A REMOTE SENSING AND GIS METHOD FOR DETECTING LAND SURFACE AREAS COVERED BY COPPER MILL TAILINGS

Russell Schimmer, Ph.D. Candidate
Department of Natural Resources and Engineering, Geomatics
University of Connecticut
Storrs, CT 06269
russell.schimmer@aya.yale.edu

ABSTRACT

This paper describes an empirically derived, remote sensing-GIS method for positively identifying and distinguishing the locations of active copper mill tailings impoundments in Arizona with a high standard of accuracy. It accomplished this by the development of a remote sensing index, which identifies the mill tailings based on three characteristics— the absence of organic material, the homogenous grain size particular to copper mill tailings, and wetness. The research was successful on two points: (1) the detection method functioned on a fixed set of input parameters, and (2) it eliminated all non-tailings features. First analyzed were nine Landsat 7 ETM+ scenes acquired in 2000, which included spatial coverage of Arizona's primary mining districts. Using a standard *NDVI* application with an applied intensity threshold range, the research developed a tailings index and GIS modeling application to detect mill tailings impoundments and distinguish these mine features from non-tailings features. The method detected the tailings impoundments of the nine highest producing copper mines active in Arizona in 2000 and four inactive copper mines. No large-scale active gold mines operated in Arizona during the study period. The GIS modeling application eliminated the non-tailings features also detected. The research then tested the method on nine additional Landsat 7 ETM+ scenes outside Arizona. In total, the combined remote sensing-GIS method detected seventeen mine-tailings features, including one gold mine tailings impoundment. Moreover, the method did not positively identify any non-tailings features.

INTRODUCTION

According to the International Copper Study Group (ICSG), world copper mine production in 2007 was projected to rise by 5.1 percent to 15.79 million tonnes (Mt), an increase of about 770,000 t compared with that in 2006 (ICSG, October 2007). For 2008, the ICSG expects copper production to increase to 17.0 Mt (+7.6 percent), owing to new mine developments and increased capacity utilization (ICSG, October 2007). Furthermore, the demand for raw copper, especially by China and India, is growing dramatically. As the demand increases so do environmental and social concerns related to the ore extraction and milling processes. Mill copper mine wastes contain variable amounts of sulfide materials and are highly acidic, requiring long-term storage and remedial management programs (U.S. EPA, August 1994). The waste produced during the extraction processes is typically placed on exposed land areas (U.S. EPA, August 1994; Lottermoser, 2003).

Using an empirical approach based on field observations of copper tailings impoundments, the research developed the normalized difference tailings index (NDTI). Modeled on the normalized difference vegetation index (NDVI), the NDTI produces a raster data set of pixels within a narrow threshold in the visual to near-infrared spectral portion of the electromagnetic scale with values of spectral intensity ranging from -0.39 to -0.35 on a scale from -1 to 1. Within this spectral range and reflection intensity threshold, large areas of non-organic materials with a homogenous grain size, typical of copper mill tailings, demonstrate a relatively strong reflectance. A GIS modeling application (the *Aggregate* model) was designed to process these spectral data and rank pixels based on, first, *density* and, second, *proximity*. Because mill tailings cover large exposed surfaces, the Aggregate model's primary purpose is to filter the positively identified raster data and reclassify them based on pixels present in kernels of high density, and then fragments of kernels within a certain proximity of each other. The final data set is a vector file containing the geographic locations of these aggregated kernels. The *NDTI-Aggregate* method refers to the combined three phases.

THE ORE EXTRACTION AND MILLING PROCESS

During the extraction process, ores are first crushed and finely ground, and then treated in flotation cells with chemicals to recover copper concentrates. More than 97 percent of annual ore tonnage processed is disposed of as mine waste (U.S. EPA, August 1994). These wastes are subdivided into three major categories—leach rock, mill tailings, and waste rock (U.S. EPA, August 1994; Lottermoser, 2003b). Mill tailings from the treatment of copper ores are the solid residue of the milling or beneficiation process (Figure 1). Mill tailings are fine-grained, wet, granular materials stored in impoundments behind earth-fill dams, and occupy large areas (U.S. EPA, August 1994; Lottermoser, 2003). Tailings are usually piped to the tailings impoundment area as slurry, which contains about 50 percent solids. Hence, active tailings impoundments generally contain a large water component. Inactive tailings impoundments can contain water from natural runoff or precipitation. Terrain, climate, and topography determine the design and management of mill tailings storage sites (U.S. EPA, August 1994; Lottermoser, 2003). Natural topography and restraining dams contain mill tailings in retention areas. Retention sites are designed to minimize interaction with the environment through dust generation, leakage of fluids, and from failure of the containment structure.

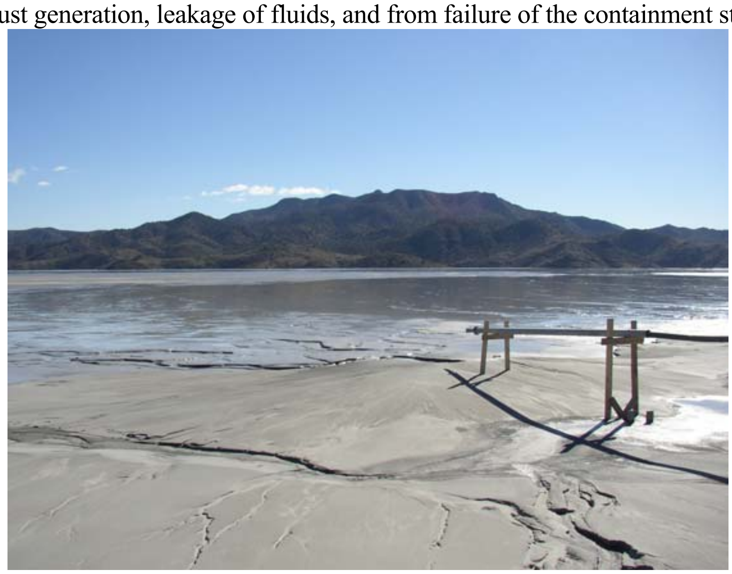

Figure 1. Photograph showing the Lower Mammoth copper tailings impoundment, Bagdad, Arizona, November 2004. Photograph by Russell Schimmer

Often, mine operations leach older mill tailings of suitably high enough residual copper content *in situ*. Since the mid 1980s, the industry has increasingly used a leach-solvent extraction-electrowinning process (SX-EW) for extracting copper from oxidized ores and mine wastes (U.S. EPA, August 1994b). The process reduces the reliance on conventional ore bodies. The SX-EW process is sulfuric acid dependent and operates at ambient temperatures. During the extraction process, the copper is in either an aqueous, or organic environment (U.S. EPA, August 1994b). In 2001, SX-EW processing accounted for 20 percent of worldwide copper production; in the United States, the total approached 30 percent (Dresher, 2007). The ICSG expects SX-EW production to grow in 2008 (ICSG, October 2007).

REMOTE SENSING APPROACHES TO IDENTIFYING AND MONITORING COPPER MILL TAILINGS

Remote sensing technology in tandem with a variety of GIS applications can be an effective tool for monitoring mine activities (Lamb, 2000). For manipulating reflectance data in the visual, near-infrared, and mid-infrared portions of the electromagnetic spectrum (.4 to 2.5 µm), ASTER, AVIRIS, and Landsat satellite images have proved excellent vehicles for determining the location and extent of mine features and tailings deposits arising from metal production. Mineral mapping is the predominant and most developed technique for mine identification and analysis (Clark et al., 1993; Clark et al., 1998; Swayze et al., 2000). Research in Sudbury, Canada (Singhroy, 2000), Cripple Creek, Colorado (Peters and Huff, 2000), South Africa (Niekerk and Viljoen, 2005), and on the Kola Peninsula

(Rigina, 2002) have used satellite images to monitor specific sites where the location and configuration of the tailings impoundments are previously known. In addition, these types of methods have proved useful in mapping inactive tailings impoundments and assessing the potential for environmental contamination, especially during reclamation processes (Peplies et al., 1982; Mars and Crowley, 2003; Vandeberg, 2003).

Making distinctions between tailings features and non-tailings features remain problematic when relying exclusively on a remote sensing method (Rigina, 2002; Vandeberg, 2003; Rockwell and McDougal, 2002). Fieldwork is usually a necessary component. But ground-truthing is time consuming and costly (Sares et al., 2004; Limpitlaw, 2003; Rockwell and McDougal, 2002, 2005), and can be restricted by access to a mine site. Described here is an empirically derived method useful for positively identifying the mill tailings of large-scale industrial mines in semiarid environments. Furthermore, the method distinguishes these impoundment sites from non-tailings features with similar spectral characteristics. The method's ability to distinguish these tailings from the surrounding terrain is advantageous because it could potentially reduce the time and resources necessary for monitoring mill tailings impoundments. Furthermore, it offers a useful method for identifying the locations and configurations of tailings impoundments where ground-monitoring access is limited or restricted.

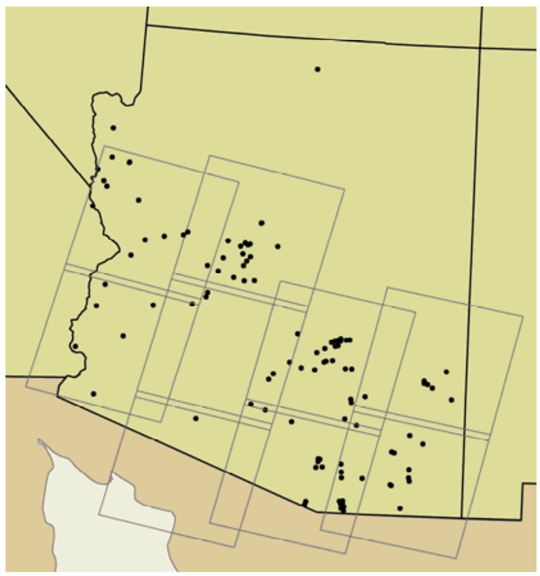

Figure 2. The circles show locations of U.S.G.S. Significant Mineral Deposits in Arizona for 1998 (Long et al., 1998). Each rectangle represents the spatial coverage of a single Landsat scene used in the method described here.

MATERIALS AND METHOD

The research obtained nine Landsat 7 ETM+ satellite scenes, acquired between April 2000 and September 2000. These nine scenes included spatial coverage of U.S.G.S. published *Significant Mineral Deposits* (Long et al., 1998) in Arizona for 1998 (Figure 2). Furthermore, Arizona offered a semiarid environment with limited vegetation coverage and exposed natural terrain suitable for testing the method's ability to distinguish mine-related features from non-mine features.

Arizona has a long history of copper extraction and numerous well-documented copper mines. For 2000, the Phelps Dodge Bagdad mine (Figures 3-5) reported the third highest output (Table 2), producing 247 million pounds of copper (Arizona Department of Mines and Mineral Resources, 2001). The Morenci mine (Tables 1 and 2, Figure 6) is the largest copper-producing complex in the U.S. In 2006 it produced 815 million pounds of copper, over half of Arizona's total (Arizona Department of Mines and Mineral Resources, 2007). Mill tailings impoundments associated with copper extraction were the primary feature of study. However, the expanded research outside Arizona did detect a number of gold mill tailings impoundments as well, likely because copper and gold mill tailings are similar in physical composition and are shown to have an overlap in sediment grain size (Qiu and Sego, 2001).

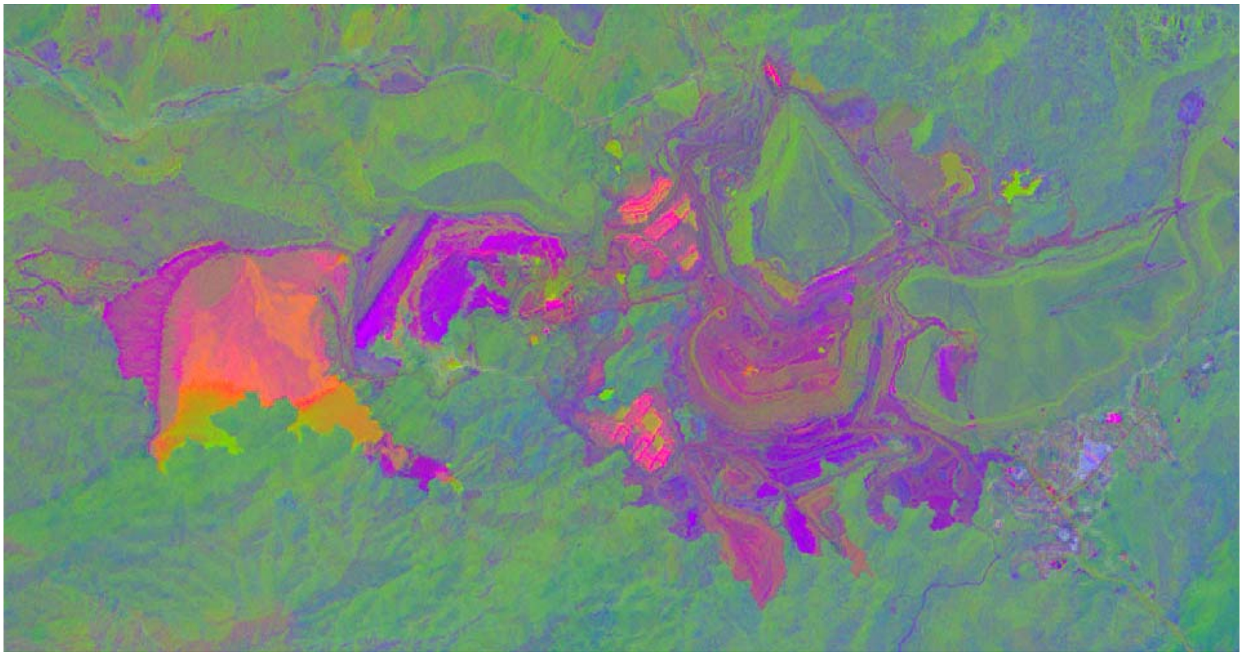

Figure 3. A 2000 Landsat 7 ETM+ scene showing the Bagdad Copper Mine in Arizona. This image was produced using a resolution merge with the Landsat 7, 15-meter panchromatic band, and a Tassel Cap spectral enhancement in ERDAS Imagine. The band grouping is RGB-651. No radiometric enhancement was applied. The large feature furthest left is the Lower Mammoth tailings impoundment, active in 2000; adjacent to it on the right is the Mulholland tailings impoundment, active from c.1977 to 1997; and the dark-violet features lower-right in the image are remnants of first generation tailings impoundments, active from c.1947 to 1977.

Departing from the more common mineral mapping approaches used to locate and map copper mines, this method focuses on three dominant physical characteristics of mill tailings—the absence of organic material, an homogenous grain size, and wetness. Based on these three characteristics, the *NDTI* measures reflectance in the visible red and near-infrared portion of the electromagnetic spectrum at 0.63-0.90 µm wavelengths.

Radiance is a function of the solar irradiance, which varies by time of year and latitude (Schowengerdt, 2007). During the preprocessing stage, each Landsat scene was converted from assigned pixel values in digital numbers (DNs) to "top-of-the-atmosphere" reflectance values using the conversion application described in the Landsat & Users Handbook (NASA, 2008). This is a two-step process. First, the process requires an applied gain and offset to each band of data to rescale the pixel assigned DNs back to radiance. Second, radiance is converted to reflectance by accounting for the solar irradiance by wavelength, as well as the earth-sun distance and the solar zenith angle. This preprocessing phase assured that the scenes contained standardized values for accurate comparison of data across different locations and times of year.

Three Physical Characteristics of Copper Mill Tailings

A Non-organic Environment. In active tailings impoundments, the frequent presence of heavy metal residues and acidic water keep the surfaces bare of organic materials. Unless active remediation efforts are undertaken, inactive impoundments can remain denude of most vegetation for prolonged periods. But some high-acidic tolerant species can survive on inactive impoundments. NDVI is a standard remote sensing application used for distinguishing healthy vegetation and is expressed as [B4 – B3/B4 + B3] (Sellers, 1985; Myneni, 1995), where Landsat 7 ETM+ band groups 3 and 4 represent the visual red and the very near-infrared portions of the electromagnetic scale (B3 = 0.63 - 0.69 µm and B4 = 0.75 - 0.90 µm). The resulting intensity data is scaled between -1 and 1, where pixels assigned positive values generally represent vegetation. Hence, NDVI is a useful tool for distinguishing the boundaries of vegetated terrain from tailings impoundments, which the NDVI primarily assigns negative pixel values.

The Homogenous Grain Size of Mine Mill Tailings. Mine mill tailings are a man-made, fine grained material. A large percentage of copper mill tailings pass through a 0.075 mm, No. 200 sieve (North Carolina Division, 2003). The amount of light scattered and absorbed by a grain is dependent on grain size (Clark and Roush, 1984). The reflection from the surfaces and internal imperfections control scattering. According to Beers Law, larger grain sizes have greater internal paths where light may be absorbed. Larger grain sizes range in size from 0.250 to 0.800 mm (Clark, 1999). A smaller grain has proportionally more surface reflections compared to internal light path lengths thus the surface-to-volume ratio is a function of grain size. If multiple scattering dominates, as is usually the case in the visible and near-infrared, the reflectance decreases as the grain size increases (Clark, 1999). Hence, the grain size characteristic of copper mill tailings should have a relatively strong reflectance in the visible and near-infrared portion of the electromagnetic spectrum, Landsat 7 bands 3 and 4.

In a laboratory comparison study examining mine tailings' properties, gold tailings contained 50% more sediment with grain sizes < 0.074 mm than did copper tailings (Qiu and Sego, 2001). However, there is a large area of grain size overlap (Qiu and Sego, 2001), which likely explains why the NDTI detected some gold mill tailings. Although this laboratory study only used a limited sampling of mill tailings, certain industry standards do exist for the crushing and milling processes. This suggests that, by adjusting the NDTI threshold parameters, the NDTI-Aggregate method might prove useful in detecting gold mine or other types of tailings impoundments.

Soil reflectance is a cumulative property that is derived from the inherent spectral behavior of the heterogeneous combination of minerals, organic matter, and soil (Goetz, 1992; Demattê et al., 2004), thus is difficult to determine (Ben-Dor and Banin, 1994). An *intimate mixture* is generally classified as a terrain dominated by sediments where different materials are in intimate contact in a light scattering surface, such as the mineral grains in a soil or rock. Depending on the optical properties of each component, the resulting signal is a non-linear combination of the end-member spectra (Clark and Roush, 1984). Conversely, the dominance of a chemically and physically homogenous material covering a large area, like tailings impoundments, should produce a homogenous reflective signature distinguishable from other fine sediment matrixes consisting of intimate mixtures.

Wetness. Active tailings impoundments contain extreme variations in sediment saturation and suspended sediment due to its water constituent. *Molecular mixtures* occur on a molecular level, such as two liquids, or a liquid and a solid mixed, e.g., water adsorbed onto a mineral (Clark and Roush, 1984). The close contact of the mixture components can cause band shifts in the adsorbate such as the water in plants. Because water is extremely light absorbent in the 0.63-0.90 µm wavelengths, the NDVI classifies pools of water and highly saturated mill tailings as non-organic, assigning these pixels negative values. However, the reflectance intensity threshold tends to eliminate deeper pools, distinguishing bodies of water from tailings impoundments. But because tailings impoundments contain extreme variations in sediment saturation and suspended sediment (Figure 4), nuances of saturation levels are discernible where light is not fully absorbed and intensity of reflectance is measurable within the threshold parameters.

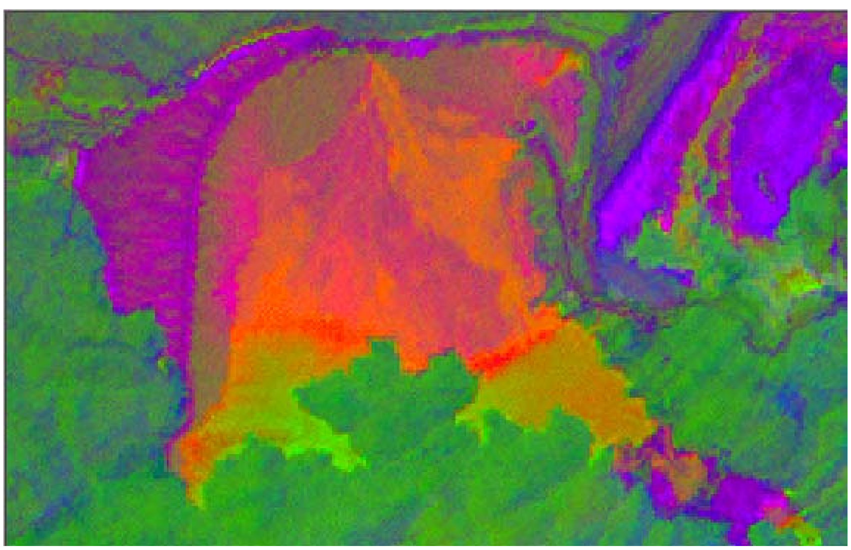

Figure 4. A 2000 Landsat 7 ETM+ scene showing the Bagdad Copper Mine Lower Mammoth tailings impoundment. In particular, the image illustrates the nuances of sediment saturation and suspended sediment in deeper pools—drier sediment (dark violet), somewhat saturated sediment (light-violet), heavily saturated sediment (peach-orange and red), and deeper pools with suspended sediment (orange-red over lime green). This image was produced using a resolution merge with the Landsat 7, 15-meter panchromatic band, and a Tassel Cap spectral enhancement in ERDAS Imagine. The band grouping is RGB-651 with an applied Standard Deviation 2.0 radiometric enhancement.

The NDTI Algorithm. In summary, active tailings impoundments are an expansive surface denude of vegetation, consisting of a high concentration of homogenous sediment, and containing a wetness component. Based on these characteristics, the research assumed that the spectral variation of tailings impoundments would be detected in a narrow spectral range produced by an NDVI application and within a threshold reflection range of negative values between -0.39 and -0.35 on a scale from -1 to 1. The following is the NDTI expression created in ERDAS Imagine 9.0 for capturing the reflective signature of copper mill tailings:

"EITHER 0 IF (NDVI < -0.39) OR (NDVI > -0.35) OTHERWISE"

The Aggregate Model in ArcGIS. Using a series of statistical analysis and reclassification tools in raster and vector, an *Aggregate* model designed to eliminate non-mine features was used to process the raster data sets resulting from the NDTI application. The Aggregate model was developed in ESRI's ArcGIS 9.2 (ArcInfo). It is composed of a two-part filtering process with set input parameters. Part one ranks pixels or cells as a function of *density*, and part two ranks kernels or shape fragments as a function of *proximity*. Finally, an edge finder application creates shapes around the remaining aggregated kernels and generates latitude and longitude coordinates for the center of the polygonal shapes formed by these aggregated kernels.

The "Focal Sum" or density filter requires three set parameters: (1) the neighborhood option is "circle"; (2) the neighborhood radius is "nine" in "cell" units; and (3) the statistics type is "sum." Because tailings impoundments are rarely rectilinear, the neighborhood option is circle. The "nine cell" input parameter is based on a spatial dimension, a mean value derived from a sampled area of unsaturated or dry portions of known active mill tailings impoundments. Nine equals the radius in cells or pixels of the circle neighborhood, which defines the constant number of cells processed, 254, for ranking each center cell across the entire data set. Landsat 7 ETM+ scenes have pixel sizes of 28.5 m x 28.5 m thus the neighborhood size equaled 0.23 km^2.

Figure 5. A 2000 Landsat 7 ETM+ scene, RGB-321, showing the Bagdad Copper Mine. The red polygon represents the results of the *NDTI-Aggregate density* filter, identifying the Lower Mammoth tailings impoundment.

The Focal Sum adds the assigned intensity value of each pixel within the specified neighborhood for each center cell location on an input raster. This value is sent to the corresponding cell location on the output raster. The resulting data set is a cluster map of low to high frequency values. The NDTI input data is floating point based on the reflectance intensity values the NDTI threshold captures. The next step reclassifies each data set according to a standard set of empirically derived breakpoints, where all pixels with a ranking value greater than 21.5 or 8.5 percent are assigned "1," and all remaining data are assigned "no data." Hence, 8.5 percent of the focal neighborhood is classified a positive NDTI value. i.e., mine feature targets cluster at greater than 8.5 percent. The resulting data sets of "1" pixels are then converted from "Raster to Polygon" (Figure 5).

The proximity filter is a customized application employing three separate tools: "Aggregate Polygons," "Feature to Point," and "Add XY Coordinates." The "Aggregate Polygons" tool requires four set parameters. Based on observations of known tailings impoundments, the following four input parameters were derived: (1) the "Aggregation Distance" is "8 kilometers"; (2) the "Minimum Area" is "2 km^2"; (3) the "Minimum Hole Size" is "3 km^2"; and (4) the "Preserve orthogonal shape" is checked. The resulting vector files contain polygon layers displaying the perimeters of the aggregated polygons and, for each aggregate polygon, a point marking the center of the polygon with "xy" coordinates. The final "xy" coordinates show the locations of detected mill tailings thus the mines. The proximity filter eliminated all of the non-mine features remaining after the combined NDTI and density filter applications. These remaining non-mine feature kernels were either more fragmented, or not spatially large enough to fall within the proximity parameters.

FINDINGS AND DISCUSSION

Findings

According to 2001 reports of active copper mines in Arizona (Arizona Department of Mines and Mineral Resources, 2001), the NDTI-Aggregate method identified nine of the ten copper mine sites in Arizona active in 2000 (Table 1, Figure 6), accounting for 99.9 percent of the state's copper production from both flotation and SX-EW processes (Table 2). But because the SX-EW process can be used to extract copper *in situ* from older mill tailings of a suitably high residual copper content, it is not always clear how much annual SX-EW production is from *in situ* older mill tailings and how much is from other types of leach heaps. Furthermore, the NDVI and *Aggregate density* filter identified four inactive tailings impoundments (Tables 2 and 3). Of these four impoundments, the *Aggregate proximity* filter did not eliminate Chilito-Christmas and New Cornelia-Ajo. Although the NDTI data gave a well-defined rendering of mill tailings impoundments, the unfiltered data also contained an assortment of non-tailings features, primarily urban landscapes and other man-made features, e.g., large neighborhoods of mobile homes, airports, and asphalt roads. In addition, the NDTI detected an area of high-altitude snow and one agricultural feature.

Table 1. Mines Detected by the *NDTI-Aggregate* Method

Feature Name	Primary Production	Figures 6 & 7 Location ID Nos.
Morenci-Metcalf, AZ	Cu	1
San Manuel-Kalamazoo, AZ	Cu	2
Miami Complex,[a] AZ	Cu	3
Ray, AZ	Cu	4
Chilito-Christmas, AZ	Cu	5
Silver Bell, AZ	Cu	6
Sierrita Complex,[b] AZ	Cu	7
Mission Complex, AZ	Cu	8
New Cornelia-Ajo, AZ	Cu	9
Mineral Park, AZ	Cu	10
Bagdad, AZ	Cu	11
Chino, NM	Cu	14
Tyrone, NM	Cu	15
Continental, MT	Cu	16
Bingham, UT	Cu	17
Yerington-MacArthur, NV	Cu	18
Newmont Mining,[c] NV	Au	19

[a] The Miami Complex included the Inspiration, Van Dyke, and Pinto Valley operations;
[b] the Sierrita Complex included the Esperanza and Twin Buttes operations; [c] in 2000 Newmont Mining controlled Twin Creeks Gold Mine, Battle Mountain Gold Mine Complex, Carlin Gold Mines, and Newmont Gold Mine.

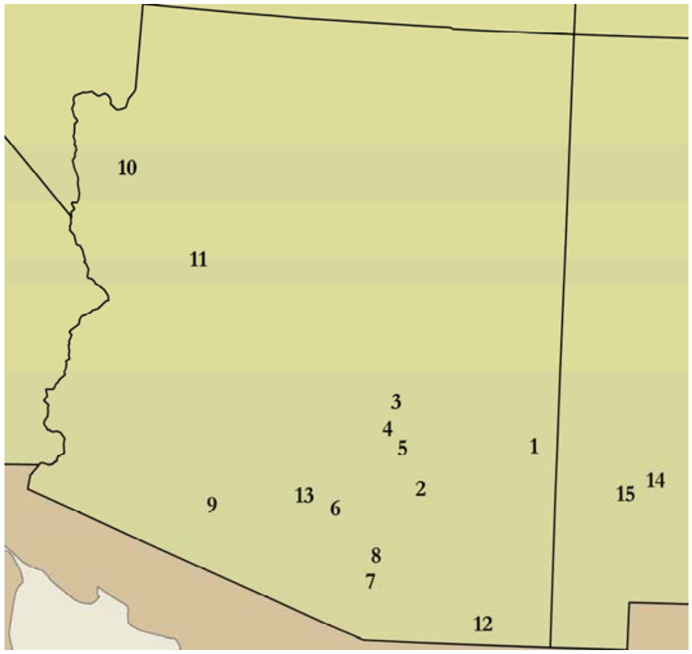

Figure 6. The numbers represent the locations of the mine features detected by the *NDTI- Aggregate* method for Arizona and New Mexico (Tables 1 and 2).

The NDTI did not detect Johnson Camp, an active copper mine in 2000 (Table 3). In 2000, Johnson Camp was on care and maintenance but continued to produce a small amount of copper by SX-EW from existing heap leaches. This mine operated as an open pit from 1975 to 1996 and was inactive from 1997 to 1998. Total production at Johnson Camp during years of operation is comparable with the detected inactive Christmas-Chilito tailings impoundments. It remains unclear why the NDTI did not detect Johnson Camp.

Table 2. Production Statistics for Active Copper Mines Detected by the *NDTI-Aggregate* Method in Arizona

Feature Name	Cu 2000[a] (million pounds)	Cu SX-EW 2000[a] (million pounds)
Morenci-Metcalf	464[b]	370[b]
San Manuel-Kalamazoo	0	23
Miami Complex[c]	0	195
Ray	202	102
Christmas-Chilito	0	0
Silver Bell	0	40
Sierrita Complex[d]	245[e]	0
Mission Complex	189	0
New Cornelia-Ajo	0	0
Mineral Park	5[f]	0
Bagdad	247[g]	0

[a] Production statistics (Arizona Department of Mines and Mineral Resources, 2001); [b] at Morenci-Metcalf, the total production was 834 million lbs., of which SX-EW production is reported as no less than an annual capacity of 370 million lbs.; [c] the Miami Complex included the Inspiration, Van Dyke, and Pinto Valley operations; [d] the Sierrita Complex included the Esperanza and Twin Buttes operations; [e] total production at Sierrita included some SX-EW production but it was not reported how much accounted for total production; [f] Mineral Park produced cathode copper, which included a limited amount of SX-EW production; [g] SX-EW production was limited and it was not reported how much accounted for total production.

The Aggregate density filter compromised the higher definition visibility of the mill tailings features, especially the heavily saturated tailings, but eliminated more than 90 percent of the non-tailings features; the high altitude snow, a fallow agricultural feature, Phoenix Sky Harbor International Airport, and the combined feature of Tucson International Airport and Davis Monthan Air Force Base remained. The Aggregate proximity filter eliminated these last four non-tailings features.

Table 3. Production Statistics for Inactive Copper Mines Detected by the *NDTI-Aggregate* Method in Arizona

Feature Name	Years of Production[a]	Total Production[a] (kt)
Copper Queen Bisbee	1921-1974	9.8×10^4
Christmas-Chilito	1905-1981	2.3×10^4
Tohono-Lakeshore	1976-1998	3.2×10^5
New Cornelia	1911-1985	4.2×10^5
Johnson Camp	1975-2000	2.3×10^4
[a] Production statistics (Raw Materials Group, 2005)		

Table 4. The Path and Row Locations of the Nine Landsat Scenes with Coverage Outside Arizona

Path and Row WRS-2	Date of Acquisition	Location Description
38, 32	08/14/1999	Salt Lake City, UT
38, 34	04/26/2000	southwest UT
40, 28	09/13/1999	Butte-Anaconda, MT
41, 32	06/02/2000	north central Nevada
43, 33	07/18/2000	west central NV-east central CA
42, 36	03/21/2000	Los Angeles, CA
34, 37	09/08/2000	southwest NM
23, 36	09/22/1999	agricultural region along the Mississippi River, MS-AK
174, 38	08/07/1999	Dead Sea region, Israel-Jordan
[a] The Worldwide Reference System (WRS)		

Using same NDTI-Aggregate method developed for detecting copper mill tailings in Arizona, nine additional scenes acquired between August 1999 and July 2001 were processed (Table 4). Of these nine scenes, five covered areas of known copper and gold mining in Montana, Nevada, New Mexico, and Utah. Four scenes covered areas known not to contain industrial copper and gold extraction in southwestern Utah, the urban landscape of Los Angeles, an agricultural region along the Mississippi River, and a scene containing the Dead Sea. Although a Landsat scene containing a landscape dominated primarily by snow cover was not included, there are well-established snow indices (Hall and Martinec, 1985) possibly useful in distinguishing snow from mill tailings features in such environments (Lindvall and Eriksson, 2003).

The NDTI and Aggregate density filter detected a total of thirteen mill tailings features, seven copper and six gold (Table 5), and three non-tailings features, including one airport. The Aggregate proximity filter eliminated all of the non-tailings features and seven of the tailings features, including those associated with five gold mines. The remaining mines identified were the Tyrone and Chino copper mines in New Mexico, the Bingham copper mine in Utah, the Yerington-MacArthur copper operation in Nevada, the Butte Continental copper site in Montana, and the Newmont Mining gold mine in Nevada (Tables 1 and 5, Figures 6 and 7). The NDTI-Aggregate method did not detect any non-tailings features on the four scenes known not to contain industrial mining.

Historically, the mining complex in Butte, Montana, has included the Anaconda mill, the Berkeley Pit (mined from 1955 to 1982), and East Continental Pit, the second largest open pit mine in Butte (Czehura, 2006). By 2000, the Butte-Continental Pit had operated for more than ten years (Raw Materials Group, May 2005). The NDTI and Aggregate density filter detected the Anaconda site, where remediation of the extensive tailings deposits remained incomplete; however, the Aggregate proximity filter eliminated it. In Utah, the NDTI-Aggregate method detected both the Bingham mine located 15 km southwest of the Salt Lake City and the expansive tailings impoundment located just west of the city. The Yerington-MacArthur operations in Nevada suspended production in 1996 (Nevada Division of Minerals, May 1997) but the extent of remediation by 2000 is uncertain.

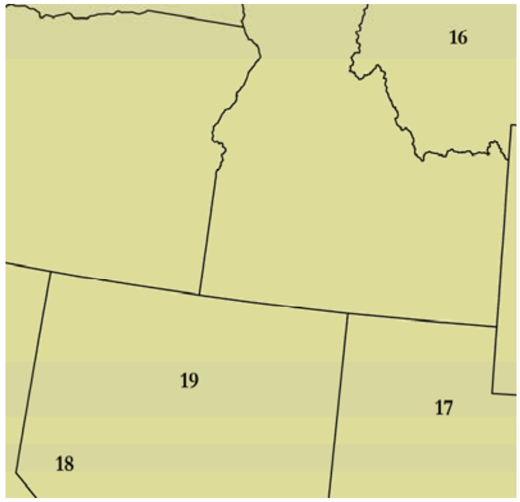

Figure 7. The numbers represent the locations of the mill tailings features detected by the *NDTI- Aggregate* method for Montana, Nevada, and Utah (Tables 1 and 5).

Table 5. The Mine Features Detected by the *NDTI-Aggregate* Method with Coverage Outside Arizona

Feature Name	Primary Production[a] (Production Year)
Butte-Anaconda, MT	Cu (1999)
Continental, MT	Cu (1999)
Golden Sunlight, MT	Au (1999)
Chino, NM	Cu (2000)
Tyrone, NM	Cu (2000)
Bingham, UT	Cu (1999)
Yerington-MacArthur,[b] NV	Cu (2000)
Newmont Mining,[c] NV	Au (2000)
Barrick Mining,[d] NV	Au (2000)
Dee Gold Mine, NV	Au (2000)
McCoy-Cove, NV	Au (2000)
Tumco Mines,[e] CA	Au (2000)
Cananea, Mexico	Cu (2000)

[a] (Raw Materials Group, 2005; Nevada Division of Minerals, May 1997); [b] the Yerington-MacArthur operations suspended production in 1996; [c] in 2000 Newmont Mining controlled Twin Creeks Gold Mine, Battle Mountain Gold Mine Complex, Carlin Gold Mines, and Newmont Gold Mine; [d] in 2000 the Barrick Gold Corporation controlled Meikle Gold Mine and Betze Post Gold Mine; [e] the first gold vein at the Tumco Mines was discovered at Gold Rock on January 6, 1884—mining in the area reached its peak between 1893 and 1899. Nearly closed (1900-10), it was reopened as Tumco (1910-13) and worked intermittently until 1941. The ghost town at the abandoned Tumco site is a California state historical landmark.

DISCUSSION

The NDTI-Aggregate method offers a tool for positively identifying and distinguishing locations of copper mill tailings with a high standard of accuracy in primarily semiarid environments. It accomplished this by the development of the NDTI, a remote sensing index that isolates the reflective signature of the homogenous non-organic and man-made material, mill tailings, and the Aggregate model, a GIS application, which filters non-tailings features. The research was successful on two points: (1) the detection method functioned on a fixed set of input parameters, and (2) it eliminated all non-mine features.

Based on different distributions of grain sizes (Qiu and Sego, 2001), the NDTI might be useful in detecting and monitoring other types of mine tailings covering expansive surface areas, e.g., gold mill tailings and coal wash, by adjusting the input parameters. For example, if the current NDTI threshold had captured a greater number of pixels representing gold mill tailings, the Aggregate density filter would have created larger and more numerous kernels. But with the current NDTI input settings, the Aggregate proximity filter eliminated five of the six gold mines detected because these gold tailings' kernels were too small in area.

Using this method with other types of satellite images, e.g., ASTER, might prove even more successful. ASTER data captures spectral data in narrower and more numerous spectral bands over the visual to near-infrared range and, in some bands, with increased spatial resolution. The spread of wind-carried sediment is also a concern. Because the method relies on large areas of homogenous sediment, tracking the spread of trace sediment is not possible using Landsat images. But by acquiring hyperspectral resolution data, e.g., LIDAR, it might be possible to detect small concentrations of more dispersed tailings sediment. Furthermore, a textural or object-oriented spectral derived index using, e.g., Definiens Developer, might prove beneficial as a means to refine or replace the current Aggregate model. Thus by continuing to develop the current method, this remote sensing-GIS approach might serve as a useful tool for accurately cataloging and monitoring copper and other types of mine activities, which produce tailings.

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