A review of methods in the field of detecting illegal open-pit mining activities

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Abstract.
Illegal open pit mining might be a very dangerous activity both for the environment and also for the people living in its neighbourhood. This kind of activity is connected with environmental degradation, disruption of sustainable development and lack of the most critical last stage of the mine’s ‘life’, i.e. land reclamation. An additional element connected with illegal exploitation is the fact of breaking the law and stealing mineral resources. Monitoring of illegal exploitation is therefore an important aspect. The presented here review was intended to investigate which methods can be used directly to detect open pit mining sites and to evaluate their effectiveness. In the reviewed works a wide variety of methods have been used, ranging from manual methods, such as photo-interpretation, to a combination of automatic methods and photo-interpretation, to fully automatic methods. Based on the analysis, it was indicated that different types of classification (supervised, unsupervised, hybrid) are the most commonly used. Besides, radar interferometry, image fusion techniques, or images spectral similarity are also used.

1. Introduction
Thanks to the large amount of funds received from the European Union, in recent years, Poland has begun a very strong development of its road infrastructure. Highways and express roads are being built, but also the quality of already existing roads is being improved, including the local ones. Construction is also developing rapidly - the outskirts of cities are being built up at an alarming pace, buildings are being constructed within a dozen or so weeks. Cities are expanding. To carry out these projects, building materials are necessary, to a large extent mineral resources, coming from the exploitation of deposits. For the construction of roads and their surfaces, mainly natural aggregates such as sands, gravels, sedimentary rocks such as dolomite, limestone, sandstone, quartzite and magmatic rocks such as basalt, granite, melaphyr, gabbro-diabase, porphyry are used [1]. In the case of residential construction, the raw materials used are: aggregates, sands, gravels [2]. As the number of such investments grows, so does the demand for the mentioned raw materials. It is a great opportunity to make a considerable amount of money on the extraction of natural aggregates that are quite commonly found in smaller or larger accumulations shallow under the ground level. Such a situation becomes an opportunity for third parties to gain financial benefits by committing a crime leading to illegal exploitation. Thus, many sites of illegal exploitation of mineral resources, mainly natural aggregates, emerge which are difficult to identify in the field or to be aware or notified of such crime.
Based on available public articles and reports, it can be indicated that there is a high risk from illegal mining in terms of human health and life, primarily due to the lack of work safety rules at illegal mining sites and poor quality equipment used. Besides, this type of activity causes environmental losses in the form of damaged natural habitats and lack of recultivation, giving the possibility of revival of natural habitats in these areas. Another aspect is economic loss - local governments' budgets do not receive taxes related to the extraction of raw materials and legally operating mining companies have their income reduced. These are essential aspects which should be taken into consideration when considering the issue of illegal mining exploitation [3–8].

Despite suspicion or notification of such sites, there is often a problem to inspect these locations, mostly due to lack of resources. For this purpose, Remote data acquisition techniques can be used to acquire data about the area of the site. These would both verify previously identified locations of illegal mining and search for those that have not been reported. Currently, there are no systems, which could help remotely detect potential sites of illegal exploitation.

The main objective of the paper is to perform a review of methods that based on detection of open-pit mining. By summarizing and systematizing a number of methods, we intend to select potentially suitable for the detection of illegal open-pit mining sites in Poland. The methods presented in the review focus on remote detection, most often using images taken from above the ground (e.g. satellite or drone images), both optical and in different spectral bands of light, or using radar interferometry.

2. Materials and methods
The process of creating a database of potential articles suitable for a literature review on methods for detecting illegal open-pit mining activities began by identifying the keywords by which the articles would be searched. The focus was on the following phrases (both in Polish and English):

- illegal open-pit mining exploitation,
- illegal mining exploitation,
- detection of illegal mining exploitation,
- detection of mining exploitation,
- illegal mining.

The following article selection criteria were used:

- access to the full content of the article,
- article discussing at least one method of detecting mining activity,
- focus on detection of open-pit mining activity,
- detection of open-pit mining activity, not only illegal mining activity, to recognize more methods.

Web portals i.e. Google Scholar [9], Google [10], Research Gate [11], Remote Sensing [12], MDPI [13], Science Direct [14], Scopus [15], Web of Science [16] and PWr e-zasoby [17] were used to search for articles.

The search resulted in finding more than a dozen articles that matched the assumed search criteria. Some of them were disqualified after initial verification, most often due to the type of mining (other than open pit) or mismatch with the research topic. Finally, the number of matching articles was limited to 6.

3. State of the art
Despite the dynamic development of measurement techniques, including remote techniques (e.g., measurements made from satellites, drones), free and easily available satellite data (optical, spectral and radar), there are still not enough works dedicated to the detection of open-pit
mining activities, especially illegal ones. We can find works that use radar interferometry and radar data to monitor deformation in the area of a waste disposal facility [18], to analyze and monitor spatial-temporal long-term deformation of an aseismic tectonic fault [19], to analyze and monitor ground surface displacement due to induced tremors [20, 21], as well as for monitoring secondary deformation that occurs after the mining operation process in closed mine areas [22, 23]. Kopeć et al. [24] used remote sensing data to calculate spectral indices and radar interferometry calculations in combination with machine learning and GIS algorithms to investigate the environmental impacts of underground mining operations. Multispectral imagery can also be used to classify land use and land cover (LULC) and to determine the changes that are occurring in the study area by comparing classifications from different periods of time [25]. In addition, remote techniques such as drones (UAVs) that take photogrammetric images can be used for creating digital surface models and then used for unmanned monitoring of open-pit mining [26] or combined with LiDAR data to monitor landslides [27]. Despite so much work using remotely acquired techniques and data, there is still a lack of solutions explicitly for detecting illegal surface mining activities.

3.1. Image classification

One of the most popular approach for such a problem is a hybrid classification. It combines the advantages of unsupervised methods (little a priori knowledge of the terrain) and supervised methods (which have better discrimination efficiency but requires labels of classes).

It has been developed by Schueler et al. [28]. It is based on two Landsat TM satellite images of 29 December 1986 and 15 January 2020 with 30m resolution. The study area covered gold mines in Ghana, more precisely in the Wassa West district. In fact, the work was initiated well before the date of the last Landsat image, from July to October 2006, when a field inventory was performed along with mapping of various land cover forms using GPS. In addition to the data analysis, additional interviews and various workshops were conducted to obtain more information about the terrain. The main part of the research involved dividing the mapped areas into test polygons, training and validation polygons in a 75% to 25% ratio, respectively. Thanks to the training data spectral classes were determined. It became the benchmarks for the remaining unmapped terrain. The hybrid classification was based on a combination of supervised and unsupervised classification. Two classified images were thus obtained and land cover changes were calculated as changes between clusters. (Fig. 1.)
After the analysis it has appeared that in almost 35 years the mining activities, the area increased from 0.2% to 41.9%. The most common situation identified there was enlargement of the mining area while reducing the forest or agricultural area. Accuracy assessment was performed on the basis of randomly selected 330 points, with a minimum of 30 points for each class. For validation purpose, an error matrix was calculated (Tab. 1). The overall accuracy was 83.3%.

Table 1. Error matrix with individual values of achieved accuracy [28].

| Class            | User’s accuracy (UAC) [%] | Producer’s accuracy (PAC) [%] |
|------------------|--------------------------|-------------------------------|
| Deforestation    | 64.86                    | 97.96                         |
| Farmland loss    | 80.00                    | 63.16                         |
| Permanent Forest | 100.00                   | 97.06                         |
| Permanent Mine   | 100.00                   | 83.33                         |
| Permanent Farmland | 88.66                | 92.47                         |
| Farmland Expansion | 85.37               | 72.92                         |
Unsupervised classification with the use of neural networks was proposed by Charou E. et al. [29]. In this case, it was related to the catchment area of the Vegoritis River. The analysis of mining area detection was started by indicating mining areas with pseudo-color composites (RGB-753). These composites highlight mining areas that have high spectral reflectance. In the next step, the IHS transformation was used to combine the SPOT panchromatic band with spectral bands derived from ASTER and Landsat to indicate land cover classes that are characteristic of mining areas. This transformation resulted in a 453-PAN color composite image. The final step involved the use of unsupervised classification, which was supported by the Self Organizing Map (SOM) method. ASTER images were classified. The use of panchromatic images combined with false color composites resulted in an indication of the extent of mining activity and its classification between active, post-mining, reclaimed and landfill pits (Fig. 2). The authors did not perform an accuracy assessment.

![Figure 2](image-url)

**Figure 2.** Result of performed classification (left) and ASTER false color image (right) for selected mining area [29].

### 3.2. Radar interferometry

The InSAR based method was used by Wang et al. [30] Four SAR images from Sentinel-1 (November 2017), four optical images from Sentinel-2, an SRTM numerical terrain model, and a map of issued licenses - as of 2017 - were selected for the study. The analyzed area included Mongolia and China. Indication of mining sites was based on the development of co-mapping, where the dark color potentially indicated open-pit mining sites. Based on the developed histograms and Otsu automatic thresholding algorithm, the images were thresholded in such
a way to indicate only the areas of de-correlation. The final step was to remove noise from the de-correlation maps and thus potential mining points were indicated (Fig. 3).

The next stage included manual verification. With the use of Sentinel-2 images, it was verified whether the indicated locations were open-pit mining sites or not. If the answer was affirmative, an analysis of the legality of exploitation was performed on the basis of a map of issued licenses (Fig. 4). The analysis resulted in maps indicating legal, illegal mining sites and mis-classified sites (Fig. 5).
Figure 4. An algorithm showing further verification of the existence and legality of opencast mining [30].

![Algorithm Diagram](image)

Figure 5. Process for refining coherence maps for selected study areas [30].

![Coherence Map](image)

The performed accuracy assessment has indicated an average accuracy of 90.74%. The lowest accuracy for the selected area was 81.82% (Tab. 2). It is also worth noting the high error value for area C, which is due to the fact that four gold mines with small dimensions were not identified on the coherence maps. The problem turned out to be too low resolution of SAR imaging (20m). Besides, even if these areas were detected, they could be removed as noise from the de-correlation maps.
Table 2. Comparison of statistics (including number of localized and classified mining sites with accuracy and errors [30].

| Study area | Identification results | Corresponding to Mining Survey | Accuracy [%] | Commission error [%] | Omission error [%] |
|------------|-------------------------|--------------------------------|--------------|----------------------|-------------------|
|            | Legal | Illegal | Non-mining | On site | Off site | Miss |            |            |            |
| A          | 17    | 0       | 6         | 14      | 3       | 1    | 82.35      | 17.65     | 6.67      |
| B          | 26    | 3       | 5         | 26      | 0       | 2    | 100.00     | 0.00      | 7.14      |
| C          | 11    | 3       | 10        | 9       | 2       | 5    | 81.82      | 18.18     | 33.71     |
| Total      | 54    | 6       | 21        | 49      | 5       | 8    | 90.74      | 9.26      | 14.04     |

3.3. Spectral similarity

A method based on spectral similarity was used by LaJeunesse Connette et al. [31]. They were using QGIS software and Landsat 8 (2002 and 2015) and high-resolution Google Earth images. The area of interest included mines in Myanmar (Southeast Asia). The process was divided into several stages. The first involved the use of Landsat images where clouds and surface water were masked, and then existing mining areas were digitized using such prepared images. For these areas, spectral patterns were calculated from 5 elements (NDVI, NBR, NDMI, Shortwave Infrared, Red reflectance) and used to find similar areas in the rest of the image (Fig. 6). In this way, potential sites for open pit mining were identified.

![Figure 6. Map of spectrally similar areas [31].](image-url)
The second step involved identifying the actual location of the mines using high-resolution images derived from Google Earth. Each area was assigned to the class of degree of certainty (high, medium, low) with which a mining site was found to exist at the indicated point.

The third step involved interviewing local community organizations as a validation of the identified potential areas. A field inspection was not chosen due to the excessive danger and limited accessibility of some sites. Local residents indicated on a map of potential exploitation points which were correctly indicated and which were not. The final, fourth, step was to calculate the area of change that occurred based on the albedo calculated for both images. Changes were indicated as exceeding the threshold for the albedo difference, or exceeding the brightness threshold for the 2015 albedo. No additional assessment of accuracy was performed beyond indicating the degree of confidence in the presence of outcrops and indications from local community organizations. The process is shown in the diagram below (Fig. 7).

![Diagram of the computational process in the proposed method](image)

**Figure 7.** Diagram of the computational process in the proposed method [31].

### 3.4. Spectral indices and image fusion

Castellanos-Quiroz et al. [32] tested a set of spectral indices and image fusion techniques for indicating areas of mining operations. ENVI and SNAP software were used for the calculations,
and the input data were Landsat 8 imagery from June 17, 2014, and high-resolution UltraCam-D and RapidEye data. The study was conducted in a selected area of Colombia. The first step was to identify the image and morphological characteristics of mining areas to easily distinguish them from non-mining areas. Then, spectral indices (9) were calculated and image fusion techniques (2) were implemented for 3 bands. Suitability was evaluated based on histograms (Fig. 8, 9) and two rules of thumb: the greater the distance between the peaks of the histograms in the graph and/or the smaller the common part of the two histograms in the graph, the greater the discrimination between mining and non-mining areas.

**Figure 8.** Comparison of histograms for the spectral indices used. The best results were obtained for index C - Iron oxide (ferric minerals) [32].

**Figure 9.** Comparison of histograms for the spectral indices used. The best results were achieved by Brovey fusion for band 2 [32].
On this basis, one spectral index and one image fusion technique were selected. To determine the single best method, it was decided to additionally calculate the Fischer index. The highest result indicated the previously selected fusion technique for band 2 (0.16669), which was better compared to the iron oxide spectral index (0.15927). The selected method was used to indicate mining areas on satellite images (Fig. 10). Accuracy assessment was based on the calculation of apparent errors. The weighted average error was 8.9%.

![Figure 10. Classified mining areas are marked in yellow in the image [32].](image)

3.5. Bimodal histogram and time series

Forkuor G. et al. [33] used time series and bimodal histograms to indicate changed and unchanged areas to detect illegal mining activities based on the indicated threshold value for the images. The study used Sentinel-1 data for the period 2015-2019, which was processed in SNAP software. The data were divided into time subsets covering one calendar year from July to June.

Time series, which are sensitive to varying dispersion characteristics, were used to indicate areas where land cover change has occurred. An algorithm of the process is indicated in Fig. 11. The formation of areas of illegal mining activity is associated with the removal of vegetation and sometimes with the formation of waterlogged areas. It was assumed that such changes would be visualized in the time series because these types of land cover have different dispersion characteristics. The next step was to determine a threshold for detecting areas that have changed and those that have not. A verification was performed using Google Earth images and the changed and unchanged areas were mapped. Difference images between time subsets were also calculated. By overlaying these images, a histogram of changed and unchanged areas was obtained. From this, detection thresholds were determined. Two methods were used: one was a supervised indication of the threshold, which is the intersection of the histograms; the other method is the use of the iterative Otsu algorithm to determine the threshold value.
The indicated thresholds were applied to the computed difference images between the subsets, resulting in binary images with an indication of changed and unchanged areas. The results were validated using LULC data and Google Earth images.

An accuracy assessment was performed for the different variants used in the calculations. User and manufacturer accuracy values were obtained. The highest accuracy was achieved by the method using VH polarization (Fig. 12) using minimum or average threshold values determined by intersecting histograms. These were respectively for the minimum threshold: UA=72.39%, PA= 84.89% and for the average threshold: UA=83.55%, PA=77.10%. The complete data are shown in Table 3.
Figure 12. Change classification result - VH polarization for the minimum intensity value and the threshold determined by the intersection of histograms [33].

Table 3. Accuracy assessment for altered areas from differential images [33].

| Feature                  | Threshold [dB] | Commission [%] | Omission [%] | Prod.acc. [%] | User Acc [%] |
|--------------------------|----------------|----------------|--------------|---------------|--------------|
| VH minimum intensities   | +1.65          | 27.61          | 15.11        | 84.89         | 72.39        |
| VH minimum intensities   | +2.78          | 15.10          | 31.03        | 68.97         | 84.90        |
| VH mean intensities      | +1.22          | 16.45          | 22.90        | 77.10         | 83.55        |
| VH mean intensities      | +2.30          | 7.42           | 53.52        | 46.48         | 92.58        |
| VV minimum intensities   | +1.62          | 27.84          | 28.52        | 71.48         | 72.16        |
| VV minimum intensities   | +2.34          | 14.65          | 42.75        | 57.25         | 85.35        |
| VV mean intensities      | +1.46          | 17.02          | 44.85        | 55.15         | 82.98        |
| VV mean intensities      | +1.99          | 10.31          | 62.87        | 37.13         | 89.69        |
3.6. CLASlite
Asner et al. [34] used the Carnegie Landsat Analysis System-lite (CLASlite) to detect and map areas of mining operations, which has very high accuracy in detecting even small changes in terrain. This system was implemented for a gold mine area in the Madre de Dios region of the Peruvian Amazon. To detect changes, Landsat images for the selected area were compiled and their numerical values were converted to reflectance values. Algorithms built into the CLASlite system allowed to indicate areas covered by vegetation and areas of bare ground. Land classes that were associated with bare earth or water were indicated as mining areas. The survey indicated an annual increase in mining areas of an average of 14% per year. Figure 13. indicates the annual areas associated with new mining activity that were detected. The accuracy of the computational process was evaluated by drawing 166 samples for which validation was performed. This was conducted in two stages. A field inventory was performed for areas that were safe, and the CLASlite system was used for the remaining areas. The areas identified were found to have a 94% overlap with the actual gold mining areas in the area.

![Figure 13. Small and large mines in Madre de Dios broken down by year of creation [34].](image)

3.7. Photo-interpretation of images
Janiski et al. [35] decided to conduct a pilot project to develop a method to detect illegal open pit mining. For this purpose, the authors used popular software (ArcGIS, MapInfo, Geomedia), satellite images derived from the Indian IRS-P6 satellite with a resolution of 10-15m on 23 September 2005, topographic maps at a scale of 1:25 000, contours of documented deposits and contours of established mining areas. The analyzed area covered two counties in Malopolska province: oświęcimskie and wadowickie (Fig. 14).
The analysis involved mapping the contours of deposits, mining areas and waste dumps on topographic maps. Next, photo-interpretation of the images was performed to indicate potential sites for open pit mining. The last stage involved field inventory of the indicated sites. Based on these results, it was determined whether a given point was an actual open-pit mining site. The authors did not perform an assessment of the accuracy of the method used. They considered it as a success as they were able to develop a method that allows indicating illegal mining sites.

4. Discussion and Conclusions
The methods indicated in the the paper are the basis for determining the direction of further research and for selecting potential methods that can be used to detect illegal surface mining activities in Poland. The authors indicated a solution related to land classification, based on supervised and unsupervised classification. For this purpose, Landsat satellite data were used to determine the spectral patterns based on which the remaining areas in the image were classified and potential mining sites were selected for further validation [28]. Panchromatic images, color composite combinations, and unsupervised classification supported by neural networks were also used to identify areas associated with mining operations [29]. Methods related to radar interferometry were also used, based on coherence and decorrelation maps and photo interpretation of images for selected areas [30]. Thanks to the possibility of obtaining individual spectral bands of satellite images, it is also possible to apply a method based on spectral similarity between existing mining areas and the sought areas of new mining [31], and to calculate spectral indices and apply fusion techniques for different bands [32]. The creation of time series and the analysis of scattering changes in different areas, combined with the use of
bimodal histograms, allowed the identification of mined areas [33]. Moreover, methods based on ready-made algorithms have their application in the analyzed topic. An example is the CLASlite system, which was used for map mining in the Amazon [34]. The simplest method of mapping changes and detecting mining activity is photo-interpretation, which was used in a pilot project in the area of the Małopolska province [35].

The satellite data used in most of the studies analyzed are easy to obtain because they are freely available. However, their low resolution may be a critical problem. Data provided by European Space Agency (ESA) have the highest resolution of 10m, the most accurate Landsat has a resolution of 15m in the panchromatic band. The pixel size of the images strongly limits the size of the detected objects, which are sometimes quite small in the case of illegal exploitation. Therefore, to detect illegal exploitation, e.g. in Poland, it would be necessary to purchase images of much higher resolution, to detect not only large excavations, but also those much smaller.

The usefulness of individual methods for detecting mining activities can be determined based on the accuracies calculated by the authors, which are presented collectively in Table 4.

| Authors | Name                        | Accuracy [%] |
|---------|-----------------------------|--------------|
| 3 Schuler et al. | image classification       | 83,30        |
| 4 Charou et al.    | image classification       | nd           |
| 5 Wang et al.      | InSAR                      | 90,74        |
| 6 LaJeunesse Connette et al. | spectral similarity | nd           |
| 7 Castellanos Quiroz et al. | spectral indices, image fusion | 91,10       |
| 8 Forksou et al.   | bimodal histogram          | 84,89        |
| 9 Asner et al.     | CLASlite                   | 94,00        |
| 10 Janiski et al.  | photointerpretation       | nd           |

However, it is worth noting that often the terrain characteristics, the images used, or the season of year, may have a significant impact on the results. Therefore, it is necessary to investigate many variables before proceeding to the actual calculation process. According to the literature review, it was indicated that the best method for detecting mining activity are CLASlite and it achieves an accuracy of 94,00% and the spectral indices and image fusion method with an accuracy equal to 91,10%.
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