Object Oriented Deforestation Mapping in Siberia – Results from the SIBERIA-II Project

SÖREN HESE AND CHRISTIANE SCHMULLIUS

Abstract: This paper presents final results on forest change mapping in Siberia as part of the EU project SIBERIA-II (Multisensor Concepts for Greenhouse Gas Accounting of Northern Eurasia). SIBERIA-II aims to understand the greenhouse gas budget and its interaction with climate change in the Eurosiberian region. Monitoring and mapping of ARD processes (Afforestation, Reforestation, Deforestation) and related land cover changes is important for national carbon budget inventories (potential source and sink function of vegetation for CO_2) and for regional biosphere modelling. Due to the complex definition of Kyoto ARD (human induced change, landuse change with specific time interval definitions) the accurate classification of these change classes is a challenge for EO data analysis methods. Object oriented image processing offers some advantages compared with other methods although none of the available classification procedures can classify reliable the underlying causes of landuse changes. Two specific characteristics of the object oriented image analysis approach are analysed in this work for the differentiation of human induced deforestation and non-human induced changes: object shape characteristics of deforestation objects and class related context information of change features.

1 Introduction

The work presented in this paper is part of the EU project SIBERIA-II (Multi-Sensor Concepts for Greenhouse Gas Accounting of Northern Eurasia) (Schmullius & Hese, 2002; Hese et al., 2002; Santoro et al., 2002). The scientific objective of the SIBERIA-II project is to integrate Earth observation information and biosphere process models such that full greenhouse gas accounting within a significant part of the biosphere can be quantified. Global estimates of the net carbon flux due to land cover changes are complicated by critical uncertainties like distribution and rate of deforestation and biomass burning, conversions from natural land cover and rate of reforestation and re-growth of deforested or burned land. The Kyoto Protocol (KP) carbon emission inventory is related to land cover changes with respect only to areas directly affected by human action through ARD (Afforestation, Reforestation, Deforestation) (Scole and Qi, 1999).

It is important to differentiate the needs by the KP and by full carbon accounting (FCA). FCA accounts for all possible sources and sinks and not only for those related to ARD under a specific and restricting definition of forest.

Differentiation between natural and human induced forest changes (as required by the KP) is a complex task and asks for an analysis of underlying causes of disturbances. As noted already in Scole and Qi (1999) forest management practices which change growth rates of forests and selective logging are not considered in the KP. Interpretation of the possible causes of forest changes is often impossible with Earth observation. Analysis of contextual and structural information using post classification analysis with contextual GIS analysis systems in multiple scales can however improve the potential of remote sensing for Kyoto ARD mapping.

Dr. Sören Hese, Prof. Dr. Christiane Schmullius, Earth Observation Section, Department of Geography, Friedrich-Schiller University Jena, Löbdergraben 32, 07743 Jena, e-mail: soeren.hese@uni-jena.de.

There will however remain restrictions to extract underlying causes of land cover changes with remote sensing. A combination of Earth observation with extensive ground truth and local forest enterprise information to deliver precise information to these questions is essential.

Different forest cover change detection approaches have been proposed in the past. Coppin and Bauer (1994) analyzed vegetation indexes using standardized differencing and selective principal component analysis. 14 change features were generated and the Jeffries-Matusita distance for best minimum separability was used as a measure of best statistical divergence to select the best change feature dataset. Copping and Bauer (1994) concluded that the most promising change features are the standardized difference of brightness, the second principal component of greenness, the second principal component of brightness, the second principal component of the green ratio and the standardized difference of greenness. This pointed towards the Kauth-Thomas brightness and greenness indexes and the green ratio as the vegetation indexes with the most relevant forest cover change information. It was also noted that analysis of change that is beyond the spectral-radiometric information would need the incorporation in a GIS framework with artificial intelligence capabilities. Other studies used direct multi-date classifications or hyper clustering (Leckie et al., 2002), change vector analysis, parcel-based change detection procedures, artificial neural networks (Gopal and Woodcock, 1996), cross-correlation analysis (Koeln and Bissonnette, 2000) and various post classification change detection methods. Important reviews of change detection methods have been published by Singh (1989), Coppin & Bauer (1996) and Lu et al. (2004).

The object-based strategy for data classification (Baatz and Schäpe (1999), Benz et al. (2004)) uses as a first stage a segmentation into different scales of image object primitives according to spatial and spectral features. This segmentation is a bottom up region merging technique starting with one pixel sized objects. In numerous subsequent steps smaller objects are merged into bigger objects (pair wise clustering) minimizing the weighted heterogeneity of resulting objects using the size and a parameter of heterogeneity (local optimization procedure) (Benz et al. 2004). This concept has the advantage to account for contextual information using image objects instead of the pixel based concept used frequently as the basic element in image processing. In a second stage rule-based decisions can be used to classify the multi scale image objects. Class based feature definitions (integrating a post classification analysis) are possible as well as the inheritance of class descriptions to form a class hierarchy. Image processing tasks can be performed using vector shape and vector characteristics. Results can be also analyzed and presented in vector format (polygons with attributes) instead of the raster cell format. This increases the flexibility of this image processing concept and integrates GIS-like data queries in an attribute database directly into the image processing and analysis approach. New attributes (like object shape or structural characteristics e.g. distance to other objects) can be used on the basis of the vector data format.

Object based image analysis has been used since 1999 for different forest classification approaches. Halounova (2004) used the object oriented approach to classify B&W aerial photos with textural features. Yijun and Hussin (2003) classified tropical deforestation in East Kalimantan using the object oriented approach and Mitri and Gitas (2002) developed an object oriented classification model for burned area mapping. Flanders et al. (2003) tested the object oriented approach for cut block delineation.

Various advantages over pixel-based approaches have been published mainly using very high resolution airborne or orbital Earth observation data. The primary advantage of reducing spectral variability in high spatial resolution data sets (spatial resolution better than 1 m) is

only one aspect of object oriented image analysis. For the development of change detection procedures new GIS-like analysis concepts are important. Object shape in different scales based on a simplification through vectorisation can potentially be used to differentiate clear cuts from other deforestation processes that do not show specific object shapes with a high rectangular fit (Hese & Schmullius, 2004). Multi-scale object information can be used to increase the classification accuracy of classes that have to be defined using textural information instead of spectral information (e.g. the spectral variability in urban areas is preferably classified using larger objects). Class related classification can be used to build rules for complex neighborhood relations to already classified image objects. This can be used to function as a classification of object structure. Such an approach can be applied e.g. to connect the classification of clear cuts to the classification of linear road objects beyond a parent change class. Transportation is prerequisite for logging activities and can be used as GIS context information. Road networks that were created in forested areas are than secondary information for the detection of logging processes.

Using the class hierarchy with inheritance of features, simple change – no-change masks can be developed that provide a powerful global (inherited) approach for the adaptation to other data sets. One drawback of the combined use of post-classification procedures using class related features and direct two-date change detection in one procedure is the complex error propagation logic that can lead to unstable classification results.

2   Data

2.1 Earth Observation Data

Multi-temporal Landsat ETM and TM5 data was acquired from 1989 and 2000 covering areas in the Krasnoyarsky Kray and Irkutsk Oblast. To correct for path radiance in multi temporal data atmosphere correction algorithms were employed using algorithms from Richter (1996).

Table 1: Landsat TM5 and ETM data

Landsat-WRS2 Path/Row	Date	Cloud Coverage	Despiking 1989/2000	Forest Enterprise
135/21	1989/2000	0%/5%	yes/no	Shestakovsky
136/21	1989/2000	0%/25%	no/no	Primorsky
140/20	1990/2000	5%/0%	no/no	Chunsky
142/20	1989/2000	1%/5%	no/no	Bolshe-Murtinsky
143/20	1989/2002	0%/5%	yes/no	Bolshe-Murtinsky

Some Landsat data showed a "salt and pepper" effect which appeared randomly at different places in the image geometry and without correlation between the different sensor bands. This noise was corrected using a threshold based selective filter technique that changes the effected pixels to the mean of the surrounding 8 pixel values if a defined threshold is exceeded. Adjacent Landsat scenes were relative corrected to an atmosphere corrected multi temporal master scene using histogram matching techniques to allow the application of train-

ing areas and signatures to larger areas. Reprojection to the Siberia-II "Albers Equal Area Conical WGS84" projection was performed for all datasets.

2.2 Training and Validation Data

Ground truth information from test territories (Table 2) with extensive forest inventory data from forest enterprises in Russia is used for this analysis (on ground forest inventory and planning (FIP) for intensively managed forests). These datasets cover different regions in Siberia and provide information about e.g. stand age of dominant species, species composition, land category information, relative stocking, growing stock volume, species composition, height of dominant species and average tree diameter (breast height diameter).

Table 2: Forest inventory enterprises in Siberia for the forest cover change analysis (IIASA - International Institute for Applied Systems Analysis - GIS ground truth database).

Test Territories	East	North	East	North
Krasnoyarsky Kray				
Bolshe-Murtinsky	91.83	56.83	94.00	57.33
Chunsky	95.17	57.42	98.25	58.08
Irkutsk Oblast				
Primorsky	102.09	55.58	102.56	55.99
Shestakovsky	102.94	56.10	104.51	56.68
Juzhno-Baikalsky	103.08	51.33	104.75	51.83

3 Method

The first step in object oriented image analysis is the segmentation into object primitives using a bottom up region merging algorithm. Three different object levels are generated for the forest change detection approach using different thresholds for object merging based on multitemporal data from 1989 and 2000. The class hierarchy that is created is based on the primary segmentation levels. A change and no-change parent class is created using a simple standardized change ratio (Coppin and Bauer, 1994) of the red Landsat band. Clouds, cloud shadows and water objects are classified with the brightness calculated for Landsat ETM and TM5. These classes are grouped together to form one class and are excluded from the change detection classification process.

The final forest change classification is done in the segmentation level with the smallest objects. Again a no-change and change "decision tree" is created using a standardized multi temporal change ratio of the red and the green channel. "Forestation on deforested areas" and "Deforestation" is classified using the multitemporal near infrared difference and NDVI thresholds. "Forestation on deforested areas" is defined as deforested in 1989 and reaching an age of 10 years in 2000. Deforestation is defined as not forested in 2000 but in a forest state in 1989. The classification is done using a NIR difference image and NDVI thresholds.
The human induced landuse conversion of agriculture land (that has not been forest before) to forested land is named "Afforestation". For the classification of this specific change class differentiation of urban areas, agricultural used areas and forested areas in 1989 is important. To integrate this additional information into the change analysis system class related features are used. Using class related features a landuse change classification can be combined with a

forest change mapping approach. A detailed explanation of the class hierarchy can be found in Hese & Schmullius (2004).

It should be noted that these class definitions do not follow exactly the definitions for Kyoto Afforestation, Reforestation and Deforestation. The improvement of an ARD-like classification system with Earth observation is still subject of ongoing research using context information to classify human induced changes and differentiate different types of changes. The remaining limitations to derive these class definitions using Earth observation (EO) have already been mentioned in this paper. Remote sensing data analysis techniques will in most cases not be able to reveal the causes of changes. Therefore a change detection system cannot successfully derive information about the accurate Kyoto ARD class definitions.

The spectral signature of clear cuts and older fire scars is very similar. Therefore differentiation should be done with additional non-spectral features. Object shape as an additional information is an important new feature type and could be used to differentiate logging activities from fire scar deforestation. However both types of forest change can be human induced (compare with Fig. 1). The description of a specific shape to detect logging activities is very difficult because only few clear cut objects show typical rectangular polygon shapes.

Some object shape descriptions following concepts of the software eCognition (Definiens, 2004) are analysed:

- *Rectangular Fit (REF):* describes the difference between a master rectangle and the considered object using the same measure of area, width and length for the master rectangle. The areas outside and inside of the master rectangle are compared (1 = complete fitting object, 0 = no fit).
- *Shape Index (SI):* describes the smoothness of the image object borders and is calculated as the ratio of the border length *e* and four times the square root of the area *A*. It is similar to the fractal characteristic of the image object shape.

$$si= e/(4 \sqrt{A})$$

- *Number of Edges:* describes the number of polygon edges.
- *Degree of Skeleton Branching (DSKB):* after the segmentation results are converted into polygons using the Douglas-Peucker algorithm the internal structure of the polygons can be derived using skeletons. The skeletons are created by performing a Delaunay triangulation of the polygon elements. Skeletons are then created by identifying the midpoints of the triangles and connecting them (Definiens 2004). A very high degree of skeleton branching is an indication of a complex and non-smooth polygon shape.
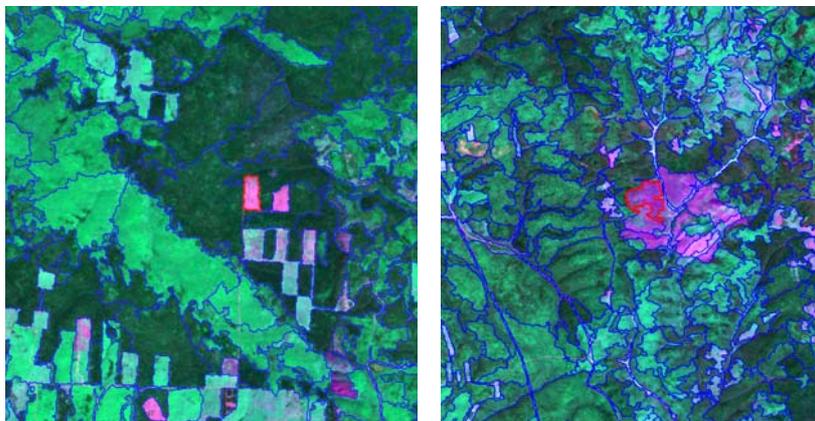

Figure 1: Left: segmentation of clear cut areas, right: fire scar area (Landsat ETM RGB: 543, Bolshe Murtinsky).

Analysing these object features for the differentiation of forest clear cuts and fire scars it was noted that none of these characteristics can differentiate clear cuts from fire scars completely. This is due to the heterogeneity of scale and shape of objects. Scale independent template matching techniques should be used that use context information and object structure from training scenarios for different regions. Comparing shape index and rectangular fit a good correlation is detected for both "clear cuts" and "fire scar" class objects but fire scar objects show a higher shape index than clear cut objects and do not reach higher rectangular fit values than 0.9 (Fig. 2).

Higher orders of SKB can be found together with much higher number of object edges at fire scar objects. SKB of order one or two only appear with clear cut objects (Fig. 3). Comparing the area statistics of fire scar and clear cut objects a differentiation is feasible (Fig. 4). Fire scar objects appear to have larger area values and as expected more polygon edges (Fig. 4). In this analysis outliers were not removed.

Shape as a description is a very complex attribute that is hard to parameterize. A new approach to object shape classification is clearly needed. Object shape should be described or classified using scale independent matching techniques that can be driven by a master object shape or possibly a master shape catalog for a specific object type.
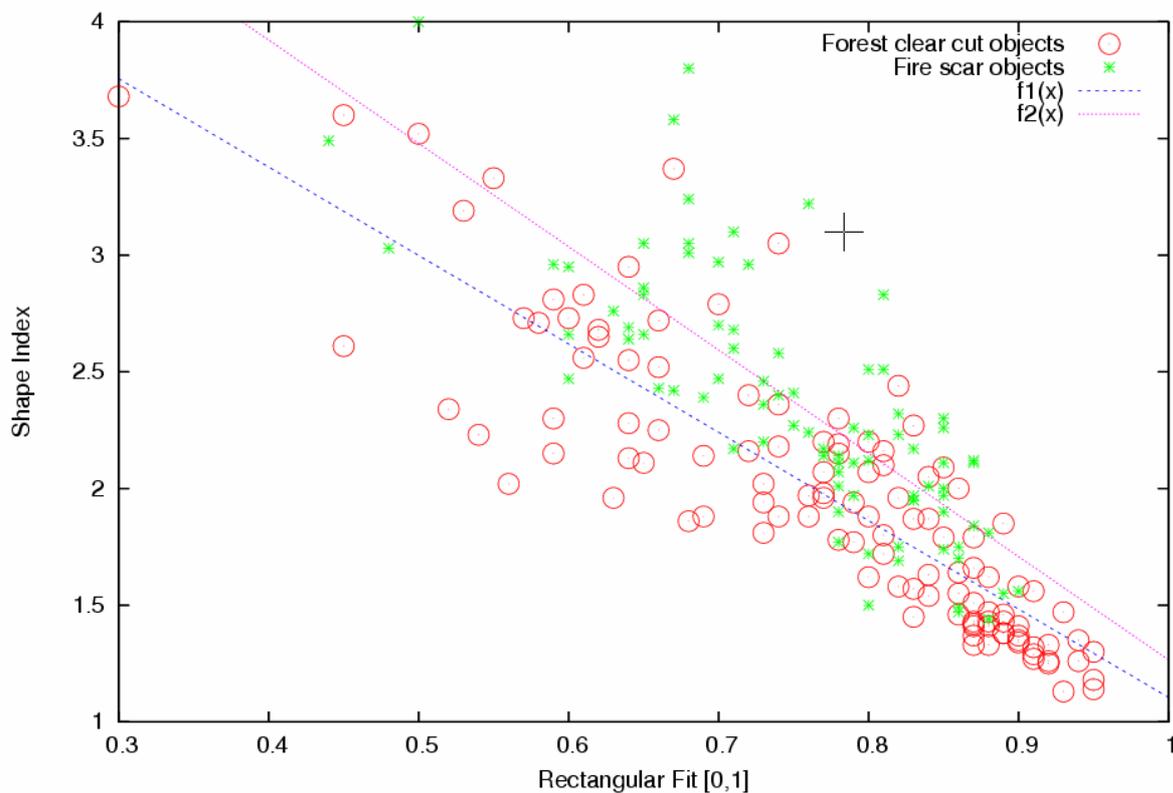

Figure 2: Polygon shape index vers. rectangular fit for fire scar objects (R=-0.86) and clear cut objects (R=-0.79)(Landsat ETM - Bolshe Murtinsky/Siberia) (medium scale object size). Outliers were not removed.
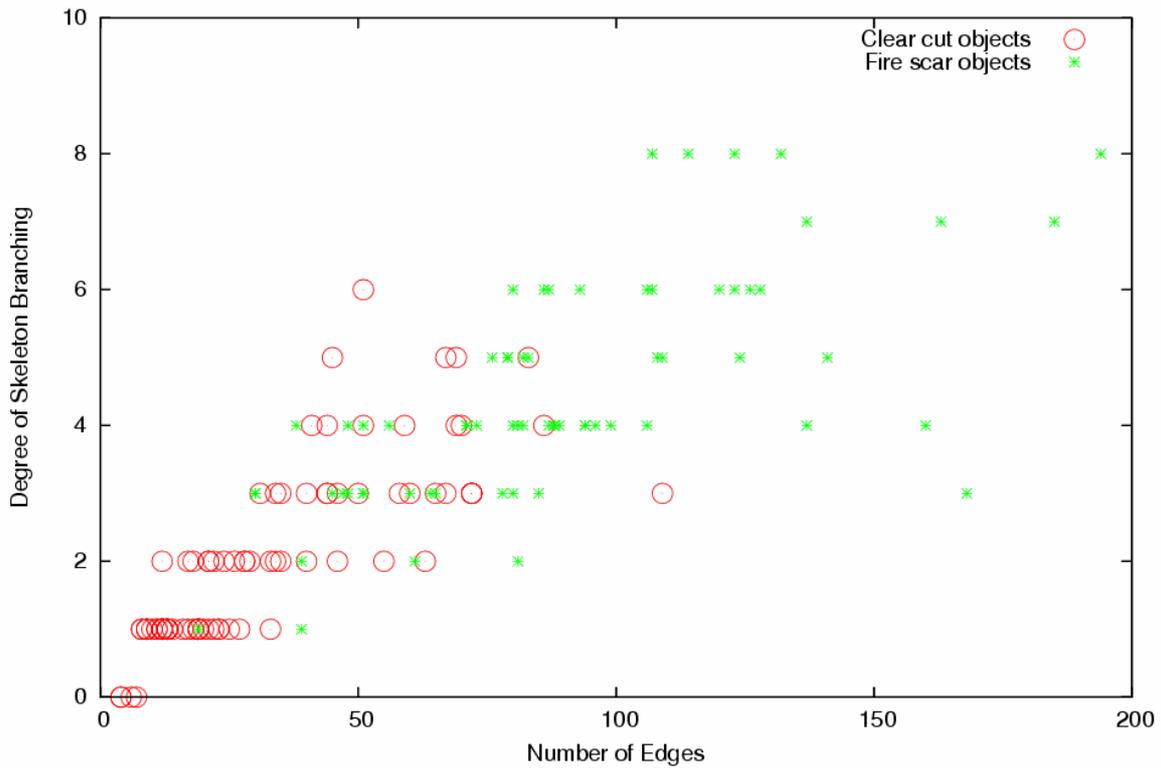
Figure 3: Degree of polygon skeleton branching vers. number of object edges for fire scar objects and clear cut objects in Siberia (Landsat ETM - Bolshe Murtinsky/Siberia) (segmentation layer with largest objects). Outliers were not removed.
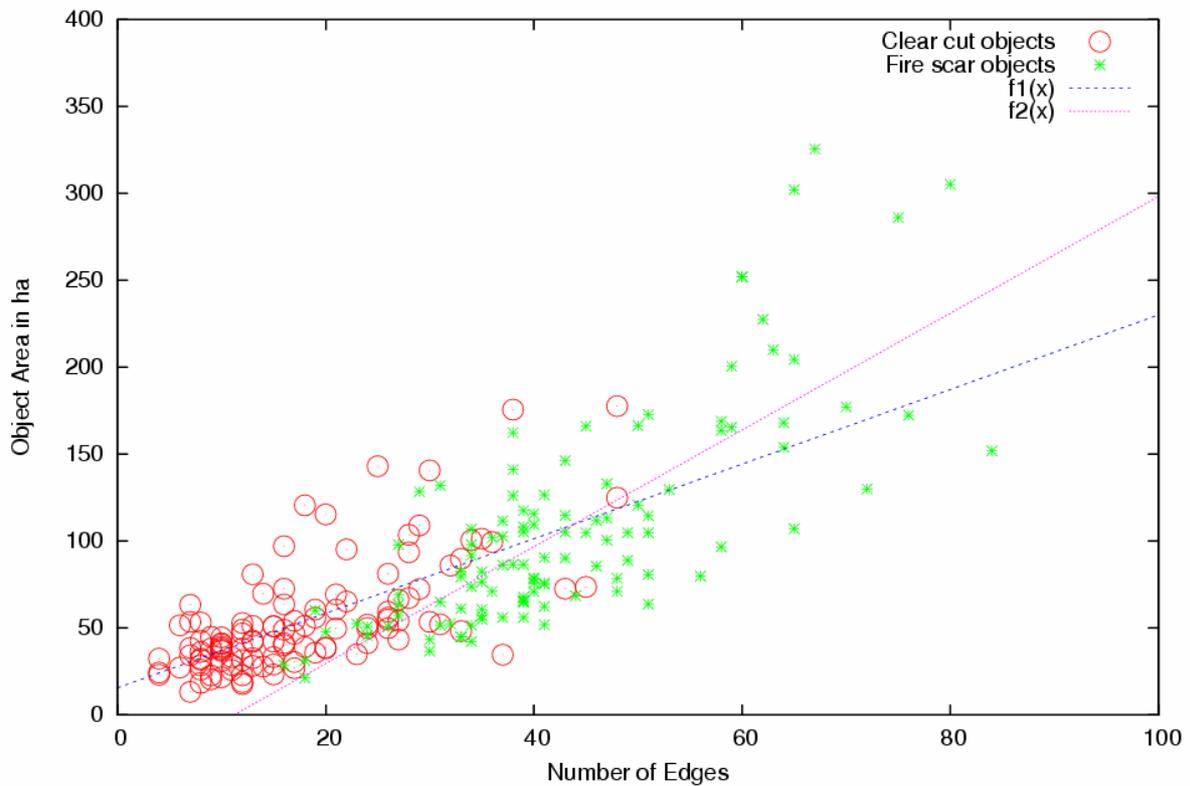

Figure 4: Object area vers. number of object (polygon) edges for fire scar objects and clear cut objects in Siberia (Landsat ETM - Bolshe Murtinksy/Siberia) (segmentation layer with smallest object size). Outliers were not removed.

4   Results and Discussion

Results of the forest change classification indicate deforestation between 57000 and 160000 ha per Landsat scene (no differentiation into clear cuts and fire scars). Regrowth of forest on deforested areas is slightly lower. Forest growth on former non-forested land (Afforestation) is neglectable (Table 3).

Results of the final classification of five different areas in the Krasnojarsk Krai in Siberia using larger datasets showed that the complex class hierarchy needed for detection of very specific changes cannot be easily transferred to other regions with different object scales and object context structure. Although the radiometry of the neighbouring datasets was changed to an atmosphere corrected multitemporal master dataset the class hierarchy had to be adapted. The differentiation into deforestation types logging and fire scars was possible within one region but not easily transferable to other regions. This was mainly due to the different object scales and heterogeneity of object shape in different regions. The final classification was not performed with this sub-differentiation. Use of context information - although promising for the stabilization of change classes - showed similar limitations when applied to other regions. The main potential of the object oriented approach for this work: the integration of complex shape, structure and context features shows in turn weaknesses when automatic application to large areas is needed. This is clearly the result of a complex hierarchical classification system that does not only pass on feature descriptions (inheritance) but does also pass on errors – creates a complex error propagation problem.
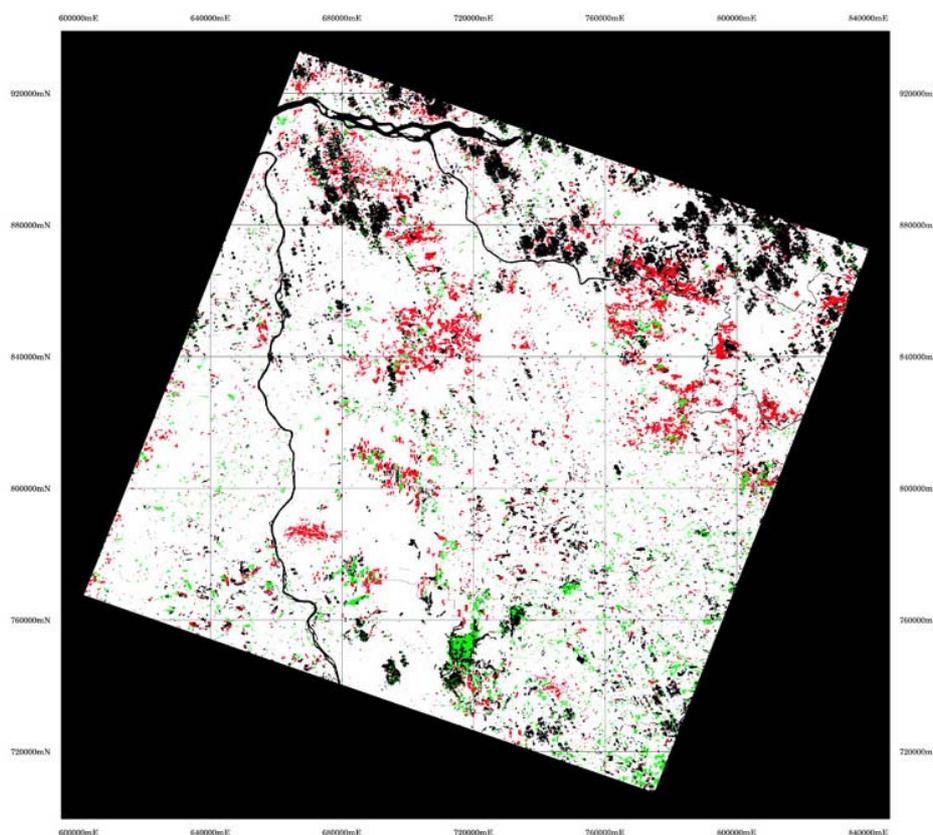

Figure 5: Example of a forest change map with deforested areas (in red), forestation on areas that have been forest before (in green) and forestation on areas that have not been forest before (in cyan) in the south of Siberia (Bolshe Murtinsky) Landsat WRS2: 142/20. Masked clouded areas, cloud-shadows and water areas appear in black.

Table 3: Forest change mapping results for selected forest enterprises in Siberia.

Test Territories	Cloud-Water-Mask (%/ha)	Defores-tation (%/ha)	Regrowth (%/ha)	Forest growth on former non-forested land (%/ha)	No-change (%/ha)
Bolshe-Murtinsky (WRS2: 143-20)	2.17 (68684)	3.31 (104981)	3.2 (101454)	0.06 (1931)	89.55 % (2837849.5)
Chusky (WRS2: 142-20, 140-20)	5.58 (178128) 5.83 (189718)	4.94 (157668) 4.15 (134878)	2.34 (74761) 3.84 (124979)	0.05 (1495) 0.20 (6386)	83.59 (2669942.0) 81.87 (2663196)
Primorsky (WRS2: 136-21)	12.53 (399370)	1.78 (56787)	1.16 (37049)	0.35 (11297)	74.26 (2365951)
Shestakovsky (WRS2: 135-21)	2.17 (68771)	3.12 (98851)	2.37 (74939)	0.00 (25)	90.91 (2880694)

Acknowledgements

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