MONITORING NATURAL RESOURCES IN CONFLICT USING AN OBJECT-BASED MULTISCALE IMAGE ANALYSIS APPROACH

E. Schoepfer [a, *], O. Kranz [a]

[a] German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Oberpfaffenhofen, Germany - (elisabeth.schoepfer, olaf.kranz)@dlr.de

ABSTRACT:

Natural resources are sometimes exploited beyond a sustainable level, spoiling natural habitats, displacing local communities, affecting people's livelihoods and even fuelling armed conflicts. The lack of precise geographic information is a critical limit in the design of appropriate provisions for prevention and response to ongoing crises related to natural resources exploitation. Vast territories have to be observed within a narrow time frame as exploitation activities can easily shift from one area to another. The areas are very difficult to access because they are widely dispersed, too remote or too insecure. Conflict situations often prevent research teams from travelling freely and thus remote sensing provides the potential for complementing more traditional means of monitoring. The study is carried out using high and very high resolution optical data at test sites which are located in the Democratic Republic of the Congo. Various natural resources exist within the test sites such as cassiterite (tin), columbite-tantalite (coltan), wolframite (tungsten) and gold. Deforestation takes place in areas for mining operations and in forests when timber is harvested, transported and sold.

This paper presents first steps towards a transferable, robust and fast analysis approach for detecting exploitation of natural resources such as mining. The method used for monitoring active sites combines object-based image and GIS analyses. The designed workflow is concentrating on three levels built on (1) a transferable feature extraction scheme using high spatial resolution (HR) images for identification of potential hot spots, (2) spatial aggregation of the results to regular grid cells and (3) a fine-scale spatial pattern analysis of the potential sites by the interpretation of very high spatial (VHR) imagery. The usability and reusability of rule sets using Cognition Network Language (CNL) enhance the efficiency of image analysis and contribute to efficient and constant monitoring at a service level to the user community. The proposed approach may contribute to focused reactions during crises and yield rapid identification of affected areas.

1. INTRODUCTION

1.1 Background

In recent years the European Union has become increasingly aware of its security environment as it has taken on a growing international profile such as in relation to negotiations with Iran or in regional crisis management operations in the Balkans, Indonesia, and the Democratic Republic of Congo (DRC).

A particular accent was put on the necessity for the European Union Member States to be able "to act before a crisis occurs", underlining the necessity to possess the relevant information tools for political and military monitoring. The need for conflict prevention was re-emphasised in the EU Commission's 2001 Communication on Conflict Prevention and in 2003 the European Security Strategy (ESS) was adopted by the European Council. It outlines diverse ranges of threats, clustered into five major security threats, among them regional conflicts and state failure.

Within the 7th framework programme the European Commission is funding the GMES-Project G-MOSAIC (GMES Services for Management of Operations, Situation Awareness and Intelligence for regional Crises) focussing – amongst others – on the monitoring of natural resources in conflict areas. The hereafter outlined research will be achieved within the framework of this project. The overall aim is the development of methodologies to reliably detect small-scale mining activities for large areas and to embed the results into the broader context of conflict mitigation policies.

1.2 Conflict Resources

Following Global Witness (2010) conflict resources are defined as "natural resources whose systematic exploitation and trade in a context of conflict contribute to, benefit from or result in the commission of serious violations of human rights, violations of international humanitarian law or violations amounting to crimes under international law." Natural resources are sometimes exploited beyond a sustainable level, spoiling natural habitats, affecting people's livelihoods and even fuelling armed conflicts. The latter has been demonstrated in several conflict research studies. A well investigated example is the mineral concentrate columbite-tantalite (Coltan) which is used as a component in electric goods such as mobile phones and laptops. At the time of the highest prices for Coltan on the world market in around 2000 armed conflicts in DRC dramatically increased. With dropping prices the role of Coltan became much less significant and has been taken over by cassiterite which is nowadays the most important mineral in terms of quantity and price. These studies imply that more detailed information about on-going activities of resource extraction might be a useful indicator for increasing conflict activities.

---

* Corresponding author.

The lack of precise geographic information is a critical limit in the design of appropriate provisions for prevention and response to ongoing crises related to natural resources exploitation. Vast territories have to be observed within a narrow time frame as exploitation activities can easily shift from one area to another. The areas are difficult to access because they are widely dispersed, too remote or too insecure. Thus remote sensing provides the potential for complementing more traditional means of monitoring.

1.3 Democratic Republic of the Congo

The DRC is one of the most mineral-rich countries in the world and especially in the North and South Kivu provinces the exploitation of minerals plays a major role. Most of the mining activities take place in the informal sector which indicates that minerals are dug with very basic tools or even by hand. The militarization of the mining sector fuels the conflict and prevents effective security sector reform, undermining sustainable peace building efforts. Uncontrolled or illicit exploitation of natural resources is accompanied by highly unsustainable practices leading to massive environmental destruction (e.g. using mercury or cyanide for gold extraction) and livelihood insecurities.

Although the conflict in the DRC officially ended in 2003 the situation in the country is different and especially in the East a militarised control over mining activities, including fighting in mining areas continues. The abuses of all armed groups against civilians are directly linked to natural resources in the sense that they are used to get control over resource-rich areas or over the ability to tax resources. In some areas military personnel are in control of mines and are organising their own digging, in other areas military groups are illegally taxing artisanal miners. Taxes have to be paid either in the mine where the material has been extracted from or along the way to the trading town or even both (Global Witness 2005; Garrett, 2008).

While the mineral coltan became increasingly important between 2000 and 2001 as a major source of funding military activities today the exploitation of cassiterite has taken over as the resource of choice for the military groups in the Kivu provinces. In eastern DRC cassiterite is found in exactly the same locations as coltan and the dominance of artisanal and small-scale mining reflecting again the general profile of mining in the entire DRC as being completely unregulated and disorganised. Although it seems to be impossible most of the mining areas in the Kivus are inaccessible by roads and the extracted material has to be carried by foot to the nearest town.

2. STUDY AREA AND DATA

2.1 Study area

The study area is situated in the North and South Kivu provinces of the DRC (see figure 1). Two distinct test sites have been selected with different land cover characteristics in order to analyze the spatial pattern behaviour of mining areas and to provide a wide-spread ground for the detection of indicators. The first area of interest entitled Numbi is located along the border between North and South Kivu provinces and is characterized by a high amount of agricultural fields at the edge of the secondary forest zone. Almost half of the test area belongs to the South Masisi Reserve. In the East the area reaches to Lake Kivu describing the border to Rwanda which leads to the following important factors: (1) access to a trade

route on one of the few asphalt roads within the DRC driving to the airport of Goma and (2) proximity to two harbours (Makelele and Kinyezire) at Lake Kivu. The second test site called Lulingu is situated in the northern part of South Kivu close to the province Maniema. This area is mainly covered by dense moist forest and secondary forest. The Ulindi River which is one of the largest tributaries of the Lualaba River splits the test site into horizontally halves. In the centre of the test site the airport Tchonka is located serving as an important trade infrastructure in this region. In the North the area is touching the Kahuzi-Biega National Park.
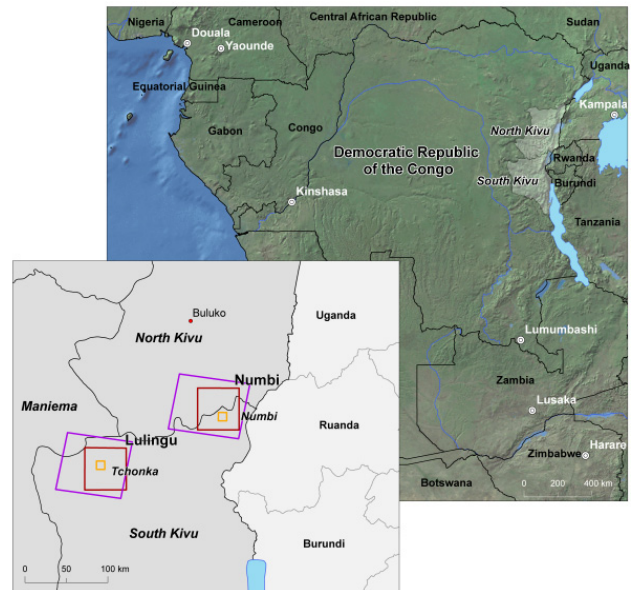

Figure 1. Overview of the Democratic Republic of the Congo highlighting North and South Kivu. The inset shows the location of the study areas (red box: HR; orange box: VHR; purple outline represents the Rapideye footprints)

2.2 Data

The study is based on a multi-scale approach using high and very high resolution optical data. The HR data comprise two multispectral Rapideye scenes with a spatial resolution of 6.5 m covering an area of 2,500 sqkm each to identify hot spots of activities to further focus on with VHR data. For this part of the study two multispectral Geoeye-1 scenes with a spatial resolution of 0.5 m in the panchromatic band for an area of 100 sqkm were acquired (see table 1).

Type of data	Region	Acquisition data
Optical HR Rapideye	Lulingu	23.09.2009
	Numbi	22.09.2009
Optical VHR Geoeye-1	Numbi	29.01.2010
	Tchonka	13.11.2009

Table 1. Overview of the data

Pre-processing steps applied to all imagery included the orthorectification and geometric correction to UTM Zone 35S (WGS 84) as well as an atmospheric correction using ATCOR (Atmospheric/Topographic Correction for Satellite Imagery), a software developed at DLR. The Geoeye-1 data were pan-sharpened to 0.5 m.

3. METHODOLOGY

The study is founded on two pillars, namely Earth Observation and Peace and Conflict research and their integrated analysis to bridge the gap between these two very different fields of research (see figure 2). This paper presents first steps towards a transferable, robust and fast analysis approach for detecting exploitation of natural resources, i.e. mining areas. The method used for monitoring active sites combines object-based image and GIS analyses (Schoepfer et al., 2007). The designed workflow is concentrating on three levels built on (1) a transferable feature extraction scheme using high spatial resolution (HR) images for identification of potential hot spots, (2) spatial aggregation to regular grid cells and (3) a fine-scale spatial pattern analysis of the potential sites using very high spatial resolution (VHR) imagery. A sub-step of the aggregation process is the selection of those objects that are within a certain distance to features like roads, settlements or rivers since it can be assumed that a certain proximity to such infrastructure is necessary for distribution of the extracted minerals. By doing this the most relevant areas can be selected for further fine-scale analysis. In the following the result is submitted to the peace and conflict research point of contacts in order to verify the results with ground truth information and to link them with socio-economic data. The provision of such a joint "early warning system" may contribute to political recommendations in conflict regions and yield rapid identification of affected areas.
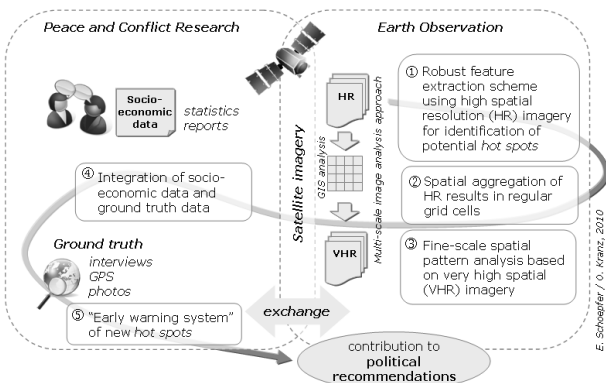

Figure 2. Interaction between Earth Observation and Peace and Conflict research to contribute to political recommendations

3.1 Object-based image analysis – High resolution data

The analysis of the satellite imagery was realised by developing a rule set using Cognition Network Language (CNL) for eCognition 8 software. CNL is an object-based procedural computer language which is specially designed to facilitate the automated analysis of complex, context-dependent image analysis tasks. It enables creating meaningful objects and addressing individual image objects in an iterative approach. If coded robust and stable the developed algorithms may be transferred to other scenes with no or only minor adjustments of parameters (Schoepfer et. al, 2006).

For the HR analysis the Rapideye scene of Lulingu was used to develop a transferable classification scheme. In an iterative approach features of interest were extracted by initial segmentation, classification, morphology, fusion and re-segmentation. In a first step clouds and shadow were masked out in the image. Particular attention was paid to this process because due to quasi-permanent cloud cover over the Great Lakes and Congo Basin a confusion of clouds and shadow with features of interest have always to be considered in this region. In a first step a contrast layer based on the difference of brightest pixels to the centre was calculated and used for an edge ratio split segmentation. These temporarily selected objects were reshaped by pixel-based growing and merged accordingly. Within these identified cloud regions clouds were classified based on a contrast split segmentation. In a following step the clouds were refined using the mean values of the NIR band and the overall brightness. Finally, the extracted *clouds* were reshaped using the pixel-based object resizing algorithm. New objects of interest were created with a spectral difference segmentation and further classified as *shadows* based on the mean values of the red and NIR band. The extracted objects were refined according to their distance to clouds and reshaped thanks to the integrated pixel-based reshaping algorithms.

After this masking procedure a basic land cover classification was performed referring to the nomenclature of Royal Museum for Central Africa (R.M.C.A.). At the beginning *water bodies*, i.e. main rivers, were extracted based on the previously calculated contrast layer and the mean values of the red band. The pixel-based reshaping proofed well to delineate the features of interest most precise. In the following the *bare ground* was subject of interest and meaningful objects were created accordingly. The Normalized Difference Vegetation Index (NDVI) was calculated using the implemented layer arithmetic algorithm. Setting the threshold to 0.7 the features were extracted in a straight forward manner. Since *settlements and roads* interfere with this class, these features were further separated using the overall brightness. Finally, the forest was distinguished between *moist forest* and *secondary forest*. In order to delineate these wide-spreading areas best, meaningful objects were generated using colour differences. In a first step initial objects were created which were fused according to the similarity of the absolute mean values in the spectral bands. The objects were assigned to the respective class by a defined threshold of the mean values of the NIR band. In total a number of seven classes were extracted and exported to a Geographic Information System (GIS).

One of the stated objectives of this research is the development of a transferable, robust and fast analysis approach. As mentioned in the study area description, the two test sites represent different landscape structure. Thus, not all classes might be present in one or the other area and vice versa. In such a case the transferability of a stand-alone rule set might be in risk. However, the reduction of a basic land cover classification to the overlapping classes of different test site in a complex region may lead to an unsatisfactory number of classes. Thus, the more sophisticated approach is to adjust the rule set accordingly by individual sub routines. Within eCognition 8 developed processes can be stored and added to a library. These so-called snippets can consist of one or more processes and can be reused in other rule sets by drag-and-dropping. In this research such a library of snippets was built up accordingly (see figure 3).

For the Rapideye scene of Numbi the following classes were added next to the ones also classified in the area of Lulingu: first of all *water bodies* were further separated between a *rivers* and *lakes* based on their geometry. Furthermore part of the study area covers the savannah zone, thus a new class called *shrubby savannah* was introduced. The class was in confusion with the class *moist forest* but could be straightforwardly separated by setting a threshold for the mean values of the NDVI and NIR band. The test site is further characterized by

agricultural activities west of Lake Kivu. These structures were classified by using also the NDVI. Refinements using pixel-based reshaping were integrated in order to generate smooth object outlines. A land cover classification with ten classes was exported in tiff-format for further analysis.
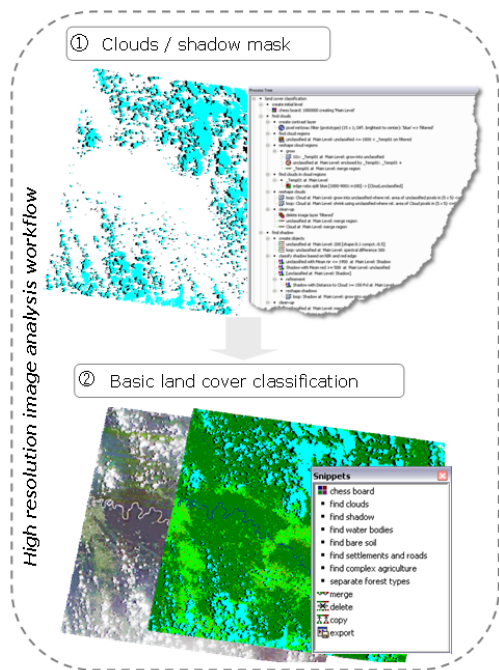

Figure 3. Workflow of the high resolution imagery: (1) Clouds / shadow mask generation and (2) land cover classification based on pre-developed sub-routines, i.e. snippets (as used for the classification of Lulingu)

3.2 Spatial analysis

For the spatial analysis the bounding box of Lulingu and Numbi were split into regular grid cells of 10 km x 10 km. The classification result was spatially aggregated to these raster cells. In other words, the number of detected features was summed up to a regular grid over the area indicating the most relevant areas to further focus on with the fine-scale analysis. In addition to this approach the concentration of mining sites gathered during a survey in the Kivu region in August 2009 by the International Peace Information Service (IPIS) was used to focus on areas with highest number of mining activities (Spittaels and Hilgert, 2008 and 2009). Before running the aggregation process only those objects were selected that are within a certain distance to infrastructure related to mining activities such as roads, rivers and dwellings. Rivers are not only important as potential distribution path but also due to the fact that minerals like coltan, cassiterite and gold are normally found in river sediments. Although there might be some exceptions most of the mining areas are within a certain distance (1) to dwellings in which the miners are living and (2) to roads/paths that allow to distribute the extracted minerals.

3.3 Object-based image analysis – Very high resolution data

After the identification of potential areas of mining activities, very high resolution imagery were acquired and pre-processed as described in section 2.2. The analysis of the data was also performed in eCognition Developer 8.0 which is even more

powerful when working with very high resolution data. At this stage of the study the objective of the image analysis approach was set on single feature extraction rather than on a full land cover classification.

The emphasis was put on the detection of (1) bare ground and (2) settlements. These two classes are the one of interest due to their relation to mining areas. Mining areas which are analysed in this study are open pit mines. Usually the miners have settled around the mine (Global Witness, 2009). Thus a mixture of bare ground resulting from mining activity and dwelling structures needs to be observed in detail. However, this approach is not straightforward due to several circumstances. Bare soil is often found in dry river beds, in agricultural fields, etc. Thus, potential mining areas are in conflict with this other small-scale features which have similar spectral reflectance.

At the beginning an initial multiresolution segmentation is performed on the pixel level. These first primitive objects are pre-separated similar to the HR analysis for *bare ground* and *settlement/roads* based on the mean values of the NDVI and their overall brightness. Agricultural fields were excluded in the following by setting a high value for the rectangular fit of the objects.

These pre-selected objects are further investigated based on their texture. Within eCognition Developer 8.0 layer arithmetics can be directly calculated on the pixel level which are available for classification. Figure 4 shows an edge extraction based on the red band to separate the edges of darker objects. It is clearly observable that dwellings representing artificial objects can be distinguished from natural features. Furthermore the rough surface of the mining site within the river bed is visible due to the high variance in texture.
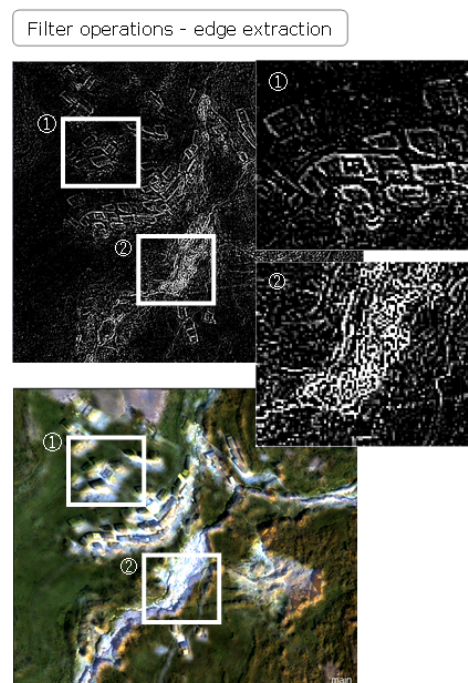

Figure 4. Filter operations for separating dwellings and bare ground (Geoeye-1 subset of the region around Numbi, scale 1:400). The inset (1) shows dwelling structures whereas (2) represents a river bed with potential mining activities

4. RESULTS

The developed algorithm for the high resolution data analysis led to a satisfactory result. To quantify the accuracy of the land cover classifications, an accuracy assessment was performed using ERDAS Imagine 2010 (Congalton, 1991). The classified images were compared to the master maps (satellite images) and evaluated by visual interpretation. Stratified random sampling was employed to choose 20 to 50 sampling points from each category. A summary of the accuracy assessment results for each classification is shown in Table 2.

Classification	Overall Accuracy (%)	Overall Kappa Coefficient
Lulingu (HR)	88.29%	0.8633
Numbi (HR)	85,50%	0.8389

Table 2. Overview of accuracy results

Figure 5 shows the final classification results of the Rapideye scenes for Lulingu and Numbi.
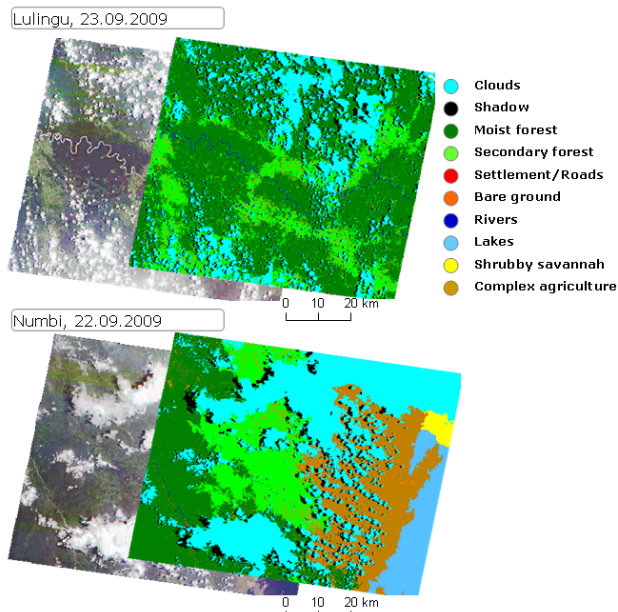

Figure 5. Classification results of Lulingu (top) and Numbi (bottom)

The result of the very high data analysis highlights a typical mining site in the DRC with a rough surface and located in a river bed (see figure 4). Although the latter is not a criterion of exclusion the proximity to river sediments might be an indicator for some kinds of mineral deposits. As pointed out above dwellings could be an additional indication for mining activities and are in this example located in close distance north-west of the mining site.

In summary it can be stated that the object-based multiscale image analysis approach provided good indications of potential mining areas over the study area. The fine-scale analysis of a specific mining site also demonstrated the capabilities of this approach to be able to gather more detailed information about certain areas of interest. Nevertheless a couple of topics were identified to be further improved in future to reach the final goal of providing a robust and transferable approach for the detection of small-scale mining sites over large areas.

5. CONCLUSIONS

The study demonstrated that the analysis of HR optical satellite data using object-based image analysis methodology provides useful indications for resource extraction activities in remote areas. By selecting certain objects according to their spatial location and their distance to features that might be related to mining activities such as roads, rivers and settlements the results can be further improved. The aggregation of extracted objects to a concentration by grid cell has proved to be a helpful approach for focussing on the most relevant areas.

It is intended to further extend this study with the main following topics: (1) The object-based image analysis approach may be further enhanced by the development of more individual snippets and finally the integration of the complete rule set within eCognition Architect, both for the high and very high image analysis approach. (2) In addition to optical satellite imagery the analysis of radar data seems to be promising not only for being able to run a frequent monitoring in this tropical region. The integrated use of both types of data might also be useful for using synergies between the different sensors. In this sense the erratic surface structure of a typical mine could be better identified by radar data whereas the overall hot spot detection will be performed with optical imagery. (3) Next to the Earth Observation (EO) data analysis the concept of using indicators for mining activities could be improved. Better knowledge about the location of certain mining areas and additional information derived from socio-economic databases can be used for refining the proximity analysis to certain infrastructure and could thus improve the selection of the most relevant areas.

REFERENCES

Congalton, R. G., 1991: A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of the Environment, Vol. 37 (1), p. 35-46.

Garrett, N., 2008: Walikale. Artisanal Cassiterite Mining and Trade in North Kivu Implications for Poverty Reduction and Security. A report by Nicholas Garrett for the Communities and Artisanal & Small-scale Mining Initiative (CASM).

Global Witness, 2005: Under-Mining Peace. Tin: The Explosive Trade in Cassiterite in Eastern DRC. A report by Global Witness, June 2005, London.

Global Witness, 2009: Faced with a gun, what can you do? War and the militarisation of mining in eastern Congo. A report by Global Witness, July 2009, London.

Global Witness, 2010: Definition of Conflict Resources. http://www.globalwitness.org/pages/en/definition_of_conflict_ resources.html (accessed April 15, 2010).

Schoepfer, E. and M. S. Moeller, 2006: Comparing Metropolitan Areas – A Transferable Object-Based Image Analysis Approach. PFG – Photogrammetrie, Fernerkundung, Geoinformatik, 1/2006, 277-286.

Schoepfer, E., D. Tiede, S. Lang and P. Zeil., 2007: Damage assessment in townships using VHSR data - The effect of Operation Murambatsvina / Restore Order in Harare, Zimbabwe. Urban Remote Sensing Joint Event. Paris 2007, CD-ROM.

Spittaels, S. and F. Hilgert, 2008: Mapping Conflict Motives: Eastern DRC. Report by the International Peace Information Service (IPIS), Antwerp.

Spittaels, S. and F. Hilgert, 2009: Accompanying note on the interactive map of militarised mining areas in the Kivus. Report by the International Peace Information Service (IPIS), Antwerp.