FOREST COVER CHANGE DETECTION IN SIBERIA

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ABSTRACT:

First results of a change detection procedure using artificial neural networks (ANNs) for the classification of Afforestation, Reforestation und Deforestation (ARD) in Siberia are presented. This work is part of the EU-project SIBERIA-II (Multi-Sensor 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 Euro-Siberian region. Monitoring and mapping of ARD processes and related land cover changes is important for national carbon budget inventories (potential source and sink function of vegetation as determined in the Kyoto protocol) and for regional biosphere modeling. To derive ARD statistics a multi temporal Landsat data set from 1989 and 2000 is relative co-registered and atmosphere corrected. In this first stage a neuronal network approach (Multi-Layer Perceptron Artifical Neural Network) for the classification of ARD is tested using the Feed-Forward – Back-Propagation trainings procedure. Training of the neural network is done using local forest enterprise information. A „two-date"-classification with different network structures is tested and possible alternative classification strategies using neural networks are discussed (integration of objects and change-feature-ratios into the network).

1. INTRODUCTION

The work on Afforestation, Reforestation and Deforestation (ARD) mapping and monitoring in Siberia is part of the ongoing EC project SIBERIA-II (Multi-Sensor Concepts for Greenhouse Gas Accounting of Northern Eurasia) (Schmullius & Hese, 2001; Hese et al., 2002). 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 carbo[1]n 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.

In the KP "*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 defined as 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 (from the Kyoto Protocol, Marrakesh Accord, annex A). "*Deforestation*" is the direct human-induced conversion of forested land to non-forested land (Kyoto Protocol, Marrakesh Accord, annex A). The definition of these terms (time and area thresholds) will be changed and adapted partly to the FRA (Forest Resources Assessment) definitions as proposed by the "Expert meeting on harmonizing forest related definitions 2002 (Food and Agriculture Organisation - FAO)". Dropping the 50 years non-forest definition in the KP for Afforestation and the differentiation of human and non-human induced deforestation in the FRA definition was proposed in order to bring UNFCCC and FRA definitions into closer agreement. 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.

For the Remote Sensing perspective the ability to discriminate forest types according to a specific forest definition is important. On the other side 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 Scole and Qi (1999) 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 and remote sensing will have to be combined with ground truth and local forest enterprise information to deliver precise information to these questions.

2. FOREST CHANGE DETECTION USING ARTIFICIAL NEURAL NETWORKS

To detect changes in forest cover different approaches have been proposed in the past. Some proposed methodologies have been: direct multi-date classifications using a combined dataset (hyper clustering) (Leckie et al., 2002), image differencing, index differencing, principal components analysis (PCA), change vector analysis, various post classification change detection methods including object oriented analysis and parcel-based change detection. A review of change detection methods is available in Singh (1989). Artificial Neural Networks (ANN) have been used for post classification approaches (double stage neural network structure) (Kushardono et al., 1995) and for direct two-date change detection (Gopal and Woodcock, 1996). One of the advantages of ANNs for change detection is the possibility to integrate multi sensor data types (Benediktsson and Sveinsson, 1997) and complementary information content (object based information, texture and spectral information) in

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one classification process (Iong Dai and Khorram, 1999). Other advantages are inherent with the character of neural networks: lack of assumptions about normality in datasets, ability to capture non-linearity (Gopal and Woodcock, 1996). Various applications of back-propagation ANNs for remote sensing purposes have been published e.g. in Benediktsson, Swain and Ersoy (1990); Benediktsson and Sveinsson (1997); Bischof, Schneider and Pinz (1992); Egmont-Petersen, de Ridder and Handels (2002) and in Serpico and Roli (1995) and for forest remote sensing in Gopal and Woodcock (1996); Machado et al. (1993) and Paola and Schwengerdt (1995). The most widely used neural network type is the Multi Layer Perceptron network (MLP) which is used together with the feed forward – back-propagation classifier (the training procedure) applying the generalized delta rule for learning. Numerous other network types have been proposed in the past for different applications. A review can be found in Egmont-Petersen, de Ridder and Handels (2002). The idea of neural networks is to mimic the computational abilities of biological systems by creating interconnected artificial neural systems. These artificial neural nodes take input information and perform very simple operations and selectively forward the information to other neurons. The connection weights between the neurons are than adjusted using a training method.

Advantages of the neural network approach compared with conventional classifiers are:
Knowledge of the statistical distribution of the data is not required. This is an advantage if there is no knowledge of the distribution function or when the data are non-gaussian.
Multi-source and -domain data can easily be integrated and added into the network by adding additional input nodes.
The use of multi-temporal data in one classification process is simple and is advantageous as it does not introduce the accumulative errors of post classification comparison procedures. The trained neural network can do change detection on a pixel by pixel or object by object basis in real time. The network can directly be trained with context information using a window of the data set without deriving specific secondary texture measures with loss of information.
Some of the drawbacks of the application of neural networks are the black-box character of the network, the weak theoretical background (which can be also interpreted as an advantage) and a complex, error-prone and computationally intensive training stage which has to be repeated whenever the nature of the input data set is changed.

3. METHOD

ARD classes had to be derived for test territories with forest enterprise information which cover different ecological regions in Siberia. The selection of test territories was performed in order to cover different forest change dynamics and to receive an overall impression using representative areas. In the first phase 5 cloud free Landsat TM-5 and ETM multi-temporal data stacks for these areas were acquired from 1989(1990) and 2000(2001) covering areas in the Krasnoyarsky Kray and Irkutsk Oblast. To correct for path radiance in multi-temporal data atmosphere correction algorithms were employed following Richter (1996). Adjacent scenes were absolute corrected to the same reference spectra to allow the application of trainings areas and signatures to neighbouring multi-temporal data stacks. Topographic normalisation and ortho-correction was postponed due to the lack of high resolution DTMs for Siberia for the area under investigation. Full DTM coverage with 50 m resolution will be available however when radar data processing from the finished SIBERIA-I project, the predecessor project of SIBERIA-II (Santoro et al. 2002) will be finalised in 2003.

The direct two-date change detection approach:
As the first step for the change detection analysis a fully connected multi-layer feed-forward network was created and trained with the back-propagation procedure that iteratively adjusts the coupling strengths or connection weights in the network in order to minimize the error between the desired and the predicted output pattern (Figure 1). The input layer is defined by the number of input data channels or feature layers whereas the output layer is defined by the number of desired classes. The network structure between these two layers consists of hidden layers with a specific number of hidden units (or neurons). The optimal structure of a network depends on the application needs and is hard to predict. For the ARD classification different network structures were tested with different numbers of hidden layers and neurons per hidden layer. Changing the network structure did not increase the average producer accuracy and the overall accuracy of the classification process.
Important for reliable results is the training with precise ground data which has to be selected according to the definition of forest in the KP (tree cover of more than 10 %, minimum area 0.5 ha, height greater than 5 m). This definition controls the threshold and category boundary between non-forest and reforestation or afforestation. In this first analysis only few change categories were defined (reforestation, clear cuts, fire scars, forest area with no changes, water area).

Two-date change detection with standardized change features:
Standardized multi-temporal change features (SMI) were created with all multispectral image channels to increase the separability of change signatures.

$$SMI_{Band5} = (Band5_{Time1} – Band5_{Time2})/(Band5_{Time1} + Band5_{Time2})$$

The resulting residual image channels represents feature change layers for the two dates and were used as additional data layers for the neural network.

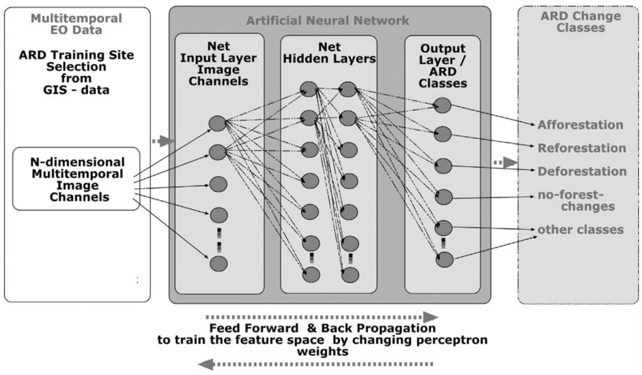

Figure 1: Multi layer perceptron neural network structure for the classification of ARD with multi-temporal data

4. RESULTS

Both results from the change detection with and without standardized change features show a signature confusion for the classes fire scar and clear cut. This reduces the producer accuracy and the user accuracy of the corresponding classes. The reforestation class showed overlap with other classes probably mainly due to the inhomogeneous nature of reforestation occurring on deforested areas. The totalization reports (Table 1) suggest a stronger deforestation compared with the reforestation processes of the selected sub area. It remains however unclear if these reforestation processes are human induced or not. In most cases in Siberia the clear cuts regenerate naturally without the direct human interference. Integrating change feature ratios increases the overall classification accuracy.

Class Name	Pixels	ANN structure: 12-24-24-5		ANN structure: 18-24-24-5 (with 6 change feature layers)	
		hectares	%image	hectares	%image
Water	367148	25047,9	2,96	33043,3	3,90
Reforestation	467444	23732,1	2,80	42069,9	4,97
Clear Cut	251414	67308,4	7,95	22627,2	2,67
Fire Scars	583878	38976,2	4,60	52549,0	6,21
No Change	7735691	691436,5	81,68	696212,1	82,25
Image Total		846501,7	100,00	846501,7	100,00

Table 1: Totalization report for the classification in hectares and %image for a neural network structure with multi-temporal data and with change feature ratios.

5. CONCLUSION AND DISCUSSION

First results of ARD mapping with ANNs indicate a potential of neural networks for complex change detection analysis. The advantages of ANNs compared with standard methods haven't been fully exploited in this work. Ortho correction and topographic normalisation was not performed due to the unavailability of full DTM coverage. The integration and use of image channel ratios for topographic normalisation was discarded due to the introduction of image noise. The integration of objects and textural information layers into the neural network classification process should be analysed to discriminate different ARD relevant classes. For the overall results with ANNs the definition of forest (fractional cover, stand height) and the training stage which should represent the class characteristics accurately is crucial for a successful classification. In this first stage of the ARD work training data for Afforestation was not available. The basic problems in this work are linked to the differentiation of human and non-human induced changes. The differentiation of deforestation types could be possible using object oriented approaches taking the shape of clear-cut-objects into account. Fire scars usually do not exhibit the same characteristic shape as human induced clear cut areas.

Post classification procedures could be combined with Neural Networks (Kushardono et al., 1995) but the disadvantage of post classification strategies is the accumulation of errors of the two parallel classifications. Nevertheless post classification procedures have been used in the past as benchmark methods for comparison with other methods. An appropriate post classification method will be also tested for ARD work.

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