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Landscape Element Classification Based on Remote Sensing and GIS Data

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Abstract

IIASA's Forestry activities within the SIBERIA II study follow two directions: first, to provide input data to both global biosphere process models and a landscape based regional model, and second, to update and consolidate the database of environmental data for the Siberian area.

For the landscape-based regional model, a landscape element classification is suggested. In the past, the landscape element classification has been performed using cartographic information of soil, vegetation, relief, climatic zones, tectonics, etc., following the Russian landscape concept of Gudilin (1987). This approach however, does not take into account the temporal variability of the various input datasets, including vegetation and land use change. This study provides an alternative to the traditional form of landscape determination.

The study examined the theoretical and practical aspects of landscape element classification based mainly on remote sensing data supplemented with GIS data following the concept of Gudilin and comparing it to other approaches (Forman and Godron, 1986, and graph-based methods).

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About the Author

Joachim Steinwendner was a participant in IIASA's Young Scientists Summer Program (YSSP) during the summer of 2002. This paper is the result of his work during this three-month period.

Joachim Steinwendner studied computer science at the University of Salzburg with a minor in techno-mathematics and systems analysis as well as sports science. In 1992/1993, he spent a year in the USA at Bowling Green State University, Ohio and graduated as Master of Science in computer science. After finishing his studies in Salzburg in 1995 he started work at the Institute of Surveying, Remote Sensing, and Land Information, University of Agricultural Sciences (BOKU) in Vienna. He collaborated in several research projects in remote sensing, e.g., in an Austrian Science Foundation-sponsored project "Theory and Practice in Pattern Recognition and Image processing", and in the SINUS-project to develop "Indicators for Sustainable Land Use Based on Remote Sensing Images", among others. Currently, he is involved a project "Geo-Graph" combining methods of graph theory and image processing for landscape ecology applications.

His main fields of scientific interest include remote sensing, computer vision, graph theory, and neural networks mainly for ecologically relevant applications.

Landscape Element Classification Based on Remote Sensing and GIS Data

Joachim Steinwendner

1 Introduction

Carbon is important in a global ecological sense for climate change and its effects on fauna, flora and humans, but it is also important in a local or national economical sense in light of emission trading according to the Kyoto Protocol. Due to their size, the Siberian boreal forests of Russia are considered a highly important carbon sink with respect to climate change. It is thus of utmost importance to first determine the state of Siberian forests, and then to monitor any changes that might occur due to natural or anthropogenic influences.

Remote sensing is an important aid to achieve these goals. Several methods and papers exist for forest classification using remote sensing data (Bauer *et al*., 1994; Binaghi *et al*., 1997; Burger and Steinwendner, 1997; Goetz and Prince, 1996). Some of these papers are based on pixel-based methods, such as maximum likelihood, minimum distance, or Mahalanobis distance. Although these methods are sufficient for many applications, they reach their limits when GIS data sources, context-information, or generally expert knowledge is required. Pixel-based methods do not allow to appropriately add this kind of information into the classification process. In this paper, a repeatable, remote sensing method describing landscape element classification is introduced and described.

1.1 Qualitative Landscape Element Classification

A landscape element is defined as the smallest discernible object in the observed environment (Forman and Godron, 1986). Examples are trees, hedges, rocks as well as agricultural parcels, and forest stands. This definition is a very flexible one in the sense that landscape elements can be very different depending on the scale of the observed environment, e.g., landscape elements in a high resolution satellite image such as IKONOS differ greatly from landscape elements of LANDSAT TM imagery.

In qualitative landscape element classification the task is to assign an ecological-aesthetical value to a landscape according to the distribution and type of landscape elements. However, in qualitative analysis a holistic rather than a statistical approach is chosen to decide over the quality of a landscape (see Figure 1).

Figure 1: Two landscapes of different scale of observed environment and ecological-aesthetical value.

1.2 Quantitative Landscape Element Classification

However, for the purposes of the SIBERIA II study,[1] qualitative landscape element classification is only partly applicable (with respect to the state of boreal forests). It is more important to obtain quantitative information from landscape elements for several purposes, e.g., leaf area index (LAI), area, average height, etc. The landscape element in this case is a spatial object that is attributed with several parameters, necessary for further analysis. However, in many applications not only the landscape elements are important but also the interaction between the landscape elements. Some examples are nitrogen and phosphor cycle in a landscape, as well as the carbon cycle, which depends, for example, on the attribute "land cover" of a landscape element. Many of the attributes of a landscape element may be derived from remote sensing images (see Figure 2). The complexity and variability of ideas about landscapes stemming from various goals, means of description, and ways of realization need a strong aggregation in order to be operational (Rojkov *et al*., 1996).

[1] An EU funded study titled "Multi-sensor Concepts for Greenhouse Gas Accounting in Northern Eurasia", of which IIASA's Forestry project is a partner.

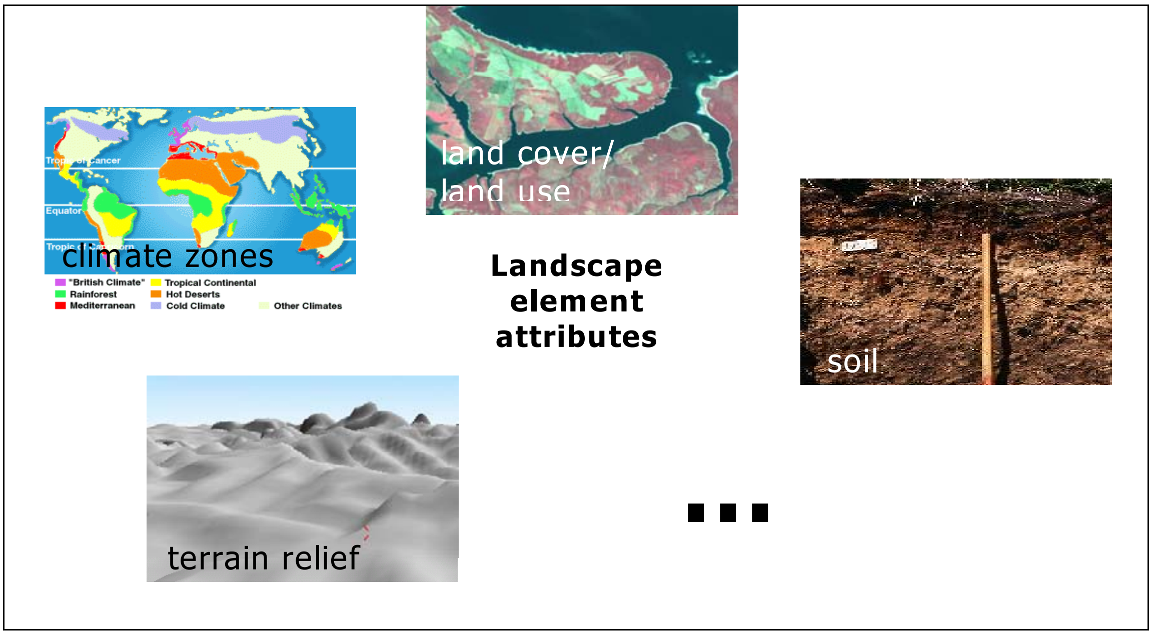

Figure 2: Possible landscape element attributes.

2 Remote Sensing Data Preprocessing

In order to obtain thematic data, important preprocessing tasks have to be performed. First of all, the satellite images have to be geo-coded, i.e., to be transferred to an appropriate map-coordinate system. This is followed by satellite image correction, including atmospheric, topographic and haze correction.

2.1 Test Site

Within the SIBERIA II study the test site Primorskii located in the area Irkutsk Oblast, was chosen (Figure 3). For this test site, ground truth data for forested area is available.

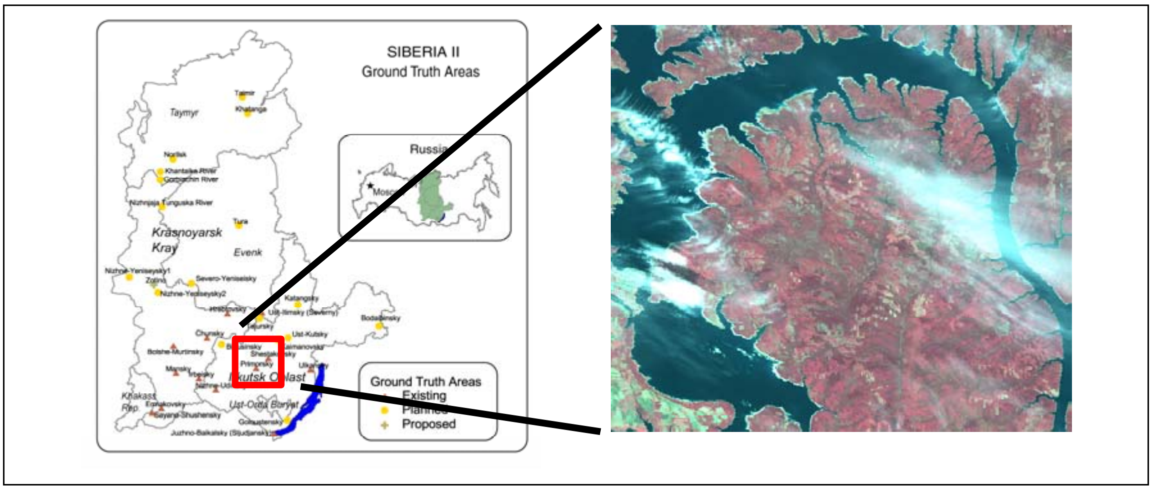

Figure 3: Test site Primorskii in the area Irkutsk Oblast.

2.2 Image Correction

In considering the establishment of a knowledge-based classification system, it is necessary to obtain image acquisition-independent image parameters. Current software-systems, e.g., ATCOR from Erdas Imagine, offer these possibilities. They are based on a physical model of the radiation transfer through the atmosphere. An example of the radiation processes is shown in Figure 4. In order to develop a classification scheme that is applicable to all Landsat images it is advisable to apply an image correction that includes atmospheric, topographic and haze correction. This correction transfers the digital numbers of the pixel values into physical units, i.e., reflectance values (see Figure 5).

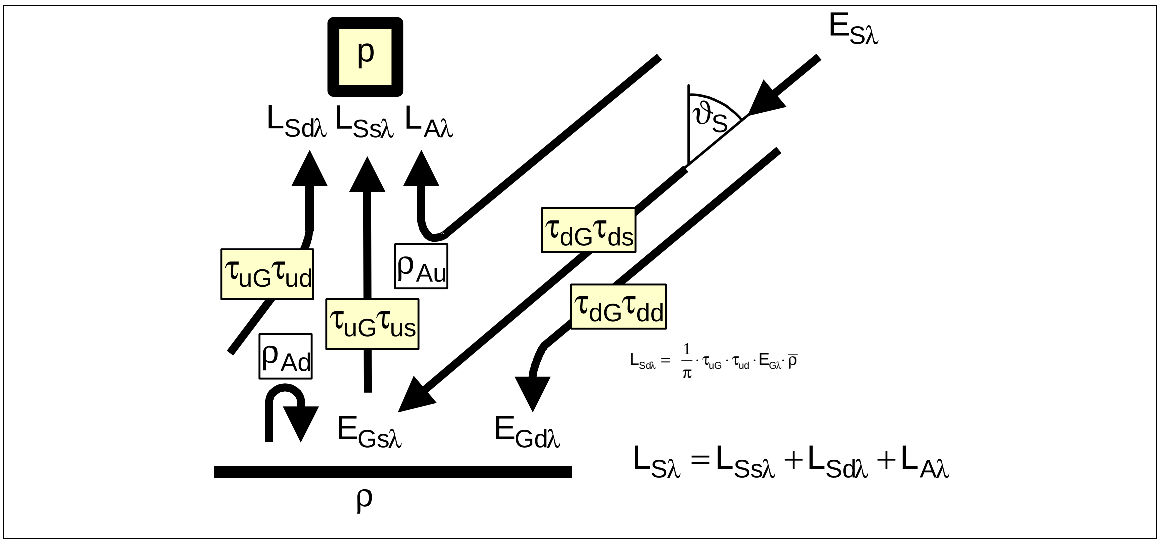

Figure 4: Physical model of radiance transfer through the atmosphere (a detailed description can be found in Steinwendner and Schneider (1999).

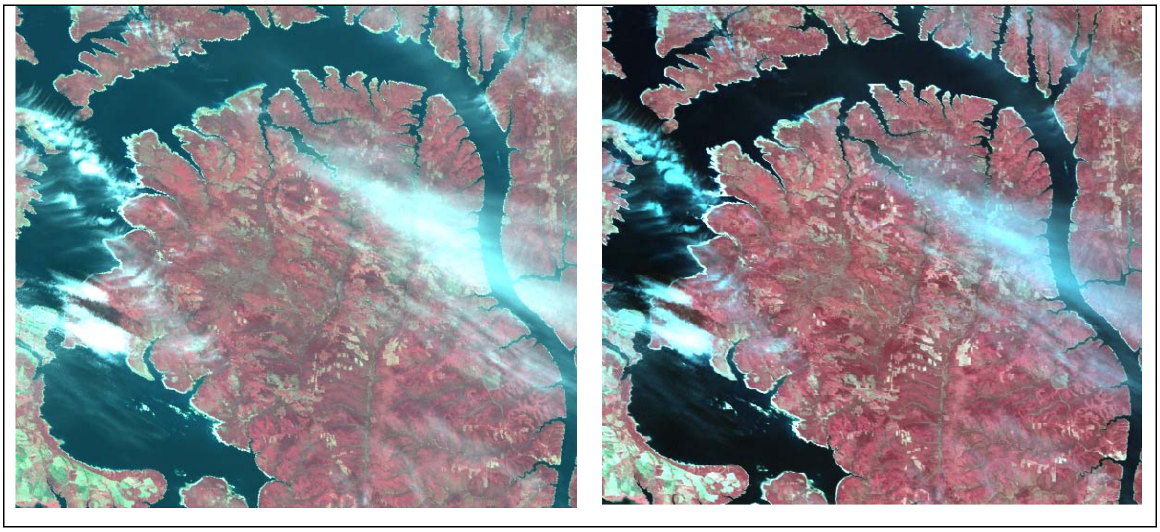

Figure 5: Left original Landsat image, right atmospheric and haze corrected image.

3 Image Segmentation for Landscape Element Delineation

Conventional remote sensing classification methods, e.g., maximum likelihood, are optimal for the search of optimal class membership in a multi-dimensional parameter space. However, this requires an gaussian distribution of the spectral signatures describing a land cover class, which is not possible. There are methods, e.g. neural net methods (Bischof et al., 1992), that do not require a gaussian distribution. However, the spectral information alone is very often not sufficient for land cover/land use classification, as some land cover types may appear similar in the provided satellite imagery and the distinction is only possible with context or corollary information. In order to use and add context information, the smallest object to classify should not be the pixel but rather groups of pixels representing a meaningful image object, e.g., agricultural parcel, fire scar, cutblock, lake, forest stand etc., although one does not yet know the meaning but only the spatial extent of the image object.

In order to achieve this, a computer vision method called image segmentation is used to derive meaningful image objects. In this work, the strategy of the eCognition software is adopted (Baatz and Schäpe, 2000).

3.1 Hierarchical Segmentation

Directly connected to the representation of image information by means of objects is the networking of these image objects. Whereas the topological relation of single, adjacent pixels is given implicitly by the raster, the association of adjacent image objects must be explicitly worked out in order to address neighborhood objects. As a consequence, the resulting topological network is very advantageous as it allows the efficient propagation of many different kinds of relational information. Each classification task addresses a certain scale. Thus, it is of importance that the average resolution of image objects can be adapted to the scale of interest.

Image information can be represented in different scales based on the average size of the image objects. The same imagery can be segmented into smaller or larger objects with considerable impact on practically all of the information, which can be derived from image objects. Thus, specific scale information is accessible. Furthermore, it is possible to represent image information in different scales simultaneously by different object layers. By bringing different object layers in relation to each other can contribute to an extraction of further valuable information. For instance, this can be derived by hierarchical networking and representation of image objects. In such a strict hierarchical structure, each object knows not only its neighbors but also its sub objects and super objects. This is advantageous because it allows a precise analysis of the sub-structures of a specific region, which is not possible without a strict hierarchical structure. Furthermore, the shape of super objects can be changed by out-grouping and regrouping sub objects, based on the shape of the sub objects.

The different techniques for segmentation in eCognition can be used to construct a hierarchical network of image objects, which represents the image information in different spatial resolutions simultaneously. The image objects are networked, so that each image object ‘knows’ its context (neighborhood), its super object and its sub objects. Thus, it is possible to define relations between objects, e.g., ‘Rel. Border to Forest’, and to utilize this kind of local context information. Starting at the pixel level, the levels are consecutively numbered (see Figure 6).

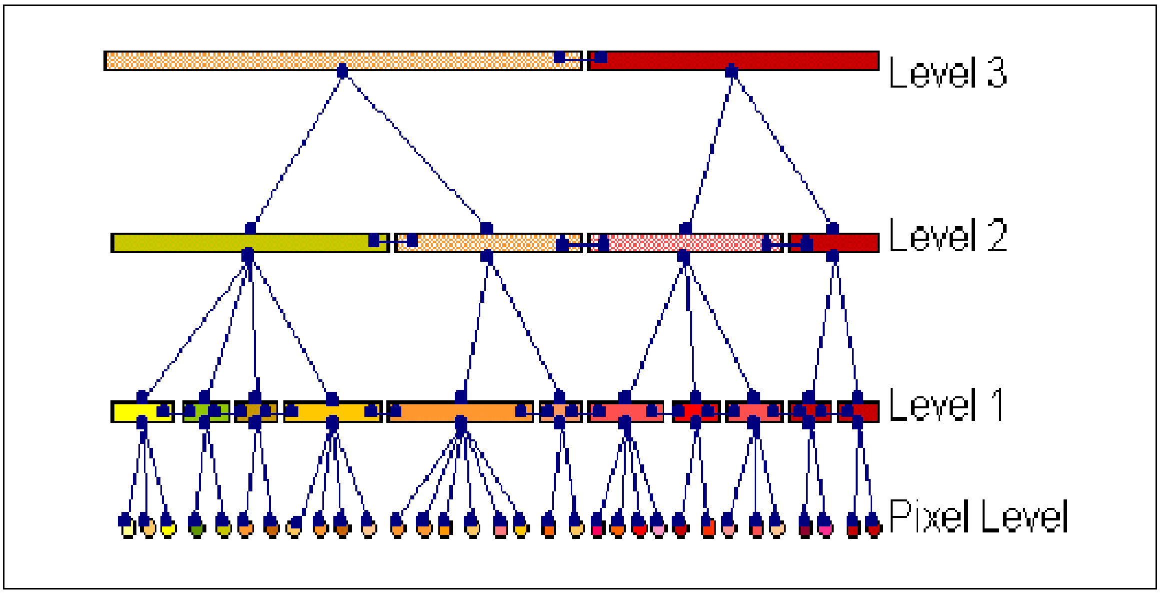

Figure 6: Segmentation hierarchy according to the multi resolution segmentation concept.

This hierarchical network is topologically definite, i.e., the border of a super object is consistent with the borders of its sub objects. The area represented by a specific image object is defined by the sum of its sub objects areas. Technically this is carried into effect relatively simply, since all segmentation techniques used in eCognition are region-merging algorithms. Each level is constructed based on its direct sub objects, i.e., the sub objects are merged into larger image objects on the next level. Merging is limited by the borders of super objects; adjacent image objects can not be merged when they are sub objects of different super objects. In eCognition, image objects are defined as being spatially self-consistent.

Figure 7 shows the results of applying this methodology to the test area Landsat image. Examples are provided showing first-level and second level segmentation. First-level segmentation provides a highly detailed segmentation of the image, providing sub landscape elements, which can then be aggregated upwards into landscapes.

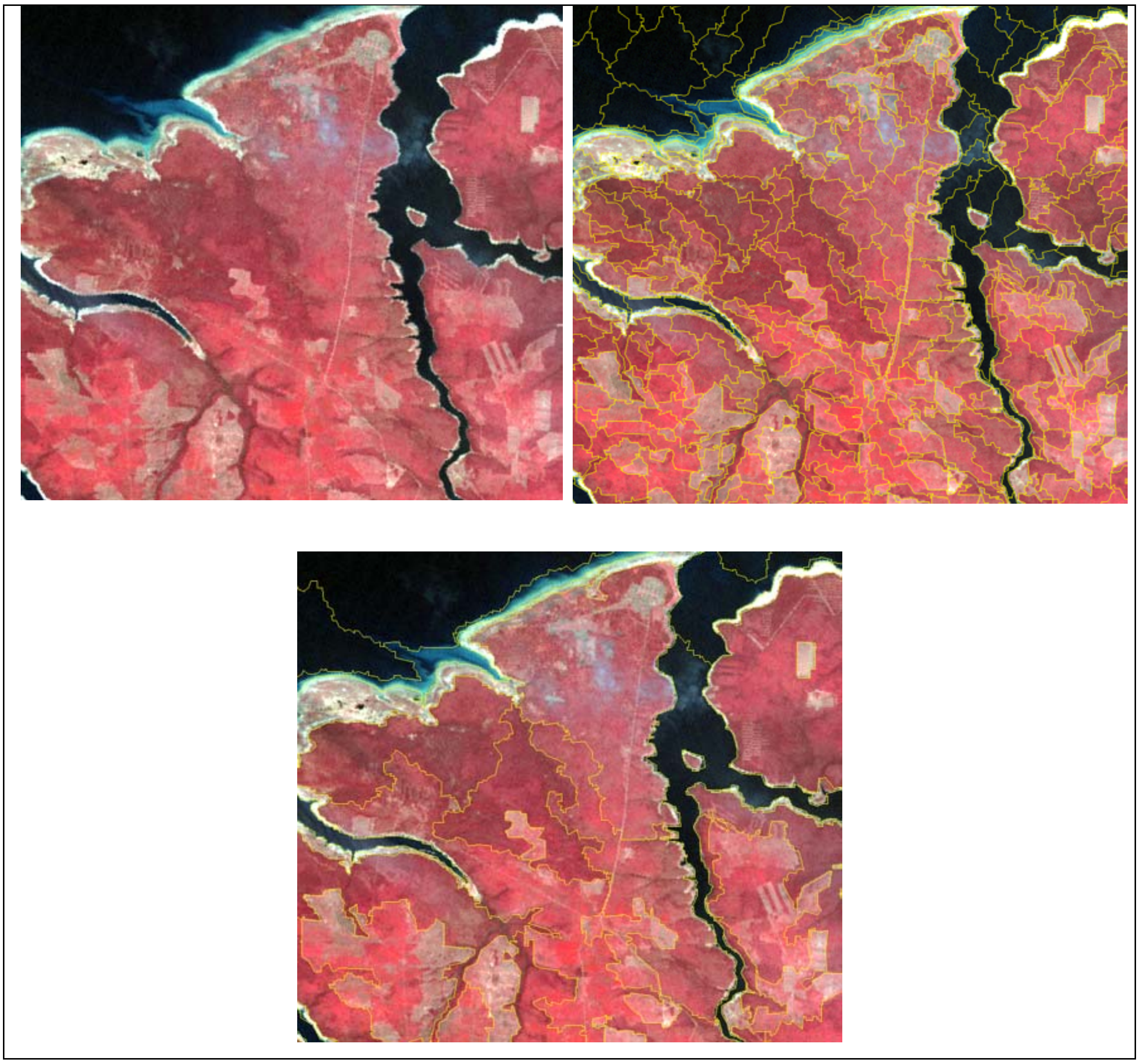

Figure 7: Top Left: Landsat image (bands 4-3-2); Top Right: superimposed with first-level segmentation; Bottom: superimposed with second-level segmentation.

3.2 Image Object Features

Beyond spectral signature, several types of object information can be used in the classification step — shape, texture, context and information from other object layers. Using this information, classification leads to better semantic differentiation and to more accurate and specific results (Figure 8). In a conceptual perspective, the available features can be distinguished to:

- intrinsic features: the physical properties of theobjects, which are determined by the pictured real-world and the imaging situation — basically sensor and illumination. Such features describe the color, texture, and form of the objects.
- topological features: these describe the geometric relationships between the objects or the whole scene, such as being left, right or at a certain distance to a certain object or being in a certain area within the image.

- context features: these describe the semantic relationships of the objects among each other, e.g., a park is almost 100% surrounded by urban areas.

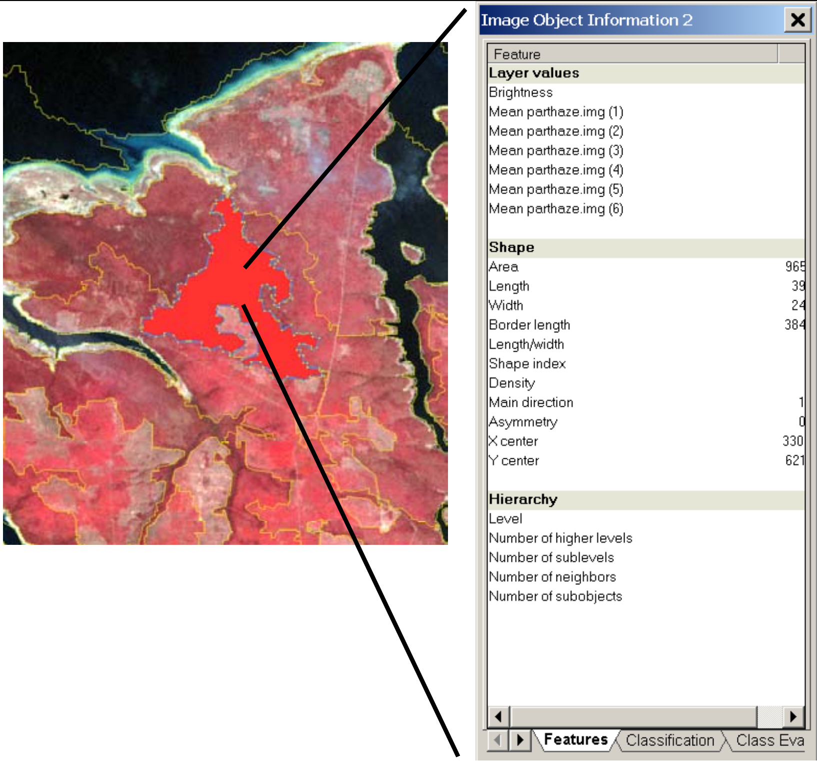

Figure 8: Image object and according image object information (spectral, shape, and topological features).

4 Conclusion

This work focused on object-oriented approaches for the acquisition of data to be used in the creation of landscape element datasets. Results confirm that the approach outlined here will in fact provide a quantifiable, repeatable procedure for the determination of landscape elements. This approach has advantages over the traditional cartographic approach to landscape segmentation by incorporating remote sensing information into the process. Identification of landscapes is an important component in the attempt at global and regional carbon cycle modeling as needed in the SIBERIA II study. Segmentation is used to find meaningful image objects, which are attributed with a set of parameters that can be used for dynamic vegetation modeling. The object-oriented approach allows for the inclusion of spatial aspects in the modeling.

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