APPROACHES TO KYOTO AFFORESTATION, REFORESTATION AND DEFORESTATION MAPPING IN SIBERIA USING OBJECT ORIENTED CHANGE DETECTION METHODS

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ABSTRACT

Mapping Kyoto protocol specific Afforestation, Reforestation and Deforestation processes with Earth observation and remote sensing is challenging because underlying causes of changes cannot be classified in most cases. Integrated data analysis techniques have to be developed that combine GIS techniques with image processing. In this work the potential of an object oriented image analysis toolbox is tested with the aim to derive classes that are also based on contextual information. For this purpose a change detection approach is developed which compares the 1989 Kyoto baseline with the status in 2000 for forest inventory test territories in Siberia with extensive ground truth information. Optical satellite data are co-registered and atmosphere corrected. A complex hierarchical object-based and multi temporal class description is developed. Results show that object shape and contextual information helps to differentiate potential human induced clear cuts and fire scar areas. This work presents the methodology of a combination of direct two-date change detection and post classification procedures which also integrates multi-scale information and contextual information. This set of rules will be applied to other areas in Siberia if this method proofs its robustness.

Keywords: ARD, Afforestation, Reforestation, Deforestation, Kyoto Protocol, change detection, object oriented classification, Siberia-II.

1 INTRODUCTION

This work on Afforestation, Reforestation and Deforestation (ARD) mapping and monitoring in Siberia is part of the ongoing EU project SIBERIA-II (Multi-Sensor Concepts for Greenhouse Gas Accounting of Northern Eurasia) [7][12][13]. The scientific objective of SIBERIA-II is to integrate Earth observation 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 [14].

In the KP the term "*Afforestation"* is defined as the direct human-induced conversion of land that has not been forested for a period of at least 50 years to forested land through planting, seeding and/or the human-induced promotion of natural seed sources.

"*Reforestation*" is the direct human-induced conversion of non-forested land to forested land through planting and seeding on land that was forested but that has been converted to non-forested land. "*Deforestation*" is the direct human-induced conversion of forested land to non-forested land (Kyoto Protocol – Marrakesh Accord – Annex A).

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.

2 KYOTO AND REMOTE SENSING

For the remote sensing perspective the ability to discriminate forest types according to a specific forest definition is important. The KP defines “Forest” as a “minimum area of land of 0.05 – 1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 per cent with trees with the potential to reach a minimum height of 2-5 meters at maturity *in situ*. ...” [Marrakesh Accords Annex A].

Differentiation between natural and human induced forest changes (as required by the KP) is challenging as it asks for an analysis of different disturbances including fire and tries to identify underlying causes. As noted already in [14] forest management practices (which change growth rates of forests) and selective logging are not considered. Interpretation of the possible causes of forest changes are very difficult. Analysis of contextual and structural information in image space using GIS-like image processing and analysis systems in multiple scales can improve the potential of remote sensing data analysis techniques for Kyoto ARD classification. 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.

3 DATA AND FOREST INVENTORY INFORMATION

Test territories with extensive forest enterprise information (stand volume, age, tree species, composition, height) which cover different ecological regions in Siberia are used. Multi-temporal Landsat data stacks for these areas were acquired from 1989 and 2000 covering areas in the Krasnoyarsky Kray and Irkutsk Oblast (Siberia). To correct for path radiance in multi temporal data atmosphere correction algorithms were employed following [11]. Adjacent scenes were absolute corrected to the same reference spectra to allow the application of training areas and generated multi temporal signatures to neighboring multi temporal data.

4 OBJECT BASED CHANGE DETECTION FOR ARD-MAPPING

Different change detection approaches have been proposed in the past (direct multi-date classifications, hyper clustering [9], image differencing, index differencing, principal components analysis, change vector analysis, parcel-based change detection, artificial neural networks [5], cross-correlation analysis [8] and various post classification change detection methods. Important change detection method reviews have been published in [15] and [3].

The object-based strategy for data classification [1][2] uses a segmentation into different scales of object primitives according to spatial and spectral features. In a second stage rule-based decisions can be used to classify the objects. Class based definitions (e.g. post classification analysis) are allowed as well as the inheritance of class descriptions to form a complex class hierarchy. The object based method has been used since 2000 for different forest classification approaches [4][6][10][16]. Different advantages over pixel-based approaches have been published mainly using very high resolution airborne or orbital remote sensing data. The advantage of reducing spectral variability in high spatial resolution data sets is only one aspect of object oriented image analysis which is of minor importance working with Landsat data. For the development of change detection procedures new GIS-like analysis concepts are important. For ARD mapping some specific aspects of this image processing approach are an advantage:

1. Object shape in different scales based on a simplification through vectorisation can be used to differentiate clear cuts from other deforestation processes that do not show specific rectangular object angles.
2. 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).

3. Class related classification can be used to build rules for complex neighborhood relations. This can be used to function as a classification of object structures. Such an approach can be applied e.g. in order to connect the classification of clear cuts to the classification of linear road objects. Transportation is prerequisite for logging activities and can be used as context information. Especially road networks that were created in forested areas can be secondary information for the detection of logging processes. The distance to cloud objects can be used for the stabilization of the classification of cloud shadows as additional criteria.
4. Using the class hierarchy with inheritance of features, simple change – no-change masks can be used that provide a powerful global (inherited) approach for the adaptation to other data sets.
5. The post classification approach (using class related features) can be directly combined with direct two-date classification (using multi-temporal signatures) in one class description.

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.

The first step in object oriented image analysis is the segmentation into object primitives. Three different object levels are generated for the ARD classification using different limits for the region growing algorithm. The mid-layer is used for the final classification and optimized to describe deforestation objects. The super and sub-layer are created primarily to aid the classification process with additional object features in useful sub- and super-scales for some specific classes. All object layers are generated based on multi-temporal data. The resulting object geometry is converted into vector layers with a polygonisation threshold optimized for the simplification of the shape of compact objects.

The change detection class description and hierarchy is based on three main classification trees. These main classes are linked to the three segmentation levels (compare figure 1). In both the finest segmentation and the mid segmentation level a change- and a no-change-class is used as parent class. Changes are differentiated from no-changes on the basis of Standardized Multi temporal change Indices (SMI). The resulting no-change – change mask is used with exact boundaries of the membership function and inherited to all sub classes. The consequence is a masking into changed and not changed regions.

e.g.: $SMI_{Band5} = (Band5_{Time1} - Band5_{Time2}) / (Band5_{Time1} + Band5_{Time2})$

Segmentation layer 1: In the finest segmentation level linear objects are classified using shape features. These objects are used in the next higher segmentation level to classify road networks. As Afforestation is expected to appear in very small scales some mono temporal inactive classes are created in this segmentation level.

Segmentation layer 2: Under the no-change class subclasses are created that define areas with no change of different character (forested, agricultural, urban areas etc.). The “change”-category is differentiated with subclasses which describe “Reforestation” and “Deforestation” using a direct two-date supervised classification approach. Deforestation is subdivided into subclasses “potential_ClearCut” and “potential_FireScar” using shape features based on polygons. Forest clear cut objects show rectangular shape characteristics and could be differentiated from fire scar object shapes. Additionally the relationship to linear objects is analyzed to use context information for the class description. In this case the existence of roads in direct neighborhood to deforestation can be used as an additional criterion for the classification into the sub class “Clear Cut”. Especially changes in the road network can be used as a criterion (therefore linear objects are setup both as a child-class of the “Change” and “No-Change” classification tree) (figure 1). Fire scar areas are characterized by rounded object shapes with higher fractal dimension. The underlying cause of the deforestation remains nevertheless to a certain degree unclear (the term “human induced” could also apply to fire scar areas since most of the fires in Siberia are triggered by human activities).

Segmentation layer 3 is designed to increase the classification accuracy of urban areas. Due to the higher spectral variations in urban areas larger objects are used to provide more representative texture measures.

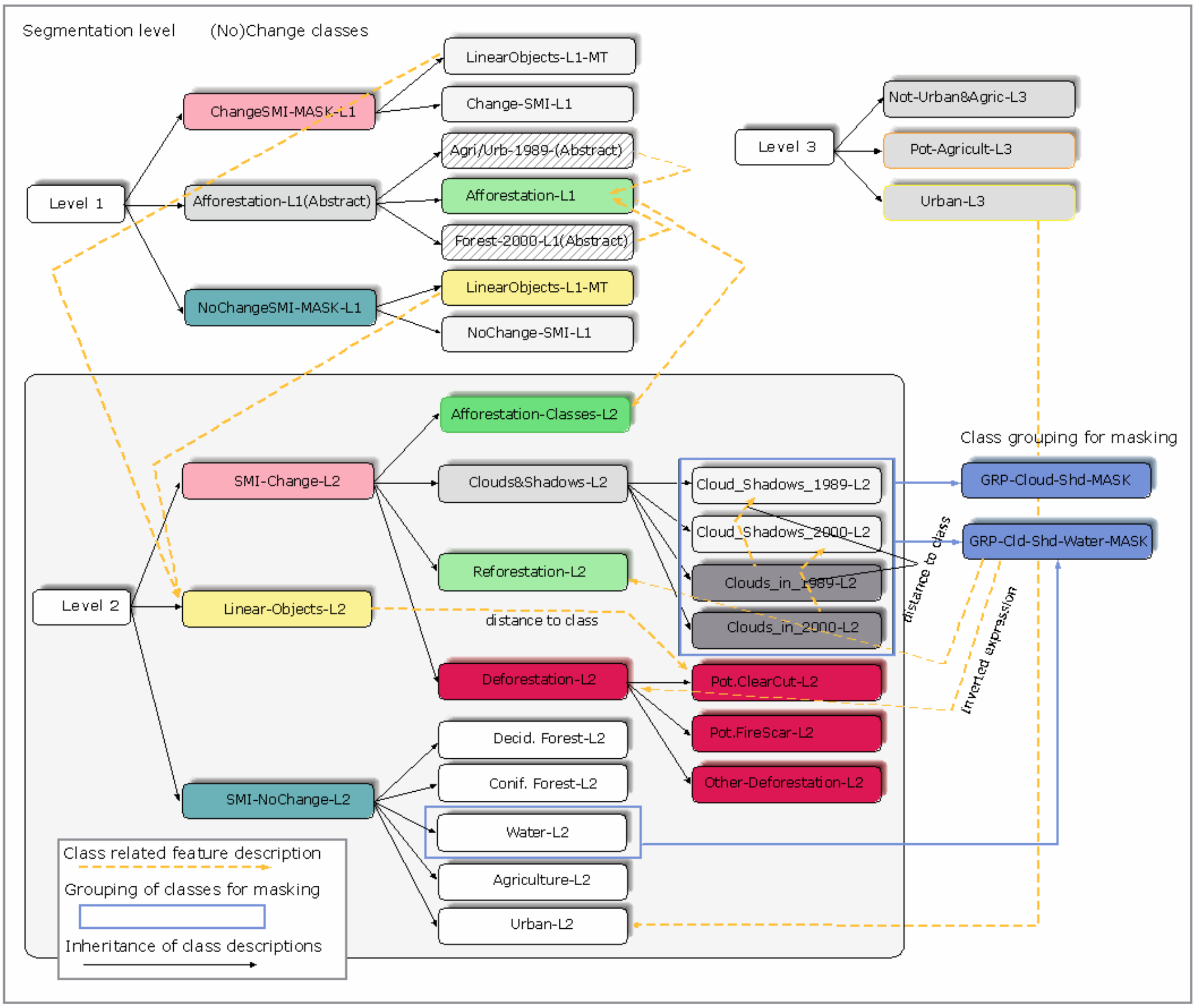

Figure 1. Hierarchical classification system for ARD mapping using three different segmentation levels. Use of class related context information and masking techniques are indicated.

The Afforestation class is based on post-classification analysis of mono temporal class definitions. This class cannot be defined using a supervised approach, as it does not appear often. Therefore training and test areas are usually not available. Cloud shadows are classified using class-related features (distance to objects classified as clouds). The resulting classes are grouped together with the class water and are used as a mask (using an inverted expression) for the classification of other classes (figure 1).

5 DISCUSSION

Creating a robust feature description of potentially human induced deforestation objects is challenging. Analyzing shape as a feature for classification different possible cut block geometries should be taken into account and the final accuracy is hard to verify. A systematic shape matching procedure would be needed to account for all possible clear cut object shapes. Selective logging cannot be detected with this approach and illegal small scale logging (if detectable) will not fit to a specific object shape description.

The classification of reforestation is complicated by the requirement to differentiate human and non-human induced reforestation. As most areas in Siberia that were deforested are not managed through planting or seeding and regrow naturally this differentiation cannot be applied to the area under investigation. Under these specific Kyoto definitions of reforestation these areas are actually not reforestation.

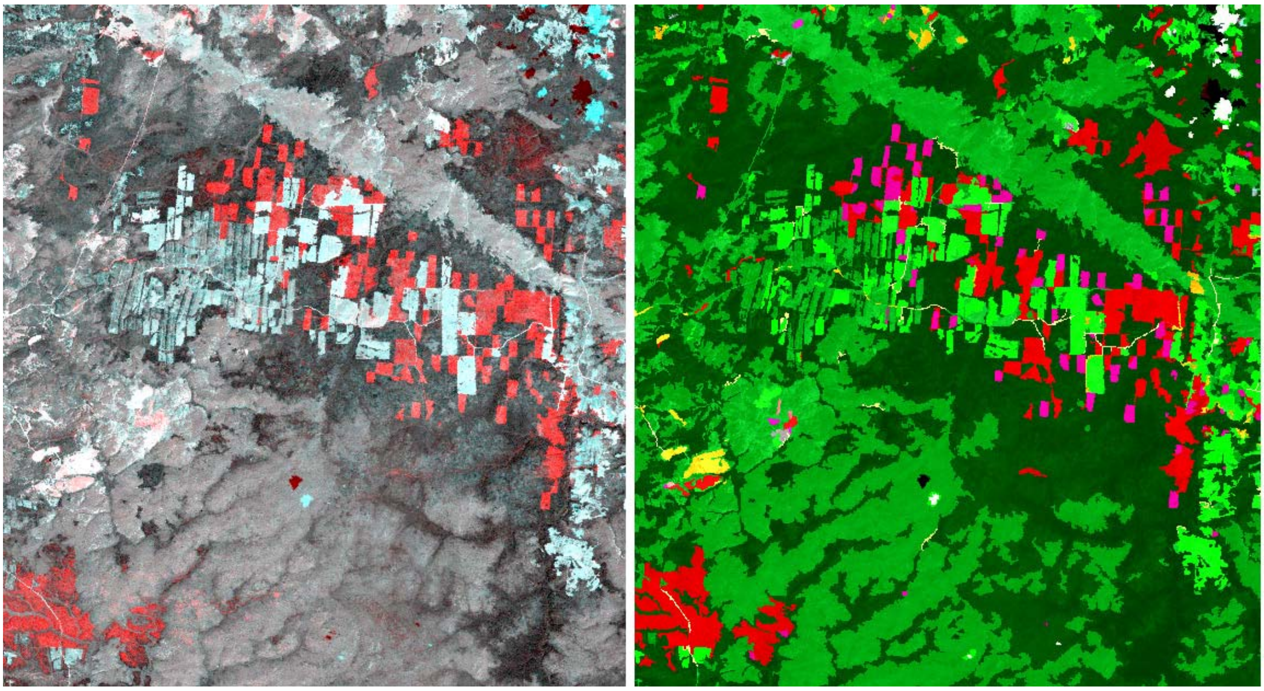

Figure 2. Object oriented multi-temporal ARD classification result. *Left:* multi-temporal 2-channel composite using channel 5 TM5 1989 and channel 5 ETM 2000. *Right:* classification result (Deforestation in red, human induced deforestation (clear cuts) in pink, no change forest objects in dark green, Reforestation in light green. Siberia/Bolshe Murtinsky.

The object oriented methodology is very much dependent on the accurate definition of objects that satisfy the needs of the class description. Using a supervised approach to change detection accurate and extensive multi temporal ground truth information is a crucial prerequisite. Historical ground truth was not available for this analysis. Atmosphere correction and relative radiometric calibration of neighboring datasets is important in order to apply a feature description for a classification of other datasets.

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