Porphyry Copper Potential of the United States Southern Basin and Range Using ASTER Data Integrated with Geochemical and Geologic Datasets to Assess Potential Near-Surface Deposits in Well-Explored Permissive Tracts

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Abstract

ArcGIS was used to spatially assess and rank potential porphyry copper deposits using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data together with geochemical and geologic datasets in order to estimate undiscovered deposits in the southern Basin and Range Province in the southwestern United States. The assessment was done using a traditional expert opinion three-part method and a prospectivity model developed using weights of evidence and logistic regression techniques to determine if ASTER data integrated with other geologic datasets can be used to find additional areas of prospectivity in well-explored permissive tracts. ASTER hydrothermal alteration data were expressed as 457 alteration polygons defined from a low-pass filtered alteration density map of combined argilllc, phyllic, and propylitic rock units. Sediment stream samples were plotted as map grid data and used as spatial information in ASTER polygons. Gravity and magnetic data were also used to define basins greater than 1 km in depth. Each ASTER alteration polygon was ranked for porphyry copper potential using alteration types, spatial amounts of alteration, stream sediment geochemistry, lithology, polygon shape, proximity to other alteration polygons, and deposit and prospects data. Permissive tracts defined for the assessment in the southern Basin and Range Province include the Laramide Northwest, Laramide Southeast, Jurassic, and Tertiary tracts. Expert opinion estimates using the three-part assessment method resulted in a mean estimate of 17 undiscovered porphyry copper deposits, whereas the prospectivity modeling predicted a mean estimate of nine undiscovered deposits. In the well-explored Laramide Southeast tract, which contains the most deposits and has been explored for over 100 years, an average of 4.3 undiscovered deposits was estimated using ASTER alteration polygon data versus 2.8 undiscovered deposits without ASTER data. The Tertiary tract, which contains the largest number of ASTER alteration polygons not associated with known Tertiary deposits, was predicted to contain the most undiscovered resources in the southern Basin and Range Province.

Introduction

Can new data and techniques still find areas of promising prospectivity for porphyry copper deposits within 1 km of the surface in well-explored areas? Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data have been used to map circular to elliptical patterns of altered rocks that identify potential porphyry copper exploration targets (Mars and Rowan, 2006; John et al., 2010). For regional assessments, ASTER hydrothermal alteration maps tend to show better lateral alteration extent and relationships between alteration units for potential deposit identification than multiple, localized, field-based hydrothermal alteration maps (Rowan and Mars, 2003; Rowan et al., 2003; Mars and Rowan, 2006; Berger et al., 2010; John et al., 2010; Mars, 2014). Although ASTER hydrothermal alteration maps typically highlight known deposits and prospects, new porphyry copper discoveries using ASTER data have been documented and include the Los Helados deposit in Chile and the Xiongmei deposit in China (Yamamoto et al., 2012; Dai et al., 2017). Thus, ASTER data could be used in well-explored areas such as the southern Basin and Range Province of the United States to look for areas of prospectivity near the surface (<1 km) that may have been overlooked due to a lack of regional, detailed hydrothermal alteration maps.

Geographic information systems (GIS) improve mineral resource assessment by providing efficient ways to compile, organize, and manage large spatial datasets, such as regional hydrothermal alteration maps compiled from ASTER data. GIS can also integrate remote sensing data with geologic and geochemical features that can be visualized and analyzed with respect to one another in a mineral assessment. Mineral assessments consider mineral deposits and prospects, geophysical, remote sensing, geochemical, lithostratigraphic, and other exploratory data to estimate undiscovered deposits within an area. Prospectivity modeling using statistical approaches and GIS provides additional methods to integrate and interpret spatial data in ways that are useful for mineral resource assessment (Bonham-Carter, 1994; Raines, 1999; Carranza, 2004; Harris and Sanborn-Barr, 2006; Raines and Bonham-Carter, 2006; Nykänen and Salmirinne, 2007; Hammarstrom et al., 2010). For example, in a previous study, Lindsay et al. (2014) applied prospectivity mapping techniques in southeastern Arizona to identify porphyry copper targets and evaluate these techniques as tools in mineral exploration

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ISSN 0361-0128; doi:10.5382/econgeo.4675, 27 p.
Digital appendices are available in the online Supplements section.
using geologic, geophysical, and Landsat remote sensing data. ASTER data, which have not been used in a regional porphyry copper assessment of the southern Basin and Range Province, have been shown to have better spectral and spatial resolution and greater hydrothermal alteration mapping capability than Landsat data (John et al., 2010).

Potential porphyry copper targets selected using ASTER data in previous studies have been used in assessments to help estimate the number of undiscovered deposits, where ranking of each potential porphyry target for assessment was done using expert judgment methods (Berger et al., 2010; Mars, 2014). In past assessments where GIS methods to evaluate potential porphyry deposits were not used to analyze ASTER regional hydrothermal alteration maps, physical properties such as size and shape of potential porphyry targets were visually estimated and spatial integration of the remote sensing data with other datasets, such as deposit types, lithology, and geochemistry, was typically not done.

This study attempts to determine if there are any areas of promising prospectivity for porphyry copper deposits within 1 km of the surface in the well-explored southern Basin and Range Province. This study uses GIS techniques to make quantitative measurements of physical properties of ASTER-mapped hydrothermal alteration, geochemical, geologic, magnetic, gravity, and deposit data in order to produce areas of ranked prospectivity defined as ASTER alteration polygons in the southern Basin and Range Province. Using GIS, the quantitatively ranked alteration polygons and other data are used in a three-part quantitative mineral resource assessment and a modified weights of evidence-logistic regression deposit prospectivity model (developed for this study) to estimate numbers of undiscovered deposits in the southern Basin and Range Province (Bonham-Carter, 1994; Singer and Menzie, 2010). GIS shape files used in the assessment are described in the digital supplements to this paper and available for download (GIS Shape File Descriptions App.).

Study Area

The study area encompasses about 300,000 km² in the United States southern Basin and Range Province, which is one of the world’s premier copper provinces hosting 44 porphyry copper deposits with total identified resources (including past production) of more than 200 million tonnes (Mt) of copper (Fig. 1; App. Table A1). The area contains known but as yet undeveloped porphyry copper deposits (such as Rosemont) and continues to be explored after more than a century of prospecting and mining activity. It includes Jurassic arc fragments, part of the Laramide arc that extends into Mexico, and post-subduction Tertiary volcanic rocks and plutons (Titley, 1995). Most of the deposits are of Late Cretaceous to early Tertiary age formed during the Laramide orogeny (~80–45 Ma), when arc volcanism related to eastward subduction of the Farallon plate beneath North America swept across the region (Barton et al., 2011). The study area is also covered by regional-scale digital geologic and ASTER hydrothermal alteration maps, stream-sediment geochemical surveys, mineral occurrence databases, and regional gravity and magnetic data (Grossman et al., 2004; Ludington et al., 2007; Mars, 2013). Thus, the extensive geologic data and large number of known copper deposits in the southern Basin and Range Province provide a well-constrained study area to develop and test the new quantitative techniques as applied to porphyry copper resource potential.

Porphyry copper deposits typically consist of chalcopyrite and bornite orebodies forming a cylindrical pattern 0.2 to 0.8 km in diameter, which are generally emplaced in intermediate to silicic igneous rocks (John et al., 2010). Hydrothermally altered rocks of porphyry copper deposits typically form cylindrical to elliptical bodies up to 2 km in diameter; however, they can extend to greater than 10 km from the deposit (Singer et al., 2008). These hydrothermally altered zones usually consist of a core of potassic-altered rock containing mostly quartz, K-feldspar, and biotite and minor amounts of sericite, surrounded by a zone of phyllic-altered rock that consists mostly of sericite, quartz, and pyrite (Lowell and Guilbert, 1970; John et al., 2010). The phyllic-altered rock zone is capped by a zone of argillic-altered rock consisting primarily of quartz, alunite, and kaolinite. In addition, the phyllic zone grades laterally outward into a propylitic-altered rock zone that typically contains albite, K-feldspar, epidote, chlorite, and calcite (Seedorff et al., 2005; John et al., 2010). Most of the southern Basin and Range Province porphyry copper deposits are capped by a weathered, oxidized supergene zone 1 to 300 m thick (John et al., 2010). Common oxidized ores found in the supergene zone typically consist of chrysocolla, brochantite, copper pitch, native copper, and malachite (John et al., 2010). Other common oxidized minerals associated with the supergene zone include limonite and jarosite.

Although hydrothermal alteration zoning is a diagnostic signature of porphyry copper deposits, Basin and Range extensional faulting and tilting of many of the porphyry copper deposits have complicated or obscured zoning patterns and made identification of potential porphyry copper deposits in the southern Basin and Range Province more difficult (Lowell and Guilbert, 1970; John et al., 2010). Thus, use of regional, yet detailed, hydrothermal alteration maps compiled from ASTER data is essential in identifying potential copper-bearing, structurally deformed, hydrothermal systems.

Data and Processing

Lithology

Digital geologic maps were combined in a database to provide a framework for delineating permissive tracts for porphyry copper deposits by selecting map units where the lithology is broadly permissive for the occurrence of porphyry copper deposits. Porphyry copper mineral deposit models (John et al., 2010) and the geologic associations of known deposits in the region guided map unit selection (Fig. 2). Permissive lithologies include intermediate composition intrusive and extrusive rocks, such as granodiorite, quartz monzonite, and andesite associated with subduction-related magmatic arcs. Digital state-scale geologic maps recompiled with consistent lithology, age, GIS database structure, and format were accessed from the U.S. Geological Survey (USGS) Mineral Resources Online Spatial Data website (https://mrdata.usgs.gov/geology/state/) and merged. Source maps include the 1:1,000,000-scale geologic map of Arizona (Richard et al., 2000), the 1:750,000-scale geologic map of California (Jennings et al., 1977, 2010),
the 1:500,000-scale map of Nevada (Stewart and Carlson, 1978), the 1:500,000-scale geologic map of New Mexico (Green and Jones, 1997; New Mexico Bureau of Geology and Mineral Resources, 2003), and the 1:125,000-scale geologic map of the East Mojave National Scenic Area (Miller et al., 2007). Other maps that provided key information include a compilation of mapping in the Needles 1° × 2° sheet, California (Stone and Howard, 1979), and the geologic map of the west half of the Blythe 30' by 60' quadrangle in California and Arizona (Stone, 2006). The Western North American Volcanic and Intrusive Rock Database (NAVDAT; www.navdat.org) provided additional information on locations, rock types, and ages of permissive host rocks for porphyry copper deposits. Additional quadrangle-scale geologic maps available in the USGS National Geologic Map Database (NGMDB) were accessed through a map view server (https://ngmdb.usgs.gov/maps/mapview/) and used to supplement smaller-scale state maps to resolve questions about age and lithology. The final map was compiled at a scale of 1:1,000,000.

Map units in the merged geologic map database were assigned to one of the following general categories to facilitate further processing: intrusive, extrusive, metamorphic, sedimentary, mélangé, surficial, or indeterminate. Extrusive and intrusive igneous map units were selected and assigned to each of three possible permissive tracts based on age (Jurassic, Laramide, and Tertiary) with one of the following categories: (1) permissive intrusive unit for the tract, (2) permissive extrusive unit for the tract, (3) nonpermissive unit for the tract, (4) basement, or (5) cover.

Fig. 1. Map of the study area (black outline) showing porphyry copper deposits that have identified resources. The area outlined in red was included in the quantitative mineral resource assessment and prospectivity modeling. Mines or groups of mines shown in figure are as follows: 1 = Bisbee-Cochise Group, 2 = Hill Copper, 3 = Bagdad Group, 4 = Copper Basin Group, 5 = Ithaca Peak, 6 = Fine Flat Group, 7 = Sheep, Mountain Group, 8 = Ajo, 9 = Casa Grande West, 10 = Chilito Group, 11 = Chino-Hanover Group, 12 = Christmas, 13 = Cobre, 14 = Copper Creek Group, 15 = Copper Flat Group, 16 = Gibson-Morgan Peak Group, 17 = Johnson Camp Group, 18 = Korn Kob, 19 = Lakeshore, 20 = Lone Mountain, 21 = Miami Group, 22 = Mineral Butte Group, 23 = Mission Group, 24 = Moreno Group, 25 = Oracle Ridge, 26 = Poston Butte Group, 27 = Ray Group, 28 = Red Hill Patagonia Group, 29 = Red Hills, 30 = Resolution Group, 31 = Rosemont Group, 32 = Sacaton Group, 33 = Saiford Group, 34 = San Manuel-Kalamazoo Group, 35 = Sanchez, 36 = Sierra Vista Group, 37 = Silver Bell Group, 38 = Sonnyside Group, 39 = Superior East, 40 = Twin Buttes Group, 41 = Two Peaks, 42 = Tyrone Group, 43 = Velol Hills, 44 = Iron Door. See Appendix Table A1 for deposit information.
For example, a Late Cretaceous to early Tertiary andesite is a permissive extrusive rock to use in defining a Laramide tract. That same unit represents basement for a younger Tertiary tract and cover for older Jurassic tracts.

Many of the permissive map units in the western part of the study area in California are listed as Mesozoic, with no distinction between Jurassic and Cretaceous (undifferentiated on Fig. 2). No Cretaceous porphyry copper deposits are known within the study area (App. Table A1), and most of the Cretaceous magmatism in the southwestern U.S. lies in batholithic belts to the west of the study that are deeply eroded and lack coeval volcanic rocks and, therefore, are unlikely to preserve any porphyry deposits that may have been associated. For these reasons, the quantitative assessment area (red, dashed line in Fig. 2) is restricted to areas where additional information allowed us to differentiate Jurassic and Cretaceous rocks.

Mineral occurrences
A database of 690 deposits, prospects, and occurrences was compiled in a geographic information system for this study. Primary data sources included the USGS Mineral Resources Data System (USGS, 2016), a database maintained by the Arizona Geological Survey (Richard et al., 2002; Vikre et al., 2014), and numerous journal articles and websites (App. Table A2). For many sites, the location was determined and updated using Google Earth. Attributes for each site include name, district, state, age information, commodities reported, deposit type, site status, comments, and references including URLs (App. Table A2).

Geochemical data
A geochemical dataset of 29,697 soil and stream-sediment (–80 and –100 mesh) samples was compiled from three USGS geochemical databases (Table 1). These databases contain geochemical data for samples that were collected and analyzed over a period of 40 years from the mid-1970s to the present. Arsenic, Au, Cu, Mo, Pb, and W were selected as pathfinder elements for porphyry copper mineralization. Interpolated grids were generated using an inverse distance weighted (IDW) algorithm and Oasis Montaj™ version 8.4 (Geosoft, 2015) software and converted to geochemical map layers in ArcGIS version 10.2 (Esri, 2013).

Multiple USGS databases were evaluated for inclusion in this geochemical data compilation; however, only data from the National Uranium Reconnaissance Evaluation (NURE),
National Geochemical Survey (NGS), and Rock Analysis Storage System (RASS) data archives (https://mrdata.usgs.gov) were included. Data were downloaded by state for Arizona, California, Nevada, and New Mexico and selected for inclusion in this study if the samples fell within the southern Basin and Range Province assessment area (Fig. 1). The southern Basin and Range boundary area was expanded by 50 km for this geochemistry compilation in order to incorporate geochemical trends that may fall near the edge of the assessment study area. Each sample in the selected databases was also filtered on the basis of analytical sensitivity (App. Tables A3, A4).

Due to the scale of other southern Basin and Range Province GIS datasets used in the assessment, As, Au, Cu, Mo, Pb, and W grid cells are 1 km² with sampling of nearest neighbor points within a search radius of 4-km distance. The parameters used for IDW are as follows: (1) a grid cell size of 1 km; (2) cell weightings of 1, 0.5, 0.2, 0.1, and 0.056, for the center cell, one cell away, two cells away, three cells away, and four cells away, respectively; and (3) a blanking distance of 4 km with a value of 0 for cells that extend beyond the data. In ArcGIS (Esri, 2013), the grids were converted from Transverse Mercator to Albers Equal Area Conic projection and classified into four or five intervals based on distribution of concentrations (App. Table A5). For some elements, the limits of detection were higher than the threshold values and the intervals of interest for this study; however, the emphasis of this study was to detect geochemical patterns that may have become evident by examining those samples (cells) that have anomalously high concentrations. Therefore, there was no effort made to approximate or replace values for those samples measured as below the detection limit.

The datasets were not ideal for generating comprehensive geochemical data layers for spatial modeling because (1) large areas lack data either because no samples were collected or samples were not analyzed for a particular element; (2) only fine-grain-size samples (<80 and <100 sieve mesh size) were included in these datasets; therefore, analyses from coarser-grain-size samples were omitted; (3) differing analytical methods with different lower limits of detection are difficult to normalize; and (4) selected threshold values were based on experience as well as statistics but can be viewed as subjective. Despite these shortcomings, the copper and molybdenum maps provided significant information for alteration polygon and deposit ranking even with limited sample coverage (Fig. 3).

### Gravity and magnetic data

Aeromagnetic and isostatic gravity anomaly data at 500-m grid interval resolution were used to define sedimentary basin depths and structural controls on permissive tracts. The 500-m interval grid aeromagnetic intensity map with International Geomagnetic Reference Field (IGRF) correction was created by stitching together existing 500-m interval grid magnetic data available for Arizona (Sweeney and Hill, 2001), New Mexico (Kucks et al., 2001), and part of Nevada (Kucks et al., 2006) using Oasis Montaj™ (Geosoft, 2015) software. The California aeromagnetic grid is unpublished (Roberts and Jachens, 1999), so an in-house copy of the grid was used with some editing. The same sources were used to create the isostatic gravity anomaly map, except for California, where a 500-m grid was not available. For southern California, station complete Bouguer gravity anomaly values were available online (University of Texas, 2014), inner zone isostatic corrections were computed using Oasis Montaj™ (Geosoft, 2015), and the outer zone corrections were interpolated from the maps of Karki et al. (1961) using a program written for this purpose. The station isostatic gravity anomaly values were gridded using minimum curvature gridding in Oasis Montaj™ (Geosoft, 2015), and the resulting grid was stitched to the grid for the other states. The grids cover the area from the United States-Mexico border north to 37° latitude and from 103° to 119° west longitude.

### Potential field data products

Color-shaded relief maps were produced for both the iso- static and aeromagnetic anomaly grids (Fig. 4). Horizontal gradient maxima were computed for each grid (Blakely and Simpson, 1986). The data were smoothed using a seven-point (3 × 3 km) low-pass filter to keep only maxima that persisted for 3 km or more. Analytic signal maxima (Roest et al., 1992) were computed and also low-pass filtered. For steeply dipping magnetization or density contacts, the two maxima will coincide; however, for gently dipping contacts, the two will be displaced from each other (“railroad tracks” enabling one to distinguish contacts with shallower dips: Gettings and Bultman, 2005). These maxima were plotted on the magnetic and gravity anomaly maps and exported as georeferenced TIFF images, one for the analytic signal and one for the horizontal gradient magnitude for the aeromagnetic and isostatic gravity anomaly maps. These images were used to help define the contacts or boundaries between areas of differing magnetization or density, which generally correspond to differing lithologies.

Porphyry targets estimated to be more than 1 km below the surface were not included in the resource assessment due to the likelihood of excessive mining costs and the surficial limitations of the remote sensing, geochemical, and deposit data used in the study. Thus, the extent of alluvial basins greater than 1 km thick was estimated using geophysical data. In order to better estimate the density contrasts from alluvial fill relative to the bedrock and to evaluate the likely range of density contrasts, density data from deep drill holes in the Arizona and Nevada Basin and Range provinces were compiled. A Monte Carlo calculation was carried out to produce boxplots of density contrast versus depth and gravity anomaly versus

### Table 1. Numbers of Geochemistry Samples Listed by State and Data Archive

| State        | NGS¹ | NURE² | RASS³ | Total |
|--------------|------|-------|-------|-------|
| Nevada       | 92   | 960   | 242   | 1,294 |
| New Mexico   | 1,311| 2,075 | 1     | 3,387 |
| Arizona      | 1,932| 7,214 | 7,057 | 16,203|
| California   | 2,940| 3,080 | 2,793 | 8,813 |
| Total        | 6,275| 13,329| 10,093| 29,697|

¹National Geochemical Survey
²National Uranium Reconnaissance Evaluation
³Rock Analysis Storage System

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depth for basins of both Arizona and Nevada, including the probable range of variations. These curves were used to estimate basin fill depths for the assessment area to define depths greater than 1 km (Fig. 5). The gravity anomalies versus depth curves are based on a finite vertical cylinder gravity model, with density contrast as a linear function of depth.

The gravity and aeromagnetic lineaments trending approximately north-northeast–south-southwest near Holbrook, Arizona, were recognized by Titley (1981) as a boundary between two Proterozoic crustal terranes, the Yavapai to the northwest and the Mazatzal to the southeast. With the new geophysical data, the boundary was refined and traced across the Basin and Range Province to the international border. Porphyry copper deposits are much more abundant in the Mazatzal terrane (Titley, 1981), and, thus, the definition of the boundary in the Basin and Range and beneath the Colorado Plateau is useful for defining assessment tracts.

ASTER remote sensing data and processing

Regional hydrothermal alteration maps of the study area were compiled using ASTER data from a previous study (Mars, 2013). ASTER Level_1B data were calibrated to reflectance, and hydrothermal alteration units were mapped using logical operator algorithms (Mars, 2013). The raster data were converted to vector data and saved as ArcGIS shape files (Mars, 2013). The ASTER hydrothermal alteration dataset covers approximately 90% of the study area; however, taking into account vegetated and shadowed areas, approximately 80% of the study area is mapped using ASTER data (Fig. 6).

In order to assess the hydrothermal alteration at a regional scale, ASTER alteration units were projected onto a 30-m spatial resolution seamless Landsat Thematic Mapper (TM) false color composite and gray-scale mosaic and an ArcGIS image mosaic basemap consisting of 2.1-m spatial resolution true color Worldview 2 data (Fig. 7A; Tucker et al., 2005; Esri, 2013). In addition, the ArcGIS basemap was used to help identify small-scale features such as prospects and outcrops.

Hydrothermal alteration units used in the study include argillic (kaolinite, alunite, pyrophyllite), phylllic (sericite), two propylitic units that consist of epidote-chlorite and carbonate (calcite, dolomite), and hydrothermal silica-rich rocks (opal, quartz; Fig. 7B; Mars, 2013). Argillic, phylllic, and propylitic

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**Fig. 3.** A. Copper interpolated grid for surficial sediment copper geochemistry. B. Molybdenum interpolated grid for surficial sediment molybdenum geochemistry. Grid cell resolution is 1 km, within a search radius of 4 km. LLD = lower limit of detection.

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1. Titley, 1981
2. Mars, 2013
3. Tucker et al., 2005
4. Esri, 2013
units were mapped at 30-m spatial resolution and hydrothermal silica-rich rocks were mapped at 90-m spatial resolution (Mars, 2013). Although iron oxide has been mapped using ASTER data, a previous regional hydrothermal alteration mapping study showed that it is difficult using ASTER-complied iron oxide maps to identify porphyry copper deposits due to the abundance of iron oxide in adjacent rocks and sediment (Mars and Rowan, 2006). Thus, no iron oxide mapping was done for this study.

ASTER mineral maps of porphyry copper deposits from previous studies typically show elliptical to circular patterns of a core of hydrothermally altered, phyllic and argillic rocks grading outward into propylitic rock (Mars and Rowan, 2006; Berger et al., 2010; John et al., 2010; Mars, 2014). ASTER mineral maps of porphyry deposits also show phyllic rocks surrounded by propylitic rocks. These patterns are interpreted to represent different erosion levels into the porphyry hydrothermal system (John et al., 2010). Phyllic-argillic-propylitic patterns are interpreted to indicate that the erosion level is in the upper part of the porphyry, whereas phyllic-propylitic patterns are interpreted to indicate erosion levels into the lower part of the hydrothermal system (John et al., 2010). Hydrothermal silica-rich rocks overprint the phyllic zone in the form of quartz veins, and the argillic and propylitic zones in the form of silicified rocks and quartz veins (John et al., 2010). These patterns of ASTER-mapped hydrothermal alteration match the porphyry copper model described in the “study area” section (Mars and Rowan, 2006; Berger et al., 2010; John et al., 2010; Mars, 2014). Using this model, potential porphyry sites in previous studies have been selected based on their alteration types, patterns, and lithology. In previous studies, a point was assigned in a GIS database for each potential site, and physical characteristics, including lithology and percentage of alteration types, were visually estimated for each point location (Berger et al., 2010; John et al., 2010; Mars, 2014). For this project, a potentially more accurate, automated method of compiling physical properties and evaluating hydrothermal alteration sites using hydrothermal alteration polygons was developed. Using polygons instead of point data allows the geographic information system to automatically and precisely record any mapped data that intersects or is in a defined proximity of the polygon area.

To generate the polygons, alteration densities of argillic, phyllic, and propylitic units were mapped using a low-pass filter (Fig. 8A, B). The low-pass filter produces a raster image in which each pixel is assigned a density value based on the
total number of alteration pixels within a given area of a pixel to determine density. A radius of 1 km around each pixel was used as the area based on the average size of hydrothermal systems for large porphyry deposits such as Sar Chesmeh, Iran, and Kounrad, Kazakhstan (Berger et al., 2010; John et al., 2010; Mars, 2014). Visual assessments of low-pass hydrothermal alteration images around known deposits in the study area and in Iran and Kazakhstan generally show that alteration pixels with low-pass values less than 19% are typically associated with transported alluvium. Thus, low-pass filter pixels with density values greater than 19% were selected (Fig. 8B). The low-pass image was then converted to vectors using ENVI image processing software (Harris Geospatial Solutions, 2013). ASTER alteration low-pass filter vector data were then projected in ArcGIS in transparent mode on a Landsat TM or an Esri Worldview 2 mosaic of the study area, and alteration polygons were manually drawn (Esri, 2013; Tucker et al., 2005; ftp://ftp.glcf.umd.edu/glcf/Mosaic_Landsat/). Manual drawing of the alteration polygons was done in order to select low-pass filter alteration associated with permissive geologic units from the ArcGIS lithologic database, combine adjacent low-pass filter alteration situated on similar permissive geology that was less than 0.1 km apart, omit low-pass filter alteration data that covered old or active mine locations, omit widespread, transported, hydrothermally altered alluvium that was not removed by the low-pass filter, and include areas outside the low-pass filter units if the alteration map indicated potential altered areas based on alteration patterns that were not associated with alluvium (Fig. 8B). Automated attempts to generate alteration polygons resulted in large false-positive areas, typically consisting of alluvium or mine waste.

Physical characteristics of each polygon, including percentages of alteration types, total percentage of mapped alteration in each polygon, polygon shape, polygon perimeter, polygon size, roundness, permisive rock type, lithology for each polygon, and geochemistry, were recorded using ArcGIS functions. All physical properties for each alteration polygon were recorded in ArcGIS attribute files classified by permisive tract (App. Table A6). Tract classification for each alteration polygon was determined by the age of deposits contained within 2 km of each polygon or, if no deposit age data were
available, the youngest age of the alteration polygon host rock was used. A total of 457 alteration polygons were compiled for the study (App. Map A1; App. Table A6).

An approximately 5 to 10% mapping error using ASTER logical operators observed in this and previous studies did produce some anomalous results (Mars, 2013, 2014). For approximately 2% of the alteration polygons, total percentages of surface alteration were greater than 100% due to multiclassified alteration units (App. Table A6). For example, the total surface percentage for a polygon might consist of 60% argillic and 45% phyllic (a total of 105%), in which 5% of the pixels were mapped as both argillic and phyllic. This was due to a few alteration polygons that were mapped by overlapping ASTER scenes. In addition, although not caused by ASTER mapping error, the hydrothermal silica-rich unit often overlaps other hydrothermal alteration units (Mars, 2013; App. Table A6).

Each polygon was ranked based on its physical properties (Fig. 9; App. Map A1; Table 2; App. Table A6). The ranking system consists of a score based on physical properties of relatively nondeformed, well-studied porphyry copper deposits from previous assessments in the Kerman belt, Iran, and Kounrad, Kazakhstan (Berger et al., 2010; John et al., 2010; Mars, 2014). Deposits at both locations contain phyllic-, argillic-, propylitic-, and silicic-altered rocks, are circular to elliptical in shape, and are situated close to other porphyry copper deposits. Thus, alteration polygons that contain similar hydrothermal alteration surface % assemblages rank higher than those that do not (Table 2). For example, if the alteration polygon contains >10% argillic and >20% phyllic surface area coverage, four points are added to the rank score. If just phyllic surface coverage is >20% or argillic is >10%, two points are added to the polygon rank score. The presence of copper or molybdenum in or near alteration polygons is also used as a ranking category based on cell values greater than 25 ppm for copper and 2 ppm for molybdenum surficial geochemistry and scanning deposits in the MRDS database that list copper as one of their main commodities within 0.5 km of each alteration polygon (Table 2). In addition, polygon size, roundness, proximity to other alteration polygons, and permissive rock types associated with an alteration polygon are categories in the ranking system (Table 2).

Three-Part Assessment

The three-part form of mineral resource assessment based on mineral deposit models provided the framework for this study (Singer, 1993; John et al., 2010; Singer and Menzie, 2010). In
applying the three-part form of mineral resource assessment, geographic areas (permissive tracts) are delineated using available data on geologic, geochemical, and geophysical features typically associated with the type of deposit under consideration, as reported in descriptive mineral deposit models. Grade and tonnage models describe the size and quality (commodity grades) of thoroughly explored deposits that fit the characteristics of the descriptive mineral deposit models. The amount of metal contained in undiscovered deposits is estimated by using grade and tonnage models combined with probabilistic estimates of numbers of undiscovered deposits, based on the assumption that the undiscovered deposits will be similar to the deposits described in the model selected. Statistical tests are performed using data from the known deposits in a study area to ensure that the appropriate grade and tonnage models are used (Singer, 2007). Probabilistic estimates are made at different confidence levels using a variety of estimation strategies to express the degree of belief that some fixed but unknown number of deposits exists within the tract; these estimates represent a measure of the favorability of the tract and uncertainty about what may exist (Singer, 2007). A number of different guidelines are available for estimating numbers of undiscovered deposits, such as considering the frequency of deposits from well-explored areas (deposit density models), statistical guides, assigning probabilities to anomalies, etc. (Singer and Menzie, 2010). In this study, we evaluate the effects of using ASTER hydrothermal alteration mineral maps, ranking mineral occurrences, and geostatistical approaches as tools for assessment.

Details of the three-part (mineral deposit models, permissive tracts, estimates of numbers of undiscovered deposits) form of mineral resources assessment are discussed by Singer and Menzie (2010). Root et al. (1992) explained the use of Monte Carlo methods to combine estimates of numbers of undiscovered deposits from three-part assessments with grade and tonnage models to produce a probabilistic estimate of undiscovered resources. The probabilistic assessment for this study focused on parts of the study area where the team considered undiscovered deposits likely to be present with the tops of porphyry systems within 1 km of the surface.

**Permissive tracts**

The fundamental geologic feature used to delineate permissive tracts for porphyry copper deposits for this study is a subduction-related magmatic arc or a postsubduction or postcollisional magmatic belt of a given age. Permissive tracts for
porphyry copper deposits are delineated as geographic areas that include volcanic and intrusive rocks of a specified age range that typically can be related to a particular tectonic setting (such as a continental margin arc or island arc). Tracts are based primarily on geologic map units that define the magmatic arc or belt and refined using distributions of known deposits, prospects, and occurrences that may be related to porphyry systems, extensions under shallow (<1 km) cover, and other characteristics documented in mineral deposit models (e.g., John et al., 2010).

For this study, the geologic features that guided permissive tract delineation were (1) the remnants of the NW-trending Jurassic arc that extended from northern Mexico through Arizona, Nevada, and California (Barton et al., 2011); (2) the northern part of the Late Cretaceous to middle Eocene (Laramide) continental margin arc that extends to the Sierra Madre Occidental, eastern Mexican Basin, and Mesa Central of north-central Mexico; and (3) a belt of middle Tertiary (Oligocene-Miocene) granitic to intermediate intrusive rocks and volcanic rocks associated with post-Laramide magmatism (postsubduction extension). These data were used to define a Jurassic permissive tract, two Laramide permissive tracts, and a Tertiary permissive tract (Fig. 10).

The Laramide tract was divided into a Laramide Northwest and a Laramide Southeast tract on the basis of the distinct break in permissive mapped Laramide rocks that corresponds to the gravity and aeromagnetic feature that defines the Holbrook lineament (Figs. 4, 10A). This boundary also marks differences in levels of exposure, indicated by relative amounts of coeval extrusive and intrusive rocks. As noted by other workers, the Laramide Southeast tract area corresponds to Proterozoic basement of the Mazatal terrane and hosts most of the porphyry copper deposits in the study area (App. Table A1; Titley, 1981). In the study area, the only known pre-Laramide porphyry copper deposits are in the Bisbee area, and the only likely Tertiary deposit is the Iron Door (Spike-E Hills), which was explored in the 1970s (Keith and Wilt, 1978; Erickson, 1988).

The geologic database served as the starting point for permissive tract delineation (Fig. 2). Using GIS tools, a 10-km buffer was applied to permissive intrusions and a 2-km buffer was applied to permissive extrusive map units by age group (Mihalasky et al., 2010). Deposits and prospects that were known or believed to be associated with a tract of a given age were plotted, and a 10-km buffer was applied to include possible areas associated with porphyry copper systems. For
Fig. 7. A) Landsat TM false color composite (band 7 = red, band 4 = blue, band 2 = green) mosaic image of the area southwest of Tucson, Arizona, showing known porphyry copper mines. B) ASTER hydrothermal alteration map of argillic, phyllic, propylitic (epidote-chlorite and calcite-dolomite), and hydrothermal silica-rich rocks projected on a Landsat TM mosaic (band 7) of southwest Tucson, Arizona. Location shown in Figure 12.
Fig. 8. A) ASTER mineral map of the area southwest of Tucson, Arizona, showing minerals used to compile the low-pass alteration map. B) Low-pass pixels with values greater than 19%. Outline of ASTER alteration polygons in white lines. Location shown in Figure 12.
each tract, the resulting buffered areas were merged using GIS tools and aggregated using a 5-km aggregation distance and a 2,000-km² minimum hole size. The lines of the resulting polygons were smoothed using a Polynomial Approximation with Exponential Kernel (PAEK) method. This cartographic tool smooths polygons based on a smoothing tolerance that was set at 5 km. Because this assessment is for porphyry copper deposits <1 km below the surface, alluvial-filled basins >1 km thick (identified from gravity anomaly maps; Fig. 5) were removed from the tracts. Laramide and Tertiary intrusions were removed from the Jurassic tract, and Tertiary intrusions were removed from the Laramide tracts. After these steps, the polygons were smoothed once again using a tolerance of 2 km.

Ranking prospects

Mineral site data were used to compile a ranked mineral site map and a table classified by permissive tract that was essential in the three-part quantitative assessment for estimating undiscovered deposits (Fig. 11; Table 3). Each of the 690 mineral sites compiled for this study was evaluated in terms of the likelihood that the site is associated with a porphyry copper system based on deposit type, commodities present, and development status (App. Table A2). Each site was assigned to a permissive tract on the basis of known age or apparent age. Radiometric ages are available for 143 sites; other sites are assigned an age based on associated geologic map units or, in some cases, ages of spatially associated igneous rocks that have been dated. Sites were assigned to one of five categories: (1) deposit with identified resources, (2) other sites that are spatially part of a deposit, (3) porphyry copper exploration targets, (4) Cu or Cu-Mo prospects, and (5) other prospects and occurrences. Exploration targets are prospects that have been recently active (post-2005); these properties may or may not remain a focus of industry over time. Note, for example, that the Red Hill (Four Metals) property in the Laramide Southeast tract is considered a target; the property has been explored by a number of companies since the 1960s with historical resource estimates of about 23 Mt at 0.42%

Table 2. Criteria for Ranking Alteration Polygons

| V | Description |
|---|-------------|
| 1 | Deposit or occurrence within 0.5 km of polygon with copper listed in ore types in MRDS database |
| 2 | Porphyry copper deposit within 0.5 km of polygon with copper listed in ore types |
| 2 | If all hydrothermal alteration types are present |
| 2 | If argillic area is >10% of alteration polygon area and phyllic area is >20% of alteration polygon area |
| 1 | Phyllic area >20% of alteration polygon area |
| 1 | If argillic area is >10% of alteration polygon area |
| 1 | If epidote chlorite area is >1% of alteration polygon area |
| 1 | Hydrothermal silica-rich area >4% of alteration polygon area |
| 2 | If rock type is granodiorite or quartz monzonite |
| 2 | If alteration polygon roundness is >90% |
| 2 | If size of alteration polygon is >20 km² and total % alteration area (excluding hydrothermal silica-rich alteration) is >40% |
| 2 | Copper or molybdenum geochemistry shows high ppm |
| 1 | If the nearest alteration polygon is <4 km |

Note: Values, if true, are 1 or 2; perfect score = 20; V = value
Fig. 10. A-C) Permissive tracts defined for the study area.
copper and is being explored by Allegiant Gold as of 2018. Cu and Cu-Mo prospects that are documented or likely to be porphyry related include sites that have been partially drilled or otherwise explored as porphyry copper targets but do not have reliably reported resources, as well as sites that have past production, including breccias, skarns, replacement deposits, and polymetallic veins. Other prospects and occurrences include sites with or without copper and other commodities that may or may not be porphyry related but are insufficiently characterized to make that determination.

Table 3. Numbers of Ranked Mineral Sites Listed by Permissive Tract

| Permissive tract | Jurassic | Laramide Northwest | Laramide Southeast | Tertiary |
|------------------|----------|--------------------|--------------------|---------|
| Number of sites  | 67       | 125                | 398                | 100     |
| Deposits with identified resources\(^1\) | 2        | 5                  | 54                 | 2       |
| Other sites that are parts of a deposit\(^2\) | 2        | 2                  | 25                 | 0       |
| Porphyry copper targets\(^3\) | 1        | 2                  | 2                  | 1       |
| Prospects\(^4\) | 54       | 111                | 309                | 91      |
| Cu ± Mo = major commodity | 19       | 42                 | 143                | 15      |
| Occurrences\(^5\) | 8        | 4                  | 10                 | 6       |

\(^1\) Tonnage production information available
\(^2\) Site within 1 km of deposit with identified resources
\(^3\) Sites currently undergoing active exploration
\(^4\) An area that is a potential site of mineral deposits, as indicated by preliminary exploration
\(^5\) Any ore or economic mineral in any concentration found in bedrock or as float, especially a valuable mineral in a concentration sufficient to encourage further exploration

Fig. 11. Map showing the distribution of ranked mineral sites.
Estimates of undiscovered resources

Estimates of undiscovered resources based on estimates of numbers of undiscovered deposits are calculated using the Economic Mineral Resource Simulator (EMINERS) Monte Carlo simulator program (Duval, 2002; 2012; Bawiec and Spanski, 2012). User input of a probability mass function (PMF) defining estimates of the number of undiscovered deposits that are expected to occur at different confidence levels (Singer and Menzie, 2010) is combined with appropriate grade-tonnage models to simulate contained resources in undiscovered deposits. In the expert judgment approach, the consensus estimate of numbers of undiscovered deposits elicited at different levels of confidence is entered directly into the program. The mean number of undiscovered deposits and associated standard deviation are based on the algorithm developed by Singer and Menzie (2005) that replicates the deposit distribution originally described by Root et al. (1992). Data for the mean expected number of deposits for each tract from the logistic regression are further processed to provide input for EMINERS, as described below.

Expert judgment approach for number of undiscovered deposits

Probabilistic estimates of numbers of undiscovered porphyry copper deposits were made by the authors for four permissive tracts after reviewing the available data, prior to the geostatistical modeling. Individual team members made independent estimates of numbers of undiscovered deposits for each tract at five confidence levels (90%, 50%, 10%, 5%, and 1% quantiles). This process was followed by discussion and additional data review to reach a consensus estimate for each tract. The mean number of deposits (N_und), standard deviation (S), and coefficient of variation (Cv%) summary statistics were calculated using a regression equation (Singer and Menzie, 2005). Estimates were first made for the Laramide Southeast and Tertiary tracts before the ASTER data were considered. Subsequently, the ASTER data were reviewed and estimates were made for all four permissive tracts to determine how the remote sensing dataset influenced the results. Criteria considered in making the estimates included the following:

1. Tract area,
2. Numbers of known porphyry copper deposits and prospects as well as distribution and numbers of possible related deposit types,
3. Numbers of copper occurrences in the tract,
4. Copper and molybdenum geochemical maps,
5. Level and recency of exploration,
6. Depth of erosion,
7. 457 ranked ASTER alteration polygons, and
8. Space constraints.

The level and recency of exploration considerations were based on development and activity status described in the activity reported in the S&P Market Intelligence (2017) database and company websites. Relative proportions of exposed volcanic and plutonic rocks were used as an indication of the depth of erosion. For space constraints, we considered how many additional porphyry systems could actually fit in a given permissive tract. For example, the surface footprint of a large porphyry system can be on the order of 200 km² or more.

Using ASTER alteration polygons to help determine undiscovered deposits

Ranked ASTER alteration polygon maps were compiled for each permissive tract (Figs. 10, 12; App. Maps A2–A4). Although a perfect score of 20 was possible in the alteration polygon ranking system (Table 2), the highest score achieved was 14. To keep the alteration polygon map as simple as possible for the expert users to interpret, rank scores were split into three categories (0–4, 5–7, 8–20) for all tracts, which were recorded in the attribute file for each alteration polygon in the GIS database. Low scores (0–4, 5–7) typically have argillic- and phyllic-altered rocks. Higher-ranked alteration polygons (8–20) typically have higher surface percentages of argillic- and phyllic-altered rocks, also have silicic- and propylitic-altered rocks, have high reported or interpolated concentration of copper and molybdenum geochemistry, and are close to other porphyry copper deposits or copper-bearing deposits and alteration polygons. There are 74 high-ranking (score 8–20) ASTER polygons in the study area (App. Map A1; App. Table A6).

In order to emphasize potential unexplored or less well explored areas of potential undiscovered deposits related to ASTER alteration polygons, areas not associated with any known porphyry copper deposits, prospects, or occurrences but containing high-ranked ASTER alteration polygons were highlighted on the alteration polygon and tract map (Fig. 12; App. Maps A2–A4). These highlighted high-ranking polygons became a crucial part of influencing expert opinion on undiscovered deposits, since ASTER data have not been used in a regional assessment of the southern Basin and Range Province and ASTER polygons highlight hydrothermal alteration that may have been overlooked in previous studies. The expert panel assumed that areas with no known deposits would be not as well explored as areas with deposits, although these areas may have been explored but no documentation preserved. This was of particular interest in the Laramide Southeast tract, where three ASTER high-ranking highlighted polygons are located in one of the most explored areas in the world for porphyry copper deposits (Fig. 12; locations A, B, and C; App. Map A2). Other notable high-ranking ASTER alteration polygons that are not associated with known porphyry deposits include three highlighted polygons in the western part of the Jurassic permissive tract, three smaller highlighted polygons in the eastern part of the Jurassic permissive tract, and two polygons in the Tertiary permissive tract (App. Maps A3, A4).

Using ASTER alteration polygon data, summary statistics of undiscovered Laramide Southeast deposits indicate an N_und total of 4.3 compared to an N_und total of 2.8 without using ASTER alteration polygons (Table 4). Undiscovered deposit estimates were also higher for the Tertiary tract using ASTER alteration polygons (N_und = 5.1) than the estimates without ASTER data (N_und = 3.8; Table 4). In addition, using ASTER alteration polygons in undiscovered deposit estimates, the Laramide Northwest tract had an N_und total of 3.2 and the Jurassic tract had an N_und total of 4.1 (Table 4). Thus, using the expert panel quantitative method, an N_und total of 16.7
undiscovered deposits is predicted for the study area using ASTER data (Table 4).

Porphyry copper potential of the study area

The southern Basin and Range region has identified resources of more than 200 Mt of copper in porphyry copper deposits, including past production (Fig. 13; Table 5). Most of the identified resources are within the region that we defined as the Laramide Southeast permissive tract. Our assessment suggests that this tract area may contain additional resources, albeit fewer than have been identified in the past (Fig. 13; Table 5). The total mean amount of undiscovered copper for the four tracts is 64 Mt of copper based on expert judgment and 38 Mt based on modeling. Nevertheless, the undiscovered in-place resources are comparable to five years of total U.S. copper mine production (Fig. 13). The Laramide Northwest permissive tract may contain about as much copper as has already been discovered, and additional Jurassic resources may also be present.

The areas of each tract covered by intrusive and volcanic rocks and by ASTER alteration anomalies (Table 4) show that the relative amounts of intrusive and volcanic rocks are equal (5%) for the Laramide Southeast tract, which is also the tract with the largest area of significant ASTER anomalies. This suggests that the Laramide Southeast tract represents an ideal level of exposure for porphyry copper deposits, whereas the Laramide Northwest and Jurassic tracts are more deeply eroded. Amounts of mapped volcanic rock are lowest for the Jurassic and Laramide Northwest tracts, whereas some 30% of the Tertiary tract is covered by volcanic rock. Thus, the three-part quantitative assessment indicates that the Tertiary permissive tract, which consists of extensive volcanic cover, may be prospective for undiscovered deposits, especially at shallow depth.

Prospectivity Mapping for Porphyry Copper Deposits Using Weights of Evidence and Logic Regression

Introduction

Spatial features from regional geologic, geochemical, and rock alteration datasets and maps were used in a GIS framework to model and generate maps showing prospectivity for porphyry copper deposits in the southwestern United States. The prospectivity model for porphyry copper deposits was developed using weights of evidence and logistic regression techniques using data compiled during a resource assessment of porphyry
Table 4. Estimates of Numbers of Undiscovered Porphyry Copper Deposits for the Southern Basin and Range

| Tract name          | Area of permissive tract in square kilometers | Deposit density | Deposit size | Total number of deposits | Known deposits | Un-discovered deposits | Explorability | Significance |
|---------------------|----------------------------------------------|-----------------|--------------|--------------------------|----------------|------------------------|---------------|-------------|
| Jurassic             |                                              | 16              | 38,561       | 2,294                     | 49             | 16                     | 4%            | 0.1%        |
| Laramide Northwest   |                                              | 15              | 15,001       | 2,294                     | 49             | 15                     | 4%            | 0.06%       |
| Laramide Southeast   |                                              | 13              | 29,583       | 2,294                     | 49             | 13                     | 2%            | 0.04%       |
| Jurassic East        |                                              | 12              | 1,023        | 2,294                     | 49             | 12                     | 2%            | 0.02%       |
| Tertiary             |                                              | 13              | 110,545      | 2,294                     | 49             | 13                     | 5%            | 0.06%       |
| Tertiary East        |                                              | 13              | 38           | 2,294                     | 49             | 13                     | 2%            | 0.04%       |

Prospectivity model for southwest U.S. study area

The prospectivity model parameters for the southern Basin and Range Province include arc setting, permissive rock types and proximity, rock alteration polygons and proximity, regional sediment geochemistry concentrations exceeding threshold concentrations, and areas lacking geochemical sampling or remote sensing coverage, indicating that geochemical and rock alteration data are missing. The prospectivity model parameters for the southern Basin and Range Province, however, do not take into account unreported sampling. The deposit diameter and area footprint results for the median and mean ore tonnage in the porphyry copper deposit model were determined in a previous study and used in the Mexico and southern Basin and Range Province prospectivity models (Table 6; Singer et al., 2008). The evidence feature classes used to define the porphyry copper deposit prospectivity model in Mexico are similar to those defined for the southwest U.S. study area for geologic and geochemical features, but differ for the mapped rock alteration features. The rock alteration features defined during the porphyry copper deposit assessment of Mexico were based on digitized polygons of rock alteration mapped using ASTER data (Singer and Menzie, 2005). ASTER alteration polygons were used in geospatial modeling of hydrothermally altered areas covering the southern Basin and Range Province study area. Similar to hydrothermally altered rocks mapped in the Mexico assessment, the southern Basin and Range Province ASTER polygons define areas of phyllic, argillic, and propylitic alteration and sericite (phylllic alteration; Hammarstrom et al., 2010). ASTER alteration polygons were used in geospatial modeling of hydrothermally altered areas covering the southern Basin and Range Province, but differ for the mapped rock alteration features. The rock alteration features defined during the porphyry copper deposit assessment of Mexico were based on digitized polygons of rock alteration shown on the 1:250,000-scale 1° × 2° quadrangle geologic-mining map series published by the Mexican Geological Survey (Hammarstrom et al., 2010, app. A). The mapped rock-alteration categories were defined by both field mapping and petrologic studies. The alteration and types used in the Mexico model include silification (consisting of a jasperite rock class and an all other silicified rocks class), sulfidation (consisting of a pyritic rock class and an all other sulfidic rocks class), potassic alteration, argillic alteration (consisting of a kaolinite class and an all other argillic rock class), and propylitic alteration and sericite (phylllic alteration; Hammarstrom et al., 2010). ASTER alteration polygons were used in geospatial modeling of hydrothermally altered areas covering the southern Basin and Range Province study area. Similar to hydrothermally altered rocks mapped in the Mexico assessment, the southern Basin and Range Province ASTER polygons define areas of phyllic, argillic, and propylitic hydrothermal alteration mapped using ASTER data and are ranked based on alteration types and densities tabulated for each polygon (Figs. 7B, 10; Table 2).

Weights of evidence are used to define alteration rank criteria in the southern Basin and Range Province that appeared to be consistent with the spatial weights defined in the Mexico prospectivity model (Table 7; App. 1; Hammarstrom et al., 2010). Cumulate descending analysis of the alteration polygon ranks used to define alteration class 1 was applied to the Laramide Southeast tract data to calibrate the alteration mapping. A buffer of 6 km, defined by the weights of evidence classes for the Mexico dataset, was applied to the southern Basin and Range Province alteration polygons in the cumulative descending analysis. Buffered alteration polygons for...
the southern Basin and Range Province consist of argillic-, phyllic-, and propylitic- (epidote-chlorite and/or carbonate) altered rocks. Cumulate descending analysis was used because many of the alteration rank polygon features overlap. The differences between cumulate areas and deposit sites were used to define distinct feature categories (Table 8). In Table 8, the contrast (C) is positive for patterns that are positively associated, negative for patterns that are negatively associated, and zero when the patterns overlap only by the expected amount due to chance. S is the estimated uncertainty of the contrast value, and prob > |t| is the probability that the contrast values of the category features are different from zero (random correlation). In Table 8A, the break in positive to negative associated rank buffer categories occurs between rank classes 8 and 9. Table 8B has reclassified these groups into three category groups with a break at the rank 8-9 transition. The alteration missing data contrast is not significantly different from zero (random correlation), which is expected for a random missing data feature. The reclassified Alt1 category (rank 9-14, 6-km buffer area) contrast value of 1.15 ± 0.36 is similar but lower than the Alt1 category contrast value of 1.6 ± 0.23.

**Logistic regression**

The evidence feature class categories defined by the weights of evidence analysis of the Mexico assessment data were used in GIS to define the southwest U.S. database used to calibrate the prospectivity model using logistic regression. Prospectivity modeling was done for each permissive tract (Fig. 14; App. Maps A5–A8). The logistic regression model provides a method to estimate the expected number of

**Table 5. Mean Amounts of Metal and Ore in Undiscovered Porphyry Copper Deposits**

| Permissive tract | Jurassic East | Laramide Northwest | Laramide Southeast | Tertiary |
|------------------|---------------|---------------------|--------------------|----------|
| Method           | Expert        | Model               | Expert             | Model    |
| Cu (t)           | 16,000,000    | 7,800,000           | 12,000,000         | 1,200,000 |
| Mo (t)           | 410,000       | 220,000             | 320,000            | 31,000   |
| Au (t)           | 410           | 200                 | 310                | 31       |
| Ag (t)           | 4,800         | 2,500               | 3,900              | 380      |
| Rock (Mt)        | 3,200         | 1,600               | 2,500              | 240      |

C1 Assessed without considering the ASTER data

**Fig. 13.** Porphyry copper estimates verses known resources.
deposits in permissive tract areas as a function of evidence feature class categories. The estimates made this way are for the expected number (mean) of deposits in the tract areas. A summary of the porphyry copper control areas, evidence feature classes, training site characteristics, and site densities, integrated for all tract areas in the Mexico assessment, is given in Appendix Table A7A. Appendix Table A7B summarizes the logistic regression results for four model scenarios (defined values for all feature classes, rock alteration data missing, sediment chemistry data missing, and both rock alteration and sediment chemistry data missing), evidence class features used in each of the logistic regression models, the \( \beta \) terms for each evidence feature class in each model, their individual standard error estimates (App. Table A7B), and the coefficients used to calculate the pooled standard deviation of the combined evidence and for this dataset (App. Table A7B). The (feature class A) \( \cdot \) (feature class B) variables in Appendix Table A7A, for example INT1 \( \cdot \) VOLC2, are interaction effects describing the additional influence of their spatial overlap, in addition to the individual parameter effects. With the exception of a few interaction terms, chi-square tests of the regression coefficients and errors indicate a greater than 94% probability that the parameters are different from zero (App. Table A7B). The coefficients in Appendix Table A7B can be used to calculate the standard error of estimate for the combined \( \beta \) terms in the logistic regression results, shown as \( SE(\sum \beta_i) \) and \( (\sum \beta_i^2) \), respectively, in Appendix Tables A8 to A11 for the individual southwest U.S. tract results.

The logistic regression model discrimination measure (C statistic) is 0.71, which is considered good to adequate for model discrimination calibration results (Hosmer and Lemeshow, 2000). The prediction/success rate analysis method of Chung and Fabbri (1999) results in an area under the performance curve of 0.91, with a kappa score of 0.83, both acceptable results.

| Feature class | Criteria | Weights of evidence results |
|---------------|----------|-----------------------------|
| Intrusive rocks | Proximity to feature | Area (km²) Sites Nonsites C² S¹ Between class |
| Int 0 | >6 km | 430,573.5 8.9 430,864.6 –2.637 0.352 10.90 <.0001 |
| Int 1 | 2–6 km | 166,790.2 15.6 166,783.6 –0.403 0.277 2.202 0.015 |
| Int 2 | 0–2 km (inside–2 km) | 126,913.4 69.2 126,844.2 2.588 0.235 8.229 <.0001 |
| Total | | 724,586.1 93.7 724,492.4 |
| Volcanic rocks | Proximity to feature | Area (km²) Sites Nonsites C S Between class |
| Volc 0 | >4 km | 351,732.7 28.3 351,704.4 –0.779 0.225 4.982 <.0001 |
| Volc 1 | 0–4 km | 251,935.5 29.5 251,888.4 0.831 0.222 10.90 <.0001 |
| Volc 2 | inside | 120,917.9 35.9 120,888.4 0.153 0.213 2.202 0.015 |
| Total | | 724,586.1 93.7 724,492.4 |
| Alteration | Proximity to feature | Area (km²) Sites Nonsites C S Between class |
| Alt 0 | >6 km | 667,210.272 51.3 667,159.0 –2.6286 0.207398 10.90 <.0001 |
| Alt 1 | 0–6 km | 49,653.1 25.3 49,627.8 1.615 0.233 6.94 <.0001 |
| Alt 2 | inside | 7,722.7 17.1 7,705.6 3.033 0.268 11.33 <.0001 |
| Total | | 724,586.1 93.7 724,492.4 |
| Sediment chemistry | Value thresholds | Area (km²) Sites Nonsites C S Between class |
| Chem 0 | Cu <40 and Mo <4 | 442,977.2 15.9 442,961.3 –2.941 0.275 4.948 <.0001 |
| Chem 1 | Cu >40 and Mo <4 or Cu <25 and Mo >4 | 237,502.7 25.6 237,477.1 –0.260 0.232 10.359 <.0001 |
| Chem 2 | Cu >25 and Mo >4 | 44,106.2 52.2 44,054.0 2.967 0.208 10.359 <.0001 |
| Total | | 724,586.1 93.7 724,492.4 |

1From Hammarstrom et al. (2010)
2Contrast: \( C = \ln\left(\frac{\text{class sites}}{\text{class nonsites}}\right)/\ln\left(\frac{\text{total sites}}{\text{total nonsites}}\right)\); contrast is a measure of association between the distribution of sites and feature patterns; contrast is positive for patterns that are positively associated, negative for patterns that are negatively associated, and zero when the patterns overlap only by the expected amount due to chance.
3\( S \) is the estimate of errors associated with the feature class contrast value due to variation in the numbers of sites and nonsites.
4\( t \) Ratio is the Student's t-test criteria used to determine that two sets of data—in this case, the contrast values of adjacent feature classes based on ordered data criteria of the feature class—are significantly different from each other.
5\( \text{Prob} > |t| \) is the probability value of the null hypothesis test that the contrast values of adjacent feature classes are identical.
Geostatistical approach for number of undiscovered deposits

The logistic regression density model using geologic, geochemistry, and rock alteration variables provides a method to estimate the total number of deposits expected to occur in a tract and, based on the known deposits occurring in the tract, an estimate of undiscovered deposits (App. 1: eq. 1–4; App. Tables A8–A11). The permissive tracts are based on geologic features and criteria; however, regional geochemistry and rock alteration data needed for the regression model may be missing from some areas and tracts. In these cases, the missing data regression models in Appendix Table A7B can be used to estimate deposit density for these areas.

Prospectivity model assessment results

The prospectivity model for porphyry copper deposits developed using weights of evidence and logistic regression techniques included parameters for arc setting, permissive rock types and proximity, ranked alteration polygons and proximity, areas not mapped by ASTER, Cu and Mo geochemistry concentrations, and areas lacking Cu and Mo geochemistry data (Table 7). The prospectivity results show a reasonable correlation with known deposits and prospects, although no deposit data from Arizona were used in the model (Figs. 9, 14; App. Maps A4–A6, A8). Higher deposit densities for each prospectivity map also tend to correlate well with mid- to high-ranked (score 4–20) ASTER alteration polygons (Figs. 12, 14; App. Maps A2–A8). Estimates of undiscovered deposits for the Laramide Southeast, Laramide Northwest, Tertiary, and Jurassic tracts were 1.4, 0.4, 6.2, and 1.9 Nund, respectively, indicating a total of 9.9 Nund undiscovered deposits in the study area (Table 4).

Probabilistic estimates of numbers of undiscovered porphyry copper deposits from both assessment methods (expert judgment and geostatistical modeling) were used as input to the EMINERS computer program to estimate amounts of contained metal (App. Table A12). The program combines the estimates with the porphyry copper grade and tonnage model of Singer et al. (2008) in a Monte Carlo simulation to produce a probability distribution of amounts of copper, molybdenum, gold, silver, and ore. For the Jurassic and Laramide tracts, the mean amount of copper estimated by expert judgment exceeded the geostatistical model results by a factor of 2 to 10; results for the Tertiary tract were comparable (App. Table A12). Selected quantiles are reported, along with the means, the probability of the mean, and the probability of no resources in supplementary Appendix Table A12.

Model performance

Independent of the actual estimates of undiscovered deposits, the performance of the porphyry copper deposit prospectivity model can be evaluated in terms of its ability to predict the relative spatial likelihood of deposit occurrence in relation to geologic, geochemical, and geophysical features in a tract. The prediction/success rate method of Chung and Fabbri (1999,

| Alteration feature class | Initial classification | Area (km²) | Sites | Nonsites | C | S | t Ratio | Prob > |t|
|-------------------------|------------------------|------------|-------|----------|---|---|---------|---------|
| Alt: Rank 9-14           | Inside Rank 9-14       | 236.2      | 1     | 235.2    | 1.2955 | 1.0167 | 1.174  | 0.101   |
| Alt: Rank 9-14 buffer   | In Alt rank 9-14 km buffer | 3,754.8   | 11    | 3,743.8  | 1.1458 | 0.3645 | 3.143  | 0.001   |
| Alt: Rank 8 buffer       | In Alt rank 8 km buffer | 1,652.3    | 2     | 1,650.3  | 0.0204 | 0.7287 | 0.028  | 0.489   |
| Alt: Rank 7 buffer       | In Alt rank 7 km buffer | 1,092.1    | 1     | 1,091.1  | -0.2695 | 1.0151 | 0.263  | 0.398   |
| Alt: Rank 2-6 buffer     | In Alt rank 2-6 km buffer | 3,186.2  | 2     | 3,184.2  | -0.6936 | 0.7285 | 0.952  | 0.171   |
| Alt: Not in rank 2-14 buffer | Not in Alt rank 2-14 km buffer | 14,136.5 | 11    | 14,127.5 | -0.7900 | 0.3642 | 1.922  | 0.027   |
| Alt: Missing data        | Missing alteration data | 5,384.4    | 7     | 5,377.4  | 0.1121 | 0.4228 | 0.265  | 0.396   |
| Total                    |                        | 29,444.5   | 35    | 29,409.5 |       |       |        |         |

Table 8. Weights of Evidence Analysis of Porphyry Copper Deposit Distribution Relative to Alteration Rank Criteria Buffers Defined for the Laramide Southeast Tract

1Category group areas and deposit sites are calculated as differences between adjacent cumulative descending accumulations of areas and deposit sites as alteration rank criteria descend from category 14 to 2

2Initial classification table

3Reclassified category table with distinct feature classes

4Sites are porphyry copper deposits in the tract that have defined resources

5Contrast: C = ln(((class sites)/(class nonsites))/((total sites)/(total nonsites))); contrast is a measure of association between the distribution of sites and feature patterns; contrast is positive for patterns that are positively associated, negative for patterns that are negatively associated, and zero when the patterns overlap only by the expected amount due to chance

6S is the estimate of errors associated with the feature class contrast value due to variation in the numbers of sites and nonsites

7t Ratio is the Student's t-test criteria used to determine if the contrast values of the feature class are different from zero (random correlation)

8Prob > |t| is the probability value of the null hypothesis test that the contrast values of the features are different from zero (random)
2005, 2008) provides a classification-threshold independent measure of the prediction performance of the models. As the prospectivity model was calibrated using data external to the southwest U.S. study area, the performance test is considered a validation test. Model prediction performance has been evaluated comparing the locations of known porphyry copper deposits in the study area relative to the prospectivity estimates derived from the model. The performance test measures the relations between the overall rate of deposit occurrence against the proportion of total map area (cumulative area fraction) as the prospectivity rank decreases (see Beguería, 2006, for a discussion of the technique and its features). The prospectivity model for the Laramide Southeast tract was used for the model performance test due to the large number of known deposits in the tract and the high degree of mineral deposit exploration in the area (Fig. 14).

Three performance curves are shown in Figure 15. The calibration curve is the fitting rate performance of deposits and feature data in the Mexico assessment used to calibrate the logistic regression model. The validation curve is the performance of the known deposits and the feature data in the Laramide Southeast tract relative to the logistic regression model predictions. The resources curve is the performance of the contained copper resources in the known deposits and the feature data in the Laramide Southeast tract relative to the logistic regression model predictions. The resources performance tests the ability of the model to predict the locations of the largest deposits. The areas under these cumulative deposit (or resource) fraction-cumulative area fraction curves are a measure of model discrimination. Discrimination measure (normalized area under the curve statistic) values of 0.5 constitute a poor model having discrimination no better than random classification; an area between 0.7 and 0.8 is considered good discrimination, and an area between 0.8 and 0.9 is considered excellent discrimination (Hosmer and Lemeshow, 2000). For the Laramide Southeast tract, the normalized areas under the performance curve statistics are 0.91 for the Mexico assessment fitting curve, 0.85 for the validation curve, 0.80 for the resources curve.
and 0.87 for the resources curve. The resources performance has a slightly higher value than the validation performance based on deposit numbers, indicating that the prospectivity model predicts undiscovered resources at an equivalent or slightly higher rate than undiscovered deposits.

Kappa statistics (coefficient of agreement) provide another test of model performance by measuring the amount of spatial agreement between attributes that were grouped by model prediction and correcting for the amount of agreement expected by random distribution between spatial data classes (Congalton, 1991; Bonham-Carter, 1994). The kappa coefficient varies from –1 for perfect negative correlation to 0 for random correlation to +1 for perfect correlation. This degree of correlation was tested using contingency table and significance tests (Bonham-Carter, 1994; Conover, 1999). Because of the correction for expected variation, kappa statistics can be used as an unbiased measure of agreement for classification groups between different models, even when the classification groups have differing degrees of spatial coverage (Bonham-Carter, 1994). For the Laramide Southeast tract, the kappa performance statistics are 0.83 for the Mexico assessment fitting curve, 0.69 for the validation curve, and 0.74 for the resources curve. These are all strong results supporting the utility of the porphyry copper deposit geostatistical model in resource assessment applications.

Summary and Conclusions

A new type of dataset consisting of 457 ASTER alteration polygons was compiled for this study using argillic, phyllic, and propylitic low-pass filter alteration density maps (Fig. 8). Each polygon was then ranked based on % of alteration types, geochemistry, size, roundness, deposit data, and proximity to other alteration polygons (Fig. 9; Table 2). A total of 74 ASTER alteration polygons with high-rank scores (8–20) are located in the study area (App. Map A1). Higher-ranked alteration polygons (8–20) typically have higher surface percentages of argillic- and phyllic-altered rocks than other polygons, have silicic- and propylitic-altered rocks, have high reported or interpolated concentration of copper and/or molybdenum geochemistry, and are close to other porphyry copper deposits or copper-bearing deposits and alteration polygons (App. Table A6).

The ASTER alteration polygons were used in the three-part quantitative assessment and the geostatistical model. The ranked alteration polygons show the lateral extent and likelihood of potential porphyry deposits based on hydrothermal alteration and other integrated datasets in a single map, which would be missed in a map showing only point data (Fig. 12). Although the study area is one of the most thoroughly explored porphyry copper districts in the world, with 43 known Phanerozoic deposits, the three-part quantitative assessment indicates that there are approximately 17 additional deposits likely to be present. Estimates of undiscovered deposits using ASTER alteration polygons were higher for Laramide Southeast and Tertiary permissive tracts than estimates made without using ASTER data (Laramide Southeast Nund of 4.3 with ASTER vs. 2.8 without ASTER; Tertiary Nund of 5.1 with ASTER vs. 3.8 without ASTER; Table 4). In addition, ranked ASTER alteration polygon and known deposit maps used to assess each permissive tract provide an integrated spatial dataset of areas of varying probability of potential deposits for unexplored and explored areas. There are three Laramide Southeast, six Jurassic, and two Tertiary high-ranked ASTER alteration polygons that are not located near any known mineralized sites and were considered to be of high prospectivity interest in the assessment area (Fig. 12; App. Maps A2–A4). Thus, the ASTER alteration polygon dataset provides a critical new tool for mapping potential porphyry
copper deposits near the surface that might be overlooked in traditional assessments.

The prospectivity model for porphyry copper deposits was developed using weights of evidence and logistic regression techniques originally used in a Mexico porphyry copper assessment (Hammarstrom et al., 2010; App. 1). Prospectivity model parameters include are setting, permissive rock types and proximity, ranked ASTER alteration polygons and proximity, areas not mapped by ASTER, Cu and Mo geochemistry concentrations, and areas lacking Cu and Mo geochemistry data (App. Table A6A, A6B). The prospectivity results show a good correlation with known deposits and prospects, although no southwestern U.S. deposit data were used in the model (Figs. 11, 14).

The geostatistical prospectivity model approach provides several advantages relative to the traditional three-part expert panel assessment approach. It provides a spatial map of the estimated variability and distribution of deposits relative to defined geologic, geochemical, and rock alteration criteria and explicitly accounts for the spatial distribution of areas with missing data in the estimates (Fig. 14; App. Maps A5–A5). The spatial prospectivity map approach allows tract areas to be aggregated or disaggregated to provide tailored estimates of undiscovered deposits and resources relative to administrative or other boundaries of interest. The geostatistical model makes explicit the uncertainty related to estimates of undiscovered deposits and their distribution, and it provides estimates of undiscovered deposits that are independent of, and can be compared with, other assessment methods, such as expert judgment.

Numbers of estimated mean undiscovered deposits based on the geostatistical model were similar to estimates made in the three-part assessment (Table 4) for the Jurassic and Tertiary tracts, but were distinctly lower for the Laramide Northwest and Laramide Southeast tracts, where known porphyry copper deposit densities are among the highest recorded for equivalent tracts on a global scale. Using ASTER alteration polygon data in the entire study area, the three-part assessment results forecast a mean estimate of 17 undiscovered deposits versus a geostatistical model forecast mean estimate of 10 undiscovered deposits. The largest variation in estimates of undiscovered deposits was for the Laramide Northwest tract, in which the three-part assessment estimate was 3.2 undiscovered deposits compared to the prospectivity model estimate of 0.4 undiscovered deposits (Table 4). We do not have current information to know which estimate is closer to the correct number of undiscovered deposits and associated undiscovered ore resources in the study area.

In their application of prospectivity models, Lindsay et al. (2014) identified eight favorable areas for porphyry copper deposits in southeastern Arizona. Their results are not directly comparable with our study because we focused on a larger area, assessed undiscovered deposits away from known deposits, split permissive areas by age, and used other datasets. Both studies, however, indicate a potential for additional porphyry copper deposits in an already well-explored region in the southern Basin and Range Province by using regional remote sensing datasets and ArcGIS to process and integrate data to define areas of prospectivity that may have been overlooked by previous exploration and assessments.

Acknowledgments

The authors would like to thank Dr. Hojjatollah Ranjbar and Associate Editor Jeremy Richards for their editorial reviews, which greatly improved the manuscript, and the U.S. Geological Survey Mineral Resources Program, which funded this project. The U.S. Geological Survey does not endorse the use of any particular software programs.

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