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Assessment of Mining Extent and Expansion in Myanmar Based on Freely-Available Satellite Imagery

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Abstract: Using freely-available data and open-source software, we developed a remote sensing methodology to identify mining areas and assess recent mining expansion in Myanmar. Our country-wide analysis used Landsat 8 satellite data from a select number of mining areas to create a raster layer of potential mining areas. We used this layer to guide a systematic scan of freely-available fine-resolution imagery, such as Google Earth, in order to digitize likely mining areas. During this process, each mining area was assigned a ranking indicating our certainty in correct identification of the mining land use. Finally, we identified areas of recent mining expansion based on the change in albedo, or brightness, between Landsat images from 2002 and 2015. We identified 90,041 ha of potential mining areas in Myanmar, of which 58% (52,312 ha) was assigned high certainty, 29% (26,251 ha) medium certainty, and 13% (11,478 ha) low certainty. Of the high-certainty mining areas, 62% of bare ground was disturbed (had a large increase in albedo) since 2002. This four-month project provides the first publicly-available database of mining areas in Myanmar, and it demonstrates an approach for large-scale assessment of mining extent and expansion based on freely-available data.

Keywords: mining; change detection; Myanmar; Landsat; Google Earth

1. Introduction

Myanmar is a geologically-diverse country containing a wide array of mineral resources, such as gold, silver, copper, tin, tungsten, zinc, jade, and gemstones [1,2]. The country has a long history of mining, but has recently emerged from decades of military government leadership during which the country's mineral deposits were poorly explored and the mining sector was underdeveloped [3]. Political reform in Myanmar since 2010 has led to greater international engagement and the easing of long-standing economic sanctions. This process has led to a rapid increase in international trade and investment in the country. Foreign direct investment in Myanmar is heavily focused on natural resource-based industries, with mining ranking as one of the leading sectors [4].

New mining legislation passed in late 2015 is intended to encourage foreign investment in Myanmar's mining industry by streamlining the process for further expansion of mineral extraction [5].

This law also requires environmental impact assessments (EIAs) to be conducted on all projects that could cause environmental or social harm [6]. Currently, both legal and illegal mining are being conducted in Myanmar at scales ranging from small artisanal mining to large open-pit mines [3,7]. The negative impacts of mining can range from toxic contaminants being released into the environment to human displacement and degradation of public health [3,7,8]. However, government records on mining in Myanmar are largely non-digital, do not encompass illegal mining activity, and are not publicly-accessible. In many parts of the country, natural resource management remains a point of contention between the central government and non-state armed groups [9,10]. As the government, civil society organizations, and local communities strive toward better understanding and management of mineral extraction in Myanmar, access to objective information about the scope and extent of mining activities will be critical.

Remote sensing techniques have been effectively applied in studies of mineral extraction worldwide. Specific applications are motivated by diverse objectives including mineral exploration [11,12], mapping of soil and water contamination [13,14], and monitoring of vegetation regrowth after mining [15,16]. Remote sensing provides a cost-effective option for assessing recent land use/land cover change due to mining across a range of spatial scales (e.g., [17–19]). This may represent the only viable method for obtaining information on mining activities in remote areas or armed conflict zones. Although fine-resolution data have been used to examine changes in surface mining extent [20–22], a large number of studies are based on Landsat imagery due to its global coverage, medium resolution (30 m), and data acquisition at regular time intervals [15,17,23–26]. Studies combining mine identification with multi-temporal change detection may also be improved by using fine-resolution data to identify and define mine boundaries, while performing change analysis based on time series of medium-resolution imagery [27].

Previous studies have used a variety of approaches to map changes in surface mining extent based on multi-temporal imagery. Many of these studies have used vegetation indices, like NDVI, to distinguish mining from other land uses within known mining regions [15,17–19,24,26]. For instance, Schimmer et al. [19] identified copper mill tailings in semi-arid regions using NDVI, wetness, and homogeneity of grain size to create a new metric specific to copper mill tailings identification. Koruyan et al. [27] also used NDVI in order to calculate changes in vegetation resulting from marble quarry expansion in a densely-vegetated area. Other studies have used the temporal trajectory of vegetation indices to distinguish mining from other types of disturbance [26,28]. However, broad-scale identification of mining change based on vegetation index thresholds may be problematic for climatically and ecologically diverse countries like Myanmar, which have high natural variability in vegetation cover. A recent study of forest cover change in Myanmar used multi-date Landsat imagery to map mining expansion for select regions with known mining activity [29], yet we are aware of no comprehensive analysis conducted at the national level.

The overall objectives of our study were to produce the first publicly-available inventory of mining areas in Myanmar and to quantify the recent expansion of surface mining. Since the number of mine areas, their locations, and the type of mineral were unknown, we employed a systematic methodology for the identification of mining areas across broad spatial scales based on freely-available data and open-source software. We then used diffuse-visible albedo, or image "whiteness" [30,31], to identify recent expansion of mining areas from Landsat imagery. The resulting database can serve as a baseline for myriad future work assessing the legality of mines, evaluating potential sources of pollution from mines, and creating a comprehensive database of mining areas in Myanmar.

2. Materials and Methods

Our methodology first focused on an efficient and effective process of identifying mining areas across Myanmar. First, we digitized polygons of known mining areas that were used as training data to derive a raster layer of potential mining areas from Landsat imagery. This filter helped to focus the search effort for manually identifying and digitizing mining areas using fine-resolution imagery.

Concurrent with digitizing, we conducted site visits to select areas for mine verification and to revise and inform the digitizing effort. Finally, we calculated mining area change by comparing the area of bare ground within mining area boundaries, estimated using diffuse-visible albedo, between 2002 and 2015 (Figure 1).

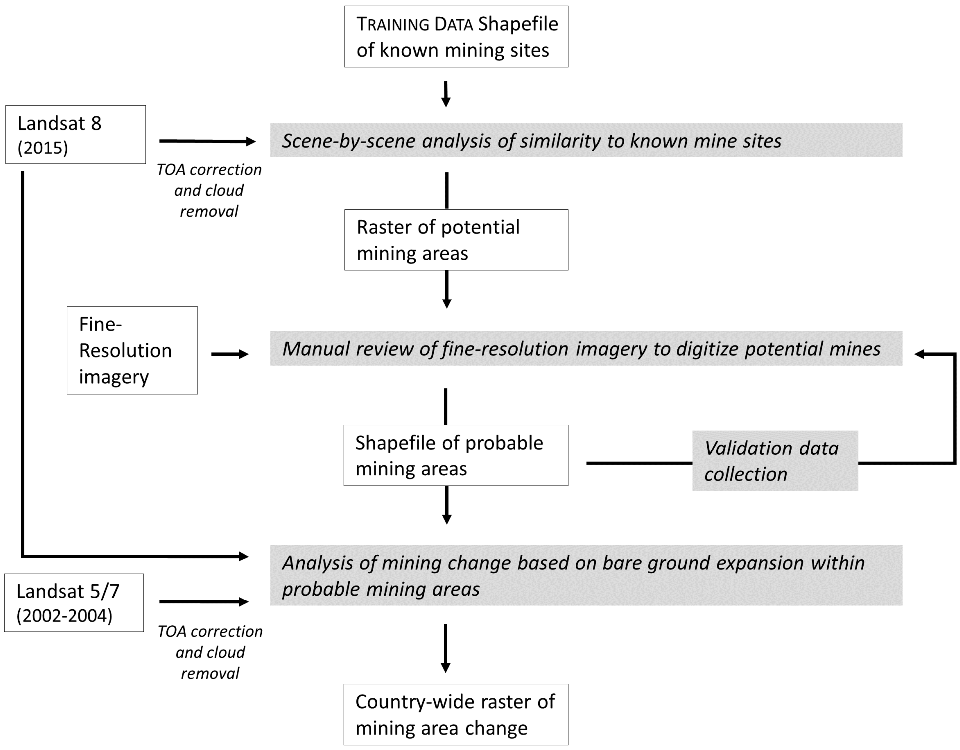

Figure 1. Inputs and processes in the identification of mining areas and mining area change. Top of Atmosphere correction is abbreviated as "TOA correction".

2.1. Identification of Potential Mining Areas

Myanmar is a country of over 67,658,000 ha, and a detailed manual review of fine-resolution imagery in all areas of the country would be time and labor intensive. In order to expedite the process of manually identifying mine sites, we developed an initial raster layer of potential mining areas. The raster layer of potential mining areas was developed using Landsat 8 Operational Land Imager (OLI) data from the post-monsoon season of 2015. All Landsat imagery acquired for this study were Level 1T geometrically-corrected data products downloaded online from the U.S. Geological Survey [32]. The images were pre-processed by converting Digital Numbers to Top-of-Atmosphere Reflectance and performing cloud removal using the Function of Mask (Fmask) algorithm [33,34] translated into the R programming environment [35] by Connette et al. [36].

Within the boundaries of each Landsat scene, we manually digitized a set of confirmed mining (compiled from expert input) areas using Google Earth imagery via the GEplugin or Open Layers Plugin in QGIS [37]. Top-of-Atmosphere reflectance data from these areas were then used as training data to identify spectrally-similar areas representing potential mine sites across the entire Landsat image. Because this method was intended to identify areas of bare earth typical of surface mining, water pixels within known mining areas (e.g., tailings ponds and rivers) were identified using the water mask output from Fmask [33,34] and excluded from the training dataset. If a scene had no confirmed mining areas, we used confirmed mining areas from an area of similar land cover as training data, usually in a neighboring Landsat scene. This analysis of reflectance data was based on five raster layers derived from Landsat 8 Bands 4–7:

- Normalized Difference Vegetation Index (NDVI): (Band 5 − Band 4)/(Band 5 + Band 4)
- Normalized Burn Ratio (NBR): (Band 5 − Band 7)/(Band 5 + Band 7)
- Normalized Difference Moisture Index (NDMI): (Band 5 − Band 6)/(Band 5 + Band 6)
- Shortwave Infrared: (Band 6/1000)
- Red reflectance: (Band 4/1000)

We used reflectance data extracted from known mining areas in order to fit a multivariate normal distribution. This distribution is parameterized by a mean vector and full variance-covariance matrix [38]. Based on this fitted distribution, we created a final raster layer of potential mining areas by calculating the probability density for the observed reflectance data at each pixel of the given Landsat scenes (see Scheme S1 for R scripts).

The resulting raster was then used to highlight areas that were spectrally similar to confirmed mining sites in the area to ensure that these areas were carefully assessed during the manual review of fine-resolution imagery. Relative-high pixel values indicated areas where the reflectance data were highly characteristic of known mining areas, whereas relative-low pixel values indicated areas where the observed reflectance data would be unexpected for a mining area. All pixels identified as cloud or cloud shadow during the pre-processing of Landsat images were treated as high-probability mine areas so that they would be carefully reviewed during the manual digitizing process. Compared to discrete classifications, which may be sensitive to the size, spatial bias, and spectral representativeness of the training data (e.g., [39]), our estimated probability surface was continuous (see Figure 2a) and allowed likely mining areas to be identified based on human interpretation of relative pixel values in a local area. This often allowed potential mining areas to be identified within landscapes that included other areas of bare ground, such as agriculture.

2.2. Identification of Current Mines with Fine-Resolution Imagery

The raster layer of potential mining areas was then used to guide the manual digitizing of mining areas across Myanmar. We systematically scanned fine-resolution imagery, with higher intensity search effort in the areas where the raster layer had high pixel values, indicating that reflectance was characteristic of mining areas. Digitizing was performed in QGIS from December 2015 to March 2016, usually using Google Earth [40] as the fine-resolution imagery source. Most Google Earth images were from 2014 or 2015 with a resolution of less than 65 cm, but in a few areas of Myanmar the most up-to-date images went as far back as 2004 (Figure S1). When recent Google Earth imagery was not available, we used imagery from Bing Maps Aerial [41], a similar web-based tool. In a small number of cases where neither source provided recent imagery, we used pan-sharpened 2015 Landsat imagery (15 m resolution) to digitize obvious mining areas. For each digitized mining area, the imagery year and source were recorded.

In order to identify mining areas to manually digitize, we used a suite of characteristics that, if present, indicated a likely mining area (Table 1). We assigned each digitized mining area a ranking of the certainty that it was actually a mine based on the features seen in the satellite imagery. The digitized areas were ranked "high certainty" for sites that were definitely a mine, "medium certainty" for areas that were probably a mine, and "low certainty" for areas that could be a mine but we were not certain based on available satellite imagery (See Figure S2 for examples of each). Medium and low certainty identifications were areas that could alternatively be identified as another type of land use or land cover, such as natural rockslides, construction sites, land clearing, and dry-zone sediment deposits. We standardized mine identification, digitizing, and confidence-ranking by having iterative group discussions and information-sharing sessions about mine site characteristics among the researchers and fostering a collaborative environment during digitizing to ensure consistency. All sites were reviewed by a second interpreter during the final stage of digitizing, and any disagreements were resolved on a consensus-basis.

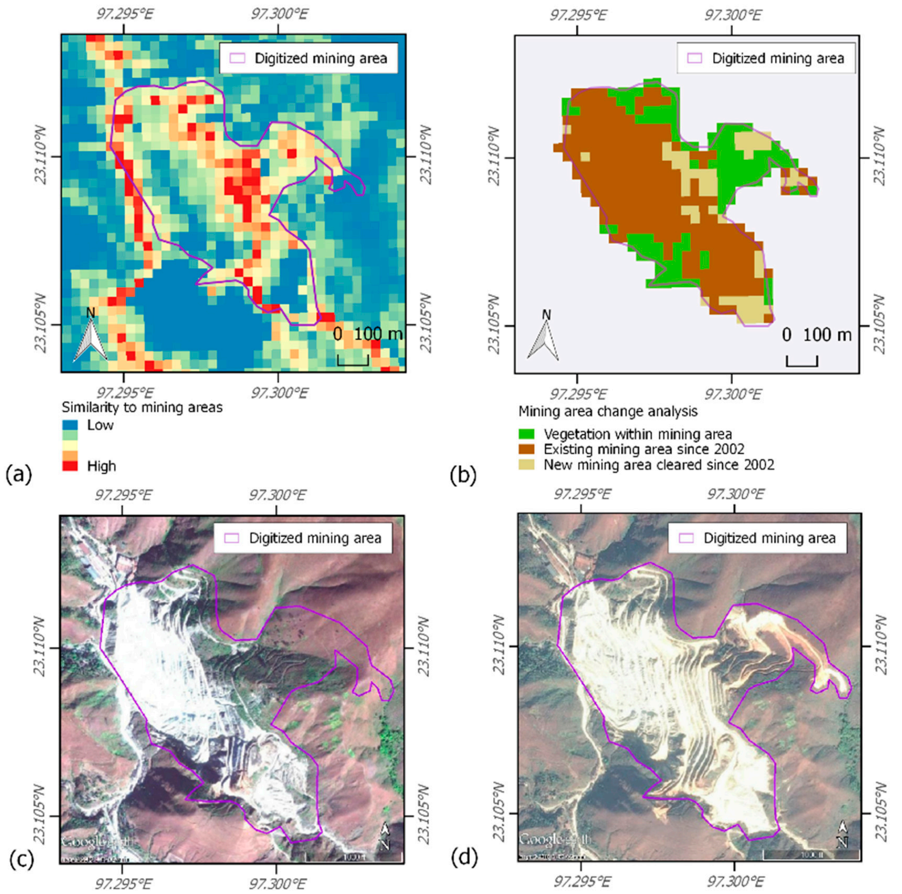

Figure 2. An example of mining area change at the Bawdwin mine in Namtu Township of Shan State. (**a**) Landsat-based potential mining raster layer identifying areas that are spectrally similar to known mine sites. This raster layer was used to guide the subsequent manual review of fine-resolution imagery; (**b**) Final raster layer output from the mining area change analysis, shown with the mining area boundary that was manually digitized; (**c**) Google Earth image from January 2010 (earliest available fine-resolution image). This imagery was not used in the analysis, but is included to illustrate mine area expansion; (**d**) Google Earth image from December 2013 (most recent fine-resolution image available), used to manually digitize the mining area boundary.

Table 1. Features of mining areas that can be identified from fine-resolution satellite images. These features were used during manual digitizing to determine the weight of evidence for identifying a mining area (meaning no single feature or combination of features indicated a high-certainty mining area).

Feature Indicating a Potential Mining Area	Description
Bare ground, particularly irregularly shaped patches	Areas lacking vegetation where the ground has been disturbed. Mining ground disturbance is often unevenly distributed because it follows mineral seams. This is in contrast to construction sites that are pre-planned.
Pools of water with unusual or varying colors	Ponds or water retention areas with different shades of blues, greens, or browns can indicate mineral processing.
Changes in river color	Sediment plumes or contaminants can cause changes in the river color at and downstream of mining areas. This is often a lightening of the river color due to increased sedimentation.
Piles of rock or soil	Storage areas for excavated mineral or earth, including ore, tailings, or gangue material from mineral processing.
Ruts or pits in the earth	Areas of excavation or mineral exploration.
Road access	In combination with the above features, this can separate a mining area from a natural feature.
Industrial buildings, processing facilities, or large equipment	Particularly in remote areas, this can indicate an industrial mining operation.

2.3. Validation Data Collection

There were significant barriers to conducting extensive field visits for the collection of validation data: (1) logistical constraints given the country-wide nature of the project and level of transportation infrastructure; (2) access restrictions because of multiple levels of bureaucracy, including sub-national governments in some areas; and (3) personal safety concerns given regional instability and the prevalence of illegal mining in some areas. Therefore, validation data collection trips were focused around meetings with local Civil Society Organization (CSO) members and limited mining area visits. This consultation with local experts allowed us to safely obtain information from a wider area than if we had tried to visit all nearby mining areas ourselves.

Field visits were made to Mandalay State (Thabeikkyin and Pyawbwe Townships, 11–15 January 2016), Kayah State (Demoso, Loikaw, and Phyruso Townships, 5–9 January 2016), Shan State (Baw Saing and PinDaya Townships, 17–20 January 2016), and Tanintharyi Region (Yephyu and Dawei Townships, 2–6 February 2016). Before each trip, we developed draft maps of mining areas digitized from fine-resolution imagery. CSO members with local expertise were then typically able to confirm the locations as mines or identify them as another land cover type. If CSO members had knowledge of additional mine sites that we could not identify from fine-resolution imagery, we did not digitize the areas, but saved the reported locations as a separate point shapefile for future reference (since the site could be misidentified, underground, or newer than available imagery). After meeting with CSO members, local liaisons facilitated field visits to nearby mining areas. Highest priority was placed on visiting sites that had some uncertainty in the accurate identification of a mining area from aerial imagery or expert consultation. Each mining area visit resulted in a report with photos, names of contributors, and geospatial data about the mine sites. These validation data collection trips served as an opportunity to improve our ability to correctly identify mining areas from fine-resolution satellite imagery, and previously-assigned certainty levels were subsequently reviewed and updated for all digitized mines in the areas of field visits.

2.4. Calculating Mining Area Change

After identifying and digitizing current mining areas, we calculated the change in surface mining extent since 2002. This analysis was performed only within the digitized mine boundaries (i.e., within current extent of the mine site). Since most mining areas have extensive exposed earth from ground disturbance, we used the change in the extent of bare ground to represent the change in mining area. Bare ground brightly reflects light, or has a higher albedo, compared to areas with vegetation. We used the expansion of areas with high albedo to calculate the change in mining area extent over 13 years.

Although multi-temporal fine-resolution imagery has been used to study mining area change at local or sub-national scales [20,22], remote sensing of surface mining change is frequently based on Landsat imagery [15,17,23–26]. Due to the national scale of our study, we developed an automated approach to mining change detection for Myanmar using freely-available Landsat imagery. Post-monsoon 2002 images from Landsat 5 or 7 and 2015 images from Landsat 8 were used for the comparison. Landsat sensors are well calibrated, facilitating monitoring over time, and the horizontal position accuracy is on par with the position accuracy expected from the imagery available on Google Earth [42]. Consideration was given to applying multispectral and panchromatic image fusion methods to combine the Landsat ETM+ and OLI 15 m panchromatic and 30 m multispectral image bands, however we decided against this approach since the Thematic Mapping instrument on-board Landsat 5 did not have a panchromatic band and our work flow relied on using reflectance values which cannot be preserved when performing image fusion. When interpreting the reported changes in mining area, it is important to keep in mind that accuracy and precision are relative to 30 m-resolution Landsat imagery and not the high-resolution imagery used in the mine identification phase of this project.

All Landsat images were pre-processed using the stand-alone Fmask tool [33,34] and had corrections for Top-of-Atmosphere reflectance performed in R. The diffuse-visible albedo, or image "whiteness", was calculated for each pixel in the 2002 and the 2015 Landsat scenes based on the following equation using Landsat 7 Bands 1–3 or Landsat 8 Bands 2–4 [30,31]:

$$(0.556 \times \text{Band 1}) + (0.281 \times \text{Band 2}) + (0.163 \times \text{Band 3}) - 0.0014$$

To identify areas where mining disturbance was new or expanded between 2002 and 2015, the following two thresholds needed to be met:

(a) The difference in albedo was large, indicating a change from vegetation (low albedo) to bare ground (high albedo), such that:

$$(\text{Albedo}_{2015} - \text{Albedo}_{2002}) > \text{Albedo change threshold},$$

where *Albedo change threshold* = 300.0.

(b) The new bare ground was very bright, likely indicating a mining area as opposed to natural reflectance, such that:

$$\text{Albedo}_{2015} > \text{Albedo brightness threshold},$$

where Albedo brightness threshold = 1150.0.

This evaluation was run for each 30 m × 30 m pixel, using the R statistical environment (see Scheme S2 for scripts) to produce a raster layer showing new mining areas, pre-existing mining areas, and areas of vegetation within mine boundaries (Table 2). The raster image of mining change was restricted to areas within the digitized 2015 mine boundaries, and areas of cloud coverage had been removed during pre-processing (converted to no data pixels). See Figure 2 for an example of the progression of imagery that led to the mining area change raster.

Table 2. Types of land cover identified for the mining area change calculation.

Mining Land Cover	2002 Land Cover	2015 Land Cover
New bare ground in a mining area	Vegetated $^{\circ}$	Bare ground $^{+}$
Existing bare ground in a mining area	Bare ground $^{+}$	Bare ground $^{+}$
Vegetation at mine sites	Vegetated $^{\circ}$	Vegetated $^{\circ}$

$^{+}$ High albedo, $^{\circ}$ Low albedo.

3. Results

3.1. Mining in 2015

We identified 52,312 ha of high-certainty mining areas, and an additional 26,251 ha medium-certainty and 11,478 ha low-certainty mining areas (Table 3). Sagaing and Kachin states have the largest areas of mining, with these two states representing 71% of all high-certainty mining area in Myanmar. Mandalay has the third-largest area of high-certainty mining, and many additional hectares of lower-certainty mining areas. Shan, Tanintharyi, and Bago have the next largest total areas of mining.

Potential mining activity was identified in every state and region of Myanmar, with 2947 distinct mine areas or potential mining areas identified (Figure 3). This count of mines was dependent on the physical interconnectedness of a mining area in the fine-resolution imagery, rather than concession areas, company management, or mine name.

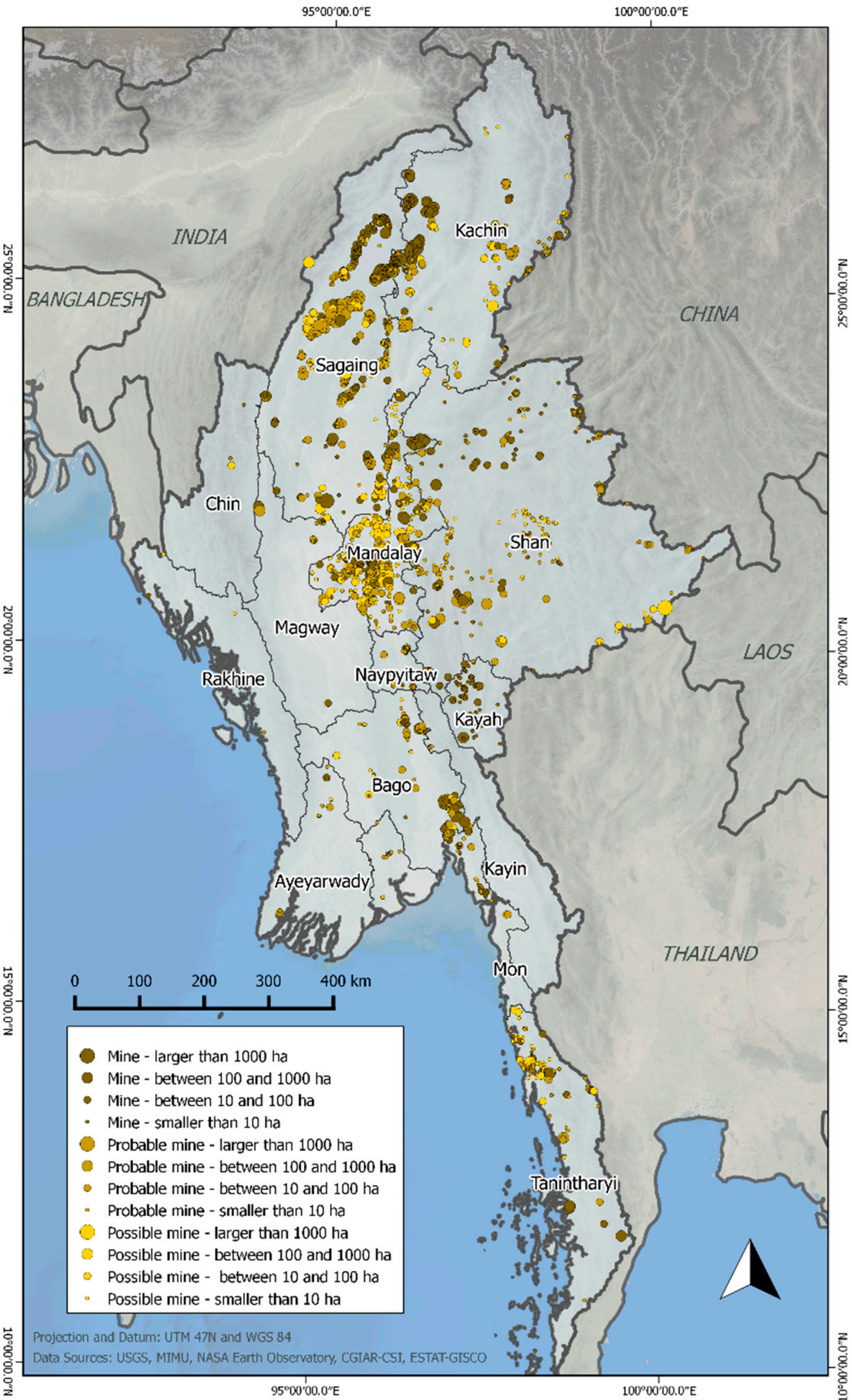

Figure 3. Locations of potential mining areas based on confidence of identification: High certainty ("Mine"), medium certainty ("Probable mine") and low certainty ("Possible mine").

Table 3. 2015 mining area identified in this study (in hectares) by state/region and certainty level [1].

State/Region	Mine (High Certainty)	Probable Mine (Medium Certainty)	Possible Mine (Low Certainty)	Total Number of Hectares
Ayeyarwady	25	97	7	129
Bago	2129	641	315	3085
Chin	125	5	12	142
Kachin	20,921	2293	1182	24,396
Kayah [2]	661	2	-	663
Kayin	118	29	-	147
Magway	861	592	-	1453
Mandalay [2]	6892	4427	3824	15,143
Mon	507	302	51	860
Naypyitaw	123	98	21	242
Rakhine	1	1	7	9
Sagaing	15,987	15,594	3677	35,258
Shan [2]	2178	1682	1791	5651
Tanintharyi [2]	1784	446	586	2816
Yangon	-	42	5	47
Total	52,312	26,251	11,478	90,041

[1] Mines on the border between two states had the area split in order to calculate the portion of the mines that falls within each state; [2] States and regions visited for field validation collection.

3.2. Mining Area Change between 2002 and 2015

For high-certainty mining areas across the country, 62% of bare ground was newly disturbed since 2002 (New bare ground/(New bare ground + Existing bare ground), Tables 4 and 5). This represented a 161% increase in the country's high-certainty mining footprint over a 13-year period. New mining areas in Kachin and Sagaing represented 79% of all new mining areas in the country that were identified with high certainty (Table 4). While those regions dominate the total mining area and make up the majority of new mining hectares, their mining expansion is not proportionally as high as other areas. In Kachin and Sagaing, 64% and 68% of bare ground, respectively, had been newly cleared since 2002, which along with Mandalay (23%) are among the states and regions with the lowest rates of mining expansion (Table 5). The total mining areas digitized from 2015 fine-resolution imagery included all areas within the digitized mine boundaries, including vegetated areas (not bare ground) and areas with cloud interference in the Landsat imagery.

The summary of mining area change for medium- and low-certainty mining areas can be found in Tables S1 and S2.

Table 4. Mining area change in hectares for high-certainty mining areas.

State/Region	New Bare Ground in a Mining Area	Existing Bare Ground in a Mining Area	Vegetation within Mining Area	Cloud Interference over a Mining Area	Total Number of Hectares	Percent of All Mining Areas Identified in Myanmar
Ayeyarwady	2	2	-	21	25	<0.1%
Bago	853	204	975	97	2129	4.1%
Chin	51	-	33	41	125	0.2%
Kachin	7515	4210	4589	4607	20,921	40.0%
Kayah	65	29	453	114	661	1.3%
Kayin	18	1	99	-	118	0.2%
Magway	406	153	280	22	861	1.6%
Mandalay	976	3331	1469	1116	6892	13.2%
Mon	254	19	148	86	507	1.0%
Naypyitaw	80	6	31	6	123	0.2%
Rakhine	1	-	-	-	1	<0.1%
Sagaing	7462	3437	3827	1261	15,987	30.6%
Shan	520	184	625	849	2178	4.2%
Tanintharyi	875	244	517	148	1784	3.4%
Yangon	-	-	-	-	0	0.0%
Total	19,078	11,820	13,046	8368	52,312	100.0%

Table 5. Percent of mining area bare ground that was newly cleared since 2002. Only states and regionss with over 100 ha of mining detected were included.

State/Region	Mine (High Certainty)	Probable Mine (Medium Certainty)	Possible Mine (Low Certainty)
Bago	81%	82%	67%
Chin	100%	-	-
Kachin	64%	63%	49%
Kayah	69%	-	-
Kayin	95%	-	-
Magway	73%	45%	
Mandalay	23%	19%	16%
Mon	93%	91%	-
Naypyitaw	93%	-	-
Rakhine	-	-	-
Sagaing	68%	86%	68%
Shan	74%	74%	93%
Tanintharyi	78%	73%	82%
Yangon	-	-	-
Total	62%	72%	48%

4. Discussion

Mining covers less than 1% of the Earth's surface but can cause significant environmental and human health impacts through physical disturbance of the landscape, sedimentation of water bodies, and contamination [43]. As a result, the ability to map and monitor mining activity is essential to understanding and managing these potential effects. Many previous remote sensing studies have focused on intensively-mined study areas encompassed by one or two satellite images and dominated by a single type of resource extraction, such as coal, gold, or oil sands [22,25–28,44]. A particularly large-scale study evaluated copper mining in part of the USA state of Arizona, a study area spanning nine Landsat scenes [19]. Some studies have also incorporated spatially-explicit mine locality information (such as permit data) to facilitate mine identification [15,26,45].

The goal of our study was to map mining areas and change in surface mining extent for all of Myanmar (44 Landsat scenes) using low-cost and time-efficient resources. Our study differs from most previous studies in the large study area, wide range of mine/mineral types, and lack of baseline geospatial data for mine sites. Due to the diversity of natural landscapes occurring in Myanmar, from the central dry zone to evergreen rain forests, mine identification in our study relied on manual interpretation of both a continuous mining probability layer and fine-resolution satellite imagery, rather than automated detection of mine sites. This process resulted in the first publicly-available inventory of mining areas in Myanmar and highlights a useful workflow for the rapid acquisition of spatially-explicit mining data across large, diverse landscapes.

The distribution of mining activity in Myanmar is ultimately determined by a series of mineral belts that run primarily north-south across the country [2]. We found that much of the country's existing mining area (71%) is concentrated in Sagaing Region and Kachin State, which possess significant gold and jade deposits. Control of natural resource revenue has been cited as an incentive behind ongoing conflict in this resource-rich area as well as a key point of ongoing peace negotiations [9,10]. In recent years, Myanmar has also emerged as the world's third largest tin producer [46]. The country's tin and tungsten deposits run from northern Shan and Mandalay States to Myanmar's Tanintharyi Region. Our study showed that Tanintharyi Region and Shan State have been the site of considerable mining expansion in recent years, while the isolated tin mines along the border between Shan State and China have reportedly been a major driver of the recent jump in Myanmar's share of global tin production [46]. Shan State also possesses significant deposits of silver, zinc, and lead [2], that have historically been an important target of mining activity [3].

Caveats and Limitations

In spite of the rapid expansion of surface mining areas documented in this study, mining land use covers just a small percentage of Myanmar's total area. Furthermore, certain types of mining may be particularly difficult to identify based on satellite imagery, such as placer (i.e., riverbed) mining, underground mining, or small-scale artisanal mining. As a result, the potential for false negative errors in the current study is likely high, suggesting that reported mining areas may be conservative at both the state/region and national level. Placer mining, often for gold, can be difficult to detect in Myanmar because flood events can quickly erase evidence of ground disturbance on sediment deposits, while sediment dredging from moveable barges may leave no indication of mining activity. Underground mining can also be difficult to detect if there are not corresponding tailings impoundments or processing facilities that can be confidently identified from satellite imagery.

We attempted to capture the potential for false identification of mining areas by assigning a certainty rating to each potential mine site. "Low certainty" mining areas included small-scale disturbance as well as areas appearing similar to surface mining that could not be confidently distinguished from other ground disturbance, such as construction sites. Ranking mine sites according to confidence in their identification ensured that as few mining areas as possible were excluded from our database, while allowing us to provide conservative summaries of mining extent and expansion based only on high certainty mining areas. Collectively, low and medium certainty mines made up 42% of all potential mining areas identified in our study. A more robust accuracy assessment for the current study would require randomized field validation data, as systematic errors made during manual interpretation of fine-resolution imagery would likely be repeated during further random screening of fine-resolution imagery.

Although the majority of available fine-resolution imagery for this study was from 2014 to 2016, the use of outdated fine-resolution imagery for mine identification in some areas would also result in underestimation of surface mining extent if new or recently-expanded mine areas were not captured in the database. Occasionally, mine site boundaries were identified based on fine-resolution imagery that was more recent than the 2015 Landsat images used in the mining change analysis. These areas are included in the mining area summary for 2015, but would have been identified as "Vegetation within mining area" in the change analysis because no bare ground was yet detected within the mine site boundary.

Finally, the use of diffuse-visible albedo to identify ground disturbance within mining area boundaries was not intended to distinguish between areas of mineral extraction, waste rock, roads, and other bare ground. These features were considered part of the areal "footprint" of mine sites in the current study and were included in summaries of bare ground due to mining activities (Table 4, Tables S1 and S2). Like other spectral reflectance indices, albedo may also have been subject to interference from terrain-shadowing or haze effects.

5. Conclusions

We mapped potential mining areas throughout Myanmar using freely-available imagery and open-source software. This study demonstrates that nationwide identification of mining areas can be accomplished without large budgets and long project timelines. In Myanmar, the availability of this new dataset will serve as a baseline inventory that can be further refined and improved. Particularly for medium- and low-certainty mining areas, we recommend that further ground-truthing and verification will be conducted.

Our analysis of mining area change also highlights the expansion of mining over the last 13 years. These data are particularly important in Myanmar, where many mining areas are difficult to access and may not be accounted for in official government figures. The government of Myanmar is making steps towards greater transparency in the management of natural resources, particularly with efforts like their bid for candidacy in the Extractive Industries Transparency Initiative [47] and the recent approval of new Environmental Impact Assessment requirements [6], yet there is currently not a publicly-available dataset of mining areas or permits provided by the government. The baseline dataset we have generated can support the enforcement and strengthening of existing regulations and allow meaningful engagement with communities on issues relating to mining.

Supplementary Materials: The shapefile of all digitized mining areas is available at the Myanmar Information Management Unit online portal at [48]. The following are available online at www.mdpi.com/2072-4292/8/11/912/s1, Scheme S1: R scripts for creating a raster of potential mining areas, Figure S1: Distribution of years and satellite platform for high-resolution imagery used to digitize mining areas, Figure S2: Examples of high, medium, and low certainty mining areas (Images exported from Google Earth Pro), Scheme S2: R scripts for mining change analysis, Table S1: Mining area change in hectares for medium-certainty mining areas, Table S2: Mining area change in hectares for low-certainty mining areas.

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