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Article

Geographic Object-Based Image Analysis Using Optical Satellite Imagery and GIS Data for the Detection of Mining Sites in the Democratic Republic of the Congo

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Abstract: Earth observation is an important source of information in areas that are too remote, too insecure or even both for traditional field surveys. A multi-scale analysis approach is developed to monitor the Kivu provinces in the Democratic Republic of the Congo (DRC) to identify hot spots of mining activities and provide reliable information about the situation in and around two selected mining sites, Mumba-Bibatama and Bisie. The first is the test case for the approach and the detection of unknown mining sites, whereas the second acts as reference case since it is the largest and most well-known location for cassiterite extraction in eastern Congo. Thus it plays a key-role within the context of the conflicts in this region. Detailed multi-temporal analyses of very high-resolution (VHR) satellite data demonstrates the capabilities of Geographic Object-Based Image Analysis (GEOBIA) techniques for providing information about the situation during a mining ban announced by the Congolese President between September 2010 and March 2011. Although the opening of new surface patches can serve as an indication for activities in the area, the pure change between the two satellite images does not in itself produce confirming evidence. However, in combination with observations on the ground, it becomes evident that mining activities continued in Bisie during the ban, even though the production volume went down considerably.

Keywords: geographic object-based image analysis (GEOBIA); feature extraction; change detection; monitoring; multi-scale; natural resources; artisanal and small-scale mining; Democratic Republic of the Congo; conflict research

1. Introduction

The Democratic Republic of the Congo (DRC) suffers from a vicious circle of violence. On the one hand, the country is ranked among the most mineral-rich countries in the world [1,2]. On the other hand, the DRC is economically one of the poorest and on the edge of a failed state [3,4]. Although the mining sector in the DRC is increasingly seen as the economic foundation for the country's post-conflict reconstruction, the sector still plays a critical role in local and regional conflicts [5]. The so-called conflict minerals—cassiterite (tin ore), coltan (tantalum ore), wolframite (tungsten) and gold to mention only a few—have become the centre of a civil war-like situation that resulted in the death of over five million Congolese in the past twelve years [6]. Especially in the eastern parts of the country (North and South Kivu as well as Katanga) the exploitation and trade of minerals fuel the armed conflict with rebel groups competing for revenues of mining activities [7,8]. The above-mentioned conflict minerals are used in essential components of common electronic products such as mobile phones, laptop computers, mp3 players, game consoles, digital cameras and others and it is widely believed that the profits have funded and continue to fund numerous armed groups [6,9].

Revenues from the conflict resources are withdrawn from the national budget, thus directly financing the rebel groups. On the one hand, these groups gain more and more profit and power, while on the other hand the government of the DRC increasingly lacks assertiveness and governmental authority. In resource-rich countries these phenomena—together with political corruption and a poor economic diversification—are common and often described as the "resource curse" [10]. Above all, the population of these eastern provinces is seriously affected by insecurity and instability; the situation causes a considerable number of displaced persons to resort to refugee camps [7].

As is the case for most armed inner-state conflicts, political intervention by supranational organizations or expeditious and efficient reaction in terms of humanitarian aid can only be accomplished if reliable information about the on-site situation is available. Remote Sensing offers a way to monitor epicentres of conflict which cannot be frequented by research teams or aid agencies without considerable effort and danger to life [11,12].

However, only a few articles have been published that emphasize the advantages of remote sensing within the context of land cover changes related to conflict activities. Most of the literature is addressing the complex relationships between socio-economic as well as political issues and natural resources either leading to or fuelling existing conflicts [13,14]. On the other hand, the Earth observation community mainly focuses on the development of approaches for monitoring natural resources and rarely addresses the link to the conflict situation. While [15] describes the suitability of Earth observation technology to determine conflict trends and improve human security in Africa, [16] discusses land use and land cover (LULC) changes related to conflict by analyzing satellite data as well as social surveys and secondary data. A direct link between detected land cover changes and forest degradation derived from Landsat

TM and ETM+ data is drawn by [17–19] by explaining the impact of the dramatic armed conflicts in DRC on forest resources.

The methodology developed in this study builds upon the multi-scale approach described in [20]. Firstly high-resolution (HR) satellite imagery is implemented in order to retrieve information on large survey extents about the location of potential mining activities. For this purpose, a transferable feature extraction scheme in an object-based image analysis environment is created and subsequently applied to the HR data. Since there is no possibility for ground truthing, it is assumed that all detected mining areas can only be potential mining areas. With the potential mining areas in question, a region of interest (ROI) can be defined to be investigated with very high-resolution (VHR) satellite data. Secondly a transferable feature extraction scheme within an object-based image analysis environment is applied to the previously mentioned VHR data to extract the potential mining areas within the ROI. And thirdly, a multi-temporal change detection analysis on the basis of the formerly applied VHR-analysis is conducted to monitor and evaluate the evolution of the detected potential mining areas.

The described methodology has a number of advantages: (1) It allows for the coverage of large survey extents and the identification of hot spots of activity by investigating HR data sets; (2) highly detailed analyses of the detected hot spot areas can be conducted as a direct follow-up of the HR-analysis and (3) the multi-temporal monitoring reveals changes over time, allowing more qualitative statements about developments and trends.

2. Mining and Conflict in the Democratic Republic of the Congo

The Democratic Republic of the Congo possesses large amounts of mineral deposits throughout the country. In the sediments of the Congo Basin, gemstones and precious metals can be found, whereas in the eastern provinces, near the African Great Rift Valley Zone, rare and highly valuable minerals like coltan, cassiterite and wolframite are mined. Coltan is a technical term composed by the first syllables of the two nouns columbite (also known as niobium) and tantalite. The latter is of extraordinary value for the electronics industry, more precisely the semiconductor industry. Because more than half of the world's known coltan reserves are found in the DRC, the global high-tech industry highly depends on Congolese coltan [7]. Cassiterite represents the basis of tin, which is also of high value to the electronics industries. Coltan and cassiterite often appear in close spatial proximity and can both be mined using artisanal methods [21].

Other types of metals and gemstones of great value are exploited in the DRC, all of which are indispensable for global industrial production [21], but are nonetheless beyond the scope of this study.

2.1. Artisanal and Small-Scale Mining

An issue of particular importance with respect to the exploitation of natural resources is the way they are exploited.

Although there are official mining concessions defined throughout the DRC, their existence does not necessarily entail an on-site enterprise that exploits the minerals with large-scale industrial methods. Especially in the eastern provinces North Kivu, South Kivu and in some parts of Katanga, artisanal and small-scale mining techniques (ASM) by civilians are the most common methods of obtaining minerals [22]. Working with a shovel and a pickaxe represents the most comfortable way of mining; most miners use their bare hands or inadequate tools such as hammers and chisels, as shown in the photographs in Figure 1.

Figure 1. Examples for artisanal and small-scale open pit mining in eastern DRC.

A large proportion of the sites are controlled by armed paramilitary groups, forcing civilian workers to pay taxes and entrance fees [23,24].

The most urgent problem of the ASM is the lack of security for miners—especially for women—who frequent the mines on a daily basis, hoping to find some grains of ore which they can sell to local traders [25,26]. For many of them, this is the only way to earn a direct income. One of the few alternatives would be to work in the agricultural industry, where income is significantly lower than and not as direct as selling minerals [24]. This is the reason why many workers, especially young women and men, join the mining teams and abandon traditional agriculture [7].

2.2. The Conflict Situation

Especially in the eastern provinces of the DRC, the absence of governmental authority leads to state-like parallel structures, resulting in armed groups, non-integrated brigades of the army and militias controlling both concessional and non-concessional mining fields. The national budget rarely benefits from these revenues of the mines, which are redirected into the financial backing of the mentioned armed groups. Thus the Congolese state hardly ever profits from the abundance of mineral resources. This fact is called the "paradox of abundance" [1] or the "resource curse" [10,27], as illustrated in Figure 2.

Figure 2. The paradox of abundance: How conflict commodities fuel warring parties and how the latter seek for revenues from the abundance of natural resources.

On the one hand, warring parties generate their revenues by exploiting minerals and thus grow more influential and powerful. On the other hand, the nation scarcely profits from the abundance, which weakens the nation and subsequently leads to an increased inability to maintain its sovereignty. Once this development gains momentum, a constantly revolving circle begins to spin, steadily weakening the sovereignty of the nation and empowering the warring parties.

3. Study Area and Data

North Kivu and South Kivu are located in the easternmost part of the DRC, sharing borders with the adjacent states of Uganda, Rwanda and Burundi. The topography is characterized by high diversity, beginning with an undulating landscape in the west up to the mountainous border region in the eastern part of the provinces. This mountain range is part of the western branch of the Great African Rift Valley Zone, reaching from North to South along the eastern national border of the DRC. The shores of the Great Lakes serve as part of the national borders to neighboring countries [28].

In the scope of this study, high-resolution (HR) as well as very high-resolution (VHR) imagery is used in order to conduct the multi-scale approach which will be described in detail in the methodology section. To cover a large area with HR data to identify hotspots of activity, the region of Southern Masisi (Figure 3, orange box) was chosen. This area has been pre-selected after detailed inspection of the eastern provinces of the DRC based on the fact that it comprises some known mining sites whose locations have been gathered from the "interactive map of militarized mining areas in the Kivus" [29]. During the analysis, the focus area of Mumba-Bibatama was identified for further investigation, highlighted as a light blue box in Figure 3. To better describe the approach and to verify the results of the detailed analysis, an additional area was defined that is not covered by the HR data. Only for this mining site of Bisie were reliable and pre-assessed information from local reports and statistics available for the period of the analysis and especially during the period of the mining ban in the Kivu provinces. This is due to the fact that Bisie is known as an official mining site as well as one of the largest sites in the eastern provinces. An estimated number of 1000 miners exploiting cassiterite are reported to work in this area. In much smaller quantities, coltan, diamonds and bauxite deposits are also found. The 85th non-integrated brigade of the Forces Armées de la République Démocratique du Congo (FARDC) was reported to be in charge of the mining site, levying taxes and admission fees for their workers [30]. A mining ban during October 2010 and March 2011 brought a major change in the security situation in the entire region. The military was withdrawn from mining sites as well as trading centres and a mining police force was established. Unfortunately, this mining police was under-staffed and under-financed which resulted again in increased activities of armed groups [31].

Figure 3. Study areas in North Kivu and South Kivu. Orange: study area for the analysis of HR data; light blue: study areas to be investigated with VHR data.

The other study area of Mumba-Bibatama is located further in the Southeast in a mountainous and agricultural region. This environment reflects the transitional zone from rainforest to savannah. Mumba-Bibatama is known as a sites where coltan and cassiterite are exploited [29]. There is no official concession for this area [32]. Furthermore, the digging sites are considerably smaller and dispersed [30]. The mining areas of Mumba-Bibatama were reported to be under indirect control of the CNDP (Congrès National pour la Défense du Peuple) in 2008 [30] and 2011 [33].

In order to guarantee maximal transferability of the method, different sensor types were used. An overview of the satellite images is shown in Table 1.

Table 1. Satellite imagery [1]—overview.

Location	Satellite	Aqcuisition Date (day/month/year)	Resolution (m pansharpened)	Extent (km)
Southern Masisi	RapidEye	1 October 2010	6.5	50 × 50
Bisie	GeoEye-1	2 April 2010	0.5	10 × 10
	GeoEye-1	8 September 2010	0.5	10 × 10
	IKONOS	10 March 2011	1	10 × 10
Mumba-Bibatama	GeoEye-1	17 August 2010	0.5	10 × 10

[1] RapidEye: ©RapidEye, www.rapideye.net; GeoEye-1 & IKONOS: ©GeoEye, Inc. (2010, 2011), provided by e-GEOS S.p.A. under GSC-DA.

Pre-processing steps applied to all images included the orthorectification and geometric correction to UTM Zone 35S (WGS 84) [34] as well as an atmospheric correction using Atmospheric/Topographic Correction for Satellite Imagery (ATCOR) [35]. The Geoeye-1 and IKONOS data were pan-sharpened to 0.5 and 1 m, respectively.

In addition to the satellite imagery, ancillary thematic data was available within the scope of the project. This data provided a set of features, such as rivers, tracks and settlements collected and digitized by DLR. It should be mentioned that the first two are polyline-vectors and the latter is a point-shapefile. Thus, the thematic layers are used as indications and refinements during the classification procedure.

4. Methodology

4.1. Geographic Object-Based Image Analysis

For the integrated analysis of the satellite imagery on multiple scales, Geographic Object-Based Image Analysis (GEOBIA) approach implemented in eCognition 8 using Cognition Network Language (CNL) was selected. With the increasing availability of high- and very high-resolution satellite sensors [36], the images thus obtained provide small-scale details about the Earth's surface and reveal additional facets which demand adequate image analysis and interpretation techniques [20,37]. Along with the increasing resolution towards less than 1 m, new application fields became increasingly important. With regard to this sub-meter resolution where even smaller objects consist of several pixels, the question of why analysis should still focus on statistical values of single pixels rather than on spatial concepts arose [38–40]. In conjunction with the rising demand for GIS-ready information—for which raster data is not well-suited [41]—this provided the basis for transferring the concept of object-based image analysis already used in computer vision or biomedical imaging to the remote sensing domain in order to complement the more traditional pixel-based methods [38,39].

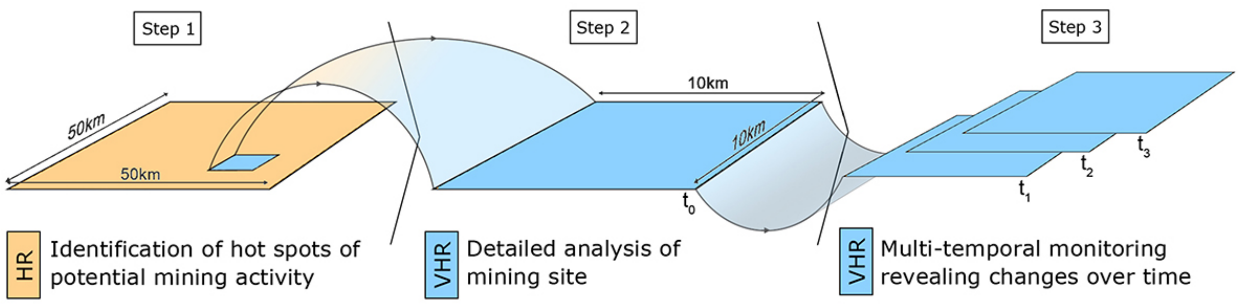
Classification starting from image objects which are generated by grouping homogenous pixels can utilize additional features next to the spectral information and have the advantage of incorporating spatial concepts such as pattern, location and neighbourhood. Different algorithms have been developed [42], first and foremost the multi-resolution image segmentation implemented in the software eCognition [43]. This bottom-up, region-growing approach aggregates surrounding pixels according to pre-defined criteria of homogeneity through a combination of different parameters, *i.e.*, scale, color and shape. Subsequently, spectral, contextual, textural as well as hierarchical information can be used to classify the features of interest [44,45]. Owing to its bridging effect through remote sensing and GIScience concepts, it was recently proposed to extend the term Object-based image analysis (OBIA) to "Geographic Object-Based Image Analysis" (GEOBIA) [39,46,47]. A review of the use of OBIA in remote sensing is given by Blaschke [39], who leaves the question open of whether or not OBIA is a paradigm. However, most recently Blaschke *et al.* [40] concluded that GEOBIA is a new and evolving paradigm.

4.2. Workflow

The illustrated workflow contains a further development of the multi-scale image analysis approach conducted in [20]. Schoepfer and Kranz [20] focused on the conceptual design of the approach. In their study, a basic land cover classification on the HR data was performed to assess the potential of the workflow without performing a detailed analysis of the VHR data. Within this preliminary study the potential of the overall concept was proven, thus in the present study, the whole workflow was applied based on [48], *i.e.*, identification of potential mining areas within the HR data and a detailed assessment of two mining sites by the analysis of VHR imagery. Conducted in the rule-based classifier environment of eCognition8, the innovative aspect of the approach is the design of the rule-sets.

The first step is to analyze HR imagery to ensure the coverage of large survey extents for the detection of potential mining areas. Subsequently, VHR imagery is analyzed to investigate the previously defined "Region Of Interest" (ROI) in high detail. The final step is to conduct multi-temporal monitoring of the detected areas of potential mining on VHR data. This procedure is shown in Figure 4.

Figure 4. Staggered workflow of the analysis.



The purpose of identifying hot spots of mining activity is to guarantee effective coverage of a large survey extent as well as the use of spatial resolution where mining sites are still detectable. One way to pursue this is to focus on spectral information only at this stage of the processing chain. Focusing on these potential mining sites, a ROI is created with a minimum size of 10 km $\times$ 10 km. All ROIs are additionally approved by experts to decide whether an order for VHR imagery is to be placed. A more detailed description of the identification of hot spot areas is provided in Section 4.3.

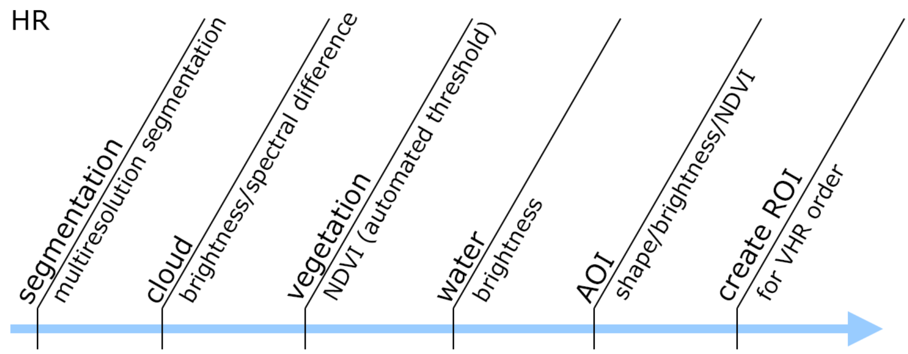
The detailed analysis of potential mining areas on VHR imagery is conducted on the previously determined ROI. The analysis of VHR data enables the initially identified hot spot of mining activities to be described much more precisely and to give more detailed indications of what might be happening in and around the mine itself. A more comprehensive description of this analysis procedure is given in Section 4.4.

The multi-temporal monitoring approach presents the final stage of the workflow. Its objective is to reveal changes over time concerning the extent of a potential mining hot spot area. The analysis itself resembles that of the preceding detailed analysis, enhanced by a post classification comparison. With eCognition8 software, two separate maps can be used to conduct the classification and subsequent synchronize the results for comparison. With respect to the primary objective of the study, only areas showing increase were considered during change detection analysis. A detailed description of this issue is provided in Section 4.5.

4.3. Identification of Hot Spots of Potential Mining Activity in Southern Masisi

At the beginning of the HR analysis, the creation of objects by means of a multi-resolution segmentation is carried out [43]. Since the potential mining areas consist only of few pixels within HR imagery, small objects are considered to be more suitable for the detection of potential mining sites. Thus the segmentation scale is adjusted to create small objects. This also explains the reason why coarser, medium-resolution satellite imagery is not suitable for the purpose of this study. The detected areas of interest (AOI) are of fairly small size and therefore we assume that less than 10 m of resolution is about the limit for detecting these small objects. The subsequently elaborated classes are used to create areas to be excluded from further analyses, such as dense forest, clouds or water bodies (*cf.* Figure 5).

Figure 5. Classification sequence for HR analysis with class (above line) and corresponding features/classification rules (below line) implemented in the rule set.



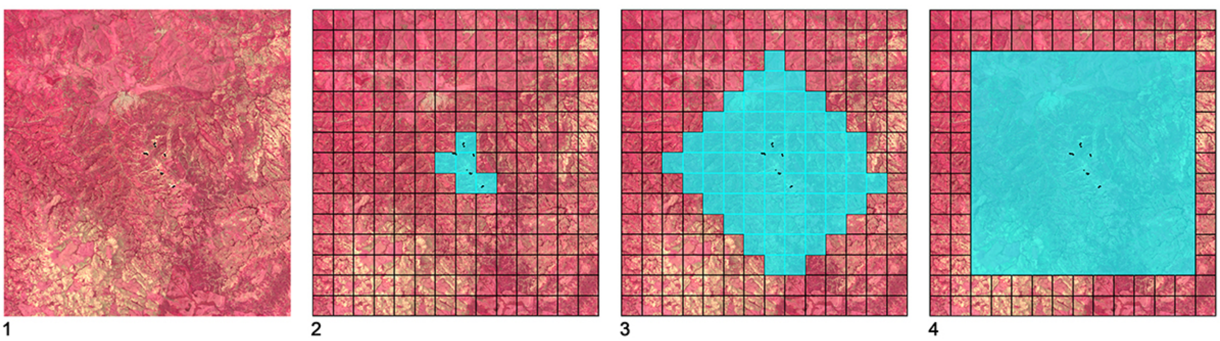
Clouds are classified using an interface of spectral values, aiming at the high values of brightness inherent to clouds. Since vegetation and potential mining areas are mutually exclusive classes, a threshold of the Normalized Difference Vegetation Index (NDVI) is applied to classify vegetated areas. The threshold chosen is as close as possible to the values of the potential mining sites in order to maximize the exclusion effect and is assessed by an iterative procedure using expert knowledge. The classification of water bodies is also a key issue because proximity to water can be a significant indicator for the existence of potential mining sites.

After clouds, vegetation and water bodies are classified, the exclusive areas are elaborated. The classification of potential mining sites—in the following called AOI—is then performed by an interface of firstly, a fairly low value of the NDVI, since there is hardly any vegetation, and secondly a high brightness value owing to their high albedo in all spectral bands typical for bare soil. However, because of some residual uncertainty, a further measure of refinement is conducted. By means of neighboring, distancing and geometric elements, the AOIs are further refined. Subsequent to this fully automatic detection, a more precise visual inspection of the resulting potential mining sites eliminates those sites that are bare soil, but too remote from settlements or at least dwellings, water bodies/rivers and roads, which all can be seen as necessary infrastructure to be expected in the vicinity of a mining area. A more specific analysis of the remaining potential mining sites is conducted on the VHR satellite images.

Building upon the AOIs, the exclusive areas become dispensable. The image is again tesselated using a rectangular segmentation algorithm where the tile size depends directly on the pixel size of the underlying satellite image. This ensures a typical tile size of approximately one kilometer, which is of importance to grow a ROI around the areas of interest classified.

The complete growing process is visualized in a series of stages in Figure 6. Starting with the deletion of the exclusive classes in (1), a rectangular segmentation with a border length of approximately one kilometer is created. Those cells containing one or more AOIs (2) are defined as the starting point for the subsequent growing process (3). Region growing is performed in all directions resulting in a rhombus. In order to restore a rectangular ROI, all unclassified tile sizes which share at least 50% of their border with a tile size classified as ROI are also classified as such. Part (4) depicts the result: A rectangular ROI, approximately 10 km $\times$ 10 km in extent, including the areas of interest precisely in the centre. These squared ROIs constitute the basis of a request for VHR imagery, for which the minimal size to be ordered is 100 sq km. In terms of a service workflow, automated region deliniation is highly valuable.

Figure 6. Screening of large survey extents: (1) Identification of seed points; (2) rectangular grid; (3) region growing; (4) ROI for VHR order.



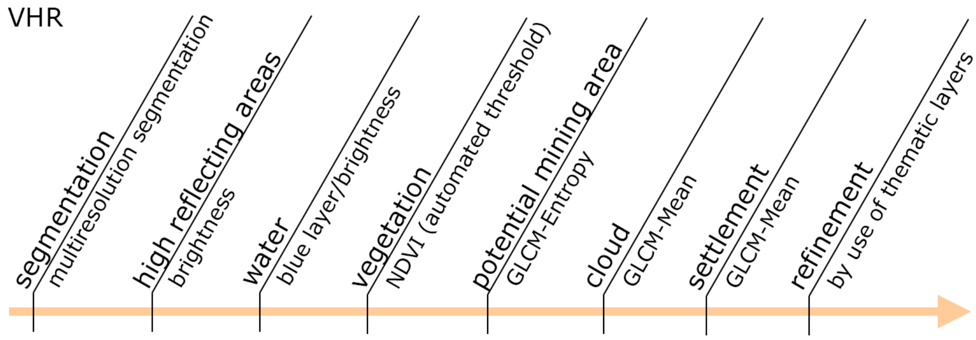
It is important to note that the ROIs generated can still contain misclassified AOIs. Thus a visual validation of the ROIs by an expert is indispensable before ordering VHR data. Only if the result of this validation is positive should the next stage of the workflow be initiated.

4.4. Detailed Analysis of Mining Sites

The detailed analysis of mining sites was conducted for both sites, for (1) Mumba-Bibatama since it represents the ROI detected from the HR analysis, as well as for (2) Bisie, which acts as verification site within this study. The results of the analyses are presented in Section 5. In Section 4.4, technical and methodological aspects are explained in detail (*cf.* Figure 7).

"Streets", "rivers" and "settlements" are the three classes available from thematic layers mentioned in the Section 3. These layers are imported to an object-based classification rule set using the Cognition Network Language (CNL) [49]. According to Tiede *et al.*, CNL "enables addressing single objects and supports manipulating and supervising the process of building scaled objects in a region-specific manner" [49]. During the following classification procedure, the thematic layers are used as indications and additional refinements [43].

Figure 7. Classification sequence for VHR analysis with class (above line) and corresponding features/classification rules (below line) implemented in the rule set.



Initial classes with exclusive character—water and vegetation—are set up on the basis of spectral values. An automatically self-adjusting set of thresholds within the rule set ensures a highly objective classification of the aforementioned classes. Furthermore, a temporary class called "high reflecting areas" is derived. The latter contains potential mining areas as well as clouds and settlements since all three of them have significantly high reflectance values but cannot be subdivided on VHR data by spectral properties only. Thus the class "high reflecting areas" must be subdivided according to other properties. One option is to take textural properties of the objects into account.

eCognition8 provides several approaches for considering textural properties, whereby a well-established method is the Gray-Level Co-occurrence Matrix (GLCM) [50]. This formula describes the neighboring gray-level values by means of a matrix of neighboring gray-level occurrences. For the purpose of subdividing the "high reflecting areas", two different kinds of these GLCM features are applied in this study. GLCM-Entropy, which is a measure for the chaotic gray value distribution of neighboring pixels within one object, and GLCM-Mean, which focuses on a smooth and regular gray value distribution of neighboring pixels within one object.

In the course of the analysis, the GLCM-Entropy feature proved to be a suitable feature for the purpose of subdividing "high reflecting areas" as well as distinguishing between potential mining sites and adjacent vegetation areas. Vegetation is represented by a smooth and regular distribution of gray value, whereas a chaotic distribution is inherent to bare soil areas. The maximum value of the GLCM-Entropy feature is detected automatically. With expert knowledge, an alterable percentage of this maximum is calculated by an arithmetic expression. The exact formula is presented in Table 2. The term "var" represents the adjustable lower value limit, whilst "x" stands for the value range between the maximum and "var". Since the threshold between potential mining sites and sparsely vegetated areas is subject to variation and depends on the specifications of each satellite image, the percentage range needs to be adjustable. Once the value range has been determined, the "high reflecting areas" applying this range are classified as potential mining areas. Subsequent to the classification, the pixel-based growing algorithm is applied to ensure a highly accurate acquisition of the potential mining areas.

Table 2. Definition of potential mining area and cloud classification.

Class	**Value Range**	**Arithmetic Expression**
high reflecting areas	Maximum-var	GLCM-Entropy-MAX $>=$ x $>$ GLCM-Entropy-var%
cloud	Maximum-var	GLCM-Mean-MAX $>=$ x $>$ GLCM-Mean-var%

The penultimate classification step encompasses a separation of the remaining "high reflecting areas" class into the subordinate classes of "clouds" and "settlement areas". This distinction is made by use of the GLCM-Mean feature according to [50]. It takes into account the regular and smooth distribution patterns of neighboring gray-level values within the objects. This feature is important for cloud signatures, which are subject to highly regular patterns as opposed to settlement areas which are composed of different sizes of buildings and paths.

The calculation of the second alterable percentage range is also presented in Table 2 and should be carried out with expert knowledge. All objects in the superordinate class which apply the range between the maximum and the determined lower value limit are classified as clouds.

The last step in the scheme presented is to classify the remaining "high reflecting areas" objects into the class "settlement area", since only objects that represent settlement areas remain in the superordinate class. At this point, the thematic layer "settlement" is taken into account. This makes it possible to reclassify distinct objects, firstly with regard to their directly neighboring objects such as rivers and streets, and secondly with regard to a distancing function, which is useful in the case of available settlement points. The refinements are to be carried out after visual interpretation of the classification result to avoid misclassifications.

With regard to the arithmetic expressions used during the detection of potential mining areas, a differentiation between arithmetic expressions for the vegetation classification and the textural calculations is obligatory. The former is a static expression which adopts the values of a given imagery and thus defines the thresholds for the classification in a fully automated manner. The latter, used for the classification of potential mining areas and clouds are expressions that require adjustments of the thresholds on the part of an experienced user.

The rule set described above applies to all four satellite imageries, *i.e.*, Bisie (3 images) and Mumba-Bibatama. The procedure was carried out and validated repeatedly. After this mono-temporal analysis, a multi-temporal approach involving two distinct points of time can be acrried out. This enables the user to detect changes over time. The corresponding procedure is described in Section 4.5.

4.5. Multi-Temporal Monitoring

The rationale for the multi-temporal analysis carried out for the Bisie mining site was due to two considerations: Firstly, the site is well-known among experts and local reports as well as statistical numbers are available. Thus it is possible to compare and to verify the findings of this study using on-site information. Secondly, there were three satellite images available, which enables change detection over different points in time.

Several preconditions have to be considered in the case of a change detection analysis. First of all, the result of change detection is strongly influenced by environmental factors such as soil moisture or plant phenology. Secondly, different techniques to detect a change are available [51–54]. For the purpose of this study, the post-classification comparison according to [36] was chosen, thus the results of the above-mentioned mining site detection using different points of time were compared with each other. It should be mentioned that change detection is conducted fully automatically and not refined manually. Thus the changes revealed have to be interpreted carefully.

Change detection was only implemented for the three images of the Bisie mining site. The purpose was to assess whether the quality and extend of changes over time can be detected. For the most effective processing, a subset of the satellite images covering the mining area and its surroundings was created before applying the analyses. In this manner, the scenes to be compared are imported into two different maps, enabling the program to classify each scene separately. The analysis procedure for each map is the same but with adjusted values of each variable for the respective scene. Subsequent to the classification process, the post-classification comparison of both scenes is conducted on a third map. This approach ensures that it will be possible to return to a particular classification and to implement alterations at any time. On the change detection map, the class of potential mining sites from both input classifications is compared directly, and the change is detected through a simple scheme: Where both classes overlap, no change is detected. Where the former potential mining class and no later potential mining class is present, a negative change can be identified, *i.e.*, a decrease in extent. In contrast, where the later potential mining class and no former potential mining class are apparent, a positive change has occurred, representing an increase in extent.

4.6. Accuracy Assessment

An evaluation of the quality of the classification of satellite imagery is elaborated on the basis of accuracy assessments. With regard to this study, a sample-based accuracy assessment according to [55,56] for each classification was produced within eCognition8 software. The software offers the possibility to conduct a class-specific accuracy assessments, *i.e.*, the samples collected are compared to the target class only which is in the present study the class "potential mining areas". All other classes are considered exclusive classes and thus are not of major interest with regard to their accuracy. In the first place, the target classes are selected. This does not entail the fact that the samples have to be located inside these classes. The samples are selected in a second step, where the classification is set to invisible. In a third step, the selected class and the samples are compared and a number of accuracy is provided.

A distinction has to be drawn concerning the resolution of the imageries, which influences the number of samples collected since, with inferior resolution, the number of pixels representing the potential mining areas is smaller. With regard to the highest resolution of the GeoEye-1 data, 100 samples were collected to conduct the accuracy assessment. In terms of the resolution of the IKONOS imagery, 50 samples were collected. The RapidEye image of Southern Masisi provides a special case, since the object sizes cover only few pixels of ground data because of the coarser resolution of 6.5 m. Thus, the class of purpose is covered by only a few objects in the imagery. This explains why merely 27 samples were collected to conduct the accuracy assessment. Since samples cannot be selected randomly in eCognition8, an independent user collected the samples while the classification of the respective imagery was set to invisible. The total numbers of samples as well as the accuracy values are shown in Table 3.

Table 3. Accuracy assessments of all imageries classified.

Location	**Acquisition Date (day/month/year)**	**Samples Classified (*n*)**	**Samples Unclassified (*n*)**	**Producers Accuracy**	**Users Accuracy**	**Overall Accuracy (%)**
Southern Masisi	1 October 2010	25	2	0.926	1	92.6
Bisie	2 April 2010	93	7	0.93	1	93
	8 September 2010	94	6	0.94	1	94
	10 March 2011	91	9	0.91	1	91
Mumba-Bibatama	17 August 2010	93	7	0.93	1	93

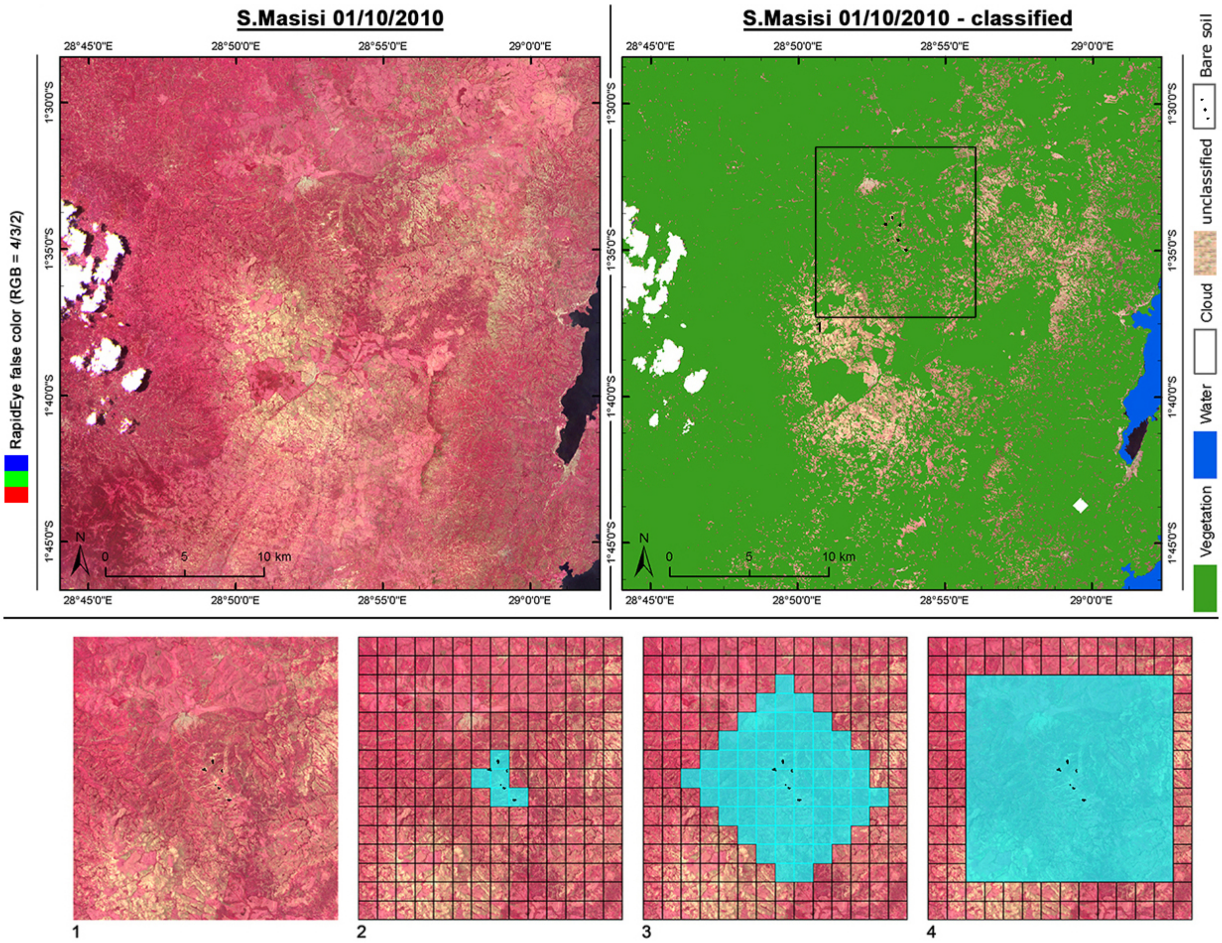
5. Results and Discussion

5.1. Results and Discussion for Identified Hot Spot Areas

The purpose of applying HR data in this study is to effectively detect potential mining areas over a large region, *i.e.*, an area of 50 km $\times$ 50 km. The classification is performed on the basis of spectral values only, as described in Section 4.3.

In Figure 8, the detailed classification of water, clouds and vegetation of the imagery for Southern Masisi is shown while the not classified areas are the remaining parts from the classification of exclusive classes. It is assumed that bare soil areas detectable with HR data are with high probability related to areas where mining could take place but they are not per se potential mining areas. Thus, a more sophisticated classification has to be conducted. Since ASM techniques are the most common methods of mineral extraction within the study area, mining sites are constituted only by few pixels on HR data with a respective resolution of 6.5 m. To tackle this challenge, an initial segmentation scale is applied which generates objects of the size of typical ASM mining locations in the region. The respective segmentation scale is assessed with expert knowledge. The resulting potential mining areas do not represent mining sites only, but also pure bare soil areas. Thus, a visual interpretation with expert knowledge or a comparison with on-site information is necessary to refine the classification result.

Figure 8. Upper map: Comparison of unclassified (**left**) and classified (**right**) imagery of Southern Masisi. Lower part: Sequence of ROI-definition as explained in Figure 6. The black box in the upper right map is equal to the subset shown in the ROI-definition sequence.

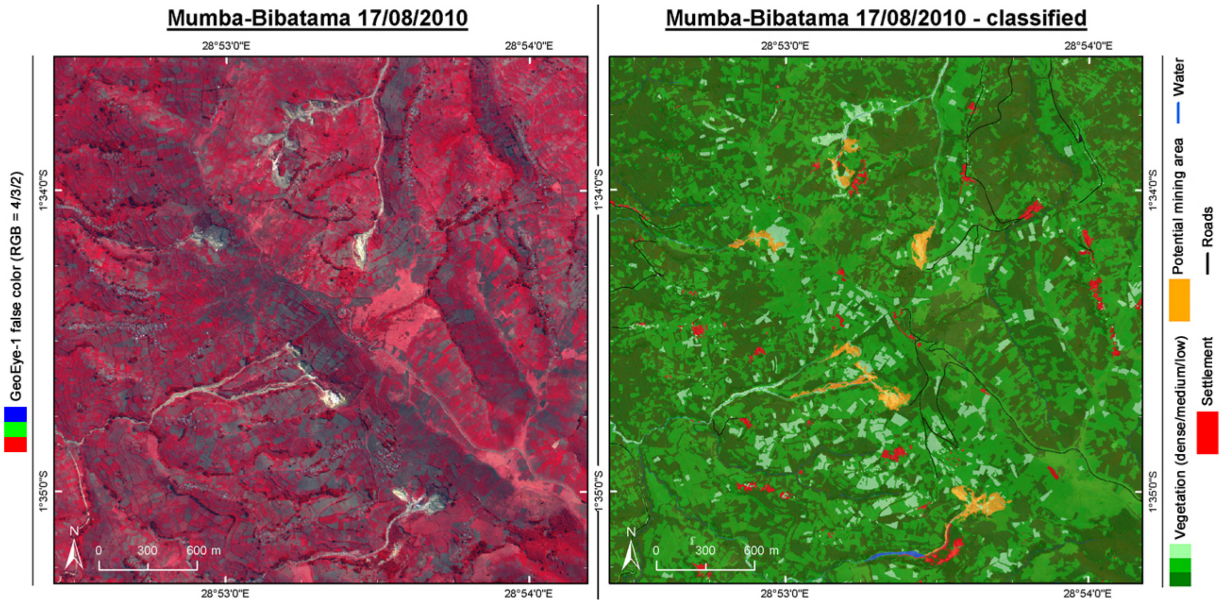


5.2. Results and Discussion for the Detailed Analysis

As mentioned in the methodology section, the rule set underlying all four of the analyses conducted is modified only with respect to a few alterable parameters.

The site of Mumba-Bibatama is presented in Figure 9. This area is of special interest for this study since there is no official mining concession to be found [32]. Despite the scarcity of local information, the mining sites detected are clearly visible on the hillside. The classification reveals that the proposed approach is able to detect the potential mining sites in at least a satisfactory manner. It should be mentioned that not all bare soil patches were classified as potential mining sites, a fact which is also reflected by the accuracy value in Table 3. Small and dispersed villages as well as water bodies and roads within the landscape were captured with the aid of the thematic layers.

Figure 9. Comparison of unclassified (**left**) and classified (**right**) imagery of Mumba-Bibatama.

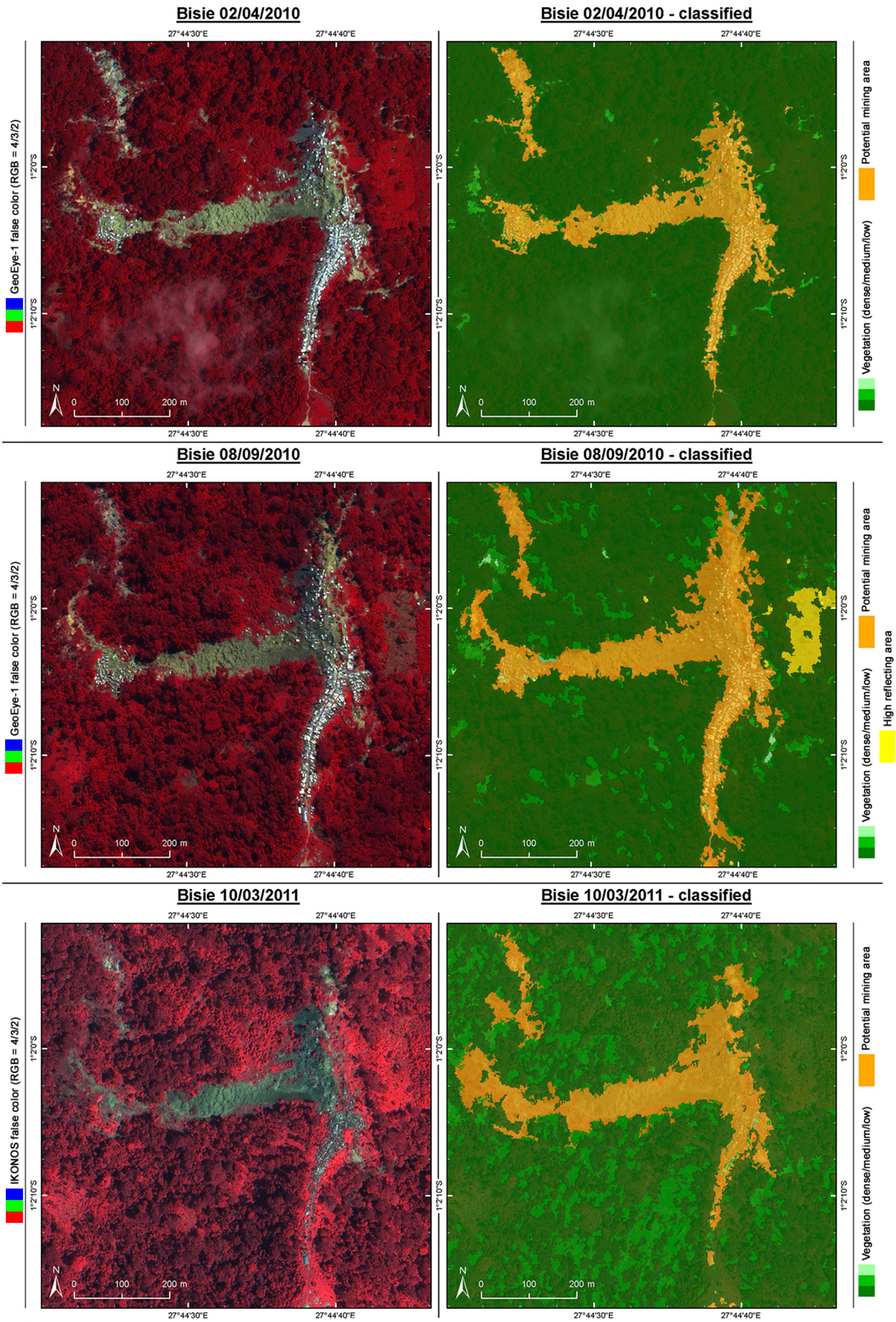


With regard to Bisie, it must be emphasized that the first two images were sensed by the GeoEye-1 satellite, while the third image was gathered by the IKONOS sensor. Thus, the spatial resolution and hence the resolution of the classification results differ between these data sets. Figure 10 shows the unclassified images and the classifications at three different points of time. Within all classifications the larger structures and dwellings on the eastern topside of the hill have not been classified explicitly. Owing to their immediate vicinity to the mining site taking into regard the focus of this study, it is estimated that they form part of the on-site infrastructure.

The mining site—mainly composed of bare soil and located in close proximity to dense forest—is captured almost to the full extent. Smaller areas of bare soil found in the adjacent rainforest are also captured and classified as potential mining areas. However, not all mining areas are identified, which is reflected in the classification accuracy values listed in Table 3. The classification result for the 8 September 2010 shows an additional clearing area to the east of the hill crest. The clearing area can be interpreted as an area where firewood or building timber is harvested. The most recent satellite imagery of the mining area of Bisie is shown in the lower part of Figure 10. It is noteworthy in the case of this image that the resolution is half the value of the two preceding images, which poses problems especially with regard to monitoring. Despite the considerable reduction in details in the image, which aggravates the classification process, the latter produced satisfying results for the image of the 10 March 2011, as confirmed in Table 3. Thus, it can be stated that, for the study at hand, the transferability and interoperability of the rule set between the different resolutions and sensors is proven.

With regard to the clearing area identified in the imagery of the 8 September 2010, the vegetation has regrown during the period from September to March. This fact reinforces the notion of aligning firewood or building timber area with regular harvesting cycles.

Figure 10. Comparison of unclassified (**left**) and classified (**right**) imagery of Bisie.



5.3. Tracking Change over Time

The Bisie mining area was monitored between April 2010 and March 2011, based on a consecutive comparison of images for three points in time. As explained in the methodology section, distinct classifications are conducted for the different points in time and then superimposed on each another, *i.e.*, blended.

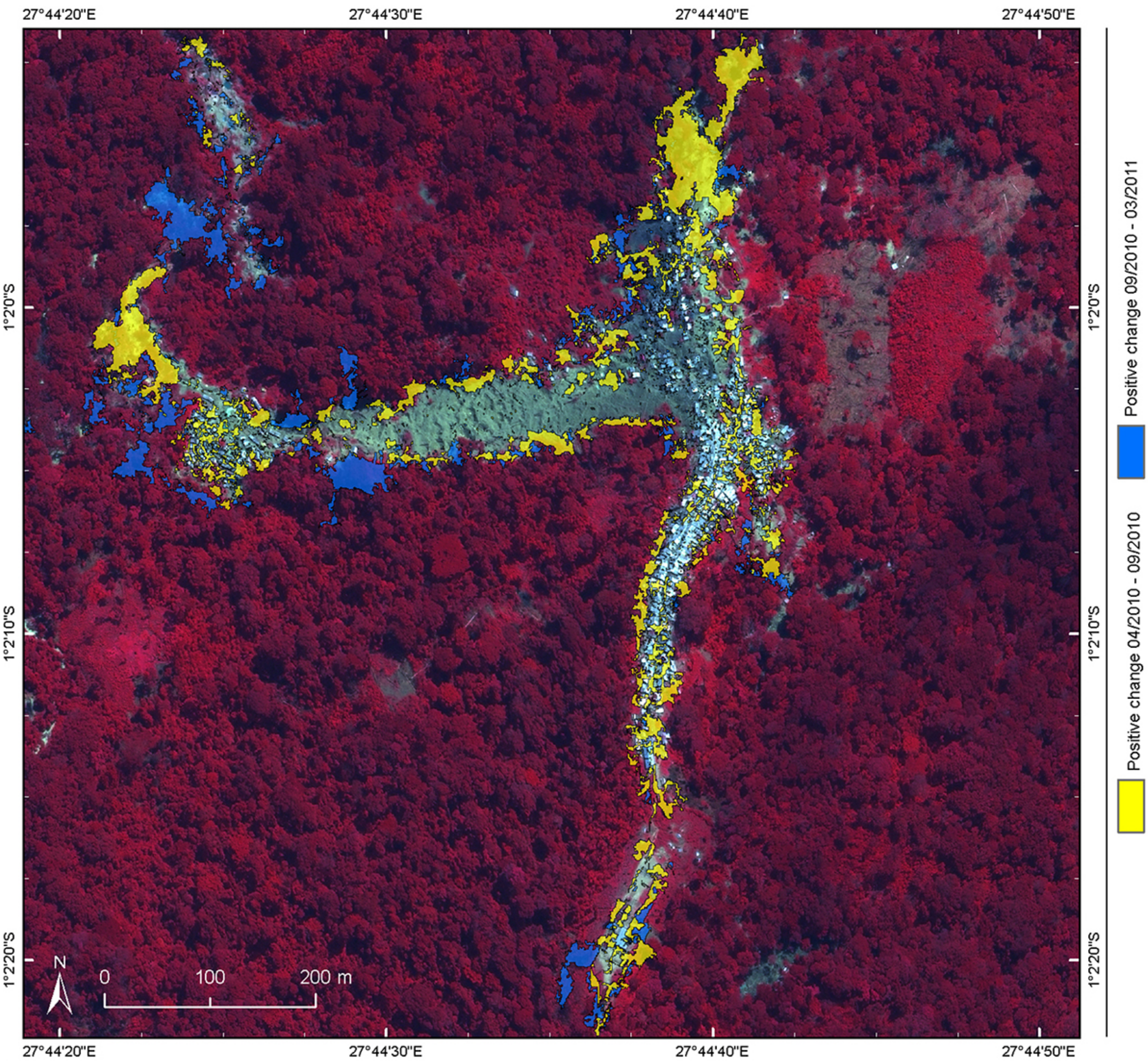
Positive changes are detected by focusing on the class "potential mining areas", since this indicates an increase in the extent of the Bisie mining site during the aforementioned period (*cf.* Figure 11). Negative changes are also detected but merely negligible and thus not presented. At this point it should be stated that the detected changes are based on an automatic analysis only and have not been manually adjusted. One reason—among others—is the lack of ground truth information with which the results could have been corroborated. Thus, both positive as well as negative changes have probably been overestimated. Nevertheless, the results give some indications about an-going acitivites in and around the mining site of Bisie. These can be linked to available local reports and statistical data. A more detailed comparison with such statistical data, e.g., the amount of cassiterite trade at local trading centres as carried out by [31] in 2011 provides substantial information and makes it possible to judge whether the results from remote sensing analysis and the trading statistics correlate and indicate the same direction of mineral extraction.

In [31] it is stated that cassiterite was traded directly after the lifting of the ban. Although the amount of 1,148,302 kg could have been taken from the stockpile together with newly mined 128,366 kg—which seems to be possible when looking at the monthly average export volume from 2010—the authors clearly state that there are further signs suggesting that mining activities were continued during the ban. It is assumed that the extracted cassiterite was smuggled out of the DRC [31]. This integration of statistical data and information gathered from reports seems to be a promising approach for reaching higher reliability especially in regions where ground surveys—which of course would provide more evidence—are hampered for security reasons.

The change between 2 April 2010 and 8 September 2010 will be described first. Figure 11 depicts the area of positive change during this time period in yellow colour. Especially in the northern part of the eastern hill crest and in the valley basin, new surface patches have opened. But not only in these regions can an increase of the mining area be observed. Also in the periphery of the mining ground, smaller parts have grown following the hillside and in the periphery of the housing and dwellings along the hillcrest. This could be a good indication for a simultaneous expansion of the settlement, hinting to an increase in the number of mine workers.

The second change detection to be addressed is the change between 8 September 2010 and 10 March 2011, represented by the blue signature in Figure 11. It has to be emphasized that this reflects a comparison of two different spatial resolutions, *i.e.*, a resolution of 0.5 m for the GeoEye-1 imagery of September 2010 and a resolution of 1 m for the IKONOS imagery of March 2011. This fact complicates the detection of changes, since the level of detail is not the same for both on both images. For example, a clearly detectable small object at the superior resolution is barely detectable on the image with the inferior resolution, thus directly influencing the result of the change detection. Since the approach does focus on very small objects, the authors state that the difference in resolution does not have a high impact on the result of the change detection, but must be kept in mind for the change interpretation. Thus, the comparison is conducted and the resulting changes indicate again an extension of the mining site. This further increase in the bare soil areas can be identified especially in the lower parts of the hillside, in the downhill region and in the valley floor. Besides these changes, smaller modifications concerning the extent of the potential mining site can be observed around the larger buildings and dwellings on the hill crest. Similar to the preceding change detection, a quantification of change cannot be regarded as certain or accurate. Measuring errors take on more importance because of the difference in spatial resolution.

Figure 11. Yellow color represents increase (positive change) in surface area from April to September 2010; blue color shows increase (positive change) in surface area from September 2010 to March 2011. Negative changes are merely negligible and thus not displayed.



Nevertheless, the outlined extension of the mining area during September 2010 until March 2011 is of special relevance. As already mentioned in Section 3, exactly within this time frame a mining ban was announced by the Congolese Government (see Section 5.4). Although the results do not provide confirming evidence, the further extension of the mining area indicates that mining activities continued in Bisie during the ban [31].

5.4. Political Background Related to the Remote Sensing Results

In response to growing international pressure to end the financing of Congo's conflict through minerals, President Joseph Kabila announced a ban on all artisanal mining activities in three eastern provinces, *i.e.*, North Kivu, South Kivu and Maniema, on 11 September 2010 [24,31,57]. The official intention was to stop the illegal organization of mineral exploitation and trade, indicating that the link between the activities and insecurity in the region had been recognized [57,58]. An additional explanation for proclaiming the ban might be to secure large industrial investments in Kivu's mining sector. Nevertheless, this sudden activity raised the question of the effectiveness of the directive and has left even the experts at the Ministry of Mines struggling with the implementation of the ban [59]. The prohibition was proclaimed only a few days after the second imagery of Bisie was captured (8 September 2010). It clearly affected artisanal miners, but progress in formalizing and certifying trade seems to show no further improvements as a result of the ban [60]. Concerning demilitarization, it has been reported that soldiers themselves started to dig and refused orders to leave the mines [57]. "No action was in fact taken against the so-called mafia-like military and civil elements the ban set out to dismantle. The military became miners themselves and forced civilians to assist them in exploiting the minerals—a form of forced labour known as "salongo". Both the UN Group of Experts and Congolese human rights groups reported of the widespread use of forced labor at mines, in particular at Bisie" [31].

The mining ban was lifted on 10 March 2011, as reported by several sources [60–62]. Fortunately, the third satellite image was taken exactly on the day of the abolition of the prohibition and thus it was possible to monitor the activities during the mining ban at Bisie. Indeed, it can be stated that the mining area and its surroundings expanded significantly from September 2010 to March 2011. Although the increased areal extension serves as an indication for increased mining activities, the pure change between the two satellite images does not provide proof. But together with ground observations, one fact becomes clear: mining activities continued in Bisie during the ban [58,60], even though the production volume went down considerably [31,62]. Military units even increased their control on exploitation and trade, which prolonged the bad humanitarian situation.

6. Conclusion

The current conflict in the eastern parts of the DRC is accompanied by the militarization of mining. In many mines of North and South Kivu, the exploitation and trade of mineral resources, in particular cassiterite, gold, coltan and wolframite are controlled by armed groups [7] that profit from illicit exploitation of natural resources while governmental authority in the provinces in question is constantly weakened [1].

Political intervention by supranational organizations or expeditious and efficient reaction in terms of humanitarian aid can only be accomplished by means of reliable information about the on-site situation. The present study aims at providing such information in terms of the detection of potential mining sites and thus complementing information gathered from local reports. Analyses of these sites are assumed to yield substantial information on the current location of epicentres of conflict. The findings of the present study can be utilized to facilitate decision-making regarding political intervention or humanitarian aid as well as to provide opportunities for monitoring future conflict situations. In this context the utilization of advanced Remote Sensing techniques following a multi-scale and multi-temporal approach is the major innovation of the presented study. The staggered workflow of the detection of ROIs by means of HR data and consequently the more detailed analysis of potential mining sites by use of VHR data can be considered as a promising approach for providing important added value information about the local situation in the mining areas. The example of the southeastern site Mumba-Bibatama, where scarcely any local information is available and the results of change detection analyses during the mining ban imposed by President Joseph Kabila from autumn 2010 to spring 2011 can be seen as a proof of concept. Together with ground observations, the detected expansion of the mining area in Bisie suggests that mining continued at this mining site during the ban. This additional information derived from satellite imagery has been called "the clearest sign of continued mining activities at Bisie" [31] by the International Peace Information Service (IPIS)—a research centre supporting governmental, non-governmental and intergovernmental development actors. In the IPIS study, the increase in the mining area has been compared with official statistical information about cassiterite trade in the region, and the authors raise the question of whether the cassiterite mined during the ban was smuggled out of the country [31]. These are good examples of the added value of information generated through the analysis of satellite imagery in conjunction with socio-economic data.

Prospectively, the estimation of population at the mining site through a more detailed analysis of the settlements structure would be of added value. A comparison of such data with in-field information coming from reports would allow for the monitoring of workers in the mine and could be regarded as another indication for an increase or decrease in the exploitation activities. Finally, the analysis of satellite stereo data with the objective of extracting digital terrain models for a more precise estimation of the activities within the mine (e.g., excavation of material) and also in its vicinity (e.g., changes in forest structure or structure of settlements) would provide added value information.

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Author Contributions

The methodological approach underlying this study was developed by Elisabeth Schoepfer and Olaf Kranz under the European Union's 7th Framework Program project G-MOSAIC (Contract No. 218822) at the German Remote Sensing Data Centre (DFD) of DLR, Oberpfaffenhofen. Fritjof Luethje further refined this approach in his diploma thesis. Fritjof Luethje implemented the methodologies and conducted the research. Elisabeth Schoepfer and Olaf Kranz conceived the concept of the study, supervised and coordinated the research activity and contributed to revision.

Conflicts of Interest

The authors declare no conflict of interest.

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