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Article

Monitoring of the Vegetation Composition in Rewetted Peatland with Iterative Decision Tree Classification of Satellite Imagery

ANNETT FRICK, Potsdam, PEGGY STEFFENHAGEN, Greifswald, STEFAN ZERBE, Bozen, Italien, TIEMO TIMMERMANN & KARSTEN SCHULZ, Greifswald

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Summary: Peatland was subject to heavy drainage and degradation throughout the world and thus is now the focus of large scale restoration attempts. The monitoring of both vegetation development and balance of matter after restoration has started is indispensable, since an important objective of peatlands rewetting is the rehabilitation of their sink function. Against this background, we investigated rewetted fens in NE Germany in order to qualitatively and quantitatively evaluate the vegetation development after restoration measures. The aim of this study was to analyse the vegetation composition with multispectral and very high spatial resolution satellite imagery. We investigated two sites with different rewetting dates and also took biomass and carbon content samples for the main plant species in order to estimate nutrient storage. We tested the applicability of various satellite sensors (QuickBird, WorldView I and SPOT) and an iterative classification scheme based on decision trees for mapping several wetland plant species (e. g. *Phragmites australis*, *Typha spp.* and *Carex spp.*) and vegetation types. We chose three different widely used decision tree classifiers for this study: AdaBoost, See5 and RandomForest. Evaluation criteria were overall accuracy and mean class accuracy. Multispectral and very high spatial resolution satellite data and the developed method allow for the identification of the most important vegetation types in rewetted fens. All applied sensors yielded good results with overall accuracies of 85% and 92%. Some classes reached lower accuracies due to different reasons (capture date, size of training set or spatial resolution of the sensor).

We found remote sensing a very valuable tool not only for the observation of the restoration success in rewetted peatland but also for the analysis of the peat accumulation potential as well as biomass and nutrient storage.

Zusammenfassung: *Monitoring der Vegetationszusammensetzung in wiedervernässten Niedermooren anhand einer iterativen decision tree Klassifikation von Satellitendaten*. Niedermoore in der ganzen Welt sind von starker Entwässerung und Degradation betroffen und stehen nunmehr im Fokus von großflächigen Renaturierungsprojekten. Das Monitoring der Vegetationsentwicklung und des Stoffhaushaltes dieser Flächen ist dabei unerlässlich, da ein wichtiges Ziel der Renaturierung die Wiederherstellung ihrer Senkenfunktion ist. Vor diesem Hintergrund haben wir wiedervernässte Niedermoorflächen im Nordosten Deutschlands untersucht. Das Ziel der Studie war es, mit Hilfe von multispektralen und räumlich höchstauflösenden Satellitendaten, qualitative und quantitative Aussagen zur Vegetationsentwicklung nach der Renaturierung zu treffen. In zwei Gebieten mit unterschiedlichen Vernässungszeitpunkten wurden Proben zu Biomasse und Kohlenstoffgehalt der dominanten Pflanzenarten genommen. Verschiedene Satellitensensoren (QuickBird, WorldView I and SPOT) wurden verwendet sowie ein iterativer Klassifikationsansatz basierend auf decision trees entwickelt, um dominante Arten (z. B. *Phragmites australis*, *Typha spp.* und *Carex spp.*) und Vegetationstypen zu klassifizieren. Drei weit verbreitete decision tree Algorithmen kamen zum Einsatz: AdaBoost, See5 und RandomForest. Die Validierung der Ergebnisse erfolgte sowohl mit Hilfe der Gesamtgenauigkeit als auch der mittleren Klassengenauigkeit. Alle verwendeten Sensoren erzielten gute Ergebnisse zwischen 85% und 92% Gesamtgenauigkeit. Einige Klassen erreichten jedoch nur geringere Werte. Dies hatte verschiedene Ursachen (Aufnahmedatum, Anzahl der Trainingsgebiete, räumliche Auflösung des Sensors). Als Fazit kann festgestellt werden, dass mit Hilfe von Satellitenfernerkundung der Renaturierungserfolg von wiedervernässten Niedermooren anhand der Vegetati-

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onszusammensetzung sehr gut überwacht werden kann. Auch eine weitergehende Analyse von Torfbildungspotenzial und Biomasse- /Nährstoffspeicherung ist damit möglich.

1 Introduction

The restoration of degraded and damaged ecosystems has become a major task throughout the world (Perrow & Davy 2002, Temperton et al. 2004, Van Andel & Aronson 2006, Zerbe & Wiegleb 2009). Particularly peatland was subject to heavy degradation and is now the focus of large scale restoration attempts. One of the crucial preconditions of successful ecosystem restoration is the monitoring of both vegetation development and balance of matter, since an important objective of peatland rewetting is the restoration of their sink function.

In NE Germany, peatland originally covered more than 10% of the total landscape (Kowatsch 2007). Due to drainage and the intensification of land use since the 1950's, most fens were strongly altered and lost their functions and services for nutrient and water retention, water purification, and habitats for plants and animals (Succow & Joosten 2001, Timmermann et al. 2009). In order to restore these ecosystems, the federal state of Mecklenburg-Western Pomerania initiated a 'Peatland conservation programme' in 2000 (Lenschow 1997). Consequently up to now, more than 10,000 hectares of fens have been rewetted. Despite investigations of such rewetted peatland on the local level (Timmermann et al. 2006, Gelbrecht et al. 2008), vegetation monitoring on the regional level has not yet been carried out. However, for the federal state government and scientists it is essential to control the progress of rewetted fens, particularly the re-initialised peat accumulation under restored conditions. We tried to fill this gap by developing a method for the monitoring of rewetted peatland with the help of satellite images. As access to the fen sites is often difficult due to flooding, remote sensing is presumably a helpful means to observe the status of vegetation cover and its change due to the altered water regime.

Several studies have successfully applied hyperspectral imagery to classify wetland vegetation (e. g. Becker et al. 2007, Pengra et al. 2007). However for operational use hyperspectral data is often not available. Since many of the wetland plant species and vegetation forms have very similar spectral characteristics the mapping with only multispectral information is difficult. Becker et al. (2007) found a minimum of seven spectral bands and a spatial resolution of 1 m necessary to obtain a good classification result. With only limited spectral information at hand (e. g. 4 bands with QuickBird or 3 bands with SPOT) classification accuracy can be improved by taking texture measures into account (e. g. Ruiz et al. 2004).

In this study, we tested the applicability of various satellite sensors (QuickBird, WorldView I and SPOT) and decision tree classifiers for mapping several plant species and vegetation types. Decision tree classifiers gain more and more in importance for remote sensing applications and often perform faster and with better results than traditional classification algorithms. Many applications regarding qualitative and quantitative environmental issues like land-cover mapping (Friedl & Brodley 1997, Hüttich et al. 2009, Otukei & Blaschke 2010), ecotope mapping (Chan & Paelinckx 2008), the monitoring of invasive plants (Lawrence et al. 2006), or the estimation of surface sealing or forest canopy (Herold et al. 2003) have successfully implemented tree-based classifiers such as RandomForest (Breiman 2001) or See5 (Quinlan 1993). The possibility to easily integrate nominal data in the classification process is a very important asset in times of ever growing thematic geo-information and a-priori knowledge. Furthermore the non-parametric approach of tree-based classifiers can be regarded as big advantage compared to the normal distribution constraints of parametric methods.

The aim of this study was to analyse the vegetation composition of rewetted peatlands with multispectral and very high spatial resolution satellite imagery. We investigated two sites with different rewetting dates and also took biomass and carbon content samples for the main plant species in order to estimate nutrient storage.

Since ground truth training samples are scarce for some ecologically very important classes we constructed an iterative tree-based classification scheme. We used three different decision tree classifiers and combined the classification results to create new training samples for a second classification run (Section 3.3). The intention of this study was not to directly compare the performance of the different algorithms but to benefit from their varying strengths and to establish an operational method for the monitoring of rewetted peatland.

2 Study Area and Data

2.1 *Study Areas*

We studied the middle and lower reaches of the Peene river and the lower reaches of the Trebel river, two large river valley systems in NE Germany (Fig. 1). The whole landscape was formed during the Weichsel glaciation, creating moraines, sandures, river systems, and large wetland areas. The climate has a slight continental character indicated by a relatively low mean annual precipitation of 540–590 mm, a mean annual air temperature of around 8.0 °C, and a temperature range of about 18 °C.

Since the Middle Ages, these peatlands have been used as meadows and pastures (Fischer 2005, Jansen et al. 2009). The change to an increasingly intensive agricultural land use since the middle of the 20th century created species-poor fen grasslands with tremendous peat losses, and a subsequent sinking of the soil surface below the water level of adjacent rivers and lakes (Succow & Joosten 2001). After rewetting since the 1990's, the site conditions strongly changed. Depending on the degree of inundation, the mesophytic grassland has changed to a vegetation mosaic of different helophytes and hydrophytes. Thus, species like *Carex spp.*, *Glyceria maxima*, *Phalaris arundinacea*, *Phragmites australis*, and *Typha latifolia*, accompanied by submersed macrophytes form a rich vegetation mosaic as is depicted in Fig. 2 (Timmermann et al. 2006, Roth

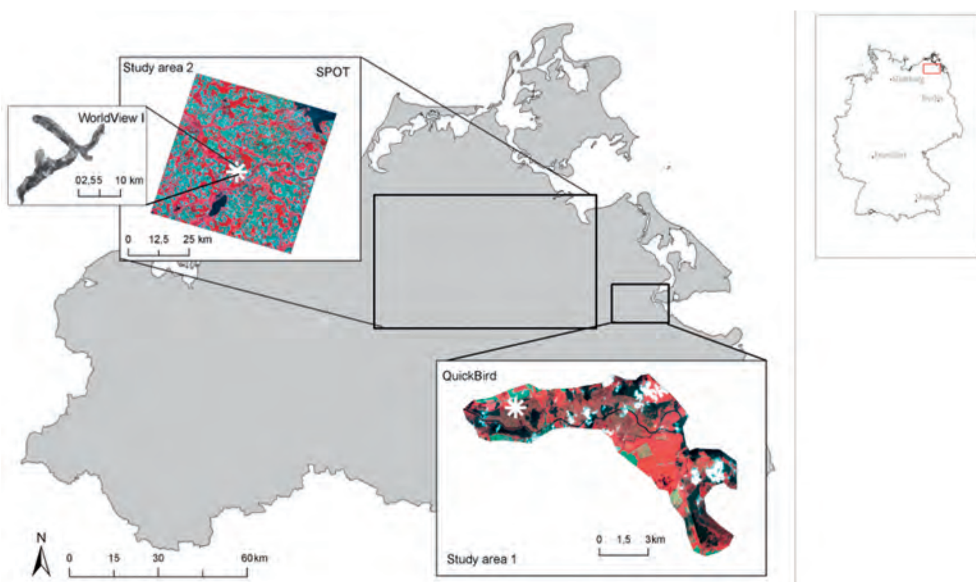

Fig. 1: Study area 1 in the lower Peene river valley and study area 2 in the lower Trebel river valley in Mecklenburg-Western Pomerania (NE Germany). The white asterisks show the location of polder Jargelin in study area 1 and polder Beestland in study area 2.

Fig. 2: View of Polder Beestland.

2000, Succow 2001, Steffenhagen et al. 2008). The water level depends on seasonal changes as well as on weather conditions. The highest water level is reached in winter and spring. Due to evapotranspiration processes it is lowest in summer. Nevertheless the vegetation mosaic is recognisable in the field throughout the whole year, but it is best differentiated in remote sensing data between early summer and autumn, when the water level is on its lowest.

Results from two different polders within those larger study areas will be presented in greater detail in this paper: polder Jargelin from study area 1 and polder Beestland from study area 2. The vegetation of both polders was mapped in 1995 and classified as Plantagini majoris-Lolietum perennis Beger 1932 nom. invers. propos. plant community (LUNG 1994–1997, Pätzolt & Jansen 2004). Polder Jargelin (33 ha) was heavily drained and served for decades as high intensity grassland. The dominating species in 1995, the year of rewetting, was *Phalaris arundinacea*. Polder Beestland (165 ha) was also drained and used as high intensity grassland with the dominating species *Phalaris arundinacea* and *Festuca arundinacea*. It was rewetted in 2002. By now, the grassland in both polders has changed to a mosaic of different helophytes and hydrophytes.

2.2 *Remote Sensing Data Source*

Our remote sensing database for study area 1 with polder Jargelin was QuickBird satellite imagery (Tab. 1). The order was tasked, unfortunately, clouds cover more than 10% of this study area and another 6% is strongly influenced by cloud shadow. Consequently, the radiometric characteristics of the data are quite impaired. For study area 2 with polder Beestland, we used as remote sensing database an archived SPOT scene and three archived WorldView I scenes (Tab. 1) since QuickBird tasking was not successful. Unfortunately, no WorldView summer scenes were available, thus we had to use images captured in April. Water level was very high at that time and large areas were still covered by water.

Tab. 1: Remote sensing data source and bands used for this study.

Study Area	Sensor	Date of capture	Geometric resolution	Spectral resolution	Radiometric resolution
1	QuickBird	04.09.2007	0.6 m PAN 2.4 m MS	450 – 900 nm 450 – 520 nm 520 – 600 nm 630 – 690 nm 760 – 900 nm	11 Bit
2	WorldView I	20.04.2008 23.04.2008 05.06.2008	0.5 m PAN	445 – 900 nm	11 Bit
	SPOT 2	25.07.2008	20 m MS	500 – 590 nm 610 – 680 nm 780 – 890 nm	7 Bit

2.3 *Field Data*

Field data for classes 1 to 12 (Tab. 2) were collected by biologists in summer 2007 for both areas. At the same time, biomass and carbon content samples were taken in mono-dominant stands from randomly chosen sites ($0.25\,m^2$) (Section 3.4). The vegetation patches were mapped in the field with help of GPS and aerial photographs. They had a minimum size of $5\,m^2$ and were afterwards geolocated by the biologists on-screen with help of the very high resolution satellite data. Training and validation samples for the other classes (13 to 16) were digitised directly from the satellite images. Ground truth for all wetland classes were then split randomly into training and validation samples (Tab. 2). Since all sites and classes were pooled for the selection process, the random selection yielded varying proportions of training and validation pixels.

3 Methods

3.1 *Pre-processing*

The processing level of all data was standard imagery (system corrected), which was then georeferenced on the basis of topographic maps, followed by a conversion to top of the atmosphere radiance. Clouds and cloud shadows were masked out. QuickBird has a very high geometric resolution of 2.4 m/0.6 m (multispectral/ panchromatic) pixel size at nadir, WorldView I even has a 0.5 m pixel size at nadir. This results in a large amount of data to be processed by the data mining tools we used for the decision tree classification. In order to substantially reduce the file size, we clustered the panchromatic masked QuickBird and WorldView I images with a number of 30 classes into spectrally homogeneous areas with the Isodata approach (Tou & Gonzalez 1974). File size was that way cut in half. This was followed by the computation of single channel means of the multispectral data (study area 1: QuickBird, study area 2: SPOT), different tex-

Tab. 2: Classes and number of training and validation sites. Pixel size 0.6 x 0.6 m for study area 1 and 1.0 x 1.0 m for study area 2.

Class ID	Class name	# of training pixels area 1	# of training pixels area 2	# of validation pixels area 1	# of validation pixels area 2
1	Open water	190	51527	33	12409
2	Floating leaved macrophytes	1942	-	177	-
3	Submersed macrophytes	108	-	21	-
4	Duckweed (*Lemna* spp.)	481	38	31	0
5	Common reed (*Phragmites australis*)	20787	25133	1935	6888
6	Cattail (*Typha* spp.)	11008	21018	1012	4907
7	Sedges (*Carex* spp.)	1308	45585	145	15466
8	Reed canary grass (*Phalaris arundinacea*)	20787	839478	483	230983
9	Seasonal flooded grassland	46	151695	5	42460
10	Mannagrass (*Glyceria maxima*)	511	2955	73	655
11	Spike rush (*Eleocharis* spp.)	219	-	27	-
12	Soft rush (*Juncus* spp.)	-	40034	-	9476
13	Woods and shrubs	91851	263576	2375	77624
14	Other classes	5643	8271	271	2585
15	Clouds	1809	-	127	-
16	Shadow	221	-	10	-

tural measures including grey level co-occurrence GLCM (Haralick et al. 1973) and several ratios as well as indices for every single cluster. Ratios, indices and texture measures are very helpful for classification since they can emphasise small differences between classes, as has been shown in many studies, e. g. for landcover classification with IKONOS data (Tassetti et al. 2010) or for tree species classification with airborne data (Li et al. 2010). Finally, more than 30 different attributes per cluster were calculated and then used as model attributes in the decision tree classification. Since not all of these might provide valuable predictive information and thus would add to computation burden we pre-selected only the most important ones using a leave-one-out approach (see following section).

3.2 *Decision Tree Algorithms*

For a detailed discussion of decision trees, see Breiman et al. (1984). Only a short introduction of the most important principles shall be given here. Decision trees can be used as predictive models and consist of different levels of nodes. The root node or whole data set is divided (split) into more homogeneous groups. This is achieved by a statistical measure (e. g. entropy) which tries to find the attribute with the most discriminatory power and then sets a threshold. Split nodes subsequently contain only part of the data and can further be divided until an end node (leaf) is reached where no further split is possible or desired. Different split criteria like information gain ratio or entropy can be used to find the thresholds. Since the tree can be grown until every single training sample is correctly classified, erroneous data may lead to a bad performance when using the tree on other samples not used for the training. To avoid this so-called overfitting, the tree can be reduced by pruning. With the help of different statistical measures the tree is cut back and thus generalised. For a detailed description see e. g. Kearns & Mansour (1998) or Quinlan (1993).

Nevertheless decision trees are considered as rather 'weak' learners compared to parametric classifiers like maximum likelihood (e. g. Chan & Paelinckx 2008). Ensemble classification methods can be used to overcome this problem. Two common strategies are boosting and bagging (Freund & Schapire 1996, Breiman 1996). In both methods several trees or several weak classifiers are combined into a new strong classifier, only the way of selecting training samples differs.

Boosting uses a special set of weights for all training samples, increasing the weight after each run for the misclassified samples and decreasing it for the correct samples. It concentrates more and more on the difficult cases and thus optimises the classifier. The final class is assigned by a weighted majority vote of all single trees. A widely used algorithm implementing boosting is AdaBoost (Freund & Schapire 1996). More information on boosting can be found in Schapire (1999) or Bühlmann & Hothorn (2007).

Bagging means that for every classification run only a subset of the whole training set is selected randomly (Breiman 1996). For each new tree a new subset is selected, while always considering the whole set of training samples. This so-called replacement can lead to some training samples being present in all the different subsets whereas some training samples are never considered at all. The final class is assigned by a simple majority vote of all single trees.

We chose three different widely used decision tree classifiers for this study: AdaBoost, See5 and RandomForest. The first two incorporate boosting and the last one uses bagging. See5 employs the information gain ratio as a split criterion (Quinlan 1993). In order to balance computation time and model accuracy we used after several trials with different settings the following thresholds: boosting with 10 trees, 25% global pruning and at least 2 cases had to be at an end node.

Firstly, all attributes that were calculated for every single cluster (ratios, indices and texture measures) were used to build a model with the 'winnowing' option of See5 in order to assess their importance and predictive information. See5 estimates the increase in the models true error rate if one attribute was left out and then orders the attributes accordingly. Seven attributes were thus selected for all following classification runs for study area 1 and

Tab. 3: Attributes used for all classification runs, sorted by importance. All attributes were calculated for every ISODATA-segment (for study area 1: based on QuickBird segments, for study area 2: based on WorldView I segments).

Study area	Attribute name	Description
1	ms3glcm1	Mean Red (GLCM) QuickBird
	ms4glcm1	Mean NIR (GLCM) QuickBird
	4min2	Difference NIR minus Green QuickBird
	2min1	Difference Green minus Blue QuickBird
	3min2	Difference Red minus Green QuickBird
	r31	Ratio Red/Blue QuickBird
	ms4glcm2	Variance NIR (GLCM) QuickBird
2	ndvi	NDVI SPOT
	2min1	Difference Red minus Green SPOT
	3min2	Difference NIR minus Green SPOT
	3min1	Difference NIR minus Red SPOT
	spot1	Mean Green SPOT
	spot2	Mean Red SPOT
	spot3	Mean NIR SPOT
	wvmean	Mean WorldView
	r31	Ratio NIR/Red SPOT
	r21	Ratio Red/Green SPOT
	glcm1	Mean WorldView (GLCM)
	glcm4	Contrast WorldView (GLCM)
	glcm8	Correlation WorldView (GLCM)

thirteen attributes were selected for study area 2 (Tab. 3). Several texture measures were among the attributes with high importance. The selected attributes vary for both areas because the remote sensing data sources are very different (QuickBird versus SPOT and WorldView I).

As a second decision tree classifier we used the multi-class implementation of AdaBoost (Freund & Schapire 1996). To balance computation time and model accuracy we finally used 30 trees after several trials with different numbers of trees. Since AdaBoost is a meta-algorithm, capable of using all different kinds of weak classifiers, we selected a simple decision tree stump, where the split criterion uses information gain. Again at least 2 cases had to be at an end node. The third decision tree classifier was RandomForest (Breiman 2001). It employs the gini index (a measure of inequality) as a split criterion. Because the computation burden is quite high for RandomForest we were not able to use more than 10 trees.

3.3 *Iterative Classification*

A certain increase in training set size was shown to improve classification quality with decision tree algorithms (Mahesh & Mather 2003) and also the joint application of multiple algorithms can increase classification accuracy (Xi et al. 2008). Since for some vegetation classes, sufficient and homogeneous ground truth data is not easy to collect, a new approach of an iterative classification was applied. We assumed that after a first classification run, based on ground truth training data with different classification algorithms, those results can be combined to extract new training information. Pixels where all algorithms decide for the same class are likely to be correctly classified. In this study, new training samples are generated from the intersection of the three classifiers. With the newly obtained training set a second classification run is completed. Through this approach the training set is increased (approx. five times the size of the initial set) and also pixels that were wrong in the initial set can thus be identified and deleted. For example, many water pixels were included in the classes floating leaved macrophytes and also in the different reed classes, those were eliminated in the second run from the training set.

3.4 *Biomass and Carbon Stock Assessment*

The aboveground biomass of the most common helophytes was harvested in 2007 in mono-dominate stands from randomly chosen sites (0.25 m^2) at the beginning of their flowering time when shoot biomass approaches net primary production (Dykyjová & Kvét 1978, Odonk & Kvét 1978) and contains the peak of nutrients (Bernhard & Hankinson 1979). Overall, we analysed the aboveground biomass and carbon stock of *Phragmites australis* (40 sites), *Typha latifolia* (48 sites), *Glyceria maxima* (32 sites), *Carex riparia* (24 sites), *Carex acutiformis* (40 sites) and *Phalaris arundinacea* (40 sites). The samples were dried for 48 h at 85 °C, weighted to determine dry mass, grinded and homogenised. Carbon content of dry mass was measured with a CHN-Analyser "Vario EL III".

Since the classification results have a very high spatial and thematic resolution, biomass and carbon storage can be calculated with a simple upscaling approach. We summarised the coverage of the investigated helophytes in the study areas and multiplied the area values with the specific biomass values [t DM = dry matter/ha] and carbon stock [t/ha].

4 Results

4.1 *Classification Accuracy*

The overall accuracy is not sufficient for the assessment of the total classifier performance, as some classes with large areas (and thus a large number of validation samples) influence the overall accuracy strongly, whereas classes with small occurrence but very high ecological importance are underrepresented. The mean class accuracy (mean of all single class accuracies) was thus used as an additional separability measure. For example the overall accuracy for study area 1 and the AdaBoost classification amounts to 92% whereas the mean class accuracy is only 80% since some small occurrence classes have a lower accura-

Tab. 4: Accurracies for the different classification algorithms trained with the intersected training sample set (second run).

	Study area 1			Study area 2		
Class ID	Ada30_2	RF10_2	See5_2	Ada30_2	RF10_2	See5_2
Open water	98,45	98,41	98,43	**87,19**	86,92	87,07
Floating leaved macrophytes	**80,76**	79,16	78,83	–	–	–
Submersed macrophytes	56,00	55,32	54,41	–	–	–
Duckweed (*Lemna* spp.)	**98,19**	95,76	90,58	96,05	96,05	96,05
Common reed (*Phragmites australis*)	**83,69**	83,49	82,74	**60,87**	60,66	60,72
Cattail (*Typha* spp.)	**78,30**	77,86	77,49	91,46	90,56	**91,62**
Sedges (*Carex* spp.)	**70,38**	67,23	66,35	**89,25**	88,85	89,08
Reed canary grass (*Phalaris arundinacea*)	**82,10**	80,62	79,24	**89,43**	89,38	89,36
Seasonal flooded grassland	55,47	**55,69**	52,51	**88,06**	87,62	87,82
Mannagrass (*Glyceria maxima*)	**60,16**	59,46	58,29	**91,46**	90,93	91,24
Spike rush (*Eleocharis* spp.)	79,61	79,14	**80,16**	–	–	–
Soft rush (*Juncus* spp.)	–	–	–	69,61	68,79	**70,49**
Woods and shrubs	**92,41**	91,97	91,01	74,50	**74,54**	74,51
Other classes	**99,87**	99,70	99,52	98,37	98,82	**98,83**
Clouds	**98,71**	98,54	98,52	–	–	–
Shadow	66,42	60,48	**69,43**	–	–	–
Mean class acc.	**80,03**	78,85	78,50	85,11	84,83	**85,16**
Overall acc.	**91,58**	91,20	90,78	**84,95**	84,81	84,89
Change in overall acc. compared to the first run	+8,13	+12,19	+1,51	–2,51	+0,23	+0,18

cy. All single class accuracies are listed in Tab. 4. The classifier with the highest accuracy (AdaBoost) was used as the final classification result. Still four problematic classes remain in study area 1 with lower accuracies than 80: submersed macrophytes, seasonal flooded grassland, sedges and mannagrass. For all these classes we had only very few training samples and also the iterative classification did not lead to a major improvement. Submersed macrophytes will always remain difficult, since they can only be detected by multispectral remote sensing if the water level is not too high above the plants. Seasonal flooded grassland can sometimes contain different reed species e. g. reed canary grass and thus leads to false misclassification. For sedges and mannagrass, a larger initial training sample would be desirable. Furthermore, the selected feature set might not be optimal for those two classes.

In study area 2, both overall and mean accuracy reached 85%. Three problematic classes remain in study area 2 with lower accuracies than 80: woods and shrubs, common reed and soft rush. Common reed and woods and shrubs in this area occurs in very thin stripes along water channels, the coarser resolution (20 m) of the SPOT multispectral data is thus certainly not adequate and the WorldView I texture was not sufficient to overcome this problem. This might be due to the different acquisition dates of the WorldView I and SPOT scenes. In April (WorldView I) phenology is only at the starting phase whereas in late July (SPOT) vegetation is at its peak. Another issue was that in April large areas were still flooded (thus providing no texture) whereas in late July the water level was at a very low point.

4.2. *Monitoring Results for Polder Jargelin and Polder Beestland*

The initial vegetation cover of dominant *Phalaris arundinacea* grassland in polder

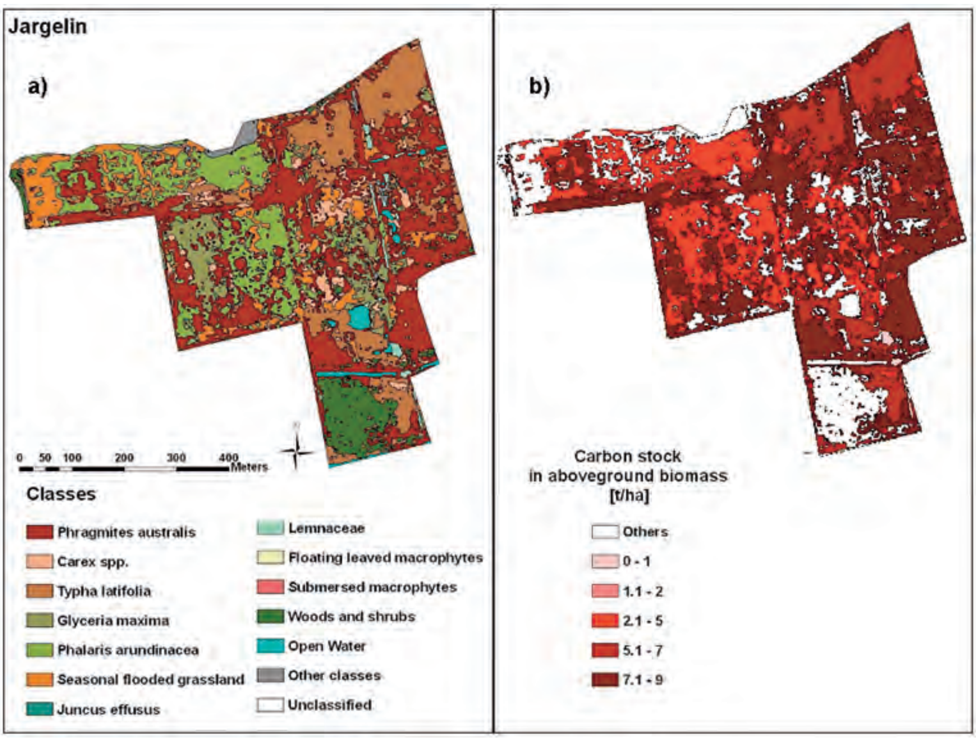

Fig. 3 a): Final classification result for the polder Jargelin in study area 1 (Steffenhagen et al. 2008). **b):** Carbon stock in net aboveground biomass of helophytes in Polder Jargelin (Steffenhagen et al. 2008).

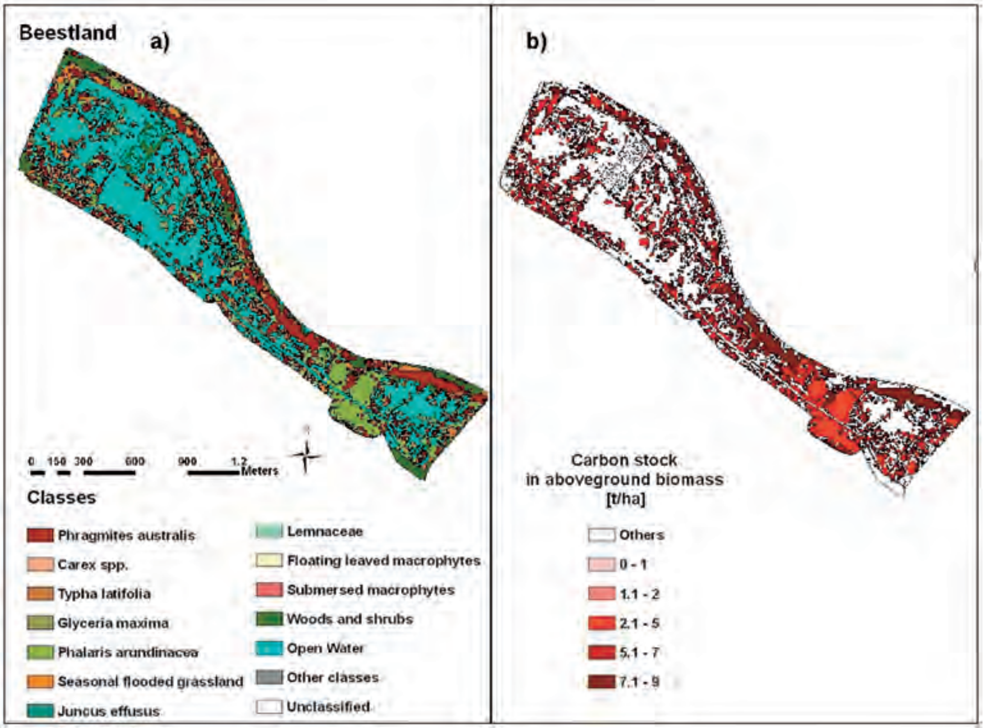

Fig. 4 a): Final classification result for the polder Beestland in study area 2. **b):** Carbon stock in net aboveground biomass of helophytes in Polder Beestland.

Jargelin has changed substantially after 12 years of rewetting as is illustrated by the classification results in Fig. 3a. Mainly reeds and sedges cover the area now. 39% of the polder are overgrown by *Phragmites australis* and sedges. This is of great importance since these species have the potential to accumulate peat, which can be interpreted as a first success in the restoration of this particular fen. Also biomass and carbon storage are highest for *Phragmites australis*.

For polder Beestland, the initial vegetation cover of dominant *Phalaris arundinacea* and *Festuca arundinacea* grassland has also changed substantially after only six years of rewetting. The classification results (Fig. 4a) indicate that the initial high intensity grassland vegetation has already changed to a helophyte dominated mosaic. Especially *Phragmites australis* could spread further starting from the dyke edges. A large part of the area is still covered with open water.

4.3 *Biomass and Carbon Stock Assessment for Polder Jargelin and Polder Beestland*

The aboveground biomass and carbon stock of helophytic vegetation during the growing season 2007 and 2008 showed a wide difference between polder Jargelin and polder Beestland (Fig. 3b and 4b). Although polder Beestland (165 ha) is nearly 5 times bigger than polder Jargelin (32 ha) the aboveground biomass and carbon stock was only twice as high as for polder Jargelin. We calculated for polder Beestland an aboveground biomass of 709 t and carbon stock of 328 t. For polder Jargelin overall aboveground biomass amounted to 318 t and carbon stock to 147 t. These differences are caused by the different dates of rewetting and also by the large areas still covered with open water in polder Beestland.

5 Discussion

5.1 *Vegetation Development*

After several years of rewetting degraded peatland, the now present vegetation still displays, according to the former land use, the grade of peatland degradation (Timmermann et al. 2009), and the present hydrological conditions (Timmermann et al. 2006). Common reed (*Phragmites australis*) is either already most abundant as in polder Jargelin or beginning to spread as in polder Beestland. Representing a cosmopolitan plant species with a broad ecological range with regard to nutrient supply, water level depth and land-use practice (Ostendorp 1988, Kühl & Kohl 1992, Thevs et al. 2007) this plant is one of the key species of nutrient rich lowland fens and river banks throughout Central Europe. Additionally, it is one of the target species in fen restoration (Wilcox & Whillans 1999, Timmermann et al. 2009). As common reed has the potential of peat accumulation it has a considerable value with regard to ecosystem services like carbon sequestration (Grosse-Brauckmann 1990, Brix et al. 2001, Mander et al. 2008).

After rewetting, only never or rarely inundated sites were covered by canary grass (*Phalaris arundinacea*). Permanently inundated sites were replaced by reeds of *Phragmites australis*, *Typha latifolia*, and *Carex spp.*. Open water, which occured on sites with high soil shrinkage, was often dominated by submersed and floating leaved macrophytes and duckweed.

Both polders cannot be compared directly since rewetting date and initial situation differ. It can be said, that the vegetation development on both study sites is successful with regards to biomass and carbon storage and also to potential peat accumulation.

5.2 *Methodological Approach*

We developed an iterative decision tree based classification approach for the analysis of peatland vegetation that can be applied to operational optical satellite sensors with different spectral and spatial resolution. Texture is very important for the separation of certain classes and thus at least a panchromatic very high resolution sensor should be used. Multispectral information can have a lower spatial resolution, though the use of 20 m SPOT imagery leads to a significant decrease in accuracy for some classes compared to 2.4 m QuickBird imagery. Particularly classes that cover only small areas or thin stripes like common reed and single trees and shrubs are better classified with QuickBird data. Furthermore and not surprisingly it can be concluded that accuracy is mostly higher for classes with larger training samples. The time of capture is also an important factor for the classification success. Images taken in April are not advisable for rewetted peatland since large areas are still covered by water.

Our intention was not to compare the different decision tree classifiers and ensemble classification methods but it can be said that all performed with similar good results for both sensors and all classes.

The suggested classification approach is straightforward and easy to implement – only computation time and the volume of data might be a problem. The developed method was applied to both complete study areas (more than 8000 ha) and yielded a valuable input not only to the observation of restoration success by rewetting but also to biomass and nutrient storage estimation. With qualified laboratory data regarding the nutrient storage and biomass production of single wetland plant species and vegetation forms the presented classification results can be a very helpful input to the further assessment of restoration results. Peatland can function as carbon sink and may influence the global climate regulation. Thus, the carbon storage and biomass production of rewetted fens are of great interest and can be estimated in high detail for large areas if adequate vegetation maps are available (Fig. 3b and 4b).

6 Conclusion

We analysed the vegetation composition of rewetted peatlands with multispectral and very high spatial resolution satellite imagery. We developed an iterative classification approach based on decision trees. Evaluation criteria were overall and mean class accuracy. Two sites with different rewetting dates were investigated and also biomass and carbon content samples for the main plant species were taken in order to estimate nutrient storage.

Multispectral and very high spatial resolution satellite data and the developed method allow the classification of the most important vegetation types in rewetted fens. All applied sensors (QuickBird; WorldView I in combination with SPOT) yield good results with overall accuracies of 85% and 92%. The use of multispectral imagery with a high spatial resolution like QuickBird leads to a higher classification accuracy for some classes compared to SPOT imagery.

With the obtained vegetation maps, the observation of successional trends on the regional level, in particular the development of peat-forming vegetation (Grosse-Brauckmann 1990, Hartmann 1999, Richert et al. 2000) was possible and thus can improve the prediction and fulfilment of precise restoration targets (Pfadenhauer & Klötzli 1996). Furthermore, the detailed extent of the identified vegetation types can be estimated and provides valuable input for other purposes such as biomass and nutrient storage assessment. Particularly the accurate area-wide analysis of carbon storage in rewetted fens is of great interest with regard to their potential contribution to green house gas emission reduction. Overall, as vegetation is one of the most important ecological indicators (Ellenberg 1996, Jansen et al. 2009), a broad range of environmental questions can be tackled with the results of our approach.

Remote sensing can be an essential tool for the monitoring of peatland since an area-wide terrestrial mapping of similar accuracy and detail is often not feasible.

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Addresses of the Authors:

Dr. Annett Frick, LUP GmbH, D-14469 Potsdam, Tel.: +49-331-2757760, Fax: +49-331-2757799, e-mail: annett.frick@lup-umwelt.de

Prof. Dr. Stefan Zerbe, Free University of Bozen, I-39100 Bolzano, Italy, Tel.: +39-04710-17150, e-mail: stefan.zerbe@unibz.it

Peggy Steffenhagen, Dr. Tiemo Timmermann and Karsten Schulz, Universität Greifswald, Institut für Botanik und Landschaftsökologie, D-17487 Greifswald, Tel.: +49-3834-775760, -864112, -775760, Fax.: +49-3834-864114, e-mail: peggy_steffenhagen@gmx.de, tiemo@uni-greifswald.de, netsrak@gmx.ch

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