World Transactions on Engineering and Technology Education
Vol.8, No.1, 2010

Land reclamation of surface mining based on imagery intelligence and spatial decision support systems

Nicos Spyropoulos†, Spyros Valmis†, Athanasios Ganas‡ & George Metaxas*

Agricultural University of Athens, Iera Odos, Athens, Greece†
National Observatory of Athens, Lofos Nymfon, Athens, Greece‡
Technological Education Institute of Piraeus, Piraeus-Athens, Greece*

ABSTRACT: Satellite-borne remote sensing instruments allow the collection of environmental and mine-related data for use in the planning and undertaking of mine restoration work on a frequent and cost-effective basis. The advantage of monoscopic and stereoscopic Earth Observation (EO) data is that the data are acquired digitally; the data can be quickly and easily processed and utilised in various information formats. Imagery Intelligence (IMINT) is the intelligence discipline comprising the exploitation and analysis of information acquired by airborne and satellite birds, cartography terrain analysis to describe, assess and visually depict physical features and geographically referenced activities on Earth. IMINT of land cover themes and elevation information from diachronic EO data are fed to a spatial decision support system (SDSS) for open mining areas, which reflects and simulates the major decision steps of a mining expert (engineer, manager) during the formulation of a restoration plan. The SDSS supports the mining expert in structuring the various restoration alternatives and exploring both environmental and economic effects of the different actions.

INTRODUCTION

Mining operations have been seen by environmentalists and conservationists alike as causing problems. Undoubtedly, the operations of mineral and coal producers have caused varying degrees of environmental damage in mining areas, which are often located in remote regions. Much of the concern has been focused on the concurrent and subsequent physical and aesthetic effects that their operations have had on the land, as a basic resource. Mining activity is only a temporary occupier of the land surface and, hence, is of a transient nature. Although active mines at any particular time are not as widespread as other land uses, they dramatically change the landscape and tend to leave evidence of their past use. Thus, results of abandonment or closure become most conspicuous to the general public.

Space Technology can be a cost-effective information tool for: 1) mine operators (at planning and restoration stage) and, 2) for local/national authorities to preserve natural resources and improve the local socio-economic activities [1]. Space technology has caused a quantum change in man's ability to monitor and understand the Earth, by the use of sensors, which gather the data from which global exploration and development have benefited over the past 20 years. Remote sensing is the gathering and interpretation of data on any physical feature without making contact.

The information is acquired by advanced sensor systems that measure and record the energy at different wavelengths of the electromagnetic spectrum. The sensors, mounted on orbiting satellites, transmit the information to Earth, where it is stored permanently for future use.

The remotely sensed data then are processed on an appropriate computer system to produce *digital photographs* or false colour images. The resulting information is used in resource exploration and development including the creation of base-maps, identification of exploration prospects, planning operations, location of sites exploration and delineation of environmentally sensitive areas requiring extra surveillance to monitor any possible impact from exploration [2].

Remote sensing/GIS is a technology most often associated with long-term management of geospatial data and, therefore, has been of limited interest or profitability to any one of the above-mentioned distinct groups associated with a mining project. This is especially true since each group has been reluctant to pay for capital improvements, which would benefit other groups but for which it may not be credited or reimbursed [3]. Imagery intelligence or IMINT is the intelligence discipline comprising the exploitation and analysis of information acquired by airborne and satellite birds, cartography terrain analysis to describe, assess and visually depict physical features and geographically referenced activities on planet Earth.

IMINT probably can best be described as a product occurring at the point of delivery, i.e. by the amount of analysis, which occurs to resolve particular problems, not by the type of data used. For example, a database containing a list of measurements of land use in time obtained from diachronic imagery is *information* but the development of an output, using analysis to determine the type of land-use changes, able to be utilised for the specific purposes of land reclamation, could be called *intelligence*.

THE AREA OF INTEREST

The study area was based on Larco's open cast nickeloferrous ore mines located in Evia Island, Greece. Their main activity is the extraction of approximately 17,000 tons of Ni per year in the form of FeNi. Actually, three mining sites (the mine of Pagontas, Sourtzi and the mine of Isoma) have been thoroughly analysed and studied. The anaglyph of these areas was comprised of elevations ranging from 0 to1,500m.

THE GEOSPATIAL DATA USED

In this study, three Landsat TM images of the path/row 183/33 were provided, with spring-summer dates of acquisition, thus lowering the sun angle variations and reducing shadowing effects. The acquisition dates were 22 May 1986, 29 June 1991 and 18 April 1997. Additionally, one KVR-1000 image, with two metre spatial resolution was acquired in May 1992 to help extract linear earth features inside the mining areas. A 3-D model was provided by a one SPOT Pan stereo pair, with a high B/H ratio, pixel size of 10m, and with acquisition date of January/February 1993.

Moreover, general land-use topo maps (1/50,000) and topographic diagrams of 1/5,000 scale were acquired from the Hellenic Army Geographical Service (HAGS) and also Geological Maps (1/50,000) from the Institute of Geology and Mineral Exploration (IGME), Athens, Greece.

THE METHODOLOGY

An important contribution of satellite sensors to land resource analysis is their potential to monitor changes that occur in land cover over an extended period of time. This measure of the change that has occurred can be obtained by comparing the brightness values (DN) for each pixel location in a scene with the corresponding values acquired for the same area, but on a different date.

However, it is worth noting that differences in brightness values between dates can occur due to sources other than those originating from changes in surface materials, giving a potential error in these simple change-detection methods [4]. Such sources include the differences in atmospheric conditions between the times of the two overpasses, scene differences introduced by seasonal conditions when non-anniversary data is being investigated, differences in sensor response between the dates involved and between sensors, if data from different satellites are used.

In this study, the EO data were used to generate digital elevation models (DEM) of mines; to classify for land cover; and to monitor land cover change.

The Landsat TM images were processed to derive land use, land cover maps and land-use change maps. The images were atmospherically corrected taking inputs from the meteorological data supplied by the Greek Meteorological Service and using the ATCOR module from the Geomatica software package. The images were also radiometrically corrected by converting DN values of TM sensors into radiance and reflectance values [5]. This is achieved by using detector calibration tables prepared for each sensor. This method uses the Radiance programme on the Geomatica image analysis system and takes into account a gain and offset, and requires no ancillary data information apart from relevant calibration tables. Therefore, brightness values for each TM bands are first converted to radiance ($mW\mathrm{m}^{-2}\, sr^{-1}\, \mu m^{-1}$), using Equation 1, and then to reflectance values using Equation 2:

$$\mathrm{RAD}_i(x,y)=[\mathrm{DN}_i(x,y)-\mathrm{OFFSET}_i]/\mathrm{GAIN}_i \quad (1)$$

$$\mathrm{REF}_i(x,y)=\mathrm{RAD}_i(x,y)/\mathrm{S.E.I} \quad (2)$$

where $\mathrm{RAD}_i(x,y)$=radiance value at pixel (x,y) in band i

$\mathrm{DN}_i(x,y)$=output digital number for band i at pixel (x,y)

GAIN_i =gain factor used for band i

OFFSET_i=offset factor used for band i

$\mathrm{REF}_i(x,y)$=reflectance value at pixels (x,y) in band i

S.E.I=solar exoatmospheric irradiance ($mW\,\mathrm{m}^{-2}\, sr^{-1}\, \mu m^{-1}$).

The result of the simple ratio calculations are images whose pixel values vary between 0 and 1. These ratio differences were rescaled to a range of 0 to 255.

The geometric correction was done using image-to-image registration based on nearest neighbour algorithm, which does not alter pixel value for the subsequent classification procedure. Root Mean Square (RMR) error of a pixel size was achieved for *X* and *Y* axis.

Change detection was performed by comparing the individual classification of TM sub-scenes (1986, 1991 and 1997). The classifications were carried out firstly by supervised method based on training areas and, then, by unsupervised method based on clustering.

Eight classes were selected including dense forest, moderate forest, sparse forest, scrubland, moderate industry built-up area, settlement built-up area, transportation roads and bare soil. Three change detection maps were also produced with the following sequence: 1997-1986, 1997-1991 and 1991-1986. In Larco's site, the pre-mining cover is considered forest and bare rock. The post-mining (restored) cover is forest and water (artificial lake).

As said, the KVR scene was used to extract (on-screen digitisation) the linear features of the mine such as roads inside the mines, position and width of exploitation benches, various buildings and other man-made objects etc, that were then added to the SDSS.

Except for inside the mining area, a Digital Elevation Model was built using the Spot stereo Pan images. The 10m DEM was also corrected, with extra brake lines using the analogue DEM produced by 1/5,000 scale topo maps and additional points selected by GPS system. The vertical accuracy managed to be close to 10m, which is insufficient for the inside mining area because of a small excavation size compared with the resultant spatial and vertical resolution.

THE SPATIAL DECISION SUPPORT SYSTEM

The Spatial Decision Support System (SDSS) is nothing else but a tool based on multi-criteria decision-making (MCDM) techniques in a geographic information system (GIS) environment. The main MCDM technique suitable for implementation in a GIS, where a small set of allocation alternatives exists, is the multi-criteria analysis (MCA), which involves the evaluation of a relatively small set of allocation alternatives [6]. These alternatives, usually about three to five and rarely more than ten, are defined beforehand and are simply evaluated against each other. Therefore, MCA is useful when the alternatives are available.

For open mining activities, the SDSS reflects and simulates the major decision steps of a mining expert (engineer, manager) during the formulation of a restoration plan. The main restoration options are where to restore and what will be the new land use. The SDSS makes a comparison between different strategies based on multiple criteria supplied by the user. The way to achieve this is the set-up of a framework for analysis, which is capable of analysing and structuring policy issues.

This framework comprises six phases reflecting the series of thoughts of a decision-maker when working on a decision for the *best* alternative [4][6]. Within the alpha phase (A), the decision-maker is supplied with background information on the issues and the accompanying problems. In phase B, the main objective and the criteria necessary to measure the potential alternatives are formulated. Such criteria are, for example, the cost of levelling; the area of restoration in terms of square metres of forest, pasture lake, etc. In the third phase (C), the decision-maker can select a set of actions (management options) which, together, form a strategy. Such actions can be considered as levelling and terracing of slopes or creation of additional road network, park, lake, etc.

All IMINT derived from either monoscopic or stereo EO data, such as land use, existence of road net, DEM, drainage network, slope and aspect of the benches, will be entered into the model, as features.

In phase D, the different actions are combined to create a strategy. In this phase several constraints have to be applied in order to score the scenarios against the criteria defined in phase B. Such constraints can be the aspect of the dump and exploitation sites facing north, dump and exploitation slope higher than 45 degrees, lake areas, etc. The constraints gain values from the features derived from IMINT. The selected strategies are scored on the criteria defined in phase B.

Then, a strategy combined with a scenario is named a restoration case. In phase E, every case will be analysed against the predefined set of criteria. In this phase, optimisation models can be applied in order to find the optimal case. In other words, there are some objective functions to optimise, in addition to satisfying the requirements on the decision variables [7]. Each of the objectives to optimise is typically a measure of effectiveness of performance of the relevant system, and could be expressed as a mathematical function of the decision variables. A basic strategy is generated, where only a limited number of measures are taken into account and executed towards creating a potential land use. All possible strategies are generated and compared to the basic one.

In phase F the decision-maker can change the weights of all the criteria and the resulting scores are recalculated for each set of weights. In this way, it is possible to determine the optimal strategy given certain criteria. At the end, the

SDSS calculates the new land use in terms of land-use type, area in hectares and the cost of different restoration strategies. The visualisation can be either 2-D or 3-D.

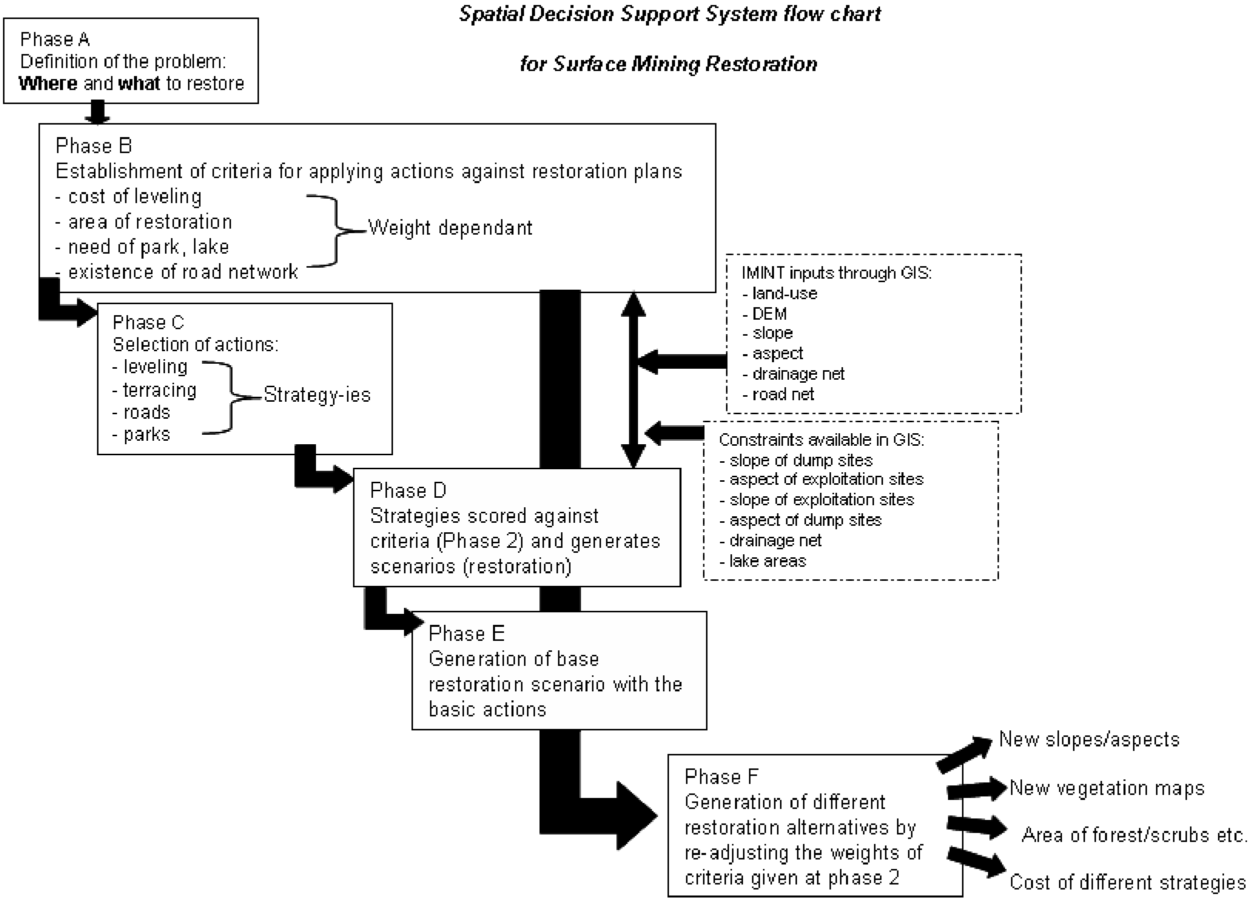

Figure 1: The Spatial Decision Support System (SDSS) flow chart.

DISCUSSION AND CONCLUSIONS

The application of change detection techniques to multi-date images acquired by satellite systems such as Landsat TM is useful for enhancing land-use changes for subsequent visual and digital identification of changed land-use categories. Several specific conclusions can be drawn from this study:

a) In order to measure accurately the difference in the brightness values between images of different dates, the images need to be registered together to within an accuracy of less than one pixel.
b) Potential sources of error introduced through variations in illumination, atmospheric conditions and sensor response, are responsible for changes in DN values between two acquisition dates. The normalisation of radiometric responses due to these errors helps the image-based change detection.
c) Ratioing or differencing red and near-infrared bands of Landsat TM images, acquired by different dates, produced change-images for visual interpretation. Principal components analysis was more useful in highlighting more subtle changes but is better suited to visual interpretation in this study.
d) The post-classification comparison is found to be better for change detection than principal component analysis and ratioing for this type of data, since areas covered by each class can be calculated quantitatively. This methodology, which has been employed, led to the compilation of land-use change maps for each of the land-use classes. However, there are many constraints, which affected the classification accuracy, such as the fragmentation of the land, the mixed and multiple land uses. The maximum likelihood classification algorithm cannot cope with the above constraints because it does not take into account useful information, such as texture, shape and context on the existent land-use classes.
e) Although the SDSS generally is not run on the Pagontas and Sourtzi mining sites because they are small, the success on running it at the Isoma site amplifies that the methodology of the imagery intelligence is useful to studying the environmental structure of the mine. The SDSS is capable of indicating where the real world restoration has to happen, since its modelled outcomes (dump sites) coincide with the same locations as those found in the KVR image and confirmed by the field visits. The KVR image and the visits also confirmed that SDSS was correct in selecting the necessary measures, such as terrace creation and tree plantations.
f) The results from this study point to the need to use better spatial resolution sensors (such as Quickbird, Ikonos-2 WorldView, Geoeye, digital satellite imagery with metre and sub-metre resolution), and to incorporate object-oriented information (eCognition approach) into the image analysis process for changing detection in land use.

Metre and sub-metre high resolution birds will provide excellent feature extraction information (conveyor belts, man-made structures, benches, sparsely planted areas, etc) and 3-D volume generation within the mine site itself, which most of the mining engineers and managers need to know, for their restoration plans [8]. Scales close to 1/1,000–1/5,000 would be ideal for such a market and these kinds of EO data may offer a potential solution, instead of costly aerial photography.

The low cost and data collection facility are important advantages that make the methodology, which has been followed, acceptable and applicable in Greece, because of the great duration of the sunshine that permits secure covering in fixed time intervals. The integration of derived imagery intelligence into a GIS system can be a standard approach for pre-mining and post-mining activities worldwide. The utilisation of IMINT information by a SDSS throughout the friendly and well-known GIS environment will be fully appreciated not only by mining experts, engineers, and managers, but also by administration authorities, whose task is to control and evaluate post-mining activities.

REFERENCES

1. Landsat Applications. Surface mining. Environmental aspects of surface mining. EOSAT notes, Issue 2 (1993).
2. Elroi, D., Opportunities for implementing GIS technologies in the mining industry. *Inter. J. of Integrating GeoTechnologies for Earth Solutions*, EO Magazine. Remote Sensing, GIS, GPS in Oil, Gaz and Mining, January (1995).
3. Spencer, C., Remote sensing provides high-tech clues for mineral exploration. *Inter. J. of Integrating GeoTechnologies for Earth Solutions*, EO Magazine. Remote Sensing, GIS, GPS in Oil, Gas and Mining, January (1995).
4. Ganas, A., Aerts, J., Astaras, T., Vente, De J., Frogoudakis, E., Lambrinos, N., Riskakis, C., Oikonomidis, D., Filippidis, A. and Kassoli-Fournaraki, A., The use of earth observation and decision support systems in the restoration of open cast nickel mines in Evia, central Greece. *Inter. J. of Remote Sensing*, 25, **16**, 3261-3274 (2004).
5. Robinove, C.J., Chavez, Jr., Gehring, D. and Holmgrem, R., Arid Land monitoring using Landsat Albedo Difference Images. *Remote Sens. Environ*., 11, 133-156 (1981).
6. De Vente, J., and Aerts, J.C.J.H., *Environmental restoration of a surface mining area. The application of remote sensing and GIS in a management information system*. In: Brebbia, C.A. and Pascolo, P. (Eds), MIS 2000, GIS and Remote Sensing. *Proc. MIS 2000 Conference*, Lisbon, Southampton: WIT Press, 393-402 (2000).
7. Murty, G.K., Optimization Models for Decision Making: Volume 1 Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI-48109–2117, USA (2008).
8. Almer, A., Banninger, C., Fernandez-Turiel, J.L. and Llorens, J.F., Automatic 3-D information extraction of open-cast mining infrastructure from simulated IKONOS data. *Proc. EOS/SPIE Symposium on Remote Sensing* (Europto Series), Florence, Italy, Bellingham, WA: SPIE, 254–260 (1999).