AN OBJECT-BASED INFORMATION EXTRACTION METHODOLOGY INCORPORATING A-PRIORI SPATIAL INFORMATION

Thomas Blaschke(1, 2), Dirk Tiede(1), Stefan Lang(1)

(1)University of Salzburg, Hellbrunner Str. 34, 5020 Salzburg, Austria, E-mail: [Thomas.blaschke; dirk.tiede; Stefan.lang]@sbg.ac.at]
(2) Austrian Research Centers, Research Studio iSPACE, Leopoldskronstr. 30, 5020 Salzburg, Austria

ABSTRACT

The progress in image data mining over the last years is significant but barely known in the GIScience community. Conversely, data mining methods rarely make use of existing spatial information. This paper describes a methodology to extract particular knowledge from spatial data. First step is to define a generic rule set similar to a supervised classification. Metainformation such as the bounding box of an image or the image centroid is straightforwardly utilized to automatically derive information from Spatial Data Infrastructures (SDI). The rule sets are then applied to other images taken by the same sensor through automated adjustments according to the metadata. We demonstrate the degree of automation for two ASTER images, one from Kashmir and one from Zimbabwe based on a worldwide data set of biogeographic regions. This successful blind test illustrates the potential to directly utilizing SDIs within a remote sensing data classification process.

1. INTRODUCTION

Remote sensing has become an essential data source for many operational tasks ranging from environmental to homeland security applications. No other survey technique can operationally provide such a regularized survey for assessing landscape patterns and change. However, remotely sensed images, like all observations of reality, are an imperfect capturing of patterns, which are themselves an imperfect mirror of the underlying processes. Some problems inherent in representing the Earth's surface are due to the central idea of arrays of 'pixel' units [13]. Cracknell [8] explores the question "What's in a pixel?" and makes the point that a pixel (the 'footprint' or ground instantaneous field of view, GIFOV) of a sensor is often larger than we would like it to be, a penalty imposed by the technology in return for the ability for the sensor to give an overview of a very large area. Unfortunately, sensor GIFOV were often imposed on us by technological or logistical constraints and not based on the needs of a particular application nor on hypotheses about the objects being explored. Increasing spatial resolution does not automatically resolve these problems. In some respects it shifts the scale or 'window of perception' [18]. Only recently, imaging methods and GIS-based spatial data analysis techniques are combined to constructing spatial data bases. In our methodology we dissect the complex task into two major steps while first developing a rule set. This step is not much different from supervised classification except that we build on image objects derived from segmentation and that we use relative values easily adoptable to any other scene. The rule sets reflect specific meta-information from the data sets to be classified. Building on objects rather than on pixels allows to obtaining and storing the revealed information and the associated spatial data in various forms including discriminant rules, prominent structures, spatial associations or topological relationships. In the entire process chain segmentation is a critical link and a sound methodology for guidance is indispensable. We will elaborate on this in the next section.

2. METHODOLOGY

Spatial data mining has gained significant progress over the last years [10], especially beyond single images, e.g. in regard to multi-temporal images [29, 9]. The enormous amount of data recorded today exceed both human's and machine's ability to analyze these. Only recently, data mining approaches have extended the scope of data mining from relational to transactional databases to spatial databases. This paper provides a somewhat different view compared to the 'mainstream' in the information extraction community. Firstly: rather than starting from the pixel perspective we put emphasis on objects. Secondly, we do not regard a remotely sensed image as completely "new" or detached from any existing information, e.g. about the area or other areas of the same biome, the same elevation range, or the same predominant general land cover. We hypothesize that in the 21^{st} century there will always be auxiliary information available. Potential frameworks for an intelligent exploitation of existing geoinformation are spatial data infrastructures (SDI).

The term SDI is often used to denote the relevant base collection of technologies, policies and institutional arrangements that facilitate the availability of and access to spatial data. A spatial data infrastructure provides a basis for spatial data discovery, evaluation, download and application for users and providers within all levels of government, the commercial sector, the non-profit sector, academia and the general public. The word infrastructure is used to promote the concept of a reliable, supporting environment, analogous to a road or telecommunications network. Spatial data infra-structures facilitate access to geographically-related information using a minimum set of standard practices, protocols, and specifications. Spatial data infrastructures are commonly delivered electronically via the internet.

The kind of information obtained from SDI is usually meta-information. Therefore, we develop a methodology to utilize spatial databases according to standardizations of SDI's. Some good examples of linking satellite imagery and web portals are realised in various application areas already. For instance, to support relief efforts for natural disasters, such as floods, earthquakes, hurricanes, etc., the capability to look at potential problem areas affected is a feature of several Web services. In the US, the National Map Hazards Data Distribution System provides a dynamic online map interface that can be used to view USGS data sets that are part of The National Map (http://gisdata.usgs.net/website/Disaster_Response/). Other examples include the National Disaster Hazard and Vulnerability atlas in South Africa [26]. Still, to the knowledge of the authors, these applications include images as graphical components but do not analyse or interpret them according to the need of the respective applications. We claim that a fast incorporation of information extraction results into national or regional data sets would be a great asset to these web services.

Cracknell [8] divides his critical examination of the 'pixel' into geometry, mixed pixels, point spread functions and resampling, and concludes that the 'pixel' is a more complicated entity than is generally acknowledged, and we must approach landscape analysis using EO data critically. Increasing spatial resolution does not solve this problem but decreases the effects of the 'mixed pixel' problem. Depending on the objects of interests and the target scales of analyses this may lead to the fact that the 'pixel problem' may be more and more neglectable, at least statistically.

The traditional method for analysing EO data in landscape research is the classification of pixels based on neighbourhood in spectral feature space. Put differently, one assumes that the classes are relatively pure or at least spectrally separable. Although not always a statistically sound method (the widely-used maximum likelihood classifier assumes normal distribution of data, which is unlikely in EO images), the methodology is considered to be successful. However, the reference to land cover *classes* is instructive, because with GIFOV of 1 km to 30 m, only the broadest land cover classes can be spectrally differentiated. Separability has been improved by the incorporation of spatial information, such as local measures of texture and autocorrelation, but is not assuaged. Spectral separability aside, there is still problems and the scale issue is just one example. A final complication to the pixel approach is the conceptual error. This error arises from errors in the design of the classification system that is generated for the landscape analysis. Finally, the pixel-centred view is usually uni-scale in methodology, exploring the pixels of only one scale of imagery and of only one scale within the image.

A variety of techniques have been proposed to wrestle the pixel approach into addressing pixel vs. ecological object discontinuities [7]. These include spectral 'unmixing' using linear mixing models, and the use of fuzzy sets and neural nets. However, by ignoring concepts of hierarchy and scale in the landscape processes driving pattern creation, these approaches are still overly pixel-centred. They adhere to a concept of the pixel as a spatial entity [13] that is assumed to have a *de facto* relationship to objects in the landscape. Uni-scalar, pixel-based monitoring methodologies have difficulty providing useful information about complex multiscale systems. If we accept that the reality we wish to monitor and understand is a mosaic of process continua, then our landscape analysis must make use of methods which allow us to deal with multiple, yet related scales within the same image and with multiple images.

The multiscale segmentation/object relationship modelling (MSS/ORM) methodology suggested by [7] segments information (usually remote sensing images plus any georeferenced information). Generally, an advantage of segmentation to classification of pixels is that the resulting division of space tends to involve fewer and more compact subregions. The multiscale segmentation based approach is designed to utilize information in the scales inherent in our spatial (image) data sets in addition to a range of auxiliary data sets, including for airborne and satellite data, but also to the scales of information inherent in single images. Technically, segmentation is not new [17] but only since around the year 2000 we can observe a rapidly increasing number of applications with is often associated with the advent of commercially available high resolution satellite imagery (Ikonos: 1999) and a commercial software package for object-based image analysis – eCognition – [2], today developed further into Definiens Software and Definiens Cognition language [27]. The idea behind is to somehow mimic how a human operator works: to create regions instead of points or pixels as carriers of features which are then introduced into the classification stage. The conceptual idea is that each of these regions corresponds exactly to one and only one object class. Furthermore, segmentation algorithms are able to handle multiple data and information sources, thus performing a fusion on feature level [12]. Over the last very few years, many new segmentation algorithms and applications have been tested in GIScience applications. Increasingly, methodological developments and qualitatively convincing results are reported [3, 5, 15, 2, 25] and a new research field called object-based image analysis (OBIA) has emerged [22, 4].

The strong motivation to develop techniques for the extraction of image objects stems from the fact that most image data exhibit characteristic texture which is neglected in common classifications, although scientists started to tackle this problem already in the 1970ies [21, 16]. In addition to spectral aspects in images, GIS principally introduces topology as a new dimension to map the relations between n-dimensional entities. We speak of objects if we can attach a meaning or a function to the raw information. Generally, the object is regarded to be an aggregation of geometric, thematic and topologic properties. The topologic relations between the object can be examined once the user has defined his or her objectives, classification scheme and scale of analysis. For a recent overview on image segmentation for remotely sensed images we refer to [5], while [25] provide a comparison of software products.

Most researchers applying a segmentation approach argue that image segmentation is intuitively appealing. Human vision generally tends to generalize images into homogeneous areas first, and then characterize focal areas more carefully as required [14]. Following this observation, we hypothesize that by creating multiple scales of segmentation, by successively grouping the pixels of an image into homogeneous image objects, a more intuitive and hierarchical partitioning of the image results. Among the most promising are Markov image segmentation, multi-fractals based segmentation [30], or segmentation based on representativeness measures [20].

In this paper we use the region-based, local mutual best fitting segmentation approach [1] as being implemented in the software eCognition [2] which developed recently into Definiens software. Methodologically, we build on the MSS/ORM approach [6] as described above. The procedure for the multi-scale image segmentation presented is a region merging technique. It starts with 1-pixel image objects. Image objects are pairwise merged one by one to form bigger objects. In this conceptualisation the procedure becomes a special instance of an assignment problem, known as pairwise data clustering. In contrast to global criteria, such as histogram threshold procedures, decisions are based on local criteria, especially on the relations of adjacent regions considering a given homogeneity criterion.

The collecting of semantic relationships brings up the issue of *a priori* knowledge. For some landscape situations, it has been hypothesized that for different scenes the similarity of object scales and object characteristics will enable nearly automated and highly accurate classification of land-use, land cover or vegetation. To achieve this, these analysis systems will have to optimize the data collected and the relationship rules applied. Urban landscapes are an example and the use of 3D models from LIDAR scanning or digital stereo orthophotography combined with spectrometer data is likely to achieve useful results. The varieties of objects in a more natural landscape add additional challenges, and the importance of semantic (human) knowledge of each particular scene may play a more important role in these studies.

3. CASE STUDY

In the empirical part we demonstrate the incorporation of external spatial databases in the classification process. In cooperation with a commercial company we could already demonstrate that objects created from a multi-resolution segmentation can further be flexibly broken down to pixel-sized objects and rebuilt to meaningful objects based on knowledge derived from the super objects: utilizing a priori knowledge about the specific scale domain of the target features is proposed [28]. In this paper we now go one step further: we use a sort of a priori metadata to calibrate our rule sets due to different natural conditions, as a result of the explicit spatial location of the target area. The concept is illustrated in figure 1.

In this study we use an existing dataset of terrestrial ecoregions of the world [24] as a data base and as a starting point for image analysis and automatical extraction of vegetated areas. For a first attempt we focussed on biomes (formally known as Major Habitat Types or MHTs) which are broad kinds of ecoregions that (1) experience comparable climatic regimes, (2) have similar vegetation structure, (3) display similar spatial patterns of biodiversity, (4) contain flora and fauna with similar guild structures and life histories, (5) have similar minimum requirements and thresholds for maintaining certain biodiversity features (6) have similar sensitivities to human disturbance.

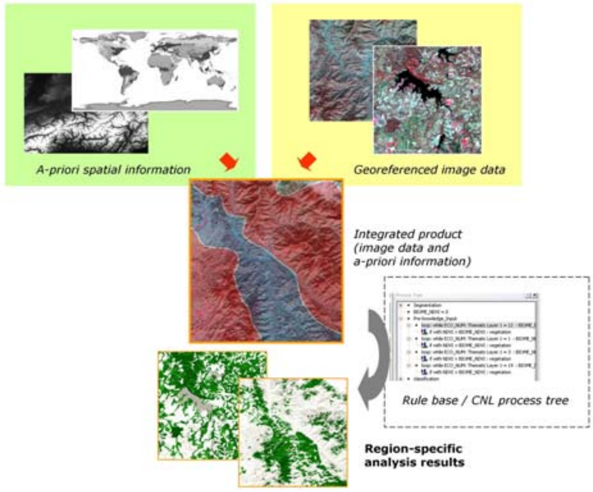

Figure 1: Workflow for biome-specific automated image analysis, integrating a-priori spatial information and satellite imagery.

In this study 14 terrestrial biomes are used to automatically derive specific variable thresholds according to the geographical location of the satellite images (figure 2).

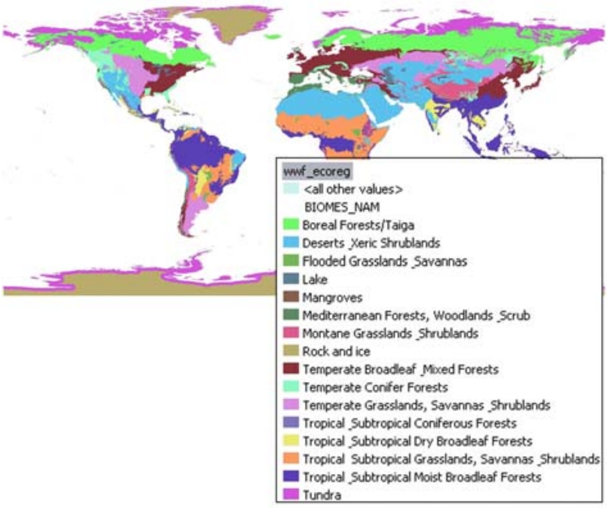

Figure 2: Biomes of the world as a-priori knowledge

For two test sites we developed a rule set which uses the Biomes information automatically to set NDVI thresholds for a vegetation classification based on ASTER images (level 1b registered radiance at sensor, VNIR, with 15m GSD). Only the three VNIR nadir bands (green, read, NIR) are used. The areas are part of the test cases used in the EU network of excellence GMOSS[1] and cover parts of Kashmir (Muzaffarabad) and parts of Zimbabwe (Banket region). Both images are Level-1B products (registered radiance at sensor), acquired in October 2005 (Kashmir) and June 2006 (Zimbabwe).

The rule sets for segmentation and classification are developed using CNL (Cognition Network Language), which is a sort of programming environment available in Definiens Developer software. CNL provides the opportunity to automatically include thematic information into the rule sets. The biome dataset serves as a thematic layer. In a first part, the rule set is defined. This process is not much different from any supervised classification except for that we build on segments rather than on pixels and that we store values in variables which can later be adopted to the respective values of other scenes. A prerequisite is a common geographic reference system (here: WGS 84).

Then, the biome dataset is automatically clipped to the extending of the input image data. The Biome Type of the map is now automatically bundled with the image data. By means of combining Branching and Looping algorithms in CNL the biome type of the target area is translated into different NDVI thresholds, which are allocated to variables used in the classification algorithm. Figure 3 shows a subset of the rule set where loops over all image objects are querying the underlying biome type and define the individual NDVI threshold for each object.

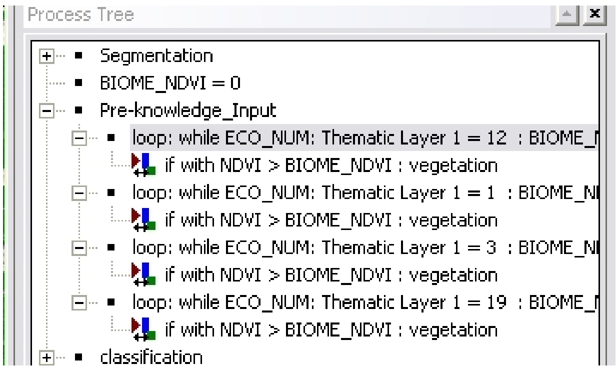

Figure 3: Branching/ Looping algorithm in CNL translating biomes into variables holding NDVI thresholds which are automatically used in the image analysis.

Preliminary results for the ASTER scene of the Kashmir region are shown in figure 4. The Kashmir scene is covering 3 different biomes types (Tropical & Subtropical Coniferous Forests, Temperate Broadleaf & Mixed Forests, Montane Grasslands & Shrublands) resulting in different classifications for each biome type.

In a blind test we applied the rule set without any changes to the ASTER image in Zimbabwe. This image is covering only one biome type (Tropical & Subtropical Grasslands, Savannas & Shrublands). We

[1] Global Monitoring for Security and Stability (http://gmoss.jrc.it)

used the same rule set for both images – changes concerning NDVI thresholds are automatically performed based on the image statistics derived.

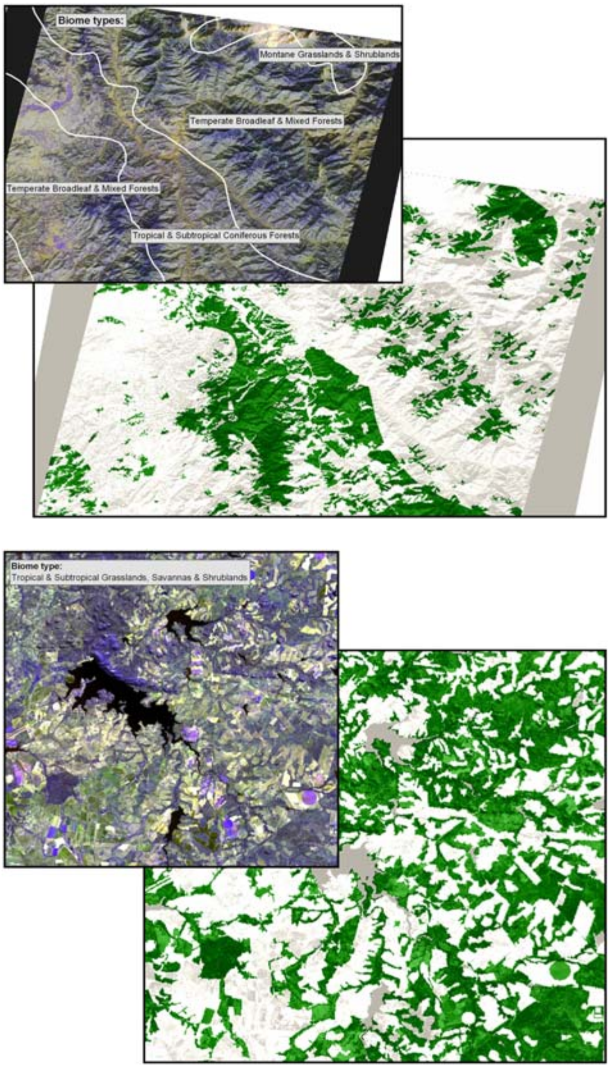

Figure 4: Classification of vegetated areas in Kashmir (upper image) and Zimbabwe (below). For both images the same rule set is used –changes concerning NDVI thresholds are automatically performed by reading biome type information from a georeferenced map (upper left and upper right).

4. DISCUSSION

This example demonstrates a first, yet operational approval of our methodology. We extracted vegetated areas to explain the usefulness of using pre-knowledge in image analysis. The approach can easily be adopted to a range of other, even more complex or manifold tasks. Instead or in addition of using ecoregions it is also possible to use DEM data, geological data, climatic maps, population data and the like as pre-knowledge information. Likewise it is going to be a big potential and a huge research task for the near future to systematically prove whether metadata of the satellite images (date, time, inclination etc.) can be automatically read into the system. This first attempt definitely encourages to proceed and to invest more work.

The approach is very different from the approaches in data mining and specifically in image information mining. It is a combination of a supervised selection and pre-definition of complex rule sets and an automation approach of information extraction. It is important to note that it is not knowledge free. But we believe that there is huge demand for such a combined way to derive information "semi-automatically" in a sense that a sophisticate rule set is created in a supervised stage and then applied un-supervised in an automated fashion. This may complement recent developments in image information mining. Clearly, this test demonstrates only a small aspect of the possibilities of integrating meta-information in the automation of classification or feature extraction procedures. We have also successfully developed a methodology to classify landforms from digital elevation models [11] and we are currently translating these models into the cognition network language to automate the process further.

The results are promising, especially concerning the problems which occurred in earlier studies on object-based delineation of single trees. These new possibilities are extending a software package to a sort of modular, process oriented programming language. Consequently the research taken herein can illuminate one aspect of a new and complex context-based classification methodology. This reflects our theoretical approach described earlier and opens ways for a hierarchical description and subsequent classification of whole landscapes.

ACKNOWLEDGEMENT

This study was made possible within the context of the GMOSS EU 6th Framework Network of Excellence (http://gmoss.jrc.at). We are grateful for data provision, stimulating discussion and all research possibilities made available within this network.

REFERENCES

1. Baatz, M. and Schäpe, A. 2000. Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. In: Strobl, J., Blaschke, T., Griesebner, G. (eds.): *Angewandte Geographische Informationsverarbeitung XII*, Wichmann-Verlag, Heidelberg, 12-23.
2. Benz, U.C., P. Hofmann, G. Willhauck, I. Lingenfelder and M. Heynen 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, 58, 239-258.

3. Blaschke, T. and Strobl, J. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GIS – Zeitschrift für Geoinformationssysteme* 6/2001: 12-17.
4. Blaschke, T. and Lang, S. 2006. Object based image analysis for automated information extraction – a synthesis. *Measuring the Earth II*, ASPRS Fall Conference 6-10 Nov. 2006, San Antonio, TX, CD-ROM.
5. Blaschke, T., Burnett, C., Pekkarinen, A. 2004. New contextual approaches using image segmentation for object-based classification. In: De Meer, F. and de Jong, S. (eds.): *Remote Sensing Image Analysis: Including the spatial domain*. Kluver Academic Publishers, Dordrecht, 211-236.
6. Burnett, C. and Blaschke, T. 2002. Objects / not-objects and near-decomposability: ecosystems and GI. In: NCGIA (ed.), *GIScience 2002*, Boulder, 225-229.
7. Burnett, C. and Blaschke, T. 2003. A multi-scale segmentation / object relationship modelling methodology for landscape analysis. *Ecological Modelling* 168(3), 233-249.
8. Cracknell, A. P. 1998. Synergy in remote sensing – what's in a pixel? *International Journal of Remote Sensing* 19: 2025-2047.
9. Datcu, M. and K. Seidel 2003. Image Information Mining - Exploration of Earth Observation archives. *Geographica Helvetica*, 154-168.
10. Datcu, M. Seidel, K. Pelizarri, A. Schroeder, M. Rehrauer, H. Palubinskas, G. Walessa, M. 2000. Image information mining and remote sensing data interpretation. *IGARSS'00 proceedings*. Vol. 7: 3057-3059.
11. Dragut, L. and Blaschke, T. 2006. Automated classification of landform elements using object-based image analysis. *Geomorphology* 81:330-344.
12. Ehlers, M., Greiwe, A., Tomowski, D. 2006. On segment based image fusion. International Archives of Photogrammetry, *Remote Sensing and Spatial Information Sciences*, Vol. No. XXXVI-4/C42, Salzburg, Austria.
13. Fisher, P. 1997. The pixel: a snare and a delusion. *International Journal of Remote Sensing* 18: 679-685.
14. Gorte, B. 1998. Probabilistic Segmentation of Remotely Sensed Images. In: ITC Publication Series No. 63.
15. Hall, O., G. J. Hay, A. Bouchard, D., J. Marceau 2004. Detecting dominant landscape objects through multiple scales: An integration of object-specific methods and watershed segmentation. *Landscape Ecology*, Vol. 19(1): 59-76.
16. Haralick, R.; Shanmugan, K, Dinstein, I. 1973. Textural features for image classification. In: *IEEE Transactions on Systems, Man and Cybernetics* 3 (1): 610-621.
17. Haralick, R.M. and Shapiro, L.G. 1985. Image segmentation techniques. *Comput. Graphics Image Process.* 29: 100-132.
18. Hay, G.J., Marceau. D.J., Dubé, P., Bouchard, A. 2001. A Multiscale Framework for Landscape Analysis: Object-Specific Analysis and Upscaling. *Landscape Ecology* 16(6): 471-490.
19. Hay, G., Blaschke, T., Marceau, D., Bouchard, A. 2001. A comparison of three image-object methods for the multiscale analysis of landscape structure. In: *International Journal of Photogrammetry and Remote Sensing* (57): 327-345, 2003.
20. Hoffmann, T. and Boehner, J. 1999. Spatial pattern recognition by means of representativeness measures. In: *IGARSS'99 proceedings*, Hamburg, Germany. Vol. I: 110-113.
21. Kettig, R. and Landgrebe, D. 1976. Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects. *IEEE Transactions on Geoscience Electronics*, Vol. GE-14 (1): 19-26.
22. Lang, S. and Blaschke, T. 2006. Bridging remote sensing and GIS – what are the main supporting pillars? *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* vol. XXXVI-4/C42.
23. Lang, S., Burnett, C., Blaschke, T. 2004. Multi-scale object-based image analysis – a key to the hierarchical organisation of landscapes. *Ekologia (Bratislava) Supplement* 23, 1-9.
24. Morrison J.C., Olson D.M., Loucks C.J.;, Dinerstein E., Allnutt T.F., Wikramanayake E.D., Ricketts T.H., Burgess N.D., Kura Y., Powell G.V.N., Lamoreux J.F., Underwood E.C., Wettengel W.W., D'Amico J.A., Hedao P., Itoua I., Kassem K.R., Strand H.E. 2001. Terrestrial Ecoregions of the World: A New Map of Life on Earth, *BioScience*, Vol. 51 (11), 933-938(6).
25. Neubert, M., Herold, H., Meinel, G. 2006. Evaluation of remote sensing image segmentation quality – further results and concepts. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. No. XXXVI-4/C42, Salzburg, Austria.
26. Sakulski, D. 2005. Geo-Information as an integral component of the National Disaster Hazard and Vulnerability Atlas. In: van Oosterom, P., Zlatanova, S., Fendel, E. (Eds.): *Geo-Information for Disaster Management*, Springer-Verlag, Berlin, 1071-1086.
27. Tiede, D. and C. Hoffmann 2006. Process oriented object-based algorithms for single tree detection using laser scanning data. *EARSeL-Proceedings of the Workshop on 3D Remote Sensing in Forestry*, 14th-15th Feb 2006, Vienna, 151-156
28. Tiede, D., S. Lang, C. Hoffmann 2006. Supervised and forest type-specific multi-scale segmentation for a one-level-representation of single trees. *International Archives of Photogrammetry, Remote Sensing and*

Spatial Information Sciences, Vol. No. XXXVI-4/C42, Salzburg, Austria.

29. Tilton J.C. Marchisio, G. Koperski, K. Datcu, M. 2002. Image information mining utilizing hierarchical segmentation. *IGARSS'02 proceedings* Vol. 2: 1029-1031.
30. Véhel, J.L. and Mignot, P. 1994. Multifractal Segmentation of Images, *Fractals*, vol.2, No.3, 371-378.