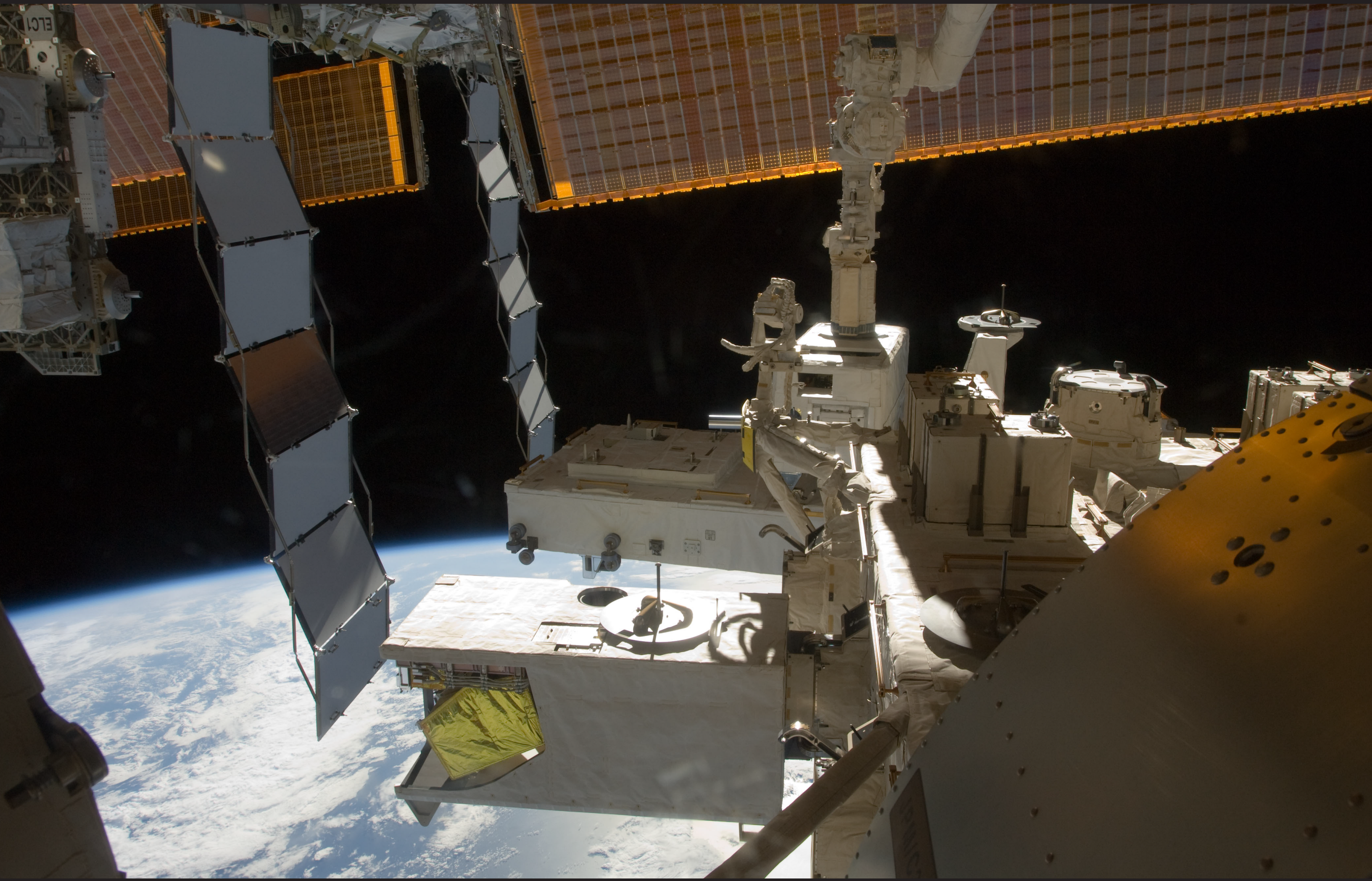

CNS
OCCASIONAL PAPER
#44 · JANUARY 2019

Eyes on U: Opportunities, Challenges, and Limits of Remote Sensing for Monitoring Uranium Mining and Milling

Grace Liu, Joseph Rodgers, Scott Milne, Margaret Rowland, Ben McIntosh, Mackenzie Best, Octave Lepinard, and Melissa Hanham

Middlebury Institute *of* International Studies at Monterey
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Acknowledgments

The researchers would like to extend special thanks to Jake Hecla at University of California, Berkley and Will Amidon at Middlebury College for their expertise, and to the MacArthur Foundation and the Skoll Foundation for their support.

Disclaimer

The views, judgments, and conclusions in this report are the sole representations of the authors and do not necessarily represent either the official position or policy or bear the endorsement CNS or the Middlebury Institute of International Studies at Monterey.

Cover image: Hyperspectral Imager for Coastal Oceans, pictured aboard the International Space Station. Credit: NASA's Marshall Space Flight Center (CC BY-NC 2.0).

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Overview

The mining and milling of uranium does not generally receive the attention that the subject deserves in the nonproliferation literature. Yet this overlooked aspect of the nuclear fuel cycle can offer analysts important clues about a country's fissile-material production. This, in turn, helps inform highly sensitive inquiries, such as estimates of arsenal size and potential for growth. Geospatial technology is uniquely helpful as a discovery and verification tool. The production of fissile material is often a closely held state secret; even for states that report production levels to the International Atomic Energy Agency (IAEA), these numbers can be difficult to verify. Remote sensing technology, such as satellite imagery paired with change-detection algorithms, can help pierce the veil of state secrecy and overcome physical barriers in order to inform analysts about this vital first step in the nuclear fuel cycle.

This is the final paper in a four-publication series that has explored the application of open-source remote-sensing data in identifying and monitoring uranium mining and milling activities. CNS Occasional Paper #34[1] gave a broad treatment of geospatial technology and open-source methods for verifying or estimating uranium production. Occasional Paper #40[2] featured North Korea and China as case studies, while Occasional Paper #41[3] focused on India and Pakistan. All papers utilized a combination of open-source data (declared and otherwise) to analyze each country's uranium production and potential and used satellite imagery analysis to identify the location of several potential covert uranium mines and mills. Geospatial technology proved extremely valuable in the verification of declared production and the discovery of unconfirmed sites.

Different remote-sensing techniques offer different advantages for analyzing mines and mills. Traditional optical imagery is often sufficient for surface-level insights. The presence of optical signatures such as tailings piles, waste ponds, suspicious buildings, and certain mining equipment can compellingly suggest that a site may be involved in uranium mining or production. Furthermore, multispectral and hyperspectral images contain details hidden to the naked human eye. Thermal and near-infrared (NIR) images can provide information about the operational status and ongoing activities at a uranium mill and mine through the display of heat signatures or by revealing

[1] Jeffrey Lewis, Melissa Hanham, Joshua Pollack, Catherine Dill, and Raymond Wang, "Open-Source Monitoring of Uranium Mining and Milling for Nuclear Nonproliferation Applications." CNS Occasional Paper #34, December 2017, https://www.nonproliferation.org/op34-open-source-monitoring-of-uranium-mining-and-milling-for-nuclear-nonproliferation-applications/

[2] Melissa Hanham, Grace Liu, Joseph Rodgers, Mackenzie Best, Scott Milne, and Octave Lepinard, "Monitoring Uranium Mining and Milling in China and North Korea through Remote Sensing Imagery," CNS Occasional Paper #40, October 2018, https://www.nonproliferation.org/op40-monitoring-uranium-mining-and-milling-in-china-and-north-korea-through-remote-sensing-imagery/

[3] Melissa Hanham, Grace Liu, Joseph Rodgers, Mackenzie Best, Scott Milne, and Octave Lepinard, "Monitoring Uranium Mining and Milling in India and Pakistan through Remote Sensing Imagery," CNS Occasional Paper #41, November 2018, https://www.nonproliferation.org/op41-monitoring-uranium-mining-and-milling-in-india-and-pakistan-through-remote-sensing-imagery/

environmental disruption. In the future, the extreme level of detail available in hyperspectral data could populate a database of spectral signatures unique to uranium ore.

Insight gained through geospatial means can vastly improve the monitoring and verification efforts of analytical organizations and international verification regimes alike. For example, Article 4a(i) of the Additional Protocol gives IAEA inspectors the right to request "complementary access" to participating nuclear facilities to investigate possible undeclared nuclear material or to "resolve inconsistencies" in a state's declared and actual production levels.[4] Detailed data gained via geospatial methods can alert authorities that a violation may have taken place or help inform the decision to request this access. As demonstrated in earlier papers in this series, geospatial technology also helps identify potential uranium-production sites in states that do not cooperate with the IAEA. Machine learning identification algorithms may simultaneously improve the speed and accuracy of identifying such sites worldwide. Below, the authors assess the advantages of different spectral techniques for analyzing mines and mills.

Optical Imagery

While hyperspectral imagery and machine learning algorithms offer analysts tantalizing new possibilities, traditional optical imagery is still of great use. Optical imagery captures and displays the red, green, and blue bands of the electromagnetic spectrum, i.e. the visible bands of the light spectrum (between ~400 and ~700 nanometers [nm]). Optical imagery is relatively easy to view and interpret, even for those who have little experience with satellite imagery, because they portray an image of the ground as it is most familiar to the naked eye.

Optical imagery is helpful in estimating the size and type of a suspected uranium mine or mill. Given the sprawling size of mining and milling operations, buildings and equipment are often visible in satellite images. Additionally, the presence of defining features such as tailings ponds and leach piles, and the changes in these over time, may indicate active operations at a site. However, signatures associated with uranium mines and mills can be nearly indistinguishable from those of other metals (such as copper), since much of the same equipment is used in both contexts.

As detailed in the previous papers of this series, uranium is commonly mined by one of three methods: open-pit mining, underground mining, and *in situ* leaching (ISL). All three mining methods present different optical signatures that can be used to identify the presence of such operations. Of the three

[4] "IAEA Safeguards Overview," International Atomic Energy Agency, n.d., https://www.iaea.org/publications/factsheets/iaea-safeguards-overview; R. Leslie, P. Riggs, V. Bragin, Q.S. Bob Truong, R. Neville, and K. Staenz, "Satellite Imagery for Safeguards Purposes: Utility of Panchromatic and Multispectral Imagery for Verification of Remote Uranium Mines," Paper presented to Annual Meeting of the Institute of Nuclear Materials Management, Orlando, Florida, 23–27, June 2002, p. 4.

methods, open-pit mining leaves the most prominent optical signature in the form of a large cavity, exposing the ore to be extracted. Underground mining is the most difficult to analyze in optical imagery because most of the activity takes place below ground. However, even underground mines can exhibit signatures such as processing equipment and waste-material piles located near the mine entrance. The ISL method creates minimal disturbance at the surface by dissolving the desired uranium into a solution underground and piping it up to be processed. Due to the minimal equipment needed to operate ISL, it is relatively challenging for analysts to identify this method, and can be easily concealed. However, the ISL method still requires a large processing plant which can be detected in satellite imagery, though it may not be collocated with the mine.

Correctly distinguishing uranium mines and mills from other mining operations remains challenging. Copper mines and mills present a particular challenge as copper and uranium mining processes utilize much of the same specialized technology and equipment.[5]

A distinguishing characteristic of most copper milling operations is the presence of an electrowinning plant. Electrowinning plants use electrolysis to purify some metals through a solution, including copper, after the leaching process.[6] Since electrowinning is rarely used in uranium mining and milling operations, the presence of such a plant can rule out uranium mining with relatively high certainty. Electrowinning stations are large and consume large quantities of energy; their presence is often accompanied by a dedicated power plant. Figure 1 shows a 3D model of the electrowinning plant at the Olympic Dam copper-uranium mine in Australia.

Figure 1: 3D model in Google Earth, Olympic Dam Electrowinning Plant, South Australia

[5] Lalitha Sundaresan, S. Chandrashekar, and Bhupendra Jasani, "Discriminating Uranium and Copper Mills Using Satellite Imagery," *Remote Sensing Applications: Society and Environment*, Vol. 5, January 2017, pp. 27–35.

[6] Electrorefining methods use electrolysis to filter out impurities from copper extracted from the ore. Derek Pletcher, *Industrial Electrochemistry* (Springer, 1982).

Leaching is a necessary component of all uranium mining methods. The leaching process dissolves the uranium into a chemical solution, which separates the uranium from the other materials in the ore. Uranium is often extracted from this leaching solution via two methods: ion exchange (IX) and solvent exchange (SX). These methods can be used individually or in combination with each other. IX, though commonly used for uranium extraction, is rarely used in other metal-extraction operations; therefore, the presence of an IX plant is a strong indicator that a mill is processing uranium ore. In addition, SX plants found at uranium mills typically feature larger extraction staging areas and smaller washing and stripping staging areas compared to SX plants at other types of base metal processing facilities.[7] Additionally, analysts should look for the presence of a smaller building, or buildings, with restricted access or increased security. Such a building might suggest the production and dissemination of sensitive materials, such as yellowcake.[8]

Figure 2: Rössing Uranium Mine, Namibia

As previously mentioned, ISL presents unique challenges for optical imagery analysts. Although ISL is a common mining method used around the world, it is difficult to detect. ISL does not leave a large optical footprint, as the mining occurs underground: small bore holes are the only visible signs that extraction is taking place. This is where analysts must get creative. Ancillary activity can give clues of ISL activity. The presence of major roads and truck lines at a superficially inactive site may reveal the

[7] However, this is only true if the mill is relying on SX alone and not in conjunction with IX.
[8] Calcination facilities are also typically found at uranium mills and are not used in other operations, but these buildings can be difficult to distinguish from other buildings at the plant through satellite imagery.

importance of a location. ISL processes use evaporation ponds and collection wells, which may be visible in certain images. Figure 3 shows an optical image of an ISL mine in Qabul Khel, Pakistan.

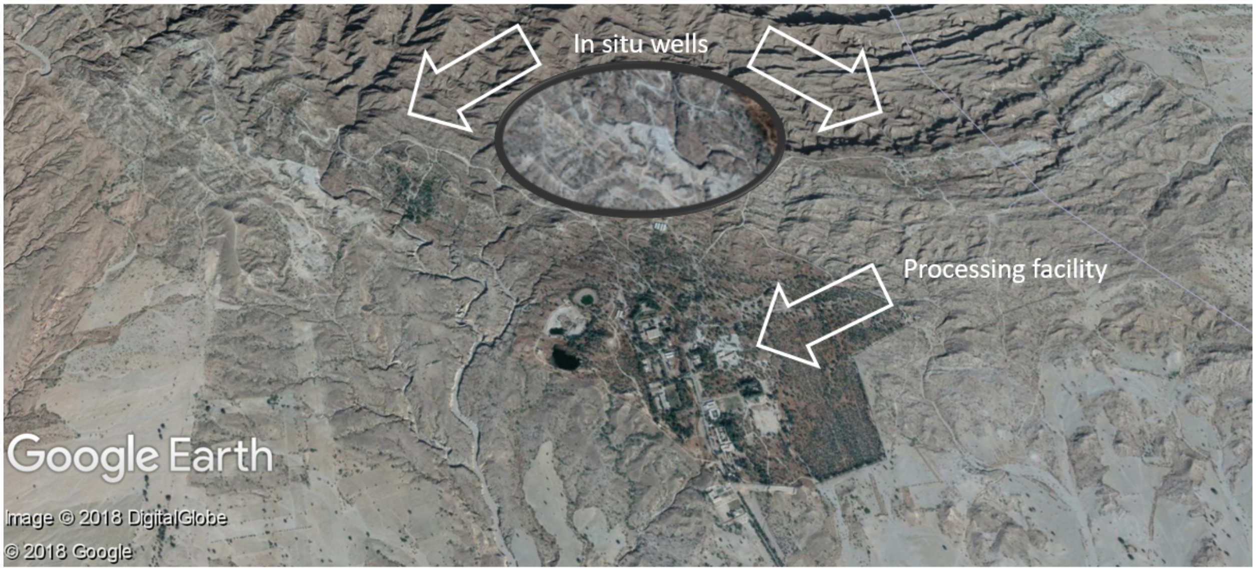

Figure 3: Suspected ISL boreholes and known uranium-processing facility, Qabul Khel, Pakistan

Estimating Production

Analysts can reasonably estimate the production capacity of a suspected or confirmed site using signatures visible in optical imagery, including the size of a facility and the amount of equipment. Mills using conventional methods for uranium extraction often utilize counter-current decantation (CCD) units, which are used to filter out impurities during the uranium-extraction process.[9] Using the quantity and size of the CCD units, paired with the suspected grade of the uranium ore, analysts can roughly estimate the production capacity of conventional uranium mills.[10] Researchers with the European Safeguards Research and Development Association developed such an equation, which was used and evaluated in Occasional Paper #40.

[9] Thickening agents are added to uranium ore to produce a slurry, which is then sent to leach tanks to extract the uranium. The remaining product is then sent to CCDs for solid-liquid separation to filter out impurities. This solution and the leached uranium are then sent to the IX or SX for final extraction.
[10] In Occasional Paper #40, CNS researchers used this equation to estimate the production of known and suspected uranium mines in North Korea.

Multispectral and Hyperspectral Satellite Imagery

Multispectral and hyperspectral sensors, which collect bands of light on the electromagnetic spectrum in addition to those within the visible range, can provide further insight into uranium mining and milling activity. Multispectral imagery can display changes in live vegetation or detect thermal heat to indicate ongoing activity at a uranium mine. Hyperspectral imagery is a type of multispectral imagery that collects and displays a denser group of bands than other multispectral images. Hyperspectral imagery can potentially aid in the discovery of undeclared uranium mines by determining the ground composition around areas of interest (AOI). The ground composition around mines, tailing piles, and waste ponds can be compared to the spectral signatures of similar areas around known uranium mines and mills to see if there is a match, indicating that the site in question is likely a uranium mine and mill.

Multispectral imagery expands analysts' range of information beyond traditional remote-sensing data, enabling more comprehensive studies on an AOI. The quality and availability of collection technologies for these types of imagery vary, but in the coming years, it is unlikely that thermal, near-infrared, and hyperspectral imagery will become more available on the commercial market. Few dedicated multispectral sensors will be launched in the next few years. Thus, the availability and quality of multispectral data will not likely increase in the near future.

Thermal Imagery

By comparing relative temperatures of objects and displaying these to the user in color overlays, thermal imaging can show whether a facility is likely operational, highlight which areas are more active than others, and even portray the recency of activity. Mining activity produces a variety of thermal signatures; waste material that is dumped into ponds is often hotter than the surrounding body of water, heated administrative buildings are warmer than the surrounding environment (especially in colder weather), and operational ore crushing and grinding equipment produces heat. The differences in temperature are visible through even low spatial resolution.

Current Challenges and Limitations of Thermal Imagery Analysis

Commercially available thermal satellite imagery is currently scarce, especially that of sufficient resolution for detailed analysis. While generalized differences in temperature are visible using even low spatial resolution Landsat imagery,[11] the image in Figure 4 of a mine near Fuzhou, China, shows some of the current challenges with thermal imagery.

[11] The National Aeronautics and Space Administration (NASA)'s Landsat program has been collecting satellite images of Earth since 1972, providing "the longest continuous space-based record of Earth's land in existence." See "Landsat Science," NASA, n.d., https://landsat.gsfc.nasa.gov/.

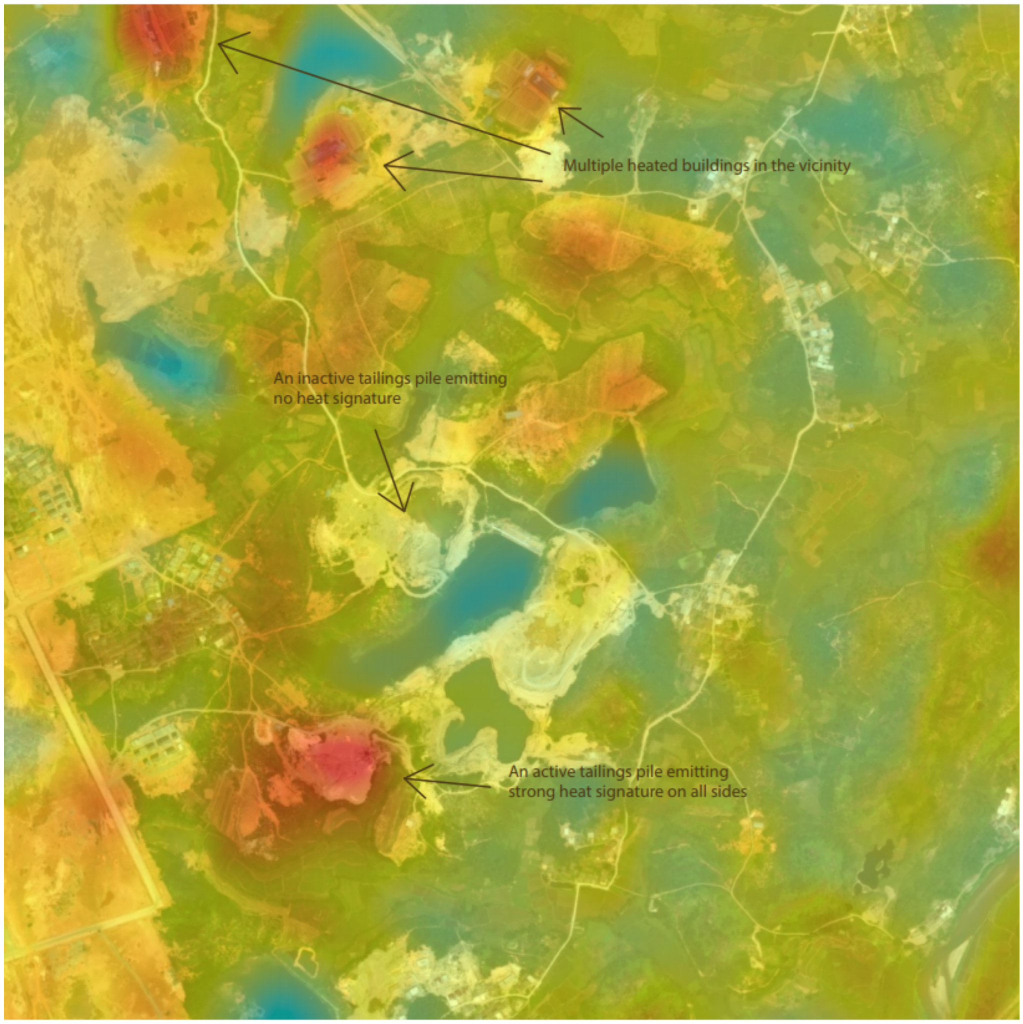

Figure 4: Thermal data overlaid on high-resolution optical imagery, near Fuzhou, China

First, the visible heat signatures are somewhat diffuse due to the low resolution of the thermal sensor, making it potentially challenging for researchers to identify the precise source of the heat. This would be particularly apt in a small area with densely packed facilities. Overlaying thermal imagery with higher-resolution optical imagery can somewhat compensate for low resolutions by putting visible heat signatures into the context of objects on the ground.[12]

Second, factors that "deceive" or distort the collection of thermal bands can result in false heat signatures. In Figure 5, a steep hillside faces southward, thus heating up considerably faster than its surroundings. Since this signature can be explained by topography, it can probably be ignored as insignificant for this analysis. Such heat signatures are one of the core challenges of thermal imagery analysis.

[12] Hyung-sup Jung and Sung-hwan Park, "Multisensory Fusion of Landsat 8 Thermal Infrared and Panchromatic Images," *Sensors*, Vol. 14, No. 12, December 2014.

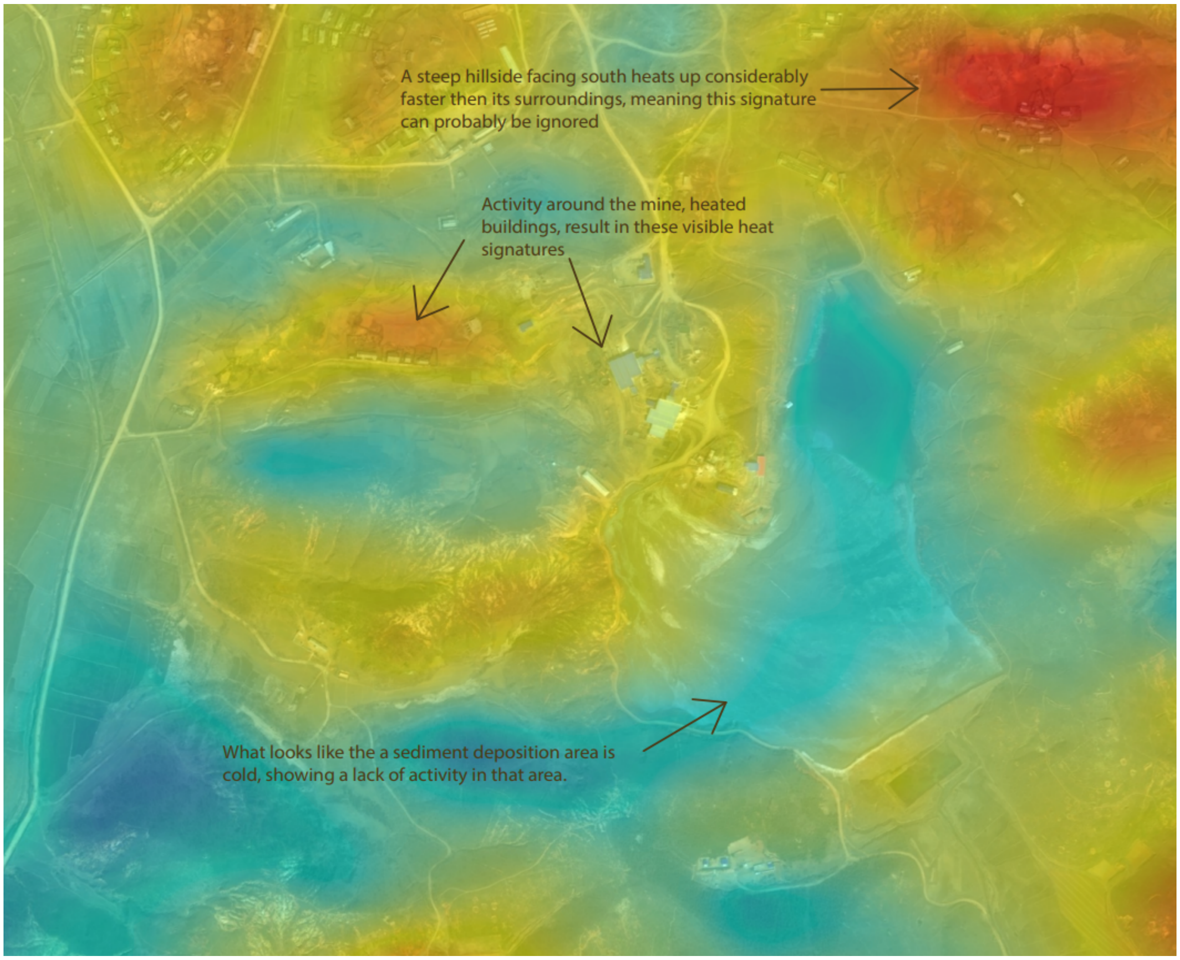

Figure 5: Thermal data overlaid on high-resolution optical imagery, near Fuzhou, China

One factor that can also interfere with thermal bands is weather. Hot air columns moving across an AOI could cause false positives, displaying heat signatures where there is no actual difference in ground temperature. While not perfect, one can correct for atmospheric noise using software such as ENVI's preprocessing atmospheric models.[13]

Certain types of clouds can cause light scattering, which also results in misleading thermal signatures. For example, subvisual cirrus clouds can have substantial effects on remote sensing because of their

[13] ENVI is an image analysis software offering from Harris Geospatial Solutions, the first version of which launched in 1991. See: "ENVI," Harris Geospatial Solutions, n.d., https://www.harrisgeospatial.com/Software-Technology/ENVI.

high concentration of non-spherical ice crystals.[14] Under these conditions, the temperatures of objects within thermal imagery can be shifted slightly.

Another limitation to thermal imagery is that object texture can significantly impact the perceived temperature of the object. For example, reflective objects, such as sheet metal, can appear colder because they reflect light at a higher rate than non-reflective objects around them. Similarly, rough and porous objects absorb more light, appearing warmer in thermal bands.

While one must be aware of all of these challenges when analyzing thermal imagery, its analysis, when available, can greatly enhance a researcher's understanding of mining and milling site activity.

Availability of Thermal Imagery

While there are challenges to thermal imagery analysis, the most current challenge for open-source researchers is the scarcity of available imagery. Presently, only three satellites collect images on thermal bands: two belong to the United States Geological Survey (USGS) and the third is in use by the National Aeronautics and Space Administration (NASA). Historically, the now-decommissioned USGS Landsat 5 also provided thermal imagery. USGS and Google Earth Engine now offer some of the higher quality historical Landsat data for free, including thermal data. Finally, while the Korea Aerospace Research Institute presently has a high-resolution thermal satellite that may become commercially available in the future, this availability is contingent on approval from the Korean government.

The Thematic Mapper instrument on Landsat 5 captured thermal images in one spectral band between 10.40 and 12.50 micrometers (μm) in 120-meter resolution,[15] and was the first publicly available thermal imagery sensor. The USGS decommissioned Landsat 5 satellite on December 21, 2012, after operating for 28 years and 10 months, officially setting the Guinness World Record title of the "longest operating Earth observation satellite."[16]

Landsat 7, one of the two current USGS thermal imagery satellites, provides thermal imagery with a spatial resolution of about 60 meters. Landsat 7 completes an orbit around the Earth every 16 days. While studies have been done using Landsat 7 imagery, the results are affected by the low resolution.[17] Furthermore, Landsat 7 has already exceeded its design lifetime by over 14 years. As the satellite ages

[14] Ping Yang and Kuo-Nan Liou, "Light Scattering and Absorption in Non-Spherical Ice Crystals," in Alexander Kokhanovsky, ed., *Light Scattering Reviews: Single and Multiple Light Scattering* (Springer-Verlag/Praxis Publishing, 2006).

[15] Irmgard Niemeyer, "Perspectives of Satellite Imagery Analysis for Verifying the Nuclear Non-Proliferation Treaty," in Gotthard Stein, Bernd Richter, Sven Nussbaum, Irmgard Niemeyer, and Bhupendra Jasani, eds., *International Safeguards and Satellite Imagery: Key Features of the Nuclear Fuel Cycle and Computer-Based Analysis* (Springer-Verlag: Berlin Heidelberg, 2009), pp. 35–44.

[16] "Landsat 5," NASA, last updated December 6, 2018, https://landsat.gsfc.nasa.gov/landsat-5/

[17] Joseph Bermudez and Andy Dinville, "Checks and Balances: Thermal Imagery Analysis of Yongbyon," 38 North, October 25, 2016, http://www.38north.org

and the failure probability of its parts increases, Landsat 7 could unexpectedly be decommissioned at any time.

Landsat 8, the other operational USGS satellite, was launched in 2013. It provides thermal imagery in two bands. Landsat 8 orbits in an eight-day offset to Landsat 7. Thus, Landsat 7 and 8 collectively sample the same location on earth every eight days. Landsat 8's thermal data is sampled at a minimum of 90-meter resolution but is statistically resampled at 30 meters in delivered images.[18] However, Landsat 8's thermal sensor has had problems. The sensor has been known to receive "stray light," causing images to appear hotter than they should. NASA has attempted to fix the problem by using an algorithm that corrects for this anomaly. The algorithm's efficacy is still under peer review.[19] In future analyses, it is important to approach findings from Landsat 8 imagery with caution and careful analysis.

In addition to Landsat, NASA's Earth Observation System satellite Terra is the third satellite currently collecting thermal images. Terra can capture 90-meter resolution thermal imagery in five spectral bands between 8.125 and 11.65 μm. Unfortunately, Terra has also far exceeded its design lifetime and will soon run out of fuel.[20]

Given that two of the three satellites that collect thermal band imagery have exceeded their design lifetime, acquiring thermal imagery from them will continue to be challenging, perhaps increasingly so, in the near future. However, recent developments in thermal-sensor availability may improve the commercial landscape. In 2015, the Korea Aerospace Research Institute launched KompSat 3A, which is equipped with a Thermal Infrared Sensor. KompSat 3A's mid-wavelength infraredimaging sensor, which operates in the 3.3-5.2-μm range, can sample thermal imagery with a resolution of 5.5 meters.[21] This resolution is significantly higher than any currently available, and holds great potential for analysts, if it becomes available.

Before the 3A was launched, many believed that the imagery from the 3A would be commercially available.[22] However, the South Korean government will not allow KompSat 3A's thermal images to be sold at this time. If KompSat 3A's thermal imagery does enter the commercial market, it would far exceed the quality of thermal imagery available on the market today, resolving many of the aforementioned challenges.

[18] "What are the Band Designations for the Landsat Satellites?" United States Geological Survey, October 18, 2018, https://landsat.usgs.gov/what-are-band-designations-landsat-satellites

[19] Susan Gowzlowicz, "An Innovative Fix for Landsat 8 TIRS Imagery," NASA, November 16, 2016, last updated December 6, 2018, https://landsat.gsfc.nasa.gov/an-innovative-fix-for-landsat-8-tirs-imagery/

[20] Tassia Owen, "Balancing Terra's Fuel Supply and Science Needs," NASA, updated December 6, 2018, https://terra.nasa.gov/news/balancing-terras-fuel-supply-and-science-needs

[21] "KOMPSAT-3A Satellite Sensor," Satellite Imaging Corporation, n.d. https://www.satimagingcorp.com/satellite-sensors/kompsat-3a/

[22] "KOMPSAT-3A," N2YO Satellite Tracking, March 25, 2015, https://www.n2yo.com/satellite/?s=40536

Near-Infrared Imagery

Near-infrared (NIR) images provide valuable information to satellite-imagery analysts. Often used for agricultural, chemical, and medical applications, NIR data is most effective in a uranium mining and milling context for revealing the environmental condition of an area, particularly the health of vegetation present in an image. NIR images can show how and to where machinery is moved, how the environment has been modified to accommodate operations, and whether environmentally damaging chemicals may be present using the state of the local biota as a proxy. NIR imagery distinguishes difference in ground composition present in an image more strikingly than optical imagery, starkly delineating lakes from marshes, AstroTurf from grass, or even real vegetation from camouflage. NIR information is relatively easy to obtain, since most modern "optical" sensors today also collect on a fourth band of information in addition to the red, green, and blue bands. This fourth band is typically near-infrared.

Thermal imagery is most effective for perceiving emitted radiation and displaying it in the form of a heat signature. However, NIR imagery perceives and displays *reflected* infrared radiation, rather than that generated and emitted by an object. NIR imagery relies on radiation emitted by the sun, which reduces in intensity as it passes through Earth's atmosphere. Objects absorb this radiation differently, and what is not absorbed is reflected. NIR imagery displays the sun's radiation after it is absorbed and reflected off of objects on Earth.[23]

NIR imagery is especially effective for evaluating vegetation health because of the effects of photosynthesis. Plants absorb blue and red-light energy as part of this process and reflect energy within the near-infrared spectrum; the healthier the vegetation, the more NIR energy it will reflect (in the wavelength band 780 nm to 2500 nm). In most processed NIR images, healthy vegetation is weighted such that it appears in a brilliant red color, with aberrations appearing darker or non-colored. This capability is very useful for defense analysts—NIR imagery distinguishes between camouflage and real vegetation, as well as the environmental impacts of military exercises like burn scars from missile tests.

In a uranium mining and milling context, NIR imagery can help clarify the environmental impact of such operations and test hypotheses of observations from optical imagery. For example, Figure 6 below shows the North Korean uranium mining and milling operation at Pyongsan and suggests significant chemical pollution in a nearby lake. In a plain optical image, the green area observed at the top of the lake might be interpreted as an algae bloom or another naturally occurring phenomenon. The NIR imagery corrects this interpretation. The farmland surrounding the operation displays as varying shades of red, but the green area in the lake remains green. This confirms that the green area is not an organic growth but is highly likely chemical runoff from the uranium-milling operation, which suggests that the lake is being used as a large tailings pond.

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[23] Ginger Butcher, *Tour of the Electromagnetic Spectrum* (Washington, DC: National Aeronautics and Space Administration, 2016), pp. 14–17;

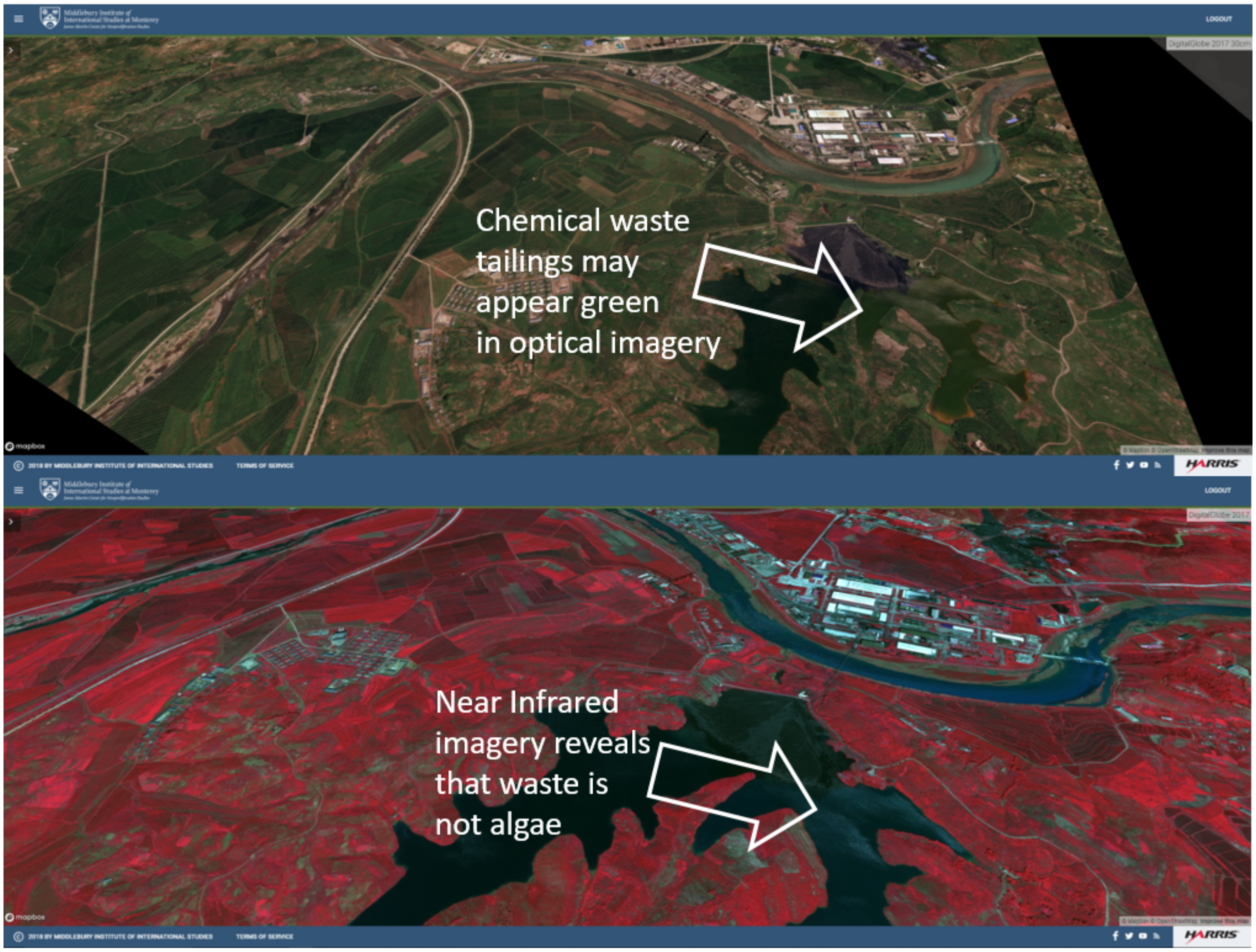

Figure 6: Comparison of optical and NIR images of a tailings pond in Pyongsan, North Korea
Source: Geo4Nonpro

Hyperspectral Imagery

Hyperspectral imagery collects on denser bands of light outside of the optical spectrum, consisting of hundreds of contiguous bands. Various wavelengths of light reflect differently off of all materials and the difference between materials can be captured in detail between hundreds of bands. Displaying the frequency of each of these hundreds of bands results in a unique "spectral profile" (see Figure 7). The density of these bands in hyperspectral imagery makes it possible to detect and display nuances between different ground materials. Theoretically, these profiles can then be catalogued into a database (like fingerprints) and referenced in the future to compare against and determine ground composition in AOIs. Highly developed hyperspectral sensors may allow analysts to identify the mineral content of mines, tailing piles, and waste ponds, and even whether material in a tailings pile may be depleted of uranium. This concept can potentially be applied to uranium mines to compare whether the soil, tailings piles, and waste ponds in uranium mines are different enough from other mines to be able to definitively tell them apart.

Initially, CNS researchers set out with the goal of performing hyperspectral analysis using Hyperion imagery to develop a general spectral signature for open-pit uranium mines. Researchers focused on selected open-pit uranium mines for analysis because the open pits provide the largest spatial and spectral signatures of all of common mining methods. In addition, open-pit mining practices often result in large tailings piles or waste ponds. Both of these objects are clearly visible in satellite imagery, and both contain minerals that should produce clear spectral profiles in hyperspectral images taken at high-enough resolutions.

Current Challenges and Limitations of Hyperspectral Imagery Analysis

Today, the only hyperspectral sensor data to which researchers have access is the Hyperion sensor that was onboard NASA's Earth Observing-1 (EO-1) satellite. The EO-1 was launched in 2000 and decommissioned in 2017. Hyperion collected on 220 bands covering the 355 nm - 2.6 nm wavelength light at 30-meter spatial resolution.[24] Unfortunately, identifying mineral content at mines is challenging at this spatial resolution given the very low average mineral concentration within ore. As CNS researchers discovered, this low uranium concentration in ore makes the mineral content of a mine indistinguishable in hyperspectral imagery at a 30m resolution because there simply is not enough uranium present for sensors to capture; this precludes the creation of a spectral signature for uranium.

As mentioned above, spectral signatures are a mechanism to identify objects based on the amount of light reflected at specific wavelengths. In an optical image, every pixel has a value for its red, green, and blue band. This indicates how much light in that particular wavelength was reflected by that object. The same process works for hyperspectral images, but with hundreds of different bands of light.

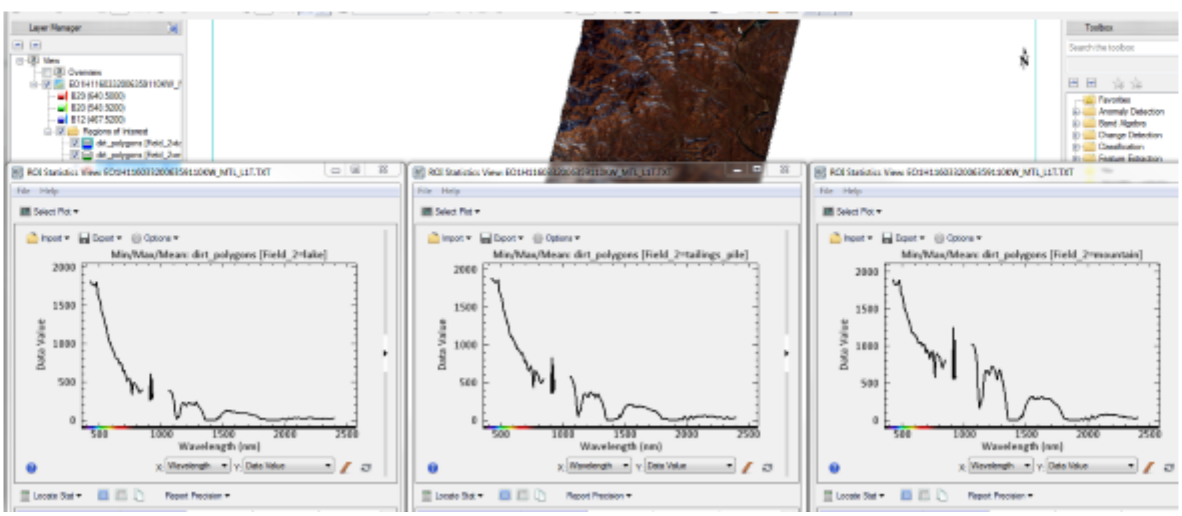

Figure 7: Signatures created using hyperspectral images from the EO-1 satellite

[24] "Earth-Observing-1 (EO-1)," USGS, August 1, 2018, https://eo1.usgs.gov/sensors/hyperioncoverage

There are several steps needed to create a spectral signature from hyperspectral imagery. First, a researcher must isolate a particular AOI using geographic information system software. This entails drawing a polygon around the AOI, which should be as homogenous in its ground composition as possible, e.g. a tailings pile, waste pond, or patch of earth. Once isolated, the researcher can calculate the spectral signature of each AOI using Hyperion imagery by taking multiple images of the same AOI and averaging the values of each band in each pixel to create 220 average bands. Each of the 220 bands' averages can then be plotted on a graph by their reflectance as seen in the image above. A general signature or spectral profile of a substance can then be built from this data. Once formulated, different objects' signatures can be compared to one another, such as an open-pit copper mine versus a suspected open-pit uranium mine, revealing anomalies or similarities that are invisible to the naked eye. But a lack of availability of high-resolution hyperspectral imagery remains a significant barrier to analysis.

Building a database of spectral signatures for uranium-mining operations would involve collecting hundreds of hyperspectral images of uranium mines on different days. Once collected, these spectral signatures could be catalogued, and each band value averaged to obtain a generalized spectral signature. To increase the precision, band values could be standardized by radiometrically and atmospherically correcting images. Radiometric correction adjusts for distortion created by the sun and the satellite's position. By accounting for the satellite angle and the sun angles that day, the algorithm for radiometric correction produces an image where each picture represents the true reflectance from the ground instead of the light that was captured by the satellite.[25] Atmospheric correction accounts for light that reflects off of the atmosphere. The atmospheric correction algorithm takes the darkest pixel in the image and subtracts every pixel by that value, recalibrating the image based on that darkest pixel. This process makes the assumption that there is at least one pixel on the image that is unaffected by reflectance, which is reasonable to assume in large satellite images.

The Future and Potential of Hyperspectral Imagery Analysis

Hyperspectral technology is much more advanced today than when the EO-1 satellite was launched. A hyperspectral sensor with better spatial resolution may be able to identify unique signatures for uranium ore and/or mines, which would assist in confirming known uranium mines and identifying undeclared ones. Creating a database of such signatures could provide the opportunity to continue to identify and verify new uranium mines, both declared and undeclared. Domestic commercial opportunities for the acquisition of new high-resolution hyperspectral imagery may arise; domestic mining companies in countries around the world could, for example, conduct overflight of their mines using drones with hyperspectral sensors, but this imagery would likely not be publicly released.

[25] Learning Module 4.1, Image Processing, "Radiometric Corrections," Humboldt State University, http://gsp.humboldt.edu/olm_2015/Courses/GSP_216_Online/lesson4-1/radiometric.html

There is also a compelling argument to be made for putting more hyperspectral sensors into space, now that the EO-1 satellite and its Hyperion sensor have been decommissioned. Current research efforts in both the nonproliferation field and other domains would greatly benefit from the release of this imagery. If available to an international organization such as the IAEA, this imagery could also augment nuclear safeguards implementation and verification. Many different entities—governments, private corporations, international organizations, or research institutes— have an interest in promoting or helping fund the launch of another satellite with a hyperspectral sensor into space. But the problem of access to the imagery would remain, as access would largely depend on who owns the satellite and sensor.

One such sensor is the DLR Earth Sensing Imaging Spectrometer, or DESIS, developed by the DLR Institute of Optical Sensor Systems and Teledyne Brown Engineering. This sensor was launched in June 2018 and orbits the International Space Station. It will record data using 235 bands, including optical and infrared bands, at a 30m spatial resolution. The explicit purpose of this sensor is to provide information on the Earth's ecosystem, and specifically, "to assess the status of forests or agricultural areas" for yield predictions. However, the same data can potentially provide information for other industries, such as mining and milling operations. No information is available on whether the sensor has begun collecting data at the time of this writing.[26]

Machine-Learning Algorithms

The growing amount of commercially available satellite data presents new opportunities and challenges for analysts. In order to take full advantage of the vast remote-sensing data available in the open source, analysts must be able to monitor and examine large quantities of geospatial information in a relatively short amount of time, which can be prohibitively time consuming if done manually. Some analysts are turning to machine learning (ML) to help mitigate this problem.

ML algorithms offer great time-saving potential for analysts. ML algorithms are computer models that use pattern recognition to produce the desired result, such as predicting where additional uranium mines or mills may be located or detecting significant change over time in an AOI. These programs can significantly streamline the initial analysis period and direct analysts' attention to mines and mills that are most active at any given point in time. Such algorithms allow analysts to focus their time and effort on images in areas that have already been screened and determined to show significant activity. Moreover, these algorithms can sift through information from all spectral bands, gathering input from the traditional red, green, and blue bands, as well as NIR and thermal bands.

[26] "Hyperspectral Earth observation instrument DESIS sets off for the ISS," DLR, https://www.dlr.de/dlr/en/desktopdefault.aspx/tabid-10212/332_read-28665/#/gallery/30167
"DLR Earth Sensing Imaging Spectrometer (DESIS)," NASA, September 19, 2018, https://www.nasa.gov/mission_pages/station/research/experiments/2039.html

ML algorithms can also scan imagery worldwide to help analysts find other potentially undeclared mines and mills. Given exciting developments in the availability of satellite data, such as the commercial satellite company Planet's ability to image the entire globe every day,[27] access to up-to-date imagery on a global scale is within reach of open-source analysts. Identification algorithms can aid in this effort and commonly take two forms, pixel-based or object-based, which are outlined below.

Pixel-based classification uses image segmentation, or a "bottom-up" approach. Such algorithms start at the level of individual pixels and methodically analyze neighboring pixels until it forms a "picture" of the object(s) of interest. By contrast, the object-based approach classifies pixels in groups. By working with groups of pixels, object-based algorithms allow analysts to create patterns with more information, including the relationship between pixels in the object. Several studies have shown that object-based classification is likely to be more accurate than pixel-based classification for change-detection algorithms.[28]

Object-based algorithms can use patterns of information at multiple levels to create a unique signature of what an object looks like. One method involves graphing the "spectral behavior" for each group of pixels, which maps the distribution of gray values to indicate an image's depth. The resulting scatterplots depict signatures that are unique to each group of pixels.[29] Groups of pixels that have similar scatterplots are likely to be similar objects or made of similar materials, which could reveal new areas that may contain the same objects of interest.

Algorithms can also determine a group of pixels' "texture" and "spectral behavior," two different classifiers that can help improve the certainty of a suspected match. Texture is the measure of variation in gray values within a group of pixels. Spectral behavior depicts the mean value of the pixels in a given area. Both classifiers, especially when used in conjunction, are unique identifiers for an object of interest. Utilizing several identifiers across several spectral bands allows the algorithm to build a multilayered profile of information about the objects of interest and search imagery around the world for similar signatures. Such algorithms have the clear potential to identify uranium mines or mills that may be unknown to the nonproliferation community.

Building a reliable, central database of spectral signatures would aid analysts looking to apply ML algorithms to open-source imagery. The database could consist of hundreds or thousands of hyperspectral signatures of areas with unique ground composition, namely tailings piles and ponds or the soil in an open-pit mine. Once collected, the spectral information could be averaged to

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[27] Planet Labs, "Planet Monitoring," n.d., www.planet.com.
[28] Dennis Duro, Steven Franklin, and Monique Dube, "A Comparison of Pixel-Based and Object-Based Image Analysis with Selected Machine Learning Algorithms for the Classification of Agricultural Landscapes Using SPOT-5 HRG Imagery," *Remote Sensing of Environment*, Volume 118, March 15, 2012, pp. 259–72.
[29] Volker Walter, "Object-Based Classification of Remote Sensing Data for Change Detection," *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 58, Issues 3–4, January 2004, pp. 225–38.

provide the values for each band, creating a generalized spectral signature. The current lack of high-resolution hyperspectral sensors makes deriving truly unique spectral signatures difficult, such as those that would demonstrate the difference between natural soil versus uranium-depleted tailings. However, even low-resolution hyperspectral imagery from the Hyperion satellite has shown promise for populating such a database, and advances in hyperspectral technology hold greater promise for the future.

The sharp uptick in imaging frequency and large-scale improvement in the resolution of modern satellite imagery offers both exciting possibilities and serious challenges for data management. ML algorithms offer analysts the possibility of automated image analysis, saving analysts significant time and effort. Analysts still face obstacles in using ML algorithms, including the current lack of high-quality hyperspectral imagery from which to build a database. But the time-saving and focus-specifying potential of ML algorithms make their use worthwhile.

Conclusion

The rapid changes and improvements in the commercial satellite industry represent substantial opportunities for open-source geospatial analysts. Numerous industries, including agriculture and construction, have also turned to commercial satellite imagery and geospatial analysis to streamline their business processes. This increase in demand from various sectors has incentivized cross-industry innovation and fueled rapid progress in the commercial satellite industry, which benefits security analysts directly and indirectly through improved analytical software and reduced imagery costs.

CNS has been an early adopter of these technologies and has often advocated for the benefits of remote-sensing data in the field of open-source security research. In this series of papers, CNS has aimed to provide an overview and exploratory study of approaches using remote-sensing techniques and geospatial analysis of an oft-overlooked aspect of the nuclear safeguards regime: monitoring the mining and milling of uranium. Previous papers in this series have demonstrated the benefits of integrating geospatial technologies into the analysis of specific countries' uranium operations, while this paper provides a comprehensive overview and details the capabilities of each remote-sensing strategy. This paper explores sensor technology and its associated imagery across the electromagnetic spectrum—from the visible light analyzed in optical imagery, to optically invisible bands such as NIR and thermal found in hyperspectral imagery. This paper also examines the potential to apply machine learning algorithms to multispectral imagery analysis, and in doing so, increase the efficiency and precision of an analyst.

Ultimately, these technologies do not replace traditional sources and techniques of analysis but can be a robust tool for both discovery and verification of uranium mining and milling activities. The competitive commercial satellite industry also offers analytical organizations and nonproliferation verification regimes alike many options for partnership with private companies. CNS has benefited enormously from working closely with our partners at the San Francisco-based Planet and the French defense contractor Airbus. Advancements in any one of these tools—remote-sensing technologies, machine learning algorithms, or analysis techniques—are mutually reinforcing and strengthen analysts' abilities to monitor uranium mining and milling activities. Nonproliferation analysts working in the open source should take advantage of these rapidly developing approaches.

About the Authors

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Melissa Hanham is the director of the Datayo Project at One Earth Future Foundation. Hanham is an expert on open-source intelligence, incorporating satellite and aerial imagery, and other remote sensing data, large data sets, social media, 3D modeling, and geographic information system mapping. She is particularly focused on the monitoring and verification of international arms-control agreements using open-source evidence. Hanham also uses open-source information to study export-control systems and proliferation finance activities. Hanham is an affiliate of Stanford University's Center for International Security and Cooperation, and is a regular contributor to Arms Control Wonk, the leading blog and podcast on disarmament, arms control, and nonproliferation. In 2018, she was awarded the Paul Olum Grant Fund for being one of the most inventive scientific and technical minds working to reduce the threat of nuclear weapons. She previously worked at the Middlebury Institute of International Studies in Monterey and the International Crisis Group in Seoul and Beijing.

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