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Towards a multi-scale approach for an Earth observation-based assessment of natural resource exploitation in conflict regions

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ABSTRACT

The exploitation of resources, if not properly managed, can lead to spoiling natural habitats as well as to threatening people's health, livelihoods and security. The paper discusses a multi-scale Earth observation-based approach to provide independent information related to exploitation activities of natural resources for countries which are experiencing armed conflict. The analyses are based on medium to very high spatial resolution optical satellite data. Object-based image analysis is used for information extraction at these different scales. On a subnational level, conflict-related land cover changes as an indication of potential hot spots for exploitation activities are classified. The regional assessment provides information about potential activity areas of resource exploitation, whereas on a local scale, a site-specific assessment of exploitation areas is performed. The study demonstrates the potential of remote sensing for supporting the monitoring and documentation of natural resource exploitation in conflict regions.

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Introduction

Environment and natural resources can play a significant role in the onset, duration and termination of conflicts. A well-known example is the Democratic Republic of the Congo (DRC), where ongoing armed conflicts are fuelled by the exploitation of natural resources such as timber, gold, diamonds and other minerals (Global Witness 2004, 2005, 2013; Bonn International Center for Conversion 2007; De Koning 2008, 2009, 2011; Spittaels & Hilgert 2008, 2009; UNEP 2009, 2015; International Alert 2010; United States Agency for International Development 2010; Burnley 2011; Melvin & de Koning 2011; Mildner et al. 2011; Cuvelier et al. 2013; Johnson 2013). Informal, illicit or illegal resource extraction is often accompanied by military or militia control of extraction sites, as well as highly unsustainable practices leading to large-scale environmental degradation and livelihood insecurities, e.g. using mercury or cyanide for gold extraction or forest destruction during selective logging. Environmental factors – in combination with socio-economic effects – can play a key role in the dynamics of conflicts. Although the interdependencies are highly complex, one can generally state that in areas with high

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value mineral resources and poor economic conditions, violent conflict situations can be sustained or even initiated (Global Witness 2009).

The lack of precise and reliable situational information is a critical issue in the prevention of, and response to, ongoing crisis situations relating to natural resource exploitation. Furthermore, conflict situations often hinder non-governmental organizations (NGOs), research teams and others from monitoring and observing such regions, as it is the case in the eastern DRC. In many cases in DRC, mining areas are very difficult to access because of the extremely bad conditions of infrastructure, the risk of violence by rebel groups and militias, or the denial of access by army units occupying the areas concerned. In such a context, Earth observation (EO)-based analyses can provide important information to complement field-based monitoring studies (Wirkus & Vollmer 2008; Zingg Wimmer & Hilgert 2011).

It is the overall objective of the research presented to assess the possibilities and limitations of EO at three different spatial scales for the detection and classification of land cover features related to the extraction of natural resources in the DRC. Therefore, a robust, object-based multiscale analysis approach, using integrated image processing and spatial analysis methods, was developed. The use of EO data aims at supporting political decision-making and at linking peace and conflict research with the remote sensing and geospatial community (Schoepfer, Blaes, et al. 2012, Schoepfer, Spröhnle, et al. 2012).

Background

Natural resources and conflict in the DRC

The DRC is one of the richest countries in terms of mineral resources in the world; economically, however, it is one of the poorest. The DRC has been at the centre of what has been termed Africa's World War, 1998–2003 (Prunier 2008). Despite the signing of a peace accord in 2003, fighting continues in the East of the country, and the DRC is still ranked very high on the Foreign Policy Failed State Index – 5th in 2015 – (Fund for Peace 2015) and poorly in the UN Human Development Index – 186th of 187 in 2014 (United Nations Development Programme 2015). Drivers of the Congo conflicts are, among others, poverty, weak state authority, access to land, exploitation of natural resources and the widespread availability of arms. Several studies have revealed that the DRC's natural wealth is fuelling, and thus perpetuating the conflict (Global Witness 2004, 2005, 2013; Bonn International Center for Conversion 2007; De Koning 2008, 2009, 2011; Spittaels & Hilgert 2008, 2009; UNEP 2009, 2015; International Alert 2010; United States Agency for International Development 2010; Burnley 2011; Melvin & de Koning 2011; Mildner et al. 2011; Cuvelier et al. 2013; Johnson 2013).

Various armed groups, as well as units of the Congolese army, control and profit from exploitation and trade of minerals in eastern DRC, so-called conflict minerals are essential components of common electronic devices. Therefore, industrial companies buying these ores produced in the DRC and adjoining countries of the Great Lakes region have been urged by international NGOs to exercise due diligence on their supply chains so as to avoid buying conflict minerals. In the last few years, international organizations, such as the International Conference on the Great Lakes Region (ICGLR), the United Nations and the Organisation for Economic Co-operation and Development (OECD), and the United States with its Dodd-Frank Act, have launched a series of initiatives to combat the international trade in 'conflict minerals', through certification of minerals, guidelines on due diligence and reporting obligations for companies, respectively.

The benefit of Earth observation

In the light of calls for stricter regulation of the mining sector, the mapping and listing of mining sites in eastern DRC is one key prerequisite, before systems of control or certification can be implemented. Besides its role as a monitoring tool, such mapping can also serve as a measure for policy planning. Knowing where the mining takes place and how intensive the activities are can help to determine

where conflict prevention measures are mostly required – for example, in redirecting the deployment of mining agents or the specific opening or closing of markets.

In 2009, the International Peace Information Service (IPIS), a Belgian research NGO, published an ‘Interactive map of militarised mining areas in the Kivus’, as a first systematic attempt to cast light onto the circle of profit by armed groups profiting from the extractive industry in the eastern DRC (Spittaels & Hilgert 2009). This was followed by an overview on the mineral sector and mapping of the mining areas in the regions surrounding the two Kivu provinces – the ‘Kivu hinterlands’ (Spittaels 2010). During this research, it became clear that mapping and inventorying mining sites in eastern DRC is a very complex and dangerous task. Nearly all mining in eastern DRC is done in an artisanal way, with very basic tools such as shovels, pickaxes or even by hand. Since artisanal mining is a largely poverty-driven activity, it is typically practiced in the poorest and most remote rural areas of a country which are often also highly insecure (Garrett 2008; Garrett et al. 2009; De Koning 2011; International Peace Information Service 2013). Thus, mineral extraction is carried out by individuals, groups or cooperatives under extremely bad conditions and moreover, many mines are very difficult to access. As a result, field surveys are cost-intensive or even impossible which brought satellite data analysis and semi-automated mapping techniques into the focus of the peace and conflict research community (Brown 2010; Kranz et al. 2010; Schoepfer & Kranz 2010; Zingg Wimmer & Hilgert 2011; Schoepfer, Blaes, et al. 2012, Schoepfer, Spröhnle, et al. 2012; Lang et al. 2015). The assessment of the situation using satellite imagery and the detection of changes through frequent monitoring can provide essential information for surveillance and situational awareness over large areas as well as focussed on certain regions of interest (Kranz et al. 2015). With respect to this study, mining sites, surrounding settlements and infrastructural facilities are of interest. The overall aim is the support of awareness raising and on the long run, a sustainable use of natural resources as a major prerequisite of conflict prevention policies (Zingg Wimmer & Hilgert 2011; UNEP 2015).

Study area and data sets

The DRC is one of the most mineral-rich countries in the world. The exploitation of minerals is a major factor in the economy of the conflict-torn East of the country, in particular in the provinces of North and South Kivu.

Different test areas were selected at three different scales within the eastern DRC. The subnational scale (1) focuses on the whole region of North and South Kivu provinces, whereas several smaller study sites were identified within these regions for studying both the regional (2) and the local scales (3) of the mining activities (see Figure 1). These areas differ in landscape and topographic characteristics, showing hilly terrain with a small-scale mixture of meadows, fields and forests or large-scale rain forests interrupted by secondary forests and fields along villages. This variety allows developing and testing of robust and transferable analysis approaches as described in the methodology chapter.

Optical data from different satellite missions with different spatial resolution were acquired (see Table 1). For the subnational analysis in the North and South Kivu provinces, 14 Landsat-5 scenes from the years 2002, 2003, 2009 and 2010 as well as six UK-DMC2 images from 2008, 2009 and 2010 were collected, all with a medium spatial resolution (MR) of 30 and 22 m, respectively. The regional analysis is based on high spatial resolution (HR) RapidEye imagery (6.5 m pixel spacing) acquired on 1 October 2010 in the area around S. Masisi. At the local level, four areas of interest, namely Bisie, Mumba-Bibatama, Numbi and Tchonka, were analysed on the basis of very high spatial resolution (VHR) GeoEye-1 satellite data (0.5 m spatial resolution) acquired on 08 September 2010, 17 August 2010, 29 January 2010 and 13 May 2010, respectively.

Methodology

The multi-scale image analysis approach is performed at three spatial levels (see Figure 2): (1) subnational scale: classification of conflict-related land cover changes as an indication of potential hot



Figure 1. Study areas in the East of the Democratic Republic of the Congo.

Notes: North and South Kivu provinces are subject for analysis on a subnational scale, whereas the large and small squares highlight the sites related to regional and local analysis, respectively.

spots for exploitation activities; (2) regional scale: detection of potential activity areas of resource exploitation, and (3) local scale: site-specific assessment of exploitation areas. Figure 2 illustrates the workflow adopted for the presented study.

Image pre-processing

Pre-processing steps applied to the satellite imagery on the subnational scale included mosaicking, orthorectification and calibration to top of atmosphere. Additionally, a topographic correction was applied to eliminate the effects of variable illumination due to relief influences (Riano et al. 2003; Richter et al. 2009). In order to tackle the cloud coverage issue, which is common for the use of optical images in equatorial areas, the Landsat-5 scenes were supplemented by UK-DMC2 imagery. Firstly, the UK-DMC2 images were resampled to 30 m to match the Landsat spatial resolution. Secondly, the gaps which resulted from masking out the cloudy areas were filled with the spectral information

Table 1. Overview of satellite data specifications and image pre-processing steps.

Analysis scale	Area of interest	Coverage (km ²)	Sensor	Spatial resolution (m)	Acquisition date	Pre-processing steps		
Subnational	North & South Kivu	125.000	Landsat-5	30	08/03/2002	Orthorectification Mosaicking Re-sampling (DMC only) Top of atmosphere correction Topographic correction		
					31/01/2003			
					07/02/2003			
					26/01/2009			
					07/06/2009			
					16/06/2009			
					18/07/2009			
					26/01/2010			
					11/02/2010			
					03/12/2010			
					19/12/2010			
					14/12/2008		UK-DMC2 ^a	30
					20/12/2009			
					24/06/2010			
Regional	S. Masisi	5.000	RapidEye ^a	6.5	17/08/2010	Orthorectification Atmospheric correction Topographic correction		
					06/11/2010			
Local	Bisie Mumba-Bibatama Numbi Tchonka	100	Geoeye-1 ^a	0.5	08/09/2010	Orthorectification Atmospheric correction Topographic correction Pan-sharpening		
					17/08/2010			
					29/01/2010			
					13/05/2010			

^aEarth observation data provided by the ESA managed GSC-DA, funded under ESA – EC Agreement on the Implementation of the Space Component of Global Monitoring for Environment and Security (GMES).

derived from the UK-DMC2 scenes. Concerning the regional and local scale, image pre-processing included orthorectification as well as atmospheric and topographic correction (Richter 1996; Krauß 2014). An additional pre-processing step was performed on the multispectral GeoEye-1 images at local scale which were pan-sharpened to a spatial resolution of 0.5 m.

Image analysis approach

For the integrated analysis of the satellite imagery on all scales, an object-based image analysis (OBIA) approach (Blaschke & Strobl 2001; Schoepfer et al. 2009; Blaschke 2010), utilising the Cognition Network Language (CNL) in eCognition 8, was applied (Batz et al. 2008). CNL is a scripting language which is designed to develop application-specific solutions. In an iterative approach, both specific object segmentation and feature extraction are optimised in order to create flexible and robust algorithms, which may be transferred to other images with no or only minor adjustments of parameters (Schoepfer et al. 2009). Image segmentation is mainly based on multiresolution segmentation as defined in Baatz and Schäpe (2000). Additionally, further segmentation techniques including spectral difference, contrast split, quadtree and chessboard segmentation were used. The classification process is based on the definition of features using spectral, contextual, geometrical and hierarchical object characteristics. An overview of the applied segmentation and classification parameters for the three analysis levels is given in Table 2.

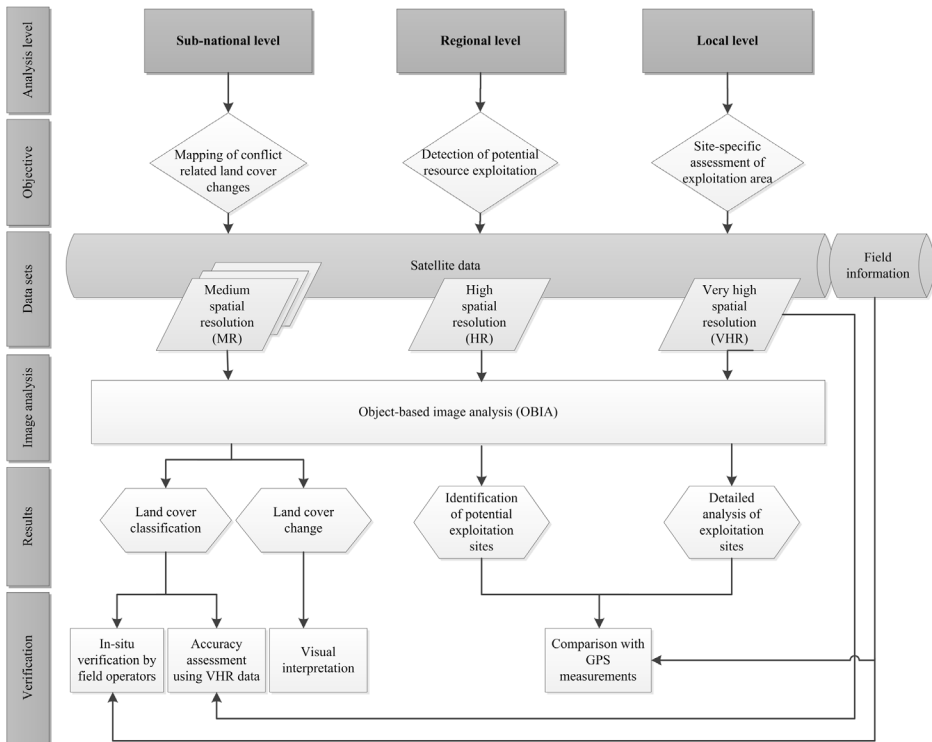


Figure 2. Workflow of multi-scale top-down approach to provide conflict-related and environmental information and to assess resource exploitation sites.

The advantage of the overall OBIA approach is the availability of information beyond the spectral image properties, the integration of expert knowledge in the extraction cycle and the transferability of the algorithm to other areas of interest. This allows for a straightforward, time-saving and more consistent analysis of different test areas and facilitates the monitoring of specific sites over longer time periods.

Subnational level – mapping conflict-related land cover changes

The aim of the analysis at subnational level was to provide status quo and change information on land cover for regions, where natural resources play a significant role in the context of the conflict situation. Such information consists in the depletion of primary natural land resources, i.e. changes in agricultural land and forest cover indicating activities that potentially fuel the conflict (e.g. illicit mining or informal logging). The information is derived from multi-temporal MR satellite data aimed at identifying possible hot spots, i.e. flash points for crisis within a country.

In a first stage, core environmental information was produced by the classification of land cover in the North and South Kivu provinces for 2010. The class definition is based on the land cover nomenclature developed in the context of the Africover project (Africover 2013). The FAO/UNEP Land Cover Classification System had been adopted by former land cover studies at national level in the DRC (Di Gregorio & Jansen 1996; Vancutsem et al. 2004). Relying on these data sets assures that all major land cover classes are taken into account and guarantees comparability between the data sets. The classification workflow starts with a multi-scale segmentation of the landscape elements based on the source imagery resulting in homogenous objects. Segmentation parameters were determined iteratively and empirically taking into account the broad range of differently sized landscape elements

Table 2. Overview of main segmentation and classification parameters focused on features of interest.

Analysis scale	Segmentation	Classification Parameters	Refinement	Class
Subnational	Contrast split: 0–255 Stepping type: add, stepping size: +2	<i>Spectral information:</i> blue, NIR, SWIR, Standard deviation (NIR, SWIR); <i>Class-related features:</i> Distance to, Rel. border, Enclosed by <i>Geometry:</i> Area	<i>Object reshaping:</i> Pixel-based object resizing, Merge region	Clouds (incl. cloud shadow)
	Quadtree: scale 40; Multiresolution: scale parameter 20 (shape 0.3, compactness 0.5)	<i>Spectral information:</i> all image bands, NDVI, modified EVI, ISO- data clustering; <i>Class-related features:</i> Rel. border to <i>Geometry:</i> Area	<i>Object reshaping:</i> Morphology operations (opening, closing), Merge region, Remove objects	Shrubland, shrub crop, herbaceous grassland, herbaceous crop, built-up, bare areas
	Quadtree: scale 60; Quadtree: scale 10 Multiresolution: scale parameter 20 (shape 0.3, compactness 0.5)	<i>Spectral information:</i> all image bands, Standard deviation, FI, Brightness, NDVI <i>Class-related features:</i> Rel. border to <i>Geometry:</i> Area	<i>Object reshaping:</i> Morphology operations (opening, closing), Merge region, Remove objects	Primary forest, woodland and mountain forest
	Multiresolution segmentation: scale parameter 20 (shape 0.3, compactness 0.5)	<i>Spectral information:</i> all image bands, NIR, NDVI, Brightness, Standard deviation (blue, NIR); <i>Class-related features:</i> Distance to, Rel. border to <i>Geometry:</i> Area, Shape index	<i>Object reshaping:</i> Pixel-based object resizing, Merge region, Remove objects	Water
Regional	Multiresolution: scale parameter 80 (shape 0.1, compactness 0.5); Chessboard: object size 166	<i>Spectral information:</i> NDVI, Brightness, Standard deviation (green); <i>Class-related features:</i> Distance to, Relative border to, Existence of; <i>Geometry:</i> Area	<i>Object reshaping:</i> Merge region	Bare soil
Local	Multiresolution: scale parameter 25 (shape 0.1, compactness 0.5); Spectral difference: Max. spectral difference 10	<i>Spectral information:</i> NDVI, MSAVI2, BSI, Standard deviation (green band); <i>Geometry:</i> Compactness, Area	<i>Object reshaping (pixel and object-based):</i> Pixel-based growing and shrinking, Merge region; <i>Neighbourhood relations:</i> Relative border to	Mining sites

occurring in the area. Secondly, a rule-based classification considering spectral, textural and contextual signatures followed in order to label these objects with meaningful classes. Detailed information on applied segmentation techniques and classification features is given in Table 2. The classification rule set defined in CNL allowed the definition of multiple spectral indices such as band ratios and normalised vegetation indices (VIs). The selection of suitable combinations of input indices defining applicable class signatures was undertaken by an iterative evaluation of the feature space. The feature space was built for the typical representatives of each land cover class. The most appropriate combination of defined features identified during this step was applied for the class assignment with further re-evaluation with respect to observed errors or misclassifications. For the selection variations and

local specifics in the class signatures occurring in the study area were taken into account based on site specific conditions for each image, i.e. acquisition date and corresponding phenological conditions as well as defined biogeographical regions (derived from the land cover nomenclature developed in the context of the Africover project (2013) and ancillary data).

Due to the high volume of data, a sequential processing was chosen. The developed rule set was applied to single Landsat scenes which were clipped at the average outline of the overlapping area of the adjacent images. The individual classifications were merged to produce a seamless land cover result. Due to the changing presence of clouds in neighbouring scenes, mismatching of cloud objects occurred at the border. These artefacts were removed by post-classification contextual matching, which corrected class discrepancies based on the application of a defined majority criteria. In the following step, a minimal mapping unit of five hectare was defined and applied. Finally, the mosaicked land cover classification output was thoroughly checked by means of expert knowledge and visual interpretation in order to reveal and to manually correct any further misclassifications.

In a second step, the changes in land cover were assessed exemplarily for North Kivu for two periods: (1) from 2003 to 2008 and (2) from 2008 to 2010. Changes were detected on the basis of image-to-image comparisons of Normalised Difference Vegetation Index (NDVI, cf. Rouse et al. 1973) differences between image pairs of Landsat-5 and UK-DMC2 scenes from the respective years. The NDVI shows the growth of green vegetation and is calculated by

$$\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}} \quad (1)$$

where ρ_{NIR} is the spectral reflectance in the near infrared channel and ρ_{RED} is the spectral reflectance in the red channel. Firstly, each image pair was histogram-matched, and secondly, the NDVI difference providing the change intensity was calculated. The scaled change intensities were subsequently thresholded to form discrete polygons and matched to fit the land cover segments. Global thresholds based on the histogram of the change intensity were applied in a first step. In a second step, the output was visually checked. In case of significant discrepancy between the automated results and the changes derived from visible inspection of the pair of images, the threshold was locally adjusted. The description of the changes was derived from the classification rule set and schema of the land cover map. Consequently, the object-based classification was carried out for segments coincident with previously detected changes.

In a last step, the detected change polygons were spatially aggregated into regular 1 km × 1 km grid cells. Grid cell-based representation of change data is particularly useful for the analysis of clusters of similar changes and the identification of hot spots, and to eliminate noise. It facilitates the comparison of different classes at the same spatial level and provides a better overview of changes of landscape structure and trends in the analysed area (Tiede et al. 2012).

Regional level – detection of potential resource exploitation

The main objective of the analysis at regional scale was the development of a fast approach for detecting potential resource exploitation. In this study, focus was set on the detection of mineral exploitation sites. The applied approach, both for the regional and for the subsequent local scale, builds upon preceding work from Schoepfer and Kranz (2010) and Luethje et al. (2014). The presented research focuses on the development of enhanced concepts through the investigation of additional data sets and improved analysis methods.

Particular attention was paid to the generation of a cloud and cloud shadow mask in order to avoid confusion with features of interest. As described in Schoepfer and Kranz (2010), several iterative steps were applied ranging from different segmentation techniques such as edge ratio split, contrast split and spectral difference to spectral-based classification and pixel-based reshaping. In order not to interfere with the desired features of interest, further pre-classification of objects was performed including the extraction of water bodies and settlement areas using both spectral and spatial interlinked object

features. Again, pixel-based object growth and resizing proved to be successful in creating real-world objects. In the main classification process, the bare soil areas – which are of main interest – were analysed. Objects were generated using the multiresolution segmentation algorithm. In an initial step, objects were assigned by the definition of two features, namely the Normalised Difference Vegetation Index (NDVI) (see (1)) and the standard deviation of the green band. The identified bare soil areas were further classified to detect potential hot spots of natural resource exploitation related to mining of minerals using the NDVI and the overall brightness. Additionally, relations to neighbour objects and geometric measures were included to fine-tune the classification results.

In order to focus on the area around the detected potential hot spot, a regular gridded layer of $1 \text{ km} \times 1 \text{ km}$ was introduced in order to spatially aggregate the information and to highlight cells of interest (Schoepfer et al. 2007). This step was realised by segmenting the overall image with a chess-board segmentation. A buffer was calculated around the identified potential mining areas in order to enlarge the detected area of interest. In the following, the number of detected features within a cell was summed up indicating the most relevant areas.

Local level – site-specific assessment of exploitation area

For the local analysis, four $10 \text{ km} \times 10 \text{ km}$ study sites were determined according to the information provided by IPIS. This information was further supported by the results of the regional analysis. Two of the four study sites are located within the area of the regional analysis which shows the highest concentration of detected potential mining areas. Similar to the subnational and regional approach, the local analysis was conducted using an object-based environment. Since mining sites differ significantly in their structural characteristics, it is important that the feature extraction process provides the flexibility of tuning the behaviour of segmentation and classification straightforwardly.

The initial rule set was developed for Mumba-Bibatama in North Kivu based on GeoEye-1 imagery from 17 August 2010. Initial object generation was achieved by applying a region-based, local mutual best fitting segmentation approach (Baatz & Schäpe 2000). The threshold for the segmentation parameters was iteratively evaluated based on visual inspection and adjusted accordingly. Since mining sites considerably differ regarding their shape, but are characterised by similar spectral information, the colour criterion was preferred to shape. The image objects were refined by applying a spectral difference segmentation, which aggregates adjacent image objects with similar spectral responses up to the maximum spectral difference. Neighbouring image objects with similar spectral properties are merged while spectrally distinct objects are preserved. This allows the creation of real-world objects and the integration of meaningful feature descriptions such as geometry characteristics in the following classification process. In case of both of the before mentioned segmentations, all image layers were equally weighted. The resulting image objects are used for further classification and class refinement procedures. The most obvious characteristic of mining areas is the loss of vegetation cover resulting from mining activities. Thus, the rule-based classification process starts with the separation of vegetated and non-vegetated areas. In a first step, the NDVI (see (1)) was employed to detect vegetation covered areas. For a better separation between remaining scarcely vegetated areas and non-vegetated areas, the Modified Soil Adjusted Vegetation Index 2 (MSAVI2) was introduced. This index is computed as follows (Qi et al. 1994):

$$\text{MSAVI2} = \frac{\left[2 \times \rho_{\text{NIR}} + 1 - \sqrt{(2 \times \rho_{\text{NIR}} + 1)^2 - 8(\rho_{\text{NIR}} - \rho_{\text{RED}})} \right]}{2} \quad (2)$$

where ρ_{RED} and ρ_{NIR} are reflectances in the red channel and in the near infrared channel, respectively. The MSAVI2 is a more sensitive indicator for vegetation density, because it raises the vegetation signal and simultaneously lowers soil-induced variations. Finally, the Bare Soil Index (BI) (Azizi et al. 2008)

was used to improve the extraction capacities of the developed rule set. The BI is calculated by using the following equation (Azizi et al. 2008):

$$BI = \frac{(\rho_{NIR} + \rho_{GREEN}) - \rho_{RED}}{(\rho_{NIR} + \rho_{GREEN}) + \rho_{RED}} \quad (3)$$

where ρ_{GREEN} , ρ_{RED} and ρ_{NIR} are reflectances in the green, red and near infrared channel, respectively. In addition, the standard deviation of the green spectral band was used in order to reduce misclassifications such as uncultivated agricultural fields which have also been identified using the various indices. Mining areas are more heterogeneous in comparison with uncultivated agricultural fields, and thus show a higher standard deviation of the reflection values in the different spectral bands. Also geometrical features like the compactness (C) and size of the classified objects after merging proved useful to eliminate misclassified objects. (C) is calculated as follows (eCognition Developer 9 2014):

$$C = \frac{l_o \times w_o}{P_o} \quad (4)$$

with l_o representing the length and w_o the width of an image object; P_o is the total number of pixels of an image object.

Following the iterative approach, previously applied features such as the standard deviation of the green band and geometric features were used to further optimize the feature extraction result. Finally, for further class refinement, advanced classification and object reshaping algorithms were applied including pixel-based object resizing (growing and shrinking) and object assignment based on neighbourhood relations.

In the following, the transferability of the rule set was tested on further areas of interest, namely Bisie, Numbi and Tchonka, showing diverse landscape characteristics. Despite these differences, only minor adaptations with respect to the definition of spectral thresholds had to be applied. This reduced significantly the time required to analyse the new images as the main rule set could have been applied, and thus, fundamentally new programming of individual rule sets was avoided.

Accuracy assessment

For the validation of the land cover classification on the subnational level, a twofold approach was selected. Firstly, standard procedures and metrics used for quantitative assessment of thematic accuracy of remote sensing data products were applied (Congalton 1991). Secondly, an *in situ* verification performed in the field by local experts was performed.

Thematic consistency validation of the land cover classification from 2010 was accomplished by interpreting VHR satellite imagery. A set of 350 randomly distributed validation points was generated within the areas covered by the VHR images in both Kivu provinces. By visually analyzing and interpreting the VHR images, the landscape in the surroundings of each validation point was characterized within a radius of 300 m. This approach allowed the correct labelling of the complex land use classes composed from several subclasses, using the criterion of predominance for the categorization. The use of a buffer with a size equal to the radius of the validation circle ensured that no class boundary crossed the sample circle.

In a second step, *in situ* field data were collected to verify the land cover classification. Five local and international NGOs contributed to this *in situ* validation. The advantage of working with local institutions is that they have many staff in the field that have a deep knowledge of the region and situation in those remote areas. The drawback is their limited experience in map reading and the lack of informatics infrastructure. Taking these peculiarities into account, a dedicated verification protocol was set up and about 650 A4 paper maps were prepared to cover the daily working area of the involved NGOs and institutions. A set of 15 points per map randomly selected on a regular grid (1 km spacing)

was proposed for the verification. The field operators were asked to mark the correct land cover at the point locations only if they reliably knew the region. Thus, not all 15 points per map may have been necessarily verified. With this verification set-up, about a third of the surface of the North and South Kivu provinces was observed by the field operators. In total, 1638 points were received from the field operators, of which only 1555 were considered as reliable. Due to the absence of applicable reference or *in situ* data, the land cover change could only be verified by visual inspection using the original satellite imagery. Potential omissions and commissions in the results were systematically inspected by the interpretation of the full bandwidth of the spectral information, i.e. various band combinations, NDVI and principal component analysis.

Mining positions identified at regional and local scale were compared with Global Positioning System (GPS) measurements made by field staff. In the area of S. Masisi on the regional scale, 35 GPS points were available, whereas for the validation of the local analysis, one to eight measurements per area existed (Spittaels & Hilgert 2009). However, regarding the validation of satellite data interpretation results using the GPS measurements, some important constraints have to be considered. Since the GPS measurements were actually not conducted for the validation of the analysis results, but for other reasons, no attention was paid to take one GPS point for each mining site. The field staff was rather instructed to localise one central point if there were several sites close to each other. Furthermore, due to security reasons, the measurements were not always taken in the mining area itself but in a safe distance. As a consequence, the GPS location of mining areas may slightly differ from those derived by semi-automatic image analysis although both refer to the same area. Consequently, it is not possible to validate the identified mining areas by a comparison with the exact position of GPS points but rather by their distance from it. Thus, for the validation of the local analysis, a buffer of a 500 m radius around the GPS points was generated. The size of the buffer was chosen based on the information provided by IPIS. In the case of the regional analysis, the number of GPS points within the aggregated grid cells covering a 3×3 neighbourhood window was analysed.

Results

Subnational analysis

The land cover map of 2010 for the North and South Kivu provinces consists of ten classes: clouds, primary forest, woodland and mountain forest, shrubland, shrub crop, herbaceous grassland, herbaceous crop, built-up and bare areas (see Figure 3).

The *in situ* expert-based assessment resulted in an overall accuracy of 94%, while the classical approach of visual comparison with higher resolution data estimated an accuracy of 79% (see Tables 3 and 4). The figures for individual classes show different user's and producer's accuracies. The shrub crop mosaic and herbaceous crops reached high accuracy figures due to its mixed definition, which played a significant role for the class interpretation in complex landscape areas. Classes with a more distinct definition such as shrubland resulted in lower accuracy figures. This was caused by the fact that boundaries between these classes are fuzzy and gradual, which affects mutual separability of the classes and consequently the accuracy of classification. In general, the classes were well discriminated and few commission and omission errors were observed.

Apparently the two different validation approaches of the land cover classification led to different results in which the *in situ* validation provided a significantly better assessment. An explanation can be that a local expert may tend to accept an assigned class rather than rejecting it. Nevertheless, the joint assessment of both visual and *in situ* assessments provides more credibility to the product rather than a single one. The accuracy of the product is satisfactory, taking into account the complexity of the landscape and individual classes in the study area.

The land cover changes were observed for North Kivu between 2003 and 2008 as well as between 2008 and 2010. The detected changes were aggregated into dedicated classes, which are possibly related to mining activities or exploitation of natural resources in general, i.e. deforestation and agricultural

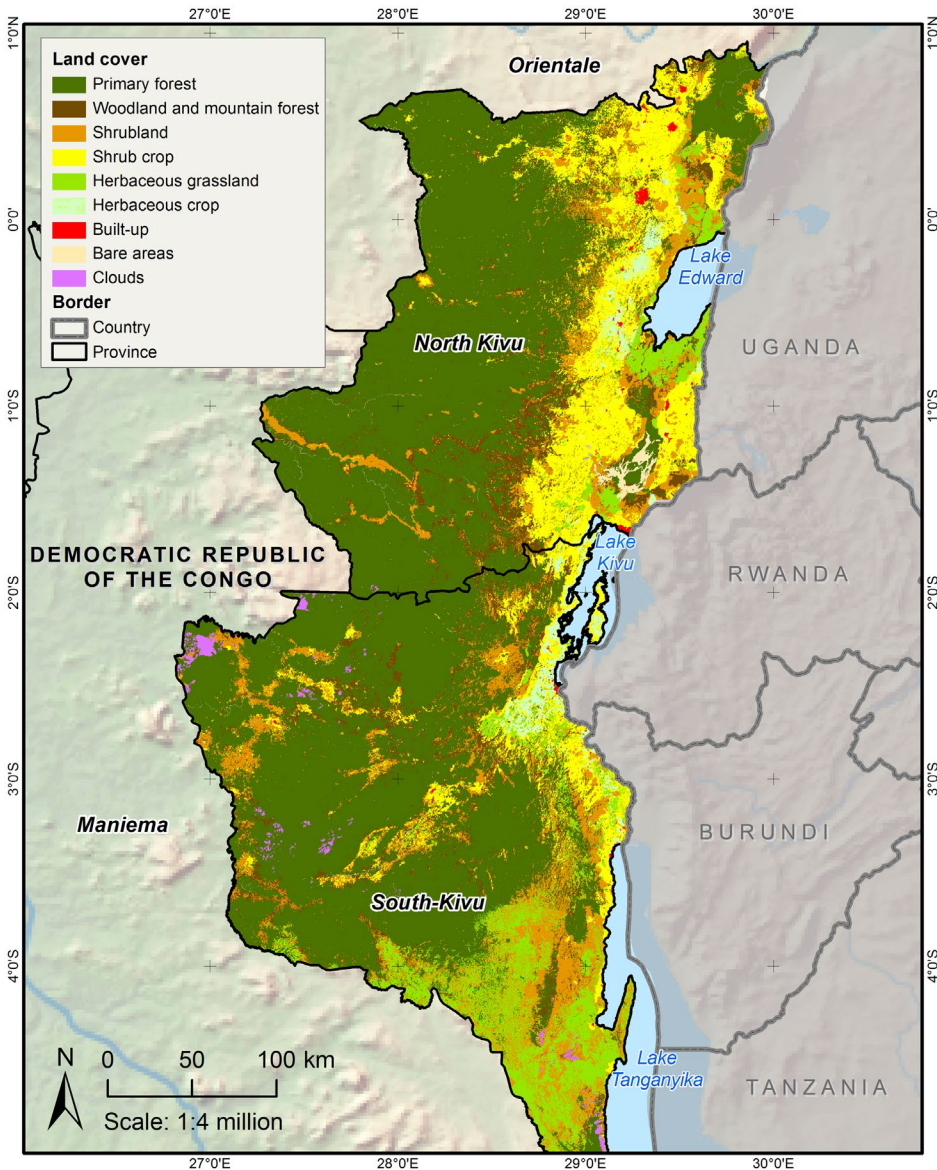


Figure 3. Land cover classification of North and South Kivu.

uptake by natural vegetation. A number of clusters of similar changes were identified from the results in the area. It was assumed that clusters of similar changes could indicate potential areas of exploitation of natural resources in conflict areas.

Figure 4 shows the change clusters for the two periods in North Kivu: (1) from 2003 to 2008 and (2) from 2008 to 2010.

Land cover changes related to deforestation are mainly caused due to population pressure and agricultural expansion which leads to environmental impacts at the edge of forested areas. It could not be confirmed that unclustered and scattered deforestation patches are related to natural resource exploitation activities. However, evolution of deforestation size and patterns could be regularly monitored at the given scale in order to identify potential hot spots. If suspected, identified spots could be linked to with the subsequent regional analysis. Land uptake by urban is also related to population growth in

Table 3. Confusion matrix obtained using a stratified random sampling design.

Reference data (VHR satellite data)									Total	User's (%)
Classified data	F	W	S	SC	HG	HC	BU	BA		
F	55	9	0	0	0	0	0	0	64	85.9
W	3	28	4	0	1	0	0	1	37	75.7
S	1	5	37	3	7	1	0	0	54	68.5
SC	0	3	8	49	3	3	0	0	66	74.2
HG	1	3	0	0	36	1	0	0	41	87.8
HC	0	2	1	8	3	45	0	0	59	76.3
BU	0	0	0	0	0	0	10	0	10	100
BA	0	0	0	0	0	0	0	9	9	100
Total	60	50	50	60	50	50	10	10	340	
Producer's (%)	91.7	56	74	81.7	72	90	100	90		

Notes: Overall accuracy: 79.1%; Kappa: 0.79. F: Primary forest; W: Woodland and mountain forest; S: Shrubland; SC: Shrub crop; HG: Herbaceous grassland; HC: Herbaceous crop; BU: Built-up; BA: Bare areas.

Table 4. Confusion matrix obtained using *in situ* field data.

Reference data (<i>in-situ</i> field data)									Total	User's (%)
Classified data	F	W	S	SC	HG	HC	BU	BA		
F	225	6	10	2	0	1	1	0	245	91.8
W	6	103	3	1	0	0	1	0	114	90.4
S	14	2	206	4	5	1	0	0	232	88.8
SC	0	0	4	535	14	5	1	1	560	95.5
HG	0	0	0	1	240		3	2	246	97.6
HC	0	0	2	2	0	118	0	0	122	96.7
BU	0	0	0	0	0	0	36	0	36	100
BA	0	0	0	0	0	0	0	0	0	-
Total	245	111	225	545	259	125	42	3	1555	
Producer's (%)	91.8	92.8	91.6	98.2	92.7	94.4	85.7	0		

Notes: Overall accuracy: 94.1%; Kappa: 0.925. F: Primary forest; W: Woodland and mountain forest; S: Shrubland; SC: Shrub crop; HG: Herbaceous grassland; HC: Herbaceous crop; BU: Built-up; BA: Bare areas.

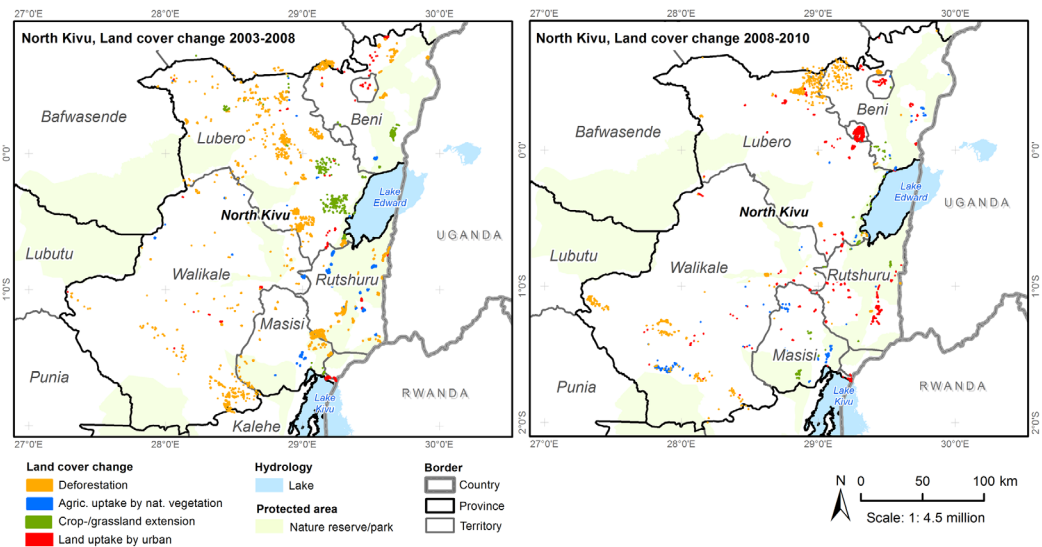


Figure 4. Land cover changes in North Kivu (1) from 2003 to 2008 (left) and (2) from 2008 to 2010 (right).

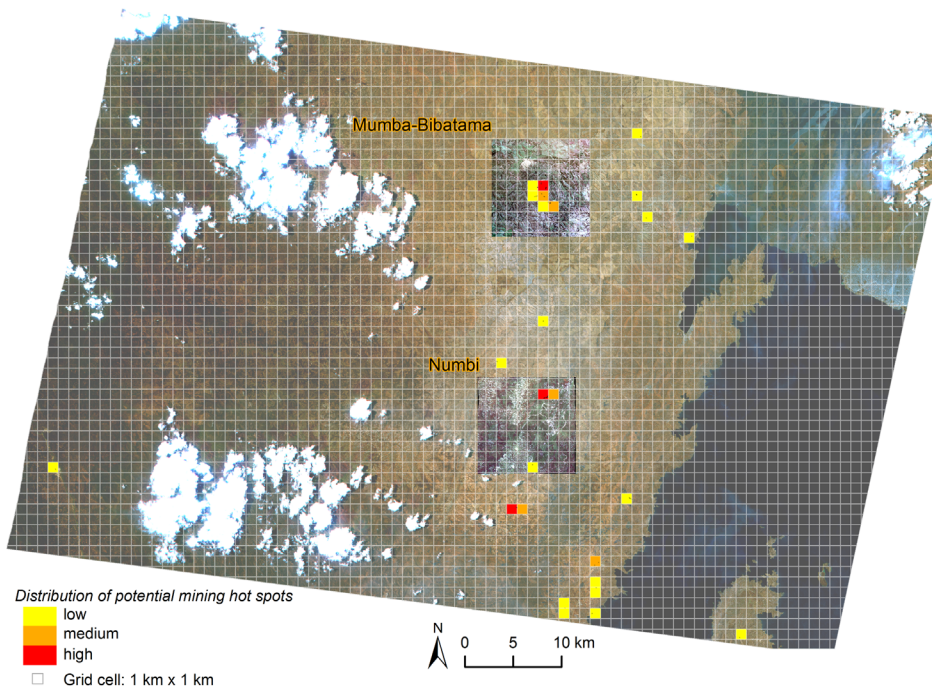


Figure 5. Distribution of potential areas of active natural resource exploitation, related to mining of minerals in the region North–West of Lake Kivu.

Notes: Darker colour corresponds to areas with a higher probability of potential mining areas, whereas brighter cells represent areas with minor probability. The small insets show very high-resolution satellite imagery.

the area under investigation, whereas changes in cropland (agricultural uptake by natural vegetation and crop-/grassland extension) depend mainly on seasonal cycles related to local agriculture practices.

Both change analysis periods 2003–2008 and 2008–2010 showed effects of fragmentation resulting from insufficient cloud-free data coverage. Thus, it has to be noted that some change clusters may not be fully detected. Operational large-scale change detection, supporting identification of artisanal mining hot spots, requires a monitoring capacity independent of cloud coverage and providing results in narrow time windows. This could be accomplished using medium resolution radar satellite imagery for change detection. However, for class labelling of detected changes, a combination of radar and optical image data is still desirable.

Regional analysis

Figure 5 shows the result of the feature extraction analysis in the area of S. Masisi as raster cells underlain by the RapidEye image from 2010. Only 26 of 4364 cells were identified as hot spot areas, i.e. potential areas of active natural resource exploitation.

Three different categories of probability areas (low, medium and high) were defined according to the number of identified features per grid cell. Red colour indicates areas with a high probability of potential mining areas (equal three or more identified potential areas of active exploitation), whereas orange cells represent areas with medium (two identified potential areas) and yellow cells areas with low probability (one identified potential area). Three cells were marked with a ‘high’ potential of mining activity, whereas five cells were marked as ‘medium’ and 18 boxes as ‘low’ probability. A visual inspection revealed that in 17 identified cells, potential mining activity exists, whereas 3 cells were highlighted due to misclassification of bare ground within built-up areas and 6 cells in agricultural areas, respectively. Of the 26 identified cells, 13 cells could be directly linked to field validated and

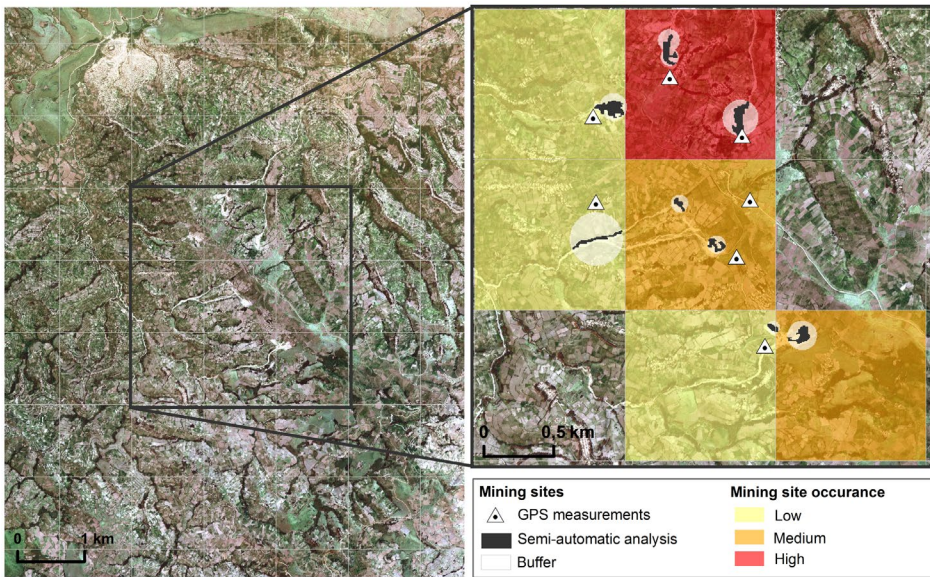


Figure 6. Area around Mumba-Bibatama shows cells with high probability of mining areas.

Notes: Classified potential mining area objects are shown as black polygons, the enlarged buffer zones of potential active mining areas are highlighted in white whereas the location of GPS measurements are illustrated as triangles.

GPS located mining sites, whereas 4 cells show potential areas which have not been recorded by GPS measurements. At this point, it has to be restated that not all mining sites are necessarily covered by the field-based assessment due to security reasons or represent new areas which did not exist at the time of GPS recording.

Figure 6 shows the delineation of identified objects, both polygons and enlarged buffer zone of potential active mining areas in the region of Mumba-Bibatama. The cells are highlighted in three different colours, i.e. yellow, orange and red, indicating the probability of mining areas from low to high. In addition, the GPS points are included in the figure as triangles. The matching of the detected potential mining area objects with the field-assessed GPS measurements is remarkable considering the coarse resolution of the image and the corresponding mapping unit of the described feature of interest.

For an overall validation, the available 35 GPS points within the RapidEye image were used to identify those cells which were missed by the classification system. The evaluation revealed that only 8 mining areas were not highlighted as potential mining hot spots within the 3×3 neighbouring cells. The automated process may facilitate the visual screening of large areas in future.

Local analysis

The introduction of indices (NDVI, BI, etc.) in the feature extraction process showed to be effective for improving the robustness of the classification. The NDVI clearly differentiated vegetation and non-vegetation in a first step of the image analysis. The MSAVI2 and BI indices were almost equally effective in separating bare soil and vegetation in the second step and performed well when used in parallel. Finally, the standard deviation feature of the image objects as well as the geometry feature proved to be powerful separators for mining sites and other bare soil areas. Although the study sites are characterised by very different landscape structures, the classification of mining sites for all regions of interest showed promising results, underlining the robustness and transferability of the applied rule set.

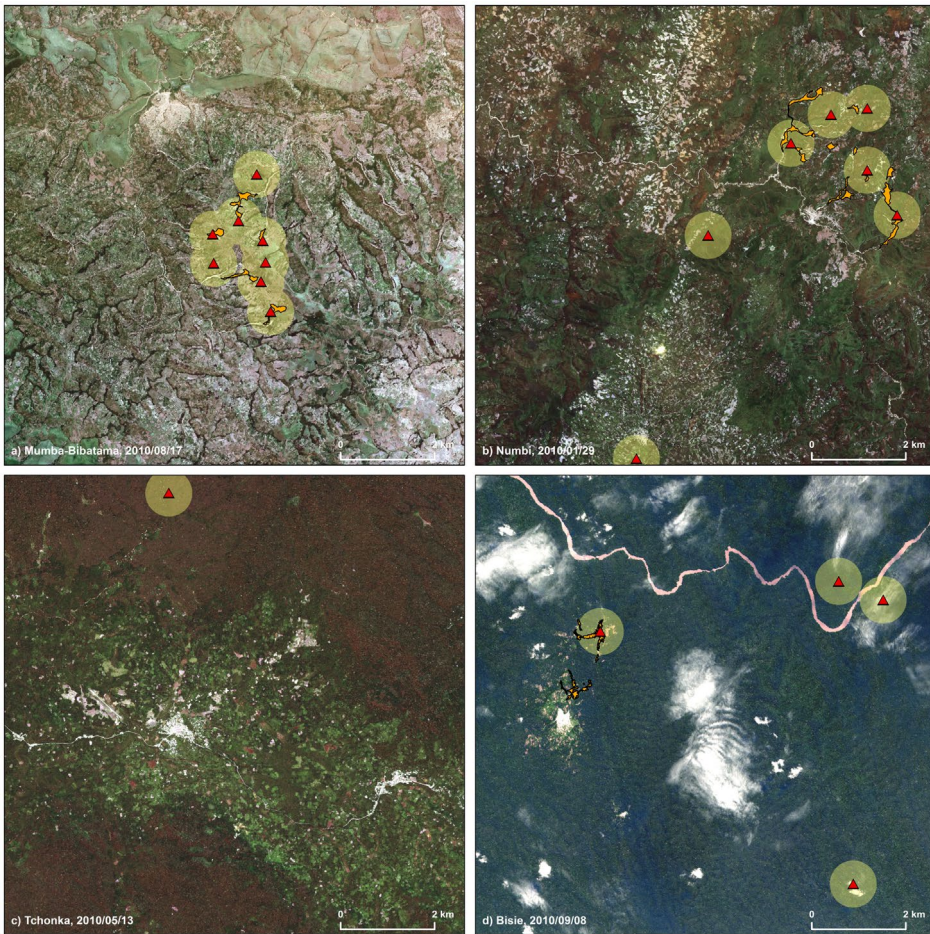


Figure 7. Overview of semi-automatic image analysis results of the local study sites. The identified mining sites are shown as orange polygons; red triangles indicate GPS locations surrounded by a yellow buffer with a 500 m radius: (a) Mumba-Bibatama (2010/08/17), (b) Numbi (2010/01/29), (c) Tchonka (2010/05/13), (d) Bisie (2010/09/08).

As shown in Figure 7, there is a high consistency between the locations of field validated mining sites (red triangles) and satellite inventoried mining sites (orange polygons). Most of the remotely-sensed potential mining sites are within a distance of 500 m from the GPS measurements.

An overview of the number of field mapped mining sites with respective GPS locations available for each study site in comparison with the analysis results is given in Table 5.

Altogether 14 of 20 GPS located sites have been identified by the analyses of satellite data. The other six sites could not be verified by the satellite imagery, even by visual interpretation, for mainly two reasons: (1) small-scale mining areas are not visible due to vegetation or cloud cover, especially in areas of primary forest or (2) there is a long interval between GPS recording and satellite data acquisition, and thus, mining activities may have already be stopped. Detailed visual inspection showed that false alarms for mining sites are mainly caused by similar spectral reflectance of bare ground and dry river beds.

Discussion

The assessment of natural resource exploitation in conflict regions suffers mostly from secure access to the area and particularly in DRC from the large areas to be monitored. Satellite remote sensing seems

Table 5. Accuracy assessment of the local analysis using GPS points.

Study area	Total number of GPS located sites	Number of verified sites	Number of non-verified sites and explanation
Mumba-Bibatama	8	8	0
Numbi	7	5	2 Mining sites could not be detected; visual interpretation did not show any mining area
Bisie	4	1	3 Vegetation and cloud cover
Tchonka	1	0	1 Vegetation cover

to be an ideal tool to overcome these limitations being able to provide a synoptic overview of large areas with the potential to ‘zoom’ into hot spot areas to obtain more detailed information. Hence, this paper looks into the multi-scale assessment of resource exploitation.

The coarser resolution assessment on the subnational scale provides with the updated land cover classification core environmental information that is lacking for a wide range of applications also beyond the conflict resources nexus. The experts performing the *in situ* verification confirmed that such basic thematic information is highly relevant in regions such as Kivu and the DRC in general where they suffer from a lack of geographic information. Even basic situation maps are useful for local institutions working in the area of regional planning, environmental protection or alike. Here, a major limitation of optical satellite data should be mentioned which is its dependence on weather conditions. In particular, in tropical regions, cloud coverage could lead to unavailability of proper optical satellite imagery over longer periods which might hinder a consistent monitoring. In contrast to optical data, synthetic aperture radar (SAR) data are independent from these weather phenomena since the applied wavelength is able to ‘look through’ clouds. Although SAR data have some limitations with respect to the identification and discrimination of some land cover classes, it might provide an alternative to optical imagery in this particular context. With the launch of the first suite of Sentinels, i.e. Sentinel-1 and Sentinel-2, a frequent global coverage of the Earth surface in full spectrum of remote sensing is becoming available free of charge to all users. The combined use of both, SAR and optical systems, should boost the sketched methodological approach of classifying conflict-related land cover changes as an indication of potential hot spots for exploitation activities.

During the development of a robust algorithm for screening large-scale areas on regional level, specific effects were encountered. Those are mainly related to the varying size of the mining areas where smaller sites may not be detected due to the coarse resolution of the satellite imagery and the limited size of the targeted features, respectively. This drawback, however, can be compensated by the fact that mining activities are agglomerated in certain regions, and thus, even if not all sites are detected from space, still the main areas of relevance can be identified. The way of highlighting the areas with the highest occurrence supports the detection of likely affected areas. The identified cells serve as indicators where visual inspection as well as VHR image analysis should be carried out in order to further explore the region.

For the characterization of the mining sites on a local scale, a transferable, flexible and easy to use algorithm was developed which was successfully tested on four different areas. The usability and reusability of rule sets showed the potential of inventorying and mapping mining sites. Difficulties are related to the similar spectral reflectance of features. However, this can be overcome by visual investigation, related to expert context information, which rendered satisfying results.

Conclusion and outlook

Current mining practices in conflict areas result in a disastrous humanitarian situation for miners and local population and have major socio-economic, environmental and political implications. The

study demonstrates the possibility of EO for supporting the monitoring and documentation of natural resource exploitation in conflict regions. On the three scales, land cover patterns and different features of interest could be observed in complex, remote and insecure landscapes and terrain. The information derived allows to detect conflict-related land cover changes over large areas and to locate and characterize mining sites, which otherwise would not be assessed. Not only can sites be detected, but one can even get an idea of the relevance of the detected sites in terms of mineral production, on the basis of the extent of the mining area. Together with local reports, field observations as well as political and economic assessments a more comprehensive picture about the complex situation in conflict regions can be provided as a basis for more confident decisions. This applies particularly for political planning at regional level but also concerning due diligence processes in the context of mineral certification and traceability.

The approach presented in this paper shows considerable potential of EO-based monitoring as a support tool for policy-making processes. It can be used to determine where intervention is required, for example, in rethinking the deployment of mining agents or the opening or closing of markets. Moreover, it allows the possible consequences of planned measures to be assessed. Further interest remains in testing the transferability of the developed methodology by applying it to different test sites within the DRC or even to other countries. Additional research potential lies in the integration of indicators which are considered to enhance both the quality of the outcome and the depth of information. Increasing activity in a mining area results in the expansion of settlements as miners are migrating. First attempts to use such indicators to enhance the accuracy of the results are currently under investigation.

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