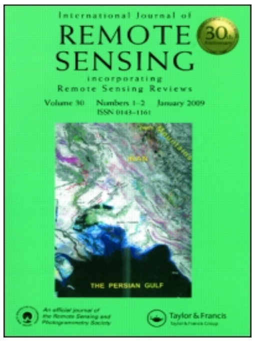

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Development of a Decision Support System based on remote sensing and GIS techniques for gold-rich area identification in SE Spain

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Abstract. Remote sensing techniques and spatial data analysis through Geographic Information Systems (GIS) have been jointly applied in a mineral exploration context to identify gold-rich potential areas in SE Spain. Results confirm the usefulness of this integrated methodological approach as an effective tool to assess mineral potential in the studied region. Satellite and airborne image analysis have offered valuable thematic information referring both to lithology and altered zone mapping from photointerpretation and digital classification. For this goal, SPOT panchromatic and Landsat TM images were merged in order to obtain high resolution image documents for photointerpretation purposes, and the Feature Principal Component Selection technique was applied to highlight hydrothermal alteration zones characterized by hydroxyl-bearing minerals. Remote sensing results were integrated, in conjunction with existing maps and data from mineral exploration surveys, into the GIS as vector or raster layers. The GIS implementation stage consisted of the creation of a relational database, including a complete set of georeferenced data, and the elaboration of a specific user interface for spatial analysis using GIS facilities in order to establish a Decision Support System (DSS). The system was used to simulate different mineral exploration scenarios, calculating and mapping a Mineral Potential Index that was interpreted in a practical sense in terms of surface reduction and economic costs.

1. Introduction

Mineral resources play an important role in support of one of the most important economic worldwide activities, namely the mineral industry. Geologists and engineers well know that to discover a new ore deposit is like finding a 'needle in a haystack'. Therefore, it is not an easy task but a long process requiring the application of a wide variety of exploration techniques involving important investment and a high potential economic risk (statistically, only 1 of every 100 exploration projects leads to an economic deposit discovery). Mineral exploration has traditionally been based on the application of a variety of prospecting methods, mainly geochemistry, geophysics, geological mapping, aerial photointerpretation and ground surveys, operatively integrated within exploration phases. The main criterion of the prospector is to identify anomalies associated with target mineral areas, gradually reducing the original extent area to a small set of anomalies. This process is complex and it needs

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both analysis and integration of the above multithematic exploration information, from which decisions must be made over time and at different stages.

In this applied context remote sensing and, more recently, GIS have shown their usefulness as support tools of great interest. Remote sensing has been used largely to determine favourable areas from medium and high spatial resolution multispectral imagery, e.g. MSS, TM, HRV and airborne ATM sensors. The results are being more and more integrated into operational exploration models based on GIS technology, which plays a relevant role in mineral exploration for decision making in order to select favourable areas, as has been highlighted by Bonham-Carter 1994 and Memmi and Pride 1997.

In this study we intend to show how both technologies, remote sensing and GIS, together with other specific methods for spatial data analysis, mainly geostatistics, would be advisable as a set of tools to help us in the task of target area selection. Two main objectives are contemplated: firstly, to evaluate the capability of satellite and airborne images for thematic mapping of the interest areas. Secondly, to implement a Decision Support System (DSS) to simulate different mineral exploration scenarios according to expert's criteria; such results will be numerically expressed by means of a Mineral Potential Index (MPI) and represented as a map.

This work has been carried out in the framework of the DARSTIMEX Project funded by the Brite/Euram Programme of the EC.

2. Study area

The study area is located in the south-east of the Iberian Peninsula in the province of Almería (Spain) and it approximately corresponds to the Cabo de Gata-Nijar Natural Park with around 350 km^2 (see figure 1). The area extends along a strip of land parallel to the Mediterranean coast of Almería, bounded to the north-west by the Carboneras Fault and the south-east by the Cabo de Gata coast. Two aspects are of relevance in this zone, the volcanic geological features (lithological and structural) and the climatological factor. The semi-arid climate provides good rock exposure for these geological remote sensing applications.

Cabo de Gata is geologically a volcanic area situated at the eastern end of the Betic Cordillera. The volcanism belongs to a calc-alkaline series and is characterized by a variety of lithologies ranging from basaltic andesite to rhyolite with a predominance of the intermediate terms, andesite and dacite (López and Rodríguez 1980). The Messinian rocks that seal the volcanic activity are represented by carbonated and marly sediments, constituting a reef complex around the outstanding features, as are the Pliocene and Quaternary deposits. During the Miocene a very intense volcanic and subvolcanic activity developed in the region generating a set of hydrothermal systems. These processes produced large areas of hydrothermal alteration (epithermal), characterized by mineral assemblages made up of quartz-alunite and clay minerals (chlorite, montmorillonite, sericite), with which the main mineral deposits are associated (Arribas *et al.* 1989, Rytuba *et al.* 1990).

From an economic point of view, three types of mineral deposits are present in the area, associated with hydrothermal processes. These ore deposits, which have been exploited from the beginning of this century, are: a) gold deposits, b) Pb, Zn, Cu, Ag polymetallic deposits in veins and c) bentonite deposits (industrial clays). This paper is focused on the first and most important, although the others have also been studied as part of this project.

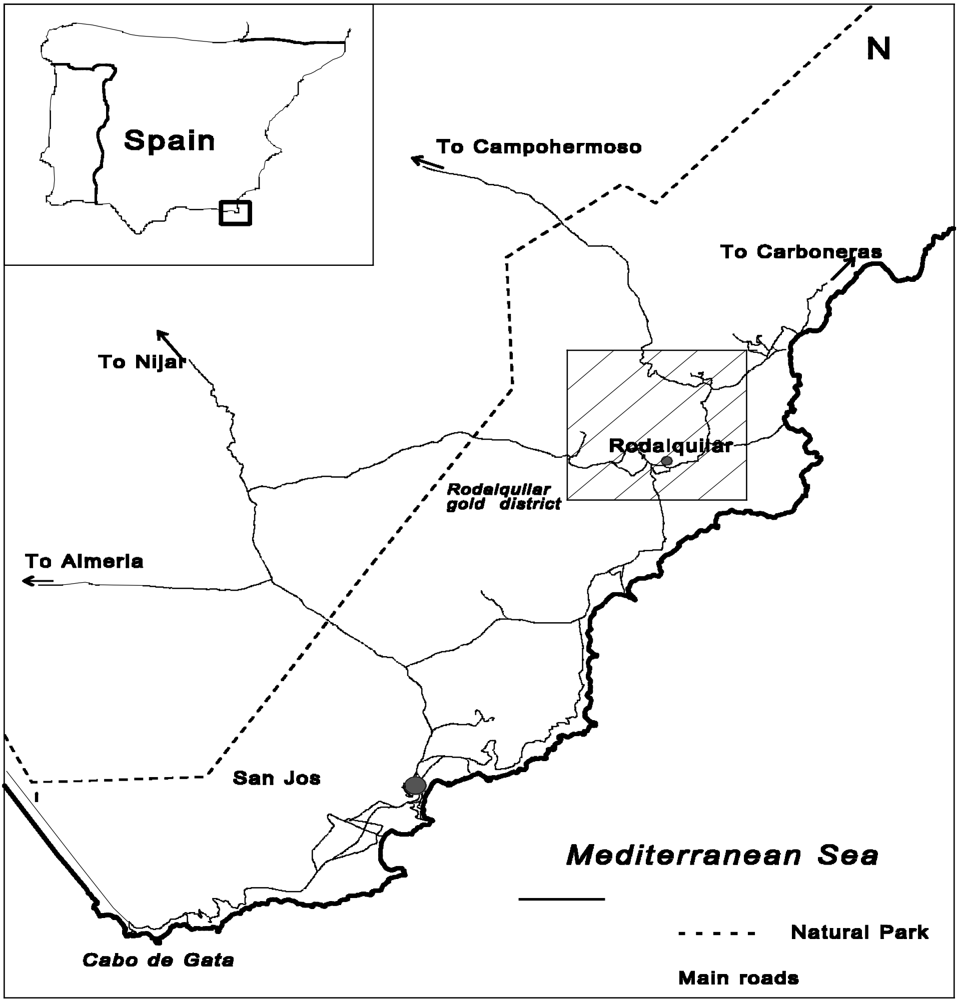

Figure 1. Location of the study area in the province of Almeria, Spain. Framed area shows the geographical location of the Rodalquilar gold district.

3. Remote sensing images and experimental data

Three principal sources of information have been used: satellite images, existing geological/exploration maps and geological exploration data. The image set is composed of three Landsat TM images (2 April, 7 July and 31 October 1991); a multispectral SPOT (23 June 1993) and a panchromatic SPOT image (2 December 1993). Moreover, airborne images were acquired from an ATM Daedalus sensor to complete detailed aspects in specific zones. Images were selected according to both favourable atmospheric and vegetation conditions for this geological context. The multispectral SPOT image was used as a complement of Landsat TM in lithological discrimination studies, while SPOT panchromatic was used for geomorphological and structural studies.

Important analogic information from previous studies was also available, such as thematic maps, regarding geological mapping, metallogenetic maps, fracturation and veins, land use, soil mapping, topography, drainage network, etc, at different scales, ranging from detailed to regional. The DEM was elaborated from digitised topography and used for radiometric corrections of satellite images. Aerial photographs were also used for interpretation given their good spatial resolution; these were scanned and merged with multispectral TM images, obtaining excellent visual quality products.

Apart from this cartographic information, abundant geological exploration data related to geochemical prospecting (minor and major elements), geophysical prospecting (gravimetry, magnetometry and aeromagnetometry), mineralogy and field radiometry were also used. All these images and the rest of the ancillary georeferenced information were introduced into the GIS database as alphanumeric tables or spatial covers.

4. Satellite and airborne image treatment

Geology has been a traditional application field for remote sensing. Mineral exploration probably covers a great part of these varied studies, focused on geological mapping (Borengasser and Taranik 1988, Harris 1991), identification of hydrothermal alteration zones (Rowan *et al.* 1977, Podwysocky *et al.* 1983), ferric oxide and oxyhydroxide mineral mapping (Schwertmann and Taylor 1977, Farrand 1997), gold exploration (Boyles 1979, Spatz 1997), etc. Based on these previous experiences we have been able to establish a simple methodology for image treatment aimed at lithological discrimination and identification of mineral potential areas related to hydrothermal alteration.

This methodology, which is described below, allowed us to generate relevant input layers for mineral potential modelling and is based on four main aspects:

- Radiometric and geometric corrections to remove image distortions and to allow adequate spatial data overlay.
- Radiometric enhancements to highlight specific rock and alteration patterns.
- Image merging and photointerpretation to generate new image products with improved resolution for geological photointerpretation.
- Image classification to distinguish main lithological units.

4.1. *Radiometric and geometric image corrections*

Atmospheric correction was made applying the dark object subtraction method (Chavez 1989), with acceptable results due to the use of clean (i.e. sediment-free) deep-water pixels located in the sea. In this respect, the colour ratio images revealed that corrections were performed properly (see figure 2). Thus, the danger of atmospheric miscorrections was minimised in subsequent band ratio analyses (Crippen 1988); thus, we assumed the images could be adequately used for mineral potential mapping in the area. Afterwards, images were geometrically corrected to eliminate geometric distortion applying the nearest neighbour method in order to preserve original radiometric information. For this, the SPOT panchromatic image was first corrected because of its higher spatial resolution, selecting a set of control points on a cartographic map. This image was later used as a reference to coregister the rest of the images by means of an image-image referentiation process. The same procedure was applied to aerial photographs, which were previously scanned at 300 dpi producing a spatial resolution of around 2 m.

Structural and geomorphological features of the area were enhanced with isotropic and directional Laplacian filters applied to Landsat TM and SPOT Pan images. This step produced a photointerpreted map of lineaments and fractures with the main structural systems, such as the NE-SW system associated with the Carboneras fault and the NW-SE system where mineralised veins are found.

4.2. *Radiometric image enhancement*

RGB colour composition is a basic procedure for geological photointerpretation applications in which groups of bands are selected depending on the features to be enhanced. Criteria based on the Index of Optimal Band Selection (IOBS) (Liu and Moore 1989) and the Optimum Index Factor (OIF) (Jensen 1986) gave excellent results, providing triplets of bands that carry more information and provide a higher contrast, e.g. RGB TM741, TM541 and TM531. In practice, the TM1 band was substituted by TM2 due to the fact that the visible blue wavelength is more affected by atmospheric scattering, and we also considered triplets that simultaneously included TM5 and TM7 bands, which are useful for discriminating clay minerals. After this, TM742 and TM475 colour composites were selected as appropriate for this application (see figure 3).

Radiometric enhancement played an important role in visual analysis of RGB colour composites, performed by different methods, e.g.: linear contrast, histogram equalization, Balance Contrast Enhancement Technique (Liu and Moore 1989) and decorrelation stretch. Band ratios were also applied to lithological and hydrothermal altered zones enhancement in order to exploit the differences in spectral slopes of mineral signatures. The classic TM5/TM7 ratio was very useful to highlight clay minerals of altered zones in which gold deposits are found. TM5/TM4 and TM3/TM1 ratios enhanced areas with iron minerals and ferric oxides, respectively. All these band quotients were interpreted jointly in an RGB TM5/TM7, TM5/TM4, TM3/TM1 colour composite synthesizing the main geological features of the region (see figure 2).

Other enhancement techniques based on Principal Component Analysis were also used. The best results were achieved by the Feature Principal Component Selection (FPCS) method proposed by Crosta and Moore (1989). This method is based on the eigenvector loading examination to assess which components concentrate information related to the spectral signature of the lithologies. The application to the six reflective TM bands showed that PC1 informed about albedo, PC2 distinguished between VIS + NIR and SWIR, PC3 vegetation, PC4 iron oxides (dark pixels), PC5 hydroxyls (bright pixels) and PC6 hematite (dark pixels). Improved results were obtained by applying the modified method of Loughlin (1991) to band subsets in order to refine lithological discrimination. TM1, TM4, TM5 and TM7 were used to characterize hydroxyl minerals and the subset TM1, TM3, TM4 and TM5 for iron oxide mapping.

4.3. *Merging and photointerpretation of satellite images*

Merging images is aimed at combining different spatial and spectral image characteristics in order to create high-resolution image documents, as in this case where SPOT panchromatic and Landsat TM images were integrated to improve visual interpretation of lithologies. In a general sense, merging methods are based on a transformation of the multispectral image, e.g. Landsat TM, to a new reference system in which intensity is an axis. Afterwards, this axis is replaced by the higher spatial resolution band, e.g. SPOT Pan, to finish the process with the inverse transformation. Some of the classical methods based on this approach are Principal

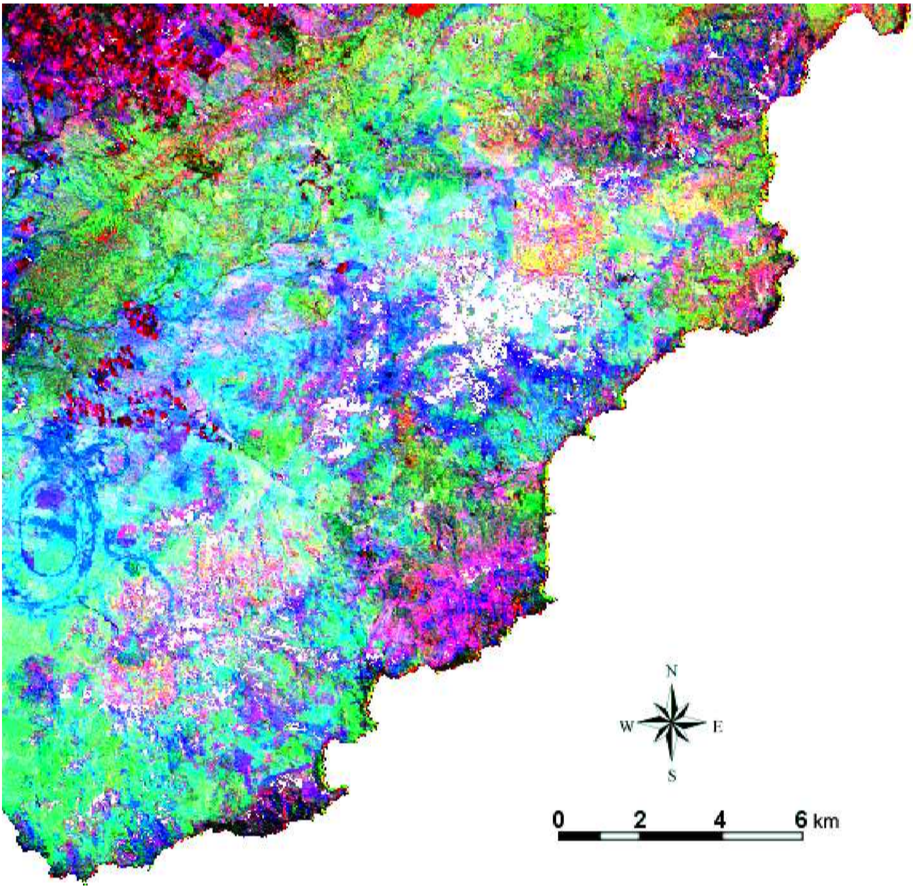

Figure 2. Landsat TM band ratio false colour composite RGB TM5/TM7, TM5/TM4, TM3/TM1. Pixels showing high normalized difference vegetation index (NDVI) have been masked out.

Component Analysis (PCA) (Chavez *et al.* 1991), Intensity-Hue-Saturation (HIS) (Buchanan and Pendergrass 1980), Spherical Coordinates (SC) (Pellemans *et al.* 1993), although others exist using High Pass Filters (Chavez *et al.* 1991).

We have statistically compared all the above methods computing the correlation coefficient between merged and original bands. The HPF method produced merged images with the least distortion of the original spectral characteristics, followed by the PCA, IHS and SC methods. Nevertheless, visual comparison of the results points to the PCA method as the most appropriate due to the visual quality of images generated, and also because it allows simultaneous operations with all bands (Rigol and Chica-Olmo 1998). Figure 3 shows the RGB 475 merged image (PCA method) of the Rodalquilar gold district together with the photointerpreted map. Main contacts between different volcanic rocks are detected, and particularly between altered and non-altered rocks. Improvements in spatial resolution enabled mapping of small volcanic outcrops not clearly seen in TM images and gave more cartographic details regarding the tertiary sediments, limestone and reef sandstone.

As a result of this process a set of thematic maps were elaborated and introduced

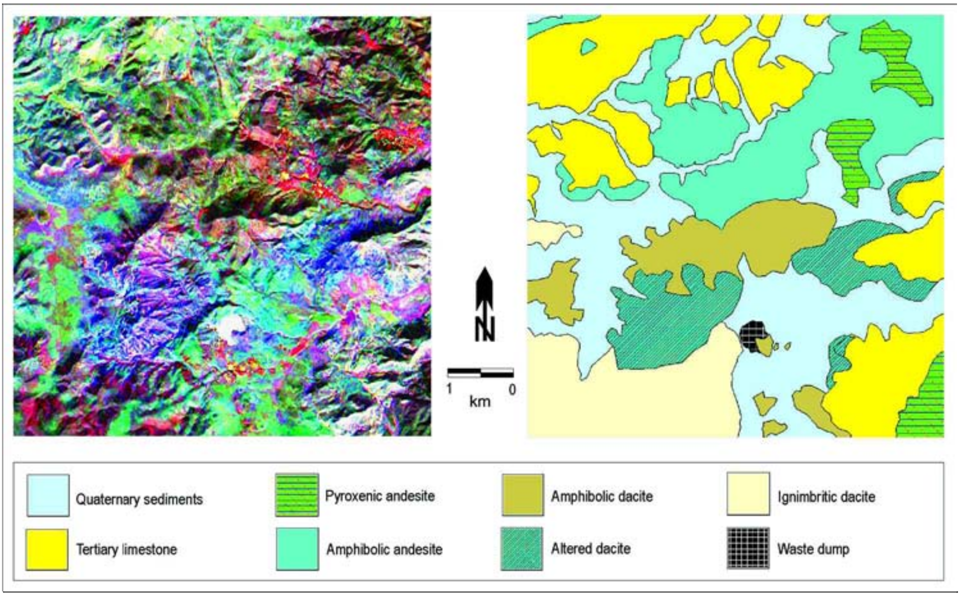

Figure 3. SPOT Pan and Landsat TM merged image of the Rodalquilar gold district (475 RGB composite) and photointerpreted lithological map. Geographical location of this district is shown in figure 1.

into the GIS cartographic database, i.e. lineaments, faults and fractures, lithology, volcanic structures and hydrothermal alteration maps.

4.4. *Image classification*

Supervised classification was carried out on the summer TM image, selecting a set of training areas and gathering complementary data of field radiometry. Previously, the topographic effect on radiometric data was corrected using the DEM, taking into account sun elevation angle and azimuth parameters. The classification algorithm applied is based on a variant of the Bayesian maximum probability decision rule (Hord 1982), which allows us to specify a priority probability for every class. As outlined by Jensen (1986) this classifier assumes the populations that provide training data are multivariate normal across all the selected features for each nominal class. Moreover, context information deduced from a geostatistical analysis of the image texture, based on the calculation of spatial variability measures of the radiometric data, was added to improve results (Abarca and Chica-Olmo 1999).

The image classified showed contacts between the main lithological classes and, essentially, highlighted the spatial distribution of hydrothermal alteration zones. The Kappa (Cohen 1960) and Tau (Ma and Redmond 1995) coefficients, 0.83 and 0.82, respectively, suggest an acceptable degree of accuracy in classification results, though we observed that a certain proportion of pixels were confused, being assigned to classes with a similar mineralogical composition. This aspect could be explained by the fact that the volcanic rocks in the study area belong to a felsic-basic transition series, it being difficult to establish the lithological limits.

Airborne ATM images (Daedalus AADS1268) were also classified using 9 bands (ATM1 and ATM11 were excluded) to obtain a more detailed cartography of the alteration zones; in this case, the Kappa and Tau coefficients obtained were 0.93 and 0.92, respectively.

5. Implementation of a Decision Support System for mineral exploration

5.1. *Methodology*

GIS technology is a powerful tool for integration and analysis of georeferenced spatial data, and its use in mineral exploration is becoming more and more widespread to help in target area selection tasks. Figure 4 represents a general scheme of the methodology followed for GIS implementation. Two main parts are illustrated: the relational database and the user interface for spatial analysis 'Decision Support System' (DSS). The relational database contains and integrates the georeferenced information coming from remote sensing imagery, existing maps and exploration/ prospecting data, expressed as tables and maps. Existing maps were digitised in 'spaghetti' mode to create vector maps with arc/node structure, and remote sensing results were digitised on screen in the case of photointerpreted images or as a simple raster layer for classified images.

Special attention was paid to integrating the mineral prospecting information available in data tables by means of geostatistical methods. In brief, this stage consisted of the following steps: variographic analysis (variogram calculation and fitting), geometric model definition (estimation area and estimation grid size) and

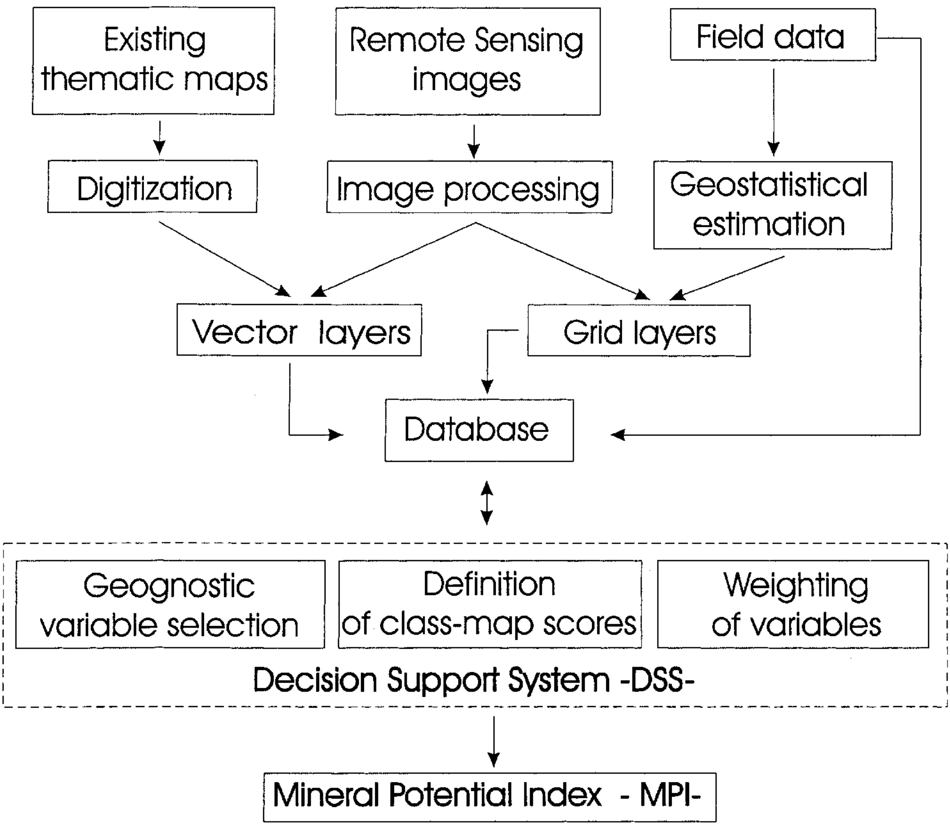

Figure 4. Flow chart illustrating the Decision Support System methodology.

kriging planning (method and estimation neighbourhood). Different geostatistical methods such as ordinary kriging, indicator kriging and co-kriging (Journel and Huijbregts 1978) were used for these specific objectives: average value estimation, anomaly mapping and multivariate estimation, giving a set of raster layers of the variables studied, e.g. geochemical data. This treatment was carried out on both experimental and transformed data, e.g. principal component analysis of geochemical data.

Table 1 gives the main information layers classified into thematic groups selected for this study.

It is widely accepted that spatial analysis is the most distinctive feature of GIS. In our approach this aspect has been tackled through the spatial analysis capabilities offered by ARC/INFO software, in order to build a Decision Support System (DSS) based on a user-interface developed using Arc Macro Language (AML). The user interface includes graphic menus (see figure 5) for model parameter definition and Exploratory Data Analysis (EDA) as well as a map algebra expression builder engine developed for this project. This tool has been designed to help in the complex task concerning decision making in mineral exploration, and it is based on three main aspects: a geological and mineral conceptual model setting, an operational mineral exploration model setting and expert's criteria to select the most representative variables directly related to mineralisations. The geological and mineral model has been established to be as simple as possible to explain the existence and the spatial distribution of mineralisations in the region; it will be used as a guide for further exploration work. Following expert's criteria three exploration phases, preliminary, reconnaissance and detailed, were defined according to the degree of information availability. Finally, a set of the most representative experimental information was chosen as 'geognostic variables' for each exploration phase (i.e. variables closely related to the mineralisations studied). Geognostic variables are the basis on which the mineral potential at any location in the region is estimated by means of ad hoc

Table 1. Main layers included in the GIS database

Thematic group	Layer	Type	Processing
Geology	Lithology	Polygons	Digitizing
	Fractures/veins	Lines	Digitizing
	Hydrothermal alteration	Polygons	Digitizing
	Metallogenetic deposits	Polygons	Digitizing
	Mineralogy	Raster	Estimation
	Volcanic structures	Lines	Digitizing
	Mineral occurrences	Points	Field survey
Geophysics	Aeromagnetometry	Polygons	Digitizing
	Magnetometry	Raster	Estimation
	Gravimetry	Raster	Estimation
Geochemistry	Geochemistry	Raster	Estimation
Remote Sensing	Lithology	Polygons	Photointerpretation
	Lithology	Raster	Digital classification
	Hydrothermal alteration	Polygons	Photointerpretation
	Lineaments/fractures	Lines	Photointerpretation
Others	Field radiometry	Points	Field survey
	Topography	Lines	Digitizing
	Drainage network	Lines	Digitizing

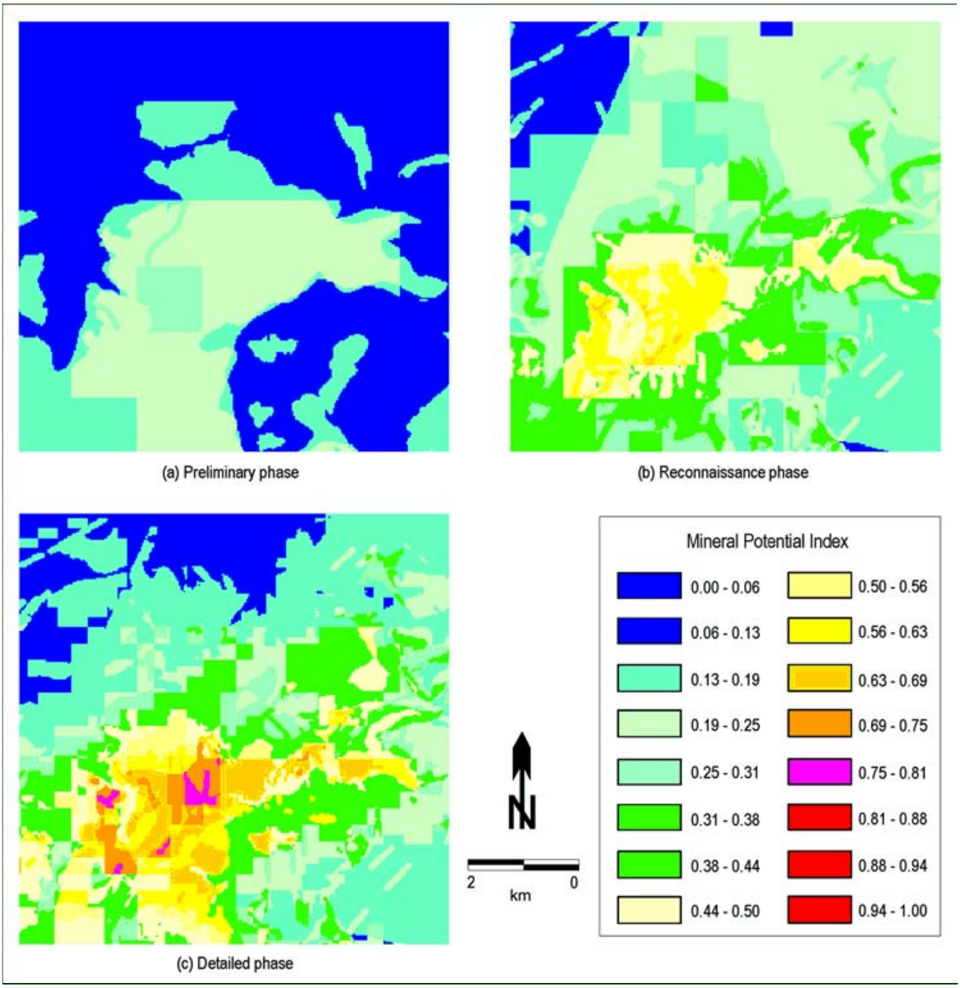

Figure 5. An example of Mineral Potential Index (MPI) maps corresponding to the Rodalquilar gold district (see figure 1 for geographical location). Results of the three mineral exploration phases: a) Preliminary, b) Reconnaissance and c) Detailed as shown.

spatial analysis methods. Obviously, result accuracy will depend on diverse factors such as type and number of variables used, information density, weight assigned to each variable and also on the cost/benefit ratio considered for each exploration phase. In this way, consider the following example referring to remote sensing information: Landsat TM images could be used in a preliminary exploration phase where the economic risk is high, because of their low cost and good results at medium scale. On the other hand, ATM airborne images would be more adequate to be used in an intermediate or detailed phase, where the risk is lower, due to their higher economic cost and higher spatial and spectral resolution.

Spatial analysis of this experimental information is complex and must resort to numerical algorithms combining qualitative and quantitative thematic variables. For this purpose the criterion based on overlaying multi-class maps (Bonham-Carter 1994) was chosen and carried out with reference to a practical concept named

'Mineral Potential Index' (MPI). This index is numerically a linear expression in which such a calculation requires us to assign scores to each class-map and weights to each input map according to the expert's criteria:

$$MPI(x) = \sum_{i=1}^{n} P_i(Z_i^c(x)/Z_{i\_\max}^c); \qquad \sum_{i=1}^{n} p_i = 1 \tag{1}$$

where $MPI(x)$ represents in terms of spatial probability the mineral potential at point x, varying in the interval [0,1], p_i are the weights assigned to the input map (geognostic variable) i, $Z_i^c(x)$ is the score for class c of the input map i at location x, and $Z_{i\_max}^c$ is the maximum value allowed of $Z_i^c(x)$, and x is any location in the study area. This simple algorithm was included in the DSS user interface and can be straightforwardly computed using a raster data model structure. Thus, DSS facilitates the simulation and refinement of diverse exploration scenarios selecting a specific exploration phase, input geognostic variables and weighting schema, as well as assessing resultant MPI spatial patterns.

5.2. *An example of DSS application for gold-rich area identification*

A brief summary of a DSS application to simulate mineral exploration scenarios for gold-rich area identification is shown, though it has equally been applied to other types of mineralisations such as polymetallic sulphurs and clay minerals. The objective is to calculate and compare MPI maps for each exploration phase, analysing the results in terms of surface reduction and economic costs. An example of class-map (favourability class) and scores values for the thematic variables considered is given in table 2. Maximum score values are considered to be different in each of the three phases in order to take into account that information could have a higher significance loading in a detailed phase than in a preliminary one.

A graphic interface allows the user to select a set of geognostic variables i (thematic maps) and weights p_i, as well as other parameters of interest such as the area limits, pixel size (grid) for calculation, weights for missing data, etc. Results are graphically shown as MPI raster maps such as those represented in figure 6, where it can be clearly interpreted as an increase in information level, from the Preliminary phase to the Detailed one, identifying and detailing the potential gold-rich areas.

To a certain degree, it would be possible to validate MPI maps numerically if we could compare their values with the 'ground truth' represented by a set of mineral occurrences. We have carried out this test for a sector of the detailed MPI map with enough information, obtaining for different simulation cases a Spearman r non parametric correlation coefficient varying from 0.54 to 0.6, between MPI values and number of occurrences per cell or pixel (size $250 \times 250\,m^2$), which reveals a relation between the two variables, as could be expected. This relationship is more clearly shown in figure 6, which compares the mean value of occurrence number and the

Table 2. An example of class-map scores for the three mineral exploration phases.

Preliminary phase		Reconnaissance phase		Detailed phase	
Unfavourable	0	Unfavourable	0	Very unfavourable	0
Favourable	0.4	Favourable	0.4	Unfavourable	0.4
		Very favourable	0.8	Favourable	0.8
				Very favourable	1

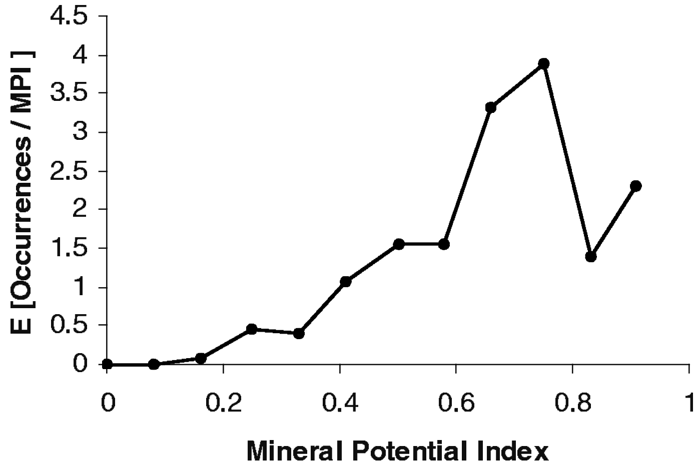

Figure 6. Mathematical expectation of number of mineral occurrences conditional to MPI value.

MPI value, i.e. the conditional mathematical expectation E[Occurrences/MPI] for each probability class of MPI.

In practice, target area selection was made applying an MPI cut-off value for each considered exploration phase, 0.2, 0.4 and 0.5 respectively, coincident with the central score values of the multi-class maps. Areas whose MPI values exceed these cut-offs were 29%, 9% and 5% of the total studied area, respectively, results that were subsequently analysed in terms of prospecting costs. In all cases, the main mineral occurrences showed high scores and were consequently confirmed as target areas (e.g. Cerro del Cinto, Triunfo, and the Maria Josefa gold mines). New potentially mineralised areas were also shown as target areas. Some of them had been previously identified by field surveys, while others need further investigation.

In addition, removing some input layers from the model or replacing detailed layers by a lower resolution version allows prospectors to estimate DSS sensitivity. For instance, removing the Landsat TM5/TM7 band ratio from the model produces a significant impact on the resulting MPI maps, while removing both ground and airborne magnetics has a low impact.

6. Discussion and conclusion

In this paper we have shown how remote sensing and GIS techniques can be integrated to construct an operational system for decision making in a mineral exploration context. Results demonstrate that remote sensing imagery plays an important role in mineral potential analysis, providing diverse thematic layers of interest. Digital analysis of satellite and airborne images has supplied basic information about lithological discrimination and, specifically, on the spatial distribution of hydrothermal alteration zones with which the principal deposits are associated. In this matter, we wish to highlight the excellent contribution of the Landsat TM and SPOT Pan integration methods in facilitating visual photointerpretation tasks. Also of great interest, were the results provided by the FPCS technique and digital classification to locate altered zones characterised by hydroxyl-bearing minerals.

These results were included as raster or vector layers in the database together with existing thematic maps and prospecting data.

GIS spatial analysis functions have permitted us to develop an MPI map by means of overlaying multi-class maps; this was used as a decision support tool for efficient planning in mineral exploration. The system allows the user to calculate an MPI map corresponding to a specific simulation case study using selected geognostic experimental variables. This index is currently calculated as a simple weighted average of the multi-class maps, where variables (maps) and weights are arbitrarily selected by mineral exploration experts. This criterion, however, can be modified by applying other techniques based on artificial intelligence such as neural networks or logistic regression (Singer and Kouda 1996 and Zhou and Civco 1996). It has been proved in the example shown that the system is an effective tool for assessing gold potential in the region, reducing the higher mineral potential areas to 5% of the original surface extent. These areas contain the main known mineral occurrences and draw attention to both previously surveyed (Rodalquilar gold district) and unknown potentially mineralised sectors. Moreover, the system can also be used to analyse the role that every thematic map can play in mineral potential assessment by means of simulating different scenarios. In general, experimental results suggest that TM band ratios and FPCS images along with fracturation and geochemical layers are the most valuable data.

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