

COMBINING OBJECT-BASED IMAGE ANALYSIS AND DATA MINING FOR CARBON ASSESSMENT IN FLOODPLAINS

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ABSTRACT:

Floodplains are crucial ecosystems regarding their function as carbon sinks. In comparison to other terrestrial ecosystems, riparian forests, even in temperate climates, have a considerably high storage capacity for organic carbon (C_{org}). Despite the importance of floodplains for carbon sequestration, the scientific basis for the creation of large-scale maps that show the spatial distribution of C_{org} is still insufficient. The idea of this research is to develop a method to model the allocation of C_{org} stocks using remote sensing and other geographic data. The research area is the Danube Floodplain National Park in Austria. It is a large pristine riparian habitat, one of very few left in central Europe. A wide variety of data was available including two very high spatial resolution (VHSR) satellite images such as Ikonos and RapidEye, historic and actual topographic maps, and various vegetation and soil parameters. In combination with the other data available, data mining can provide a powerful tool to improve the classification process and to determine the importance of single geofactors. So far various OBIA of an Ikonos scene and additional data were performed to classify vegetation types. In this study, the machine learning algorithm for classification and regression trees (CART) of eCognition 8.7 is under investigation.

The eCognition CART classifier extracted all continuous information from the various satellite images including mean layer values, indices, texture and combined it with geographic parameters such as height, slope, existence of river beds, distance to river and ground water level. We evaluated three different parameter combinations. The results show the complexity of the intricate network of side channels, small islands and the multifariousness of the interactions within a small-scale model of C_{org} such as the Danube floodplain. With an increased number of parameters the classification accuracy increases, but it is still considered moderate.

Results of the modeling process shall contribute to the prediction and assessment of C_{org} for floodplain areas in tropical and subtropical zones, which play a more prominent and important role in the global carbon cycle.

1. INTRODUCTION

1.1 Estimation of carbon stocks in floodplains

Floodplains are crucial ecosystems not only as hotspots of vitality and biodiversity, but also regarding their function as carbon sinks. In comparison to other terrestrial ecosystems, riparian forests, even in temperate climates, have a considerably high storage capacity for organic carbon (C_{org}). Despite the importance of floodplains for carbon sequestration, the scientific basis for the creation of large-scale maps that show the spatial distribution of C_{org} is still insufficient. Although carbon distribution can be mapped on global or national level, but with insufficient regional validation (Gibbs and et al. 2007; Groombridge and Jenkins 2002; UNEP-WCMC 2008). Yet, there are no large-scale maps showing the actual allocation of the C_{org} storage inside riparian soils and vegetation on local or regional level. Various studies have their focus on C_{org} stocks in alluvial soils (Busse and Gunkel 2002; Giese et al. 2000; Hazlett et al. 2005) or subtropical wetlands (Matsui et al. 2009; Mitsch et al. 2010) and soils (Grimm et al. 2008). Cierjacks et al. (2011) have provided statistical models on the spatial distribution of C_{org} stocks in Danubian floodplain vegetation and soils. However, these studies were exclusively field-based. Data have been collected by cost-intensive ground surveys. In order to assist and fasten the estimation of C_{org} , even for larger or less accessible wetland and riparian areas, methods of remote

sensing and the use of geoinformation systems (GIS) are valuable techniques.

Several studies have used remote sensing in general (Farid et al. 2008; Munyati 2000; Ozesmi and Bauer 2002) and object-based image analysis (OBIA) for the analysis of wetlands (Kollár et al. 2011; Rokitnicki-Wojcik et al. 2011; Wagner 2009). However these studies were more related to habitats and did not focus on the assessment of biomass or C_{org} .

The remote sensing analysis of C_{org} stocks in various habitats was described by various authors (Awaya et al. 2004; Behrens and Scholten 2006; Hilker et al. 2008; McBratney et al. 2003; Neeff et al. 2005; Olofsson et al. 2008). Most of these studies have focused either on C_{org} stocks in soil or vegetation, there is no comprehensive approach so far.

Besides pure remote sensing also the combined use of remote sensing and additional geodata has been described by some studies (Gibbs and et al. 2007; Goetz et al. 2009). Examples for those data mining methods include Self-Organized Maps (SOM), Random Forest estimations or approaches with commercial software applied to rewetted peat lands (Frick et al. 2011) as well as farmland in Montana (Brickley et al. 2007). Applying the theoretical knowledge to our research in the Danubian Floodplains, various approaches were done to estimate the amount of above and below ground C_{org} .

A first approach to determine the C_{org} content by VHSR and DEM data through OBIA and a Monte-Carlo simulation has

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been performed (Suchenwirth et al. 2012). As an advantage, this method could create a spatial distribution map of C_{org} . However, this estimation was based on the specific C_{org} content of the classified vegetation types and did not consider other geofactors.

A second approach was to identify parameters with a punctiform data mining approach based on the software package See5. This approach considers all available data that might have an impact on the amount of C_{org} and determines their importance. The advantage of this method was that a wide variety of available geodata could be analysed and taken into consideration in order to improve the model. However, the results of these methods still had deficits regarding the accuracy and included information which is not generally available as continuous information, i.e. as raster data.

Therefore the research idea of this study is to develop a method to model the allocation of C_{org} stocks using remote sensing and other spatially continuous, i.e. area-wide, available geodata.

1.2 Data Mining

Methods of data mining and knowledge discovery in databases (Fayyad et al. 1996) have been frequently applied in the recent years, also due to the increasing number of available geofactors (Qi and Zhu 2003) and indices based on remote sensing (Yang et al. 2007; Moisen et al. 2006; Quintano et al. 2011). A large variety of geodata requires a tool to understand the individual relevance of each factor and to carefully select the parameters that have an increased significance for the modeling process.

Given the complexity of spatial distribution of C_{org} in the Danube floodplains (Cierjacks et al. 2010; Cierjacks et al. 2011; Suchenwirth et al. 2012) on the one hand, the amount, variety and consistency of data on the other hand, a tool defining the importance of the single geofactors is necessary. Data mining is described as a 'non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable' patterns in data (Fayyad et al. 1996). Often, these patterns concern the categories to which a situation belongs, e.g. if a process will give a high, medium or low yield on a batch of raw material. Data mining can be regarded as one step in the process of knowledge discovery in databases (KDD)(Fayyad et al. 1996). Kaichang et al. (2000) have been using data mining methods for the classification of Landsat data, while Stümer et al. (2010) have assessed C_{org} in forests by Self-Organized Maps (SOM) and Frick et al. (2011) and Bricklemeyer et al. (2007) used the commercial software See5 for their estimations of C_{org} .

2. METHODS

2.1 Research Area

The research area has a size of about 11.3 km² and is situated in the Danube Floodplain National Park in Austria (16.66° E, 48.14°N). The National Park is located between the Austrian capital Vienna and the Slovak capital Bratislava, and stretches along the river Danube for about 36 km. The river has an average width of about 350 meters, and is not barred. There have been few human impacts onto the area apart from the construction of the Marchfeld dike in the 19th century to protect areas on the northern riverbank from inundation and to ease navigation on the river. Throughout history, the area served as imperial hunting ground. In the 1960ies, forest structures were altered through the plantation of hybrid poplars (*populus x canadensis*), especially on the southern riverbank. In 1996 the area was declared a national park, thus banning any commercial enterprise within its precincts. Despite the previous

human interventions, the area has remained one of the last large pristine riparian habitats left in Central Europe, recognized by the IUCN as a Riverine Wetlands National Park, category II.

The National Park's environmental conditions include the Danube river's water body, side channels and oxbow lakes, gravel banks, riparian forests and meadows, reed beds and xeric habitats. The main soil type is haplic fluvisoil (calcaric), calcaric gleysols are less important; the climate is continental with a mean annual temperature of 9.8°C and mean annual precipitation of 533 mm [Schwechat climate station, 48°07'N, 16°34'E, 184 meters above sea level (ZAMG 2002)].

The area was selected for its high-ranking protection status, a good base of geographic data and the high number of studies in the area (Cierjacks et al. 2010; Cierjacks et al. 2011; Ellenberg 1986; Lair et al. 2009; Suchenwirth et al. 2012; Wagner 2009; Zehetner et al. 2009).

2.2 Data

A wide variety of data was available including two very high spatial resolution (VHSR) satellite images such as Ikonos and RapidEye, historic and actual topographic maps, digital elevation model and data on the medium groundwater level.

A cloudless Ikonos 2-image (22nd of April 2009) was purchased as well as a satellite image scene of the area derives from the sensor RapidEye (recorded on August 1st 2009). In addition to the spectral values several ratios and texture parameters (Haralick et al. 1973) were calculated (Table 1). A digital elevation model (DEM) derived from LiDAR data has been used to compute height and slope. Increased slope values can indicate historic riverbeds of the main stream or overgrown side channels (as an indicator for softwood), which cannot be detected directly through spectral values. Also the height above ground (sea level) has been included into the knowledge-base.

Available geodata	Derived Parameters	Abbreviation
Ikonos image (April 22 -2009) RapidEye image (August 1-2009)	Spectral values, indices (Ikonos: NDVI, vegetation classification; RapidEye: NDVI, tNDVI, modNDVI, b4NDVI, SRI,[b2-b1], [b3-b1], [b3-b2], [b5-b4], [b5-b4], [b3/b1], [b4/b2],[b5/b2]), texture (GLCM homogeneity, GLCM mean, GLCM correlation, GLCM contrast, GLDV entropy)	Ikonblu, Ikongrn, Ikonred, Ikonrir, ikonndvi; Classification; b1, b2, b3, b4, b5; b2mb1, b3mb1, b3mb2, b5mb4, b3db1, b4db2, b5db2;
Digital Elevation Model	Height, slope	DEM, slope
Historical (military mapping surveys) and actual topographic maps	Existence of river beds, distance to river	hist1, hist 2, hist 3; dist
Ground water model	Ground water level	MGW
Ground survey data from 2008 and 2010	C_{org} contents and stocks	

Table 1. Available geodata and derived parameters

Vegetation types had been classified by OBIA of the Ikonos image and the slope model (Suchenwirth et al. 2012).

The historic and also actual topographic maps were provided by the Austrian Federal Office for Metrology and Survey (BEV). The historic maps range from three topographic land surveys, the First (1764 to 1806), Second (1806 to 1869) and Third Military Mapping Survey (1868-1880). The information can be used to localize historic riverbeds. A ground water model with heights of medium and low ground water was provided by the Vienna University of Technology.

In two terrestrial surveys in 2008 and 2010, a total of 104 samples from vegetation and soil were taken. C_{org} content of soil and vegetation have been measured and calculated (Cierjacks et al. 2010; Cierjacks et al. 2011); these data were randomly separated in training data (70%) and test data (30%) for the data mining process.

2.3 Method

The idea of this study is to develop a spatial model based on a combined approach of data mining and OBIA with remote sensing and other spatially continuous geodata for the estimation of C_{org} stocks in soils and vegetation. For the implementation in this study, we used the commercial software package eCognition Developer 8.7.1. In this new approach, OBIA shall be attached to data mining.

The ground survey data set containing the information on the total C_{org} stocks in vegetation and soils (to the depth of 1 meter) was grouped into 5 quintile classes (Class 1: up to 230 Mg C ha⁻¹; class 2: 231-300 Mg C ha⁻¹; class 3: 301-360 Mg C ha⁻¹; class 4: 361-445 Mg C ha⁻¹; class 5: more than 445 Mg C ha⁻¹). A CART creates classification rules in the shape of a decision tree. Decision trees show hierarchical rules according to which a dataset is classified. At the beginning of a decision tree is the basic population of the data; during the classification process, the dataset is split up according to binary rules (Quinlan 1986; Breiman et al. 1984). To prepare the decision tree, the parameters are distilled out of the datasets. During the data mining process, the program searches appropriate mechanisms for the partition of the dataset.

The OBIA was performed on a multiresolution segmentation with a scale parameter of 200, the homogeneity criterion includes a shape of 0.1 and a compactness of 0.5. The CART algorithm is trained with the quintile classes and applied onto the parameters using the 'classifier' tool in eCognition 8.7.1, with a classifier depth of 10, a minimum sample count of 6 and 9 cross validation folds.

To evaluate the classification accuracy, the user's accuracy (UA, also known as commission error), producer's accuracy (PA, also known as omission error), and the overall accuracy (OA) were calculated as well as the Kappa (K) and the Kappa Overall (KIA) statistics. The Kappa coefficient serves as an additional measure of agreement between the classes represented in the classified image and on the ground. The measure describes which level of agreement is due to chance; a K value of 1 describes a very high classification accuracy, a K value of 0 a very low accuracy.

3. RESULTS

Three different results from the CART processes were compared. Figures 1-3 and Tables 2-4 show CART-based models of C_{org} stocks and their accuracy assessment. The CART models are based on the use of

b) spectral values and NDVI of RapidEye and Ikonos sensors and values from the digital elevation model, slope, and medium ground water level (Figure 2, Table 3), and c) all available parameters (Table 1): Figure 3 and Table 4. The models created by the CART classifier show the complexity of data models. With an increasing number of parameters also the number of parameters actually implemented in the classification rises.

The accuracy results of the CART-based classifier are slight to moderate (Congalton 1991). The overall accuracy (OA) ranges from 0.115 (a), Table 2) to 0.196 (b), Table 3) to 0.432 (c), Table 4), the Kappa Overall statistics (KIA) from -0.043 (a), Table 2) to 0.033 (b), Table 3) to 0.283 (c), Table 4).

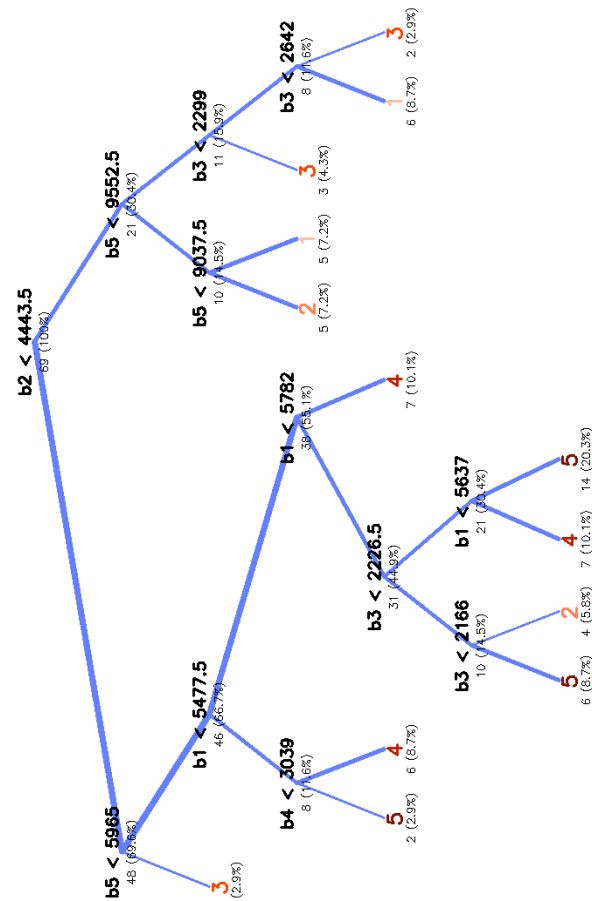


Figure 1. C_{org} model based on RapidEye spectral bands (a)

Quintile class	1	2	3	4	5
Producer's Accuracy	0.158	0.167	0.001	0.115	0.080
User Accuracy	0.431	0.188	0.003	0.181	0.008
KIA per class	0.080	-0.101	-0.063	-0.062	-0.321
Overall Accuracy	0.115				
KIA	-0.043				

Table 2. Accuracy Assessment of C_{org} - Classification based on RapidEye spectral bands (a)

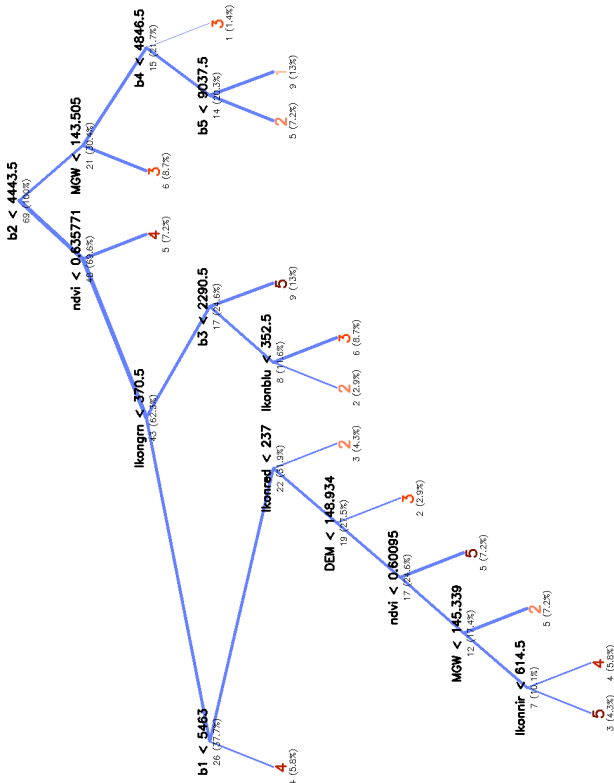


Figure 2. C_{org} model based on spectral values and NDVI of RapidEye and Ikonos sensors and values from the digital elevation model, slope, and medium ground water level (b)

Quintile class	1	2	3	4	5
Producer's Accuracy	0.149	0.133	0.158	0.336	0.080
User Accuracy	0.420	0.185	0.238	0.387	0.008
KIA Per Class	0.070	-0.085	0.024	0.134	-0.321
Overall Accuracy	0.196				
KIA	0.033				

Table 3. Accuracy Assessment of C_{org} - Classification based on spectral values and NDVI of RapidEye and Ikonos sensors and values from the digital elevation model, slope, and medium ground water level (b)

Quintile class	1	2	3	4	5
Producer's Accuracy	0.313	0.161	0.632	0.667	0.058
User Accuracy	0.536	0.419	0.450	0.585	0.008
KIA Per Class	0.204	0.063	0.485	0.513	-0.026
Overall Accuracy	0.432				
KIA	0.283				

Table 4. Accuracy Assessment of C_{org} - Classification based on all available parameters (c)

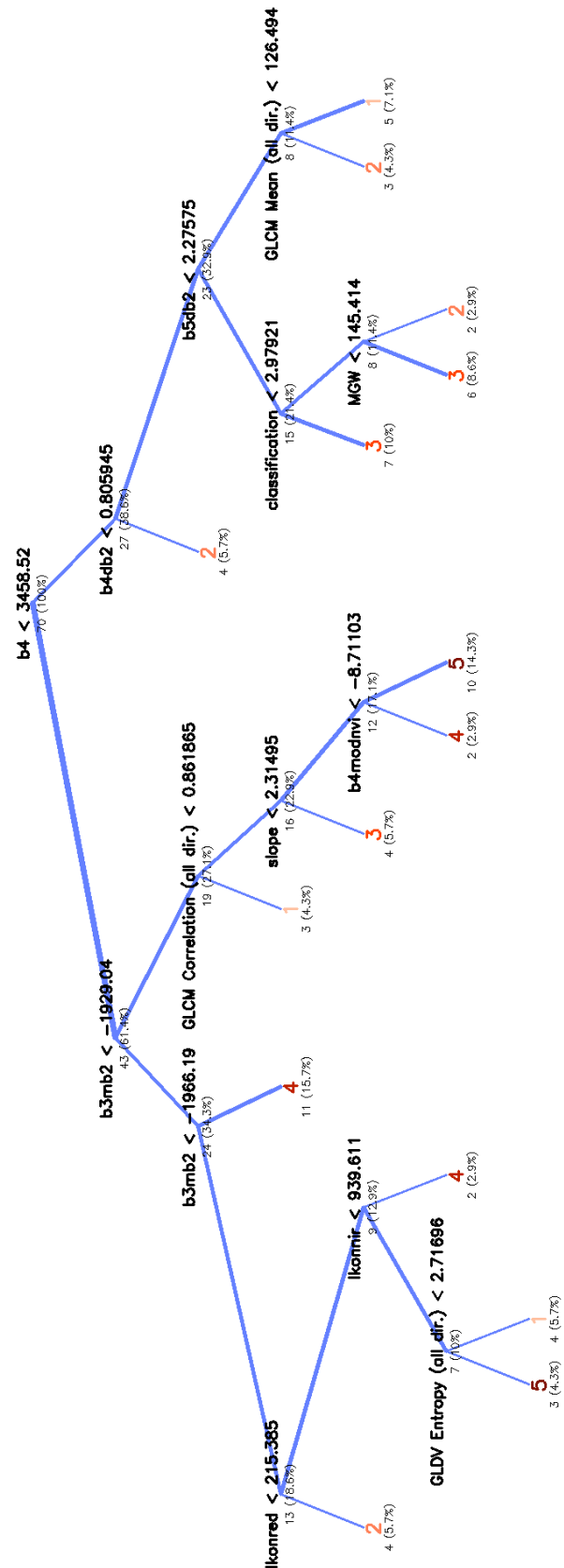


Figure 3. C_{org} model based on all available parameters (c)

4. DISCUSSION AND CONCLUSION

The work shows a complex model of C_{org} stocks in floodplains that includes a wide variety of data. The more parameters offered to the CART process, the more parameters are actually used. For the remote sensing channels and indices, the near infrared and red edge channels and derived indices are of increased relevance for the classification. This was also shown in a study by Schuster et al. (2012).

Regarding the accuracy of the single quintile classes, there are obvious confusions between the classes. The fifth quintile class has the lowest accuracies, with UA ranging from 0.01 to 0.08, and PA ranging from 0.058 to 0.080. For the other classes, UAs are higher (up to 0.585, quintile class 4, Table 4) as well as PAs are higher (up to 0.667, quintile class 4, Table 4).

With an increasing number of parameters, the OA of the classification rises, yet the accuracy is still moderate (Congalton 1991) even though considering a full range of area-wide available features (Table 4). It is evident that an increasing number of parameters included in the CART improves the classification results. The CART is dependent on the amount and quality of the input data. However, further research on the C_{org} model will be necessary. Approaches of kNN or SOM (Stümer et al. 2010) may be taken into consideration.

The work can also be an important contribution to support a European biomass inventory (Gallaun et al. 2010) or to provide information on global carbon stocks. Results of the modeling process may also contribute to the prediction and assessment of C_{org} for floodplain areas in tropical and subtropical zones, which play a more prominent and important role in the global carbon cycle.

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