OBJECT-ORIENTED WAVELET MULTI-RESOLUTION IMAGE ANALYSIS OF THE SIBERIA GBFM RADAR MOSAIC COMBINED WITH MERIS IMAGERY FOR CONTINENTAL SCALE LAND COVER MAPPING

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ABSTRACT:

Boreal forests and wetlands play an important role in the climate system, in particular through biosphere-atmosphere flux exchanges. They are an important pool of carbon and their role as sink or source of greenhouse gases is not fully understood. Accurate mapping of the vegetation of Siberia can therefore contribute to a better understanding of these processes at regional scale and of their effects on the climate through regional biosphere modeling. The potential of the combination of radar data with medium-resolution optical data to obtain regional scale land cover mapping is investigated using multi-spectral imagery from the MERIS sensor at 300 m resolution and a high resolution radar mosaic (pixel spacing of 100 m) covering Western and Eastern Siberia compiled in the framework of the Global Boreal Forest Mapping project, an initiative of the Japan Agency for Space Exploration (JAXA). For this purpose, capabilities of oriented-object image analysis associated to wavelet multi-resolution techniques are investigated. Results show that wavelet multi-resolution textures bring relevant additional information for land cover classification. Suggestions are made for the implementation of an object-based wavelet multi-resolution texture estimator.

1. INTRODUCTION

Eurasian boreal forest and peat bogs are important ecosystems in relation to climatic change. By forming peat, bogs serve as significant long-term sinks for atmospheric carbon dioxide The boreal forest is an important sink of carbon dioxide through the photosynthesis process. At the same time, bogs release methane, a greenhouse gas 20 times more powerful than carbon dioxide, into the atmosphere and forest release carbon by respiration and due to biomass burning (fires). Anomalies in temperature and precipitation in northern Russia over the past few years have been viewed as manifestations of anthropogenic climate change (Thompson and Wallace, 2001). If the actual trends of climate change are maintained, it should have a strong impact on the Eurasian boreal ecosystems such as change in ecosystem boundaries (shifts in forest-type zones and species range), change in permafrost zone, changes in fire disturbances, change in forest growth rates and productivity, changes in bio-diversity and insect disturbance. Major international concerns are the melting of the frozen peat bogs of the sub-arctic regions in North Western Siberia that would release billions of tons of methane in the atmosphere (Kirpotin and Marquand, 2005) and the increase in 'wild' fires in Eurasian boreal forests although 87% anthropogenic in origin (Mollicone et al., 2006) still is linked to the higher likelihood in fire ignition and propagation caused by the large recent climate anomalies in 1998, 2002 and 2003. Also, virtually nothing is known about how climate change could affect the existing bog ecosystems at longer time scales which could have important repercussions for global carbon cycling. In this context, the need for accurate and up-to-date regional land cover mapping of the Eurasian Boreal ecosystems and in particular of the boreal forest and the peat bogs is increasing for global change science as well as implementation of environmental treaties and development programs (Bartalev et al., 2003). However the Eurasian Boreal zone includes some of the most remote, inaccessible and infrequently mapped ecosystems of our planet and an international effort should be promoted to update the last forest inventory of North Eastern Russia that is more than 50 years old (Strakhov 2001) and the last regional land cover map of the Eurasian region produced during the GLC2000 project (Global Land Cover for the year 2000, Bartalev et al., 2003). The first difficulty to map boreal Eurasia and more specifically Siberia stems from the huge geographic extension (10,007,400 km^2, similar in size to the continental United States) that extends eastward from the Ural Mountains to the Pacific Ocean, and southward from the Arctic Ocean to the hills of north-central Kazakhstan and the borders of both Mongolia and China. The second difficulty resides in the different scales of interest from thousands and thousands of small lakes that form the bogs to the million of hectares of boreal forests. Since the GLC2000 project based on standard SPOT4-VEGETATION products at 1 km resolution, some newer and more accurate satellite image mosaics involving the overall Siberia started to show up in the last years giving new emphasis to land cover mapping project of the region, in particular the MODIS mosaics, the MERIS composites and the GBFM radar mosaic. In this study we set the stage for the development of methods suitable for exploiting the combined capabilities of radar and optical instruments for thematic mapping at regional scale of the Boreal ecosystems in Siberia. The main data source is provided by a high resolution radar mosaic (pixel spacing of 100 m) spatially more accurate for bogs. lakes and river mapping while the potential of the combination of radar data with medium-resolution optical data is investigated using imagery from the MERIS sensor at 300 m resolution. Multispectral information is necessary to distinguish bogs from the other land covers and the different types of forests at a larger scale. To the purpose, capabilities of multi-scale object-oriented image analysis is investigated in a first step combining a multi-resolution segmentation, based on a fractal net evolution approach, and an object-oriented fuzzy classification that is fed with all available data and information sources. Results are validated using detailed land cover maps derived from high resolution imagery (30m) from the LANDSAT TM sensor and available ground-data. In a second step wavelet multi-resolution techniques are tested to derive complementary information from radar image texture for such regional land cover mapping.

2. STUDY AREA AND DATASETS

2.1 Ecosystems of study area

The study area is located 59º40′ N - 84º30′ E and belongs to the vast West Siberian lowland which is characterized by flat terrain where the poor drainage led to development of huge wetland ecosystems. The region is covered with peaty bogs and forests. The forest belongs to the Middle Taiga zone with larix, picea and abies species. Birch forest is present in the areas where deforestation or forest fires occurred. The peaty bogs are composed of ridge-hollow complexes with islands of dwarf pine shrubs. The area is drained by the Ob River and its tributary the Kel. The flood plains of major rivers are covered with riparian vegetation. Figure 1 shows the study area location on the GBFM mosaic.

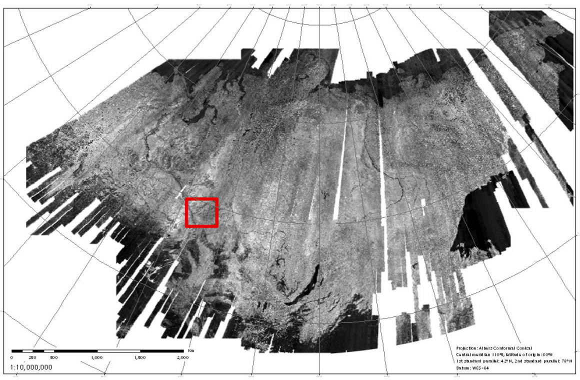

Figure 1. Location of the study area on the GBFM mosaic

2.2 Satellite images and ancillary datasets

Three sources of data were used together for classification: a subset of the GBFM JERS-1 radar mosaic, a MERIS image and ancillary information coming from the SRTM Water Bodies.

2.2.1 GBFM JERS-1 radar mosaic

A radar mosaic of Siberia was produced in the framework of the Global Boreal Forest Mapping Project, an initiative of the Aerospace Exploration Agency of Japan (JAXA). The mosaic is composed of some 530 strip-images (typically covering 80 km by 2500 km each) acquired in 1997-98 by the L-band SAR aboard the JERS-1 spacecraft. Coverage includes the area between the Ural Mountains in the west, Bering Strait in the east, Arctic Ocean in the north and the Korean Peninsula in the south. The GBFM Siberia mosaic is a good source of thematic information due to well-known radar backscatter characteristics (sensitivity to moisture content and surface roughness, independence on weather conditions and small sensitivity to seasonality). The mosaic features good relative radiometric calibration due to a number of radiometric corrections, and therefore it is suitable for automatic classification. The systematic radiometric distortions caused by antenna pattern and other system induced errors have been removed. The strip-images were mosaiced together using a block adjustment procedure (least square minimization of discrepancies) based on homologous features in overlapping areas, an a number of ground control points derived from auxiliary data, such as GeoCover Landsat mosaics, and topographic maps. Pixel spacing is 100m, tie-points rms error (internal geometric consistency) is 80.4 m (Northing) and 117.4 m (Easting); absolute geocoding (with repect to external measurements) rms error is 273.3 m (Northing), 277.0 m (Easting).

2.2.2 MERIS multispectral image

The Medium Resolution Imaging Spectrometer instrument aboard the ENVISAT satellite is a 68.5 ° field-of-view pushbroom imaging spectrometer that measures the solar radiation reflected by the earth at a ground spatial resolution of 300m in 15 spectral bands in the visible and in the near infra-red. To test our methodology, we used a single date MERIS image of the 07/06/2003 delivered by ESA in the framework of the GLOBCOVER project. This image is partially covered by clouds and we executed a simple cloud screening using a threshold in the channel 3 (blue) of MERIS (485 - 495 µm).

2.2.3 Landsat TM

For validation of the middle resolution land cover classification, we used an orthorectified Landsat TM image of the 07/07/1999 delivered by the NASA`s Global Orthorectified Landsat Data Set (Tucker et al., 2004). This image is cloud free and positional accuracy is <50 m RMSE.

2.2.4 SRTM Water Bodies

The version 2 of the SRTM data (Shuttle Radar Topography Mission, Homepage of SRTM data: http://www2.jpl.nasa.gov/srtm/) was produced by the National Geospatial-Intelligence Agency. The data set exhibits well defined water bodies with absence of spikes and wells (single pixel errors). The absolute horizontal accuracy is 20 m circular error with 90% of confidence. The lakes greater than a 600-meter minimum length and 183-meter minimum width are depicted and double line drain (river) depiction begins as the river width exceeds 183 m for a length of 600 m or more and ends when the width of the river becomes 90 m or less and does not widen back to > 90 m within 1 km downstream.

All the data were co-registrated using the GBFM JERS-1 radar mosaic as a reference.

3. OBJECT-ORIENTED LAND COVER CLASSIFICATION

A fractal net evolution approach (FNEA) underpins our object-oriented land cover classification. The fractal net evolution approach incorporates an object-oriented framework and image segmentation techniques. In particular, it utilizes fuzzy set theory to extract the objects of interest, at the scale of interest, by segmenting images simultaneously at both fine and coarse scales, then building image semantics between levels and their elements (Blaschke & Hay, 2001).

The FNEA is embedded in the Definiens Professional Earth commercial software (previously called eCognition) that we used for segmentation and image classification.

Two image object levels constitute the image object level hierarchy used in this work. The first image object level is obtained from a multi-resolution segmentation based exclusively on the radar backscatter from the GBFM mosaic. Multi-resolution segmentation is a region-merging algorithm that starts with a single pixel and a pairwise comparison of its neighbors with the aim to minimize the resulting summed heterogeneity.

Then a second image object level is processed by merging the objects with a Spectral Difference algorithm using the channels 5 (555 – 565 µm, green), 8 (677.5 – 685 µm, red) and 13 (855 – 875 µm, near infra-red) from MERIS. Spectral Difference algorithm merges neighboring objects according to their difference in mean reflectance value. This second image object level is composed of larger objects with borders delimitations defined by the segmentation resulting from the radar 100 m image and extension size defined by the reflectance similarity from MERIS in the green, red and near infra-red channels.

A multi-scale land cover classification was processed from the two image object levels using semantic rules between levels. The first level of classification was used primarily to extract rivers and lakes while the other land cover classes were distinguished from the second image object level. A classification rule-set was defined using fuzzy membership functions on both levels.

Lakes are identified using both SRTM Water Bodies ancillary dataset and GBFM radar image. The first image object level classification rule-set states that if an object is overlapping an identified lake from SRTM Water Bodies with a low backscatter area on the GBFM image, then it's effectively a lake. Objects that don't overlap an identified lake from SRTM but have a low backscatter and an elliptic shape are also considered as lakes. In the study area, we noticed by photo-interpretation that low backscatter elliptic objects are mainly lakes. Rivers are also defined by low backscatter in the GBFM image and overlap with identified river from SRTM Water Bodies.

On the second image object level, land cover classification fuzzy rules are based on the 5, 8 and 13 MERIS. The riparian vegetation is defined using both fuzzy membership functions in the 5, 8 and 13 channels of MERIS and a distance to the river defined in the first image object level. The resulting classification distinguishes 8 land cover types plus clouds:

- Anthropic area and bare soil
- Bogs
- Broadleaf forest
- Dark taiga
- Lichen and moses
- Riparian vegetation
- Lakes
- Rivers
- Clouds

Figure 2 shows the classification results.

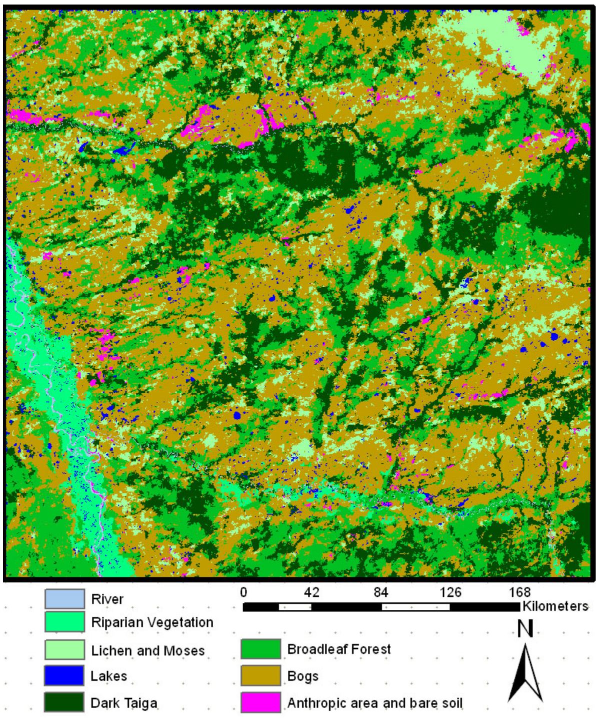

Figure 2. Land cover classification result

4. ACCURACY ASSESSMENT

The resulting land cover classification is validated using as reference a pixel-based supervised maximum likelihood classification of a Landsat TM image. The training areas were established based on visual interpretation of the Landsat image and expert knowledge developed by comparing ground data with numerous Landsat scenes. The broadleaf and dark taiga are grouped for accuracy assessment in a single class forest since they were not identified on the Landsat classification. Table 1 shows the error matrix and the accuracy. Overall accuracy is high (0.725) as well as Kappa (0.67).

Confusion Matrix								
User Class \ Sample	Lake	River	Forest	Bogs	Riparian Veg.	Anth. Area & bare soil	Lichen & Moses	Sum
Lake	84	0	0	1	3	1	0	89
River	0	24	0	0	2	0	0	26
Forest	4	0	101	0	9	8	4	126
Bogs	7	1	3	88	24	33	40	196
Riparian Vegetation	1	4	0	0	55	10	0	69
Anth. area & bare soil	1	1	0	0	0	29	0	31
Lichen & Moses	0	0	0	2	0	2	41	45
Sum	97	29	104	91	93	83	85	582
Totals								
Overall Accuracy	0.725							
KIA	0.6739							

Table 1. Land cover classification accuracy assessment

5. IMPROVEMENT OF THE LAND COVER CLASSIFICATION USING RADAR TEXTURE

The land cover methodology presented previously didn't benefit from the high texture content of the radar images. Radar texture could enlarge the uncorrelated feature space used in classification. We test here the usefulness of textural features extracted by multi-resolution decomposition provided by a wavelet frame that acts as a differential operator. The method is described in detail in [De Grandi et al., 2006]. In a nutshell, textural features are captured by spatially local estimates of: i) variance of the smooth signal, ii) variance of the wavelet coefficients. Intuitively, these measures are sensitive to sharp transitions (contours of areas with different reflectivity, point targets), and to edge density, smoothness and swing (at a given scale) within extended targets. Proper normalization of the estimated wavelet variance is introduced for dealing with multiplicative speckle noise.
In this application the two first dyadic scales in the wavelet decomposition are used. Therefore textural features that develop with characteristic scales of 100 m and 200 m are considered. Also we disregard directional effects and measure the variance of the squared sum of the wavelet components along the row and column directions.
This type of texture in radar imagery of the Siberian ecosystem has not been studied previously and there is no clear assumption or theoretical explanation on how such texture should be used in land cover classification. We base therefore our analysis purely on experimentally observed correlation between textural features and thematic classes. These observations indicate a strong correlation between group of land cover classes and texture range of values. We define three groups of land cover classes based on their textural behavior:

Group 1: riparian vegetation, river, anthropic area and bare soil
Group 2: broadleaf forest and dark taiga
Group 3: bogs, lakes, lichens and moses

For each group we define three ranges of wavelet variance values and we observe how the spatial distribution of each range matches the corresponding land cover group. The texture values considered here are the mean texture values of the second image object level.

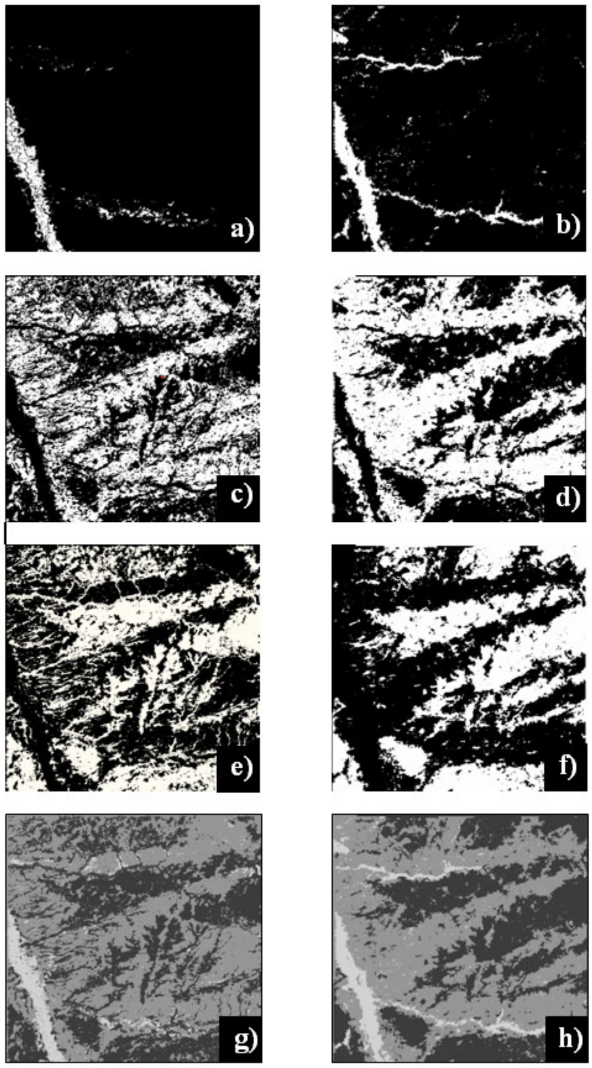

Figure 3. Wavelet variance scale 1 versus land cover groups
a) land cover group 1, b) high wavelet variance, c) land cover group 2, d) medium wavelet variance, e) land cover group 3, f) low wavelet variance, g) land cover group 1 (light grey), 2 (grey), 3 (dark grey), h) wavelet variance, high (light grey), medium (grey), low (dark grey).

In figure 3, the spatial distribution of the land cover groups and the texture range values calculated for the second image object level are compared. We can observe how similar are the spatial distribution of the land cover groups compared to the texture range values. Table 2 shows the error matrix resulting from the comparison of the texture range values with the land cover groups. Accuracy assessment is based on 50 object samples for each land cover group. Overall accuracy is 0.73 and Kappa is 0.6. This high accuracy demonstrates that wavelet texture can contribute positively to land cover discrimination.

In view of these results, work is currently under way to modify the wavelet variance computation from point-estimates using a local smoothing kernel to an object-wide estimator. This passage would allow for far better accuracy of the estimator, provided that good criteria can be found to check the stationarity of the wavelet variance process within the object.

Confusion Matrix				
User Class \ Sample	Broadleaf forest, Dark Taiga	Bogs, Lichen, Moses, Lakes	Riparian, Anth. Area, Bare soil, River	Sum
Low_wl-scale 1	42	10	4	56
Medium_wl-scale 1	7	38	16	61
High_wl-scale 1	1	2	30	33
Sum	50	50	50	150
Totals				
Overall Accuracy	0.7333			
KIA	0.6			

Table 2. Texture-based classification accuracy assessment

6. CONCLUSION

The combination of L-band radar data and MERIS imagery allows us to resolve some major classification confusions that occur when only radar data is available. The spectral information can be very useful for example in distinguishing between agriculture and wetlands, alpine meadows and bogs, urban and high biomass vegetation etc. Object-oriented image analysis facilitates the use of combined radar, multispectral and ancillary data in a transparent classification process avoiding complex image fusion.

In the next months, ESA will deliver through the GLOBCOVER project a 16 monthly MERIS composites of the globe covering the entire Siberia. Those composites will be cloud screened and orthorecitified. Using both the GBFM JERS-1 mosaic and the GLOBCOVER MERIS composites, it will be then possible to produce a land cover map of Siberia at 100 m resolution. According to our preliminary results, such a classification could benefit from a texture extraction approach based on an object-based wavelet variance estimator.

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