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Using information layers for mapping grassland habitat distribution at local to regional scales

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ABSTRACT

The Natura 2000 network of protected sites is one of the means to enable biodiversity conservation in Europe. EU member states have to undertake surveillance of habitats and species of community interest protected under the Habitat Directive. Remote sensing techniques have been applied successfully to monitor biodiversity aspects according to Natura 2000, but many challenges remain in assessing dynamics and habitat changes outside protected sites. Grasslands are among the most threatened habitats in Europe. In this paper we tested the integration of expert knowledge into different standard classification approaches to map grassland habitats in Schleswig Holstein, Germany. Knowledge about habitat features is represented as raster information layers, and used in subsequent grassland classifications. Overall classification accuracies were highest for the maximum likelihood and support vector machine approaches using RapidEye time series, but results improved for specific grassland classes when information layers were included in the classification process.

Introduction

The Natura 2000 network of protected sites is the main policy strategy to address biodiversity conservation in Europe. This ecological network was set up based on the legal requirements of the European Habitat Directive (Council Directive 92/43/EEC on the conservation of natural habitats and of wild fauna and flora, short HabDir) and the Birds Directive (Council Directive 2009/147/EC). The HabDir requires EU member states to undertake regular monitoring and reporting on the status and future prospects of the protected habitats and species. A set of parameters has to be evaluated for the protected sites and for the total potential range of a given habitat within the territory of each member state. Spatially explicit and updated information is thus needed which up to now is mainly collected through field surveys by experts in floristic and ecology.

Earth observation (EO) has been applied successfully in biodiversity monitoring (Nagendra et al., 2013; Turner et al., 2003; Strand et al., 2007; Wang et al., 2010). The ability of EO to provide relevant information depends on the land type investigated (e.g. dry grassland, tropical forest, alpine mires), the applied scale (local to continental) and the quantity and quality of sensor data (active, passive sensor, spectral, spatial and temporal resolution) (Nagendra, 2001; Strand et al., 2007). To monitor Natura 2000 habitat changes, multi-temporal optical or radar satellite image data (Weiers et al., 2004; Bock et al., 2005; Franke et al., 2012) with very high spatial and spectral resolution have been applied (Förster et al., 2008; Hall et al., 2012; Spanhove et al., 2012). Object-based classification approaches were proposed as especially suitable to map habitats, due to the ability to include ancillary information such as shape or proximities at different spatial scales in one classification logic (Langanke et al., 2007; Díaz Varela et al., 2008; Blaschke et al., 2011).

The application of EO to monitor biodiversity can be grouped into direct and indirect approaches (Turner et al., 2003). Advanced sensors such as hyperspectral and very high spatial resolution sensors have aided the direct identification of individual species (Gillespie et al., 2008), but are often considered as too costly by monitoring experts (Vanden Borre et al., 2011). It is therefore common to study indirectly biodiversity through ecological indicators. Duro et al. (2007) classified these indicators into four groups measuring: (a) physical conditions, such as climate and topography, (b) vegetation production, productivity or function (c) habitat suitability with respect to its spatial arrangement and structure and (d) metrics of disturbance indicating biodiversity changes. The identification of a habitat according to the HabDir requires an integrated view, spanning across these categories. It involves not only the definition of land cover (addressed through its observable

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vegetation form) but also the occurrence of key species and other biophysical parameters such as topography, aspect or soil characteristics (European Commission, 2007). Therefore, EO based habitat monitoring needs to be adaptive to the characteristics of each habitat type, rather than following a single uniform image processing approach. The use of information layers (IL) presented in this paper takes this into account. Ecological expert knowledge about habitat definition and distribution is related to observable ecological features using EO.

The term IL used here refers to image features extracted from EO or other geodata, stored as standardized raster data sets and used in subsequent classifications (Buck et al., 2013). Depending on the extracted feature, IL can represent:

- Spectral IL: information derived from the original spectral data sets through further processing steps, other than pre-processing (like atmospheric correction, top-of-atmosphere reflectance conversion), e.g. band combinations to calculate vegetation indices, variance reduction through principal component analysis.
- Temporal IL: multi-temporal information derived from image time series.
- Structural IL: information about 2D and 3D visible structures within the image, e.g. lines which give a hint for tracks from agricultural machines, slope directions, plant height.
- Non-image IL: geo-referenced information derived from non-image data sets, e.g. rainfall intensity, animal stock rates or soil type maps.

In this paper, IL was applied to classify grassland habitats in Schleswig-Holstein, Germany. Grassland habitats are an important component of biodiversity in Europe (Silva, 2008; Halada et al., 2011). The intensification of agricultural land use as well as the abandonment of traditional management practices put these habitats under increasing pressure (Henle et al., 2008; Navarro and Pereira, 2012). Protective legislation such as the Cross Compliance regulations (EU regulation 73/2009) could not stop the regional decline of grassland (Nitsch et al., 2012). Regional authorities require regular and up to date information on grassland distribution and quality to better monitor these habitat changes.

Methods

Defining the grassland habitats and corresponding information layers

The study site (625 km^2, 9°32′ E, 54°15′ N) is part of the Atlantic biogeographical region located in the federal state of Schleswig-Holstein, Germany. It is framed by the lowland rivers Eider, Treene and Sorge, and dominated by farming and agricultural lands (Fig. 1).

The following Natura 2000 grassland habitat types are declared by the regional monitoring agency (*Landesamt für Landwirtschaft, Umwelt und ländliche Räume*, LLUR) as of special concern: Semi-natural dry grasslands and scrubland facies on calcareous substrates (*Festuco-Brometalia*) (habitat code 6210), *Molinia* meadows on calcareous, peaty or clayey-silt-laden soils (*Molinion caeruleae*) (habitat code 6410), lowland and lowland hay meadows (habitat code 6510). In the Natura 2000 guidelines, these habitats are mostly defined by their plant species composition (European Commission, 2007), a gradient which is difficult to detect with EO techniques (Schmidtlein and Sassin, 2004; Feilhauer et al., 2013). The high spatial within-class variability, the spectral similarity of classes and their temporal variation (Feilhauer et al., 2013; Schuster et al., 2015) make the classification of grassland vegetation challenging. Species composition of grassland is highly related to land use intensity (Waldhardt and Otte, 2003) and previous studies classified grassland habitats by using land use intensity parameters (Jacobsen et al., 2000; Schuster et al., 2012; Franke et al., 2012). In our study we adopted a grassland classification system using ecological and land use features. Four different grassland classes were defined together with the LLUR monitoring experts (Table 1). They are characterized by features used by the LLUR in a visual interpretation of grassland using aerial photographs and vector information on soil distribution.

Compared to other grassland habitats, intensive grasslands experience a higher number of mowing events (up to four) over a given vegetation period. Dry grasslands are never mowed, while wet and mesophilic forms are cut only once at different times during the summer season. Field checks showed that dry grasslands often do not form a homogeneous vegetation cover but are a composite of bare soil, small shrubs and herbs. Wet grasslands are moderately homogeneous in terms of coverage, while mesophilic

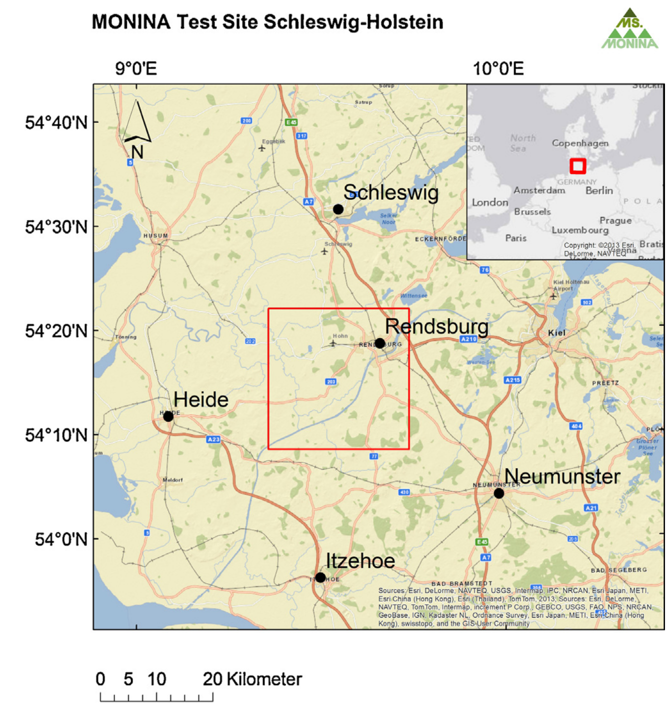

Fig. 1. Test site (red square) in Schleswig-Holstein, Germany. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Definition of grassland classes.

Grassland type	Biomass	Mowing season	Homogeneity	Soil moisture	Slope orientation	Line structures
Dry grassland 62xx	Low-medium	Not applicable (n/a)	Low-medium	Very low	South	n/a
Wet grassland 64xx	Low-medium	August	Low-medium	High	n/a	Low occurrence
Mesophilic grassland 65xx	Medium-high	June	Medium-high	Medium-high	n/a	Low occurrence
Intensive grassland GI	Medium-high	2–4 times (May, June, August, September)	High	Low-medium	n/a	n/a or low occurrence

Adapted from Buck et al. (2013).

Table 2
Input datasets.

Input data	Date	Description
RapidEye satellite images	18 April 2011 06 May 2011 26 August 2011	5 m pixel size, 5 bands (blue, green, red, red edge, near infrared)
Orthophoto	27/28 June 2011	0.15 m pixel size, 4 bands (blue, green, red, near infrared). Resampled to 5 m pixel size
Digital elevation model	2005–2007	ASCII grid derived from airborne laser scanner data, 1 m pixel size
Soil map	Continuously compiled since the 1930s	Polygon shape file
Land Parcel Identification System (LPIS) data	2011	Polygon shape file. Agricultural parcel outlines
Field data sets	2009–2012	Training data collected through field visits and expert photointerpreation

Adapted from Buck et al. (2013).

and intensive grasslands are very homogeneous. Abiotic factors such as soil moisture and sun exposition play a major role in grassland distribution in Schleswig-Holstein. Dry grasslands are more likely on southern slopes and on nutrient-poor soil types with low water retention capacities. To improve wet soil conditions a typical land amelioration technique in the test region is to establish small drainage ditches, visible in aerial photos as regular linear structures.

Data pre-processing and information layers calculation

Using the grassland class definitions (Table 1), information layers were calculated taking a variety of data sources and image algorithms (Table 2). Multi-temporal RapidEye satellite image data of the growing season 2011 was atmospherically corrected using ATCOR-2 prior to analysis. All information layers were resampled to 5 m raster GeoTIFF images to match the RapidEye spatial resolution and pixel values were standardized to 0–1 (Fig. 2). All data were re-projected to the reference system UTM 32N, WGS84.

Biomass was calculated as a proxy using the red edge NDVI (Gitelson et al., 1996), an adaptation of the normalized difference vegetation index (Tucker, 1979), to use the capability of the red edge spectral range of the RapidEye images (Schuster et al., 2012). Homogeneity was computed as the inverse standard deviation of all pixels within a 5×5 pixel kernel using the orthophotos. Visual inspection by the LLUR experts confirmed this parameter as helpful interpretation feature. Up to four time windows (3 weeks each) with expected mowing activities were compared for the detection of the mowing cycles IL. A detected biomass decrease of at least 10% between two subsequent time windows was regarded as one moving event. Depending on the grassland class, different time windows were checked.

Linear structures were extracted from the orthophotos using a Gaussian line model (Steger, 2013). The extracted lines were analyzed for length and curvature. Artefacts (short and curved lines) were deleted. At the end of the process the line segments were converted back into a greyscale image. Slope orientation was extracted from the digital elevation model (Table 2). Soil moisture was extracted from the soil map data and converted into thematic raster layers. This integration of additional GIS data is a common way to improve a classification process (Förster and Kleinschmit, 2013). A mask was created based on the Land Parcel Identification data (LPIS) to remove non-agricultural land from the classification process. LPIS is a regularly updated GIS database representing agricultural land as part of the Integrated Administration and Control system to implement the Common Agricultural Policy in Europe (EU regulation 73/2009). A parcel based segmentation was calculated based on the RapidEye image data from April 2011 to divide the LPIS parcels into spectrally homogeneous segments using the multi-resolution segmentation algorithm implemented in the software eCognition (Benz et al., 2004; applied scale parameter = 150, shape factor = 0.5, compactness factor = 0.8).

Classification approaches

All classification approaches in this study were trained and validated on field data, based on surveys performed in 2009, 2011 and 2012. The survey data was cross-checked by the LLUR through a visual photointerpretation using orthophotos from 2011. Crops were included in the classification process to mask out arable land. The field data were collected across the test site and covered in total about 388 ha (62xx = 34 ha, 64xx = 41 ha, 65xx = 45 ha, GI = 52 ha, crops = 94 ha, maize = 122 ha). The data were randomly divided into half (training and control group).

Several classification approaches were tested to evaluate the use of information layers for grassland classification. Maximum likelihood classification (MLC) was performed using all spectral bands from the multi-temporal RapidEye data (Table 2). MLC is a supervised classification method which describes the membership probability of a given pixel to a pre-defined class and is a common approach in EO (Lu and Weng, 2007). This parametric approach assumes a normally distributed input data set. In complex landscapes, where multiple data sets are combined, non-parametric classifiers such as support vector machines (SVM) may provide better results (Huang et al., 2002; Xie et al., 2008). SVM performs well where a determined distribution of the data is not assumed (Plaza et al., 2009; Mountrakis et al., 2011), an advantage over other EO methods, where the distribution is usually unknown and not normally distributed (Fauvel et al., 2009). We applied the SVM using three different input data sets (1) SVM (input data RapidEye), (2) SVM + IL (IL), (3) SVM + IL + RE (IL and RapidEye).

Results and discussion

The results were evaluated with the field data to compare the validity of the different classification results (Fig. 3) using an error matrix (Congalton, 1991). All approaches present overall accuracies above 80% (Table 3). The highest score is reached by SVM (89.0%), closely followed by MLC (87.9%), SVM + IL + RE (85.7%) and SVM + IL (83.7%). Cropland and maize are usually very well discriminated, achieving accuracies around 90–100% in all approaches. Intensive grasslands (GI) are also well classified, with accuracies above 75%, but lower user's accuracies (SVM + IL 59.9%). On the other hand, the classification of the natural grassland habitats (62xx, 64xx and 65xx) is very weak in most cases. The only successful approach in classifying dry grassland 62xx is the MLC (95.6% producer's accuracy and 78.8% user's accuracy) (Table 3). For this classification, good producer accuracy is also given in the SVM (93.1%) and SVM + IL + RE (99.2%), although the user's accuracies are very low (37.1% and 23.4%, respectively). In the same line, SVM + IL

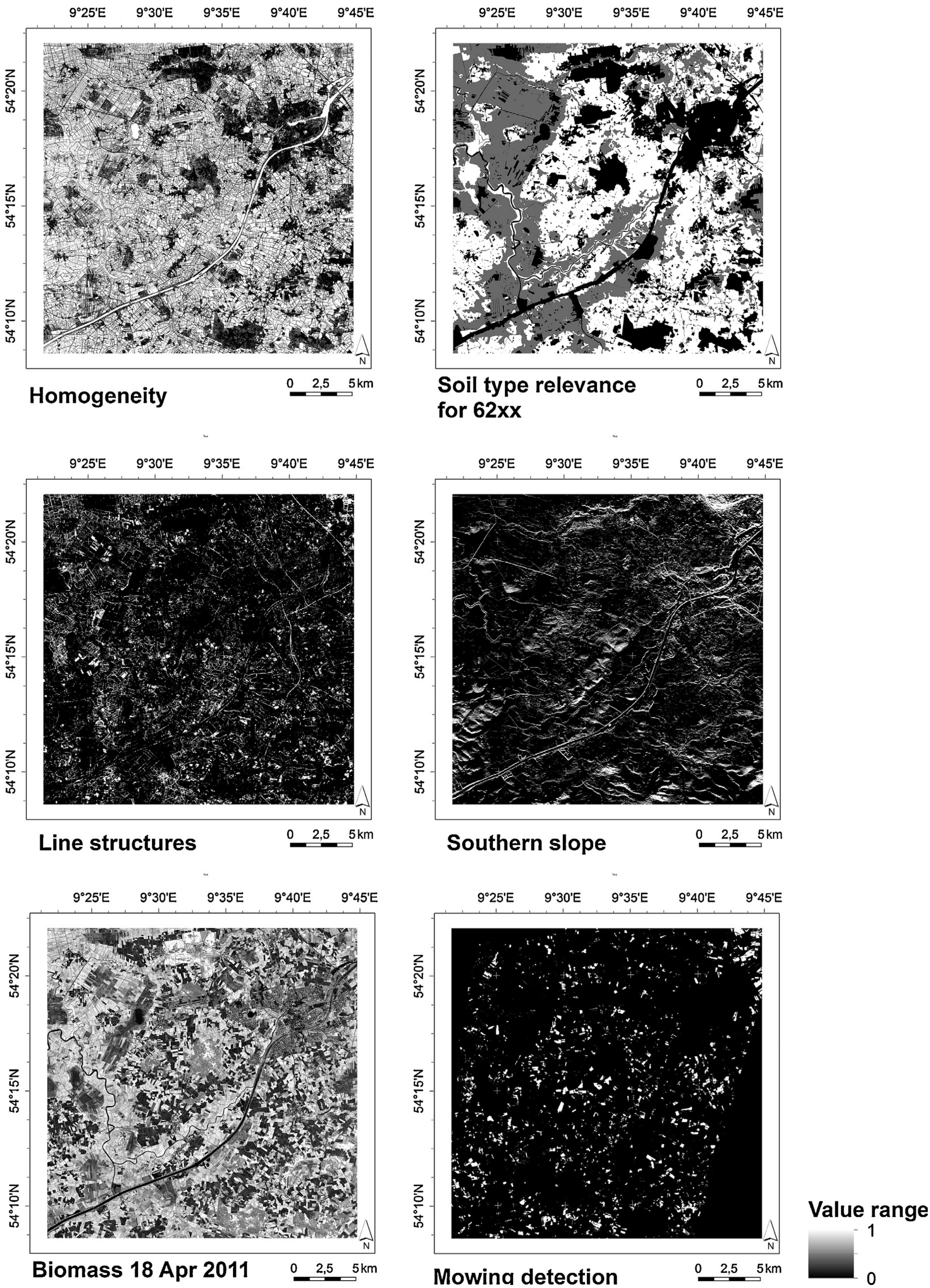

Fig. 2. All information layers were standardized to a value range from 0 (black) to 1 (white).

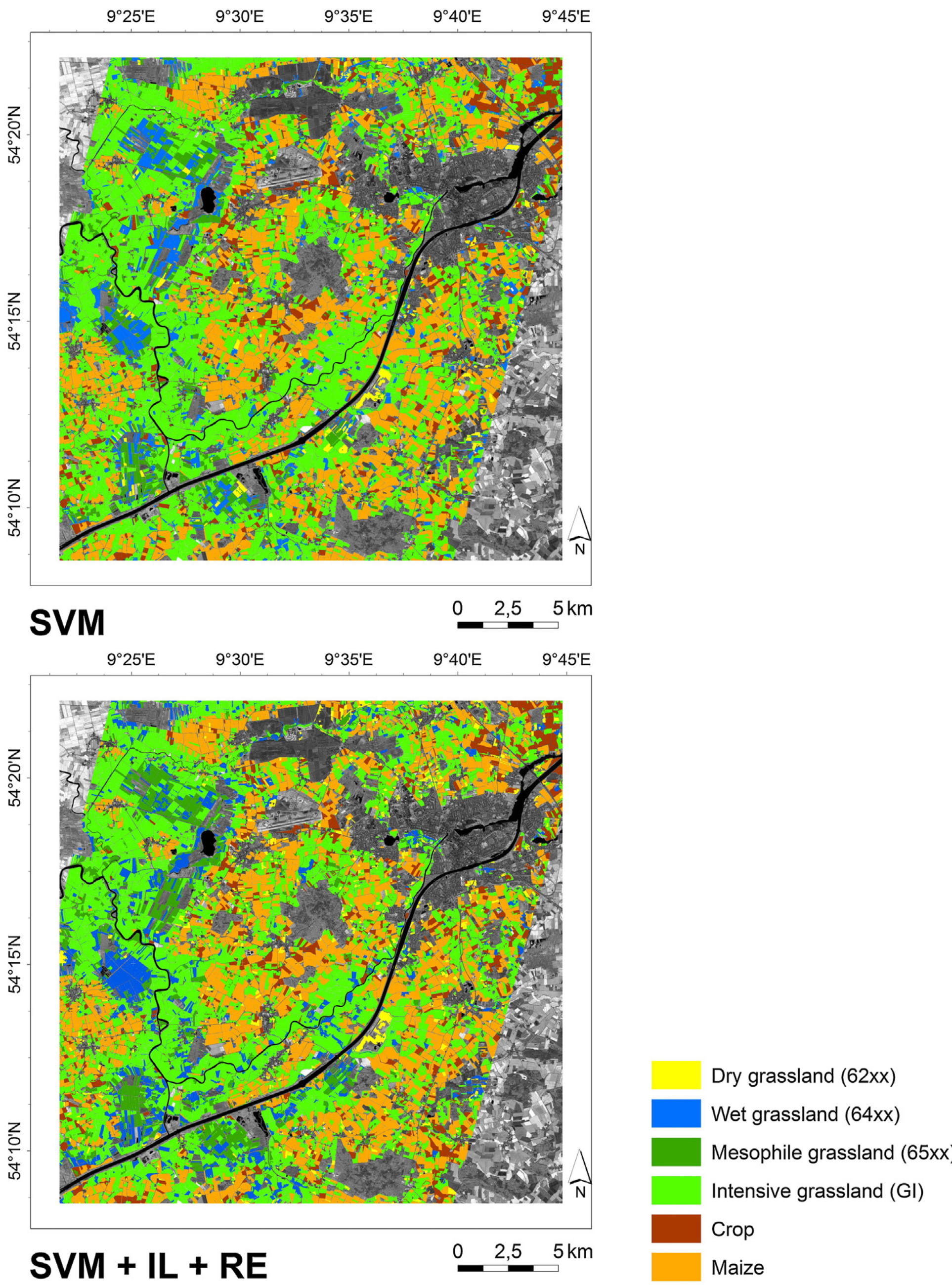

Fig. 3. Classification results for SVM and SVM + IL + RE.

Table 3
Accuracy assessment for the different classification approaches.

	MLC		SVM		SVM + IL		SVM + IL + RE	
	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy
GI	90.3%	74.2%	98.4%	76.5%	96.0%	59.9%	98.4%	76.4%
62xx	95.5%	78.8%	93.1%	37.1%	58.5%	52.1%	99.2%	23.4%
64xx	38.1%	58.6%	28.8%	64.5%	27.9%	80.5%	36.6%	57.2%
65xx	41.7%	29.2%	34.2%	29.3%	40.1%	31.4%	57.6%	40.9%
Crop	96.2%	99.9%	99.7%	99.9%	85.1%	93.7%	85.8%	99.8%
Maize	100.0%	100.0%	100.0%	100.0%	92.1%	88.0%	99.8%	96.3%
Total	87.9%		89.0%		83.7%		85.7%	

performed well in the user's accuracy for the 64xx class (80.5%), but poorly in the producer's accuracy (27.9%).

However, using the IL, the SVM classification of the natural grassland types improved. Indeed, SVM + IL + RE achieved the highest accuracy results for 62xx (99.2% producer's accuracy) and 65xx (57.6% producer's and 40.9% user's accuracy). The SVM approach identified the wet grassland reference sites well (user accuracy of 80.5%), but largely overestimated its distribution (low producer accuracy of 27.9%) (Fig. 3). This discrepancy was smaller for the mesophile grassland (65xx), but accuracies never exceeded 60% in all approaches. Classification confusion mostly occurred within the three grassland classes 62xx, 64xx, 65xx, while intensive grassland and cropland/maize were very well classified in all approaches. This was a surprising find since Schleswig Holstein, 62xx and 64xx occupies very different environments and presents different ecological parameters (Table 1). Dry grasslands (62xx) grow on dry soils, with low biomass and ground cover, but are relatively species-rich including small shrubs. Mesophile grassland (64xx) presents high biomass, full ground cover and is more homogeneous in terms of species composition, being dominated by fewer species. However, 64xx grasslands dry up in the summer season and the senescent leaves remain in place over autumn/winter, if the fields were still too wet for mowing in autumn. New sprouts grow then under a big amount of dry leaves in spring. From an EO point of view, the high proportion of bare soil and lignin from the small shrubs in 62xx, and the big amount of dead leaves in 64xx can present similar reflectance. This might be one of the sources of confusion between these two classes. Asner (1998) showed that standing litter significantly affected the spectral reflectance of grassland canopies. This limitation might be solved using other type of EO data, such as from hyperspectral sensors, which can better discriminate biophysical parameters of grassland (Darvishzadeh et al., 2008; Psomas et al., 2011) or LIDAR information suitable to separate shrubs according to their height (Hellesen and Matikainen 2013).

One of the major drawbacks of the applied classifiers is the assumption that the classes are mutually exclusive, with discrete boundaries separating them. This raises the question whether the class definitions are adequate to be used in EO, or whether the type of input data was sufficient to separate the classes. In fact, the species that form 65xx and intensive grasslands are similar (LLUR, personal communication) and vegetation often changes along a gradient, so abrupt classification can lead to erroneous results (Schmidtlein and Sassin, 2004) and a loss of information. Rocchini et al. (2013) recently reviewed approaches to better address this uncertainty in ecosystem mapping, such as fuzzy set theory and spectral un-mixing. Although hyperspectral sensors are capable of detecting plant species composition (Gillespie et al., 2008), they are not operationally capable yet to cover large regions with sufficient spatial resolution at low cost. Therefore, we had to aggregate our grassland types to general groups (62xx, 64xx and 65xx), representing classes still acceptable to the LLUR.

The aim of the IL approach was to enhance the spectral information by using additional data sources, such as information about the soil or management practices. The mowing IL was considered by the LLUR as very important to distinguish grassland types in Schleswig-Holstein. The prevailing cloud coverage of the region complicates the acquisition of multitemporal high resolution satellite data within one vegetation period. The three RapidEye images available for this study were not suitable to discriminate the expected mowing events (up to four times per year) as defined in the expert description models. With increasing numbers of operational satellite systems, data availability might improve and allow a better discrimination of mowing events. Alternative data sources could be included to improve results. Schuster et al. (2011) showed the potential of using radar satellite data (TerraSAR-X) to detect mowing events in the context of Natura 2000. The required time series of high resolution radar and optical data are currently not available for operational monitoring due to costs reasons. The upcoming Copernicus satellite sensors (www.copernicus.eu), especially the Sentinel-1 (C-band radar) and Sentinel-2 (multispectral optical sensor), will provide cost-free data sets for future information layer concept applications.

In all tested classification approaches, natural grasslands are clearly separated from croplands, intensive grasslands and maize. This information is important for future monitoring, since there are growing concerns about the conversion of natural grasslands into intensive grasslands and croplands at alarming rates (LLUR, personal communication; Nitsch et al., 2012). The methods demonstrate that a yearly surveillance of natural grasslands dynamics and conversion into other human-managed land forms can be achieved using EO.

Conclusions

The characterization of habitats according to the HabDir is mainly based on species composition and functionality. This botanical-ecological definition is difficult to align with current EO methods to monitoring habitats. When monitoring habitats careful consideration needs to be given to the need for floristic information by practitioners and the possibilities of EO. Remote sensing is a powerful tool for environment monitoring at a landscape level, because it provides both temporal and spatial continuous information (Pettorelli et al., 2014). With the future launch of hyperspectral satellites (e.g. the German EnMap is planned to be launched in 2018), more refined grassland classes might be achieved, albeit at coarse output pixel sizes (e.g. 30 m for the mentioned EnMap sensor).

The proposed information layers presented in this study demonstrate the potential to improve established classification approaches using expert knowledge about grassland habitats in the Atlantic biogeographical region in Germany. If extended or transferred to other biogeographical regions in Europe, the class definitions (based on the ecological expert knowledge) can be adapted to reflect the differing grassland characteristics and classes. The IL applied here depended on the quality and temporal coverage of the input data. In the present study, three RapidEye images were not sufficient to identify the different mowing practices in the test region. Therefore, the use of additional data is recommended for better habitat discrimination. The future constellation of Sentinel satellites and its higher temporal resolution (around 5 days in Europe) will support the retrieval of temporal features, such as mowing events from cloud-free images. Non-optical sensors such as LIDAR or radar can improve grassland classification (Hellesen and Matikainen, 2013; Schuster et al., 2015; Zlinszky et al., 2014) and hyperspectral data can discriminate additional habitats features, such as lignin composition, presence of soil, senescent matter or litter. The strength of the IL approach is its flexibility to address specific habitat features, rather than following a single uniform image processing approach. It can bring EO and vegetation experts closer together to reach a better acceptance of remote sensing for Natura 2000 monitoring (Vanden Borre et al., 2011).

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