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OPERATIONAL FOREST MONITORING IN SIBERIA USING MULTI-SOURCE EARTH OBSERVATION DATA

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Forest cover disturbance rates are increasing in the forests of Siberia due to intensification of human activities and climate change. In this paper two satellite data sources were used for automated forest cover change detection. Annual ALOS PALSAR backscatter mosaics (2007–2010) were used for yearly forest loss monitoring. Time series of the Enhanced Vegetation Index (EVI, 2000–2014) from the Moderate Resolution Imaging Spectroradiometer (MODIS) were integrated in a web-based data middleware system to assess the capabilities of a near-real time detection of forest disturbances using the break point detection by additive season and trends (Bfast) method. The SAR-based average accuracy of the forest loss detection was 70 %, whereas the MODIS-based change assessment using breakpoint detection achieved average accuracies of 50 % for trend-based breakpoints and 43.4 % for season-based breakpoints. It was demonstrated that SAR remote sensing is a highly accurate tool for up-to-date forest monitoring. Web-based data middleware systems like the Earth Observation Monitor, linked with MODIS time series, provide access and easy-to-use tools for on demand change monitoring in remote Siberian forests.

Keywords: *remote sensing, SAR, MODIS, time series, forest change monitoring, near-real time.*

INTRODUCTION

In order to mitigate the consequences of climate change caused by land use change, it is important to improve information on the terrestrial distribution of carbon sources and sinks. This can be provided through accurate and reliable vegetation cover change monitoring. Due rapid rates of change and vast area of land cover, remote sensing techniques are increasingly proposed as globally consistent environmental monitoring tools (Cihlar et al., 2002). Remote sensing acquires data over large areas with high repetition frequency, and at a relatively low cost. These techniques are recommended for forest monitoring to inform international climate policy and related international programs (e. g., REDD; Reduced Emissions from Deforestation and Forest Degradation), and initiatives (e. g., ALOS K&C; ALOS Kyoto & Carbon Initiative and GFOI; Global Forest Observations Initiative). Remote sensing has already been demonstrated to be capable of contributing to the current and future measurement and monitoring of carbon sources and sinks, through its ability to provide systematic, globally consistent estimates of land cover (LC), land cover change (LCC), forest disturbances, and aboveground biomass (AGB). Multiple publications are available on optical, radar, as well as LiDAR (Light Detection and Ranging) EO (earth observation) data for LCC and biomass estimation.

The Russian Federation is of special monitoring concern. It is the most forested country in the world, with forest covering 49 % of its total area (FAO, 2012). The forests of the Russian Federation represented 90 % of the carbon sink of the world's boreal forests from 2000 to 2007 (Pan et al., 2011). At the same time, they also provide the largest source of uncertainty in global carbon stock calculations (Pan et al., 2011). Moreover, tree cover loss in the Russian Federation from 2000 to 2012 was the highest in the world, totaling more than 5 million hectares in the year 2012 alone (Hansen et al., 2013). This tree cover loss is mainly due to fires, which are the biggest overall cause of forest loss in boreal ecosystems. Fires are a particularly damaging form of disturbance in the Russian boreal forest. This is because conifers dominate and most of the forest is unmanaged and unprotected (Shvidenko et al., 2011). Current model predictions indicate that the number of fire events in the boreal zone may double by the end of 2100 (Shvidenko et al., 2011). Illegal logging also poses a huge problem for the monitoring of Russian forests. According to established sources like World Wide Fund for Nature (WWF) Russia and the World Bank, illegal clear-cutting in Russia is estimated to account for approximately 25 % of all logging activity in this country (WWF, 2014). Moreover, due to the lack of funding for monitoring efforts, some forested regions in Siberia have not been inventoried for more than 25 years (Hüttich et al., 2014*a*).

The number and availability of Earth Observation (EO) resources is continuously increasing. Interactive and interoperable access to satellite time series data is increasing, as demonstrated by various EO data infrastructure projects, such as the Siberian Earth System Science Cluster (SIBESSC, Eberle et al., 2013*a*), NASA Giovanni (Acker & Leptoukh, 2007), and the Earth Observation Monitor (EOM, Eberle et al., 2013*b*). The application of data middleware systems enables operational monitoring of remote forest territories in a near real-time mode, as shown for Central Siberia (Hüttich et al., 2014*b*). User-friendly clients for accessing and analyzing operational frequently updated EO time series provide opportunities for the monitoring of forest disturbances and dynamics. In order to quantify the accuracy of both spatial and temporal high resolution forest disturbance monitoring techniques further research has to be focused on the integration of multi-source change detection techniques.

The objective of this paper is to analyze multi-source optical and Synthetic Aperture Radar (SAR) EO data for forest disturbance monitoring for a test site in Central Siberia. In order to evaluate the capabilities of selected operational satellite data products for forest change monitoring, two operational satellite data sources were analyzed with a focus on forest loss. Forest loss is defined as a disturbance, or a change from forest to a non-forest stage without tree cover.

ALOS PALASAR data with the high spatial resolution of 25 m were used for the application and assessment of pre-classification change detection techniques for assessing the yearly extent of forest loss. Further, time series of the Enhanced Vegetation Index (EVI) with a temporal resolution of 16 days (2000–2014) from the Moderate Resolution Imaging Spectral Radiometer (MODIS) were integrated in a web-based data middleware system. Using the Earth Observation Monitor (EOM, www.earth-observation-monitor.net) an operational monitoring system was used for assessing for the capabilities of a near-real time detection of biomass loss in the forest ecosystem of Central Siberia, and to analyze temporal patterns of forest cover loss related to logging activities, fire events or other disturbances.

STUDY AREA

The study area is located in the Asian part of the boreal forest, in southern Central Siberia (Fig. 1). The area covers approximately 620 000 km^2 (longitude: 92–105° E; latitude: 53–60° N) and belongs to two Siberian Federal districts: Krasnoyarsk territory and Irkutsk region.

The test site is characterized by a continental climate, with long, severe winters and short (from mid-June to mid-September), warm, and relatively wet (as high as approximately 70 mm in a month of rainfall) summers. The coldest months are December and January, with temperatures of around –20 °C during the day, and the warmest months are June and July, with temperatures above +20 °C. Annual precipitation is approximately 400 mm with the most rainy season from July to October (based on weather data from the SIB-ESS-C portal, data

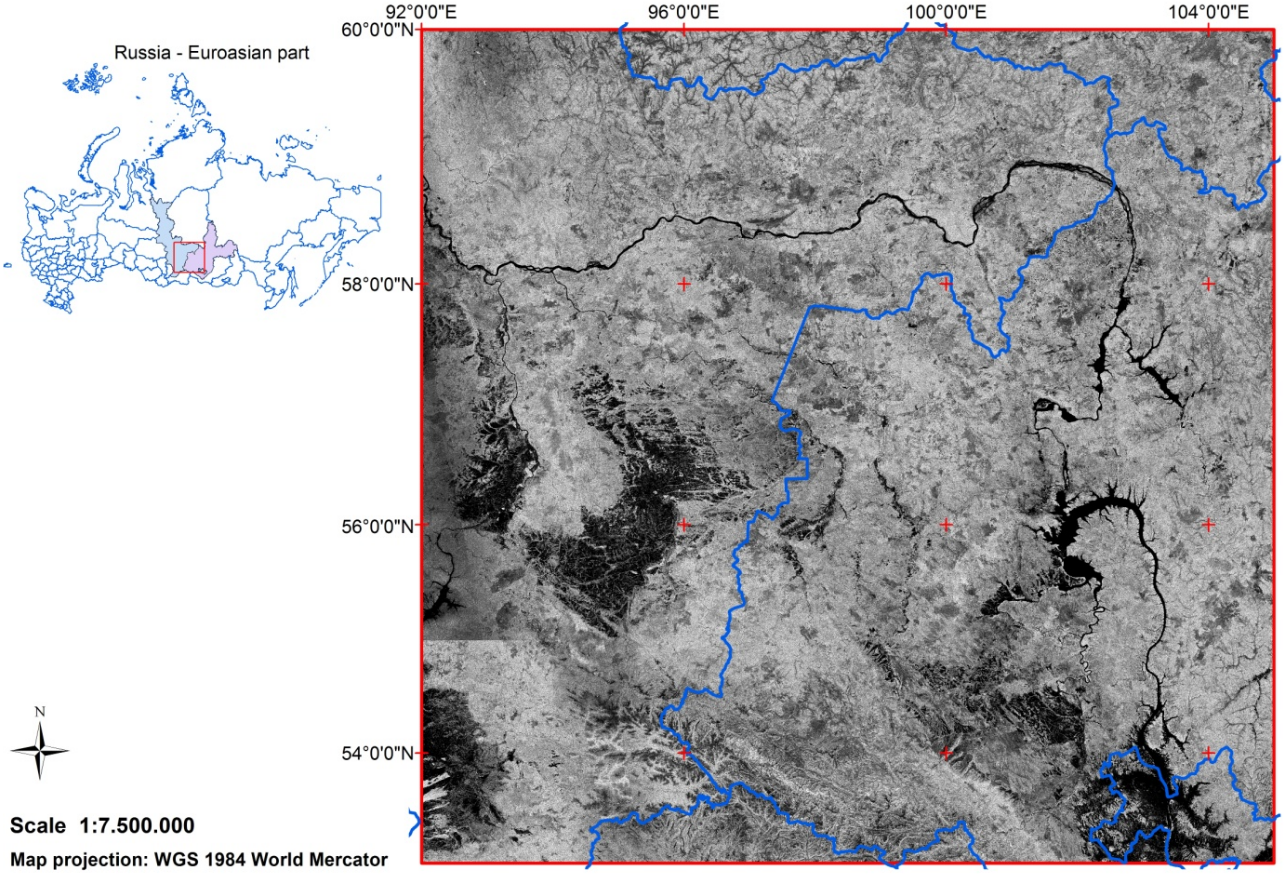

Fig. 1. The study area is located in two Siberian Federal districts: Krasnoyarsk territory and Irkutsk region, within Angara river basin. In background mosaic of 91 tiles of ALOS PALSAR HV-intensity data for 2010; amplitude data source: ALOS K&C © JAXA/METI.

source: World Meteorological Organization). The study area is covered mainly by forest; forest cover is approximately 70 % (based on Land Cover Map for Central Siberia (2010) © IKI, ZAPÁS project). The main dominant species in the study area are spruce (*Picea*), pine (*Pinus*), fir (*Abies*), and larch (*Larix*). Deciduous species are also present, mainly birch (*Betula*), aspen, and poplar (*Populus*), which are typical for early succession stages of such forests. These forests are hardly managed or protected, leading it to suffer disturbances such as wild fires, logging, and insect outbreaks (Schmullius et al., 2001; Shvidenko et al., 2011).

DATA

ALOS PALSAR backscatter mosaic data. For the forest loss detection ALOS PALSAR yearly backscatter mosaics with a 25 m spatial resolution were used. The data were acquired using L-band frequency in the Fine Beam Double (FBD) mode in two polarizations, horizontal transmitted and received (HH) and horizontal transmitted and vertical received (HV), with a 34.3° incidence angle, from May to October for the years from 2007 to 2010. The data were available through the ALOS K&C Initiative led by the Japan Aerospace Exploration Agency (JAXA). An example of an RGB composite of PALSAR mosaic for the selected area with clearly visible clear-cuts is shown in Fig. 2.

For Siberian test sites, a total of 364 of 1 degree tiles were delivered as level 1.5 data, which means radiometrically, slope-corrected, and orthorectified SAR amplitude data (Shimada et al., 2009; Shimada, 2010). According to Shimada et al. (2009) visible artifacts and unusual backscatter values were set to no data (< –34 dB HV / < –32 dB HH). The upper limit of the backscattering coefficient was +8 dB for both polarizations. The obtained data were converted from digital number (DN) into normalized radar cross section (NRCS) on the dB scale, according to the equation:

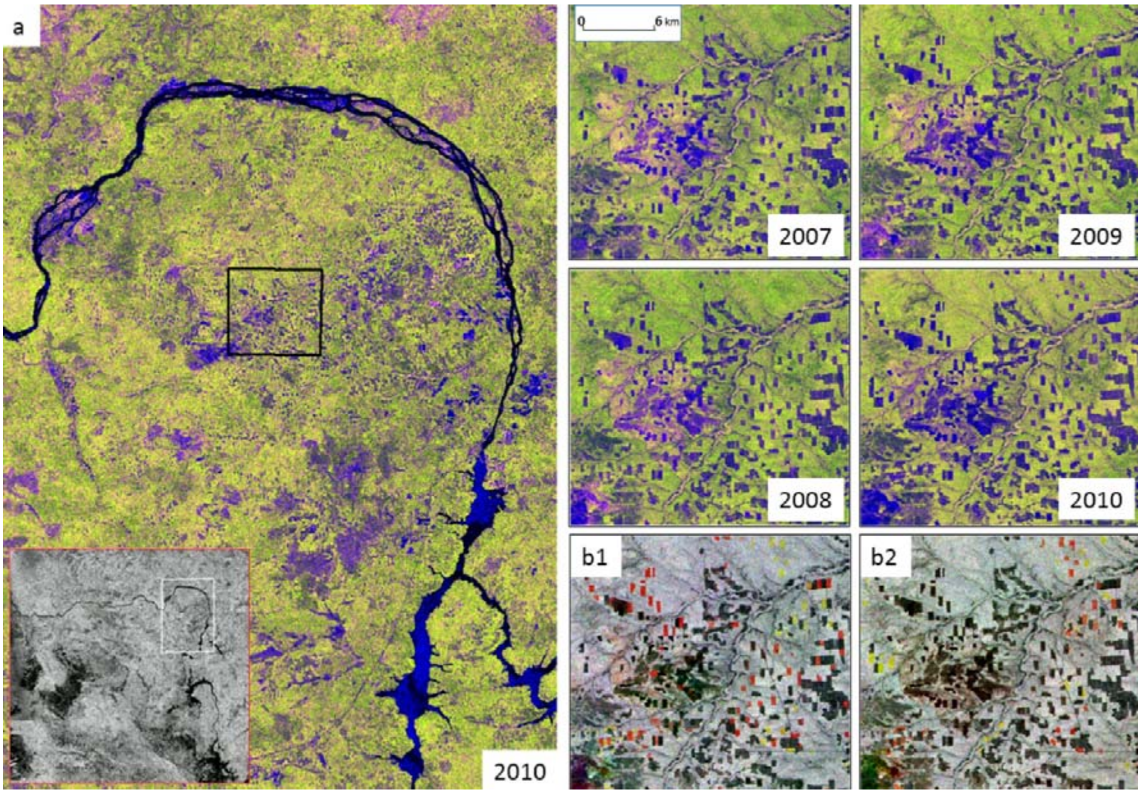

Fig. 2. RGB composite of PALSAR 25-m mosaic: a. red: HH-intensity, green: HV-intensity, blue: ratio HH/HV; HV-intensity b1. red: 2007, green: 2008, blue: 2009, b2. red: 2008, green: 2009, blue: 2010.

$$\sigma^0 \text{ [dB]} = 10 \times \log_{10} (DN^2) + CF, \quad (1)$$

where σ^0 is the backscattering coefficient (sigma nought) on the logarithmic scale, DN represents amplitude value, and CF is a calibration constant, which in this case is equal to –83 dB.

Optical satellite data. In addition to the SAR products, data acquired by optical sensors were also used. Landsat-5/-7 data with less than 10 % cloud cover for 2007–2010 were available via the United States Geological Survey (USGS) Earth Explorer portal. The MODIS Vegetation Continuous Fields (VCF; Collection 5) were downloaded from the Global Land Cover Facility portal (GLCF). In addition, very high resolution KOMPSAT-2 data were available through the European Space Agency CAT1 project (ID 13300). The data were used as reference LC information for validation.

MODIS time series were retrieved from USGS and integrated in the Earth Observation Monitor. The NASA MODIS MOD13 standard vegetation indices (VI) products include the normalize difference vegetation index (NDVI) and the enhanced vegetation index (EVI) to effectively characterize bio-physical/ biochemical states and processes from vegetated surfaces. There exists a complete, global time series record of 6 VI products from each of the Terra and Aqua MODIS sensors, at varying spatial (250 m, 1 km, 0.05°) and temporal (16-day, monthly) resolutions to meet the needs of the research and application communities. For this study the MODIS EVI product with 250 m spatial resolution was used.

METHODS

Forest loss monitoring using ALOS PALSAR data. A number of methods exist for forest mapping and change monitoring. In general, these methods can be grouped into post- and pre-classification techniques (Coppin et al., 2004). The first group of methods compare classification products either on the pixel, or segment level, with changes detected based on statistical analyses. The advantage of this approach is that not only change or no-change areas are detected, but also the type and direction of changes. However, the drawback is that the quality of the final change detection product depends on the accuracy of individual classifications. Unlike the post-classification method, the pre-classification technique employs unclassified images. Methods used to identify change areas include image differencing or rationing, bi-temporal linear data transformation (principal component analysis; PCA; multivariate alteration detection; MAD), image regression, and Change Vector Analysis; CVA (Coppin et al., 2004). Using the differencing approach, the ALOS PALSAR HH and HV-backscatter change was reported to be between 2 and 3 decibels; dB (e. g., Fransson et al., 2007; Santoro et al., 2010). Implementing HH, HV, HH/HV ratio, and HH-HH images difference maps, Dong et al. (2012) developed a decision tree algorithm to produce ALOS PALSAR-based forest maps for southeast Asia, with a high reported overall accuracy of 86 %.

In this study for a forest loss monitoring a pre-classification approach with a decision-tree classifier was implemented. Due to the short duration of the dataset, only changes from forest to non-forest were considered. In order to identify common classification thresholds different multi-temporal metrics were used. First the PALSAR mosaics were filtered by applying temporal and spatial filters. A multi-temporal filter averaging intensity values in a local window around each pixel in each image was used (Quegan & Yu, 2001). The window size for the filtering was calculated using the equivalent number of looks (*ENL*):

$$ENL = \frac{(mean)^2}{variance}. \qquad (2)$$

The higher *ENL*, the smaller is the scattering caused by speckle or image noise and the better is reduction of speckle effect (Quegan et al., 2000; Yu et al., 2008). As a trade of between resolution and information loss a 7 × 7 filter window size was selected. All available mosaics in HH and HV polarization were used for the filtering process.

After filtering, the multi-temporal metrics were employed (Bruzzone et al., 2004). They compare the single pixel values over all annual mosaics. In total eight multi-temporal metrics were calculated: minimum backscatter, maximum difference, maximum-minimum ratio (MMR), standard deviation, saturation, normalized standard deviation, mean average variability (MVA), and logarithmic measure based on normalized standard deviation (LMNSTDEV) (Fig. 3).

The largest class separability was calculated for HV-polarization. This observation is in agreement with the previous results (Santoro et al., 2009, 2012; Morel et al., 2011) that the ALOS PALSAR data in HV polarization are more sensitive to detect forest change comparing with HH polarization. The forest to non-forest change thresholds were detected using non-parametric support vector machines (SVM). This approach employs the statistical distribution of the data values to create hyperplane, which is aplane that separates the dataset into defined number of classes. Samples of forest and non-forest areas were collected using Landsat-TM images. The thresholds were derived by visual interpretation of the hyperplanes in the multi-temporal scatter plots. From the analysis of the plots it was concluded that the values of the mean backscatter and minimum backscatter were not suitable for forest change detection.

A clear threshold was observed using MMR, saturation, LMNSTDEV, and MVA. Maximum difference was also found to be a useful variable. For the final automatic yearly forest disturbances monitoring the pre-classification approach based on a ratio was used according to the equation:

$$10 \times \log_{10}\left(\frac{\sigma_1}{\sigma_2}\right), \qquad (3)$$

where σ_1 and σ_2 represent backscatter values of the year 1 and year 2, respectively.

Only HV-polarized mosaic data were used for the yearly forest loss monitoring. The processing steps are presented in Fig. 4. Forest change areas were classified using a simple threshold approach – a threshold of –2 dB was finally implemented. Using a reference map and LC information, other changes in non-forest areas were then masked. Further improvement of the classification results was done by removing small patches (2 ha) and by employing a shape compactness using following equation (Bogaert et al., 2000):

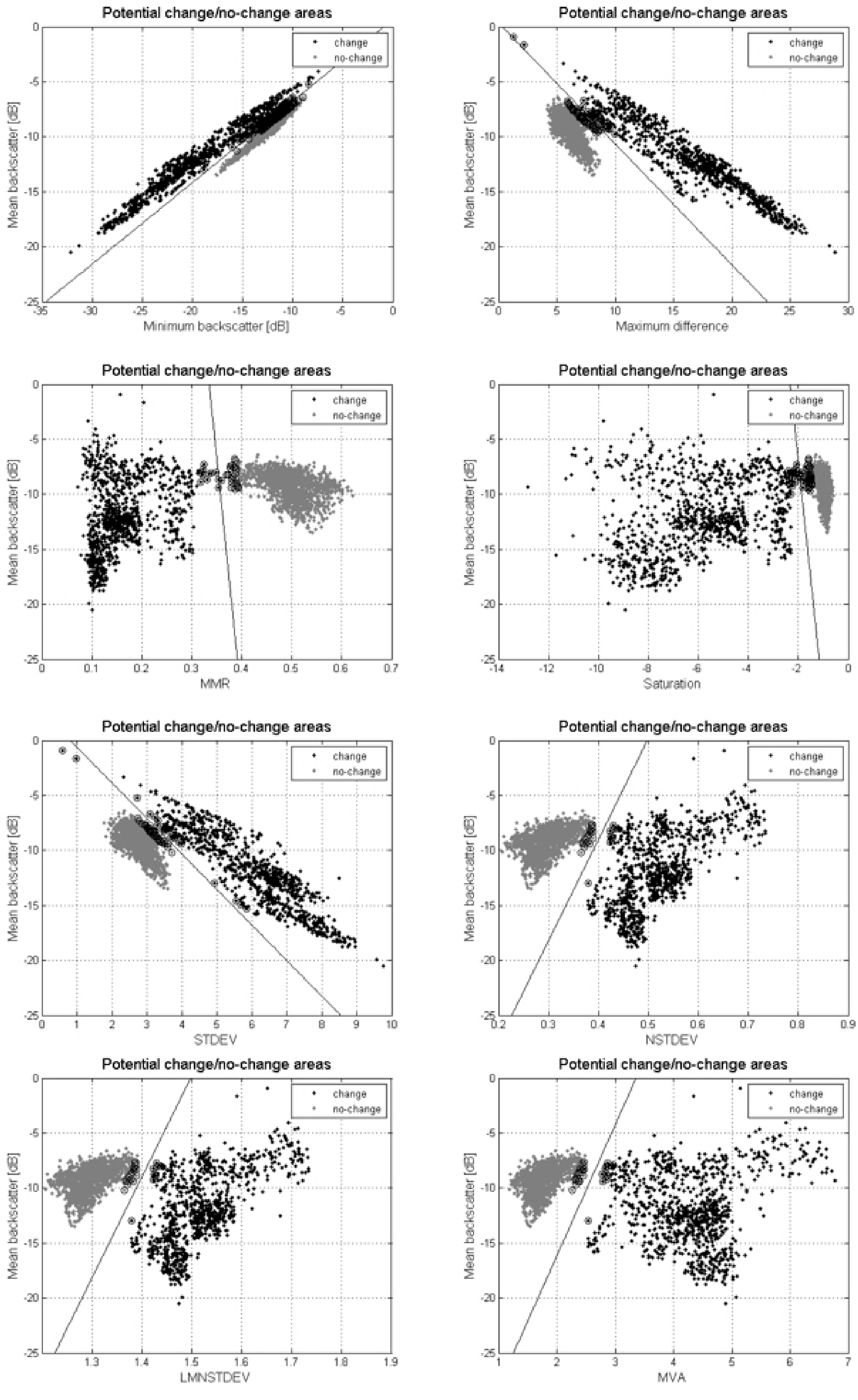

Fig. 3. Multi-temporal metrics to identify thresholds for forest change/no-change areas classification using ALOS PALSAR data.

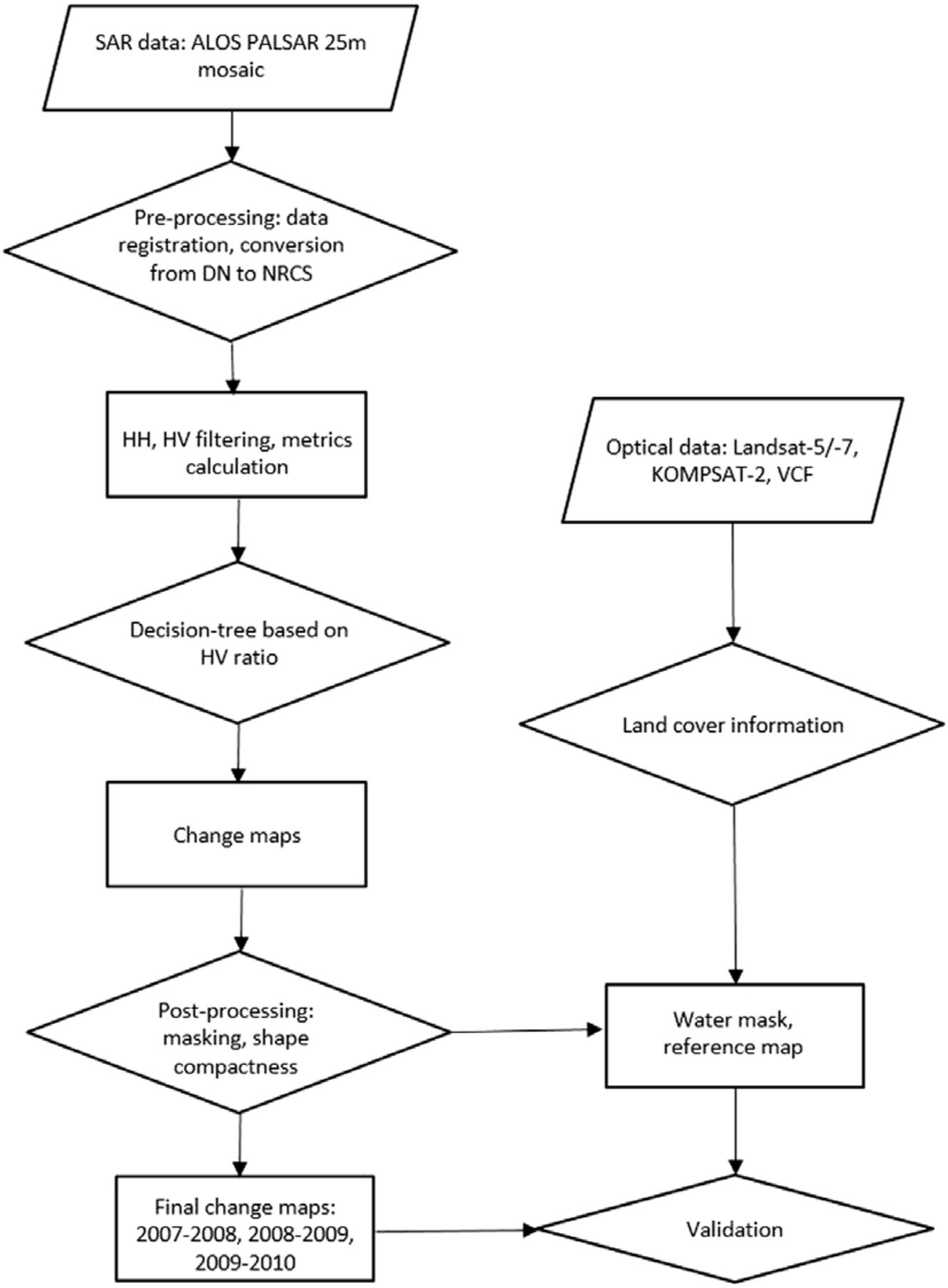

Fig. 4. Workflow for large-scale forest disturbances monitoring.

$$\frac{4\sqrt{A}}{P}, \tag{4}$$

where A represents area, and P perimeter.

The accuracy of change classifications was assessed by comparing the change results with reference maps. Data from two consecutive years were used to check whether the change from forest to non-forest was correctly classified. The overall accuracy was calculated as a ratio of total number of correctly classified pixels over the total number of pixels using 50 randomly distributed points.

Operational forest monitoring using the Earth Observation Monitor (EOM). The Earth Observation Monitor (Eberle et al., 2013*b*) is a web-based data middleware system for land observations. The geoportal functions as a web-based visualization and analyses platform for selected EO time series form the MODIS data product line. The geoportal provides standard-compliant Web Services based on a Data Processing Middleware (Eberle et al., 2013*a*) and statistical analysis and processing functions. Analyses tools comprise seasonal time series decomposition by moving averages, break point detection by additive season and trends (BFAST, Verbesselt et. al., 2010) and greenbrown, analyzing trends and trend changes in gridded time series like from satellite observations or climate model simulations (Forkel et al., 2013). BFAST integrates the decomposition of time series into trend, season, and remainder components with methods for detecting and characterizing change within time series. BFAST detects multiple abrupt changes in seasonal and trend components of the EVI time series. In this study BFAST was applied on MODIS EVI time series from 2000 to 2014 to detect change events (break points) in the VI time series. The analyses were conducted using the EOM date middleware by selecting a part of the study area for the high-resolution SAR-based forest loss detection. The BFAST output, a spatially explicit temporal information of change events (break points), was compared with local scale reference data on forest logging activities and the ALOS PALSAR forest loss mapping results. Areas were integrated in the cross-validation only where in both time series components (season and trend) a breakpoint occurred.

RESULTS AND DISCUSSION

ALOS PALSAR based forest loss detection. Resulting change map is given in Fig. 5. Changes were identified and validated using the ALOS PALSAR L-band data with 25 m spatial resolution and LC information extracted from the optical-based products. Analyzing the generated maps, most of the forest loss can be observed in 2007–2008 and 2009–2010. This is reflected in the forest loss statistics presented in

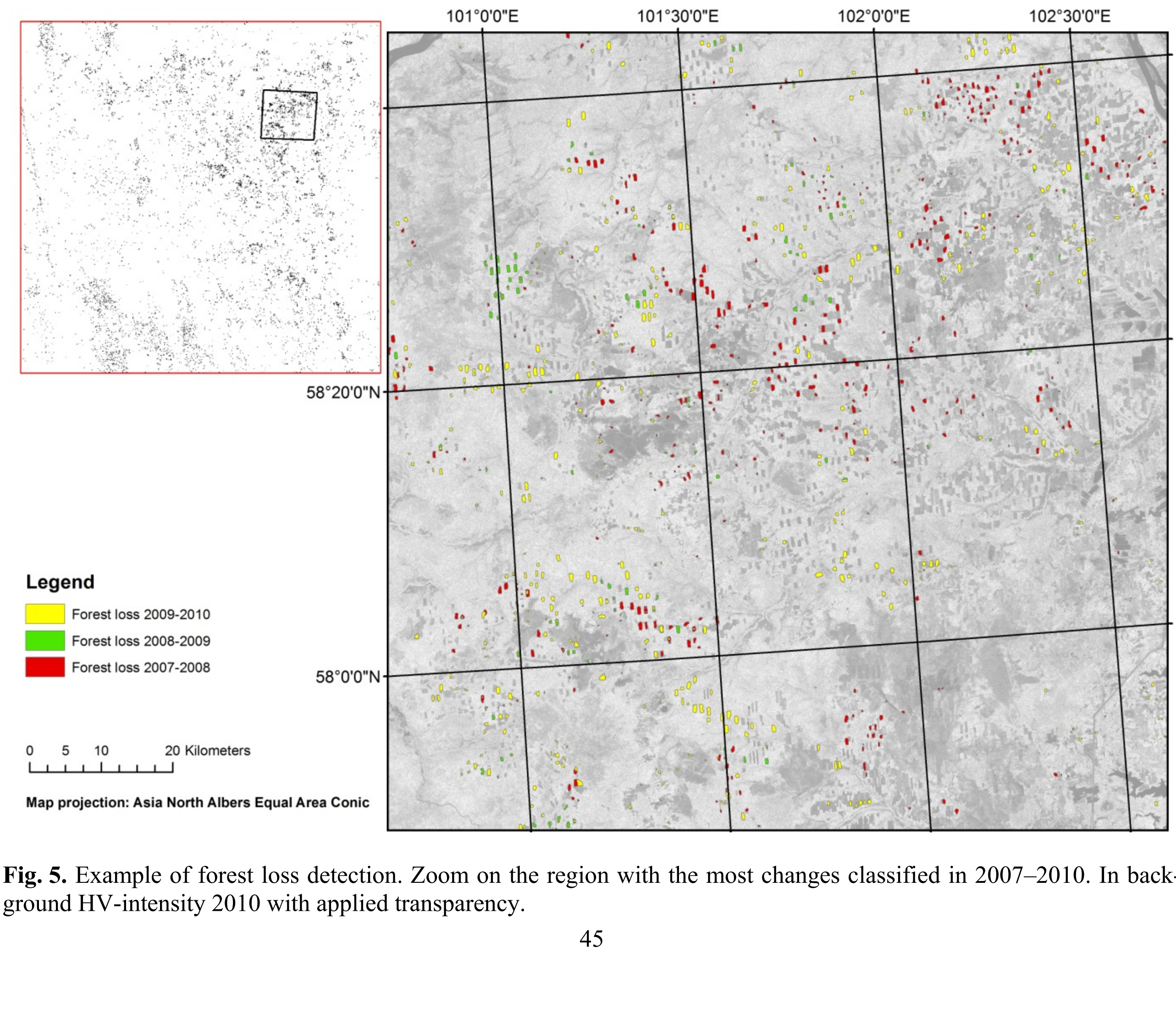

Fig. 5. Example of forest loss detection. Zoom on the region with the most changes classified in 2007–2010. In background HV-intensity 2010 with applied transparency.

Table 1. Forest loss statistics based on ALOS-PALSAR and Landsat data

Years	Overall accuracy of forest loss detection, %	Forest loss, km^2	Forest loss vs. forest cover, %	Forest loss by Hansen et al., 2013, km^2	Forest loss by Hansen et al., 2013 vs. forest cover, %
2007–2008	66	669	0.1	2.666	0.5
2008–2009	76	212	0.04	1.706	0.3
2009–2010	70	631	0.1	2.055	0.4
2007–2010	–	1.512	0.24	6.427	1.2

Table 1. The forest loss area was compared with the freely available results of global forest loss obtained by Hansen et al. for the study area (Hansen et al., 2013). Hansen et al. defined the forest loss similarly as in this study as «a stand-replacement disturbance, or a change from a forest to non-forest state». The global maps were created using Landsat data.

Hansen's results showed the same trend as the present study, with the most forest loss taking place in 2008 and 2010. However, the size of mapped areas of forest depletion differ by 1.997 km^2 in 2008, 1.494 km^2 in 2009, and 1.424 km^2 in 2010, with larger areas identified in Hansen's products. In particular the highest discrepancy, eight times difference, was observed in year 2009. The reason for the extreme difference may result from the Hansen's annual product generation. The «Forest Loss Year» product is a disaggregation of total «Forest Loss» to annual time scales (Hansen et al., 2013), which may overestimate forest loss in case of years with less forest disturbances occurred. Most of the forest loss change for both studies was observed in the northeastern area of the Siberian study region.

The average accuracy for the present study was over 70 %. The highest validation result was obtained for the forest change analysis between 2008 and 2009. This can be explained by

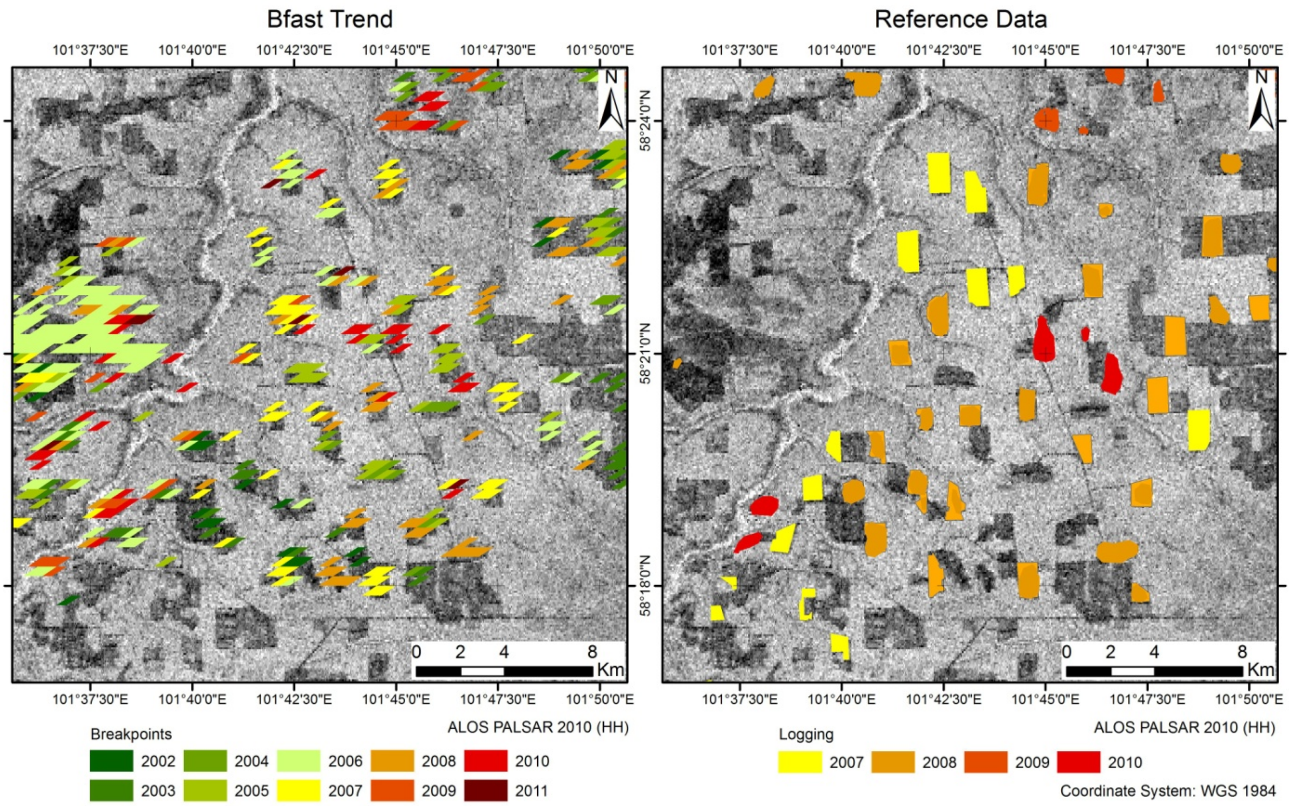

Fig. 6. Comparison of forest disturbance dates (breakpoints) based on BFAST (left) with local scale ALOS PALSAR and forest inventory based forest disturbance event information (right), overlain ALOS PALSAR HH-backscatter image from 2010.

the fact that the difference image between those years resulted in the least number of misclassifications, meaning that the mosaics that were created used data acquired under similar weather conditions.

Operational MODIS-EVI-based breakpoint detection. Phenologically-driven land cover changes were mapped using the BFAST tool implemented into EOM data middleware. Hereby, only areas were selected as change patterns where in both time series components (trend and season) a minimum of one breakpoint occurred. The result was a map of change dates (breakpoint) indicating inter-annual dynamics of forest disturbances. Fig. 6 shows the change areas detected between 2000 and 2014, compared to the ALOS PALSAR-based change areas and local scale forest inventory data.

The example from Abanskii region demonstrates that most of the forest disturbances were captured using the operational change monitoring method within EOM, e. g. a fire event was detected for 2006 and numerous clear cutting areas were detected between 2004 and 2011.

The breakpoints detected by EOM were cross-compared with the ALOS PALSAR based change areas and local forest inventory data. Fig. 6 shows a good agreement of MODIS and reference local scale forest disturbances. Most of the clear cuts were detected with the fully automatic approach. A general agreement is visible by comparing the change event dates. A validation was conducted by selecting 100 reference points within the local scale test sites. The breakpoints were cross-validated for the trend and the seasonal component.

Fig. 7 visualizes the temporal match and scattering of the breakpoint detection for trend and season.

It is obvious that breakpoints derived with the trend component have a better temporal match rate than the season-based break points. Depending on the number of reference points per year the trend-based breakpoints show a high temporal variation (e. g. 2006, 2008, 2010), whereas the medial shows a good temporal match. Breakpoints detected by the seasonal component show a general shift towards the actual date. This is particularly visible for the early disturbances in 2006 and 2007.

Despite the temporal mismatch, the seasonal breakpoints show a less distinct temporal variability. The accuracy metrics prove this observation (Table 2). The trend-based breakpoint detection achieved an overall accuracy of 50 %, while the season-based change detection shows an accuracy of 43.4 %.

The accuracies varied between the years. The best producer's accuracy was detected for 2010. Due to a smaller number of reference points a

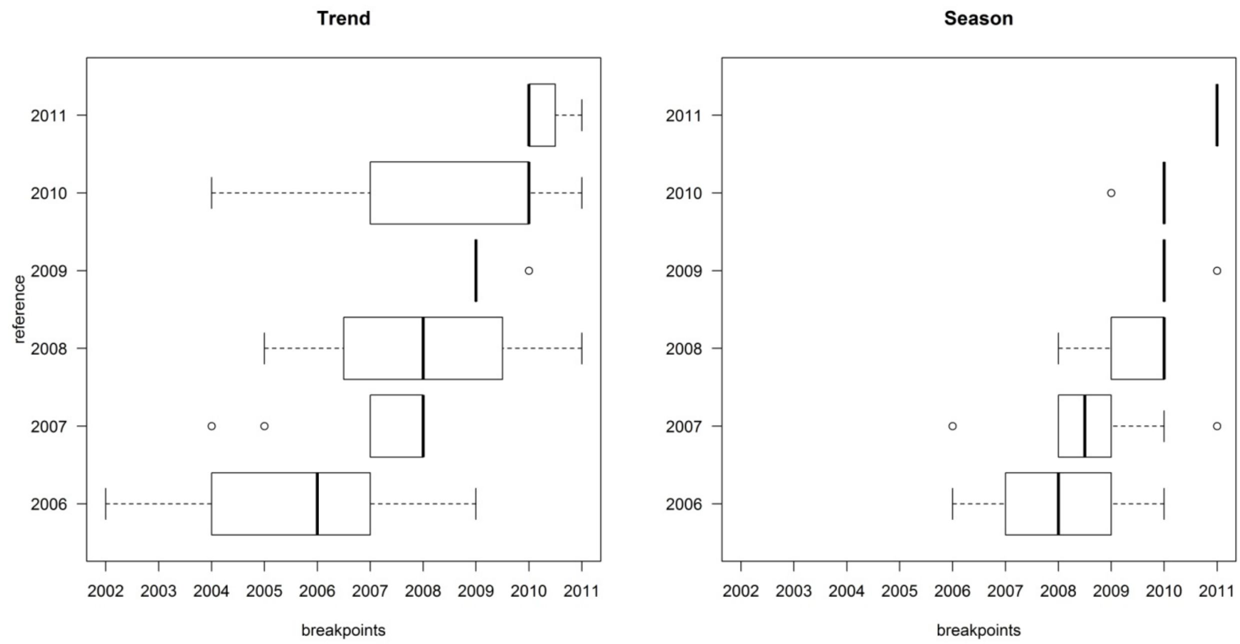

Fig. 7. Cross-comparisons of BFAST breakpoint derived from MODIS EVI time series analyses for the trend and the seasonal component of the time series.

Table 2. Accuracy assessment for BFAST break point detection

Trend	Reference								
Breakpoints	Years	2006	2007	2008	2009	2010	2011	Total	Producer's accuracy
	2002	1	0	0	0	0	0	1	0.00
	2003	3	0	0	0	0	0	3	0.00
	2004	1	1	0	0	2	0	4	0.00
	2005	1	1	2	0	5	0	9	0.00
	2006	**5**	0	1	0	5	0	11	0.00
	2007	3	**4**	2	0	0	0	9	44.44
	2008	2	7	**1**	0	6	0	16	6.25
	2009	2	0	2	**4**	1	0	9	44.44
	2010	0	0	2	1	**31**	3	37	83.78
	2011	0	0	1	0	1	**1**	3	33.33
	Total	18	13	11	5	51	4	102	Overall **50.00**
	User's accuracy	27.78	30.77	9.09	80.00	60.78	25.00	–	
Season	Reference								
Breakpoints	Years	2006	2007	2008	2009	2010	2011	Total	Producer's accuracy
	2006	**1**	1	0	0	0	0	2	0.00
	2007	5	**0**	0	0	0	0	5	0.00
	2008	6	4	**1**	0	0	0	11	9.09
	2009	0	3	1	**0**	0	0	4	0.00
	2010	4	1	3	4	**20**	0	32	62.50
	2011	0	1	0	1	1	**1**	4	25.00
	Total	16	10	5	5	21	1	58	Overall **43.40**
	User's accuracy	6.25	0.00	20.00	0.00	95.24	100.00	–	

good user's accuracy was also reached for 2009.

Better matches of the trend-based breakpoints can be explained by the distinct detection of a phenology-driven decline of the EVI value within the EVI time series trend. The breakpoint will be assigned to the date where the land cover change occurred.

A different situation is apparent in the seasonal breakpoint detection. Due to a delayed temporal response on a seasonal level, the breakpoints were detected in one of the following seasons after the disturbance event which leads to a general delay of the change date detection towards the following years. The final result was based on a synergy of both breakpoint detection methods. The most reliable result achieved the combination of the seasonal and the trend-based change date detection, as shown in Fig. 6.

CONCLUSIONS

Monitoring Russia's forests is of a special interest due to the vast size of these forests. Since traditional, ground-based methods cannot efficiently monitor changes over entire forest cover, remote sensing appears to be a suitable tool for operational forest monitoring.

This paper demonstrated the application of a SAR-based and an optical operational satellite data source for operational forest cover change monitoring. These datasets are operational and freely accessible through USGS (MODIS) or being released on annual basis by JAXA (ALOS PALSAR annual mosaics) and being integrated in geoportals focussing on multi-source forest monitoring (Hüttich et al., 2014*b*).

Firstly, it was demonstrated that SAR remote sensing data have a great potential for automated large-scale forest change monitoring in the boreal zone in a high spatial resolution. Only SAR images can provide sufficiently regular data, due to the ability to operate and collect data under all weather and sunlight conditions. The results demonstrated great potential for L-band sensors using HV cross-polarization data for large-scale forest mapping, as was reported in previous studies (e. g. Santoro et al., 2012).

Using ALOS PALSAR mosaics with 25 m spatial resolution, forest cover loss was mapped with reasonable accuracy. The data were provided by the ALOS K&C Initiative as level 1.5, co-registered tiles. The changes in the study area were identified with approximately 70 % accuracy. However, higher accuracy would be expected if the data were corrected due to further time series variations (e. g., Motohka et al., 2014). The coherence of the large-scale product should hopefully further decrease the number of misclassifications and other data-related errors for the boreal zone. The 46-day revisit time of the sensor is not a limitation in this part of the world due to the stable environmental conditions during winter. This is of particular importance in order to fully use the potential of ALOS PALSAR data within an operational large-scale forest-monitoring system.

Secondly, in addition to SAR data, frequently available time series data tracking the phonological activity, such as the MODIS EVI product with a 16-day temporal resolution provide another important data source for regional scale forest disturbance tracking. Combining operational satellite time series with the BFAST change detection method implemented in the EOM data middleware system enables a fast and easy to use forest monitoring tool. The integration of data acquisition, time series quality enhancement, data integration and analyses in a web-based environment enables a broad applicability of EO data for local and regional stakeholders, environmental scientists, and land managers. The MODIS-based BFAST change detection produced an overall accuracy of 50 % for an observation period of 14 years. Within this period, two years (2009, 2010) showed a user's accuracy of 80.0 and 60.8 % which proved the applicability of the method. For local scale analyses we demonstrated a good matching to reference data but the application and integration in forest management processes required a sound understanding of the SAR data processing and analyses. User friendly data access and analyses can be improved by using data middleware systems such as the EOM platform. Up to now, a fully operational system can be used based on the NASA MODIS vegetation indices product line. Further developments will focus on the implementation of SAR-based time series products and newly available satellite time series.

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ОПЕРАТИВНЫЙ МОНИТОРИНГ ЛЕСОВ СИБИРИ С ИСПОЛЬЗОВАНИЕМ МНОГОСЕНСОРНЫХ ДАННЫХ ДИСТАНЦИОННОГО ЗОНДИРОВАНИЯ ЗЕМЛИ

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Воздействие антропогенного фактора и климатических изменений вызывает рост степени нарушенности лесов Сибири. В данной работе использованы данные двух спутниковых сенсоров для автоматизированного выявления изменений площади лесов. Погодичные мозаики изображений обратного рассеяния радиоимпульсов со спутникового радара ALOS PALSAR за период с 2007 по 2010 г. были использованы для мониторинга сокращения площади лесов. Временные ряды улучшенного вегетационного индекса (Enhanced Vegetation Index – EVI) за период 2000–2014 гг. на основе съемки спектрорадиометра среднего разрешения MODIS (Moderate Resolution Imaging Spectral Radiometer) были интегрированы в веб-систему для оценки возможности обнаружения нарушений лесного покрова в близком к реальному масштабе времени с использованием методов поиска разрывов в усредненной сезонной кривой и линии тренда (BFAST). Средняя точность определения сокращения лесных площадей по радарным данным (Synthetic Aperture Radar – SAR) составила 70 %, в то время как средняя точность оценки изменений лесных площадей по данным MODIS методом поиска разрывов в линии тренда составила 50 % и для метода разрывов в сезонной кривой 43.4 % соответственно. Тем самым была продемонстрирована возможность использования данных радарной съемки (SAR) как высокоточного инструмента для оперативного мониторинга лесов. Интернет-геопорталы типа «Мониторинг Земли» (Earth Observation Monitor) предоставляют простой в использовании интерактивный инструментарий для оценки изменений в лесах Сибири.

Ключевые слова: *дистанционное зондирование, радар с синтетической апертурой (SAR), спектрорадиометр среднего разрешения (MODIS), временные серии, мониторинг изменений лесного покрова в режиме реального времени.*