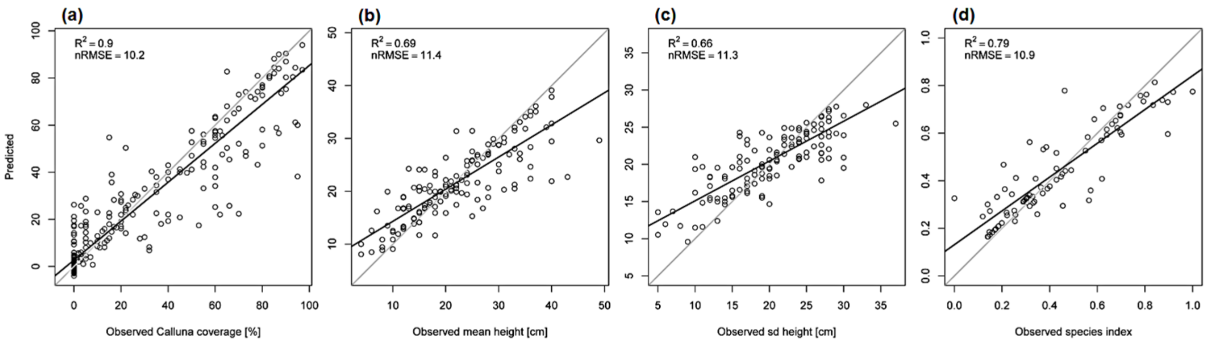

Fig. 4. *Scatterplots represeting the modelling results. An overestimation of the extreme values can be observed for modelling Calluna coverages (a), whereas for the height models (b, c) extreme values seem to be rather underestimated.*

associated contrast-textures were not meaningful. Three SAR-bands of VH polarization were prominent: of the descending pass, the mean band, and the texture *entropy*.

The canopy height models (mean height and standard deviation) reached R^2s of 0.69 (nRMSE = 11.4%) and 0.66 (11.3%), respectively (Fig. 4b, 4c). Highest mean canopy height of around 40 cm was predicted for the dense *Calluna* stands, lowest can be found in the light meadows and the open sandy sites (ca. 7 cm). High structural diversity (standard deviation of vegetation height) with values above 25 were found for edge regions of dense *Calluna* patches as well as for the mosaicked vegetation of shrubs and grassland. Grassland generally featured low values around 10. Although the importance-scores varied for both models, the mean VH-band and the variance-texture of the descending VH-band were comparably important.

The spatial representation of co-occurring vegetation based on a model with an R^2 of 0.79 and an nRMSE of 10.9% (Fig. 4d). The sparse calcareous meadows in the Southeast of the study area are home to the areas representing the highest species index values up to 0.95. Lowest values around 0.1 can be observed in areas featuring severe grass encroachment. Two bands in the red edge (740, 783 nm) showed high importance values concerning this model. The model outcomes of the transfer remote sensing dataset were similar to the reference dataset. Table 2 is summarizing the model results for both remote sensing datasets.

Table 2. *Regression results (SVM) for the single quality layers for both remote sensing datasets*

				Calibration dataset		Transfer dataset	
Product	**RS data**	**Reference (n)**	**Pred. (n)**	**R^2**	**nRMSE (%)**	**R^2**	**nRMSE (%)**
Calluna cover	Multispectral & SAR	400	34	0.90	10.2	0.90	9.8
Mean height	SAR	160	14	0.69	11.4	0.67	11.8
SD height	SAR	160	14	0.66	11.3	0.55	12.6
Key Species	Multispectral	85	20	0.79	10.9	0.76	11.6

Habitat mask, habitat state and conservation status

The habitat mask enabled us to separate *Calluna* heathland from the other habitats with an accuracy of 84% (Kappa = 0.63). *Calluna* heathland covered an area of 158 ha (33% of the study area). As 37 plots of the test dataset were found to be outside the habitat mask we proceeded with 313 reference plots for assessing the fit of the conservation status mapping.

The three quality layers *Calluna* coverage (R), structural Diversity (G) and key-species index (B) span the RGB color space in Fig. 5A. This continuous map is able to reveal gradients of habitat states described by different stand attributes. Reddish colors indicate mono *Calluna* stands. Green pixels feature a high structural diversity with low *Calluna* coverage and a low species index. This mainly applies to species poor zones influenced by grass encroachment. Less structured meadows that are home to many characteristic species are shown in blue. Although they lack sufficient *Calluna* coverage (< 30 %) they appear as fringes of *Calluna* heathland in the map due to the smoothing of the habitat mask. Apart from that, transitional zones between these three extremes

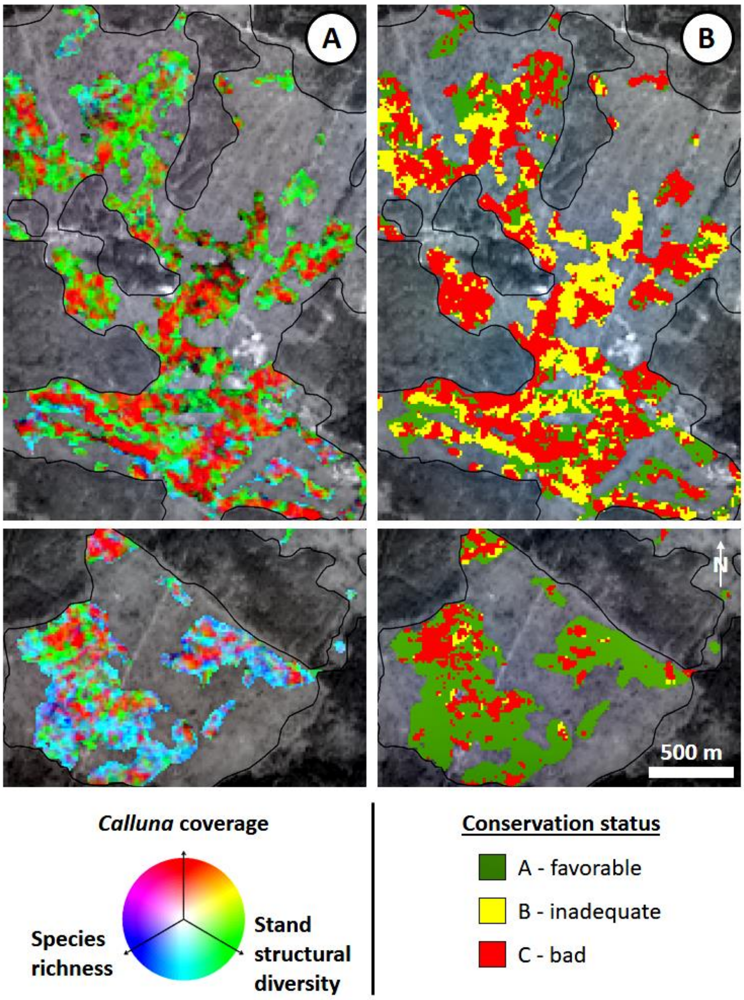

Fig. 5. *The habitat state of Calluna heathland is visualized via an RGB-representation (A) in two subareas of the study site; see Fig. 1D. Pixel colors correspond to their values resulting from the three remote sensing proxies Calluna coverage (red), stand structure (green; represented by the coefficient of variation between standard deviation and mean vegetation height) and co-occurring vegetation (blue). A habitat mask was applied based on Calluna cover ratios above 30%. Thresholds from expert judgment were applied to the three quality layers in a decision tree process for classifying the conservation status per pixel (B). As Calluna coverage does not directly affect the conservation status classification, there might be cases where a shift between two classes can be seen in (B) that is not apparent in (A).*

can be found, appearing in yellow, cyan, and pink. Areas where there is co-occurrence of high scores of the three layers appear in brighter colors. However, as the parameters are more or less mutually exclusive, this situation is fairly rare. This continuous illustration was not validated in a statistical manner, but examined visually. The represented patterns of varying *Calluna* habitat states were predominantly in agreement to what we expected from fieldwork.

Concerning the derived conservation status classes using expert thresholds we found that tall and less structured vegetation with the absence of characteristic co-occurring species lead to a 'C'-assignment ("bad" conservation status, 37% of the habitat). This is mostly the case for old, dense *Calluna* stands (see Fig. 5B). Areas that show rather low values for the species index, too, but feature a more diverse stand structure are considered as "inadequate" ('B', 21%). The most prominent example in the study area is moderate degraded heathland, where grass encroachment already suppresses the occurrence of low-growing grasses and herbs. Besides the absence of characteristic vegetation, several successional stages of *Calluna* may occur leading to a higher structural diversity. Class 'A' ("favorable", 42%) is found when there is a high score of characteristic co-occurring vegetation, expressed by a medium to high species index. In an ideal case this coincides with a heterogeneous stand structure; a case that is often found in peripheral zones of dense *Calluna* stands. Summarized, *Calluna* habitats in the southern part of the study area are mainly in a "favorable" status (due to the occurrence co-occurring vegetation desired by nature conservation) except some patches of overaged heather. This classification result was compared with the field estimates (n=313) resulting in an overall fit of 79% and a Kappa of 0.68 (Table 3). The number of 'A'-samples falsely classified as 'C' was particularly low (n = 6).

By transferring the procedure to a second remote sensing dataset from beginning of June, another set of quality layers could be obtained with comparable correlations (Table 1). Applying the decision tree with the same parameters resulted in a fit of 69% (Kappa =0.53) in comparison to the field samples. It can be seen from Fig. 5 that the general patterns of conservation status classes are similar between both datasets. Rather extensive deviations from 'C' to 'A' are observable in the upper part of the northern subarea.

Table 3. *Confusion matrix for assessing the fit of the conservation status map.*

Classified Data	Reference Data			Total	User's Accuracy
	A	B	C		
A	**88**	12	10	110	0.80
B	10	**65**	9	84	0.77
C	6	20	**93**	119	0.78
Total	104	97	112	313	
Producer's Accuracy	0.85	0.67	0.83		

Overall fit = 79%, Kappa = 0.68.

2.3.4 Discussion

The aim of this study was to derive conservation status classes of dwarf shrub heathland in a rule-based procedure. This could be achieved based on continuous quality layers that were obtained from regressing in situ data against spaceborne multispectral Sentinel-2 and Sentinel-1 SAR imagery. The single quality layers on their own provide useful templates for ecologists and site managers; in combination they reveal a variety of stand attributes describing habitat states. This allows for detecting transitions and gradients that are not apparent in patch-wise conservation status representations as required by reports according to the European Flora Fauna Habitat convention. Moreover, the procedure allows after-the-fact revisions of thresholds used to define the conservation status which is hardly possible with field-based assessments.

The overall fit of 79% in the estimation of conservation status classes was comparably high regarding the result of 65% achieved by Schmidt et al. (2017b) following a similar procedure based on airborne hyperspectral remote sensing. This is remarkable, as only ten S2 bands were used in this study in contrast to a much broader selection of bands provided by the AISA-sensor. This means that, even though, atmospheric conditions, illumination and observation angles might have played a role, a reduction in wavebands could be advantageous if the right wavelengths are selected. Band selection and a respective noise reduction can improve modelling accuracy (Landgrebe, 2005). This would be in accordance with other studies that increased the classification or unmixing accuracy through waveband selection techniques, focusing on absorption features (van der Meer, 2004) or implementing a minimum noise fraction (Fassnacht et al., 2014). Data reduction has frequently been used in image spectroscopy data processing to facilitate an efficient analysis and to improve feature extraction (Harsanyi and Chang, 1994). Evidently, the Sentinel-2 bands are in a good position for vegetation analyses (Clasen et al., 2015).

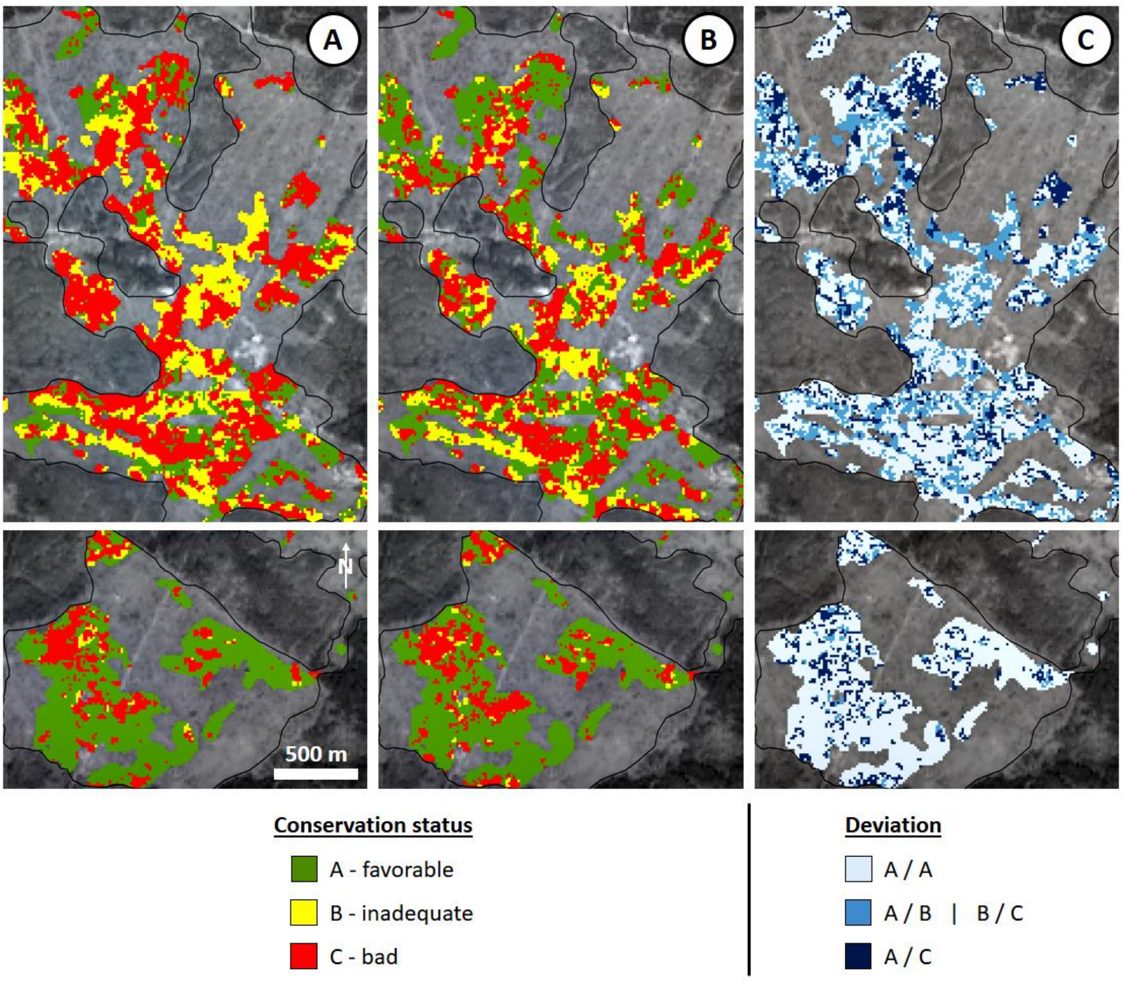

Fig. 6. *Conservation status map of reference dataset from end of June (A; same as Fig. 5B) in comparison to the result from the dataset acquired around three weeks before (B). Deviation between both classification maps is shown in (C). An agreement of 62% between both results can be observed, while deviations of one or two classes were similar (20% and 18%, respectively). The habitat mask that was developed based on the calibration dataset from end of June was applied to all three maps to enhance comparability.*

Contribution of the single layers

We encountered mapping problems in areas with low *Calluna* coverage. In some areas pixels with no or very low *Calluna* coverage values were predicted to have coverages of up to 20%. This uncertainty may simply be caused by minor influence on the reflectance by low coverage of *Calluna* or by overexposure effects of areas with high amounts of sand or litter (Nagler et al., 2000). Moreover, *Calluna* coverages above 25% were slightly underpredicted. Here, other approaches may deliver more accurate results, e.g., via endmember extraction (Delalieux et al., 2012). However, we assume that this does not affect our classification result as the habitat mask summarizes zones with values above 30%. Differing from the approach of Schmidt et al. (2017b) we used the distribution of *Calluna* cover for identifying the target habitat; stand structure and co-occurring vegetation were then used in a decision tree classification to assign the three status classes. This procedure is more similar to what is described in the field guidelines.

The patterns represented by the species index were in agreement with what we expected from field work. Although the species index does not directly tell us whether adequate numbers of characteristic species are present, it provides information on the probability of their occurrence. A high species index indicates that the pixel is more likely to represent good habitat conditions in terms of co-occurring vegetation (Neumann et al., 2015). The depicted gradient from the species-rich calcareous grassland in the south of the study area to the degraded heathland in the north, where characteristic species only occur in small numbers, can also be observed by reference to plant strategies in previous work of Schmidt et al. (2017a) that based on airborne hyperspectral data. The species index was mainly useful in separating ‘A’ from both other classes; ‘B’ and ’C’ often featured similar scores. This can be observed when both maps in Fig. 5 are compared - especially in the southern part. It is apparent that there is often no gradual change from ‘A’ over ‘B’ to ‘C’, but a direct transition from ‘A’ to ‘C’. Here, the peripheral zones (in “favorable” conservation status) are directly neighboring overaged *Calluna* patches. That is why stand structure is crucial for separating ‘B’ and ‘C’.

Modeling the mean vegetation height delivered sound results. It allows for identifying the patches of old and tall *Calluna* plants as well as meadows of grasses and herbs in between. The standard deviation of the vegetation height was meaningful when used in combination with the mean height (as the coefficient of variation). Considered individually, the patterns were rather inconclusive. The combination of both height layers could serve as indicator of the occurrence of *Calluna* growth phases.

Transfer of the decision tree between calibration and test dataset

When applying the decision tree to the test dataset, the fit decreased to 69% (calibration reference = 79%). Studies that examined the transferability of decision tree classifications can rarely be found (Kalantar et al., 2017), and, if any, with respect to object-based analysis (Hofmann et al., 2011).

Modeling results of the quality layers were comparable between both remote sensing datasets. Here, we are in agreement with Feilhauer and Schmidtlein (2011) who reported minor deviations in model accuracies for different dates when examining similar habitats. Thus, short-term variation in image attributes due to slight changes in phenology probably had a minor impact on model performance. However, the optical-based species index representation most likely caused

the switch from class ‘A’ to ‘C’ in larger patches in the upper part of Fig. 6C. The deviation of one class is partly attributed to the poor performance of modelling the standard deviation of vegetation height for the transfer dataset.
To achieve more robust results, using multi-temporal remote sensing information (Buck et al., 2013; Schuster et al., 2011; Zlinszky et al., 2015) and also the inclusion of multi-seasonal data (Mack et al., 2016; Stenzel et al., 2014; Tarantino et al., 2016) would be worth considering.

Spaceborne satellite data

We consider *Calluna* habitats relatively easy to map, which was also stated by Corbane et al. (2015). However, subtypes are difficult to differentiate as reported in earlier work (Barrett et al., 2016; Diaz Varela et al., 2008) and including structural information like LiDAR or SAR data into monitoring procedures is a potential solution to this problem. Since passive optical and SAR sensors respond to different target characteristics, their role in vegetation mapping can be viewed as complementary (Aschbacher and Lichtenegger, 1990; Liu et al., 2006), i.e. refer to mostly optical vs. structural vegetation properties related to two individual criteria of the Habitats Directive (Schuster et al., 2015). We consider Calluna-heathland as appropriate test site for exploring fine-scale structural parameters (Mücher et al., 2013).

Relative importance of the multispectral S2-bands varied between models for the quality layers (Table A1). The importance of the visible spectral region for remote sensing of upland heath (presumably with high coverage of *Calluna*) was also reported by Barrett et al. (2016) who focused on distinguishing heath classes. Moreover, the first band representing the red edge region (705 nm) and one SWIR-band (1610 nm) showed high importance for the *Calluna*-model, whereas for the species index-model it was nearly the other way around. Red edge-bands were important (except 705 nm), but those in the visible region weren’t. However, the index-model benefitted from the contrast-textures from the RGB spectrum. Summarized, reflectance in the visible spectral range (leaf pigments or influence of plant structure, such as leaf angle) is especially important for remote sensing of *Calluna*, whereas the species index map mainly relies on the spectral region of the vegetation red edge.

Of the four SAR source bands descending VH was most important for modelling the quality layers, followed by descending VV and ascending VH, whereas the VV-band of the ascending pass showed minor importances. It is remarkable, that averaged SAR-bands with different passes (especially VH, in our case) are worth to include into the modelling process. The use of SAR texture layers was in agreement with previous studies that reported the features *variance* and *entropy* to be helpful for discriminating vegetation based on SAR data (Anys and He, 1995; Kucuk et al., 2016). We hence think that medium-resolution C-band SAR has potential to support mapping tasks similar to the presented approach.

Polarimetric SAR (PolSAR) would probably allow for more precise determinations of vegetation structure as more information about the scattering process of objects could be extracted (Betbeder et al., 2015; Metz and Marconcini, 2014), whereas SAR interferometry has been shown to be more suitable for deriving vegetation height (Balzter et al., 2007; Wegmuller and Werner, 1997). However, these methods are mainly used in forests or concerning broad-scale classification tasks. LiDAR-derived determinations of vegetation height and structure may allow for more precise fine-scale results (Zlinszky et al., 2015). UAV-based Structure-from-Motion approaches could be low-cost alternatives over smaller areas (Gonçalves et al., 2016; Schmidt et al., 2017b).

Applicability to Natura 2000 monitoring scheme

The general modelling scheme shows that there is a possibility to monitor heathland habitats based on the mapping guideline of the Habitats Directive and Copernicus products only. However, since the Natura 2000 guidelines are not developed from a remote sensing perspective, the underlying parameters need to be slightly adapted for this use (Schmidt et al., 2017b).

From a conservationist's perspective an object-based monitoring product might be preferred, since the national and federal reporting obligations often require clear patches-wise representations. However, converting pixel-wise to object-based results means loss of information due to generalization. Especially in the case of the determination of the extreme conservation status classes "favorable" and "bad", conditions might average in the intermediate class. In a theoretical sense this is part of the Modifiable Areal Unit Problem (MAUP), which states that the values assigned to areal units depend on the geographic position or limitation of these units and on how the values aggregated (Openshaw, 1983).

We believe that the focus on larger patches is borne from a limitation of field-based approaches that need to refer to such units because pixel-wise mapping in the field is difficult. In our case, the original spatial information can be reported without loss. Although an aggregation of pixels would be feasible we prefer to report the original pixel information.

Differences to related studies

Neumann et al. (2015) were able to map probabilities for both habitat types and conservation status classes by using a species-based ordination space. Concerning *Calluna* heathland they report a strong correlation (0.93) in the external validation between kriging grids on the ordination plane for terrestrial mapping and habitat functions. Conservation status probabilities were not transferred into discrete classes, but that would be easy to realize by means of thresholds.

The applicability of rule-based approaches has been demonstrated in other studies (e.g., Villa et al., 2015; Zlinszky et al., 2015). Haest et al. (2017) also applied knowledge-based rule sets for the quality assessment of Natura 2000 heathland habitats. They do not deliver representations of the three required status classes per pixel, but a patchwise mapping of conservation status indicators, such as cover of encroaching grasses and trees. This enabled them to distinguish between two status classes ("favorable" or "unfavorable") per indicator by applying exact thresholds from the field guidelines. They conclude that the application of thresholds upon habitat quality indicators represents a sound approximation of a rather complex assessment procedure that monitoring experts are accustomed to.

Similarly, Regan et al. (2004) focus on formalizing the decision process of experts; in this case for conservation status assessments of single species. They explain that subjective assessments are often inconsistent and can hardly be repeated as they are influenced by, i.a., personal judgements and systematic biases (Burgman, 2001; Plous, 1993; Tversky and Kahneman, 1982), and because the underlying reasoning is almost impossible to visualize (Keith and Ilowski, 1999; Rush and Roy, 2001). They conclude that capturing the logical ordering of information, assumptions and reasoning, and transferring them into explicit rules allows for critical evaluation, refinement and reapplications. We consider our approach to be in agreement with this statement as thresholds to derive the conservation status can be revised after-the-fact, whereas this is hardly possible with field-based assessments. Reapplications and transfers were also envisaged when developing the methodology, however, results indicated that this is fraught with problems.

The presented approach is in our perspective not restricted to Natura 2000 shrublands. We assume our concept to be transferable to similar ecosystems characterized by a dominant shrub layer featuring few dominant species, or even one. For example, Xian et al. (2015) also mapped single quality layers for heathlike landscapes in the USA, which they called ”shrubland components”, such as coverage of shrubs and herbaceous vegetation as well as vegetation height attributes. However, these products were in a much larger geographic extent and no quality assessment was included.

2.3.5 Conclusion

In this study, we implemented rule-based field guidelines for quality assessment of dwarf shrub heathland by using fused spaceborne Sentinel-1 SAR and multispectral Sentinel-2 remote sensing data.

The results indicate that the conservation status assessment by means of three modelled quality layers does reflect field-based information. According to our findings, co-occurring vegetation (besides the key species *Calluna*) is crucial for separating pixels representing a “favorable” conservation status from those representing an “inadequate” or “bad” conservation status, while the latter classes could be distinguished by means of the stand structure.

We recommend that future remote sensing mappings of habitat quality should take greater account of including SAR data as it can deliver complementary information to optical imagery and is now freely and regularly available over the European Union’s Copernicus system.

The strong orientation towards the field guidelines was thought to help bridging the often mentioned gap between applied conservation and the remote sensing community that mainly exists due to communication problems (Skidmore et al., 2015). Our approach could be used for a relatively complete characterization of an area in a relatively fast way and thus provides a useful tool for site managers and decision makers. It still relies on field work (for model calibration) but the process of mapping is, in comparison to field work, less prone to biases and more capable to depict spatial mosaics.

We think that transferring operational field-based assessments into remote sensing approaches can be promising. Alternatively, existing assessment guidelines could be re-formulated in joint endeavor in order to improve their compatibility with remotely-sensed data. Essential biodiversity variables (EBVs; Pereira et al., 2013; Pettorelli et al., 2016) could play a key role in this respect.

Acknowledgements
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Appendix

Table A1. *Variable importance of the single remote sensing bands for the SVM models. Sen. = Sensor; Res. = Spatial resolution of source bands; Textures: _Var = Variance; _Ent = Entropy; _Con = Contrast.*

Sensor	Variable	Variable importance			
		Call. cover	Mean height	STDEV height	Species Index
S1	VH.asc	0.24	0.23	0.22	-
	VH.desc	0.33	0.33	0.22	-
	VV.asc	0.19	0.15	0.13	-
	VV.desc	0.25	0.28	0.19	-
	VH.mean	0.34	0.36	0.30	-
	VV.mean	0.26	0.27	0.21	-
	VH.asc_Var	0.09	0.25	0.25	-
	VH.asc_Ent	0.29	0.03	0.04	-
	VH.desc_Var	0.08	0.38	0.28	-
	VH.desc_Ent	0.37	0.10	0.11	-
	VV.asc_Var	0.05	0.17	0.15	-
	VV.asc_Ent	0.24	0.03	0.03	-
	VV.desc_Var	0.17	0.32	0.24	-
	VV.desc_Ent	0.17	0.02	0.03	-
S2	B2.490	0.45	-	-	0.11
	B3.560	0.67	-	-	0.08
	B4.665	0.42	-	-	0.20
	B5.705	0.52	-	-	0.10
	B6.740	0.29	-	-	0.44
	B7.783	0.26	-	-	0.34
	B8.842	0.34	-	-	0.25
	B8A.865	0.29	-	-	0.26
	B11.1610	0.43	-	-	0.24
	B12.2190	0.23	-	-	0.26
	B2.490_Con	0.01	-	-	0.18
	B3.560_Con	0.01	-	-	0.18
	B4.665_Con	0.01	-	-	0.17
	B5.705_Con	0.01	-	-	0.10
	B6.740_Con	0.01	-	-	0.01
	B7.783_Con	0.01	-	-	0.02
	B8.842_Con	0.05	-	-	0.06
	B8A.865_Con	0.02	-	-	0.01
	B11.1610_Con	0.00	-	-	0.13
	B12.2190_Con	0.01	-	-	0.13

2.4 Assessing the functional signature of heathland landscapes

Johannes Schmidt, Fabian E. Faßnacht, Angela Lausch, Sebastian Schmidtlein

Abstract

Wall-to-wall information about the state and change of vegetation is needed in many ecological applications, such as the monitoring of large conservation areas. In support of this task, remote sensing can provide valuable information that is complementary to the results from field work. Remote sensing is also well suited for change detection, but the question arises how a rate of change can be expressed in a generalized and objective way that allows comparisons between different areas. We think that true comparability can hardly be achieved by using conventional vegetation classification approaches, which are not transferable if they take account of the individuality of areas. To reach such comparability, an approach would be needed that combines generality with flexibility to adapt to local conditions.

Therefore, we propose that the local vegetation is broken down into basic strategy types as proposed by Phil Grime in 1974. He observed general rules in the occurrence of three general plant strategies: competitive ability (C), stress tolerance (S), and ruderal strategy (R). Our research question is whether these strategy types can be used to derive functional signatures of landscapes as a basis for comparison between conservation areas.

We used the CSR concept to map plant strategies in a heath landscape based on remote sensing data. Average Grime CSR values of vegetation samples were regressed against airborne hyperspectral imagery, resulting in spatial representations of C, S, and R (val. r^2 of 0.55, 0.59, and 0.28, respectively). Based on this continuous information we created functional signatures for two subareas of the study site, the 'CSR-fingerprints'.

We found clear differences in the CSR signatures of different parts of the investigated area. We think that similar differences in time can also be assessed using the same approach. This could provide a simple but powerful expression of the state of vegetation that would be comparable across regions and time. We therefore assume that the method is suitable for comparative studies with a focus on vegetation functioning. While it does not explicitly take into account differences in species composition, it can also work as an early warning system with follow-up investigations in areas subjected to change.

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2.4.1 Introduction

Remote sensing has been proposed as a supplement to conventional methods in the monitoring of large conservation areas (i.a. Lausch et al., 2016; Mücher et al., 2013; Vanden Borre et al., 2011b). However, the individuality of areas poses problems for obtaining comparable results on the extent and direction of change from remote sensing data. Large conservation networks (such as the European Natura 2000 network) are good examples where comparable results are desirable or even required.

The Natura 2000 network consists of a multitude of habitat types and stretches across broad biogeographic regions. This causes difficulties in comparing impacts on equal footing. Therefore, the question arises whether we can generalize the remotely sensed information about landscapes in a way that enables valid comparisons across large regions without losing too much detail.

So far, several studies have investigated the potential of remote sensing to support tasks connected to the European habitats directive. Luft et al. (2014) and Corbane et al. (2015) provide a good overview in this context. Although there have been several studies focusing on heathland (e.g., Delalieux et al., 2012; Mücher et al., 2013; Spanhove et al., 2012) only a few have focused on gradient mapping. One study heading towards such a direction was presented by Neumann et al. (2015), who combined species ordination and hyperspectral imagery to create continuous maps of habitat type probabilities and conservation state affiliations. Another study dealing with species ordination (and axes rotation) was from Neumann et al. (2016), who used PLSR modeling to characterize floristic gradients.

One potential way to compare diverse habitats would be to consider general plant strategies in combination with remote sensing. Here, we propose the combination of remote sensing with Grime's concept of plant functional types (Grime, 1974) for making generalized comparisons between conservation areas and for tracing changes within these areas. The approach is based on the observation that three fundamental plant strategies are widespread among plant species: competition (C), stress tolerance (S) and tolerance against disturbance (R). Competitive plants dominate in areas where nutrient supply is sufficient and disturbance plays a minor role. Long-term extreme conditions (e.g., dry soils, low nutrients) lead to the occurrence of stress tolerant species while ruderal strategists are adapted to frequent disturbances. Most plants can be located in the feature space between these three extremes. Describing vegetation by means of this concept “is particularly efficient between the power of its predictions and the simplicity of its assumptions” (Hunt et al., 2004:164).

Apart from individual species, Grime’s plant strategies can be used to describe plant communities (Allen and Starr, 1982; Hunt et al., 2004). Averaged CSR values and frequency distributions of strategies provide a functional description, which helps to reduce the complexity of complete vegetation surveys without disregarding processes within the vegetation system. Changes in a community’s CSR strategies illustrate processes such as eutrophication and dereliction (Hunt et al., 2004; Ling, 2003), as well as responses to changes in pH (Stevens et al., 2010). Grime’s concept can also be helpful in predicting the response of vegetation to climate change, by illustrating significant differences among communities due to relatively rapid environmental changes. This has been observed, for example, in a shift from a competitive marginal community to a ruderal annual vegetation (Abrahams, 2008). The influence of alien species can also be described in this framework. Pysek et al. (2003) and Lambdon et al. (2008)

applied Grime's concept to the development of vegetation after the cease of land-use and after restoration, respectively. Prévosto et al. (2011) showed how particular states of succession are represented by different patterns of plant strategies. Moog et al. (2005) investigated the influence of different management systems on the strategies of plant communities. Finally, the understanding of ecosystem resistance and resilience can be evaluated based on which strategies occur (Hodgson et al., 1999). The dominance of one or the other of the CSR strategies is a strong signal about the environmental situation in an area. Even though the details are unknown, it is clear that shifts in the success of these strategies indicate a fundamental change in the ecosystem.

The mentioned studies highlight the potential of Grime's concept as a universal generalization approach to monitor the status and changes of habitats. Recently, a number of studies have shown that Grime's concept is compatible with optical remote sensing data. Specifically, certain plant traits that are linked to Grime's strategy types (e.g., specific leaf area, leaf dry weight, and canopy height) were found to affect canopy reflectance as measured by optical remote sensing systems (Grime, 2006; Sandmeier et al., 1998; Schmidtlein et al., 2012; Verhoef, 1984). For example Schmidtlein et al. (2012) successfully mapped plant strategies in a swamp and peatland area by regressing the plant functional attributes against hyperspectral data.

Alternatively, other indicator values could be considered, such as the frequently-applied Ellenberg's indicator values (Ellenberg et al., 1991). This method enables to map environmental gradients via nine ordinal scales representing bioindicators (e.g., water supply, soil fertility, soil pH). Additionally, several studies have proved the ability to map Ellenberg values based on remote sensing (e.g., Möckel et al., 2016; Schmidtlein, 2005). Using Ellenberg's indicator scale enables for more 'focused' mappings, whereas the CSR approach depicts the entirety of the local vegetation ecology. Ellenberg indicator values are derived from observed distributions of species along environmental gradients while CSR scores are linked to traits. Therefore, there should be a closer link between CSR scores and reflectance in comparison to Ellenberg values. In practice, however, CSR scores and Ellenberg values are highly correlated (e.g., competitive ability and indicator values for soil fertility).

Here, we aim to further develop the approach of Schmidtlein et al. (2012) in order to derive what we define as a functional signature of conservation areas. This functional signature is meant to reflect the relative frequencies of plant strategies in the corresponding sites. Changes in the local occurrences of strategy types as detected with remote sensing methods are likely to be indicators of relevant processes deserving a closer investigation in the field.

In the current study, the main objective was therefore to answer the question of whether this functional signature of a landscape (what we call the 'CSR-fingerprint') reflects patterns and processes relevant for conservation and management.

2.4.2 Material and methods

A supervised clustering was performed on field samples to derive vegetation types, which were assigned to the CSR ternary. Moreover, field-based CSR scores were regressed against airborne hyperspectral remote sensing to obtain continuous maps of plant strategies. Extracting data from the maps enabled us to create functional signatures of two subareas within the CSR ternary ('CSR fingerprints'). The workflow of the study is displayed in Fig. 1.

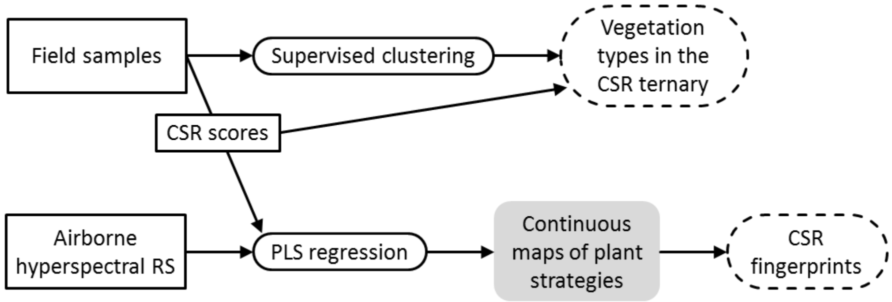

Fig. 1. *Workflow of the study.*

Study area

The study area of the Oranienbaum Heath (OH) is located in the Elbe-Mulde-lowland in Saxony-Anhalt, Germany (Fig. 2), and encompasses ca. 10 km^2. The northern part of the study area is dominated by cover sands while the south features ground moraines and shows a more diverse topography (Felinks et al., 2012b). The average precipitation of the region is 550 mm per year. Forests were partly replaced by more or less open pasture several centuries ago. Heavy fires in the first half of the 20th century and the use as a military training ground by the soviet army after 1945 maintained the open landscape as well as a number of historic pasture plant communities (John et al., 2010). Today the open area has a size of 550 ha. After the military withdrawal, the heath and grassland ecosystems came to be threatened by the increase of bushgrass (*Calamagrostis epigejos*) and the encroachment of pioneer tree species (birch, aspen, and pine). A landscape management project (Lorenz et al., 2013) with grazers such as Konik horses and Heck cattle was initiated to maintain the current open habitat structure with its typical plant species.

Four habitat types could be identified in the study area according to the European habitat classification system. For non-forested areas in the OH, typical communities include dwarf shrub associations dominated by *Calluna vulgaris* (codes H 2310, 4030), which grow on dry, lime-deficient soils. The stands of *Calluna vulgaris* are often interspersed by Cryptogams and xeric grassland. With insufficient usage or management these stands are often replaced by dominant grasses or pioneer trees such as *Betula pendula* or *Pinus sylvestris*. In an optimal state in terms of conservation (Aerts and Heil, 1993), sandy heaths include gaps with a low cover of grasses, shrubs and trees while heather dominates the canopy. In the absence of disturbance, heathlands are rapidly encroached by woody pioneer species. Planned burning, grazing, or mowing are possibilities for maintaining an optimum state (Verbücheln et al., 2002). These *Calluna* heathlands cover 43 % of the total open landscape in the OH. Another habitat type is inland dunes with open *Corynephorus* and *Agrostis* grasslands (H 2330), which are characterized by open sandy grassland appearing on acid soils. Between the single tufts, cryptogams appear frequently. As pioneer vegetation, this type needs open sandy patches and a low nutrient level. Finally, calcareous sandy grasslands (H 6120) appear on alkaline sandy soils and are often neighboring other low-nutrient grasslands and *Calluna* heath. Species richness as well as functional diversity (heterogeneity of strategies per sample) culminates in these grasslands with *Koeleria macrantha* and *Peucedanum oreoselium*. Mosaics of calcareous grassland and *Calluna* heath occur frequently in the south. Larger zones of degraded heathland encroached by *Calamagrostis epigejos* can be found in the northern and central parts of the OH.

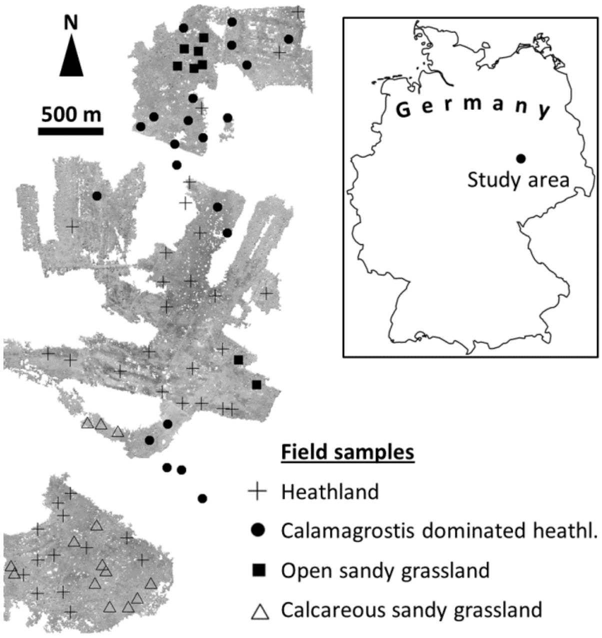

Fig. 2. *Study area with field sampling plots. The grouping of the plots results from the supervised clustering. Forested and wetland areas were masked. The locations of 80 field samples are displayed (five outliers removed). The plots apparently appearing in the masked areas are located in small open glades and could thus be considered. The study area was divided into three subareas representing connected open landscapes: a northern, a central and a southern part. The study area is located near Dessau, Saxony-Anhalt, Germany (N 51.77350°, E 12.36120°).*

As mentioned above, the prediction of CSR strategies is only expected to be stable in broad formations. Therefore, differing models should be developed for differing formations. Here, forests were not included since they are not relevant for nature conservation in the study area. The non-forested part (including woody dwarf-shrub vegetation) could be separated into sub regions representing successional stages. This enabled the comparison of two functional 'fingerprints' within the study area (northern and southern subarea). In the northern part (100 ha), larger areas of open sand with pioneer species occur along with scattered patches of *Calluna* heath as well as grass encroachment. The central part of the OH (215 ha) is mainly vegetated by old, dense *Calluna* stands. Other areas are covered by pioneer communities on open sand. Herbaceous meadows also occur and are partially dominated by encroaching grasses. The southern area (105 ha) is characterized by a combination of grassland and heather stands as well as mosaics of both vegetation types. Here, the calcareous meadows are dominated by small grasses and herbs that build up the sparse vegetation.

Fieldwork and CSR allocation

The vegetation survey was performed in August 2014, beginning 17 days after the acquisition of the remote sensing data. To ensure that the heterogeneity of the vegetation was represented, the plots were located using stratified random sampling. The strata were based on a precedent habitat mapping by Felinks et al. (2012b). Plots were only established if the surrounding 15 m around a random point was determined to be homogenous (also in terms of co-occurring vegetation). Otherwise, the plot was relocated by a maximum distance of 15 m to ensure a homogeneous area, or skipped in case of no available homogeneity. Vegetation was recorded in 85 plots measuring 3 x 3 m (Fig. 2), and included the coverage of vascular plants as well as the portions of bare soil, cryptogams and dead plant material (litter and wood).

To allocate our field plots to vegetation types, we applied a supervised clustering on the basis of characteristic indicator species according to the regional mapping guide of LAU (2010) (e.g., *Calluna vulgaris*, *Corynephorus canescens*, *Helichrysum arenarium*, *Koeleria macrantha*, and *Peucedanum oreoselinum*). For this purpose, we used the Isopam algorithm (Schmidtlein et al., 2010) in its supervised mode. Isopam (Eichel et al., 2013; Feilhauer et al., 2011) forms clusters on the basis of optimum separation by species with high specificity for clusters. It uses the isomap-algorithm (De'Ath, 1999) for an ordination and the PAM-algorithm (Kaufman and Rousseeuw, 1990), which groups data into clusters around medoids. The method is implemented in R (R Development Core Team, 2013) in the package 'vegan' (Tenenbaum et al., 2000).

Furthermore, for each field plot the individual species were assigned to CSR strategy types according to tables provided by Hodgson et al. (1999) and Pierce et al. (2013). Hunt et al. (2004) describe how to characterize a community of several species with the aid of a CSR-index. Based on the species cover, a weighted mean C-, S-, and R-value was computed for every vegetation sample. We used untransformed cover values as proposed by Hunt et al. (2004). In the next step, the vegetation samples were assigned to the nearest strategy in the CSR-feature space, resulting in a single CSR strategy label for each observation.

Hyperspectral remote sensing

The hyperspectral data (sensor: AISA dual) was acquired on July 18, 2014. The spectral range from 0.48-2.27 µm was covered with 200 bands. The water absorption features around 1.4 and 1.9 µm were excluded from all further processing steps. The pixel size of the four registered stripes was 3 x 3 m. After georeferencing using orthophotos with a resolution of 100 cm (MLU Sachsen-Anhalt, 2012), we corrected cross-track illumination effects within the stripes. After mosaicking, the remaining noise was removed by applying a Minimum Noise Fraction Transformation (forward and backward) in ENVI (Exelis Visual Information Solutions, 2013). Forested areas were masked out before further processing of the data.

Linking remote sensing and CSR strategies

In order to create maps representing the CSR-strategies in the study area we used a partial least square regression (PLSR) to build models between reflectance and scores on the C-, S-, and R-scale, respectively. PLSR (Wold et al., 2001) is able to deal with high-dimensional and collinear data, including hyperspectral data (e.g., Cole et al., 2014; Schmidtlein et al., 2012; Smith et al., 2003). Based on the covariance between the predictor and response variables, it computes new predictor components which are then used to build a linear regression model. The algorithm is implemented in the R-package 'autopls' (Schmidtlein et al., 2012), and also includes a backward selection of significant components (Okujeni et al., 2014; Schwieder et al., 2014). Five samples were removed due to their outlying positions within the 'influence plots' provided by the 'autopls'-function. Thus, 80 data points served as basis for the three independent models (C, S, and R). Pixels with values out of range of the CSR-indices (beyond -2 and 2) were masked. Finally, a color composite map was created with the three modeled layers represented as red (C), green (S), and blue (R) channels.

The CSR fingerprint

The functional signature is created by extracting the C, S, and R values from the continuous representations of strategy types. Following the approach of Hunt et al. (2004), these data were projected to the triangular feature space. The resulting ternary plot is pseudo three-dimensional because there are only two degrees of freedom. This disadvantage is outweighed by the ease of interpretation (see Hunt et al., 2004). The ternary diagrams were created using the R-package 'ggtern' (Hamilton, 2016). The density plots are based on a two dimensional (bivariate) kernel estimation, with contours surrounding points with a density-parameter, the kernel 'K' (Silverman, 1986).

2.4.3 Results

Classification of vegetation samples

The isopam-algorithm returned four plant communities that could be related to Natura 2000 habitat types (Fig. 2 and 3). The heather stands are pooled in group 1 (crosses) and occur all over the area. Cluster 2 (dots) contains degraded heathland dominated by *Calamagrostis epigejos*. These plots are mainly located in the northern part of the study site. Pioneer communities with *Corynephorus canescens* are summarized in group 3 (squares). They occur in the open sandy parts

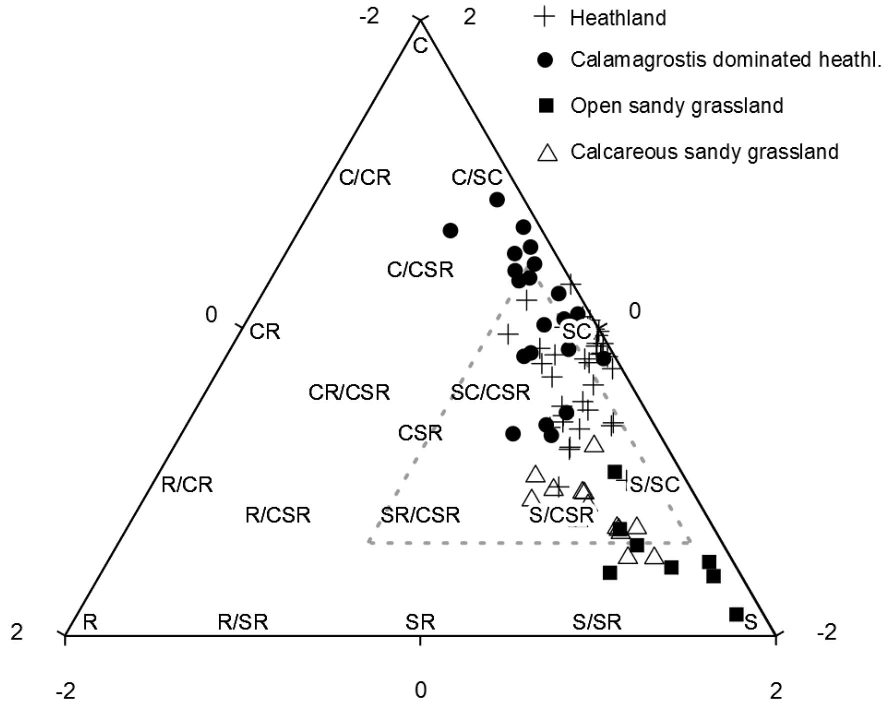

***Fig. 3:** Vegetation types in the CSR-ternary. The vegetation of the studied landscape tended to be adapted to stress or to have (to a lower degree) competitive abilities while ruderal strategists were not important. Samples that were mainly covered by Calluna vulgaris are located around the 'SC'- and 'SC/CSR'-strategies. Calcareous grassland-plots were assigned around 'S/CSR'. The adaption to stress by C. canescens communities is shown by the relation to 'S' and 'S/CSR'-strategies. The Calamagrostis-samples occupied a broader ecological range, between 'C/SC', 'SC', and 'SC/CSR'. The dashed gray lines indicate the positions of the ternaries from Fig. 4.*

in the North and the Center of the OH. The second major habitat of the southern part is the calcareous grassland, represented by cluster 4 (ternaries).
In the CSR-ternary (Fig. 3), most of the *Calluna* heath plots are located closely around the 'SC'-position. The reason is that *Calluna vulgaris* itself is regarded as 'SC'-strategist. Depending on the coverage of grasses and forbs, the samples have higher values of C, S, or R, respectively, and shift to the neighboring strategies accordingly. Especially high cover of *Calamagrostis epigejos* results in high scores on the C scale ('C/SC'-strategy). More ruderal plots were closer to the 'SC-CSR'-type. The adaption to stress of the *Corynephorus canescens* communities translates to positions in the lower right of the CSR-triangle. Most of the calcareous grassland samples can be found around the 'S/CSR'-position of the ternary.

Table 1. *Results of the three models (C, S, and R).*

	# obs.	# pred.	# comp.	r^2 (cal)	r^2 (val)	rmse (val)	masked cells > 2 (%)	masked cells < -2 (%)
C	80	9	2	0.59	0.55	0.42	-	0.53
S	80	7	6	0.65	0.59	0.39	1.72	-
R	80	26	4	0.42	0.28	0.24	-	3.15

Mapping plant strategies

The PLSR regression resulted in cross-validated r^2-values of C: 0.55, S: 0.59, and R: 0.28 (see Table 1). The number of predictors for the models of C and S were similar (9 and 7) while the regression of R-scores used more predictors (26).

The maps of the northern (a) and southern (b) subareas in Fig. 4 illustrate the distribution of plant strategies. The colors of the pixels correspond to the predicted values of the three models. The map shows prevailing stress strategies in sandy areas not yet invaded by *Calamagrostis epigejos*. The arrival of the latter species leads to a conspicuous increase of competitiveness in vegetation (bright red, mainly in the northern part). *Calluna*-dominated vegetation shows medium adaption to competition and stress tolerance (reddish to orange; with tendencies to red and green depending on the co-occurring vegetation). Meadows with low, xerophytic grasses and herbs are home to stress strategists. The calcareous grassland in the south mainly belongs to this type (gray blue). The absolutely lowest C-values are found in the dry zones with open sandy soil in the north, where *Corynephorus*-dominated pioneer communities prevail (turquoise). Ruderal species rarely found their way into the study area or are at least not dominant in the current vegetation. Some meadows which are commonly frequented by grazers are characterized by the relatively highest R-scores (violet).

Taking the CSR-fingerprints

Fig. 4d contains the 'CSR-fingerprints' obtained by displaying the CSR values of 5,000 random samples taken from the model output in the ternary. Due to high cover ratios of heather in both subareas, the fingerprints are located around the 'SC'-type. In the northern part of the OH a slight gradient characterized by low ruderality prevails. It ranges between competitive *Calamagrostis* stands ('C/SC') and pioneer vegetation on open sand ('S'). The south is dominated by calcareous grassland and *Calluna* patches, often occurring in mosaics. As this vegetation is better adapted to stress the fingerprint is shifted towards the strategy types 'SC' and 'S/CSR'.

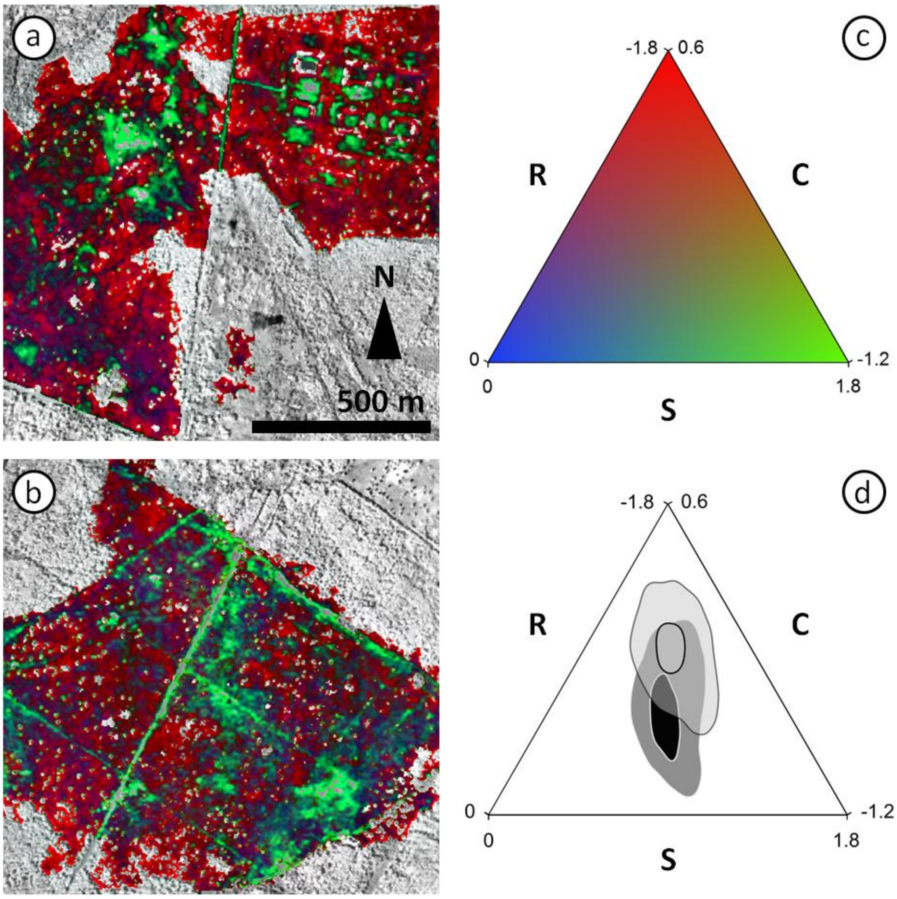

Fig. 4: *RGB-composite map and the CSR-fingerprints. RGB-composites based on the three modeled layers (C, S, and R) for the northern (a) and the southern (b) subareas. The three color scales were rescaled corresponding to the feature space of the 'CSR-fingerprint'. Reddish areas indicate relatively high competition. Less competitive vegetation is illustrated in gray blue while turquoise and green indicate an adaption to stress. The CSR-fingerprints (d; light gray: north, black: south) are represented by density contours based on samples (n = 5000), which were extracted from the maps. The inner contour indicates a density of K > 50, the outer contour of K > 15. Here, the ternary was shrunk to the area within the original CSR space, where the fingerprints emerge (see Fig. 3). The axes were all scaled to a range of 1.8. The fingerprints show the adaption of the vegetation for the two subareas. The similarity of the regions (prevailing strategies around 'SC') is mainly based on high cover ratios of Calluna. Differences between the areas are shown by shifts towards strategy specifications (north: 'C/SC' and 'S', south: 'S/CSR').*

2.4.4 Discussion

Here, we applied hyperspectral remote sensing data to create a functional characterization of a nature conservation area by means of Grime's strategy types. The resulting maps and functional fingerprints provide an overview of the prevailing strategies of plants in adaptation to local soil conditions and disturbances. Below, we will separately discuss difficulties in the mapping methods and three characteristics of the newly proposed functional fingerprint.

Difficulties in mapping the plant strategies

The remote-sensing based maps showed a variety of stress tolerant species, a low abundance of competitors and an even smaller number of ruderal strategists. The outcome for C and S was considered to be reasonable considering the heterogeneous vegetation of the study area. The low result for R was expected as almost no vegetation of this strategy type can be found in the study area.

This agrees well with expectations for such relatively unproductive (Grime and Pierce, 2012) and nutrient-limited areas (Grime, 2001). While the general patterns agreed well with the known situation in the study area, in some cases similarity in the reflectance of species belonging to different strategies hampered the modeling process. This problem arose particularly within *Calamagrostis* dominated areas and non-ruderal grassland. High ratios of litter within the *Calamagrostis* stands may have resulted in a reflectance that resembled the signal of sandy soils in non-ruderal sites (Nagler et al., 2000). One way to tackle this problem would be to apply a classification approach, which can be more powerful when dealing with spectrally similar classes. We provide an example for such an approach in the appendix.

Our regression performances did not achieve the results of Schmidtlein et al. (2012) which is the only study following a comparable approach. One reason might be that the ecological gradients in the OH are less pronounced than those examined in the study of Schmidtlein et al. (2012). The study area of Schmidtlein et al. (2012) was characterized by mature communities with distinct species compositions (due to comparably large gradients of water and nutrient availability), whereas in the OH the vegetation is characterized by several successional stages of a single ecosystem that is additionally undergoing major changes due to recent land use changes and management actions. Therefore, the spectral differences due to changing vegetation compositions are likely to be more subtle in the OH and therefore more challenging to map with remote sensing. Nevertheless, the modeled patterns were sound and in agreement with what we observed in the field.

What do the fingerprints show?

Based on the C, S, and R abundances obtained from remote sensing, we created what we call 'functional fingerprints' of two subareas of the OH. As intended, we observed clear differences between the functional fingerprints of the two considered subareas (Fig. 4). Compared to the southern subarea, a conspicuous shift of the center of the fingerprint towards competition can be observed in the northern subarea. We relate this shift to the occurrence of heathland dominated by *Calamagrostis* (see Fig. 3). This degradation is caused by a combination of mechanical disturbance in combination with nutrient enrichment (due to abandonment and atmospheric input). These factors have also been observed to support grass encroachment in earlier studies (Heil and Diemont, 1983; Marrs and Lowday, 1992). In Central Europe, the encroachment of *Calamagrostis* was found to decrease the species diversity of heathlands (Heil and Diemont, 1983) as well as grasslands (Bobbink and Willems, 1987; Somodi et al., 2008) due to shading by large amounts of live plant material and litter (Tilman, 1993). According to Grime and Pierce (2012) *Calamagrostis* represents a specialized competitor which is able to monopolize resources and excludes most other species.

Assuming that the two subareas represent different successional stages of heathlands, it would be possible to illustrate the development of the habitat over time via a changing CSR-fingerprint. Applying our method, this would differ from the successional pathways of sites presented by Grime (1977) and Wilson and Lee (2000). Instead of one point (representing one site) moving through the ternary, the shape of the fingerprint (representing several sites; here: 5,000) would change over time. This would provide a more detailed and differentiated insight since the majority of the vegetation is displayed. Seizing upon the suggestion of Pierce et al. (2013), the CSR-fingerprint could be one possibility of depicting four-dimensional representations of vegetation.

The CSR-fingerprint as a tool for monitoring

As described in the previous section, the CSR-fingerprint could serve as a tool for tracking ecological changes over time by summarizing the composition of plant strategies for each remote sensing acquisition, and thereby characterizing the status of conservation areas.

Grime et al. (1997) stated that CSR functional types "can be reconciled with the individuality of plant ecologies in the field and provide an effective basis for interpretation and prediction at various scales from the plant community to regional floras" (p. 260). Initially, this idea referred to the allocation of community data in the CSR-triangle. Using the benefits of remote sensing, we extend the approaches of Grime (1977) and Hunt et al. (2004) by creating a functional signature for continuous areas. We think that this approach offers the ability to illustrate continuous representations of strategies across the area and gives an intuitive graphical representation of the plant strategy pattern of an area.

According to Grime (2006:133) "useful predictions of the impacts of management can be made in circumstances where all the component species in a plant community or area of landscape such as a nature reserve can be classified with respect to the CSR strategy". The same applies to responses to changing environmental conditions (Grime and Pierce, 2012). Compared to the mapping of species or traits, one central advantage of the fingerprint-approach is the provision of a general feature space which is, in theory, transferable to a variety of habitats within broad formations. If applied to datasets from multiple time points, the fingerprint-approach could theoretically provide indications on ecosystem change across any conservation area. As recurring vegetation samplings are required for monitoring purposes, standards could be set up to develop a consistent framework for regions or certain ecosystems. Furthermore, the idea offers a way to provide data for better insights in vegetation functioning of landscapes. Parts of the community with rapid changes could become visible. This makes such a method a candidate for broad scale early warning systems for large conservation networks.

Transferability of the approach

A few aspects should be discussed regarding the transferability of our study. The timing of our investigation was in agreement with the findings by Feilhauer and Schmidtlein (2011) who reported best detectability of heathland vegetation types in late June or July. Remote sensing data acquired much earlier or later in the vegetation period would probably deliver lower signal to noise ratios. Therefore, one important requirement for using the proposed method in a monitoring system would be to ensure phenological stability in the remote sensing data.

Other sources of variability are spatial and spectral resolution of the imagery. Although the advantages of hyperspectral data are widely known, we expect that also imagery with a much lower spectral resolution (e.g., Sentinel-2 images) can be used for similar analysis. Obviously, the pixel size should be chosen in relation to the depicted vegetation and its spatial heterogeneity. For sound modeling it is advantageous when the vegetation represented by a single pixel is similar in terms of its strategy orientation.

A further requirement for the application of the suggested method is that models must be separately fitted for different broad formations (i.e. forests, scrubland, or grassland), as the relation between CSR types and spectral information is likely to differ notably across these formations. However, when the approach is transferred to another area within the same broad formation we assume it to be directly usable; despite a changing species composition (local field data for model calibration is of course a requirement). This assumption is based on the fact that the CSR concept classifies species according to their ecological adaption, not considering if they are congeneric. Thus, plant communities that show similar adaptions to certain environmental situations should also have similar traits and therefore similar positions within the (spectral-based) CSR feature space. This can be observed in the study area, and we assume that the same applies for other areas.

2.4.5 Conclusion

We showed that the approach of mapping Grime's plant strategies, which had previously been tested in small study areas, can be realized in larger and more complex landscapes.

Furthermore, our study proposed a functional signature (which we called 'CSR-fingerprint') of the landscape that described the area not only on the basis of pointwise field samples but as a visualization of functional patterns in an area. With our approach, Grime's idea of showing paths of vegetation succession could be extended by adding a landscape perspective.

The CSR fingerprint is not meant to provide complete information about local vegetation types, but rather to complement conventional vegetation maps. Changes in the functional signatures can be quantitatively compared in terms of amount of change, which is not the case for conventional vegetation maps. The generalized framework allows, for example, an estimate about acceleration or slow-down of environmental changes in conservation areas, and may be a starting point for in depth investigations in areas of rapid change.

Acknowledgements
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Appendix

While the above-mentioned procedures led to a continuous representation of each strategy type, we aimed at creating additional maps based on a categorical representation with the dominant strategies of each location. We expected that a classification approach could better distinguish between spectrally similar plots which differ in their affiliation to a strategy type. Using a Random Forest model (Breiman, 2001) as implemented in R, the hyperspectral image was classified on the basis of the CSR-label assigned to each observation.

The categorical strategy map (Fig. A1) shows the results of the RF classification which resulted in an overall accuracy of 76 % (Table A1). The classification error was highest for the 'C/SC'-type (0.36), followed by 'SC/CSR' (0.3) and 'S/SC' (0.26). The classes of 'S' and 'SC' showed better results, both had an error of 0.17.

Problems were caused by overlaps of strategy types within the spectral feature space. In particular, the types 'S/CSR' and 'SC/CSR' are notable as transitional classes. As expected, classes that are located at the edges of the spectral feature space were easier to distinguish. That was the case for the bright (high reflectance below 0.65 µm and above 1.2 µm) areas of the 'S'-class representing sandy grassland as well for the dark 'SC'-class (heathland) which is characterized by high absorption and shadowing.

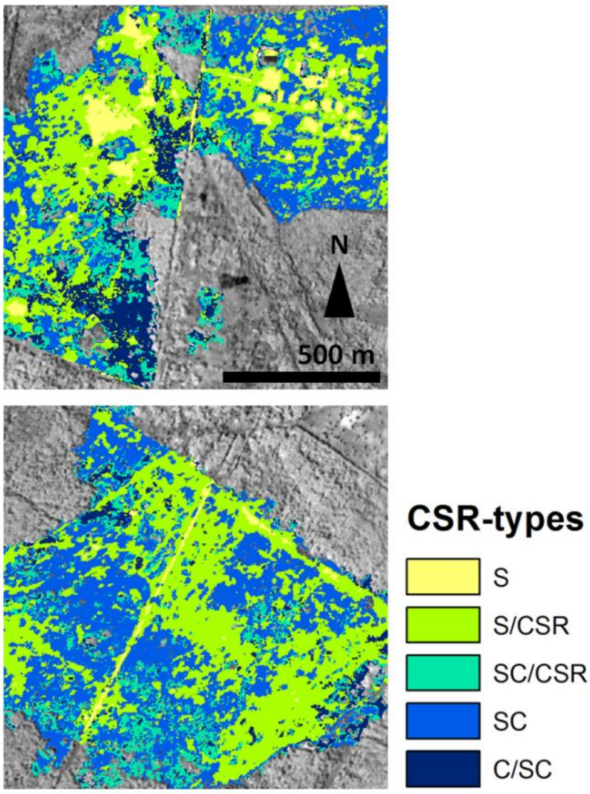

Fig. A1. *Prevailing CSR strategy types in the Oranienbaum Heath. Sandy areas are covered by pioneer vegetation adapted to stress ('S'). Sparse meadows represent a more generalist vegetation resulting in the 'S/CSR'-class. Calluna heath is mainly displayed as 'SC'. The transitional vegetation between heath and meadows is reflected by 'SC/CSR'. Degraded heathland dominated by Calamagrostis is assigned to a more competitive type ('C/SC').*

Table A1. *Confusion matrix of the Random Forest Classification.*

Classified Data	Reference Data					Total	User's Accuracy
	C/SC	S	S/CSR	SC	SC/CSR		
C/SC	7	0	3	1	0	11	0.64
S	0	5	1	0	0	6	0.83
S/CSR	2	1	17	2	1	23	0.74
SC	1	0	1	25	3	30	0.83
SC/CSR	0	0	1	2	7	10	0.70
Total	10	6	23	30	11	80	
Producer's Accuracy	0.70	0.83	0.74	0.83	0.64		
Overall Classification Accuracy = 0.76							

3 Synthesis

This thesis presents an integrated, remote sensing-based approach to support the management and nature conservation of heathlands. The obtained results include products that are closely oriented towards the demands of conservation authorities as well as prospective concepts charting a path towards future vegetation monitoring.

3.1 What's new?

Conservation authorities in Europe demand habitat quality assessments based on mapping units representing homogeneous vegetation. Study one of this thesis is the first approach directly offering such a product by the use of remote sensing data. Even though other object-based results have been presented before, a patch-wise mapping depicting the conservation status based on the demanded traffic light system (green: "favorable", yellow: "inadequate", red: "bad") has - until now - never been presented. As the field guidelines rarely provide instructions that could be adapted by a remote sensing procedure, we addressed the problem from several perspectives. Finally, the results confirm that (at least with the given research setup) patch-wise quality assessment of heathlands cannot be not achieved with sound accuracies. Therefore it is suggested to rather focus on procedures differing from the one that was carried out.

In order to narrow the gap between the remote sensing community and conservationists, a new, integrated approach was proposed in the second study. Evaluation criteria from field-based assessments were broken down into three parameters and consequently transferred to remote sensing proxies. The proxies provide valuable information for the management and reveal, when combined, gradients of heathland vegetation expressed by varying stand attributes. The step from a continuous map to discrete quality classes was achieved by formalizing the decision process of field experts, and transferring them into rule sets subsequently applied to the remote sensing proxies. The final product was a pixel-wise mapping of Calluna-heathlands' conservation status, and therefore very close to what is demanded by applied nature conservation.

The third study is a further development of the second study in which the airborne data applied in the second study was replaced with spaceborne data from the Copernicus system. These data have the potential for operational, consistent and regular monitoring at high temporal resolution as they deliver weekly high-resolution data. In this study, for the first time, synergetic use of spaceborne SAR and multispectral imagery was tested for a Natura 2000-related quality assessment. Again, three remote sensing proxies were mapped, and rule sets were applied to define the habitat status. In this case, the rule sets can be considered even more similar to what is described in the field guidelines as compared to study two. The transferability of the approach was exemplified by means of an independent remote sensing dataset.

Study four presents another form of remote sensing-based vegetation monitoring that uses general plant strategies for deriving information about habitat quality. It was demonstrated that remote sensing of these plant strategies is also feasible in larger and rather heterogeneous landscapes by presenting a map of heathland vegetation adapting to environmental conditions. Assigning the continuous information about plant strategies to the initial triangular feature space enabled to derive a functional signature of the vegetation ("CSR fingerprint"). This signature provides a detailed expression of the functional orientation of vegetation at a single glance. Hence, it is considered that landscapes can be described by means of this functional signature. The possibility of comparisons across regions and time was demonstrated by comparing two subareas of the study site that represent heathland vegetation in different successional stages.

In combination, the four studies provide an application-oriented concept to combine field and remote sensing data to assess the state of vegetation of Natura 2000 habitats. By the example of a heathland landscape, and in the context of an established monitoring system, it was demonstrated that remote sensing offers a wide range of possibilities to support site management and conservationists: starting from basic products demanded by conservation authorities, over procedures integrating Earth observation information into existing field guidelines, towards future-oriented monitoring procedures using general plant strategies.

3.2 Conclusion

In 1992, members of the European Union agreed on transnational standards for nature conservation (the Habitats Directive), along with implementing a system comprising protected areas of conservation value (Natura 2000 network). Today, an effective, objective and consistent schemes are needed that are able to cope with the monitoring demands that are associated with such a continental network; i.a., with respect to large extents, diversity of sites, and the heterogeneity of mapping approaches. With respect to that, there is a need to consider remote sensing as an information source of reliable, consistent and objective wall-to-wall data with potential to support the framed monitoring tasks. In addition to that, these schemes can only be realized based on transdisciplinary methodological standards.

It can be assumed that it takes more than presenting fancy maps based on elaborate methods from remote sensing to gain acceptance from conservationists. Procedures that use Earth observation for conservation mapping must be brought more into line with field ecology. They should approximate what is needed and try to report the required information in a clear and comprehensible way. On the other hand, remote sensing has traditionally been recognized as data source, unidirectionally providing information to ecology and conservation; a perspective that is wrong and obsolete. Remote sensing products related to conservation demands should not be considered to replace field mappings, but rather as a support to ecologists by providing complementary, spatially explicit information.

This thesis focused on demonstrating the beneficial implementation of remote sensing information into existing conservation mapping procedures by the example of European heathland habitats. Most likely, the full potential of remotely sensed information aiding nature conservation can only be achieved in interdisciplinary cooperation: both parties have to know and understand each others' needs, and be aware of the advantages and limitations of common approaches in the communities. Open, undogmatic attitudes and the development of interdisciplinary procedures are necessary in order to support environmental management and decision making in the future.

The future of conservation monitoring is probably found in joint arrangements between different communities, such as the EBV-concept that was developed in cooperative effort between remote sensing and ecology. This thesis could be regarded as a regional implementation of the proposed EBV assessment concept. Based on combining in situ information and remote sensing data we obtained spatial predictions of single variables that cover, when combined, a considerable range of the EBV metrics (see Table A1). Hence, a holistic conservation mapping approach on the regional scale is presented which conforms to this future-oriented monitoring concept. The approaches are embedded in an established monitoring system (the European Habitats Directive) and therefore the results refer to specific demands of applied nature conservation. By using free, globally available satellite data for the conservation mapping, this work aimed at presenting methods that could, in theory, be transferred to similar habitats and extended to larger scale applications. Here, a Central European heathland served as exemplary study site. Even if this area may be relatively small related to the global scope of the EBV concept, applications with respect to applied conservation that involve specific objectives and aim at comprehensible and repeatable procedures should rather be regarded as expedient in the interests of future monitoring actions.

The periodic reports related to the Habitats Directive demand for maps depicting the conservation status of habitats base on homogeneous mapping units. It was demonstrated that these products can be obtained with medium accuracies by using multi-sensor synergies and multi-seasonal data. However, we consider pixel-wise mappings as more informative in the context of vegetation monitoring. We assume that the decision of conservation authorities to focus on larger patches is borne from a limitation of field-based procedures. Vegetation mapping in the field needs to refer to such units because pixel-wise representations cannot be provided. Nowadays, this constraint could be overcome by the additional value of remote sensing; the original spatial information can be reported per pixel without loss. Therefore, these pixel-wise maps are (unlike patch-wise maps) not limited in revealing gradients or slight shifts of habitats, which is important for vegetation monitoring. Moreover, as shown in this thesis, pixel-wise procedures also allow for obtaining demand-oriented products for nature conservation (conservation status classification). Here, operationalizing experts' decision making process is proposed as a basic, application-oriented method to derive quality classes, which is a vivid example for an interdisciplinary procedure: it is shown that field guidelines that ought to be applied to mapping units were adopted for pixel-wise representations obtained from remote sensing data. As the method is thought to be transferable to similar regions with only minor adaptions, it could be a valuable supplement to field mappings. Furthermore, the results emphasize the need to derive appropriate and meaningful remote sensing proxies. Since they can provide targeted and significant information about the state of vegetation at a single glance, they represent appropriate means in order to support site managers and policy makers. For example, instead of focusing the occurrence of single indicator plant species for deriving habitat quality classes it is maybe more appropriate to consider remote sensing-based proxies providing information about plant assemblages (potentially indicating the probability of a species to exist). This could be accompanied with mapping of variables detached from regulatory perceptions about what is "favorable" or "bad", along with actions promoting the first and countering the latter.

Even though it is an important aspect of habitat quality assessment, the integration of structural vegetation parameters was underrepresented in previous remote sensing-based approaches. Reasons may be found in the traditional focus on optical imagery and the lack of accessibility to active data. This thesis demonstrates that UAV-based Structure-from-Motion approaches could be a flexible and low-cost solution for obtaining precise structural information - at least for small sites. It was shown that this information provides meaningful training data for upscaling approaches regarding both optical and SAR imagery. Moreover, the use of SAR is likely to increase due to the provision of free Sentinel-1 SAR data by the European Space Agency. Including SAR imagery provided a remarkable benefit for pixel-wise mapping. Here, it was successfully used for deriving information about vegetation structure that is helpful for habitat quality assessment of dwarf shrubland. However, the findings allow the conclusion that SAR data is even more informative regarding the habitat quality assessment when the backscatter information is aggregated in small patches. This could be considered in future mappings and deserves further investigation.

Approaches that consider a certain degree of generalization could be helpful with regards to comparability and transferability. Grime's concept of general plant strategies, which has its roots in field ecology, has been proven to be compatible with remote sensing, even in complex and heterogeneous landscapes. By creating functional signatures for different parts of the study area, we demonstrated that conspicuous differences exist between different successional stages of heathland vegetation. Therefore, it is assumed that changes in vegetation over time can be tracked. Hence, the initial idea to reveal paths of vegetation succession within the functional feature space was extended by adding a landscape perspective. It allows for visualizing other relevant processes as well (for example, grass and tree encroachment), what makes it interesting for site managers, too. In theory, the procedure would also be feasible for comparing distinct landscapes, however, this has to be tested. The functional signatures we presented only occupied a small part of the feature space, hence there is plenty of space left for integrating of a wide range of habitats, including rather extreme habitats that comprise more competitive or more ruderal vegetation.

Environmental changes demand adaptations in behaviors and strategic orientations of species. Roughly speaking, this also applies to various groups of stakeholders that share interest in monitoring related impacts. Today, there is a need for new strategies and approaches to cope with the demands of a rapidly changing environment, where process on different scales interact in manifold ways. For monitoring vegetation, joint efforts from different communities are most likely the key to keep track of shifts and impacts. Even though, respective methods do not directly protect endangered sites or species, they are needed to support the management of fragile and increasingly endangered systems. By linking established methods from field ecology and remote sensing, modules for an integrated concept were combined that meet the requirements of different stakeholders. The thesis presents suitable products, and proposes interdisciplinary ways of how to establish these products, for an operational use of Earth observation in future vegetation monitoring.

Appendix

Table A1. Selected essential biodiversity variables (EBVs) reported by Pereira et al. (2013) and Pettorelli et al. (2016) and corresponding implementations in this thesis.

EBV class	Examples of variables (potentially) meeting EBV requirements	Indicators	Implementation (study)
Species populations	Species occurrence	Population and extinction risk trends of target species, and species that provide ecosystem serviced; trends in invasive alien species; trends in climatic impacts on populations	Cover key species (2.2, 2.3)
Species traits	Specific leaf area	Trends in extent and rate of shifts of boundaries of vulnerable ecosystems	Maps of plant strategy types (2.4)
Community composition	Taxonomic diversity	Trends in condition and vulnerability of ecosystems; trends in climatic impacts on community composition	Index co-occurring vegetation (2.2, 2.3); CSR signature (2.4)
Ecosystem structure	Fractional Cover, Vegetation height, Ecosystem distribution	Extent of forest and forest types; mangrove extent; seagrass extent; extent of habitats that provide carbon storage.	Cover key species, Stand structural diversity (2.2, 2.3)

*Natura 2000 conservation status assessment (studies 2.1, 2.2, 2.3) would qualify as an EBV at the European level as all conditions are met (Zlinszky et al., 2016).

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Ich erkläre hiermit, dass ich die vorliegende Arbeit selbstständig verfasst, keine anderen als die angegebenen Quellen und Hilfsmittel benutzt, die wörtlich oder inhaltlich übernommenen Stellen als solche kenntlich gemacht und die Satzung des KIT zur Sicherung guter wissenschaftlicher Praxis beachtet habe.

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