GIS analyses and favorability mapping of optimized satellite data in northern Chile to improve exploration for copper mineral deposits

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ABSTRACT

Data integration and analyses within a geographic information system (GIS) can improve exploration and detection of mineral deposits. We applied a GIS-based analysis and classification strategy of satellite data to the rich and well-explored Eocene–Oligocene porphyry copper province of northern Chile, attempting to recognize the distinctive signature of such giant ore deposits. Image-based favorability mapping is a supplementary exploration tool and is only applicable to exposed deposits. Additionally, favorability mapping can be used in conjunction with geophysical and geochemical data to improve exploration for buried deposits.

The study area covers part of the Central Andean Precordillerá with world-class porphyry copper deposits. La Escondida mining district was selected as a training site, because Landsat satellite images are available for pre- and synmining times. Analyses of geological, structural, and optimized remotely sensed data of this mining area can help to identify some common characteristics of altered rocks and associated porphyry copper ores. To the already known geological and structural setting, optimized Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper (ETM) data, transformed by principal component analysis, inverse principal component analysis, band “ratioing,” and spectral mapping of magmatic host rocks, show typical rock alterations for the training sites at La Escondida mining district, Quebrada Blanca mining district, and other areas. These optimized data provide important surface indicators for detection and visualization of altered rocks and mineralization.

Optimized images are classified to separate target areas of altered rocks from nontarget areas without alteration. The resulting classifications of all image transformations are combined numerically in a favorability map, which shows the spatial distribution of target areas related to hydrothermally altered rocks. This approach, in combination with geological field work, provides a new impetus for exploration strategies and localization of hydrothermally altered rocks with related mineralization. On the basis of these results, mineral exploration can be improved by the use of optimized and classified satellite data in other, less examined copper provinces of similar arid-semiarid climatic conditions throughout the world.

Keywords: Landsat, GIS, favorability mapping, porphyry copper ores, Central Andes.

INTRODUCTION

Remote sensing and geographic information systems (GIS) have proven valuable for mineral exploration in several ways: mapping of regional lineaments with related mining districts, mapping of local fracture patterns that may control ore deposits, detection of hydrothermally altered rocks associated with ore deposits, and providing basic geologic data at low costs within a short time (Sabins, 1986). An integrated data manipulation allows numerical analyses of classified satellite data with respect to altered rocks and corresponding mineralization.

In the past, strategies were developed for terrestrial prospecting of nonrenewable resources. To demonstrate the need for further methodological developments in mineral exploration at a regional scale, two strategies are briefly explained to illustrate their disadvantages and risks.

The classical approach for mineral exploration is the conceptual model described by Bonham-Carter (1994). This model is a multi-stage activity based on a successive reduction of target areas in defined steps, taking into account typical characteristics of known mineral deposits. It proceeds from a small scale, by definition, of general zones of potential interest for a given type of mineral deposits, and continues to a large scale, showing the location and ranking of potential drilling sites. This progressive reduction of target areas involves two main risks. On one hand, potentially interesting areas cannot be recognized in the early steps and therefore are not evaluated. On the other hand, no further research is applied in the neglected areas, and potentially important new data are missing. That means the database might be incomplete and so would not be considered suitable for GIS analyses.

Another approach was developed by Billa et al. (2002). Based on the geographic information system Andes, initialized by the French Bureau de Recherches Géologiques et Minières (BRGM), a favorability map was calculated. The GIS Andes (http://gisandes.brgm.fr/) covers the entire Andean margin of South America and contains topographic data in combination with geological, geophysical, geochemical, and metallogenic data (Cassard, 1999). Favorability mapping, which quantifies the exploration potential along the region, was calculated by predefined criteria, taking into account some features common to all known deposits of a certain type. The GIS Andes of the BRGM does not contain magnetic and Landsat data, although these data sets represent two important thematic GIS layers for mineral exploration.

To reduce the risks involved in the described strategies, we applied GIS analyses and favorability mapping for the Eocene–Oligocene Central Andean porphyry copper belt with a voluminous database containing surface information from lithology, structural geology, and locations of known ore deposits in combination with satellite data and geophysical information from gravity and magnetics.
Image-based favorability mapping is applicable only to exposed deposits, but it can be used in conjunction with geophysical and geochemical data to improve exploration. Integrated GIS and its image-processing environment allow numerical analyses of classified data with respect to altered rocks and related mineralization. The entire working area in the Central Andes covers 350 × 350 km from lat 20.5°S to 24°S, and long 66°W to the Pacific coast of Chile. To examine the reliability of the method, a preliminary favorability map for the training site at La Escondida mining district was calculated. Further results for other training sites (Quebrada Blanca, Chuquicamata, Spence, and El Abra) also demonstrate that the method presented here is able to detect highly mineralized bodies. Based on these results, which were derived from analyses of well-known training sites, mineral exploration can be improved elsewhere in other porphyry copper provinces in arid areas—e.g., Kerman (Iran), Sumbawa (Indonesia), and Turquoise Hill (Mongolia)—by providing spectral base maps and optimized images.

GEOLOGY AND MINERALIZATION OF THE CHILEAN CENTRAL ANDES

The active western margin of South America, particularly its Central Andean segment (see Fig. 1), is the largest known base- and precious-metal province of the Earth (Sillitoe, 1992). Inside this province, the northern Chile region between lat 20° and 27°S hosts five world-class giant porphyry copper deposits, i.e., Quebrada Blanca, El Abra, Chuquicamata, La Escondida, and El Salvador (see locations in Fig. 1). In addition, this region contains several large to intermediate deposits and is active in exploration for new resources.

The present-day Central Andean forearc of northern Chile is bordered to the west by the Peru-Chile trench, where the oceanic Nazca plate subducts underneath the continental margin, and to the east by the Western Cordillera. This forearc has elevations higher than 5000 m and was mainly formed by Miocene to Holocene volcanic rocks. The forearc morphostructure (Fig. 1) is dominated by the Coastal and Domeyko Cordilleras, which are separated from each other by the Intermediate Depression north of lat 24.5°S. The morphostructural anomaly of the Atacama Basin separates the Domeyko and Western Cordilleras between lat 22° and 24°S.

The old basement of the Central Andes is thought to have been formed by a mosaic of Proterozoic terrains colliding with the autochthonous margin of South America until the early Paleozoic (Mpodozis and Ramos, 1989). Late Paleozoic magmatic rocks of dominantly felsic composition commonly crop out along the Domeyko Cordillera (or Chilean Precordillera of Reutter et al., 1996), which formed a large igneous province along the entire western margin of Gondwana (Mpodozis and Ramos, 1989). The Mesozoic–Cenozoic history of this region is characterized by the construction of at least three distinct north-south magmatic arcs that progressively migrated eastward from the Coastal Cordillera (Jurassic–Early Cretaceous) to the Intermediate Depression (Late Cretaceous–Paleogene) and to the Domeyko Cordillera (Eocene–early Oligocene) before the final movement toward the Western Cordillera. The mechanism responsible for the eastward migration of magmatic arcs is still controversial and could be related to the truncation of the margin by subduction erosion and/or the flattening of the subducted slab produced by the westward overriding of the continent after the South Atlantic opening (Mpodozis and Ramos, 1989; Stern, 1991; Behn et al., 2001).

The construction of each magmatic arc can be related to particular metallogenic processes. The geotectonic conditions during the Eocene–Oligocene arc seem to have been optimal for the formation of the huge porphyry copper deposits that characterize the Domeyko...
Cordillera. Northeast-directed convergence during the Eocene (Somoza, 1998) favored the development of a trench-parallel fault system (Domeyko or West Fissure fault zone) that accommodated dextral transtension along the evolving magmatic arc (Reutter et al., 1996; Tomlinson and Blanco, 1997a, 1997b). The final emplacement of (grano)dioritic plutonic clusters at shallow depths, generally in places where the Domeyko fault zone intersects trench-oblique structures, and the associated development of prolific hydrothermal systems were probably enhanced by the relaxation of the dextral transtensive stresses and the eventual reversal of the strike-slip polarity to sinistral during an early Oligocene plate reorganization (Reutter et al., 1996; Richards et al., 2001). This event coincides in time with the main hypogene sulfide mineralization epoch of the giant porphyry copper deposits between 34 and 31 Ma (Ossandón et al., 2001; Richards et al., 2001; Padilla et al., 2001). After that, the gradual acidification of the Chilean forearc, culminating at 15 Ma, and the associated downward movement of the groundwater table, was responsible for supergene oxidation of the hypogene zones. This was accompanied by the formation of enriched sulfide blankets, in situ copper oxide zones, and lateral mobilization of copper to form exotic deposits (Sillitoe and McKee, 1996). These supergene processes significantly enhanced the economic potential of the Domeyko Cordillera metallogenic provinces (Sillitoe, 1992).

Although each deposit along the Domeyko Cordillera is an individual case, some characteristic ore and alteration assemblages are common to them all. The hypogene sulfide mineralization normally consists of chalcopyrite ± bornite ± chalcocite ± covellite ± enargite and is associated with a hydrothermal alteration system that developed in at least three main stages: initial, pervasive potassic (K-feldspar + biotite) alteration; a later stage of quartzfeldspar and quartz sericite alteration in vein and breccias near main faults; and a final stage of advanced argillic alteration that introduced pyrophyllite ± alunite ± quartz + pyrite (Padilla et al., 2001; Ossandón et al., 2001). The subsequent supergene enrichment process was associated with the leaching of these upper zones and the accumulation of large chalcocite blankets below the water table. Above that, the leaching process stabilized some hydrated copper minerals (i.e., atacamite, chrysocolla, and brochantite) and left a highly leached rock profile containing limonites (jarosite, hematite, and goethite), clay minerals (kaolinite), and alunite (Sillitoe and McKee, 1996). The tops of these lithocaps normally correspond with the present-day topographic surface.

Recognition of the leached cap as an integral part of the giant porphyry copper systems of the Domeyko Cordillera was fundamental for the exploration strategy culminating with the discovery of La Escondida in the early 1980s (Richards et al., 2001) and has guided exploration for new deposits in this belt during the following decades. Other current exploration targets in northern Chile, both in the Eocene–Oligocene belt and the less studied Paleocene belt, are potentially concealed deposits underneath the Miocene piedmont gravels that cover parts of the Domeyko Cordillera (e.g., Gaby prospected by CODELCO) and fill the Intermediate Depression (Fig. 1). GIS-based analyses of large databases, looking for the recognition of the structural, geological, and geochemical signatures associated with porphyry copper deposits, are expected to be more useful and efficient for recognizing exploration targets that potentially crop out at the surface rather than for those covered by gravels.

GEOSCIENTIFIC DATABASE

Data modeling and interpretation are carried out by the use of commercial GIS (ArcGIS) and digital image processing systems (Erdas Imagine). GIS analyses with numerical data integration, visualization, and presentation provide a wide variety of digital techniques. A critical step in GIS-based analyses is the buildup of a voluminous database containing data from various geoscientific disciplines and data sources (Ott et al., 2002). The database used here contains remotely sensed data (University of Maryland, http://gfc.umd.edu/index.shtml), geological and structural data (SERNAGEOMIN, 2003), magnetic (CODELCO) and gravity data (Freie Universität Berlin, http://userpage.fu-berlin.de/~geoinfhb/Welcome.html), topographic data (U.S. Geological Survey, http://seamless.usgs.gov/), and databases of mineralization and ore deposits (SERNAGEOMIN).

This unique data collection allows correlation of spectral and geological data for delineation of altered rocks and mineralization. Figure 2 shows different thematic layers of the GIS database for La Escondida mining district. This world-class porphyry copper ore was chosen as a training site (reference area), because spectral signatures of host rocks from pre-mining Landsat TM data are undisturbed, whereas syn-mining Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data are contaminated by mining activities. Landsat satellites measure the electromagnetic radiation reflected by the Earth’s surface. The information is stored in seven bands of the electromagnetic spectrum and can be used to assess the mineralogical characteristics of exposed rocks. Landsat data may assist first pass mapping in the detection of altered rocks and mineralization. This is what Agar and Pavez (1999) called “old dogs with new tricks.” At the moment, hyperspectral data are not available for regional studies at small scale, or else only at high cost.

DIGITAL IMAGE PROCESSING OF LANDSAT DATA

Remotely sensed images are in digital form as two-dimensional arrays of digital numbers for several spectral bands. Digital numbers represent the energy or radiance captured by satellite sensors for defined bandwidths. Digital numbers are coded in an 8-bit binary range with 256 values from 0 to 255. For improved visualization and interpretation, the data are displayed in red, green, and blue color guns, resulting in >16 million colors. Nevertheless, uncompressed data are not suitable for further digital image processing and need to be enhanced for visual interpretation and digital analyses. First, some preprocessing techniques should be applied to the original data to remove influences of atmospheric scattering during data acquisition. Besides this, the appearance of neighboring Landsat frames in a mosaic from differing seasons and weather conditions results in differing image contrasts and brightness. To remove these effects, statistic parameters of the histogram distribution (mean value, minimum and maximum values) of each satellite frame must be adjusted. Second, selective image-processing techniques should be applied to enhance rock types and improve visualization of altered rocks. The applied techniques are introduced briefly. More detailed explanations of digital-image-processing techniques in geology are described, among others, in Colwell (1983), Campbell (1987), Richards (1992), Lillesand and Kiefer (1994), and Drury (2001).

Image Preprocessing of Landsat Data

Landsat data provided by the Global Land Cover Facility is already geometrically corrected by use of the linear nearest neighbor method. The accuracy of the geometric correction is proved with global positioning system (GPS) data acquired from various field campaigns of the gravity group at Freie Universität Berlin (Germany). The spatial accuracy of geoencoded satellite data, expressed as the root mean square error of GPS control points, is <30 m and can be ignored.

The reduction of atmospheric scattering and the adjustment of image histograms are essential data pre-processing techniques in producing high-quality images, mosaics, and spectral
GIS analyses of optimized Landsat data

Atmospheric Correction

Atmospheric scattering in multispectral data varies with wavelength. The scattering effect is stronger in the visible spectrum (0.4–0.7 μm), and only small in the shortwave infrared region (1.6–2.2 μm). Figure 3 shows a Landsat TM image subset from 4 May 1990 of the Pacific coast and parts of the basement area in the Coastal Cordillera near Antofagasta. The correction is done by use of the histogram minimum method. Mathematically, this image correction is a subtraction of dark pixel values from the data sets. This correction is important for further spectral analyses of rocks and other materials. The image appears much clearer, and color intensity improves. Therefore, the visual discrimination of various rock types, as well as the recognition of structures, improves dramatically.

Histogram Matching (Data Adjustment)

Data adjustment is another important image operation by histogram matching of neighboring satellite frames. Histogram matching is necessary if a mosaic of several data sets is calculated. Landsat data acquired at different times under different seasonal and climatic conditions will result in inhomogeneous image appearance. Statistical parameters, such as minimum values, maximum values, mean values, and standard deviations of all spectral bands, are compared. Differences for all digital values are calculated and adjusted, making the apparent distribution of brightness values in two or more images as close as possible. Mathematically, histogram matching is calculated by algebraic expressions. Figure 4 shows an example of nonadjusted, compared to adjusted, Landsat data in the border area of Chile and Argentina. Rocks and other surfaces show different hues in uncorrected data. The corrected image mosaic shows homogeneous hues without any apparent boundaries of neighboring Landsat frames. Thus, any differing appearances need to be adjusted.

Image Optimization

Since the 1980s, remote sensing has become an operational tool for geological applications. Satellite data are used for geological mapping projects and for environmental and exploration studies. On the basis of spectral signatures and physical rock properties, many digital-image-processing techniques for mineral exploration have been developed and applied. Absorption of radiance (light) wavelengths corresponds to the vibrational-rotational energy of chemical bonds in minerals. The commonly used –OH bond absorptions in the infrared region can be used to fingerprint mineral types and in some cases, compositions if spectral resolution is sufficient, i.e., hand-held spectrometers and some satellites with narrow bandwidths. Most of the porphyry deposits consist of zonal patterns of mineralization and wall-rock alteration. Hydrothermal alteration produces clay and other silicate minerals, e.g., argillic and phyllic zones. Supergene alteration results in the formation of iron oxide minerals (see Fig. 5). In contrast to the use of unprocessed Landsat false color images, these mineral assemblages can be

Figure 2. Perspective view of different thematic layers of the database in the vicinity of La Escondida mining district. Upper layers represent optimized Landsat data derived from band ratioing, principal component analysis (PCA), and inverse PCA. Lower layers represent topographic data, lithology, and aeromagnetic data. Bottom layer is one of the calculated favorability maps. This study focuses on optimized Landsat data, whereas the other data sets are not used at this time.
detected by optimized and transformed Landsat data (Abrams et al., 1983; Goetz et al., 1983; Podwysoki and Segal, 1983; Amos and Greenbaum, 1989). Image classification and favorability mapping criteria are defined by altered rocks, and their characteristic spectral properties are derived from optimized images.

The following examples are derived from Landsat TM data acquired 27 October 1989. The image subset shows the vicinity of the open pits at La Escondida mining district (see Fig. 1). More recent Landsat ETM+ data acquired in 2000 were rejected for further image transformation, because the spectral signature at La Escondida mining district is contaminated by extensive mining activities and thus is not suitable for spectral analyses. A color-coded difference image between Landsat TM and ETM+ data was calculated for change detection. The high degree of mining contamination is detected by definition of a cutoff value of 10% (see Fig. 6). Black indicates no change between TM and ETM+ data, whereas green means an increase of spectral reflectance by 10%, and red indicates a decrease of 10%. An increase is characterized by extensive mining activities, with dust surrounding the mining areas. The decrease results from shadows of deepened open pits and new ponds.

Principal Component Analysis (PCA)

Strong correlation between Landsat TM bands produces an elongate ellipse in bivariate plots of data points. This strong correlation indicates a high degree of redundancy within the data. Spectral information shows little color variation and poor contrast because of the redundancy. Therefore, recalculation and rotation of the original feature space axes redistribute and spread the data points in the new bivariate plots. One method to remove redundancy is the calculation of principal components (see Fig. 7). Principal components are calculated in two ways. The unstandardized PCA uses the covariance matrix obtained from the input multispectral data and is applied here. Determination of eigenmatrices and eigenvalues characterizes the signal and noise information for each component. The standardized PCA is calculated with a correlation coefficient, obtained by division of the covariance of spectral band pairs and their standard deviations.

The first principal component (PC) calculated from the Landsat data is defined by the greatest variance (86%) from all TM bands that contain significant albedo (the ratio of the amount of electromagnetic energy reflected by a surface to the amount of energy incident upon it) and topographic information. The second PC shows lower variance (11%) and contains topographic information and fair lithologic contrast. The
third and fourth PCs contain ~2% of the variance and display good lithologic contrast. The fifth and seventh PCs show a small amount of variance (<1%) and display the occurrence of clay minerals. The PCA image in Figure 8 is the result of the fifth (clay), fourth (lithology), and third (lithology) principal components displayed in red, green, and blue. This PCA color image reflects best the distribution of altered diorites and clay minerals. Spectral anomalies of altered rocks are highlighted in purple to red and can be recognized clearly. Anomalous colors represent various rock types. In summary, spectral differences between rocks may be more apparent in PC images than in individual bands. The anomalous PC colors derived do not correspond to spectral reflectance and absorption of rocks because of the data transformation.

Inverse Principal Component Analysis (Inverse PCA–Decorrelation Stretch)

PCA calculates new coordinate axes by rotating the original feature space axes. To conduct inverse PCA, the obtained principal component images are rotated, stretched, and then rotated back into the original feature axes. The rotation of axes enables the cloud of data to be stretched in two up to n-directions instead of only one direction along the major axis of the original elliptical distribution. This technique is known as decorrelation stretch or inverse PCA. The feature space defined by these new axes can be filled more efficiently (see Fig. 9). As an effect of the inverse PCA, the resulting images are chromatically enhanced and decorrelated. Because of more or less original hues of surface rocks, the image is more interpretable than the principal components with resulting anomalous hues.

Figure 10 shows the result of inverse PCA. The image is a color composite of the highly decorrelated bands 5, 3, and 1 in red, green, and blue. This inverse PCA color composite reflects best the distribution of altered intrusive rocks and clay minerals. Spectral anomalies of altered intrusive rocks are highlighted in yellow and reddish colors.

Band Ratios

Multispectral satellite data can be displayed as gray-tone images of single bands, or as three-band color composite images. The use of all available spectral bands by various arithmetic combinations provides new information for specific applications, especially localization of altered rocks, clay and iron minerals, and vegetation. Band “ratioing” of multispectral satellite data is a well-established image enhancement in geologic remote sensing. Ratios are calculated simply by dividing the digital numbers of one band by the corresponding numbers in another. In practice, floating point values of ratio images range from –4 to 4, and therefore need to be stretched to 8-bit integers with 256 values for better visualization. Color ratio images are obviously less correlated than the original bands and are therefore chromatically enhanced. The contribution from atmospheric effects varies with wavelength. Before calculating ratios, the data must be statistically adjusted to minimize the effects of atmospheric scattering. Additionally, ratio images reduce the influence of relief and shadows.

It is important to note that ratios calculated from visible and shortwave infrared Landsat bands are suitable for the detection of clay and iron minerals (see Fig. 11). In the shortwave infrared part of the spectrum, vibrational transitions in materials are associated with the presence of –OH ions. The commonly used –OH bond absorption can be used to fingerprint mineral types. Therefore, a color ratio image is calculated from TM bands 5/7, 3/1, and 4/3 in red, green, and blue (Fig. 12). The color variations of ratio images express more geologic information than conventional false color images. The 5/7 ratio is called the clay-band ratio, owing to strong absorption and reflection of clay minerals in bands 5 and 7 with high ratio values for clay mineral–bearing areas. The 3/1 ratio is called the iron ratio.
Figure 6. Extensive mining activities produce dust and other pollutants that cover the wider mining area. Spectral signatures of rocks are contaminated by dust coverage and generate anomalous colors. Syn-mining satellite data include such contamination and are not suitable for spectral mapping on the basis of spectral properties. Pre-mining satellite data are not affected by contamination and show authentic spectral properties. To demonstrate the influence of mining activities, a difference image is calculated for La Escondida mining district of Escondida Norte, and Zaldivar pre-mining Landsat TM and syn-mining Enhanced Thematic Mapper (ETM+) data for detection of changes. Black indicates no change of digital numbers between TM and ETM data. Red indicates a decrease of digital numbers by 10% (shadow and water), whereas green indicates an increase of 10% generated from dust coverage with resultant higher digital numbers. Therefore pre-mining TM data are used for image optimization.

Figure 7. Bivariate plots of data from two Landsat bands produce an elongate ellipse of points in the two-dimensional feature space because of strong correlation. Principal component analysis (PCA) begins by shifting the origin of the plot (A) to a point defined by the mean values of the two data sets (B). The axes are then rotated so one is aligned with the maximum variance in the data (C). This axis becomes the first principal component (PC), combining contributions from both bands. The second axis, perpendicular to the first, expresses the lower variance in the data and becomes the second principal component. Furthermore, because successive components are chosen to be orthogonal to all previous ones, the data are uncorrelated.
Principal component image derived from Landsat TM data

Figure 8. The PCA image is the result of the fifth (clay), fourth (lithology), and third (lithology) principal components displayed in red, green, and blue. This PCA color image reflects best the distribution of altered diorites and clay minerals. Spectral anomalies of altered rocks are highlighted in purple to red and can be recognized easily. Anomalous colors represent various rock types. Sedimentary rocks are displayed in bluish to greenish colors, felsic volcanics are displayed in pinkish to purple colors, and intrusives are displayed in deep purple and red colors. Quaternary deposits are shown in various but bright colors. In summary, spectral differences between rocks may be more apparent in PC images than in individual bands. Anomalous PC colors derived do not correspond to spectral reflectance and absorption of rocks because of the data transformation. Current open pits at La Escondida mining district are marked by symbols.

Figure 9. Bivariate plots of two bands with principal component axes (A). The first principal component has been stretched after rotation of the axes to principal component space (B). In the next step the second principal component has been stretched (C). This produces a decorrelation in the principal component space. Decorrelated data are rotated back to the original feature space (D). Stretching and back rotation of principal components are called inverse principal component analysis. The effect presented by this technique produces chromatically enhanced images.
Inverse principal component image derived from Landsat TM data

Figure 10. Image is a color composite of the highly decorrelated bands 5, 3, and 1 in red, green, and blue. This inverse PCA color composite reflects best the distribution of altered intrusive rocks and clay minerals. Spectral anomalies of altered intrusive rocks are displayed in yellow and reddish colors. Sedimentary rocks are displayed in various colors, ranging from pink to blue and green. Felsic volcanic rocks are displayed in deep blue to blue green. Alluvial deposits show characteristic pink and purple colors but vary with chemical composition of bedrock. Because of more or less original hues of rocks, the image is more interpretable than the principal components with resulting anomalous hues. Current open pits at La Escondida mining district are marked by symbols.

Figure 11. Spectral reflectance curves of iron minerals superimposed with Landsat TM bands from the visible and near infrared region. In the visible blue region (Landsat band 1) iron minerals show low reflectance owing to strong absorption (Fe-O charge transfer), whereas in the visible red and near infrared regions (Landsat bands 3 and 4) there is high reflectance owing to strong reflection. Calculation of band ratios highlights the occurrence of iron minerals in rocks (modified from Drury, 2001).
Figure 12. This image shows a color ratio image (band ratios 5/7, 3/1, and 4/3 in red, green, and blue) derived from Landsat TM data. Digital enhancement and information extraction allow discrimination of altered intrusive rocks from unaltered rocks. Altered intrusive rocks are highlighted in yellow and red colors. Sedimentary rocks are displayed in blue colors. Felsic volcanic rocks show brown to purple colors together with green. Alluvial deposits show pink to purple and blue colors, depending on the bedrock composition. Current open pits at La Escondida mining district are marked by symbols.

Figure 13. Clay-band ratio image (5/7) derived from Landsat TM data. The 5/7 band ratio has bright signatures for altered rocks, because the lower reflectance values of band 7 are in the denominator, which results in higher ratio values. Rocks with high clay-mineral content can be clearly identified from spectral anomalies with high pixel values displayed in white. Color variations of ratio images express more geologic information than conventional color images. Current open pits at La Escondida mining district are marked by symbols. Note the high spatial correlation of spectral anomalies with current open pits.
owing to strong absorption and reflection of iron in bands 1 and 3 with high ratio values for iron-bearing areas. The ratio 4/3 combines data from visible and near infrared bands and highlights healthy vegetation. An advantage of the color ratio image is the improved visualization of distribution patterns of both iron and hydrothermal clays. Altered intrusive rocks, which are of high interest for detection of mineralization, are highlighted in yellow and red colors.

Clay and iron minerals are good indicators of hydrothermally altered rocks and porphyry copper deposits (Lowell and Guilbert, 1970). The clay-band 5/7 ratio of La Escondida mining district is shown in Figure 13. The 5/7 ratio produces bright signatures for altered rocks, because the lower reflectance values of band 7 are in the denominator, which results in higher ratio values. Clay-rich rocks can be clearly identified from spectral anomalies with bright pixel values.

**Spectral Mapping of Rocks**

Improved digital classification of rocks is another important digital-image-processing technique applied in geological and environmental remote sensing. Discrimination of various rock types is necessary for geoscientific mapping and classification. In particular, knowledge of the spatial distribution of different rock types can point to potential host rocks of mineralization. In addition to visual interpretation of satellite imagery, supervised digital classification is a powerful tool in GIS-based analyses.

Spectral mapping of rocks is based on spectral analysis and mapping derived from spectral reflectance curves of rock samples and minerals that were measured by portable or laboratory spectrometers (Carmichael, 1986). Such curves provide a comparison standard for identifying spectra of unknown materials. Spectral mapping is performed by comparison of spectral properties, derived from reference areas, with spectral curves from spectral libraries (e.g., Jet Propulsion Laboratory, U.S. Geological Survey) implemented within the image-processing system Erdas Imagine. Spectral properties are determined from the pre-mining host rock data from the open pit at Escondida Norte, representing the mineral assemblage of an altered dioritic complex (see Fig. 14). All pixels having the same spectral properties in comparison to the image-processing-system library are classified as rock class “altered diorite” with bright pixel values in a single-band, gray-tone spectral map (see Fig. 15). Finally, the spectral map shows the occurrence and distribution of altered diorites and potential porphyry copper ores.

**FAVORABILITY MAPPING**

In the previous section, some digital-image-processing techniques were introduced. In general, results from band ratioing are not merged with results derived from spectral mapping and PCA, and vice versa. To combine advantages of each technique, optimized images from PCA, inverse PCA, band ratioing, and spectral mapping are classified separately in a first step. In a second step the classification results are merged by nonweighted algebraic expressions into a map representing areas of hydrothermally altered rocks and mineralization. This new approach in digital mapping combines optimized satellite data derived from various image-processing techniques with spatial statistics. It improves prediction of potential target areas in mineral exploration and is called favorability mapping. Thus, an integrated GIS and image-processing environment allows numerical and statistical analyses of classified data with respect to altered rocks and associated mineralization.

**Supervised Classification**

Supervised classification of optimized satellite data is conducted by selection of sample areas within potential host rocks and calculation of their spectral signatures. On the basis of the spectral signatures, supervised classification with the Minimum Distance Classifier is performed for each optimized image derived from PCA, inverse PCA, band ratioing, and spectral mapping. Target areas are defined by pre-mining spectral properties gained from a training site (area of interest) within the dioritic host rock at Escondida Norte. The pre-mining signatures from Escondida Norte are preserved and are not contaminated by mining activities. The resulting classification images (see Figs. 16–19) are recoded in two classes, enhancing the target areas: red indicates target areas of potential hydrothermally altered rocks, whereas nontarget areas without occurrences of altered rocks are translucent. The number of target area pixels from all classifications is calculated from the image statistics and compared with the total pixel number of each data set.

**GIS-Based Favorability Mapping**

Based on the results of supervised classification with the Minimum Distance Classifier, a favorability map is calculated. Favorability mapping is performed by nonweighted algebraic expressions owing to the fact that the classified data are acquired only by spectral properties of rocks.

Favorability values range from 0 (nontarget) to 4 (target with high favorability) by adding all counts of target values derived from PCA, inverse PCA, band ratioing, and spectral-mapping classification results.

**Test Area at La Escondida Mining District**

Figure 20 shows the favorability map of the test area at La Escondida mining district with current open pits at La Escondida, Escondida Norte, and Zaldívar, marked by symbols. Classified target areas of altered rocks are color coded in yel-
Figure 15. This image shows a spectral map of Landsat TM data wherein the data are trained and classified with spectral properties of dioritic rocks. Rocks of dioritic composition can be clearly identified from spectral anomalies with high pixel values displayed in white. Note the high spatial correlation of spectral anomalies with current open pits.

Figure 16. Classification result derived from calculated PC image (see Fig. 8). Target areas of altered rocks in the classified PC image correspond to reddish to purple colors in the PC image. Clustering of target areas is well defined in the central part of the image, whereas in the southern and northern parts, clustering is thinned out. Number of classified target-area pixels derived from PCA is 3.0% of total pixel number.
low to dark red, according to their favorability value from low to high, showing the spatial distribution of altered rocks. Low favorability values (yellow) mean the appearance of target pixels in one of the four calculated classification images derived from PCA, inverse PCA, band ratioing, or spectral mapping. Medium favorability values (orange and red) imply occurrences of target pixels in two or three classification results, e.g., PCA, band ratioing, and spectral mapping. High favorability values (dark red) show locations of target pixels in all four classification images.

In general, smaller target clusters with the shape of linear features are related to roads and valleys covered with dust from the mining areas, except in a smaller area in the upper right corner (location 4 in Fig. 20). This area might be of interest for further research.

Statistics from the favorability map indicate that 92% of the test area is classified nontarget in each of the four techniques. Nearly 8% of the data values correspond to low and medium favorability values. High favorability values that represent targets from all four classification results are missing (Table 1).

Test Area at Quebrada Blanca Mining District

To prove this approach of favorability mapping, maps of other test areas are calculated. There are additional results from porphyry copper deposits at Chaquicamata, El Abra, and Quebrada Blanca. The results of the test area at Quebrada Blanca are particularly suitable for testing the quality of this GIS-based exploration strategy, because the known intrusive complex and its ore deposit are classified with high accuracy.

Figure 21 shows the favorability map. Classified target areas of altered rocks are color coded in yellow to dark red, owing to their favorability value from low to high as discussed previously for the test area at La Escondida mining district. The clustering of target pixels is well defined only in the central part of the image, where the mine is shown by the symbol (Fig. 21). In the southwestern part, clustering is thinned out but outlines another potential mineralization.

Statistics for the test area at Quebrada Blanca show a great diversity of target numbers from the favorability map. Percentage values of targets range from 1.9, classified by clay-band ratio, to 22.9, classified by spectral mapping.

Spectral mapping of granodioritic rock is calculated the same way as previously described for the training site at La Escondida mining district. It is remarkable that a high percentage value is shown for Quebrada Blanca mining district. The reason for this is the occurrence of a Paleozoic granodioritic complex south of the Eocene granodiorite in the central part of the test area. Spectral signatures of the Paleozoic and Eocene granodiorites are similar. They are both classified by the spectral-mapping technique, although they are of different ages. Misclassification is not corrected to show the sensibility of spectral mapping.

Statistics from the favorability map indicate that 75% of the test area is classified as nontarget in each of the four classified images. Nearly 25% of the data values correspond to low and medium favorability values. Only 0.4% are classified as high favorability values, the result from targets within all four image optimization techniques (Table 1).

DISCUSSION

Data integration and GIS-based analyses improve the delineation of altered rocks and mineralization. A combination of various image-processing techniques of remotely sensed imagery provides detailed information of new potential target areas in mineral exploration. Satellite data can be digitally optimized to known copper deposits, but this methodology has not been commonly employed for prospecting under postmineral rock cover, which

![Classification result of altered rocks derived from Landsat TM inverse PC image](https://pubs.geoscienceworld.org/gsa/geosphere/article-pdf/24/2/236/3335249/i1553-040X-2-4-236.pdf)

Figure 17. Classification result derived from inverse PC image (see Fig. 10). Target areas in the classified inverse PC image correspond to yellow colors in the inverse PCA image. Clustering of target areas is well defined in the central, southern, and northern parts of the image. In other areas, the target clustering is thinned out. Number of target-area pixels derived from inverse PCA is 3.2% of total pixel number.
Classification result of altered rocks derived from Landsat TM clay-band ratio image

Figure 18. Classification result derived from clay-band ratio image (see Fig. 13). Target areas in the classified clay-band ratio image correspond to light colors that represent high digital numbers in the clay-band ratio. Clustering of target areas is well defined in the central and southern parts of the image, whereas in the northern parts, clustering is thinned out. Number of target-area pixels derived from clay-band ratioing is 3.8% of total pixel number.

Classification result of altered rocks derived from Landsat TM spectral mapping

Figure 19. Classification result derived from spectral mapping (see Fig. 15). Target areas in the classified spectral-mapping image correspond to light colors in the spectral map. Clustering of target areas is well defined all over the image, but in small areas. Number of target-area pixels from spectral mapping is 0.4% of total pixel number.
Favorability map of altered rocks at La Escondida mining district

Figure 20. Favorability map from the training site at La Escondida mining district. Calculated favorability map shows the spatial distribution of altered rocks. Note the high spatial correlation of host rocks with the current open pit at La Escondida (location 1). In the pre-mining Landsat data, there is evidence for altered magmatic rocks for the current pit at Escondida Norte (location 2), because it is calculated to be a major target area and verifies the results of this favorability mapping. Current open pit at Zaldivar (location 3) is not calculated as a major target area. A reason for this might be that Zaldivar (1) is a supergene copper deposit, formed by transported aqueous solutions in addition to precipitation by groundwater and is therefore not correlative with altered rocks near the surface, or (2) is under postmineralization rock cover and cannot be detected by satellite sensors.

Table 1. Favorability mapping statistics of classified target pixels related to hydrothermally altered rocks

<table>
<thead>
<tr>
<th></th>
<th>Image optimization</th>
<th>Inverse PCA</th>
<th>Clay-band ratio</th>
<th>Spectral mapping</th>
<th>Host rock diorite</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Classified target pixel numbers of training site at La Escondida mining district</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Target pixel number</td>
<td>8250</td>
<td>9918</td>
<td>10638</td>
<td>1146</td>
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<tr>
<td>Nontarget number</td>
<td>279219</td>
<td>278451</td>
<td>267831</td>
<td>286323</td>
<td>284022</td>
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<tr>
<td>Target pixel % value</td>
<td>3.0</td>
<td>3.2</td>
<td>3.8</td>
<td>0.4</td>
<td>1.0</td>
</tr>
<tr>
<td>B. Classified favorability values of training site at La Escondida mining district</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Favorability value</td>
<td>0 (nontarget)</td>
<td>1 (low)</td>
<td>2 (medium)</td>
<td>3 (medium)</td>
<td>4 (high)</td>
</tr>
<tr>
<td>Target pixel number</td>
<td>265700</td>
<td>15700</td>
<td>4300</td>
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<td>0</td>
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<tr>
<td>Favorability % value</td>
<td>92.1</td>
<td>6.0</td>
<td>1.4</td>
<td>0.5</td>
<td>0.0</td>
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<tr>
<td>C. Classified target pixel numbers of training site at Quebrada Blanca mining district</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td>Target pixel number</td>
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<td>107787</td>
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<tr>
<td>Target pixel % value</td>
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<td>5.5</td>
<td>1.9</td>
<td>22.9</td>
<td>2.4</td>
</tr>
<tr>
<td>D. Classified favorability values of training site at Quebrada Blanca mining district</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Favorability value</td>
<td>0 (nontarget)</td>
<td>1 (low)</td>
<td>2 (medium)</td>
<td>3 (medium)</td>
<td>4 (high)</td>
</tr>
<tr>
<td>Target pixel number</td>
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<tr>
<td>Favorability % value</td>
<td>75.7</td>
<td>18.8</td>
<td>2.7</td>
<td>1.4</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Note: PCA—principal component analysis.
blanks much of northern Chile. Potential field data from gravity and aeromagnetics are available and will be integrated for further research. Magnetic anomalies and anomaly patterns of buried copper deposits—e.g., Spence and Gaby—will be conducted later.

Results from two training sites, La Escondida and Quebrada Blanca mining districts, show the strength of numerical favorability mapping. There is a strong correlation of classified target areas from satellite data with corresponding porphyry copper deposits. This newly developed exploration strategy using satellite data improves the delineation of potential altered rocks and mineralization. This favorability mapping, conducted by numerical analyses and classification of various processing techniques (PCA, inverse PCA, band ratioing, and spectral mapping), is comparable to gamma-ray spectrometer data integration (K-Th-U) for Precambrian basement mapping described by Harris et al. (1998).

Finally, a priori knowledge defined by test areas is most important in defining and testing spectral signatures and other information for delineation of altered rocks and mineralization in regional areas. On the basis of this knowledge, the next step of this research will be favorability mapping of the entire study area in looking for new potential mineralization in the Central Andes of northern Chile. This newly developed methodology, with the results presented in this paper, is a supplementary exploration tool and might be of great interest to exploration companies for further research in other less studied copper provinces.

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