MONITORING FLOODING DAMAGES CAUSED BY MINING ACTIVITIES

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ABSTRACT

Coal and steel mining has long been one of the most important economic activities in Germany, particularly in the Ruhr area. According to the Directive 2006/21/EC article 13, mining companies are responsible for the environmental impacts derived from their activities and must implement compensatory measurements. Ground removal during the extraction of the mineral provoke permanent changes in ground compacting. During mine exploitation and even after mine closure, the surface above the galleries or close to open mine pits may experience ground movements and subsidence. In some extreme cases, the substrate can collapse or reach groundwater level, with the consequent emergence of a flooded area in surface. The objective of the present study is to locate mine-related flooding using remote sensing techniques. Only few operational platforms provide continuous spatial and temporal data that can be used to track temporal phenomena such as flooding at landscape level. RapidEye has been selected for presenting high temporal resolution and a fine pixel size, which permits the identification of small mine-related flooding areas. As a trade-off, RapidEye is a multispectral sensor, reducing the accurate delineation of water masses, and was launched relatively recently, in 2009. Moreover, the spectral discrimination of flooded areas is particularly difficult, since they are usually shallow waters where the bottom can be seen, leading to a non-pure water spectral signature. Besides, the challenge of this study is to distinguish natural or human-made water masses from mine-related flooded areas further from delimiting water masses, which is intended to be overcome with the multi-temporal analysis. In this study we are proposing simple and semi-automatic methods to locate potential mine-related flooded areas that can be implemented in a spatial data infrastructure (SDI) with a user-friendly geoportal in order to be used by mining and environmental institutions. The tool is intended to support the evaluation of damages derived from mining activities and provide spatial and temporal information for their management at a landscape level.

INTRODUCTION

The Ruhr area in Western Germany has a large tradition in coal and steel mining, which has been the motor for the development of industrial and energetic economy in this side of country. Despite the mining sector is the origin for the prosper economy of the area and the demographic development, it is also responsible for severe damages in infrastructures (houses, train lines, roads) and in the environment (flooded of forested areas and croplands) (fig. 1). If we only focus in the consequences derived from the extraction of the minerals, it is observed that mine areas are affected by ground movements and re-adjustments during and after the exploitation phase of the mine life cycle. The vibration of the extracting machines and explosions used to open the galleries produce irreversible changes of the compacting and cohesion of the substrate above and around up to the surface and kilometres around the mines (fig. 1) that can last decades after the closure of the mine. As a consequence of these material re-adjustments, the ground surface slowly sinks. This effect is sometimes combined with changes in groundwater’s dynamic. Due to fissures in the rocks, water access upper layers and soak the materials, which increase their weight. In this case, it is more likely that the subsidence of the ground surface leads to a sudden collapse of the surface. Even the subsidence of the surface occurs slowly or suddenly, in some occasions groundwater reaches the surface and form ponds (1). The European Directive 2006/21/EC states that mining companies are responsible for the environmental and civil damages derived from their activities, and as described particularly in the article 13, for the monitoring of wastes and minimization of impacts on groundwater. The purpose of the current investigation is to support mining companies and governmental institutions to monitor mine-related flooding by means of GIS and remote sensing techniques. This research is part of the R&D project GMES4Mining, which intends to provide geoinformatic tools to support different phases of the mining life cycle. These tools can provide users with holistic data in time and space, in form of image data that can be statistically evaluated. Data of different type can be stored and analysed through statistical tools in a spatial data infrastructure (SDI) and shown in a user-friendly geoportal (2).

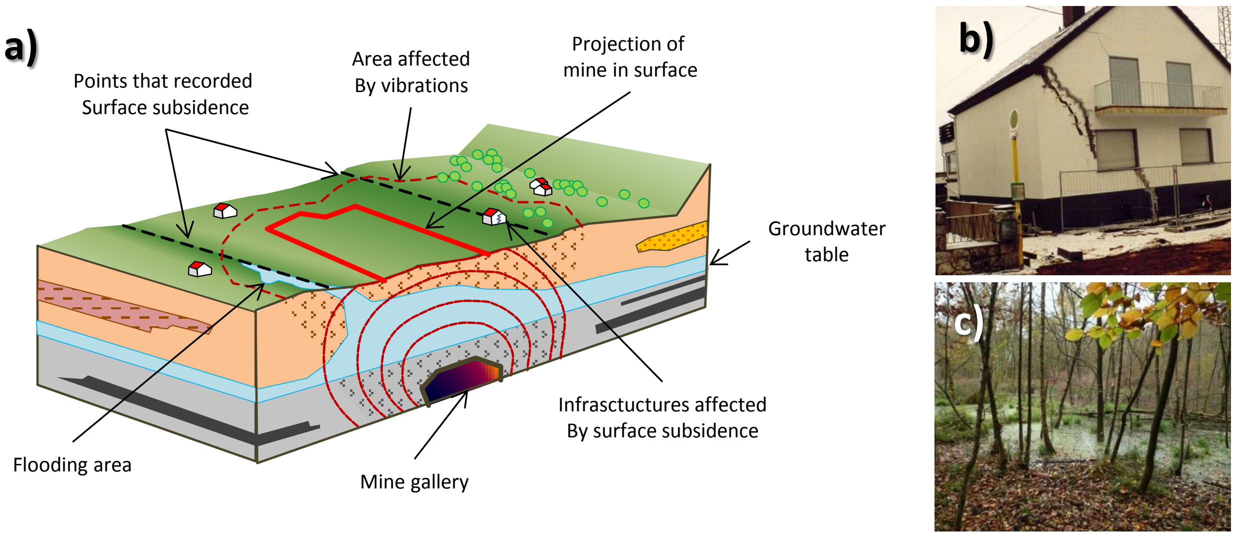

Figure 1. a) 3D scheme of changes in substrate and groundwater dynamics around a gallery mine. B) Damages caused in infrastructures and c) the environment (flooding) due to ground movements.

METHODS

Study site

The Prosper-Haniel mine is one of the most productive hard coal mines in Germany. Approximately 3.2 million tons per year of high-quality coal are extracted, which is primarily used for the production of electricity. The coal is planned to be gained until 2018 in four mining operations at depths between 700 m and 1246 m (www.rag.de). Kirchheller Heide *(central coordinates: 51°34'74"N, 6°50'31"E)* is a forested area within the Natural Park "Hohe Mark" located in the area of the Prosper-Haniel mine (North-Rhein Westfalia, Germany). The area lies on the Low-Rhein sandstone plate, between the Lippe and Emscher valleys. Many streams run along the area, such as the Rotbach and the Schwarzbach. Since 2000 and up to date, several cases of flooding have occurred in forests and croplands within Kirchheller Heide, due to the ground subsidence provoked by mining activities. The process is monitored in the field by the local forestry authorities.

Image acquisition and pre-processing

RapidEye is a constellation of five satellites intended to provide full coverage of the Earth surface in few days. For the case of Europe, it is possible to have data every 5 days (nadir) and eventually daily acquisitions, if the sensors are pointing off-nadir. Nowadays, it is the platform that covers larger areas in smaller time gaps using a fine pixel resolution (5 m). Although flooding events have been reported since 2000 in Kirchheller Heide, in the present study we only cover the last years, since RapidEye was launched in 2009. A temporal series of nine RapidEye dataset between April 2009 and September 2012 was used. Given the high temporal resolution of the RapidEye constellation, it was possible to select cloud-free images. The data was in L3A process level, meaning that it was orthorectified using similar parameters. Co-registration was made when necessary using a reference image (RapidEye from 26-07-2012). All data was atmospherically corrected using FLAASH.

Low albedo and change detection analysis

Due to its high latent heat, water is able to absorb most of the light that it receives, in all spectral frequencies. This physical characteristic of water conditions its particular spectral signature: water presents a low reflectance in all wavelengths. The greatest spectral difference in comparison to other elements in nature relies in the infrared region. Taking advantage of that, water bodies can be delimited by selecting the pixels of the scene that present low albedo (3). In the case of RapidEye data, the mean of bands 4 and 5 was calculated as a measurement of albedo. The delineation of water masses was made on the basis of the histogram of albedo values. Low albedo values potentially correspond to water bodies. Another advantage of albedo is that water bodies and dark objects (such as dark shadows, bituminous roofs and coal) present a very different response in comparison to the rest of objects in the scene. In the histogram, this is expressed as two different groups of values. We established the local minima between these two groups as the value threshold to delimit water bodies. Therefore, values under the threshold were selected (binary data: 1) and all other values masked (binary data: 0). Afterwards, water masks were summed up in order to detect water bodies that experienced changes in the studied time frame.

Implementing the methods in a spatial data infrastructure (SDI)

One of the objectives of the GMES4Mining project is to integrate data of different kind and project results in a spatial data infrastructure (SDI) and provide a geoportal that allows the exploration, visualization and analysis of the data. The mentioned geoportal was developed in order to allow users (i.e. mining companies, governmental institutions) to access the data and also provide basic tools for analysis and processing techniques without particular software or licensing requirements. The Geoserver software is used for publishing the data, which is then accessed and visualized in a JavaScript-based web portal. In order to perform descriptive statistics and some straightforward image processing techniques on the raster data (i.e. albedo calculation; histogram minimum local value calculation) the statistics software R is implemented on a server and connected via Rserve. The analysis is controlled and executed directly by the user through the web interface of the geoportal.

RESULTS

As explained in the method section, albedo was calculated for each RapidEye scene selected for this study (fig. 2). The threshold to separate water masses (lower albedo values) from the rest of targets in the scene was calculated by exploring the histogram of albedo values. Albedo values corresponding to water are clearly separated from other targets; therefore, the threshold to discriminate water masses has been defined as the local minima between lower and upper albedo values, in the histogram (table 1). This threshold is scene-dependent and varies from one image to another, being independent of differences between images, such as illumination or weather conditions.

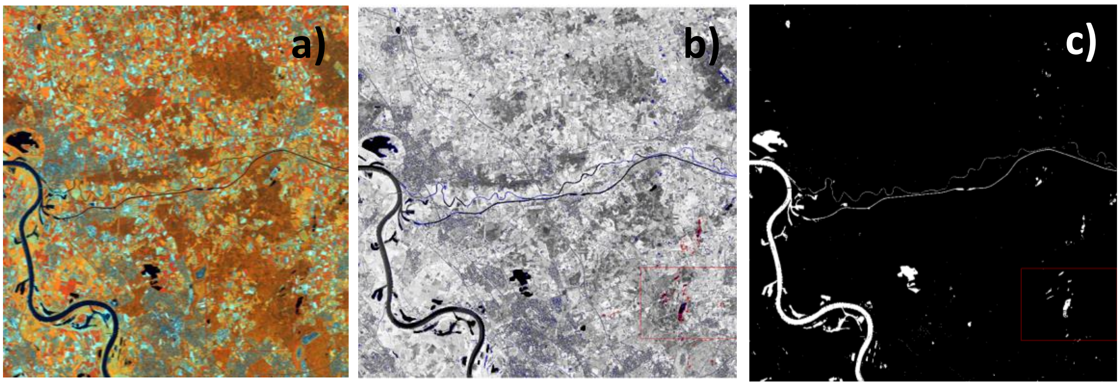

Figure 2. a) RapidEye infrared combination, b) low albedo and c) water mask, according to estimated threshold. Ruhr area (Germany), 26.07.2012.

In order to evaluate the accuracy of the water masks, the Kirchheller Heide test site was evaluated. Water areas were digitalized for each date. Producer's accuracy, user's accuracy and kappa coefficient were calculated by building a true/false matrix (true: water pixels within water polygons/no water pixels out of water polygons; false: water pixels out of water polygons/no water pixels within water polygons) (table 1). In general terms, the accuracy is above 70%. Errors of commission occur in shaded areas (i.e. shadows of buildings in urban areas), bituminous roofs, and coal deposits. Errors of omission are observed in shallow water bodies with white bottoms, water with high content of sediments (organic or inorganic) or water that reflect sun glint.

Table 1. Low albedo thresholds and accuracy results.

Date	Sensor	Threshold	Producer's accuracy	User's accuracy	Kappa coefficient
04.09.2012	RE5	488	69.3	0.7	0.79
26.07.2012	RE3	884	76.3	0.8	0.83
03.09.2011	RE5	439	74.5	0.7	0.81
27.06.2011	RE3	711	80.3	0.8	0.85
30.05.2011	RE4	779	81.8	0.8	0.86
02.04.2011	RE3	678	80.1	0.9	0.82
03.06.2010	RE5	533	79.5	0.8	0.84
17.09.2009	RE4	685	71.2	0.8	0.74
21.04.2009	RE3	804	81.8	0.8	0.83

VZA: View Zenith Angle; VAA: View Azimut Angle

In a following step, all water masses were summed up together in order to detect changes in their extension (fig. 3). Water masses present a value different to zero; consequently, the sum of them will always give a value different to zero. Water masses which did not experience changes in the given time frame, independently of their nature (natural or human-made; rivers, ports, lakes, etc.) present the maximum value (in our case, value: 9) and can be discarded. Water masses that changed (including mine-related flooded areas) are represented in the intermediate values (fig. 3). The result of this exploration can be evaluated by experts in order to decide which are potential flooded areas and discard other elements (i.e. enlargement of a port). The limitations of this change detection analysis are that errors from the water masks are accumulated and the information about the date of occurrence is missed. Therefore, it is not possible to interpret whether the change is negative (drought or water body that is shrinking) or positive (flooding or water body that is growing).

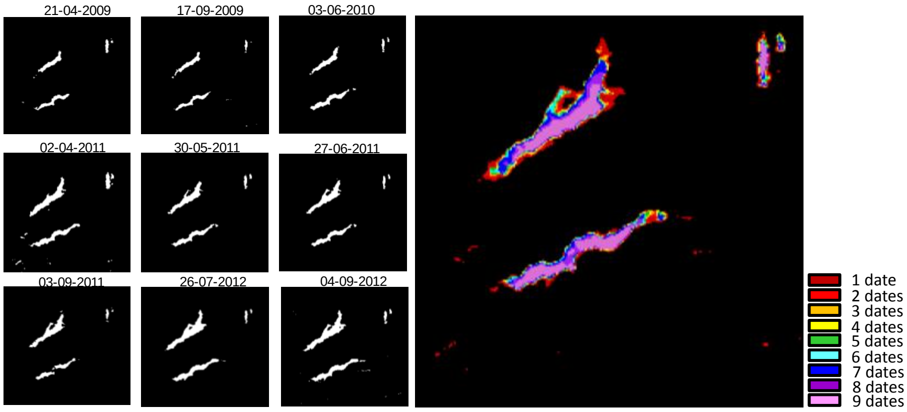

Figure 3. Left: water masks for a known flooded area in Kirchheller Heide for the period 2009-2012. Right: results of the change detection using those nine RapidEye water masks.

The original data and results of this research were successfully implemented in a spatial data infrastructure so external users can explore the data, perform their own analysis or consult our results, via a geoportal (fig. 4).

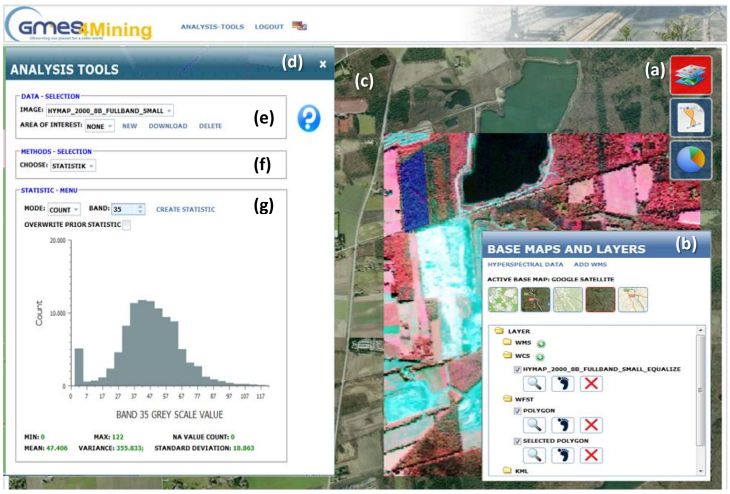

Figure 4. Elements of the geoportal: (a) key access to different layer managers and functions, (b) layer manager window, (c) displayed raster data, (d) Dialog window for methods and analysis, (e) data selection pull-down list, (f) method selection pull-down list, and (g) Results/Statistics window.

CONCLUSIONS

The present study intends to create a tool to support mining companies and environmental institutions for the identification and monitoring flooded areas provoked by current or old mine activities. The proposed approach uses multispectral / multi-temporal RapidEye data and simple statistics (calculation of albedo, thresholding of low albedo values and change analysis) in order to cover large areas and time frames and implement the data and results in a user-friendly geoportal for users and managers.

RapidEye has a convenient pixel resolution and time resolution; for these reasons it has been selected for this study. However, the Ruhr area has been affected by mine-related flooding for a long time before 2009. In order to monitor flooding processes that occurred before 2009, Landsat is a suitable option, since it has been operational since 1972 and the pixel size of 30 m still permits the location of some flooded areas (4). Nevertheless, caution must be taken, since Landsat data from different missions (MSS, TM, ETM+ and OLI) shall not produce water masks with the same precision and should not be compared in multi-temporal analysis. Moreover Landsat 7 ETM+ was damaged after 2003 and the failed scanner lines do not coincide in different scenes, so they are not comparable. Another reason to use RapidEye is that the low albedo method provides good results using only VNIR data. For that reason, the selection of a sensor for flooding monitoring was not limited by a larger wavelength range that includes SWIR data.

From the methodological point of view, little literature has been found about delineation of water bodies using remote sensing data, and particularly using multispectral data. Different methods have been proposed, with limited success: spectral water indices, tasselled cap, classification tools, etc. (3). In the opinion of many authors, the principal challenge is that water is considered a single target, despite its characteristics can highly modify the spectral signature, for example, the presence of cyanobacteria or aquatic plants, sediments, the depth of the water layer, the composition of the bottom, etc. (3). Our results present unfortunately moderate errors of accuracy, given the difficult task of delineating all kind of water types. However, the accuracy achieved using low albedo is higher as expected with other methods (internal analysis, not published). Moreover, in contrast to other methods to locate water masses (i.e. target detection, classification methods), it does not require training data.

The method employed to discriminate water bodies in this paper was inspired in the work of (3). Their method achieved better results because it refines the results achieved after calculating low albedo. On one hand, the authors used a broader threshold on low albedo data that selects more potential water pixels and afterwards it removes erroneous classified pixels (i.e. shadows in vegetation) by exploring the slope of specific wavelength intervals of the selected water pixels. However, the method from (3) was developed for hyperspectral data. In our case, the spectral signature of RapidEye data does not allow to explore these spectral ranges separately, with the consequent weaker accuracy results. With the launch of EnMap in the next years, it is expected that the proposed workflow to detect mine-related flooded area in this paper will take advantage of multi-temporal hyperspectral data at a landscape level. Then, better methods for water bodies delimitations, such as that described by (3) will be able to be used at a landscape level and in a multi-temporal frame.

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