Interoperability of Geo-information in Remote Sensing-based Biodiversity Monitoring

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Summary

Rapid technological advances coupled with modern analysis methods has increased the quantity of geographical data and has therefore improved monitoring of local, regional and global environmental phenomena at much finer detail. Despite these advances, insufficient data interoperability remains to be a barrier to reusability, discovery and access to geographical information. To overcome this heterogeneity it is crucial to generate syntactic interoperability, which determines fixed standards in data exchange, but also semantic interoperability, a possibility to generate comparability by using shared descriptions with unambiguous meaning stored in semantic systems. In the field of nature conservation, semantic heterogeneity is a big challenge since national and regional data acquisition methodologies vary broadly. Moreover, trans-national data (which are required for multi-national legal processes like the EU Habitats Directive (HabDir), the Water Framework Directive or INSPIRE) are generated bottom-up, using mostly national or regional acquisition guidelines.

This dissertation addresses four aspects of interoperability in nature conservation. The first part provides a methodology for semantic mediation of remote-sensing based data products, which were generated in different countries in Europe by taking into account differing sensor types and base classification schemes. The results indicate that automated, semantic-based data transformation is feasible, but is highly dependent on the conceptualisation of the respective nomenclatures. Therefore transparent, hierarchical nomenclatures are far more important for transferability than the sensor or study area.

The second part applies the developed method in an up-scaling application to generate a comparable automated delineation of selected habitats in different countries by generating transferable aggregation rules. For the different habitats in the two sites an accuracy of above 70% was achieved in regard to a manual, expert-based delineation. This meets approximately the percentages of the comparison of two manual delineations since the process of manual delineation is always subjective and highly dependent on the personal qualification and perception of the surveyor and therefore inherits a high degree of uncertainty.

The third part addresses the challenge of generating reproducible and formalised information in remote-sensing analysis in a semantic, ontology-based classification approach. This approach combines advanced machine learning algorithms and ontological data management and classification. It produces results with similar quality to established machine learning algorithms like Extra Tree Classifier (ET) but preserves transferable classification rules and ontological formalism.

The fourth part evaluates the automated aggregation approach of part two in respect to manual, expert-based delineation and gives recommendations for the international guidelines in terms of scale effects, minimum mapping

units and the potential of the usage of remote sensing-based data sets in automated up-scaling procedures for European legal purposes.

Semantic systems inherit great potential for nature conservation in terms of data storage, information retrieval and derivation and comparability of data. This thesis shows this potential by proving feasibility of semantic transformation between different nature conservation data sets, the application of this transformation procedure in up-scaling processes, and the ability to use semantic-based technologies in classification procedures. It therefore indicates that using semantic systems for data interoperability in nature conservation is possible but underlies, up to now, certain limitations. From a technical point of view the main restrictions are the absence of theme-specific controlled vocabularies and semantic infrastructures which are increasingly developed and provided by regional and international authorities. With regard to the content of the nature conservation data, limitations occur because of the high degree of uncertainty in data acquisition, semantic impreciseness of data descriptions and natural gradients in the composition of habitats.

Zusammenfassung

Technologische Veränderungen gepaart mit modernen Analysemethoden haben die Menge an geographischen Daten in den letzten Jahren erheblich erhöht. Diese Entwicklung hat das Potential, lokale, regionale und globale Umweltphänomene in einem verbesserten Detaillierungsgrad zu erfassen. Trotz dieser Fortschritte bleibt ungenügende Dateninteroperabilität ein Hemmnis für die Wiederverwendbarkeit, die Auffindbarkeit und den Zugang zu geographischer Information. Um diese Datenheterogenität zu überwinden ist es zunehmend entscheidend semantische Interoperabilität zu gewährleisten. Semantische Systeme geben die Möglichkeit Vergleichbarkeit zwischen Datenpaketen zu generieren indem sie gemeinsame eindeutige Beschreibungen nutzen. Im Bereich des Naturschutzes ist semantische Heterogenität eine große Herausforderung, da sich nationale und internationale Erhebungsvorschiften zwischen den verschiedenen Ländern erheblich unterscheiden. Darüber hinaus werden transnationale Richtlinien wie die Flora-Fauna-Habitat Richtlinie oder die Wasserrahmenrichtlinie mit buttom-up Ansätzen erstellt, wobei mehrheitlich nationale und regionale Erhebungsrichtlinien verwendet werden.

Diese Dissertation adressiert vier Aspekte von Interoperabilität im Naturschutz. Der erste Teil stellt eine Methode zur semantischen Mediation von fernerkundungsbasierten Datenprodukt vor, die in unterschiedlichen Ländern Europas mit unterschiedlichen Sensortypen und Nomenklaturen erstellt wurden. Die Ergebnisse zeigen, dass eine automatisierte semantische Datentransformation möglich, die Qualität der Ergebnisse allerdings stark von der Konzeptualisierung der zugehörigen Nomenklaturen abhängig ist. Daher sind transparente, hierarchische Nomenklaturen für die Vergleichbarkeit wesentlich wichtiger als Sensoren oder das Untersuchungsgebiet.

Der zweite Teil wendet die entwickelte Methode in einer räumlichen Hochskalierungsanwendung an, um mit Hilfe von überführbaren Generalisierungsregeln vergleichbare, automatisierte Abgrenzungen von ausgewählten Habitattypen in unterschiedlichen Ländern zu erzeugen. Für die verschiedenen Habitattypen in den zwei Untersuchungsgebieten konnte eine Übereinstimmung von über 70% zu einer manuellen, expertenbasierten Habitatabgrenzung erreicht werden. Das entspricht etwa einem Vergleich von zwei manuellen Abgrenzungen da der Prozess der manuellen Kartierung immer Subjektiv ist, stark von der persönlichen Qualifikation und Wahrnehmung des Kartierers abhängig ist und somit einen hohes Maß an Ungenauigkeit beinhaltet.

Der dritte Teil adressiert die Herausforderung, reproduzierbare und formalisierte Information mit Hilfe von Fernerkundung in einem semantischen, ontologiebasierten Klassifikationsansatz herzustellen. Dieser Ansatz kombiniert fortschrittliche Methoden des maschinellen Lernens mit ontologischem Datenmanagement und Klassifikation. Er erstellt Ergebnisse

mit vergleichbarer Qualität wie etablierte Algorithmen des maschinellen lernens, bewahrt aber transferierbare Klassifikationsregeln und ontologischen Formalismus.

Der vierte Teil evaluiert den automatisierten Aggregationsansatz des zweiten Teils hinsichtlich einer manuellen, expertenbasierten Habitatabgrenzung und gibt Empfehlungen für internationale Richtlinien in Form von Skaleneffekten, Mindestkartiereinheiten und dem Potential der Nutzung von Fernerkundungsdatensätzen in automatisierten räumlichen Hochskalierungsanwendungen.

Semantische Systeme beinhalten ein großes Potential für den Naturschutz in Form von Datenspeicherung, Informationsgewinnung und der Ableitung von Datenvergleichbarkeit. Diese Arbeit zeigt dieses Potential auf indem sie die Machbarkeit semantischer Transformation zwischen verschiedenen Naturschutzdatensätzen belegt und deren Anwendung in räumlichen Hochskalierungsanwendungen aufzeigt. Darüber hinaus werden Möglichkeiten zur Nutzung von semantischen Systemen für Klassifikationsprozesse aufgezeigt. Die Arbeit zeigt daher, dass semantische Systeme für Dateninteroperabilität im Naturschutz nutzbar sind, aber bislang einigen Einschränkungen unterliegen. Von einem technischen Punkt sind die maßgeblichen Restriktionen nicht vorhandene thematische, kontrollierte Vokabulare und semantische Infrastruktur, die zunehmend von nationalen und internationalen Behörden entwickelt und bereitgestellt werden. Hinsichtlich des Inhalts von Naturschutzdaten ergeben sich Einschränkungen aufgrund der Unsicherheiten in der Datenaufnahme, der semantischen Ungenauigkeit bei der Datenbeschreibung und natürlicher Verläufe der Pflanzenzusammensetzungen von Habitaten.

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Acronyms

BD	Birds Directive. 3, 4, 74
CBD	Convention on Biological Diversity. 4, 54
CLC	Corine Land Cover. 96
CS	Citizen Science. 97
DEAP	Distributed Evolutionary Algorithms in Python. 66
DEM	Digital Elevation Model. 59
DL	Description Logic. 17, 18, 39
DSM	Digital Surface Model. 58
DT	Decision Tree Classifier. XI, XIII, 56, 62, 64, 66–69, 71, 97
DTM	Digital Terrain Model. 59
DUL	Dolce Ultra-Light ontology. 21, 30
EAGLE	EIONET Action Group on Land monitoring in Europe. 56, 58–60, 97
EEA	European Environmental Agency. 2, 97
EIF	European Interoperability Framework. 6
EO	Earth Observation. 96–98
ESP	estimation of scale parameter tool. 51
ET	Extra Tree Classifier. II, XIII, 56, 57, 66–68, 71, 97
EU	European Union. 3, 5, 6, 74, 95
EUNIS	European Union Nature Information System. 4, 56–58, 60, 62, 65, 68, 69, 97
GEMET	GEneral Multilingual Environmental Thesaurus. 97

GEOBIA	Geographic Object Based Image Analysis. 54, 55, 58, 95
GI	Geoinformation. 1, 6, 91, 94
HabDir	EU Habitats Directive. 3–5, 12, 21, 53, 54, 57, 74, 97
HR	high resolution. 14
ICT	Information and Communications Technology. 6
INBO	Research Institute for Nature and Forest. 9, 77
INSPIRE	Infrastructure for Spatial Information in the European Union. 2, 3
JRC	Joint Research Centre. 3
KS	kernel size. XII, 50, 73, 79–83, 86–88, 92
LC	Land Cover. 56
LOD	Linked Open Data. 97
LU	Land Use. 56
LUP	Luftbild Umwelt Planung Gmbh. 9
MAUP	Modifiable Area Unit Problem. 50, 74, 83, 88, 95
MMU	Minimum Mapping Unit. XII, XIII, 38, 42, 43, 45–47, 49–51, 73–76, 78–83, 86–88, 92
MPI	Morphometric Protection Index. 68
MS	Member state of the European Union. 5
NDRE	Normalized Difference Red Edge Index. 67, 68, 71
NDVI	Normalized Difference Vegetation Index. 16, 68
OBIA	Object Based Image Analysis. 50, 95
OGC	Open Geospatial Consortium. 2, 12
OWL	Web Ontology Language. VIII, 2, 6, 12, 13, 17, 22, 30, 33, 37–39, 51, 54, 55, 60, 61, 65, 69, 71, 91, 92, 98
RDF	Resource Description Framework. 2, 6, 12, 13, 22, 30, 55, 91, 98
RLP	Rheinland Pfalz - Rhineland Palatinate. 57, 58
RS	Remote Sensing. 6, 8, 11–14, 16, 18, 22, 28–30, 53–57, 60, 94

SAC	Special Areas of Conservation. 4, 33, 50
SDI	Spatial Data Infrastructure. 91
SHDI	Shannon's diversity index. XII, 82, 83
SKOS	Simple Knowledge Organization System. 6, 91
SPA	Special Protected Areas. 4
SPARK	Spatial Reclassification Kernels. 36, 41, 42, 49, 73, 78, 96
SSN	Semantic Sensor Network Ontology. 21
TPI	Topographic Position Index. 59, 67, 68, 71
TRI	Terrain Ruggedness Index. 68
UMTHES	Umwelt Thesaurus. 97
VHR	very high spatial resolution. 16
VITO	Flemish Institute for Technological Research. 9
W3C	World Wide Web Consortium. 2, 6, 13, 21
WFD	EU Water Framework Directive. 12
XML	eXtensible Markup Language. 2, 38, 39, 55

1

Introduction

This thesis consists of four papers that are addressing the interoperability challenges of Geoinformation (GI) systems and data management in the field of nature conservation monitoring. The selected papers have been published or submitted in peer-reviewed journals and are reprinted here as chapters of this thesis. This chapter provides the introduction of the thesis, which relates the individual parts to each other and puts them into perspective. That includes background information, a description of the problems, and how the solutions I propose resolve these problems.

1.1 Data interoperability - A major challenge in the big data era

The rapid increase in quantity of geographical data and advanced analysis methods holds great promise for the monitoring of local, regional and global phenomena regarding the earth's surface and environment, but insufficient data interoperability remains to be a barrier to reusability, discovery and access to geographical information (Parsons et al., 2011). The increasing quantity of earth observation data leads on the one hand to a higher degree of automation in the analysis and therefore has the potential to be comprehensible and reproducible. On the other hand it is one of the big challenges in the field of (geo-) information science to develop standards and methods to structure and compare these heterogeneous data (Perego et al., 2012) to be able to find suitable data sources and integrate them in processes of large-scale analysis (Knoblock and Szekely, 2013). To overcome this heterogeneity, it is crucial to generate syntactic and schematic interoperability, which determines fixed standards in data exchange (like the ones from the Open Geospatial Consortium (OGC)), but also semantic interoperability. Semantic interoperability makes it possible to generate comparability by using shared descriptions with unambiguous meaning stored in semantic systems (Bishr, 1998). Due to initiatives like the Infrastructure for Spatial Information in the European Union (INSPIRE) and fixed exchange formats and standards developed by the OGC and World Wide Web Consortium (W3C), the implementation of syntactic interoperability in Europe has already made significant progress whereas semantic and schematic interoperability has yet to be realised.

Currently, most Earth System Science data are held and managed in hierarchical (simple folder structures) or relational file systems (e.g. data bases) (Parsons et al., 2011). Connections or relationships between data of different origins are facilitated by using metadata (e.g. in eXtensible Markup Language (XML) schemas) or primary key/foreign key relationships stored in relational databases. An increasingly popular, more specific concept of linking data is the idea of the semantic web, which interrelates data through a graph data model that does not rely on a fixed schema. The advantages are that nodes of information can be easily added (horizontally scalable), discovery of information can be facilitated because the user does not have to have detailed knowledge of the underlying schema to generate queries and the degree of comparability between data of different sources can be derived automatically through evaluation of the given linkages. The Resource Description Framework (RDF))[1] and the associated OWL[2] represent the W3C standards for the storage of semantic web data. Currently, there are large projects by European institutions (e.g. European Environmental

[1] https://www.w3.org/standards/techs/rdf#w3c_all
[2] https://www.w3.org/standards/techs/owl#w3c_all

Agency (EEA), Joint Research Centre (JRC)) (Perego et al., 2012) to foster the usage of these technical advances in founded projects (like GeoKnow [3], SmartOpenData[4], MELODIES [5]), in the INSPIRE working groups (Tschirner et al., 2011) or by the institutions itself [6] [7]. Interoperability on the European level shall therefore be provided by taking into account common linked reference vocabularies (so called thesauri or shared vocabularies), which are considered to be the most promising solutions for resource annotation (Bishr, 1998; Fugazza, 2011). This includes the representation of the INSPIRE registry[8] (which serves as a terminology for INSPIRE metadata) and the INSPIRE data model (Tirry et al., 2014) in RDF as well as additional topic-related dictionaries (Perego et al., 2012) which shall be developed by trans-national domain experts.

1.2 Implications of data heterogeneity for European nature conservation strategy

In the field of biodiversity monitoring, geographical data is collected as a basis for trans-national legal processes in Europe. Comparability of this data in terms of spatial distribution is especially important because area and evaluation status determine the funding strategy defined in the prioritised action framework (PAF) of each member state.

1.2.1 European legal tools for biodiversity preservation and subsequent classification schemes

Human population growth combined with rapid industrialisation, urbanisation and modern intensive agricultural techniques have caused a dramatic decline in the quality and area of Europe's habitats (Mücher et al., 2009; European Environment Agency, 2007). This trend is widely recognised by national and international institutions, which therefore ratified a binding international convention to conserve wild flora and fauna and their natural habitats known as the Berne Convention (Council of Europe, 1979). To comply with the convention, the European Union (EU) adopted the EU Habitats Directive (HabDir) and the Birds Directive (BD) in 1992 - two key elements of Europe's nature conservation policy. Part of this directive is the founding of the largest international network of protected areas known as

[3] http://geoknow.eu/Welcome.html
[4] http://www.smartopendata.eu
[5] http://www.melodiesproject.eu/
[6] http://www.eea.europa.eu/about-us/what/seis-initiatives
[7] https://datahub.io/organization/eu-linked-data
[8] https://ies-svn.jrc.ec.europa.eu/projects/registry-development/wiki/RDF_format

the Natura 2000 network (Popescu et al., 2014). The EU's environmental policy framework additionally includes non-binding legal instruments like action plans (e.g. the EU biodiversity action plan), strategies (e.g. the EU biodiversity strategy) and further programmes. Furthermore, the EU also aims to fulfill its international commitment to the Convention on Biological Diversity (CBD), which forms an international agreement on biodiversity protection signed by 168 participating countries.

The Natura 2000 network includes around 18% of the European land surface identified in 28 countries. It can be divided in Special Protected Areas (SPA) for birds (protected under the BD) and respectively the Special Areas of Conservation (SAC) for the HabDir. Due to the variety of regional, national and european habitat classifications and mapping approaches there is a wide range of definitions and nomenclatures of habitats. Even on the European level there are several schemes such as the CORINE Biotopes (Moss and Wyatt, 1994) nomenclature, the Palaearctic habitat classification (Devilliers and Devilliers-Terschuren, 1996), the Annex I of the HabDir (European Commission, 2007), the European Union Nature Information System (EUNIS) habitat classification (Davies et al., 2004), the Phytosociological alliances of the European Vegetation Survey (Rodwell et al., 1995), the Natural Vegetation of Europe (Bohn and Gollub, 2006), and the BioHab General Habitat Categories (Bunce et al., 2008). Since even the classification schemes that are relevant for the HabDir, namely the EUNIS and the Annex I, still differ methodologically and regarding their content (Mücher et al., 2009), it seems like a unreachable goal to directly compare and link the large number of regional and local nomenclatures. In fact, most of the Natura 2000 information originate from national or local mappings, which are translated from the local nomenclatures into the corresponding Natura 2000 or EUNIS class. This is, due to the number of defining parameters (area coverage of certain land cover types, appearance of species or species compositions, trophic level etc.) not a straightforward task and therefore includes considerable inaccuracy. Due to these reasons pan-european data comparability is hardly attempted in the nature conservation domain which hampers consistent monitoring, retrieval and examination of nature conservation areas.

1.2.2 Interoperability of remote sensing-based products in the field of Natura 2000 monitoring

Remote sensing offers vast opportunities for the large-area monitoring of biodiversity (Corbane et al., 2015). This includes the mapping of land cover and broad habitat categories at an over-regional to global scale (Hansen et al., 2013; Friedl et al., 2010) but also more detailed assessments deriving individual species or other fine scale indicators (Förster et al., 2008; Spanhove et al., 2012). But, as there is a variety of sensors, resolution and analysis procedures, the present approaches often lack in reproducibility, transferability and comparability since there is no shared conceptualisation in the developed applications (Nieland et al., 2015b). At present, there have been no standardised classification methodologies to get harmonised output products, and no benchmarking system even exists for the great variance of remote sensing-based analysis techniques. In practice, remote sensing always depends on data availability in combination with the right classification procedure. Forcing data producers to use standardised approaches would in many cases lead to less customisation and less quality of remote sensing output products (Vanden Borre et al., 2011). Hence, the remote sensing community is increasingly aware of the discrepancy between tailored regional products and comprehensive applicability. However, international policies (such as those mentioned in section 1.2.1) strongly rely on the comparability of spatial data collected on a regional level. Therefore, traditional remote sensing classification approaches do not always reach an operational user-basis especially when used to deliver very detailed and often locally-adapted environmental information. In fact, they are often driven by application examples and intended to measure and classify specifics that are defined in existing directives, guidelines, and the subsequent nomenclatures.

A possible solution to overcome this heterogeneity problem is to build up well-formalised shared vocabularies and link them to the tailored remote-sensing products to be able to infer comparability automatically and thereby preserve higher-level interoperability.

1.2.3 Interoperability of field mapping for nature conservation in Europe

Until now, almost all European Natura 2000 data and statistics are based on extensive field surveys. Habitat delineation in the field is a complex task which requires extensive ecological knowledge and experience. Field surveys are therefore very time-consuming and expensive and hard to realise comprehensively over large areas. Since habitat mapping responsibilities are at the Member state of the European Union (MS) level or even at the level of the federal states in most countries, the acquisition methodologies broadly vary across the EU. Most MS have their own mapping guidelines which are afterwards transformed or aggregated into valid classification schemes accepted for the HabDir reporting.

Several studies showed that, due to the subjectivity and personal perception of the surveying ecologist, the conventional mapping procedures can not achieve sufficient comparability, even when using the same nomenclature and interpretation guidelines (Cherrill and Mcclean, 1999; Cherrill and McClean, 1999). This effect is compounded when trying to compare data from different sources with different conceptualisations. Therefore, multiple studies try to develop methodologies to structure, store and link observed field data to fixed semantic systems to achieve broader interoperability, reusability and improve retrieval of such information (Bowers et al., 2010; Cao et al., 2011; Walls et al., 2014). This seems like a consequent step to support digital administration processes and foster discovery and use of governmental data (Reichman et al., 2011). In order to use the limited financial options of the EU in the best possible way and be sure to support the most endangered areas, the comparability of the respective information is essential.

1.2.4 Semantic systems' role in data interoperability

The European Interoperability Framework (EIF) defines interoperability as "the ability of disparate and diverse organisations to interact towards mutually beneficial and agreed common goals, involving the sharing of information and knowledge between the organisations,.., by means of the exchange of data between their respective Information and Communications Technology (ICT) systems" (Commission, 2010). This includes legal and organisational but also technical and semantic interoperability. In this definition technical interoperability refers to the specification of open interfaces, data formats and protocols whereas semantic interoperability describes the understandability of the precise meaning of exchanged information by people, applications and institutions involved. Goals of the establishment of semantic interoperability are to make information and processing tools accessible and detectable as well as understand and employ the discovered information independent of software, platform or its physical location. The European Commission therefore sees the urgent need of an organised joint effort towards harmonisation of methodologies and processes (Commission, 2010) by expanding semantic interoperability. Semantic interoperability and the use of semantics for the integration of geographic integration is also subject of many studies in the GI community (Janowicz et al., 2012; Rodriguez and Egenhofer, 2003; Visser et al., 2002; Kavouras et al., 2005; Lutz et al., 2009). Therefore, different types of analysis methods and semantic data structures were utilised to generate comparability between geographical information. It can be achieved by using semantic data structures of different logical strength, such as RDF-based data models which represent a family of W3C recommendations originally designed for metadata, controlled vocabularies with its W3C standard Simple Knowledge Organization System (SKOS) or so-called triple/quad stores which are databases which use graph structures for semantic queries. In this thesis, I propose using OWL standard as it is able to store ontologies of richer expressiveness by providing additional concept constructors such as equality, characteristics and cardinality of concepts.
An ontology is an *"explicit formal specification of a shared conceptualisation"* (Gruber, 1993), where conceptualisation can be described as a way of thinking about a domain (Uschold, 1998). By using ontologies to enrich Remote Sensing (RS)-based data products with machine-interpretable semantics, implicit relationships between the descriptions of datasets can be found by

performing automatised logical reasoning (see chapter 2 and 3). To use the full potential of semantic systems for data interoperability there are still several open research questions, especially regarding semantic comparability and semantic queries to foster information retrieval.

1.3 Hypothesis and Research Questions

To overcome the semantic heterogeneity problems presented in the previous section and support data interoperability on an international level, the first overall objective is to demonstrate the applicability of semantic systems to support pan European data interoperability in the field of biodiversity monitoring. This objective is addressed by designing a technique for automatised semantic annotation of remote sensing imagery in an ontology-based classification process and developing a procedure for automatised data transformation of classification schemes of different origins and locations. The second overall objective is to evaluate the importance of spatial scale and up-scaling processes for the European nature conservation strategy.

This objective is addressed by developing an automatised aggregation procedure for habitats which can be utilised in conjunction with a systematic analysis of the scale parameter and can be linked to semantic systems to generate overall interoperability.

Based on the two overall objectives the following research questions are presented:

1. Which methods are feasible to generate data interoperability in the field of biodiversity monitoring in Europe?
2. How can semantic systems support up-scaling processes in hierarchical remote sensing-based classification frameworks to generate interoperable outcomes?
3. What possibilities are there to combine machine learning algorithms with ontologies to utilise the benefits of semantic data storage?
4. How important is scale as a parameter for the interoperability of nature conservation areas?

1.4 Structure of this thesis

The structure of this thesis is summarised in figure 1.1. The first chapter introduces the interoperability problems and efforts in Europe to resolve them, focusing on the nature conservation domain and especially the European conservation network Natura 2000. Furthermore it provides the main research subjects, the research questions, gives an overview and outline of the thesis.

Chapter II proposes an observation-based, bottom-up ontology engineering approach for remote sensing applications. This methodology was used to resolve semantic heterogeneity problems in remote sensing classification results by taking into account ontology-based automatic reasoning in combination with matchmaking processes based on semantic generalisation. Chapter III proposes a spatial aggregation approach, which is based on the developments of Chapter II. It combines automated up-scaling processes based on spatial reclassification of pre-classified remote sensing imagery and semantic data transformation. This chapter therefore gives a practical example of semantic mediation and interoperability of geo-spatial data in the field of remote sensing-based biodiversity monitoring.

Chapter IV proposes a new RS classification methodology using data mining approaches to fill the so-called "semantic gap" by providing automated semantic annotation.

Chapter V gives a closer look at the aggregation procedure proposed in Chapter III and examines the influence of a minimum mapping unit and the kernel size of the reclassification algorithm for the automated delineation of certain Natura 2000 habitat classes. Finally, chapter VI synthesises the results and gives and overall conclusion regarding the proposed research questions. Furthermore it provides recommendations for future research.

Chapters II to VI were written as stand-alone manuscripts and were published or are pending publication in international peer-reviewed journals. The chapters were published or submitted as follows:

Chapter II Nieland, S., Kleinschmit, B. and Förster, M. (2015): Using ontological inference and hierarchical matchmaking to overcome semantic heterogeneity in remote sensing-based biodiversity monitoring. International Journal of Applied Earth Observation and Geoinformation, 37, pp. 133-141. doi: `http://dx.doi.org/10.1016/j.jag.2014.09.018`

Chapter III Nieland, S., Moran, N., Kleinschmit, B. and Förster, M. (2015): An ontological system for interoperable spatial generalisation in biodiversity monitoring. Computers & Geosciences, 84, pp. 86-95. doi:`http://dx.doi.org/10.1016/j.cageo.2015.08.006`

Chapter IV Moran, N., Nieland, S., Kleinschmit, B. (2017): Combining machine learning and ontological data handling for multi-source classification of nature conservation areas.International Journal of Applied Earth Observation and Geoinformation, 54, pp. 124-133. `http://dx.doi.org/10.1016/j.jag.2016.09.009`

Chapter V Nieland, S., Kleinschmit, B. and Förster, M. (Preprint submitted to Landscape Ecology): Finding the optimal scale for habitat mapping - a remote sensing-based aggregation approach

The stand-alone manuscripts were developed in teamwork. Hence, more than one author were included in the writing process of the presented research. Apart from chapter IV all chapters were written by the author of this thesis and were than subsequently revised by the co-authors. Chapter IV was written by Thomas Niklas Moran as it was part of his master thesis. The conceptual development and research idea of this chapter was developed by the author of this thesis and refined and implemented by Niklas.

The utilised data sets were partly pre-processed by cooperation institutions. The data which were used but not processed as part of this work are named here:

- Chapter II and III and V are based on remote sensing classification results produced by the Research Institute for Nature and Forest (INBO) and the Flemish Institute for Technological Research (VITO) for the study site Kalmthoutse Heide in Belgium. The classification of the study site Döberitzer Heide was conducted by Luftbild Umwelt Planung Gmbh (LUP).
- All data sources used in the classification process in chapter IV were provided by AgroScience GmbH. This includes the segmented orthophotos as well as indices of the digital terrain and surface model and the satellite imagery.

Each chapter includes the subsections introduction, methods, results, discussion, and conclusion resulting in a limited amount of recurring material throughout the thesis. Considering the inner structure of the stand-alone manuscripts, these redundancies are retained to allow the reader the undisturbed study of single aspects of this work. Due to this repetition and to reasons of readability, subsections were not included in the table of contents of this work. The contents of the pre-published articles have remained unchanged in this thesis.

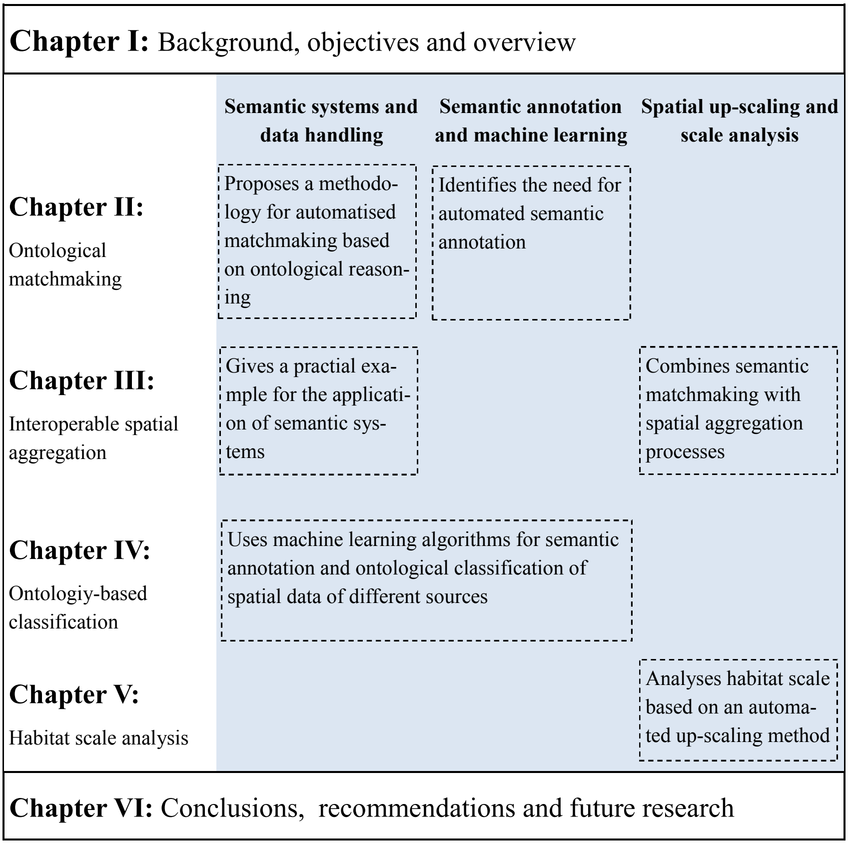

Fig. 1.1: Outline of the thesis

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Overcoming semantic heterogeneity in biodiversity monitoring

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Summary. Ontology-based applications hold promise in improving spatial data interoperability. In this work we use RS-based biodiversity information and apply semantic formalisation and ontological inference to show improvements in data interoperability/comparability. The proposed methodology includes an observation-based, "bottom-up" engineering approach for remote sensing applications and gives a practical example of semantic mediation of geospatial products. We apply the methodology to three different nomenclatures used for RS-based classification of two heathland nature conservation areas in Belgium and Germany. We analysed sensor nomenclatures with respect to their semantic formalisation and their bio-geographical differences. The results indicate that a hierarchical and transparent nomenclature is far more important for transferability than the sensor or study area. The inclusion of additional information, not necessarily belonging to a vegetation class description, is a key factor for the future success of using semantics for interoperability in RS.

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2.1 Introduction

Semantic interoperability's importance for data harmonisation has often been discussed in geographic information integration (Janowicz, 2012; Hess et al., 2007; Kavouras et al., 2005; Rodriguez and Egenhofer, 2003; Visser et al., 2002; Lutz et al., 2009). In addition to syntactic interoperability, thoroughly defined by OGC standards, heterogeneity of underlying semantics represent an unsolved barrier for data integration, data discovery and knowledge sharing - especially in a variety of RS-based applications (Arvor et al., 2013; Blaschke, 2010).

Although RS products and classification procedures often implicitly use semantics for developing rule-sets or indicators there is a lack of structured, computer-readable formalisation within the given classification approaches. RS-based classification conceptualises a real world object or phenomenon (entity) and produces its mapping (symbol). When trying to compare classification results, naming conflicts (different descriptions for the same conceptualisation or one ambiguous description for different conceptualisations) and conceptual conflicts (different conceptualisations for the same mapping) occur, leading to semantic heterogeneity (Kuhn, 2005).

The described heterogeneity hamper the examination of RS output information which is especially problematic when it is required for multi-national legal processes as is the case for the HabDir ((Council Directive) 92/43/EEC, 1992) and the EU Water Framework Directive (WFD) ((Council Directive) 2000/60/EEC, 2000). A comparable thematic depth is needed for the subsequent decision making process. Due to the semantic diversity of RS results, such products are either not considered useful or in the early stages of development (Manakos, 2013). Several approaches (Lutz et al., 2009; Visser et al., 2002; Rodriguez and Egenhofer, 2003; Durbha et al., 2009; Mena and Illarramendi, 2000; Kavouras et al., 2005; Schwering and Raubal, 2005) were applied to achieve semantic interoperability of spatial data by using ontologies based on the RDF or OWL. What these approaches all have in common is the matchmaking process; a technique used to find equivalent information that fit to the particular subject of interest. Matchmaking between spatial datasets can be generated by using similarity values. Often based on dictionaries, thesauri, other RDF/OWL-based data structures (Hess et al., 2007; Rodriguez and Egenhofer, 2003; Kavouras et al., 2005; Fonseca et al., 2006) or geospatial concepts and their geometrical models (Schwering and Raubal, 2005), similarity values indicate the degree of correspondence between entities. Additionally, matchmaking can be achieved by reasoning about the formalised concepts of one specific domain ontology (Decker et al., 1998) and its aligned upper level ontology (Cruz and Sunna, 2008). Multi-ontology systems in combination with query rewriting techniques have also been used to generate matchmaking (Mena and Illarramendi, 2000). Furthermore, a “hybrid ontology“ approach where a shared vocabulary is applied for the formalisation of concepts and inter-ontological reasoning was used in several systems (Lutz et al., 2009; Visser et al., 2002; Durbha et al., 2009).

Several studies have proposed using observations for geo-ontologies. (Janowicz, 2012; Couclelis, 2010; Frank, 2003). In so-called observation-driven engineering approaches ontological primitives (classes in the ontology that are not conceptualised) represent elementary concepts that can be derived from observations. Therefore, included primitives are restricted to observations or derived by aggregation of observed phenomena. Conceptualised classes in the developed ontology can be assigned to upper level ontologies to foster a broader interoperability. Starting with the semantic descriptions of observations in a bottom-up ontology engineering approach preserves the benefit of semantic diversity and local conceptualisations without giving up interoperability (Janowicz, 2012).

Recent approaches of RS classification are bound to semantic web standards proposed by the World Wide Web Consortium W3C and therefore allow the utilisation of semantic reasoning in the classification process (Andrés et al., 2012; di Sciascio et al., 2013; Belgiu et al., 2014). These approaches are not broadly used in the RS community, despite recent discussions touting their benefits (Arvor et al., 2013). Heterogeneity in classes based on RS analysis are resulting from the fact that classification procedures are specified through electromagnetic signals, whereas indicators of field surveys and nomenclatures reflect the composition of parameters defined in the particular area of research or cognitive interest. In many cases RS classification techniques are adapted to classes which are optimised for manual interpretation of aerial imagery or fieldwork through the aggregation of the primitive classification results to the target classes. Consequently, these primitive classifications conceal information because users or customers only have the generalised mapping without its underlying conceptualisation.

A better conceptualisation of RS outputs in RDF/OWL-based structured metadata would not only lead to a better re-usability and exchangeability, but would additionally improve spatial information retrieval (Arvor et al., 2013). Inferring relations between data requirements or products and existing data or nomenclatures is a benefit that is already broadly used in other research areas (Bard and Rhee, 2004).

The main objectives of this work are to

- propose an observation-based, bottom-up ontology engineering approach for RS applications, which will be used for solving semantic heterogeneity problems in RS classification results by taking into account ontology-based automatic reasoning in combination with matchmaking processes based on generalisation,
- give a practical example of semantic mediation of geospatial data in the field of RS-based biodiversity monitoring

- and analyse certain criteria of selected areas (similarity of sensors, number of classes, similarity of geographical region) in regard to their influence on used indicators and subsequently their effect on data interoperability.

A big future challenge of RS research is to transform local or regional classification outputs into interoperable, comparable information. Since there are existing interoperability approaches in other research domains, we contribute to the existing research by addressing the need for interoperability with a novel semantic approach that is based on ontological subsumption.

2.2 Methodology

This section proposes a bottom-up, observation-based ontology engineering approach and shows how it can be used for data interoperability in a prototype application.

2.2.1 Study sites and existing habitat data

We analyse RS classification results of Natura 2000 heathland areas and corresponding nomenclatures for this study. The Natura 2000 sites are heathland and grassland habitats in Flanders (Belgium) and Brandenburg (Germany).

Kalmthoutse Heide[1] (abbr. FL), located in northern Belgium is mainly covered with dry and wet heathland, inland dunes, water bodies and forests Chan2012.

The 6 broader habitat classes at level 1 are gradually arranged into subcategories that reflect the definitions of the habitat structure as well as the structures and functions that are crucial for the assessment of habitat quality (Thoonen et al., 2013).

The second study site, Döberitzer Heide[2], located in eastern Germany is characterized by heathland and grassland vegetation, humid meadows and woods on predominantly dry and sandy soils.
For the Döberitzer Heide, two classification hierarchies are available (see table 2.1). The nomenclature for multi-temporal, high resolution (HR) and hyper-spectral analysis (abbr. BB-HyMap) extends the federal nomenclature towards specific plant communities. These plant communities are used as indicators for the evaluation of habitat conservation status (Schuster et al., 2015). Additional class attributes were already included in the federal nomenclature. Since only parts of the developed and well-formalised BB-HyMaP nomenclature have been classified within this study, a synthetic dataset was created to acquire more significant information about the quality

[1] http://natura2000.eea.europa.eu/Natura2000/ SDF.aspx?site=BE2100015
[2] http://natura2000.eea.europa.eu/Natura2000/ SDF.aspx?site=DE3444303

Table 2.1: Description of classification hierarchies and datasets used for ontological conceptualisation

Nomenclature	Hierarchy levels	Number of classes (total)	Number of classes per hierarchy level (top to most detailed)	Nomenclature created by (date of publication)	Developed for sensor (spatial resolution (m)/number of bands)	Dataset/ classification provided by
Brandenburg (abbr. BB-HyMap)	4	61	6 17 18 20	Förster et al. (2012) Schuster et al. (2015)	RapidEye (6,5x6.5/5) HyMap (5x5/126)	part of this study
Brandenburg (abbr. BB-VHR)	5	33	2 2 9 20	Frick and Weyer (2005)	QuickBird (2.4x2.4/4)	Frick (2006)
Flanders (abbr. FL)	4	51	6 12 18 15	Thoonen et al. (2013)	AHS-160 -Airborne Hyperspectral (2.5x2.5/63)	Thoonen et al. (2013)

of the semantic transformation process. It uses the extent and pixel-size of BB-VHR and includes one band with corresponding class values.

The multi-temporal classification was performed by Schuster et al. (2015) with 21 RapidEye scenes covering dates from March to October (Schuster et al., 2015). The classes were created using federal habitat descriptions and field-based mapping in Brandenburg.

Habitat classification with very high spatial resolution (VHR) imagery was realised using a knowledge-based classification approach. The development of the classification procedure can be divided in the following steps. Initially, suitable indicators are selected, which are limited to those that can be derived from VHR RS imagery. In the next step, these indicators can now be used to develop a hierarchical classification schema. To validate the separability of the determined classes by using a discriminant analysis, each class has to be associated with representative ground truth areas. The developed hierarchical schema is the basis for the multi-level, pixel-based classification procedure. To be able to analyse the variability in the imagery statistically, the classification procedure uses a hybrid system of supervised and unsupervised classification modules (Frick, 2006). Therefore, image data has to be structured and relative values (Normalized Difference Vegetation Index (NDVI), texture, spatial arrangement) have to be derived.

2.2.2 Hybrid ontology model

The basis of this work is a hybrid ontology model, which combines single and multiple ontology approaches (Wache et al., 2001; Lutz and Klien, 2006; Lutz et al., 2009; Visser et al., 2002). The fundamental concept of this approach is to describe the classification results of different regions, each with its own ontology. In contrast to multiple ontology approaches, the concepts of the "local" ontologies are based on primitives and properties of a shared vocabulary that are stored in upper level domain ontologies (Guarino, 1998; Lutz et al., 2009). The main advantages of this methodology are to keep the flexibility of a multi-ontological approach and preserve comparability by using a shared vocabulary. An important characteristic of the shared vocabulary is its independence from existing classification approaches and sensors. Compared with the observation-driven ontology engineering approach proposed by Janowicz (2012), the shared vocabulary's classes describe an observed phenomenon instead of merely conceptualising possible spectral signatures or indices of sensors. In this work the shared vocabulary stores qualitative attributes of the RS classification process, while the local ontologies formalise the classification outputs. Semantic annotation of classification products are realised in the prototype software using a PostGIS database back-end.

Furthermore we describe the shared vocabulary ontology as a "domain ontology", while ontologies that formalise specific concepts of a respective region are referred to as "local ontologies".

2.2.3 Description logics and reasoning

In this work Description Logic (DL) is used for formal knowledge representation, providing the formal basis for the web ontology language (OWL) (Schmidt-Schauss and Smolka, 1991). For the ontological modelling the *Attributive Concept Language with Complements* (ALC) is used, which includes so-called elementary descriptions and concept descriptions (see table 2.2). Basic syntactic elementary descriptions represent atomic concepts (unary predicates), atomic rules (binary predicates) and individuals (constants), whereas complex concept descriptions are built from these elementary descriptions with concept constructors (union, intersection, complement, universal restrictions, existential quantifications) (Baader and Werner, 2003; Lutz et al., 2009). The universal concept includes the set of all individuals in the domain. The bottom concept defines an empty set.

A DL knowledge base can be divided into a TBox containing the terminology (description of relations between concepts and roles) and an ABox containing assertions about named individuals and concepts. Since this work focuses on relations between complex concept descriptions, further developments refer to the TBox language features.

Table 2.2: Concept constructors of the developed ontology

(A|)	(A|)	(atomic concept)
top	$\top$	(universal concept)
bottom	$\bot$	(bottom concept)
(not E)	$\neg$ E	(complement)
(and E)	$E_1 \cap E_2$	(intersection)
(or E)	$E_1 \cup E_2$	(union)
(only E)	$\forall$ R.E	(universal restriction)
(some E)	$\exists$ R.E	(existential quantification)

Implicit relations between complex concepts and atomic concepts can be inferred automatically by performing logical reasoning. The first task is to determine whether a newly defined concept makes sense or is inconsistent. The second reasoning task is to decide whether a complex concept A is subsumed by a concept B. subsumption in a TBox T is identifiable in every model of T if the set of concepts denoted by A is a subset of the set denoted by B (Donini, 2003) (see figure 2.1.1).

$$\text{If } A^{\mathcal{T}} \subseteq B^{\mathcal{T}} \text{then } A \sqsubseteq^{\mathcal{T}} B \tag{2.1}$$

Equivalence between concept A and B with respect to T can be proven if the set of concepts denoted by A equates the set denoted by B for every model I of T (Donini, 2003) (see figure 2.1.2)

$$\text{If } A^{\mathcal{T}} \subseteq B^{\mathcal{T}} \text{then } A \equiv^{\mathcal{T}} B \tag{2.2}$$

Disjointness between concept A and B with respect to T can be proven if the union between the set of concepts denoted by A is null for every model I of T (Donini, 2003) (see figure 2.1.3).

$$A^{\mathcal{T}} \cap \ B^{\mathcal{T}} = \emptyset \tag{2.3}$$

Since reasoning over big ontologies is often time-consuming we use the reasoner Hermit, which is based on a hypertableau and hyperresolution calculi providing fast and efficient reasoning capabilities and making this task technically feasible (Motik et al., 2009).

Hence, it is possible using the reasoner to build up one RS classification hierarchy of two regions (a and b) by formalising classification keys with shared vocabulary in DL. Figure 2.1 shows a schematic representation of subsumption (1), equivalence (2) and disjointness reasoning (3) and illustrates the construction of a combined concept hierarchy (ab).
However, the constructed hierarchy's structure needs to be taken into account as it is not an undirected graph in which every node only has one super-element, but is instead a directed acyclic graph, whose elements can have multiple super-elements.

2.2.4 Hierarchical matchmaking

Since the main focus of this work is to find relations in RS outputs classified in different regions and with differing methodologies, we developed an algorithm which is able to perform equality tests between the concepts of the two regions on ascending levels of the inferred hierarchy.
Since RS-based nomenclatures are often described in a hierarchical way, matchmaking based on "ontological subsumption" (furthermore referred to as hierarchical matchmaking) is a practical technique for achieving comparability. We decided against using a similarity model because of the hierarchical structure of the RS outputs, the very detailed descriptions and the minimal differences between the classes in RS products (Cruz and Sunna, 2008; Rodriguez and Egenhofer, 2003).

Inputs to the algorithm (see algorithm 1) are sets of concepts of region A (C_a) and region B (C_b) (see Figure 2.2). Region A and B include complex concept descriptions (C_{a1}, C_{a2}, C_{a3},..., C_{an}/ C_{b1}, C_{b2}, C_{b3},... C_{bn}) which formalise the region's classification results by using elementary descriptions of the shared vocabulary. The function *getequivalentClasses*(C_{ai}) returns equivalent classes of C_{ai} that are situated in region B. If any direct equivalences are given back from the reasoner the destination concepts can directly be assigned to the origin concept (C_{ai}). If not, the number of hierarchy levels *above* concept C_{ai} have to be identified (getNumberofSuperClassLevels(C_{ai}))(that means the number of potential upscaling processes until reaching the universal concept). The function

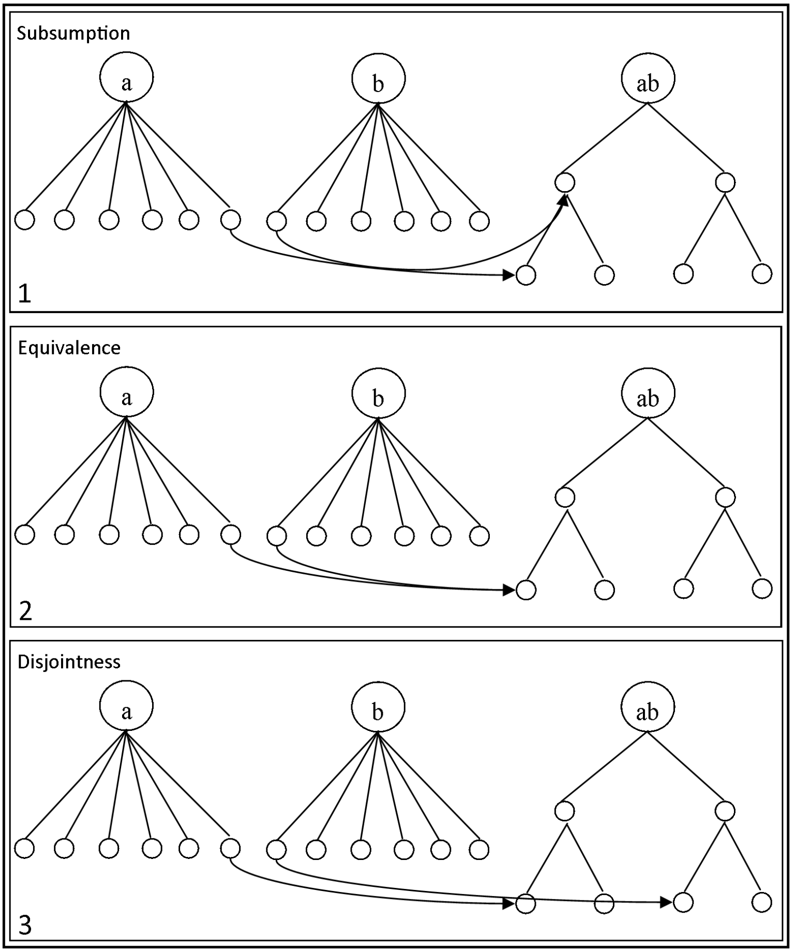

Fig. 2.1: Schematic representation of subsumption, equivalence and disjointness reasoning

testLevelEquivalence() returns concepts of the hierarchy level z that are equivalent to the origin concept C_{ai} and are situated in region B. Therefore searching for the correct stage in the classification schema is iteratively extended to the next general level until a match can be found. Thus, the return value of the algorithm is a set of pairs including the origin concepts (C_{ai}) and corresponding destination concepts (C_{bx}). Since the algorithm is able to generate equivalence checks between all concepts included in the local ontologies, all possible transformations between the nomenclatures have been realised (see table 2.3).

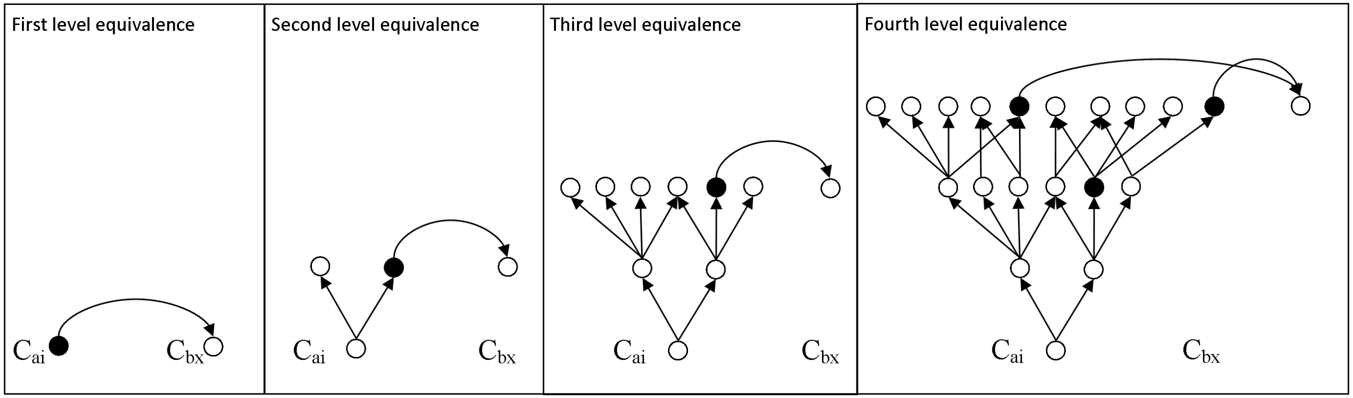

Fig. 2.2: Finding matches between concepts C of region a and b in iteratively extending generalisation levels

Algorithm 1: Finding matches between concepts C of region a and b in iteratively extending generalization levels

```
Data: A finite set of concepts of region A (C_a), which includes
      Concepts(C_a1, C_a2, C_a3,.., C_an) and region B (C_b), which includes
      the concepts(C_b1, C_b2, C_b3,..., C_bn)
Result: A set of matching pairs
def getMatchingPairs(C_a):
    for i in C_a:
        if getequivalentClasses(C_ai) != null:
            matchingPairs[C_ai] = getequivalentClasses(C_ai)
        else:
            numberOfSuperClassLevels =
             getNumberOfSuperClassLevels(C_ai)
            for z in range(0, numberOfSuperClassLevels):
                if testLevelEquivalence(C_ai, z) != null:
                    matchingPairs[C_ai] = testLevelEquivalence(C_ai, z)
                    break
    return matchingPairs
```

2.2.5 Formalisation of classification outputs

Well-formalised semantics of classification keys are the fundamental basis of this work.
The Dolce Ultra-Light ontology (DUL) [3] provides the basis for the Semantic Sensor Network Ontology (SSN) [4] (Compton et al., 2012), developed by the W3C's Semantic Network Incubator Group, and the Stimulus-Sensor-Observation ontology design pattern (Janowicz and Compton, 2010). We chose DUL as top-level ontology mainly to provide broader interoperability to applications realised with SSN and respectively DUL, as this is a recommended framework to model monitoring services based on sensor observations.

Furthermore, we formalise certain heathland and grassland habitats protected under the HabDir. The basic concepts, which are stored in a shared vocabulary and used to describe important indicators for these habitats, have been adopted from the developed classification schemes. From an ecological point of view, the so-called "indication" is the most suitable principle to generate scientifically correct and comprehensive examination of objectives regarding nature conservation (Frick, 2006). The derived indicators should be particularly sensitive to changes of relevant environmental factors. Indicators are parameters which can be measured or derived to determine and evaluate a complex ecological phenomenon that cannot be described directly (Niemeijer, 2002). To develop correct and consistent indicators, the indicators were cross-checked with the developers of the regarded classification hierarchies.

[3] http://www.loa.istc.cnr.it/ontologies/DUL.owl
[4] http://purl.oclc.org/NET/ssnx/ssn

Therefore, the shared vocabulary represents a hierarchy of indicators, which are detectable by using RS classification techniques. This is stored in an OWL2 RDF/XML syntax based ontology, including implicit concept constructors such as relations between classes (e.g. disjointness), equality and characteristics of properties (e.g. symmetry).

Figure 3.2 shows a fragment of the domain ontology describing a RS-based biodiversity indicator entity. Concepts are illustrated as ellipses, black arrows denote inheritance relationships while grey arrows show concept constructors. The hierarchy includes examples of implicit relations between indicators. For instance, domination of common rushes (Juncus effusus, L.) can be used as a wetness indicator, and fallow land is an area not currently used by humans. Indicators which are mutually exclusive (e.g. used and unused or wet and dry), can be described as disjoint. By inferring this simple ontology fragment there is already implicit knowledge revealed. For example, habitats which are dominated by common rushes cannot be dry, or habitats with the attribute "Natural" cannot be used for agriculture. Currently, the shared vocabulary includes 120 concepts describing indicators for remote sensing-based Natura 2000 habitat monitoring [5].

In the local ontologies, basic concepts for RS-based classification can now be described through the analysed indicators. For instance a concept "Gt" (dry grassland) of region A can be described as:

$$
\begin{aligned}
\text{Gt:}\quad & \text{Gt} \subseteq \text{G} \\
& \text{Gt} \equiv ((\exists \text{hasQuality.Dry}) \cap \\
& (\exists \text{hasQuality.SandDominated})) \cup \\
& ((\exists \text{hasQuality.Dry}) \cap \\
& (\exists \text{hasQuality.Grassdominated}))
\end{aligned}
$$

while a concept natural permanent dry grassland in region B can be formalised as:

$$
\begin{aligned}
\text{Gpnd:}\quad & \text{Gpnd} \subseteq \text{Gpn} \\
& \text{Gpnd} \equiv ((\exists \text{hasQuality.Grazing}) \cup \\
& (\exists \text{hasQuality.Mowing}) \cap \\
& (\exists \text{hasQuality.Natural})) \cup \\
& ((\exists \text{hasQuality.SemiNatural}) \cup \\
& (\exists \text{hasQuality.Dry}) \cap \\
& (\exists \text{hasQuality.Grassdominated}))
\end{aligned}
$$

By inferring these classes "Gpnd" can be identified as a subclass of "Gpn" (natural permanent grassland) and "Gt". That means, "Gpnd" includes all attributes of "Gt," therefore "Gt" is a potential up-scaling/transfer target class.

[5] http:/www.user.tu-berlin.de/simon.nieland/ontologies/MS_MONINA_InteroperabilityOntology.owl

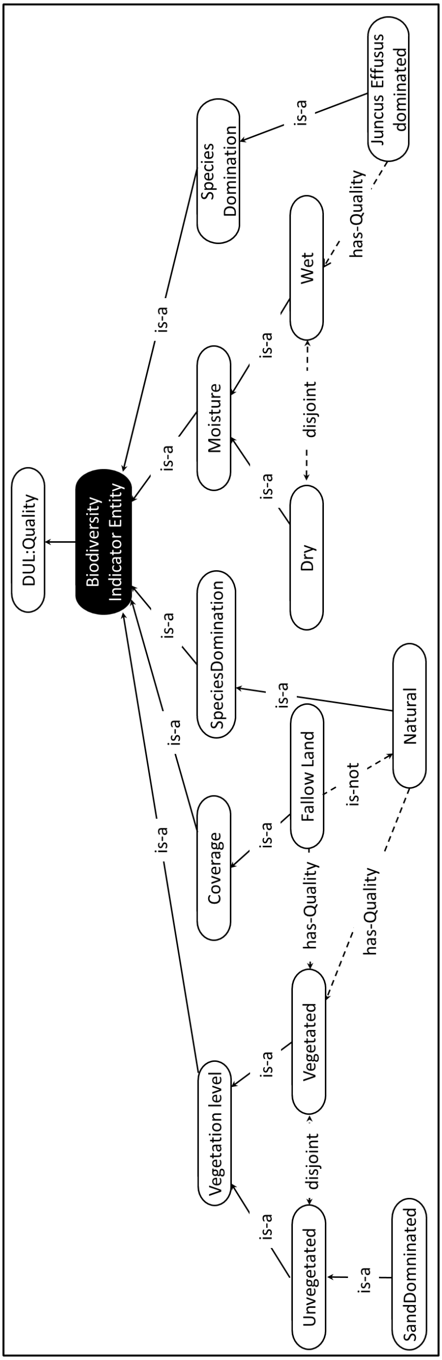

Fig. 2.3: Ontology fragment of the shared vocabulary representing biodiversity indicator entities.

2.2.6 Validation

In order to achieve an objective validation, a reference transformation was created by taking into account ecological expertise from test sites and classification hierarchies. First, all the classes of the test sites were listed in a table and related indicators have been added by analysing detailed class descriptions. Secondly, indicators have been compared and used as a basis for finding equivalent classes in the other nomenclatures. For example, the class "dry grassland rich in cryptogams" (BB-VHR) can be described as dry grassland dominated by cryptogams ($>30\%$) with potential parts of open soil. This class was developed for the assessment of class 2330 (inland dunes with open Corynephorus and Agrostis grasslands). By analysing the nomenclature of FL class Sfm, we can identify it as a corresponding category since it includes low, open vegetation on (partly) fixed sand dunes, predominantly covered by mosses and lichens ($\geq 60\%$).

To achieve an objective validation of the semantic transformation in terms of thematic accuracy, efficiency and practicability, the results were compared to the manual transformation for the two test sites. To evaluate the correctness of the results we adopted the concept of recall and precision, which is mainly used in information retrieval (Korfhage, 1997). In our case, precision describes the percentage of found valid equivalence relations on all relations, whereas recall illustrates the portion of found valid equivalence relations on all valid relations.

2.3 Results

Table 2.4 shows the result for the test case Flanders to BB-VHR nomenclature. Note that not all of the classes of the nomenclature are present in the dataset and that the classification procedures use classes at different levels of the hierarchy. Therefore the total number of classes in table 2.4 does not have to match one level of the hierarchy (see table 2.1). The results shown in table 2.4 indicate that there is just one equivalent class in the two regions; consequently, thematic up-scaling was applied for all other classes in order to achieve comparable datasets in regard to their content. Therefore the generalisation level is expressed by the number of up-scaling procedures necessary to generate equivalent geospatial datasets of the two exemplary test cases. Table 2.3 gives an overview of necessary up-scaling processes in the performed semantic transformations.

Figure 2.4 illustrates the classification result of study area FL (level 1), which was derived from an airborne hyperspectral scanner. Level 2 shows the same dataset visualised in the nomenclature of classification BB-VHRS, whereas level 3 demonstrates the nomenclature used for classification of BB-HyMap imagery. Due to the necessary semantic upscaling processes the nomenclatures of level 2 and level 3 contain fewer classes, but the main

Table 2.3: Number of necessary up-scaling processes per transformation

Number of up-scaling processes	Number of classes BB-VHR-Flanders	Number of classes BB-HyMap-Flanders(%)	Number of classes Flanders-BB-HyMap(%)	Number of classes Flanders-BB-VHR(%)	Number of classes BB-HyMap - BB-VHR(%)	Number of classes BB-VHR - BB(HyMap)
0	8 (38.1%)	13 (21.3%)	3 (12.5%)	1 (4.1%)	13 (21.2%)	9 (42.3%)
1	8 (38.1%)	20 (32.8%)	14 (58.3%)	8 (33.3%)	22 (36%)	8 (38.1%)
2	-	7 (11.5%)	6 (25%)	13 (54.1%)	11(18%)	-
3	-	10 (16.4%)	-	1 (4.1%)	5 (8.2%)	-
Not transferable	5(23.8%)	11 (18.0%)	1 (4.1%)	1 (4.1%)	10 (16.3%)	4 (19%)
Classes (total)	21	61	24	24	61	21

Table 2.4: Result semantic transformation from Flanders (FL) to Brandenburg (BB-VHR). Classes of the origin region Flanders are named in their original description. The first letter represents the broad habitat category (H - Heathland, A - Arable land, S - Sand dunes, G - Grassland, F- Forest, W - Water). The remaining letters indicate the attributes of the classified habitat (t - temporary, b- bare, c - crops/ or Calluna dominated (heath classes), o - other, w - wet, e - Erica dominated, d - dry, a- adult/ or agriculture (grassland), y - young, m - mixed age/ or molinia encroached (heathland)/or maize (arable land), g - grass encroached, j - Juncus Effuses dominated, n- natural or seminatural, f - fixed).

Origin class (FL)	Destination class (BB - VHR)	Number of thematic up-scaling processes
Acm	SpeciesOfArableLand	2
Aco	SpeciesOfArableLand	2
CLOUD		
Fcpc	SpeciesOfArableLand	2
Fcps	Wood	2
Fdb	Vegetated	2
Fdqz	Wood	2
Gpap	GrasslandIntensive	1
Gpar	GrasslandIntensive	1
Gpj	SpeciesOfWetGrassland	0
Gpnd	SpeciesOfDryGrassland	1
Gt	GrasslandIntensive	1
Hdca	DrySandHeath	2
Hdcm	DrySandHeath	2
Hdco	DrySandHeath	2
Hdcy	DrySandHeath	2
Hgmd	SpeciesOfDryGrassland	1
Hgmw	Grassland	2
Hwe	Heathland	3
Sfgm	SpeciesOfDryGrassland	2
Sfmc	MossDominatedAreas	1
Sfmp	MossDominatedAreas	1
UNCLASS		
Wou	Water	1
Wov	Water	2

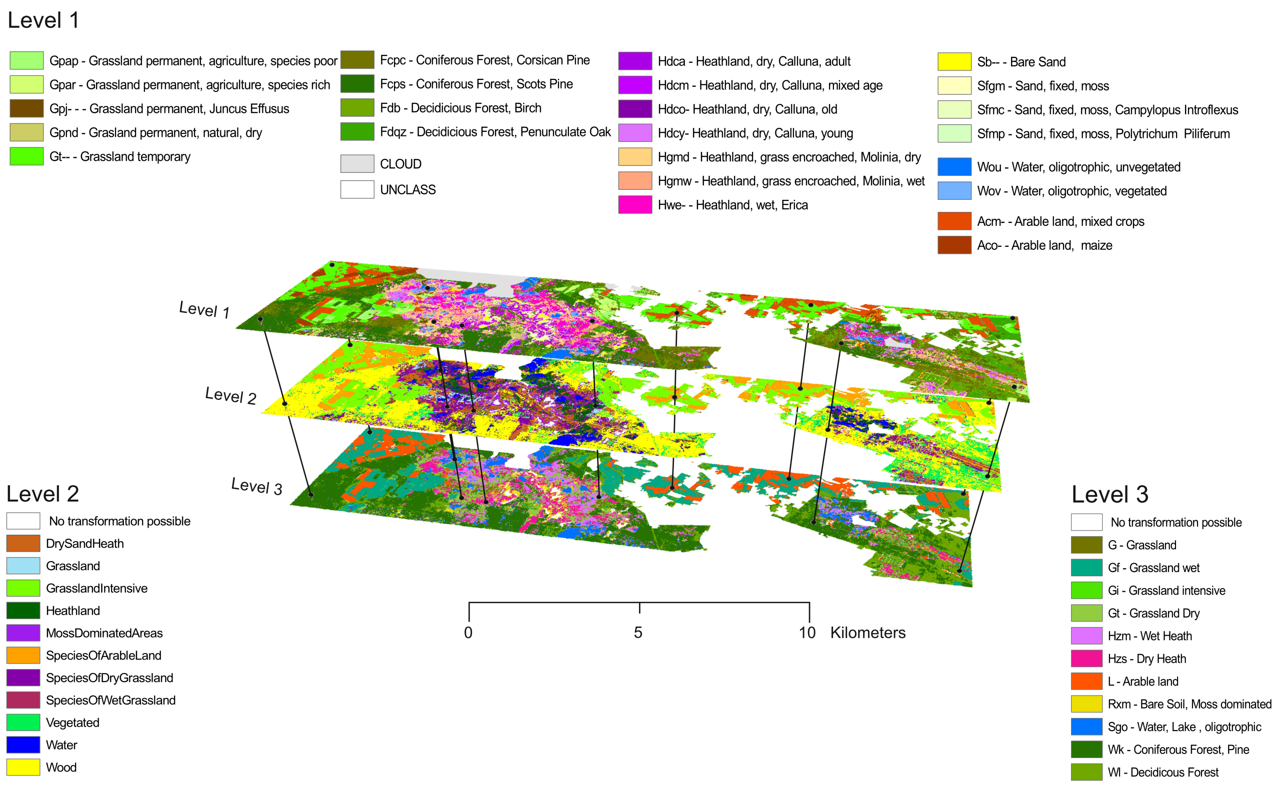

Fig. 2.4: Semantic transformation of datasets FL (Level 1), BB-VHR (Level 2) and BB-HyMap (Level 3)

categories (heathland, arable land, grassland, open soil, forest and water) can be differentiated in all levels. Moreover, it shows that nearly all classes and a high percentage of spatial coverage could be transferred. Table 2.5

Table 2.5: Results of semantic transformation

Transformation type	Total correct relations	Discovered relations	Correct relations	Prec.	Rec.
FL → BB-HyMap	24	23	21	91.3	87.5
FL → BB-VHR	24	23	21	91.3	87.5
BB-HyMap → FL	61	57	51	89.5	83.6
BB-HyMap → BB-VHR	61	51	44	86.3	72.1
BB-VHR → FL	21	21	17	81.0	81.0
BB-VHR → BB-HyMap	21	19	18	94.7	85.7

shows that for some classes more than one relation is correct. For example "Grassland Intensive" in region BB can either be transferred to Gp (Grassland permanent) or to Gt (Grassland temporary) in nomenclature FL. Both classes describe intensively used agricultural grassland and the difference is only in degree of usage. Whereas Gp is permanent grassland used for hay and/or pastures, Gt is periodically used for crops. If there is no equivalence detectable and the manual transformation also does not show any relation class, the discovered relation "no equivalence" is considered to be correct.

All results have precision values between 81.0 and 94.7 and respectively recall values from 72.1 to 87.5. Transfers from Flanders to Brandenburg nomenclatures seem to perform slightly better than transfers from BB-HyMap nomenclature. For BB-VHRS nomenclature, transfer results are diverse, with one very good result from BB-VHR to BB-HypMap and one slightly worse result from BB-VHRS to FL. Generally, transfers from Flanders to Brandenburg achieve better results than the reverse, whereas the intra-regional transformation has no clear tendencies in terms of the quality of the transformation process.

2.4 Discussion

In this study we presented an ontology engineering approach for RS applications (in this case heathland and grassland habitat classification), and introduced a hierarchical matchmaking algorithm that found direct relations between nomenclatures based on different RS classification methodologies and sensors in different regions.

Generally, the presented approach of using ontology engineering and matchmaking for interoperability issues in RS-based monitoring is feasible. The results show that in most cases the prototype application produces equivalent outcomes to manual work.
The outcomes indicate that the transfer between nomenclatures designed for very similar sensors (like FL and BB-HyMap) do not show better results than transferring between sensors with very different spectral and spatial resolutions (BB-VHR and FL, BB-VHR and BB-HyMap). Since we have only analysed three nomenclatures this trend cannot be clearly confirmed. Moreover, the quality of the formalisation as well as the geographical region and the effects of sensor similarity (in terms of spatial and spectral characteristics) seem to have an impact on interoperability. Nomenclatures that are used for similar or equal sensors, such as the ones in FL and BB-HyMap, produced good results in both directions, whereas nomenclatures of the same region (BB-VHR and BB-HyMap) had varying results. Also, results of the transfer between nomenclatures from different sensors and regions (BB-VHRS and FL) produced mostly (BB-VHR to FL) successful results. Therefore the influence of class formalisation seems to be higher than regional and sensor differences.

The described indicators and methodologies of image analysis for biodiversity monitoring reflect the challenge of evaluating and designating nature conservation areas predominantly from RS information. Since at present most of the monitoring data is generated by manual field work, the results had to be evaluated by taking into account ecological health criteria. We see two main reasons for the gap between ecological and RS perspectives. Problems in the matchmaking process occur if the integrated logic of the hierarchies, which are mainly ecological conceptualisations, do not match the logic of the underlying ontology.
Another problem occurs when the RS-based indicator does not correspond with one from an ecological perspective, or a class does not contain all indicators which are necessary for an accurate evaluation. In this case it would be necessary to include indicators that cannot be assessed by RS into the shared vocabulary. Addition of ecological indicators in the shared vocabulary could improve interoperability with more field-based nomenclatures and observations aiding in transferability. From a RS perspective, the definition of a classification hierarchy is often neglected and poorly documented. Before starting an actual classification, the RS and ecology experts should be more detailed in class descriptions by giving more metadata and additional attributes to better substantiate class choice. With these descriptive variables a better transferability could be implemented without using the same nomenclature for nature conservation classes.
In comparison to other studies on ontology alignment and interoperability issues (Visser et al., 2002; Rodriguez and Egenhofer, 2003) the proposed matchmaking approach is focused on the unique requirements of remote sensing classification semantics. Approaches based on similarity measures,

as used in many examples for semantic mediation (Cruz and Sunna, 2008), are more flexible in regard to the structure of the ontology, but due to their complexity (weighting of relations, symmetry/asymmetry) and calibration difficulties lead to unacceptably high false matches. Regarding the varying challenges and demands of RS research, standardisation does not seem realistic. In fact, the diversity in methods and implied semantics reflects the variety of conceptualisations in different regions, which are based on culture and social conventions (Vanden Borre et al., 2011). Therefore, semantic heterogeneity of habitat objects should not be understood as a "problem", but rather a challenge on how to structure, describe and store information in a way that allows inference on relations and comparability.

The main problem in modelling ontological concepts is that experts have to include as much implicit knowledge as possible. Solving the implicit knowledge problem would then require fewer criteria for successful reasoning (Klien, 2008). Therefore it is necessary to request the expert to include certain attributes for classified concepts. In order to achieve completeness in formalisation, critical attributes for differentiation have to be identified and included explicitly.

Although the approach might be influenced by slight regional adaptations (e.g. different plant communities of a more Atlantic or Continental influenced heathland), we show that a transfer of results is possible without a time-consuming adaptation and re-application of the various classification algorithms. Since resources for RS tasks are limited, the introduced hierarchical matchmaking is an appropriate solution for the still-existing heterogeneity of RS products.

2.5 Conclusion

The proposed methodology shows potential in terms of the transferability of RS output products. The storage of classification meta-information in OWL/RDF ontologies based on existing upper ontologies (DUL) leads to a better usability and comparability of RS products. Using knowledge-based reasoning for interoperability issues in RS seems to be an obvious step and is increasingly supported by experts of different research fields (Arvor et al., 2013; Janowicz, 2012). This work is a first step in developing capable methodologies for this challenging task. The results of the exemplary case showed, that a good formalisation of classes is crucial for good interoperability. Giving domain experts the chance to formalise the semantics of the object of study in a computer readable way is a significant step towards the interoperability of RS-based monitoring data.

Furthermore, the developed ontology represents a basis for a number of possible applications. Using the presented ontology for cross-regional, semantic-based generalisation and information retrieval of RS output data would be a further step towards comparable reporting in monitoring activities.

3

Interoperable spatial generalisation in biodiversity monitoring

Simon Nieland, Birgit Kleinschmit, Michael Förster

Summary. Semantic heterogeneity remains a barrier to data comparability and standardisation of results in different fields of spatial research. Because of its thematic complexity, differing acquisition methods and national nomenclatures, interoperability of biodiversity monitoring information is especially difficult. Since data collection methods and interpretation manuals broadly vary there is a need for automatised, objective methodologies for the generation of comparable data-sets. Ontology-based applications offer vast opportunities in data management and standardisation. This study examines two data-sets of protected heathlands in Germany and Belgium which are based on remote sensing image classification and semantically formalised in an OWL2 ontology. The proposed methodology uses semantic relations of the two data-sets, which are (semi-) automatically derived from remote sensing imagery, to generate objective and comparable information about the status of protected areas by utilising kernel-based spatial reclassification. This automatised method suggests a generalisation approach, which is able to generate delineation of SAC of the European biodiversity Natura 2000 network. Furthermore, it is able to transfer generalisation rules between areas surveyed with varying acquisition methods in different countries by taking into account automated inference of the underlying semantics. The generalisation results were compared with the manual delineation of terrestrial monitoring. For the different habitats in the two sites an accuracy of above 70% was detected. However, it has to be highlighted that the delineation of the ground-truth data inherits a high degree of uncertainty, which is discussed in this study.

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3.1 Introduction

Reducing biodiversity loss is a key global environmental challenge and is addressed by a variety of global, national, and regional initiatives (Butchart et al., 2010). To properly assess progress made in retaining the existing biodiversity, advanced measuring and monitoring systems are needed (Magurran et al., 2010). Although there are a number of differently scaled monitoring programs, comparing acquired data is a crucial but often neglected task. The European Habitats Directive (Council Directive) 92/43/EEC (1992) was established to provide a consistent and comprehensive basis for biodiversity monitoring and nature conservation activities. The so-called Natura 2000 network collects this information as reports produced by each member state every six years. Due to the federal structure of the European Union and the differences in data delivery approaches of the various nature conservation authorities there is a high demand for innovative technical solutions to realise a comparable, comprehensive monitoring program.

Generally, information about biodiversity can be gained by field mapping, species modelling, and remote sensing. Various publications have highlighted the benefits of remote sensing in conservation biology and demonstrated standarisation of monitoring results and hence transferability is possible. Yet, even for the remote sensing-based mapping of the Natura 2000 areas, various methods of deriving nature conservation data (semi-) automatically (Thoonen et al., 2010; Bock et al., 2005; Frick and Weyer, 2005; Vanden Borre et al., 2011; Schuster et al., 2011; Corbane et al., 2015) are available. It is necessary to generate applications that are able to use the produced information to generate interoperable and therefore comparable outcomes. International decision-makers rely on the comparability of this kind of information to evaluate policy options. Since remote sensing-based products in the field of Natura 2000 monitoring are usually generated for local or regional purposes and produced with a range of sensors, image processing methodologies and nomenclatures; thematic harmonisation of this spatial information is crucial for international policy-making (Arvor et al., 2013; Schmeller et al., 2014).

Classes derived by remote sensing are often based on indicators (e.g. the Normalised Difference Vegetation Index, homogeneity, biomass, etc.) (Buck et al., 2014) which have to be restructured to vegetation or habitat classes defined in regulations (as is the case for the Habitats Directive). However, there is often a data mismatch between what administrative classes represent and the information contained in a remote sensing signal. To give an example: using a remote sensing signal we can accurately differentiate between open soil, heath, and grassland. However, in a certain combination (percentage) and spatial proximity, these three components form a heathland habitat according to the habitats directive. To automatically aggregate this class, a spatial reclassification is needed.

This work proposes a spatial reclassification approach, which is able to extend existing generalisation methods (Thoonen et al., 2010; van der Kwast et al., 2011) by using semantic relations and inference to generate comparability of the outcomes of different regions with regard to its content. It represents a further enhancement and detailed evaluation of the methodology developed by Nieland et al. (2014). This procedure is independent from classification approaches and sensors and can therefore be applied to data from multiple input sources to generate interoperable data-sets.
The main objectives of this paper are to:

- propose a kernel reclassification algorithm that is able to generalise remote sensing classification results to Natura 2000 habitats and show its functionality and applicability,
- give a practical example of semantic mediation and interoperability of geo-spatial data in the field of remote sensing-based biodiversity monitoring by combining spatial reclassification with ontology-based data handling.

3.2 Related work

The utilisation of ontological reasoning for interoperable data management is an increasingly accepted method in the field of geo-spatial research. This refers mainly to applications, which use shared conceptualisations to generate comparability of categories included in different data models (Durbha et al., 2009; Buccella et al., 2009; Lutz et al., 2009; Visser et al., 2002). Ontologies can be used to facilitate information exchange between different components of workflows (van Zyl et al., 2012; Zhao et al., 2009), as a bridge between different data structures (Nieland et al., 2015a; Kavouras et al., 2005), nomenclatures or databases (Martino and Albertoni, 2011) or as a basis to advance retrieval (Visser et al., 2002) and discovery (Stock et al., 2013) of information. An overview of recent usage of ontologies in GIScience is given in table 3.3.

In the field of remote sensing, ontologies have been applied by using observations (Andrés et al., 2013; Belgiu et al., 2014; Forestier et al., 2013; di Sciascio et al., 2013) as a basis for further reasoning. This so-called observation-driven geo-ontology engineering approach (Janowicz, 2012; Couclelis, 2010) uses ontological primitives (concepts in the ontology that cannot be further reduced) that can be derived from observations. Semantic descriptions of categories can be further conceptualised by taking into account these primitives in a bottom-up approach and then assigned to upper level ontologies to foster a broader interoperability. This technique therefore allows semantic diversity of categories and local formalisation without giving up comprehensive interoperability. Although there are promising approaches in ontology-based classification there are, until now, very few applications (Lutz et al., 2009) that make use of its possibilities for improving interoperability. Previously the way to compare remote sensing classification results was to have remote sensing experts manually map the classified categories. In order to cope with the constantly increasing amounts of data and remote sensing classifications, there is a need for automatised methods that are able to generate comparable data. This is especially needed for supranational and international treaties and obligations. Spatial Reclassification Kernels (SPARK) have been developed for remote sensing-based classification of heterogeneous categories in the urban environment (Barnsley and Barr, 1996). This methodology has been adapted for use in the field of habitat mapping as it properly deals with between-class spectral confusion and within-class spectral variation of especially very high resolution satellite data (Keramitsoglou et al., 2005; Kobler et al., 2006). It has already been used to generalise biodiversity indicators to habitat patches (Thoonen et al., 2010).

Table 3.1: Fields of ontological research in GIScience and exemplary publications

Research field	Area of application	References
Remote sensing	Agent-based image analysis for Remote-sensing data	Hofmann et al. (2015)
	Detection of building types from airborne Laser Scanning	Belgiu et al. (2014)
	Coastal image interpretation	Forestier et al. (2013)
	Classification of high resolution satellite imagery	Andrés et al. (2012) di Sciascio et al. (2013)
Interoperability of geo-spatial data	matchmaking using similarity measures	Kavouras et al. (2005) Hess et al. (2007), Schwering and Raubal (2005)
	matchmaking through reasoning	Durbha et al. (2009) Cruz and Sunna (2008) Nieland et al. (2015a)
Workflow management	wildfire detection generic/theoretical description	van Zyl et al. (2012) Zhao et al. (2009)
Data discovery and retrieval	environmental impact of port extension	Stock et al. (2013)
	transfer of land-cover products	Visser et al. (2002)

3.3 Method

This section illustrates the developed methodology of generalising remote sensing classification results to Natura 2000 habitat patches. It furthermore highlights the possibility of developing an application, which is able to interact with a OWL ontology to produce fully interoperable results. By taking advantage of the underlying semantics, the application is able to use the logic and relations of the given class descriptions to generate comparable Natura 2000 habitats throughout different regions and classification approaches.

3.3.1 Method overview

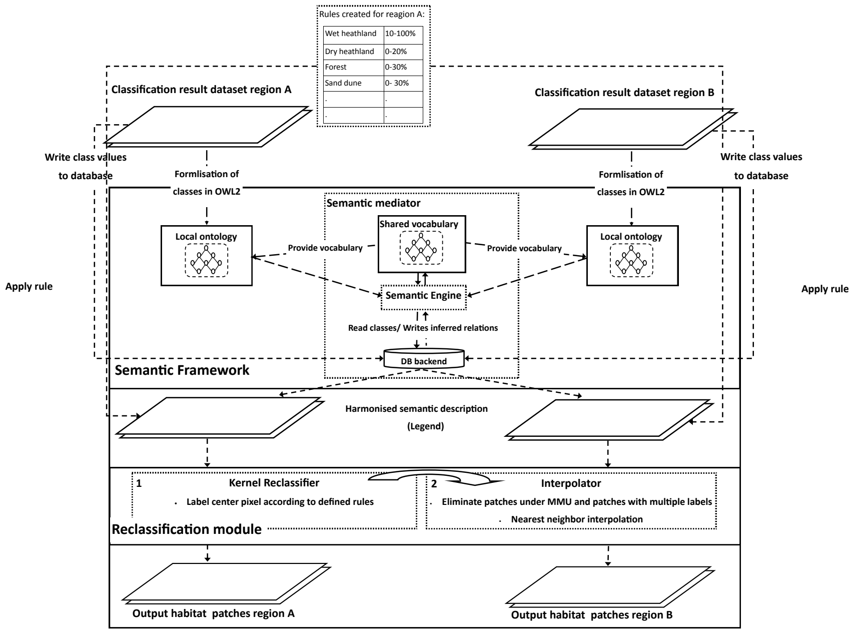

Fig. 3.1: Overview of the applied methodology. The semantic framework uses a hybrid ontology model to transfer classification nomenclatures of one test site to another. By taking into account the results of the transfer, generalisation rules of region A can be applied to region B. The reclassification module aggregates classified categories to actual habitat patches in a two step approach, on basis of these generalisation rules.

The semantic backbone of this work is a semantic framework, which includes the formalisation of remote sensing classification outputs of exemplary heathland sites in Belgium and Germany (see section 3.3.8). Figure 3.1 illustrates the methodological concept and the technical workflow of this work. The formalisation takes the form of a hybrid ontology model, which includes a shared vocabulary and several local ontologies (see 3.3.2). These local ontologies formalise classification outputs of the observed test sites (see Figure 3.1). Since the ontology is stored in OWL2/XML we are able to perform mediation between the concepts of the local ontologies by using a semantic engine, which achieves comparability by taking into account hierarchical matchmaking developed by Nieland et al. (2015a). The data storage and management can be accomplished in a database backend, which stores class values of region A and region B. Therefore the semantic engine reads the class values of the test regions from the database, performs a semantic mediation between the associated concepts in the local ontologies and writes the resulting class relations back into the database. Thus, the system is able to export data-set A with data-set B's legend and vice versa and apply generalisation rules of test region A to region B.

Within the system, the generalisation is performed in the reclassification module, which is divided in a kernel reclassifier and an interpolator. The reclassifier performs the actual reclassification which is then followed by the interpolator module. The interpolator eliminates patches under the (MMU) and patches with multiple labels are assigned to the nearest unambiguous class. Finally, the interpolator performs a nearest neighbor interpolation to fill in the generated gaps (see section 3.3.5). The system outputs habitat patches in both regions, that are produced with equivalent rules with respect to the content of the classes.

The software is built on several open source programming frameworks with a PostgreSQL database backend. The reclassification module is developed in the Python programming language using numpy/scipy (Oliphant, 2007) packages for numerical programming and interpolation. Spatial operations and analyses have been generated by using GDAL version 1.11.1 and Python GDAL bindings. Time-critical parts have been realised in C++ using the python ctypes library. The manual ontological formalisation has been realised with the open source software Protégé [1] while the semantic reasoning has been implemented with the help of OWLAPI and the HermiT hypertableau reasoner (Motik et al., 2009) in Java. The reclassification tool is freely available [2] and will be published under an open source license. The code for semantic reasoning and database management can be requested from the authors.

[1] http://protege.stanford.edu/
[2] https://gitlab.tubit.tu-berlin.de/simon.nieland/kernelreclassification.git

3.3.2 Formalisation of remote sensing classification outputs in OWL2

The hybrid ontology model has been developed manually and contains a shared vocabulary, which includes possible attributes of heathland and grassland habitats and provides a structured vocabulary and their logical relations to the so-called "local" ontologies. Additionally, this OWL2/XML ontology includes implicit concept constructors like relations between classes, (e.g. disjointness), cardinality, equality and characteristics of properties (e.g. symmetry) or richer typing of properties. Figure 3.2 illustrates an ontology fragment of the shared vocabulary. It shows a biodiversity indicator entity with selected, associated concepts. Indicator concepts are illustrated as ellipses, continuous arrows represent inheritance relationships while dashed arrows show concept constructors. The graph structure includes examples of implicit logic relations between indicators. Currently, the shared vocabulary includes 120 concepts for Natura 2000 heathland habitat evaluation. The top concept is a so-called biodiversity indicator entity, which is a super concept of actual indicators like moisture, species domination or dominating fixators that can be further subdivided in more specific indicators (e.g. dry or moist, grass dominated or dominated by cryptogams etc.). Concept constructors describe on the one hand e.g. that an area, which is dominated by xeric grassland is dry or a dune that is fixated by mosses is rich in cryptogams (equivalence). On the other hand concept constructors can express disjointness (concepts that do not have a common element) like e.g. dry and moist.

3.3.3 Inferring class relations

This work uses DL for formal knowledge representation stored in an OWL2 ontology (see 3.3.2). It can be used to automatically infer implicit class relations of the underlying ontology by performing logical reasoning (Donini, 2003). Therefore, it is possible to achieve matchmaking between classes in different regions by using ontological subsumption, and equality tests in ascending levels of the classification hierarchies (Nieland et al., 2015a). This task was implemented in a semantic engine, which is able to transfer nomenclatures of different origin into another by taking into account the local ontologies and respective shared vocabulary (see Figure 3.1).

3.3.4 Generalisation rules

Since a lot of ecological research and knowledge has lead to the current national and international nomenclatures in the field of biodiversity monitoring and evaluation, the aim of this approach is to use this knowledge to generalise data sources of different origins (e.g. sensor type, region, methodology) with regard to their content to achieve comparable results.

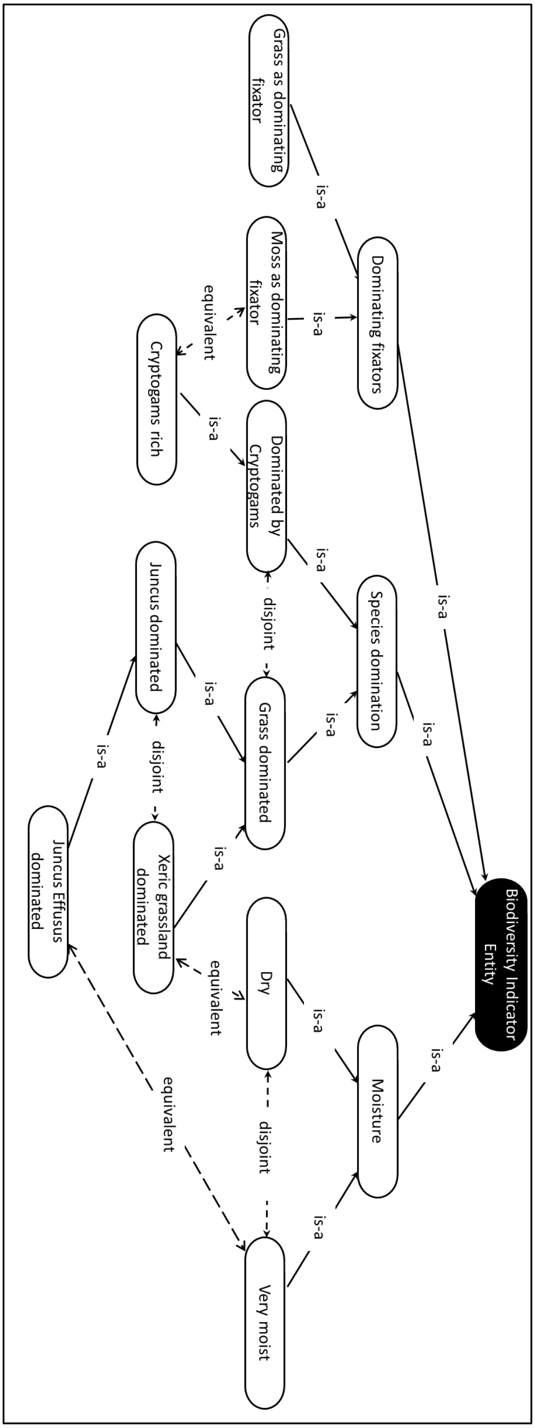

Fig. 3.2: Ontology fragment of the shared vocabulary representing biodiversity indicator entities (adapted from Nieland et al. (2015a))

For this study, generalisation rules for several heathland habitat types have been adapted from the previous study of Thoonen et al. (2010) (see table 3.2). The rules describe habitat classes with ranges of percent spatial coverage of classified indicators.

Table 3.2: Exemplary generalisation rule for class 2330

Indicator	range of occurrence within a habitat
Heathland	0-50%
Dry Heathland	0-50%
Wet Heathland	0-10%
Heathland grass-encroached	0-50%
Heathland grass-encroached, molinia, wet	0-10%
Heathland grass-encroached, molinia, dry	0-50%
Sand	0-100%
Sand bare	0-70%
Grassland	0-100%
Grassland permanent, natural, dry	0-100%
Grassland permanent, natural, wet	0-100%
Grassland permanent, artificial	0-100%
Grassland temporary, artificial	0-100%
Water	0-10%
Agriculture	0-10%

3.3.5 Generalisation algorithm

For the spatial generalisation approach, a method that is based on a modified SPARK approach was used (Barnsley and Barr, 1996). This contextual classification method uses the spatial arrangement and size of pre-classified satellite imagery to define more complex classes. We realised the algorithm by using an adjustable, rectangular moving window, which analyses the local characteristics of coverage to assign a generalised class value to its centre pixel. As already mentioned, Natura 2000 habitat classes (e.g heathland) can contain a complex mixture of sub-classes, for example a composition of wet or dry heathland, bare sand, ruderal or wet grassland, water bodies, shrubs etc. In contrast to the original SPARK methodology, our procedure does not contain a pre-classification process, since it uses already existing remote sensing classification results generated by local experts. Another modification to the original SPARK algorithm is that the rules for applying a label to a centre pixel are already well defined in the national nomenclatures. Therefore these coverage rules, based on expert knowledge, can be used instead of template kernels that are representative of the habitat classes to be derived (see section 3.3.2). The proposed method uses a two-step approach to overcome known drawbacks (see section 3.5) in traditional spatial reclassification kernels (van der Kwast et al., 2011) (see figure 3.3).

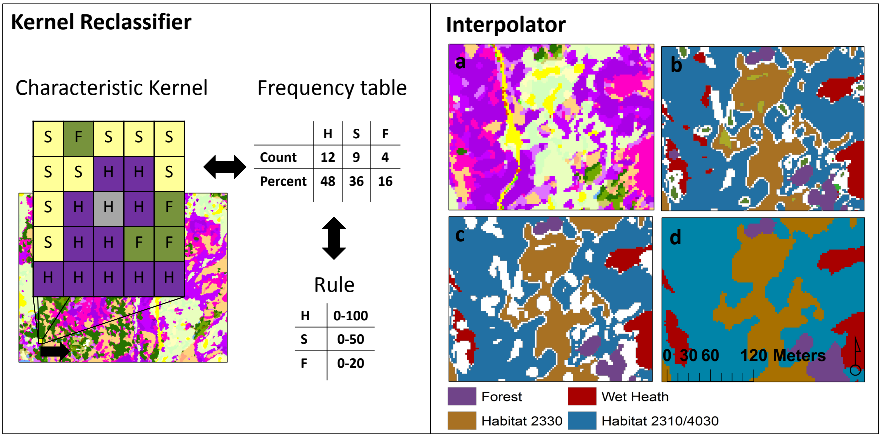

Fig. 3.3: Two step approach of the modified SPARK methodology. Part A shows the kernel reclassifier with an schematic 5x5 kernel. Input is a classification result, which illustrates the classified categories in different colors (see Part A and Part B(a)). The kernel includes three classes (Sand(S), Forest(F), Heath (H)). The kernel reclassifier performs a calculation of the class frequency in a frequency table and compares the outcomes to the associated rule. If the kernel correspond to all formulated rules the centre pixel (grey) can be assigned. The Interpolator eliminates patches that have not been assigned (b) and patches that are under a certain MMU (c) and interpolates gaps in a nearest neighbor interpolation procedure (d).

In the first step of the procedure a moving window labels its centre pixel according to the predefined rules (see section 3.3.4). The appropriate size can be defined by iterating the process over prevalent window sizes (3x3, 5x5, nxn, 33x33) (see section 3.3.6). Making sure that the spatial variation of the subject of interest fits to the result and avoiding too big kernel sizes at the same time reduces smoothing effects and leads to more significant results (van der Kwast et al., 2011).

Since the rules were created for manual fieldwork and adapted to this methodology, areas of multiple labels occur in the result. Mostly transition areas have been affected by this phenomenon. Due to the circumstance, that transitional areas are explicitly excluded in the class descriptions they were not included in the mapping. Thus, in the second step the algorithm eliminates patches with multiple labels and patches that are under a given minimum patch size (see 3.3.6). Consequently, pixels which have been assigned to multiple labels, have been assigned to the nearest unambiguously defined class. If the pixel has been assigned to disjoint classes, then it is eliminated and gets interpolated. Subsequently, the processing step uses a nearest neighbour interpolation[3] procedure to fill the emerging gaps by assigning the value at the data point closest to the point of interpolation.

Furthermore, it is possible to use relations between the semantic descriptions of the components, which are used in the generalisation rules to enhance interoperability between Natura 2000 objects. Therefore it is necessary to know that for example class "Hdc" (heath, dry, calluna dominated) of one region is equal to class "Dry sand heath" of another region. Since we are able to derive equality relations by inferring class relations of the underlying ontology (see 3.3.3), generalisation can be performed in several regions equally.

3.3.6 Optimal kernel size and MMU

To examine the best fitting kernel size and minimum mapping unit (MMU), the percentages of the output objects, generated in the reclassification procedure, can be compared to the average coverage of a reference data-set. For the description of the results, accuracy assessments were performed for each combination of kernel size and MMU using the F-measure (Halder et al., 2009). This class-wise assessment index represents the harmonic mean between precision (p) and recall (r) of a class i as:

$$(F)_i = \frac{2 * p_i * r_i}{p_i + r_i} \tag{3.1}$$

The kernel size and MMU, in which the F-measure is at its maximum, can be considered as best fitting. Therefore, window sizes from 3x3 to 33x33 (and respectively MMU's from 100 to 1300 m^2) were calculated to determine the ideal parameters by analysing the results of the applicability tests (see 3.3.7 and 3.4.3). As expected, the optimal parameters are strongly dependent to the characteristics of the respective target class. Therefore an optimal kernel size and corresponding MMU was calculated for each Natura 2000 target class and applied to the data sets of both test sites.

[3] http://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.interpolate.griddata.html

3.3.7 Validation

The results of the interoperable spatial generalisation described above, were validated by two independent methods (see Figure 3.4).
For validating the functionality of the method, the percentage coverage of the remote sensing-based input data-set was compared with percentages of the resulting objects. This comparison will give an indication of the general quality of the generalisation method based on the originally used input data-set. In the first step of this procedure the percentage of coverage will be calculated for each resulting habitat object. In the next step the results will be compared to the percentages of the generalisation rule and will be evaluated (see Table 3.5).

Since high quality functional validation results do not ensure correctness of the result with respect to nature conservation and biodiversity monitoring, the practical applicability of the method was evaluated by an independent data-set. To implement this, the percentage coverage of the field-based mapping of the focus habitats (data-sets were available for both study sites) was compared with percentages of the resulting generalised objects (see Figure 3.4).

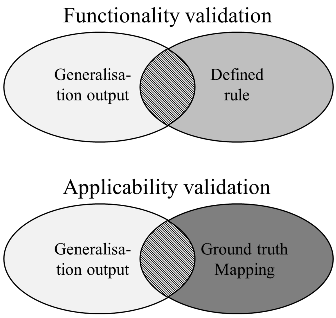

Fig. 3.4: General Framework of the validation methods. The hatched area stands for the percentage of correctly assigned objects.

3.3.8 Study sites and analysed habitat classes

The input data-sets for this study are the results of remote sensing-based classification of Natura 2000 heathland areas in the regions Kalmthoutse Heide (Belgium/Flanders) and Schorfheide (Germany/Brandenburg). The data-sets extend over an area of approximately 20 km^2 in Belgium and 115 km^2 in Brandenburg respectively. The focus of this work are selected heathland habitat classes. The classifications, performed by Thoonen et al. (2010) and Frick and Weyer (2005), used different sensors and classification methodologies (Nieland et al., 2015a). In order to minimise scale effects, the data from Schorfheide (resolution 0.6 m * 0.6 m) was resampled to the resolution of the Kalmthoutse Heide (2.4 m * 2.4 m) using a majority resampling technique. Table 3.3 shows Natura 2000 classes that are present

Table 3.3: Analysed Natura 2000 classes and number of applied rules

Habitat code	Habitat name	Number of rules
2330	Inland dunes with open Corynephorus and Agrostis	16
4030 / 2310	European dry heaths or Dry sand heaths with Calluna and Genista	16

in both test sites. Since there are only marginal differences between class "Dry heath with Calluna and Genista" (2310) and "European dry heath" (4030) the two classes cannot be easily distinguished with remote sensing imagery. As the baseline classifications used both habitat classes as a joint class, the subsequent spatial generalisation in this work is adopting the nomenclature. The two test sites vary in their history, heterogeneity, as well as species composition. While the Kalmthoutse Heide is situated in the atlantic biogeographic region with a higher share of moisture related indicator species, the Schorfheide is situated in the continental region, with less precipitation and fewer species. Moreover, the Kalmthoutse Heide is a former military training ground while the Schorfheide is a former hunting ground and is dominated by wetlands and natural forest (Holsten et al., 2009). Besides these differences, the general composition of heathland habitats are the contribution of open soil, heath and (to a lesser extend) grassland and/or forest. These components should be comparable within a consistent nature conservation network in Europe to ensure proper assessment of necessary genetic and functional diversity. These two very different sites of the same habitat types are suited to test a reliable transfer of an interoperable spatial generalisation.

3.4 Results

The results of the spatial generalisation process were evaluated for optimal MMU and kernel size, the functionality as well as the applicability on the available data-sets.

3.4.1 Optimal MMU and kernel size

The results show, that in the case of Flanders there are differences between optimal MMU and optimal kernel size in applicability and functionality tests (see table 3.4). The optimal MMU varies between 400 and 1000 m^2, depending mainly on the habitat type.

On the contrary, the optimal kernel size is much smaller when applied for the functionality validation (between 5 and 11) compared to the applicability validation (between 17 and 27). For the further validation process we chose the optimal MMU and kernel size regarding the applicability and functionality tests in the test site Flanders.

Table 3.4: Results of the assessment of the best fitting MMU in Flanders and Brandenburg. The field "type" describes either functionality evaluation (func.) and applicability evaluation (app.) in the test site Flanders

Habitat class	type	optimal kernel size	optimal MMU
2330	func.	5	600
2330	app.	17	900
2310/4030	func.	11	1000
2310/4030	app.	27	400

3.4.2 Functionality evaluation

Table 3.5 shows the results of the functionality tests for the test site in Flanders and Brandenburg. The high percentages of polygons according to the respective rule (73.74% to 100.0%) shows that the algorithm generates patches that are mostly corresponding to the defined rules. However, the best fitting MMU and kernel size (see table 3.5) according to the F-measure does not correspond to the optimal MMU and kernel size according to the functionality test. Therefore, the results of this assessment are improved by taking into account the optimal kernel size of the functionality evaluation (see table 3.4).

3.4.3 Applicability evaluation

Table 3.5 shows the results of the accuracy assessment in the test sites Flanders and Brandenburg. The higher user accuracies for class 2310 and 2310/4030 than producer accuracies in the optimal applicability in Flanders suggests that the algorithm tends to underestimates these classes. The results for the optimal functionality are underestimated for class 2330 and strongly overestimated for class 2310/4030.

Table 3.5: Assessment of the functionality and applicability of the generalisation algorithm in Flanders and Brandenburg. The data-sets were produced by taking into account the optimal kernel size of the applicability (appl.) evaluation (2330: MMU - 900, Kernel Size - 17; 2310/4030: MMU - 27, Kernel Size - 400) and the functionality (func.) evaluation (2330: MMU - 600, Kernel Size - 5; 2310/4030: MMU - 1000, Kernel Size - 11) in Flanders.

Test site	Habitat class	Type	Polygons corr. to rules (%)	Polygons not corr. to rules (%)	Number of polygons	prod. acc.	user acc.	F-measure
Flanders	2330	appl.	23(71.8)	9(28.2)	32	50.09	56.67	53.18
	2310/4030		53(84.1)	10(15.9)	63	46.93	55.94	51.04
	2330	func.	60(98.36)	1(1.64)	61	43.16	55.52	48.56
	2310/4030		56(98.25)	1(1.75)	75	88.81	34.04	49.21
Brandenburg	2330	appl.	38(44.7)	47(55.3)	85	33.30	82.96	47.53
	2310/4030		37(100)	0(0)	37	82.58	58.47	68.47
	2330	func.	73(73.74)	26(26.26)	99	31.06	68.65	42.77
	2310/4030		60(100.0)	0(0.00)	60	84.26	60.26	70.26

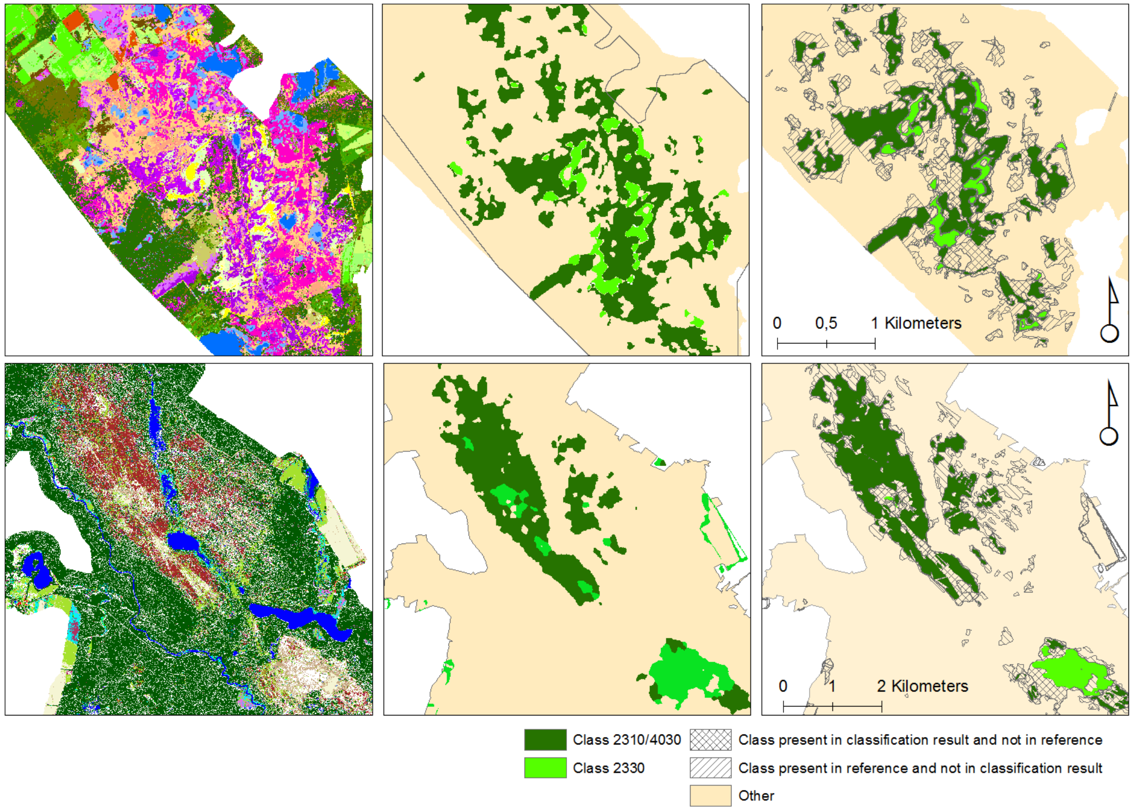

Fig. 3.5: Results of the generalisation in Flanders (top) and Brandenburg (bottom). From left to right: 1. The classification outputs. Each colour represents one derived class 2. Results of the generalisation algorithm 3. Re-classification outputs and manual delineations (transparent)

In the region of Brandenburg, the results for the optimal functionality have similar trends like the results of Flanders. For the optimal applicability class 2330 shows an underestimation whereas class 2310/4030 is overestimated. Therefore it seems, that the semantic transformation does not necessarily downgrade the quality of the generalisation. For 2310/4030 the transferred generalisation rules even show much better results than the ones in the origin region.

Figure 3.5 visualises the outcomes of both test sites. A visual evaluation gives the impression that the core areas of respective classes could be derived correctly in both test sites but the outer delineation differs. Especially in parts where rather small gaps between two areas of the same class occur, the manual delineation tends to have more distinct generalisation than the automatised method.

3.5 Discussion

The presented approach shows that a transferable spatial generalisation method for habitat classes derived by remote sensing products is possible. The described framework derives convincing results for its functionality, while the applicability, for several reasons discussed below, is not completely given.

The modified SPARK methodology uses a two-step approach to overcome two of the three drawbacks as stated by van der Kwast et al. (2011). The first drawback is the inability to specify window size *a priori*. The two other disadvantages are target class-boundary smoothing effects and the fact that rectangular kernels often do not sufficiently represent the shape of the object of interest. By using differing window sizes and MMUs, we ensure that (see section 3.3.6) the spatial variation fits to the result. Furthermore, using improperly sized kernel sizes can be avoided. Moreover, smoothing effects are reduced and more significant results are produced. Eliminating ambiguous pixels assigned to multiple classes in the interpolation module also contributes to reducing smoothing effects. In fact, conservation areas rarely have strict thematic borders, therefore smoothing effects can not be regarded as an important factor in this field of object recognition. Comparing automated classification approaches to manual delineation is always difficult since manual interpretation can never be objective and results do not perfectly match the defined rules (Spanhove et al., 2012). Thus, the differences regarding the best MMU and kernel size in the functionality and applicability evaluation can have three different types of errors, beside the ones resulting from the methodology itself.

First, the rules can be incorrect and do not adequately represent the defined classes. Although the rules were selected with great care and together with ecologists and regional experts, the very general scope of the Habitats Directive does not adequately convey the specific objectives of regional nature conservation (Förster et al., 2008). Local experts, for instance, tend to overestimate locally relevant species and underestimate locally abundant species. These errors are highly significant for Natura 2000's mapping of SACs.

Second, there are inaccuracies in the remote sensing-based analysis and respective output data-sets. Obviously, there are different uncertainties in remote sensing outcomes (Rocchini et al., 2013), which vary from dividing gradual changes in vegetation composition in discreet classes to scale issues, depending on the spatial resolution of the remote sensing data-set. A variety of different methods have been developed for ecosystem monitoring to take these uncertainties into account: Maximum Entropy Modelling (Stenzel et al., 2014), regression models (Feilhauer et al., 2011), multivariate analysis (Schmidtlein et al., 2007), fuzzy logic approaches (Rocchini et al., 2010), *a priori* additional knowledge via geo-data (Förster and Kleinschmit, 2014), and spectral unmixing (Somers et al., 2011). Generally, the main reason for uncertainties in remote sensing analyses is a improper scale match between field data and the resolution of the remotely sensed data (Small, 2001). This can either produce smoothing effects on the reflectance variability (by using too coarse resolution)(Avena et al., 1999; Lechner et al., 2009) or lead to intra-class variation and noise if the spatial resolution of the remotely sensed data is too high (Nagendra and Rocchini, 2008; Rocchini et al., 2013). In our case, especially for indicators with small spatial occurrence, the mixed pixel problem has significant influence on uncertainty. However, the proposed method retains this implicit error while generalising. Nevertheless, it might be the case that the selection of the most appropriate MMU and KS minimizes the discrepancy between the field sampling and the spatial resolution of the remote sensing-based product.

Third, the manual delineations do not fit perfectly to the defined habitats. The best fitting kernel size and MMU in the presented method are dependent on the applicability and functionality of the algorithm. But good results in the functionality test do not necessarily ensure good results of the applicability and vice versa. However, the greater the differences between best fitting MMU and kernel size based on applicability and the ones based on functionality, the more correspondence between created rules and delineated habitat patches based on fieldwork diverge. Unfortunately, at present no standard spatial reference size (e.g. MMU) for habitat monitoring in Europe exists. This question should be addressed to ecologists and included in future mapping guidelines. Habitats requiring a large contiguous area, should have a larger MMU applied, while small-sized habitats should be classified with a finer MMU (Förster et al., 2008). In a larger context this is part of the Modifiable Area Unit Problem (MAUP), which states that the areal units can be arbitrary and modifiable, depending of the method of aggregating or generalizing the geo-information (Openshaw, 1984). The resulting bias can lead to the so-called ecological fallacy (Holt et al., 1996). There are a variety of proposed techniques solving the MAUP by supplying more objectivity to the method of generalizing. Object Based Image Analysis (OBIA) is often used for segmenting remote sensing images to derive the intrinsic scale of the dominant landscape objects composing a scene (Hay et al., 2003). The estimation of scale parameter tool (ESP) is frequently used to find the optimal balance between over and undersegmentation (Dragut et al., 2010). The proposed method of this study to estimate the optimal MMU could solve the problem, that each landscape element or habitat implies its own intrisic scale and requires subsequently a different unit-size.

With the discussed points in mind, especially in regard to the impreciseness of the reference data, the generalisation results are quite good. The transfer of generalisation rules also produced satisfying results. For class 2310/4030 the analyses show even better outcomes in the destination region than in the origin region, whereas the results for class 2330 are only slightly worse in the destination region (see table 3.5). The analyses show that the described methodology produces objective, comparable and reproducible generalisation results in different regions in regard to the content of the respective nomenclatures.

Therefore, patch reconstruction with the help of spatial reclassification is a possible solution for the challenge of creating objective Natura 2000 habitat delineation.

3.6 Conclusion

This work addresses the urgent need to improve data availability and comparability in the field of nature conservation monitoring to assist European countries with the challenging task of protecting threatened species and habitats (Schmeller et al., 2014). We showed that automated delineation of heathland habitats using spatial reclassification on the basis of remote sensing classification results is technically feasible. Furthermore, generalisation rules can be transferred to another region by taking into account the semantics of the respective classification nomenclatures stored in an OWL ontology.

Since the described procedure is dependent on several inputs, the uncertainties in the accuracy assessment are rather high. The quality of the generalisation process is always linked to the quality of the remote sensing classification outputs. Furthermore, uncertainties in the generalisation algorithm and respective interpolation can produce lower accuracies. Finally, manual object delineation is always subjective and therefore also includes rather large uncertainties.

4

Combining machine learning and ontological data handling

T. Niklas Moran, Simon Nieland, Gregor Tintrup gen. Suntrup, Birgit Kleinschmit, Michael Förster

Summary. Manual field surveys are expensive and time-consuming and could be supplemented and streamlined by using RS for biodiversity monitoring. RS is critical to meet requirements of existing laws such as the EU HabDir and more importantly to meet future challenges. The full potential of RS has yet to be harnessed as different nomenclatures and procedures hinder interoperability, comparison and provenance. Therefore, automated tools are needed to use RS data to produce comparable, empirical data outputs that lend themselves to data discovery and provenance. These issues are addressed by a novel, semi-automatic ontology-based classification method that uses data mining algorithms and OWL ontologies that yields traceable, interoperable and observation-based classification outputs. The method is tested on EUNIS grasslands in Saarburg, Rheinland-Palatinate. The developed methodology is a first step in developing observation-based ontologies in the field of nature conservation. The performed tests show promising results for the determination of the grassland indicators wetness and alkalinity with an overall accuracy of 85% for alkalinity and 76% for wetness.

Published as *Combining machine learning and ontological data handling for multi-source classification of nature conservation areas* in the International Journal of applied earth observation and geoinformation

4.1 Introduction

Recognizing the importance of functioning ecosystems to reduce biodiversity loss, the European Union has implemented an environmental conservation framework to protect and conserve vital habitats in accordance with the CBD. An integral part of this framework is the HabDir ((Council Directive) 92/43/EEC, 1992), which established the Natura 2000 network of habitats. The directive requires member states to conserve and monitor designated habitats and submit a report every six years. Environmental data to determine biodiversity status must be collected to comply with reporting requirements. Comparing data used for these reports is difficult because of varying data collection methods and acquisition nomenclatures used by nature conservation authorities in each member state (Vanden Borre et al., 2011). The main issue is in the subjective nature of field surveys to identify habitats (Cherrill and McClean, 1999; Cherrill and Mcclean, 1999; Hearn et al., 2011; Nieland et al., 2015b). Furthermore, habitat status is mainly generated in bottom-up approaches taking into account the national and regional interpretation guidelines (Vanden Borre et al., 2011; European Commision Joint Research Centre, 2013). This subjective and time-consuming task of conducting field surveys could be partially replaced with an automated RS method that uses Geographic Object Based Image Analysis (GEOBIA) to reduce subjectivity, costs and time.

RS offers opportunities to collect and automatically interpret large amounts of computer-readable data useful for nature conservation and biodiversity monitoring (Corbane et al., 2015; Vanden Borre et al., 2011; Mayer and Lopez, 2011). RS image analysis implicitly incorporates the expertise of the person performing the analysis, reducing reproducibility as the analyst ultimately chooses class membership in non-crisp boundaries between classes. This can be divided into RS knowledge (spectral signature, remote sensing indices, etc.) and field knowledge (feature properties, spatial relations, etc.) (Andrés et al., 2013), which is often neither completely nor explicitly defined as it is based on trial and error but influences the classification (Arvor et al., 2013). To ensure accuracy and applicability of classification outputs for conservation, experts with detailed knowledge of the sites are needed to interpret the RS data. The distance between the high-level semantics used by experts to describe domain concepts and the low-level information quantified from data is referred to as the "semantic gap" (Smeulders et al., 2000).

Ontologies can help bridge the "semantic gap" and allow for better data transferability, knowledge and workflow management (provenance) and logical consistency (Janowicz, 2012). The standards-compliant format designed and adopted to express rich semantics and enable the "Semantic Web" is called the OWL [1]. The format supports multiple syntaxes yet defines

[1] http://www.w3.org/TR/owl2-overview/

the RDF (subject, predicate, object triplets) saved as XML as a common exchange format. Moreover, through the use of reasoners (inference engines) that infer logical consequences over axioms and asserted facts and verify consistency, one can discover new knowledge (Arvor et al., 2013; Andrés et al., 2013). RS and field expert knowledge can be digitized in ontologies, thus allowing for a hierarchy of concepts for improved automatic image annotation and retrieval using concepts from both fields to produce more accurate results (Srikanth et al., 2005). Janowicz (2012) advocates for more observation-driven ontologies and for including machine learning, statistics and data mining to construct ontological primitives. While published research on using observation-based ontologies for biotope classifications is limited, the available research using ontologies in RS research is briefly summarized below.

Ontologies modeled on the Land Cover Classification System and the General Habitat Category were integrated into tools used to monitor and protect areas in the EU (Arvor et al., 2013). The authors note that using the taxonomy of the different classification systems makes it possible to include expert knowledge in the process. Lucas et al. (2015) used pixel-based analysis and GEOBIA for greater classification accuracy which relies on a rule-base created by an expert. Other research includes urban building classification using a three-layered architecture (di Sciascio et al., 2013) and another using semi-automated classification using the Random Forest classifier to determine variable importance of features from airborne laser scanner data (Belgiu et al., 2014). Ontologies have also been paired with different algorithms to automatically acquire classification rules: a genetic programming algorithm (Forestier et al., 2012) and the C4.5 data mining algorithm (Sheeren et al., 2006). In biodiversity monitoring research, ontologies have been demonstrated to improve spatial data interoperability (Nieland et al., 2015a,b) and have been shown to aid in discovery of new relationships to consider for habitat management (Pérez-Luque et al., 2015). The addition of fuzzy data types to OWL and the development of a fuzzy spatial reasoner holds great promise for the future of GEOBIA ontology research using remote sensing (Belgiu et al., 2014; Bobillo and Straccia, 2015). More recently a multi-scale fuzzy spatial reasoner was developed that could have significant impact on this research (Argyridis and Argialas, 2015).

Even though researchers recently developed a number of indicators using different sensors for habitat evaluation (Nagendra et al., 2013), classification procedures and rule-sets were not formalized to be computer-readable and therefore suffer from similar transferability and reproducibility problems as manual habitat mapping (Arvor et al., 2013; Nieland et al., 2015a,b). Therefore, a formalized computer-readable ontology could help solve these problems and allow scientists to see how the classification was performed and be aware of possible incompatibilities before combining data (Janowicz, 2012). Furthermore, there are no standardized trans-national habitat evaluation RS indicators (Lucas et al., 2015; Vanden Borre et al., 2011).

Therefore, technical solutions to increase interoperability by thematically harmonizing environmental data and systematize data collection methods from remote sensing inputs in an automated workflow are needed.

The EIONET Action Group on Land monitoring in Europe (EAGLE) is an expert group that seeks to harmonize Land Cover (LC) and Land Use (LU) nomenclatures using an object-oriented data model that eases translations between nomenclatures (Arnold et al., 2013). The many different nomenclatures used in Europe each have their own specific thematic conceptualization suited towards a specific scale and data collection method- reducing the ability to compare thematic maps. Since LU and LC are interconnected and influence one another, nomenclatures often incorporate both definitions into one class making separation difficult. To overcome this problem the EAGLE data model describes landscapes in three main components: land cover (abiotic, vegetation, water) land use (agriculture, forestry, etc.) and characteristics (bio-physical, cultivation etc.). The increased interoperability and transferability of RS data and the semantic layer on top helps decision-makers to better assess and compare outcomes.

In this paper we propose an automated system that can classify dry, mesic and wet grasslands according to the EUNIS biotope classification schema using earth observation data, existing thematic maps (biotope, forestry, etc.), and expert knowledge formalized in an ontology with rules generated by machine learning algorithms. Combining machine learning algorithms with ontology-based classification has, to our knowledge, not yet been done and is a first in remote sensing research. This method contributes to the goal of empirically derived rule creation and enhances data interoperability and comparison as proposed by Janowicz (2012). The main goals of this paper are:

- to develop a RS classification methodology using a DT approach in combination with ontological formalism to generate highly interoperable, reproducible and exchangeable classification procedures and results,
- apply the methodology to indicators used to separate grassland habitats defined under EUNIS
- and evaluate the developed approach by comparing it to an ensemble classification algorithm (ET). [2].

4.2 Method

This section proposes an ontology-based classification approach which uses a DT for the semantic annotation procedure. It furthermore describes the study area including available geo-data and the semantic conceptualization of classes in the nature conservation domain. To evaluate the generated results the outcomes were compared to a highly randomized tree classifier called

[2] http://scikit-learn.org/stable/modules/ ensemble.html#extremely-randomized-trees

ET, which is a tree-based ensemble classifier (Breiman, 2001) known to be suitable for this kind of classification problems (Qian et al., 2014; Franke et al., 2012; Hladik et al., 2013; Barrett et al., 2014).

4.2.1 Study area, data and classification nomenclature

The study area for this work is the administrative district of Saarburg. The district has an area of approximately 200km^2 and is located in the southwest of the federal state of Rheinland Pfalz - Rhineland Palatinate (RLP), Germany. Luxembourg borders the area to the west and the federal state of Saarland to the south. RLP is influenced by western European Atlantic climate and there is an economically and culturally important viticulture industry along the Mosel and Rhine rivers (see figure 4.1).

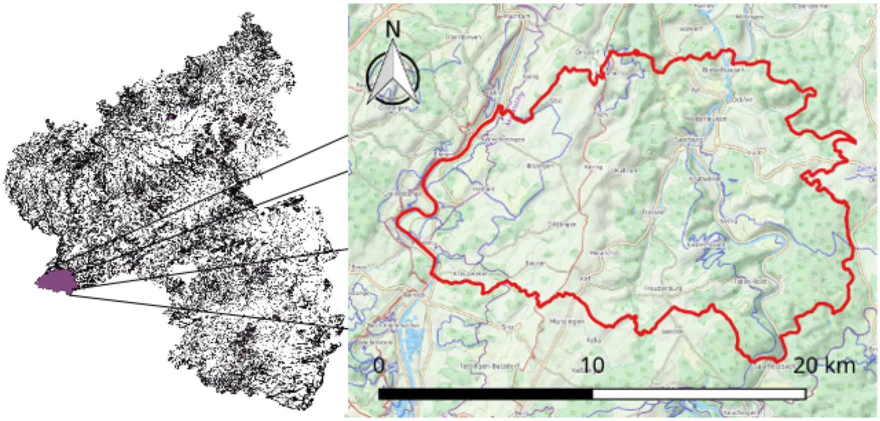

Fig. 4.1: The location of Saarburg (in purple) in relation to Rhineland-Palatinate. Map on right ©Thunderforest, Data©OpenStreetMap contributors.

To evaluate the developed methodology this work tries to demonstrate possibilities to support the federal administration of RLP performing their regional biotope mapping as well as fulfilling its European reporting obligations defined in the HabDir. Therefore we chose the nomenclature of the EUNIS to classify biotopes as it directly satisfies the HabDir and has already been semantically transferred to the local mapping nomenclatures. A consistent classification process could be realized by describing EUNIS classes with biophysical and anthropogenic indicators that are supposed to be derivable with the help of the available data bases. To achieve an accurate formalization of the regarded habitats, selected indicators defined in EUNIS, were adopted to meet the requirements of RS analysis. Furthermore certain indicators of EAGLE's object-oriented data model were used to describe land use, land cover and additional characteristics (biophysical and anthropogenic). The EAGLE terms were adopted when possible to increase interoperability and further re-use. Table 4.1 illustrates the selected EUNIS categories and subsequent descriptive indicators.

Table 4.1: Class descriptions of of classified Natura 2000 habitats. A '-' denotes 'none' and the first letter of each value is used to safe space. Vegetation type: {graminaceous, herbaceous}

EUNIS class	description	vegetation type	wetness level	acidity
E	Grasslands and lands dominated by forbs, mosses or lichens	h	-	-
E1	Dry grasslands	g	dry	-
E1.2	Perennial calcareous grassland and basic steppes	g	dry	alkaline
E1.7	Non-Mediterranean dry acid and neutral closed grassland	g	dry	neutral/ acid
E2	Mesic grasslands	g	mesic	-
E3	Seasonally wet and wet grasslands	g	wet	-

The thematic reference data consists of the federal biotope map (partially updated 2015), agricultural data (updated every year), forestry data (2014) and a soil map that is based on the ALKIS (Amtliches Liegenschaftskaster Informationssystem- Automated Land Registration Map) (partially updated 2015). To generate valid and consistent testing and training data for the classification, these data were combined to create a comprehensive thematic data basis for RLP (see figure 4.2). Consistency checks and manual validation have been carried out to ensure reliability and account for different quality and age of the underlying data sources. To ensure the comparability of these base data sets, they were characterized with a common semantic reference model of indicators that have been developed on the basis of the EAGLE data model and the EUNIS (see subsection 4.2.3). Thus, all base data sets were conceptualized by using the developed indicators (such as wetness, alkalinity etc.) and can therefore be used as testing and training data for certain categories that therefore serve as class labels for the machine learning algorithm.

All described processes are based on pre-segmented data, generated using GEOBIA. For this pre-segmentation step mainly two types of data were taken into account: digital, multi-spectral (B, G, R, NIR) orthophotos (Year:2012-2013, 0.2m resolution) and a Digital Surface Model (DSM) (0.5m resolution) which was generated by applying automated stereo matching. To receive object heights the DSM was normalized by the subtraction of a LiDAR based DTM (res. 0.5 m). These data therefore represent the basis for all segmentation and classification procedures. The iterative object-based pre-classification was performed by Tintrup gen. Suntrup et al. (2015) in a multi-resolution approach (Baatz et al., 2001). A basic land cover extraction is performed by the segmentation process which also follows the EAGLE data model when possible. This includes the main land cover classes trees, shrubs, herbaceous/graminaceous vegetation, bare soil, heath, lichens and mosses, reeds, artificial surfaces, water plants and forbs. Furthermore, based on the available input data (Digital Terrain Model (DTM), Digital Elevation Model (DEM) orthophotos), various zonal statistics could be calculated for the resulting objects (see 4.6). Hence, the actual classification process is based on two RapidEye scenes from 2014 with 34 indices derived from the DTM, DEM and orthophotos.

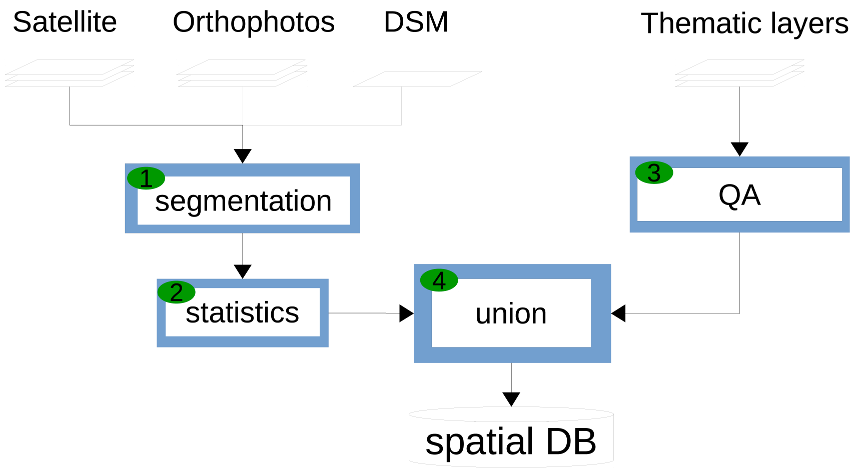

Fig. 4.2: 1) The segmentation process uses orthophotos, satellite (RapidEye) and a DSM. The min/max, mean, median, mode, std deviation is calculated for SAGA wetness index, Topographic Position Index (TPI), etc. 3) The QA (quality assurance) removes conflicts in the thematic maps (biotope, agriculture, etc) 4) The segmented data that fits within the thematic polygons is unioned together.

4.2.2 Overview of the ontological classification process

Figure 4.3 gives an overview of the method using the indicator *wetness* as an example. The wetness level is essential to differentiate dry, mesic and wet grassland habitats according to the second level of the EUNIS nomenclature (see table 4.1). The developed system is comprised of (1) the preparation of reference data, including a spatial union of the base data sets (pre-segmented, pre-classified aerial photos and thematic maps (see 4.2.1) and the attachment of subsequent semantic characteristics (see 4.2.3), (2) the selection of training and validation data (see 4.2.6), the generation of classification rules (see 4.2.4) using machine learning algorithms and finally (4) the ontology-based classification process (see 4.2.5).

The software relies on a PostgreSQL database with PostGIS extensions and various open source Python and Java libraries to interact with the database, convert files and execute a *reasoner* over the created OWL ontology (see 4.2.5). This reasoner can perform A-Box and T-Box reasoning over the defined axioms. Relationships between objects (subsumption, disjointedness, etc.) are discovered and checked for consistency during T-box reasoning. Using software, such as Protégé, users can see how the defined axioms are related in the stored OWL knowledge base and check for logical consistency. If OWLIndividuals (objects) are in the knowledge base then A-Box reasoning can also be performed finding if any of the individuals fit into the defined classes.

4.2.3 Semantic characterization

Semantic characterization is crucial as the resulting segmentation output determines the quality of the later identification step as the data mining algorithms require characteristic biotopes to train on. Using EUNIS class descriptions and interpretation guidelines (European Commission, 2007), a set of indicators tailored to the available input data for our test area were created. Detailed analysis of the EUNIS nomenclature showed that some indicators do not lend themselves to easily be detected by RS data. Therefore indicators were added to produce a meaningful formalization of the classes. The formalization can be written to an OWL ontology, which is able to store complex logical connections (axioms) in an OWL file.

An OWL ontology is composed of classes, individuals and properties. Classes are sets of individuals and properties come in two forms: an object property defines a relationship between two individuals and a data property places a data type constraint on the individual (W3C OWL Working Group, 2009). We use environmental variables (e.g., wetness, acidity, vegetation type, etc.) from the classification schemes and concepts from EAGLE to preserve interoperability by using this well-formalized vocabulary. All used indicators for this research are shown in Table 4.1. Examples of the EUNIS classes, *E1 Dry grasslands* and *E1.2 Perennial calcareous grassland and basic steppes*

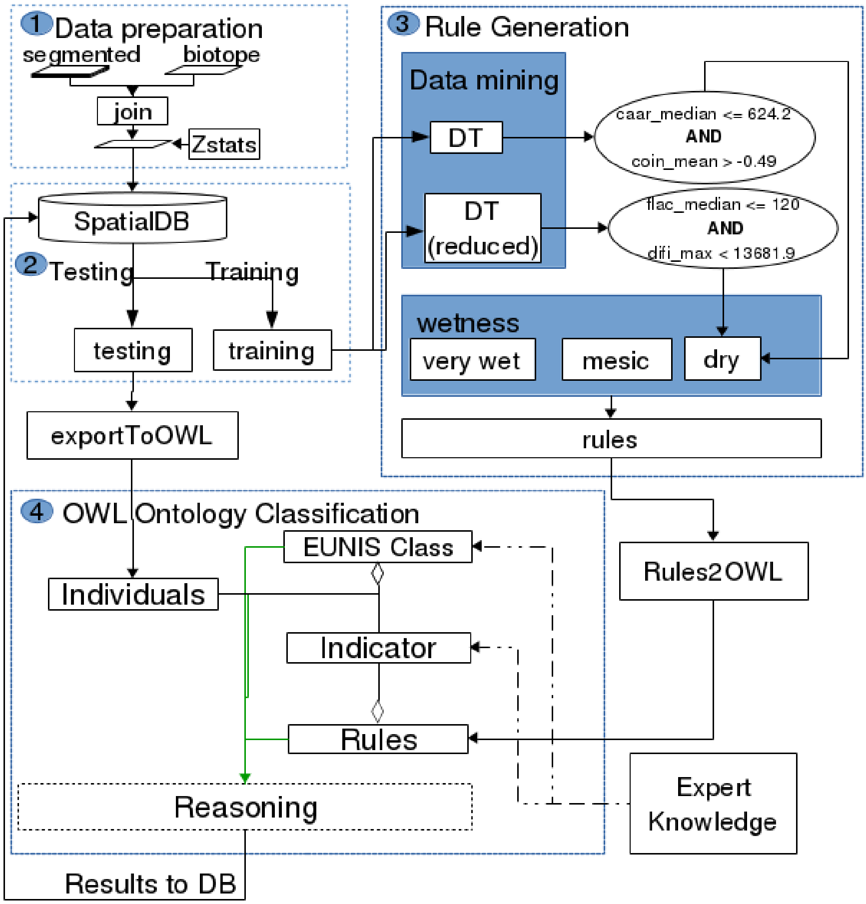

Fig. 4.3: 1) The thematic maps (land cover, biotope, soil, etc.) are unioned together and spatial statistics on various parameters (e.g. spectral, terrain, texture, etc.) are calculated for each combined polygon. 2) Training and testing data are created and saved in the database. 3) The rules are generated for each indicator from training data. 4) The rules are imported into the OWL ontology along with the testing data as individuals. The reasoner performs A-box reasoning to determine class membership.

modeled with selected remote sensing indicators are written in description logic (DL) below:

$$
\begin{aligned}
\text{E1} \quad & \equiv \exists \text{has\_eagleVegetationType } \{\text{"graminaceous"}\} \\
& \sqcap \exists \text{has\_natfloWetness } \{\text{"dry"}\}
\end{aligned}
$$

and

$$
\begin{aligned}
\text{E1.2} \quad & \equiv \exists \text{has\_eagleVegetationType } \{\text{"graminaceous"}\} \\
& \sqcap \exists \text{has\_natfloWetness } \{\text{"dry"}\} \\
& \sqcap \exists \text{has\_natfloAcidity } \{\text{"alkaline"}\}
\end{aligned}
$$

Since the EUNIS nomenclature exclusively differentiates grasslands between alkaline and acid **or** neutral acidity status, class E1.7 is formalized as follows:

$$
\begin{aligned}
\text{E1.7} \quad & \equiv \exists \text{has\_eagleVegetationType } \{\text{"graminaceous"}\} \\
& \sqcap \exists \text{has\_natfloWetness } \{\text{"dry"}\} \\
& \sqcap (\exists \text{has\_natfloAcidity } \{\text{"neutral"}\} \\
& \sqcup \exists \text{has\_natfloAcidity } \{\text{"acid"}\})
\end{aligned}
$$

Figure 4.4 shows two fragments of the developed domain ontology. All EUNIS grassland classes beginning with E are sub-classes of the category "EUNIS". All derived indicators are sub-classes of the concept "Indicators". Class vegetationType, shows a peculiarity, since it has been characterized as tree **or** shrub **or** herbaceous, whereas graminaceous is an indicator and sub-class of herbaceous at the same time. The same counts for the concept "wetness", categorized as wet **or** dry **or** mesic and acidity, categorized as acid **or** neutral **or** alkaline (see table 4.1).

4.2.4 Rule generation

The DT classifier, which is an "optimised classification and regression tree (CART)" was chosen as the base classifier for this methodology (Breiman et al., 1984). It generates rules to separate indicator labels, such as dry, mesic and wet that are then formalized in an OWL2 ontology to be able to use ontology-based reasoning for classification. To realize this task, the DT was parsed using a depth-first search algorithm (Cormen, 2009). Starting with the root node, the algorithm follows the left branch, visiting all children until it reaches the terminal leaf node. This branch lineage becomes the first rule. The nodes of the DT contain decision thresholds, the values variable shows the number of samples assigned to each class at that node (see figure 4.5) multiplied by the class weight and the entropy displays the information gain at that node. The class weight is calculated as:

$$\frac{\text{n\_samples}}{\text{n\_classes} * \text{bincount (y)}} \tag{4.1}$$

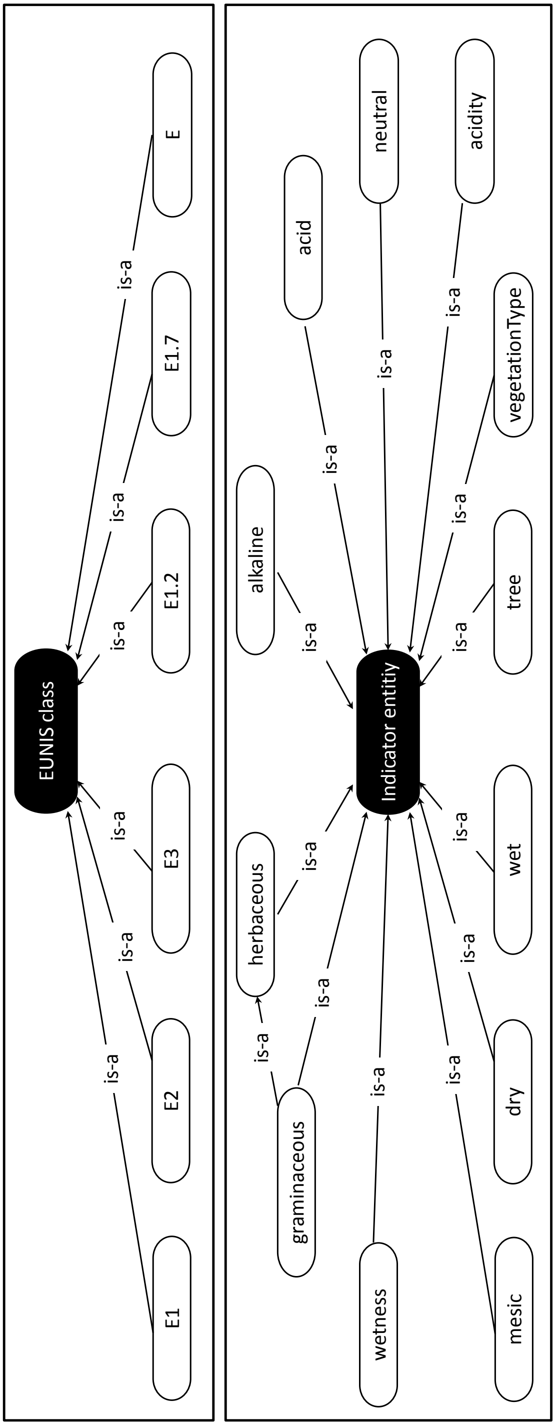

Fig. 4.4: Fragments of the developed base ontology.

All nodes visited before reaching the leaf node are chained with a logical “AND” together to create a rule. The rule is assigned to the class with the most members correctly classified at that leaf node. The process continues until all leaf nodes are visited. The rules are joined together by logical “OR"s and become a set of rules for the indicator under investigation. A portion of a decision tree trained on the indicator class ,*wetness* is depicted in figure 4.5.

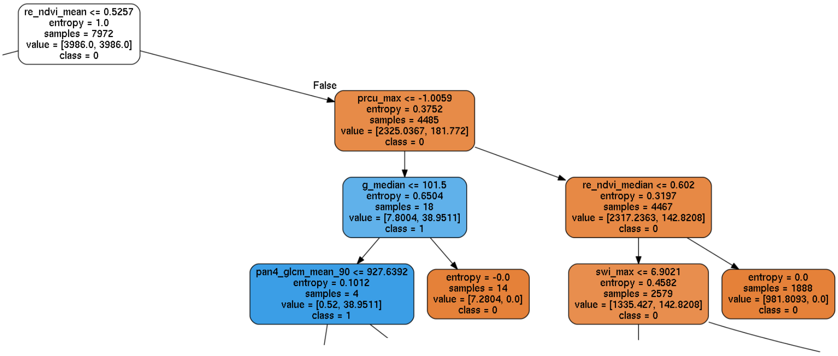

Fig. 4.5: A section of the right-side of a DT trained on alkaline indicator with the white node being the root node. Blue is alkaline while orange is not alkaline (class 1 and 0, respectively).

An example rule from the DT is shown below. The class "0" (non-alkaline) from “alkaline” has a rule that is generated by the decision tree algorithm as seen in 4.1 below. The first name is the feature/statistic’s name, followed by a threshold. For the DT, the last number is the node in the tree where the threshold comes from. This information is not currently being used.

Listing 4.1:

```
re_ndvi_mean,>,0.525677,0,
prcu_max,>,-1.005882,162
re_ndvi_median,>,0.602015,168
```

Listing 4.2:

```
<ObjectUnionOf>
  <ObjectIntersectionOf>
    <DataSomeValuesFrom>
        <DataProperty IRI="#has_re_ndvi_mean"/>
        <DatatypeRestriction>
          <Datatype abbreviatedIRI="xsd:double"/>
          <FacetRestriction facet="&xsd;maxExclusive">
            <Literal datatypeIRI="&xsd;double">0.5257</Literal>
          </FacetRestriction>
        </DatatypeRestriction>
```

```
    </DataSomeValuesFrom>
    <DataSomeValuesFrom>
        <DataProperty IRI="#has_prcu_max"/>
        <DatatypeRestriction>
          <Datatype abbreviatedIRI="xsd:double"/>
          <FacetRestriction facet="&xsd;maxExclusive">
            <Literal datatypeIRI="&xsd;double">-1.0059</Literal>
          </FacetRestriction>
        </DatatypeRestriction>
    </DataSomeValuesFrom>
    <DataSomeValuesFrom>
        <DataProperty IRI="#has_re_ndvi_median"/>
        <DatatypeRestriction>
          <Datatype abbreviatedIRI="xsd:double"/>
          <FacetRestriction facet="&xsd;maxExclusive">
              <Literal datatypeIRI="&xsd;double">0.602</Literal>
           </FacetRestriction>
        </DatatypeRestriction>
    </DataSomeValuesFrom>
   </ObjectIntersectionOf>
</ObjectUnionOf>
```

Listing 4.2 shows listing 4.1 in an OWL/XML representation. The rule has a collection of DataSomeValuesFrom within a nested datatype restriction corresponding to the rule threshold. A class can be defined by many rules containing multiple datatype properties that are chained together with logical AND (intersection) operators. The rules are then joined by a logical OR (union) operator as can be seen in the outer ObjectUnionOf. The rule can be written in description logic as shown in 4.2.4.

$$\begin{aligned}\text{non-alkaline} \equiv\ & \exists \text{has\_re\_ndvi\_mean}\{> 0.535677\} \\ & \cap\ \exists \text{has\_prcu\_max}\{> \text{-}1.005882\} \\ & \cap\ \exists \text{has\_re\_ndvi\_median}\{> 0.602015\}\end{aligned}$$

4.2.5 Ontology-based classification

After the algorithms produce rules for each indicator, these are added as facet restrictions to the OWL ontology. The polygons from the testing table are loaded from the database as OWLIndividuals into the same ontology. Furthermore, a reasoner can perform A-Box and T-Box reasoning over the defined axioms. In this procedure relationships between objects (subsumption, disjointedness, etc.) are discovered and checked for consistency during T-box reasoning. Using software for ontology engineering and management, such as Protégé, users can see how the defined axioms are related in the stored knowledge base (OWL) and check for logical consistency. If OWLIndividuals (objects) are in the knowledge base then A-Box reasoning can also be performed finding if any of the individuals fit into the defined classes. As EUNIS is an hierarchically structured classification scheme, testing that the formalization follows the same hierarchy is important. In this work the reasoner FaCT++ was used to classify all polygons by applying A-box reasoning over the rules. The classification results by the reasoner are written to the database (see figure 4.3). For the calibration and selection of suitable parameters for the classification algorithm the evolutionary search algorithm sklearn-deap[3] was used based on the Distributed Evolutionary Algorithms in Python (DEAP) (Fortin et al., 2012; Beyer and Schwefel, 2002).

The optimal parameters for the DT were determined by using 10 evolutions, a population size of 50, tournament size of 3 and a gene mutation probability of 0.1 (Fortin et al., 2012). The parameters for the DT that influence classification accuracy include: minimum samples leaf, minimum samples split, the max depth, the max features and the criterion ('entropy' or 'gini').

4.2.6 Validation

For the training and testing of the described algorithm, only polygons greater than $10m^2$ were selected. Furthermore they had to be identified as herbaceous or graminaceous plants according to the pre-segmentation. Finally, to evaluate the quality of the results in respect to recently more popular ensemble classification approaches the outcomes were compared to an ET reference classification (see table 4.2). We use precision[4] (positive predictive value), recall[5] (sensitivity, true positive rate), and f-score[6] to determine the accuracy of classification results. The precision score (4.2) is a reflection of how many of the objects that were classified were true positives. Recall (4.3) shows the classifier's ability to find all relevant objects (positive samples). The f-score is the harmonic mean of the precision and recall.

$$\frac{\text{true positives}}{\text{true positives} + \text{false positives}} \tag{4.2}$$

$$\frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \tag{4.3}$$

$$2 * \frac{\text{precision * recall}}{\text{precision} + \text{recall}} \tag{4.4}$$

First the rules are generated for each indicator and the metrics in 4.2, 4.3 and 4.4 are saved for accuracy analysis and for later scrutiny. The results for each indicator is saved in the database. Objects that meet the rule as defined in 4.1 are assigned to that class. The classified result is then compared with the actual class label to determine the quality of the results. The data were divided into 60% for training and 40% for validation. The DT undergo a

[3] `https://github.com/rsteca/sklearn-deap`

[4] `http://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision_score.html#sklearn.metrics.precision_score`

[5] `http://scikit-learn.org/stable/modules/generated/sklearn.metrics.recall_score.html#sklearn.metrics.recall_score`

[6] `http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html#sklearn.metrics.f1_score`

5-fold cross validation to verify results and the DT with the highest overall accuracy DT was chosen.

4.3 Results

4.3.1 Classification

For both indicators the ET classified more accurately than the DT in both precision and recall. The difference in recall between the classifiers was smaller than the precision. The small difference between recall, precision and f-score suggests that the DT balances precision and recall. The classifiers ranked features differently according to importance but the TPI was used by both classifiers to classify grassland wetness.

Table 4.2: Classification results of indicators using ET. The average value illustrates a weighted average over all regarded objects

Indicator	Class	Precision	Recall	F-score	Support
alkaline	non alkaline	0.99	1.0	0.99	5036
	alkaline	1.00	0.69	0.82	203
	avg	0.99	0.99	0.99	5239
wetness	dry	1.0	0.73	0.85	200
	mesic	0.95	1.00	0.97	4455
	wet	0.95	0.65	0.77	584
	avg	0.95	0.95	0.94	5239

Table 4.3: Classification of indicators using DT and FaCT++ reasoner. The average value illustrates a weighted average over all regarded objects

Indicator	Class	Precision	Recall	F-score	Support
alkaline	non alkaline	0.99	0.99	0.99	5036
	alkaline	0.70	0.75	0.73	203
	avg	0.98	0.98	0.98	5239
wetness	dry	0.65	0.72	0.69	200
	mesic	0.95	0.93	0.94	4455
	wet	0.62	0.69	0.65	584
	avg	0.90	0.89	0.90	5239

4.3.2 Most important features

The ET relied heavily on TPI while the DT determined RapidEye Normalized Difference Red Edge Index (NDRE) was the most important feature with TPI being second most important.

Table 4.4: Top 5 features as selected by ET and DT for wetness indicator and alkaline indicator

indicator	ET	DT
wetness	TPI	RapidEye NDRE
	Wind Effect	TPI
	SAGA Wetness Index	SAGA Wetness Index
	Diffuse Insolation	Catchment Area
	Morphometric Protection Index (MPI)	Wind Effect
alkaline	Wind Effect	NDVI from RapidEye
	Diffuse Insolation	TPI
	TPI	Green from Orthophotos
	RapidEye NDRE	Diffuse Insolation
	SAGA Wetness Index	Terrain Ruggedness Index (TRI)

As can be seen in table 4.4 the ET ranked one parameter's different statistics as the most important; in the case of wetness the TPI and for alkalinity the wind effect index.

4.3.3 Reasoning

Figure 4.6 shows the result of the reasoning process. In comparison to the original class model (see figure 4.4) the reasoner generated a consistent class hierarchy in a subsumption procedure. Therefore, parameters (e.g. wet, dry, alkaline) of the indicator categories acidity, wetness, vegetation type were identified as sub-classes of the respective category. In addition, the indicator "graminaceous" was recognized as a sub-class of "herbaceous". Even more important are the results of the reasoning process for the EUNIS classes. Based on the assigned indicators the hierarchical structure of the nomenclature was revealed. This refers to level two of the EUNIS nomenclature which were assigned as sub-classes of E because E has only one specifying indicator (herbaceous) whereas E1, E2 and E3 have one additional indicator (dry, mesic, wet). Furthermore the identification of graminaceous as sub-class of herbaceous led to the conclusion that: E1 must be a sub-class of E because E contains the indicator herbaceous whereas E1 contains the indicator graminaceous. The classes E1.2 and E1.7 were assigned as sub-classes of E1 because they include the indicator dry and additionally have an acidity indicator.

Saarburg has only one EUNIS dry alkaline grassland type: E1.2. The reasoner classifies E1.2 with 95% precision. The high precision rate means that dry alkaline grasslands are rarely incorrectly classified. The classifier was not able to identify all relevant positive samples and had 7 false positives. The only other explicitly defined non-alkaline biotope (neutral/acid) is E1.7, which had too few objects for training and testing.

4.4 Discussion

Since one of our research aims was to use the EUNIS nomenclature formalized in an OWL ontology to generate reproducible, interoperable and exchangeable classification outputs, we chose the DT as the base classifier for the proposed methodology. This study therefore follows the request of Janowicz (2012) to combine machine learning processes with semantic-based data handling to preserve interoperability and re-usability of classification processes by using semantic web standards like OWL2. The results clearly show the advantages of ontological classification approaches (see section 4.3.3) in terms of knowledge management and the ability to use ontological reasoning for classification, subsumption and consistency purposes. Ontological classification can support broader interoperability by applying usable and exchangeable W3C standard compliant data structures and allow vocabularies to be shared via Linked Data. Being able to analyze the rules generated and at the same time perform T-Box reasoning on the conceptual model (in this case EUNIS) allows a clear iterative process where experts can tune the conceptual model or find errors in the reference areas. Furthermore this reduces the likelihood of systemic errors from going unnoticed when using a "black box" model which analyze data in n-dimensional space which is hard for humans to interpret. Importing and using vocabularies from other scientific fields such as geology can potentially increase accuracy. The results therefore confirm previous studies on ontological classification and knowledge management (Forestier et al., 2012; Belgiu et al., 2013; Argyridis and Argialas, 2015) and additionally indicate possibilities of a direct integration of ontologies in machine-learning-based classification processes. The classification shows promising results for the indicators alkalinity and wetness with an overall accuracy of 85% for alkalinity and 76% for wetness. This confirms the results of related studies (Franke et al., 2012; Otukei and Blaschke, 2010), which successfully applied the DT algorithm for grassland conservation and land cover change. The proposed methodology facilitates formalized conceptualization by being able to visualize class hierarchies and interact with the results of A-box and T-box reasoning. New relations between classes can be defined with varying relationships (intersection, union, etc.) and terms can be imported from different linked data sources. Even though the classifier only reached 70% and 65% precision score for alkaline grasslands and dry grasslands respectively (4.2), it was able to correctly classify 95% of dry and alkaline grasslands (E1.2).

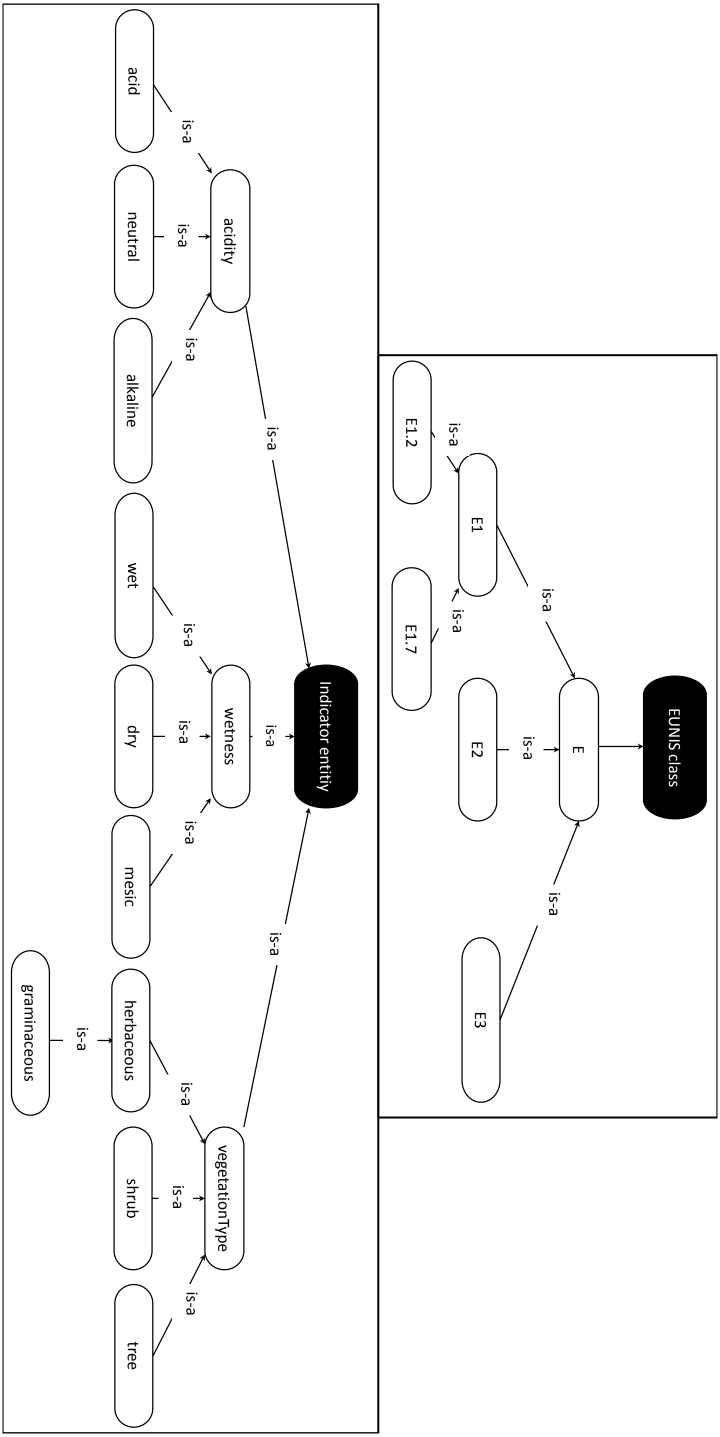

Fig. 4.6: Fragments of the inferred ontology

By using the hierarchy, polygons can be inspected to determine which of the rules were not met for class membership. Furthermore, the high recall rate in identifying dry alkaline grasslands suggests that the EUNIS conceptualization is accurate.

In comparison to the ET classifier (overall accuracy for 90% for alkalinity and 86% for wetness) the DT classifier shows considerable lower results. This leads to the conclusion that the ET classifier is better suitable for this kind of classification problem and that the ontological approach should be extended to ensemble-based classifiers in the future.

The importance of the TPI in determining the wetness of grasslands suggests that the wetter grasslands are found in areas lower than their surrounding. The DT's use of the NDRE to classify the wetness of grasslands is also supported by other studies (Schuster et al., 2012). Furthermore, inspecting the incorrectly classified polygons points to a problem with smaller boundary polygons which straddle dry and mesic biotopes. The same proved to be true for wet polygons that were wrongly classified as mesic.

4.5 Conclusion

This work illustrates a methodology for the combination of ontology-based knowledge management and machine learning for classification of multiple spatial data sources. The main advantages include facilitating expert knowledge management and the reasoning capabilities of ontologies like subsumption and consistency checks. Furthermore, the generated ontology can be uploaded to the Linked Data Cloud or be used in other studies. Alternatively, the applied DT classification methodology shows good results but does not reach the accuracy of ensemble-based classifiers like the ET, the methodology shall be transferred to ensemble-based classifiers in the future.

4.6 Appendix

4.6.1 Ontologies

The OWL ontology with rules generated by the DT algorithm used in this study is located at: `http://www.niklasmoran.com/ontologies/saarburg_grasslands.owl`

4.6.2 Indices used for classification

Table 4.5: Indices used for classification. OP describes indices of the orthophotos, SAT describes indices derived from RapidEye satellite data.

Based on dtm/dem	Based on multi-spectral orthophotos (OP)/ satellite data (SAT)
Aspect	Red, Green, Blue (OP)
Catchment Area	Bare Area Index
Convergence Index	Normalized Difference Vegetation Index (Op & SAT)
Curvature Classification	Normalized Difference Wetness Index (Op & SAT)
Double Difference Vegetation Index	Near Infrared (Op & SAT)
Diurnal Anisotropic Heating	Panchromatic (OP)
Diffuse Insolation	Normalized Difference Red-Edge (SAT)
Flow Accumulation	Grey-level Co-occurrence Matrix (GLCM)
Morphometric Protection Index	
Multiresolution Ridge Top Flatness Index	
Multiresolution Valley Bottom Flatness Index	
Profile Curvature	
Slope	
SAGA Wetness Index	
Total Insolation	
Topographic Position Index	
Terrain Ruggedness Index	
Wind Effect	
Normalized Digital Surface Model	

5

Finding the optimal scale for habitat mapping

Simon Nieland, Birgit Kleinschmit, Michael Förster

Summary. The size and scale of habitats is an important mapping parameter in habitat monitoring as it strongly influences the assessment of protected areas. To objectify Natura 2000 monitoring, procedures are needed to identify optimal mapping scales of habitats.
Objectives This work proposes a workflow for automated delineation of selected Natura 2000 heathland and grassland habitats based on remote sensing outputs and aggregation rules. It examines the influence of a MMU and KS for the automated delineation of certain Natura 2000 habitat classes and compares a manual with an automated aggregation procedure.
Methods This work uses an aggregation procedure based on SPARK to delineate certain heterogeneous habitats and illustrates a methodology of finding the optimal MMU and KS for each habitat type. It furthermore compares automated aggregation results with manual delineation performed by surveyors.
Results The automated, remote sensing-based aggregation approach achieved similar correspondence to Natura 2000 mapping rules as the manual mapping (between 30-60% agreement). Optimal MMU and KS depend on the particular Natura 2000 habitat type. Combined, multi-class assessments achieved better results than analyses with only one destination class.
Conclusions This analysis showed that each habitat type has its optimum mapping scale, which cannot easily be implemented in manual interpretation guidelines. Automated class assignment makes scale specific evaluation easier and can improve the spatial accuracy and comparability of the results. Natura 2000 management should try to develop well-balanced interpretation guidelines, which better represent the conceptualisations applied in the mapping methodologies.

Submitted as *Finding the optimal scale for habitat mapping - a remote sensing-based aggregation approach* to Landscape Ecology

5.1 Introduction

The loss of biological diversity is one of today's key environmental challenges. Preserving nature is a global concern, as it provides critical ecosystem services (Vanden Borre et al., 2011). The HabDir and the BD of the EU can be regarded as international legal tools for nature protection and are the legal basis for Natura 2000, the largest international network of protected areas (Popescu et al., 2014) . In order to create a sustainable and comprehensive monitoring program across Europe, the HabDir obliges each EU member state to provide a report on the status of the designated nature conservation areas every six years. Reports are expected to use the habitat types from the "European Nature Information System" (EUNIS) or the habitat types listed on Annex I of the Habitats Directive (Evans, 2006). Since data of these nomenclatures are mostly derived from national or local mappings and subsequent nomenclatures, there is an interoperability gap regarding the thematic content of this kind of information (Nieland et al., 2015b; Louette et al., 2011).

Mapping habitats requires sufficient experience in surveying, a thorough knowledge of plant species and sociology, soil processes, management activities and environmental dynamics in general (Schmidtlein et al., 2014). Since there is often no clear thematic border but rather a floristic gradient between different habitat classes, delineation is always subjective and dependent on the personal perception of the surveying ecologist (Schmidtlein, 2004). Additionally, on-site habitat delineation is particularly difficult as in most protected zones there are areas, which cannot be accessed or surveyed comprehensively. Therefore, the spatial variability of the mapped areas is often inadequately represented (Lucas et al., 2007) and mappings of different surveyors, using the same standard mapping method, rarely match each other (Cherrill and McClean, 1999). In fact, on an international level, agreements between maps are even worse since data sets, which use a European nomenclature, are mostly derived from national products with differing descriptions and conceptualisations. These incongruences are problematic for harmonization and comparability of Europe's nature conservation data. Förster et al. (2008) and Vanden Borre et al. (2011) state that until now, there is no existing standard, which defines the spatial reference size of a habitat (e.g. a MMU)). Mapping guidelines sometimes include MMU's but these are mostly the same for all habitats and reflect rather practical issues (e.g. the operability of the mapping in the field) than the optimal size in regard to characteristics and variability of a certain class (Vanden Borre et al., 2011). As a matter of fact different habitat types are mapped in differing scales due to the experience of the surveyor and the spatial characteristics of the designated class which leads to scaling, grouping and zoning problems described in the MAUP (Openshaw, 1984). It is known, that the MAUP has a substantial influence on all kinds of ecological studies, especially the ones dealing with aggregation issues (Jelinski and Wu, 1996).

For example prevalent tree species like Luzulo-Fagetum beech forests (Natura 2000 code 9110) are mapped rather extensively, whereas habitat types with very special requirements regarding the local characteristics like e.g. Molinia meadows (Natura 2000 code 6410) are mapped on a very detailed level. This is especially relevant for habitat types that contain different types of land cover and respective species (e.g. a heathland habitat that contains water, bare sand, dry heath, wet heath, dry grassland etc.). Due to its heterogeneous structure and comparatively small dispersion area, heathlands represent a challenge for Natura 2000 monitoring and are therefore perfectly suitable as a use-case for the application of aggregation approaches (Thoonen et al., 2013). Often, the delineation of habitats has a direct influence on the outcome of preservation assessment. If, for example, a dry heathland area is delineated very strictly the preservation status would be considered favourable, but the same area could have an unfavourable preservation status by expanding the outer border to parts which have negative influence on the designation (e.g. in our example grass or tree encroached areas). Therefore, in regard to interoperability of nature conservation data, fixed standards for habitat delineation are needed to ensure comparable monitoring across Europe (Manakos 2013).

Remote sensing has considerable potential to realise this challenging task by providing biophysical and biochemical indicators of ecosystem functioning (like Leaf Area Index etc.) (Skidmore et al., 2015) and is able to map some fine-scale indicators (e.g. ground cover of certain species), which can be used to estimate the conservation status of habitats (Spanhove et al., 2012). When considering remote sensing data for mapping or monitoring biodiversity, the spatial resolution (sensor pixel size) of the sensor is an important parameter influencing the estimation and measurement of vegetation diversity (Levin, 1992; Stohlgren et al., 1997) and therefore crucial for the reporting of ecologically valuable habitats. This is especially relevant when assessing a suitable scale to map the object of interest (Hengl 2006; Stohlgren et al. 1997), which inherits a number of scale matching problems (Rocchini et al., 2010). It is an often underestimated but essential part of remote sensing products to find the right balance between pixel size and species diversity sampling unit (Rocchini et al., 2015). Similarly, when generalising remote sensing classification results of species to habitats, the number of included pixels should be larger than the number of classes required for the generalisation rules, while a generalisation with a high number of pixels might lead to omitting smaller areas. A method to generalise classification results are Reclassification Kernels as introduced e.g. by (Barnsley and Barr, 1996), which are utilized in several application fields, such as urban mapping (van der Kwast et al., 2011) or habitat delineation (Keramitsoglou et al., 2015). While it is well known that reclassification kernels and the MMU influence the quality of a generalisation product, to our knowledge there has been no systematic study to date to find suitable parameters for habitat mapping. Furthermore no studies respond to the demands of (Corbane et al.,

2015) and (Vanden Borre et al., 2011) to analyse the typical surface area range in which especially heterogeneous habitat types occur. Therefore, this work

- proposes a workflow for automated delineation of selected Natura 2000 heathland and grassland habitats based on aggregation rules,
- examines the influence of MMU and kernel size (KS) for the automated delineation of certain Natura 2000 habitat classes and
- compares a manual with an automated generalisation procedure and evaluate the results in regard to the descriptions of the respective interpretation manuals.

5.2 Method

Method This section gives an overview of the spatial aggregation procedure, illustrates the evaluation approach and shows the methodology of finding the optimal MMU and scale (kernel size) for each habitat type and comparing automated aggregation results with manual delineation performed by surveyors.

5.2.1 Study area and Data

The input data set for this study is a remote sensing-based classification of an area in the nature conservation area Kalmthoutse Heide in Belgium[1] (see figure 5.2). The area is approximately $20km^2$ and is mainly covered by dry and wet heathland, grassland, water bodies and forest. The classification was performed by Thoonen et al. (2010) and is based on AHS-160 Airborne hyper-spectral images (2.5m ground resolution). The classification process uses a hierarchical classification framework which takes into account contextual information. It includes over-arching land cover types on the first level (such as heathland, grassland, forest, water, sand dunes, arable land) and iteratively classifies those areas into more detailed habitat characteristics until the fourth level is reached (the age structure of the *Calluna Vulgaris*, or grassland species like *Nardus Stricta* etc.) (Thoonen et al., 2013).

5.2.2 Generalisation Rules

Since habitat types are mostly composed of several indicators a generalisation regarding the content and the spatial distribution of their characteristics and coverage is needed. According to the Natura 2000 manual (European Commission, 2007), for example a heathland habitat of the class "4030-European dry heath" can include parts of bare soil, dry and wet heathland,

[1] http://natura2000.eea.europa.eu/Natura2000/SDF.aspx?site=BE2100015

shrubs, encroached grassland areas and mosses or lichens. Therefore rules of percent coverage are necessary to delineate the habitat (see table 5.1). These rules are mainly included in the descriptions of the respective nomenclatures (cite interpretation manual). Basis for this work are rules created by the INBO taking into account the mapping guidelines of the habitats directive (Thoonen et al., 2010). Table 5.1 shows the observed Natura 2000 habitat classes. Since class “4030 - European Dry Heath” and class “2310 - Dry Sand Heath with Calluna and Genista” were not considered as dividable by remote sensing these two classes have been combined for this work. It is even difficult for surveyors to differentiate between 2310 and 4030 areas in the field and for certain areas both habitat types were identified as correct (De Graaf et al., 2009).

Table 5.1: Selected Natura 2000 habitats, descriptions and subsequent generalisation rules. Abbreviations: heathland (H), dry heathland (Hd), wet heathland(Hw), grass encroached heathland (Hg), grass encroached, wet heathland dominated by molinia (Hgmw), grass-encroached, dry heathland dominated by molinia(Hgmd), sand (S), grassland (G), dry, permanent natural grassland (Gpnd), permanent grassland dominated by juncus effusus (Gpj), agricultural permanent grassland (Gpa), temporary grassland (Gt) , sand and dry, permanent natural grassland (SandGpnd), arable land (A), forest(F), water (W)

Habitat code	Description	Generalisation rule (ranges in % ground coverage)
2330	Inland dunes with open Corynephorus and Agrostis grasslands	H:0-50, Hd:0-50, Hw:0-10, Hg:0-50, Hgmw:0-10, Hgmd:0-50, S:0-100, G:0-100, Gpnd:0-100, Gpj:0-10, Gpa:0-10, Gt:0-10, SandGpnd:50-100, F:0-15, W:0-10, A:0-10
2310/ 4030	Inland dunes with Calluna heath/ European dry heath	H:30-100, Hd:0-100, Hw:0-50, Hg:0-100, Hgmw:0-50, Hgmd:0-80, S:0-70, G: 0-70, Gpnd:0-70, Gpj:0-10, Gpa:0-10, SandGpnd: 0-70, F:0-30, W:0-10, A:0-10
4010	Northern Atlantic wet heaths with Erica tetralix	H:30-100, Hd:0-50, Hw:0-100, Hg:0-100, Hgmw:0-100, Hgmd:0-50, S:0-10 ,G:0-10, Gpnd:0-10, Gpj:0-10, Gpa:0-10, Gt:0-10 , SandGpnd:0-10 , F:0-30 , W: 0-30 , A: 0-10

5.2.3 Generalisation Algorithm

The Aggregation algorithm is based on the SPARK introduced by (Barnsley and Barr, 1996). This contextual aggregation procedure generates complex classes out of existing thematic raster datasets. Based on an adjustable, rectangular moving window, the number of pixels according to each thematic class can be analysed and the percent coverage of the classified characteristics can be calculated for each kernel. As already mentioned each class has its individual descriptions and can contain a complex mixture of spatial characteristics, such as bare sand, dry grassland species or heath species on dry soil etc. If the percentages regarding the coverage fit to the pre-defined rules (see table 5.1) the centre pixel can be assigned to the respective class (see figure 5.1).

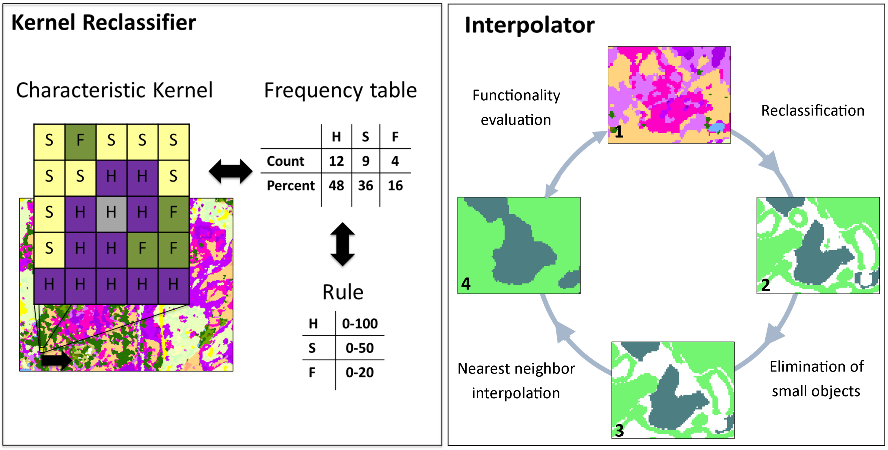

Fig. 5.1: Overview aggregation algorithm. The Kernel Reclassifier (left) uses a characteristic, rectangular moving kernel to produce frequency tables for each sector, which are compared to the respective rule. If the frequency table matches the requirements of the corresponding rule, the centre pixel is assigned to the subsequent habitat class. The interpolatorion (right) uses the results of the reclassification (2), eliminates objects that are smaller than the defined MMU (3) and interpolates the occurring gaps with a spatial nearest neighbour interpolation (4). The results are then evaluated regarding its functionality by taking into account the base dataset (1) (see section 5.2.4). Adapted from (Nieland et al., 2015a)

For this work the original SPARK algorithm was partly adopted, as it was not necessary to include a pre-classification process, since the procedure uses existing remote sensing classification results instead of classifying the imagery itself. Another difference to SPARK is that the aggregation rules were defined by taking into account respective class descriptions (see section 5.2.1) instead of generating characteristic template kernels that typify the habitat classes.

To provide consistent and unambiguous results the proposed procedure uses a two-step approach (see figure 5.1). In the first step the kernel labels its centre according to the defined rule. This procedure iterates over prevalent KS (3x3 to 45x45 = $56m^2$ to $12,656m^2$) to examine its influence on the level of correspondence between the percent coverage according to the rule and the actual generated coverage. Since the rules are created for manual fieldwork and based on ecological characteristics rather than being perfectly adjusted as non-overlapping rules, multiple labels do occur in the results. These pixels are mostly transitional areas, which according to the interpretation manual, are not to be classified as a certain class. In the second step the algorithm eliminates pixels with multiple labels and areas that are below an adjustable MMU and performs a nearest neighbour interpolation to fill the resulting gaps. In order to evaluate the correctness and the benefit of the second processing step the results were calculated including the second step (all classes at once) and without the second step (every class separately). The former will be further referred to as "multi-class approach" whereas the latter will be called "one-class approach". In order to examine influences of the MMU on the level of correspondence to the defined rules the results were iteratively calculated for MMUs between $100m^2$ to $9,900m^2$ in steps of $100m^2$. A kernel size larger than 45x45 and an MMU greater than $9,900m^2$ was not calculated because overlaps of different habitat types occur. Especially the classes with a smaller spatial extent (inland dunes / 2330) would not be detected, because a surrounding larger class will be increasingly preferred with a growing kernel size and smaller patches would be erased due to a large MMU (see figure 5.2). Moreover, combining high kernel sizes and large MMU's result in very few objects. That means there is mostly only one very large object left, which is relatively consistent regarding its spatial characteristics. Therefore, results with higher KS and MMU stay stable until dropping to zero when this object would be deleted.

5.2.4 Evaluation

To evaluate the automated delineation results and compare them to the respective rules, the number of pixels of the original classification result inside each delineated habitat object was calculated and compared to restrictions of the corresponding rule. This can either be done for the manual delineation or for the automated delineation in each scale (MMU and kernel size) (see 5.3). This procedure provides on the one hand information about objectivity and manual mapping compliance and gives on the other hand the possibility to determine optimal MMU and kernel sizes for each habitat class. Therefore, the evaluation will be divided into two parts, the functionality evaluation (proves the correctness of the rules) and the applicability evaluation (proves the correspondence of the generalisation result and the manual delineation) (Nieland et al., 2015b).

5.3 Results

The following section illustrates the results of the manual and automated habitat delineation and assesses the reproducibility, comparability and accuracy of the resulting datasets. Since very few strict habitat borders exist and transitions between habitat classes are gradual rather than abrupt, there is, in most cases, no right or wrong delineation. Therefore, we try to analyse to which degree the produced areas fit to a certain standard (in our case the rules developed on basis of the HabDir and reference field) and which scale (MMU) is appropriate for the mapping of certain habitat classes. Regarding the results, there is a recognisable overestimation of class 2310/4030 and an underestimation of class 4010 in the automated delineation, while class 2330 has no clear trend regarding under- or overestimation (see figure 5.2). The multi-class approach (top) appears more generalised and connected, whereas the one-class approach is more fragmented, especially for class 4010.

Table 5.2 illustrates the level of agreement between the generated rules and the manual delineation of the protected areas. It shows the percent correspondence of the manually delineated habitat areas that match the respective rule to the ones that do not match the rules. It furthermore shows the results for all regarded objects and additionally divides the results in three size classes (under 0.5 ha, 0.5-1 ha and over 1 ha). The overall correspondence ranges between 44.89% for class 4010 to 61.74% for class 2310/4030. Class 2330 has better rule-correspondence with objects under 0.5 ha and worse results over 1 ha, whereas class 2310/4030 shows better results with larger objects (over 1 ha) and performs worse on small objects (under 0.5 ha). Class 4010 has similar correspondence in all size classes (40.00%-46.66%).

Figure 3 shows the evaluation of the multi-class approach in a heat map illustration. For the functionality evaluation, the maximum values range from 89.47% (class 4010) to 100% (class 2330 and 2310/4030) correspondence. It can be recognised that MMU as well as KS have an influence on the results. The best results for class 2330 occur with average to high MMU ($800 - 9900m^2$) and small KS (3 to 10), whereas class 4010 has its optimum at very high KS (41-43) and MMU ($6000 - 9900m^2$). Class 2310/4030 achieves the highest functionality results for medium to high MMU (over $4000m^2$) in all KS. Since high KS as well as high MMU are reducing the number of areas that have to be investigated, the calculations of areas with high KS and MMU refer to only a few objects per class.

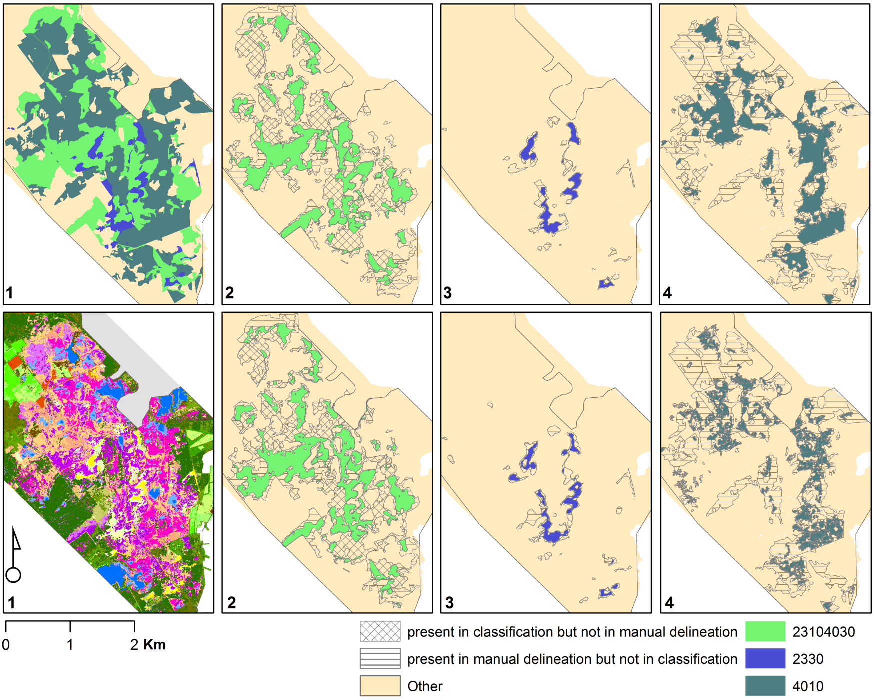

Fig. 5.2: Results of the aggregation of the multi-class (top) and single-class (bottom) approach. From left to right: (1) top: The manual delineation. Each colour represents one class. Bottom: The classification result. Each colour represents one derived class (2-4) Results of the aggregation algorithm (with optimal combination of MMU and KS) of class (2) 2310/4030 (KS: 7, MMU: 5700), (3) 2330 (KS: 21, MMU: 9500) and (4) 4010 (KS: 3,MMU: 1800) compared to the manual delineation. The crosshatched part illustrates areas that are present in the automated classification result and not in the manual delineation. The linear hatched part illustrates areas that are present in the automated classification result and not in the manual delineation.

The applicability evaluation illustrates the correspondence between the multi-class, two-step reclassification approach and the manual delineation. The values describe the percent spatial correspondence of the automated reclassification and the manual delineation. The results show an optimum agreement between 40 and 55.5 per cent but, in contrast to the functionality evaluation for class 2330 and 2310/4030, the best results occur at higher KS and MMU. Class 2330 has an optimum around KS 23 and MMU 9900m^2, whereas class 2310/4030 generates an optimum around KS 9 and MMU 5500m^2. Class 4010 has its optimum at KS 3 and small to medium MMU (around 2000m^2). To discuss and evaluate the results of the automated

Table 5.2: Agreement between manual delineation and rules. Obj (Sum) specifies the total amount of manually delineated objects per class. The per cent agreement illustrates the proportion of resulting objects, which are matching or not matching the corresponding rule.

Habitat class (HabDir)	Spatial dimension (m^2)	Obj. according to rule	Obj. not according to rule	Obj (Sum)	Per cent agreement
2330	total	16	17	33	48.48
	<5000	5	5	10	50.00
	5000-9900	7	5	12	58.33
	>1000	4	7	11	36.37
4010	total	101	124	225	44.89
	<5000	42	48	90	46.66
	5000-9900	18	27	45	40.00
	>9900	41	49	90	45.56
4030/2310	total	142	88	230	61.74
	<5000	53	48	101	52.48
	5000-9900	32	17	49	65.31
	>9900	57	23	80	71.25

delineation in respect to scale questions it is essential to make sure that a bigger KS and larger MMU leads to output objects with a higher mean surface area. The results show a strong correlation between object area and KS and MMU. The bigger the used MMU and KS, the bigger the resulting mean area in the output data set. The same relationship holds the Shannon diversity index, which measures the fragmentation in the resulting data set in respect to the subsequent classes. SHDI describes the proportion of the landscape occupied by the class i. As anticipated, the fragmentation is high for small KS and MMU and becomes smaller with rising values of both variables (see figure 5.3).

The functionality evaluation of the one-class approach shows similar percent ranges to those in the multi-class approach (see figure 5). They reach from around 23% (medium to big KS and small MMU in class 4010) to 100% (high MMU and small KS in class 2330 and high MMU in all KS for class 2310/4030). Class 2330 and 4010 seem to prefer small KS and medium to high MMU's whereas 2310/4030 has good results at high MMU in all KS.

The applicability evaluation shows a similar trend in all three studied habitat classes. High KS's have better agreement to the manual delineation whereas the MMU seems to have a limited influence on the correspondence.

$$SHDI = -\sum_{i=1}^{m} P_i \, lnP_i \tag{5.1}$$

Figure 5: Relation between SHDI, MMU and KS in the output data set. Colours indicate the SHDI total of the output datasets.

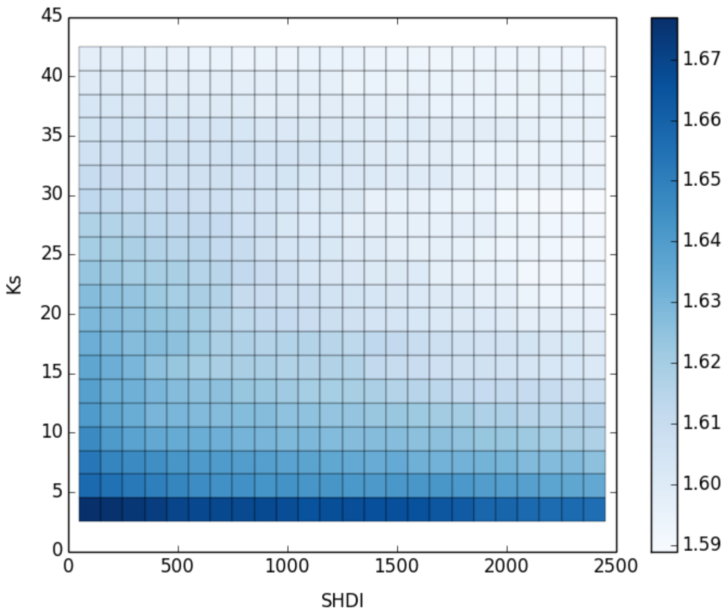

Fig. 5.3: Relation between SHDI, MMU and KS in the output data set. Colours indicate the SHDI total of the output datasets.

5.4 Discussion

The presented work compares an automated habitat aggregation approach to a manual approach and tries to evaluate the underlying principles of their structure. That involves on the one hand the composition of the habitat areas in respect to land cover categories and other biophysical parameters and on the other hand the minimum size of the habitats. The rather low correspondence of the manual delineation with the developed aggregation rules clearly reflects the subjectivity of field mapping mentioned by (Cherrill and McClean, 1999) and (Lucas et al., 2007) and illustrates the MAUP in the practical work of field surveys. Comparability of aggregated ecological data remains challenging and hinders interoperability on an international level.

Dry grasslands on inland dunes (2330) have a rather small ecological niche. Therefore, the rules defined by (Thoonen et al., 2010) are set very rigidly, especially for the occurrence of forest, water, agriculture, intensively used grassland, and wet heathland in the kernel (see table 5.1). Hence, in linear delineation as well as in kernel-based generalisation, this class is non-contiguous and fragmented (see figure 5.2-1 and 5.2-3). This is can also be seen in the functionality evaluation (see figure 5.4 and 5.5), where 2330 shows

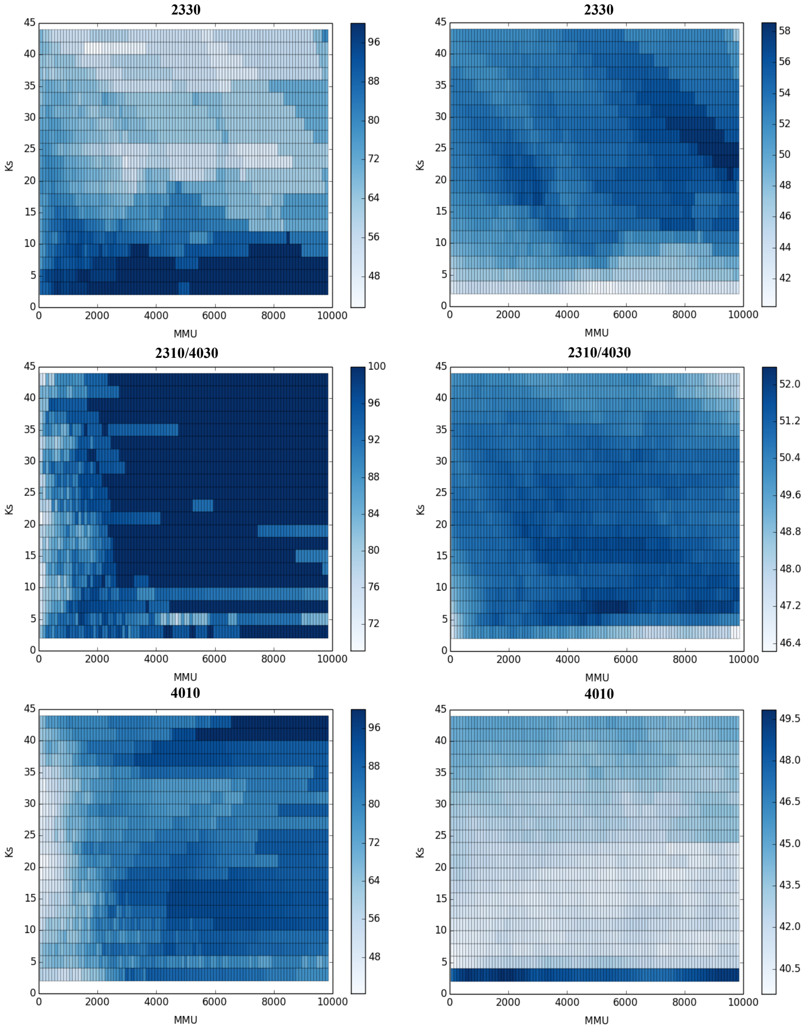

Fig. 5.4: Left: Functionality evaluation of the multiclass, two-step classification approach. Right: Applicability evaluation of the multiclass, two-step classification approach. Colours indicate the level of correspondence (in %) to the defined rule.

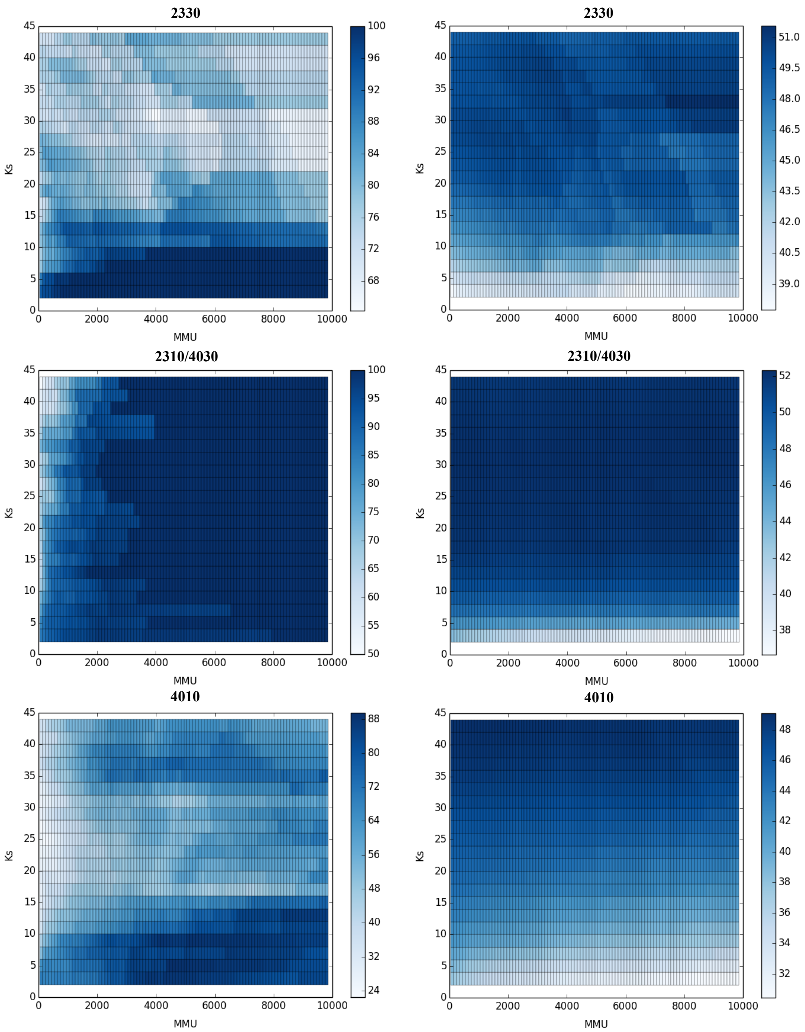

Fig. 5.5: Left: Functionality evaluation of the one-class classification approach. Right: Applicability evaluation of the multiclass, two-step classification approach. Colours indicate the level of correspondence (in %) to the defined rule.

best results at low KS (3-11) which reflects the small spatial dispersion of this class. The manual delineation tends to be more generalised, which is evident by looking at the peak around MMU $8000-9900m^2$ for a KS of 21 to 31 in the applicability evaluation for the one-class and the multi-class approach (figure 4 and 7). The MMU seems to have limited influence on functionality and applicability, since it is clearly positive to retain even small patches, while a maximum patch size (when the first correctly classified habitat patches drop out of the generalisation process) was not reached until MMU of $9900m^2$. The conflicting results of the applicability evaluation and the functionality evaluation lead to the conclusion that either the manual delineation does not adequately correspond to the rules, or that the rules are not sufficiently suitable for the mapping of the respective classes.

The dry heathland (2310/4030) has a larger spatial dispersion than the other classes in the study area. The defined rules are more general than for 2330 and cover wider ranges of the different heathland types as well as forest (see table 5.1). Consequently, dry heathland areas, when implementing the generalisation rules cover larger areas. However, the rules clearly overestimate the spatial expansion of this class compared to the manual delineation independently from the selection of KS and MMU. For rule functionality, the level of correspondence increases with larger MMU (above approx. $2000m^2$) and KS (above approx. 9) for the multi-class and one-class approach, which can be expected with more general rules, preferring larger patches. Since the manual delineation seems to be more specific (preferring smaller patches) than the generalisation rules, the relatively small optimal KS (7) and MMU ($5700m^2$) for the applicability also indicate that the manual delineation have been detailed for these habitat classes. Further, in some parts of the study site, the presence of wet and dry heath is very fragmented which makes distinguishing between the different habitats hard and subjective. Therefore, from an ecological view, both classes are possible in some cases depending on the delineation.

The rules for wet heathland (4010) areas include larger ranges for most heathland types as well as water, while minimizing the inclusion of different grassland types. Applying the rules irrespective of MMU and KS leads to an under-representation of the habitat compared to the manual delineation. While the rules performed best for smaller KS (3-13) in the one-class reclassification, the trend is inverse (KS of 43 and 45 perform best) with the multi-class approach. This is also reflected in the applicability evaluation. Larger KS results in a better applicability in the one-class reclassification, while the KS of 3 has the highest level of correspondence in the multi-class approach. When comparing the resulting habitat maps it is clearly visible that the reclassification at KS 3 produces many small objects which were eliminated and added to the class 2310/4030, when the KS was higher than 3. Therefore, KS 3 estimates a higher spatial proportion of 4010 in the test area, which leads to better results at KS 3 in all MMUs. The reasons for the underestimation of class 4010 are on the one hand that the heathland occurs in the undergrowth of trees and is therefore only partly recognisable with remote sensing images, on the other hand some areas were assigned as 4010 in the manual delineation which are allocated as 2310/4030 in the automated delineation. From the authorsâĂŹ perspective this is partly because class 4010 is overestimated in the manual delineation. Better-balanced rules can be a solution for this problem.

Generally, the manual delineation tends to be more generalised than the automated one. Even with large KS and very smooth habitat borders the manual delineation supplies more generalised information. The results of the one-class and the multi-class approach show similar quality, but when looking at the maps (see figure 5.2) the multi-class approach is much cleaner with less unwanted fragments and therefore superiorly reflects a manual delineation approach. Given the overall results of this systematic aggregation, it could be shown, that a generalisation of habitats from basic remote sensing derived vegetation classes is possible. The functionality of the classes could be tested sufficiently. While smaller and more disperse classes show a higher level of correspondence at smaller KS, largely distributed habitat show better agreement at larger KS. The MMU was less influential, because the accuracy did not decrease with MMUs greater than 1 ha, which is very surprising because of the absence of a MMU in the interpretation guidelines. Only for the class 2310/4030 there is a clear tendency to show a higher functionality with larger patches. Overall, it seems that the correct composition of the habitat as defined in table 1 (and reflected via KS) is much more important than the overall size of a habitat (as reflected by the MMU). The applicability of the results depends to a large extent on the reference data from the manual delineation of habitats. Manual delineations tend to predefine a certain patch size of the habitats, which can be found in the optimal levels of correspondence of the applicability tests. However, this contradicts very often the findings of the functionality. While the best application of the rules for dry grassland on inland dunes could be found at low KS, the best applicability was found at much higher KS, due to the inherent generalisation process of the manual mapping. The inverse phenomena could be found with dry heathland areas, where the generalisation results came up with more general patches than the manual mapping. Subsequently, the optimal KS of the functionality test was much lower than for the applicability evaluation. Generally, the results of the multi-class approach are more difficult to interpret than for the one-class approach. This can be expected as the aggregation implicitly includes the habitat or plant competition. The multi-class approach worKS very well for classes with mainly non-overlapping rules (as classes 2330 and 2310/4030 in this case). However, overlapping rules cause misleading results for the separation of habitat types. An example is the high level of correspondence for class 4010 at KS 3. The class rules between 2310/4030 and 4010 overlap, leading to strong over- and underestimations. Therefore, overlapping in class definition should be handled with great care to prevent imbalanced results.

Functionality and applicability evaluation can have different types of errors (Nieland et al., 2015b). This includes firstly the manual delineation and the rule-base of the habitats. Although habitat mapping in the study area was performed with great care, the results often include a generalisation, which does not match the given rules of aggregation. As shown in this example, it is not just a matter of defining a MMU or KS per habitat, but rather to define the expected coverage percentages of different vegetation components, when going out in the field. This should decrease the discrepancy of manual mapping and applying the rule-base. The aggregation rules are chosen to correspond with the HabDir, but the objectives of the regional nature conservation agency are not always in agreement with the more overarching general European goals do not perfectly (Förster et al., 2008). Remote sensing classification might also include a variety of impreciseness (Rocchini et al., 2013) ranging from gradients in habitat changes (instead of crisp classes) to scale issues between classes and sensor resolution (Small, 2001).

5.5 Conclusion

Automated remote sensing-based aggregation procedures can be a big advantage for the designation of nature conservation areas especially in respect to reproducibility and comparability of mapping results on an international level. This procedure increases objectivity which is on the one hand a big benefit for comparability and comprehensive evaluation of nature conservation areas, but may on the other hand hamper site managers to include site specific characteristics depending on the personal expertise and experience. This analysis clearly showed that each habitat type has its optimum mapping scale, which, due to the increasing complexity, cannot easily be implemented in manual interpretation guidelines. Automated class assignment makes scale specific evaluation easier and can therefore also improve the spatial accuracy of the results. Moreover, the presented study reveals spatial inconsistencies between expert derived generalisation rules from species to habitats (functionality) and expert-based field mapping results (applicability). It might be valuable for future mapping and monitoring to provide an upper and lower spatial limit (in terms of KS or MMU) derived from functionality to match these expectations when applying the rules in the field. The results furthermore illustrate that the spatial extension of the observed area (KS) is more important than the actual area of the individual object (MMU). Therefore, the MAUP has a higher relevance to the results than the MMU. This leads to the conclusion that Natura 2000 management should not focus on MMUs but rather try to develop well-balanced interpretation guidelines, which better represent the conceptualisations applied in the mapping methodologies.

6

Synthesis

This chapter provides a synthesis of the presented thesis by relating the developed results to the overall objectives stated in the introduction of this work. This comprises a detailed discussion of the research questions including the consequent outcomes and recommendations for future research.

6.1 Conclusions

This thesis investigates the interoperability problems and their possible solutions in the context of biodiversity monitoring. Based on the research questions stated in the introduction, this section discusses the results of the previous chapters and gives a summarised recapitulation based on the individual research questions and the two overall research objectives.

Thus, the overall objective to demonstrate applicability of semantic systems to support pan European data interoperability will be answered by reflecting the findings of the first three research questions and the associated chapters 2, 3 and 4. All developed methodologies showed the potential and feasibility of semantic systems for data interoperability and proved the applicability of ontologies for data management.

The second overall objective to evaluate the importance of spatial scale and up-scaling for European nature conservation could be answered in chapter 3 and 5 and will be reflected in the associated research questions. These chapters clearly demonstrate the importance of spatial consideration for remote sensing-based nature conservation and support the application of automated up-scaling and segmentation processes.

6.1.1 Suitable techniques for data interoperability in Natura 2000 monitoring

Research Question: *Which methods are feasible to generate data interoperability in the field of biodiversity monitoring in Europe?*

Overcoming data heterogeneity in trans-national data infrastructures is a widely known challenge in the GI community (see chapter 1). As stated in several publications (Fugazza, 2011; Perego et al., 2012; Fonseca et al., 2002; Bishr, 1998), semantic systems are the most promising solution to tackle the demanding task of data heterogeneity. In the field of nature conservation there are several initiatives which deal with comparability and exchange of biodiversity information (Walls et al., 2014; Lapp et al., 2011) taking into account so-called thesauri or shared vocabularies. The establishment of shared vocabularies spanning different research domains is desireable, but requires lots of domain specific discussions and effort. Efforts mainly focus on the structure and storage of knowledge which is certainly important but seems often too conceptual for scientists conducting research. However, there is a lack of straightforward application examples when dealing with observed biodiversity data, especially in the remote sensing domain.

Chapter II and III propose a matchmaking approach between remote sensing classification results of different study areas in different countries by using semantic systems. The results clearly show that semantic transformation of remote sensing-based classification results is technically feasible. However, the quality of this kind of automatised comparison always strongly depends on the conceptualisation of the classes and class hierarchies. Since there is, until now, no well-established vocabulary for remote sensing and nature conservation, a shared vocabulary was built up to explicitly describe the available data products. Without this tailored reference vocabulary a satisfying semantic transformation would have not been possible. Therefore, there should be a focus on developing such shared vocabularies and support institutions and networks with the aim of developing these valuable thesauri.

The results of chapter II demonstrate that more detailed nomenclatures are more likely to be transferable to nomenclatures that focus on certain elements of the subject of interest than the reverse. The nomenclature used in the Kalmthoutse Heide, for example, was created especially to evaluate heathland areas but also includes good formalisation for other broad habitat types, whereas the nomenclature of the Döberitzer Heide has a strong focus on Natura 2000 grasslands. Consequently, there have been more semantic up-scaling processes while transforming from Döberitzer Heide to Kalmthoutse Heide than from Kalmthoutse Heide to Döberitzer Heide. Regarding the thematic accuracy in combination with the number of necessary semantic up-scaling processes per transformation, it seems that an increase of the number of semantic up-scaling processes leads to decreasing accuracy of the transferability. The results show that the storage of classification meta-information in OWL/RDF ontologies and conceptualisation of the subsequent classes with shared vocabularies lead to a better usability and comparability of remote sensing products. Using formalised knowledge bases and reasoning capability for interoperability issues in remote sensing seems to be an obvious step and is increasingly supported by experts of different research fields (Arvor et al., 2013; Janowicz, 2012).

There are two main requirements which are fundamental for realising automatised matchmaking processes in GI systems. First, there have to be well-formalised, structured reference vocabularies (domain ontologies) which allow formalisation of the often highly specialised applications and data products. These vocabularies have to be developed by the respective domain experts and stored in formal data structures of the semantic web (e.g. RDF, SKOS or OWL). Second, data producers have to use these references or respectively include semantic annotation in their analysis or production chains.

For the Natura 2000 legal purposes, matchmaking approaches represent the opportunity to evaluate the status of European's nature conservation areas comprehensively and therefore ensure the protection and support of the most threatened regions. The statistical comparison of nature conservation areas in different countries or regions could be realised by taking into account semantic matching procedures in Spatial Data Infrastructure (SDI)'s (Lutz et al., 2009). Integration of automated semantics in SDI's would furthermore improve the discovery, retrieval and usability of this kind of information. On the regional and local level the use of semantic reference systems can help to fulfill international reporting obligations by integrating or transforming data into the data models required by international institutions.

6.1.2 Semantic systems to support up-scaling processes in hierarchical remote sensing-based classification frameworks

Research Question: *How can semantic systems support spatial up-scaling processes in hierarchical remote sensing-based classification frameworks to generate interoperable outcomes?*

The question of comparability of designated areas split up in two main principles. On the one hand there is the subjectivity of the delineation of individual habitat areas which exist in all manual mapping procedures (Cherrill and McClean, 1999). On the other hand there is the problem of agreement between habitat classes and local or regional nomenclatures in regard to their content (Vanden Borre et al., 2011). While chapter II focuses on the semantics of the content and their comparability, chapter III uses an up-scaling approach to generate reproducible, objective delineation based on remote sensing classification results. Additionally, Chapter V concentrates on the question how to generate an objective delineation of certain habitat types in regard to MMU and the observed surrounding area, which is in this case the KS of the utilised kernel.

The methodology proposed in chapter III uses a spatial reclassification approach which is based on an ontology utilising its ability to compare data in regard to its content. To realise this task the matchmaking method, described in Chapter II, was taken into account and connected to a spatial up-scaling algorithm. This has been realised on the basis of remote sensing classification results in different study areas. The results of chapter III show that data of different origins, using different nomenclatures can be used and understood by algorithms for automated geo-processing using an OWL ontology as communication interface. The algorithm matches new input data to the one it expects and applies the method based on this information. The results demonstrate that the generated products are not of lesser quality because of the application of the automated matching. In fact the "alien" data (in this case it has been the data from Döberitzer Heide) produced slightly better results than the one of the original data source. The results of this study clearly indicate that a combination of semantic systems and spatial analysis is a further step toward harmonisation of data production and the respective results.

There are three major obstacles which can hamper the implementation of this semantic approach. First, there are ecological differences in the certain bio-geographical regions which forces adoptions of aggregation rules to the conditions of the particular area. This can be exclusively realised with the help of expert-knowledge. Since the classes and rules are formalised in the ontology such a manual check and adaption is possible and can be easily implemented. Second, the methodology is, until now, only tested for certain heathland and grassland classes (Inland dunes with open Corynephorus and Agrostis (2330), European dry heaths or Dry sand heaths with Calluna and Genista (2310/4030)). These classes were chosen because of their spatial variability and heterogeneity regarding the distribution of the individual components. A feasibility test for other Natura 2000 classes has not been realised yet, therefore transferability to other classes can not be ensured. Third, due to its dependence on several inputs, the uncertainties of the methodology are rather high. The quality of the aggregation is always connected to the quality of the remote sensing classification outputs. However, the manual delineation of habitats faces similar uncertainties and therefore produces comparable results to the automated approach (see chapter 5).

6.1.3 Combination of ontologies and machine learning algorithms for classification

Research Question: *What possibilities are there to combine machine learning algorithms with ontologies to utilise the benefits of semantic data storage?*

Freely available images from satellite systems like Sentinel, Landsat and MODIS in combination with new possibilities of processing big amounts of data in cloud-based processing frameworks are currently opening the door to spatial analysis of higher temporal and spatial dimension. In times of massively increasing volumes of remote sensing data future challenges of remote sensing research will shift away from being able to cope with limited data availability to being able to find the right data regarding the corresponding use case. In order to support image retrieval of remote sensing images and comparability of the results of remote sensing analysis it is crucial to link the low-level features of the images to the knowledge provided by experts executing the respective analysis. This barrier of linking semantic information with numerical values is known as the "semantic gap" and represents a recent research focus in the field of image analysis (Forestier et al., 2012; Arvor et al., 2013) and image retrieval (Liu et al., 2007). The term "semantic gap" is defined by lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation (Smeulders et al., 2000).
Narrowing the semantic gap is a highly admired objective in remote sensing image analysis (Belgiu et al., 2014; di Sciascio et al., 2013; Andrés et al., 2013; Argyridis and Argialas, 2015), automated image annotation (Zhang et al., 2012) and retrieval (Liu et al., 2007). Whereas in the field of image retrieval the combination of ontologies and supervised learning is quite common (Smeulders et al., 2000), in remote sensing image analysis ontologies are primarily used to formalise expert knowledge and utilise ontological

inference for classification purposes (Lampoltshammer and Wiegand, 2015; Belgiu et al., 2014; Argyridis and Argialas, 2015).

Even though a number of indicators for habitat evaluation were developed recently (Nagendra et al., 2013; Skidmore et al., 2015), classification procedures and rule-sets are in most cases not formalized to be computer readable and therefore suffer from equal transferablity and reproducibility problems as manual habitat mapping (Arvor et al., 2013; Nieland et al., 2015a,a). Furthermore, there is no standardised set of indicators using RS for trans-national habitat evaluation (Lucas et al., 2015; Vanden Borre et al., 2011). Therefore a formalised, computer-readable ontology can help to and allow scientists to see how the classification was performed and be aware of possible incompatibilities before combining data (Janowicz, 2012). Hence, technical solutions to increase interoperability by thematically harmonising environmental data and systematise data collection methods from remote sensing inputs in an automated workflow are needed.

Following the request of Janowicz (2012) to include machine learning, statistics and data mining in ontology development, chapter IV proposes a methodology for automated annotation of remote sensing images based on a decision tree classifier. This ensures extensive transferability, knowledge and workflow management and logical consistency together with the ability to use self-learning algorithms to analyse huge amounts of data. The results show that automated semantic annotation of remote sensing imagery can be achieved by using decision trees to generate formalised knowledge bases including numerical features as ontological primitives. Using this advantage in combination with an inference engine as actual classification tool preserves the advantages of ontological reasoning, like subsumption, logical consistency, reproducibility and interpretability of the generated data without losing the power of supervised learning classification algorithms. The outcomes show similar classification accuracy as other widely-used supervised classification techniques, such as the extra tree classifier which represents a highly randomised ensemble method similar to random forest.

Bridging the semantic gap in satellite image interpretation is a big step towards an interoperable GI infrastructures in which image retrieval, image classification and the comparability of the generated products can be realised by utilising semantic systems. The formalisation of expert information is an important step towards sustainable knowledge management and allows comprehensive re-use of the developed achievements. Main drawback in the use of ontologies for knowledge management lies in the complex and difficult development process of such semantic knowledge bases (Forestier et al., 2013). This involves a huge joint effort of domain experts and semantic engineers which is currently only partly realised in institutional activities (see section 1.1).

6.1.4 Scale as parameter for habitat mapping

Research Question: *How important is scale as a parameter for the interoperable mapping of nature conservation areas?*

The concept of scale is the focus of numerous studies on the analysis of spatial information and remote sensing for nature conservation (Levin, 1992; Jelinski and Wu, 1996). Scale ranges from finding the right pixel size for the respective application (Hengl, 2006) to the evaluation of scale-effects for plant sampling (Stohlgren et al., 1997) or spatial thresholds and up-scaling procedures (Hay et al., 1997). Also GEOBIA focuses on scale issues as the segmentation is strongly affected by the respective target scale (Dragut et al., 2010; Blaschke, 2010). One of the main challenges in OBIA is finding the right scale parameters as a basis for the segmentation process (Dragut et al., 2010; Hay et al., 1997, 2005; Kim et al., 2008), which represents a typical example of the MAUP (Openshaw, 1984; Hay et al., 2003).

In the field of Natura 2000 monitoring scale is an essential factor since it influences the evaluation of designated areas (Stohlgren et al., 1997) and the absence of scale as a mapping parameter can lead to tremendous heterogeneity in the generated spatial data sets (Corbane et al., 2015). Since remote sensing maps land cover components and biophysical indicators, habitats have to be aggregated by combining these components to form habitat classes. Based on the MAUP (Openshaw, 1984), these spatial aggregation processes lead to unequally distributed classes if there is no consistent, automated procedure in place to correct for this. Manual field mapping performed by surveying ecologists is also affected by this problem. The subjective assumptions of field experts when delineating a heterogeneous habitat object can heavily affect the evaluation status of designated areas. As a matter of fact this evaluation status is basis for the assignment of new conservation areas and the allocation of EU funds for protection. Therefore, site managers prefer to negatively evaluate their habitat areas. From a local perspective, this is a feasible procedure which tries to achieve the best support for the respective site, but lacks in consistency when comparing different regions. From the EU perspective this is problematic because there are only limited funds for nature conservation which should be allocated where they are most urgently needed and incompatibility of the data leads to potential misuse of the designated funding. To strengthen data interoperability and comparability on an international level it is necessary to minimise the influence caused by the MAUP by applying consistent aggregation procedures. Therefore it is crucial to identify the optimal scale parameter for the mapping of Natura 2000 habitats and develop automated aggregation procedures based on objective measurements (like remote sensing).

Chapter V compares an automated habitat aggregation approach to a manual approach and furthermore tries to evaluate the underlying principles of their structure. That involves on the one hand the composition of the habitat areas in respect to land cover categories and other biophysical parameters and on the other hand the minimum size of the regarded areas. The results of this analysis show that kernel reclassification algorithms can successfully be utilised to aggregate remote sensing classification results to Natura 2000 habitat classes which can be a a big advantage for the reproducibility and comparability of mapping results on an international level. Furthermore it illustrates that each habitat type has its optimum mapping scale but for the quality of the aggregation results the size of the regarded surrounding is it is a more important mapping parameter.

6.2 Future Research

In this thesis different aspects of interoperability of geo-data for biodiversity monitoring have been highlighted. This led to several research questions and challenges that could not be handled within the scope of this thesis. The most crucial points are enhancement of the developed methodologies and their transfer to other use-cases, the design and management of common vocabularies tailored to the specific needs of automatised or partly automatised biodiversity monitoring and the further developments towards better retrieval of multi-source satellite images using semantic searches.

6.2.1 Enhancement of the developed methodologies and their transfer to other use-cases

In times of coalescing spatial data infrastructures in Europe, semantic transformation of existing and newly derived geo-data into data models of other regions or thematic resolutions is a necessary step to achieve data comparability. The developments of chapter 2 have shown promising results for transformation of Earth Observation (EO)-based classification products in the field of Natura 2000 heathland areas. The approach has demonstrated to be feasible for the comparison of the data and can now be transferred to other use-cases. This can be either to fulfill the requirements of over-regional reporting obligations (like Natura 2000 or Corine Land Cover (CLC)) or to compare data, derived in different regions or nomenclatures directly. From a methodological perspective the applied hierarchical matchmaking approach should be compared to an approach based on the semantic similarity.

Up-scaling of geo-information is crucial in many tasks dealing with spatial phenomena. Chapter 3 and 5 propose a pixel-based aggregation approach for Natura 2000 heathland habitats which is based on SPARK. With this approach it was possible to aggregate EO classification results to spatially heterogeneous Natura 2000 habitats. Since there are other heterogeneous habitat types (e.g. orchards, mixed forests etc.), this approach should be applied for other use-cases to show its potential for an operational implementation. Furthermore, the algorithm is rather generic and can be applied and tested on different thematic aggregation problems.

The benefits of ontology-based classification could be demonstrated in 4. Since the utilised DT algorithm only partly achieved the classification accuracy of the benchmark classifier (ET) the classification procedure should be extended to ensemble methods in the future to generate more robust classification products with higher quality.

6.2.2 Design and management of common vocabularies

Spatial data recorded by different sensors (e.g. sensor networks, Citizen Science (CS) or remote sensing images) leads to a rapidly increasing amount of datasets with numerous, autonomous and independent sources. To handle these complex and heterogeneous data structures semantic systems and conceptual modeling are the most promising solutions for overarching data management (Embley and Liddle, 2013; Gil and Song, 2015). Since recent research showed the importance of emerging EO systems (Lausch et al., 2016) and existing geo-data (see chapter 5) for biodiversity monitoring, the border to so-called "big data" analysis in this research field is already transcended and the amount of available data will continue to increase exponentially in the next years.

The key for enhanced data exchange, reuse and retrieval is the development of standard metadata in the form of shared vocabularies. For the HabDir, the EEA has taken the first step by providing rdf triples for the GEneral Multilingual Environmental Thesaurus (GEMET) and EUNIS. Existing vocabularies such as the Common Thesaurus Framework for Nature Conservation (Martino and Albertoni, 2011) and Umwelt Thesaurus (UMTHES) should be extended to remote sensing needs to respond to the change of data acquisition methods in biodiversity monitoring and allow for comparisons with past data. Habitat areas would thus be characterised by deriveable indicators instead of using species or plant communities which are used in conventional approaches. Currently, there is no existing vocabulary for remote sensing observations or subsequent derivable indicators. Chapter 2 suggests one solution for a shared vocabulary of Natura 2000 heathland and grassland habitats. This proposal has to be discussed with and refined by other researcher and experts to come to a common understanding of which ecological indicators are necessary to properly describe habitats. To harmonise remote sensing analyses a special working group which deals with data comparability and collaboration could be a big benefit. One first step for this task could be the exposure of the increasingly accepted EAGLE data model as Linked Open Data (LOD). The EAGLE data model already includes a systematic object-oriented characterisation of landuse and landcover components, which are suitable to describe basic and even more complex landscape features. To use EAGLE components as base features for remote sensing analyses would be a big step towards interoperability of remote sensing products.

In order to keep track with the ongoing expansion of EO data, there is no alternative to linking data to corresponding meta-information to provide possibilities of enhanced information retrieval and analysis.

6.2.3 Image and information retrieval

The increasing availability of EO data suitable for the monitoring of nature conservation areas raises new challenges regarding the retrieval of appropriate images for classification (Arvor et al., 2013). With soaring amounts of available EO data from international institutions (like Landsat, Sentinel, etc.) but also emergent private companies (like PlanetLabs, Digital Globe etc.), the challenge of remote sensing experts will change from having to cope with the limited amount of data to finding the appropriate data out of a nearly unmanageable quantity of collected images. The conventional way of finding the right image in a satellite archive is only based on very limited meta-data information and requires a lot of time and manual work. Therefore, one can assume that, in the future, a high percentage of high quality satellite images will not be used because it is too time consuming and expensive to find suitable data. This makes automated semantic annotation of images or even single pixel essential. Having a set of meta-data automatically linked to all incoming satellite images would certainly increase the discovery of the right image for the particular classification problem. This includes spatial and temporal information as well as basic land cover components or even more complex ecological indicators stored in a semantic knowledge base. Therefore it would be a great benefit to enable semantic searches for satellite imagery by using either OWL inference, RDF path traversal or graph database systems. This facilitates the inclusion of spatial, temporal and thematic operators to the image retrieval process by taking into account contextual, semantic information. Therefore, a much broader range in queries would be possible, reaching from simple temporal requests to combined searched of images which include for example a certain spatial extent in a particular time period with a minimum percentage of a certain land cover type.

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Author's Declaration

I prepared this dissertation without illegal assistance. This work is original except where indicated by special reference in the text and no part of the dissertation has been submitted for any other degree. This dissertation has not been presented to any other University for examination, neither in Germany nor in another country.

Simon Nieland

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