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Remote sensing of artisanal and small-scale mining: A review of scalable mapping approaches

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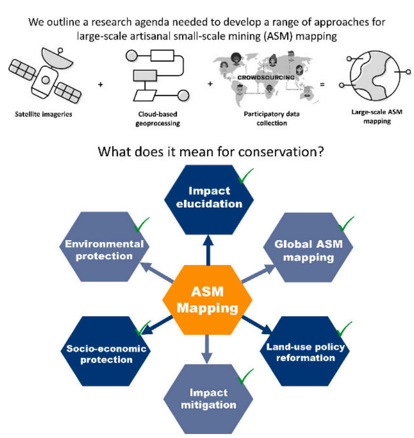
HIGHLIGHTS

- It is imperative to upscale Artisanal Small-scale Mining (ASM) monitoring.
- Disproportionate regional focus limits global ASM spatial data.
- Data fusion is a promising approach for accurate large-scale ASM mapping.
- Local community involvement is vital for on-ground spatial data.
- Integrate cloud processing and participation approach for large-scale monitoring.

GRAPHICAL ABSTRACT



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ABSTRACT

Artisanal and small-scale mining (ASM) significantly influences the socio-economic development of many low-to-middle-income countries, albeit sometimes at the expense of environmental and human health. Characterized by its labor-intensive extraction from confined (<5 ha) or peripheral mineral reserves, congregated ASM practices can rival the spatial footprint of industrial mines. The unregulated and informal nature of many ASM activities presents monitoring challenges that remote sensing (RS) methods aim to address. While local-scale ASM mapping has seen success, scaling these methods to regional or global levels remains unclear. We review literature on mapping ASM to determine: (1) if studies represent the global distribution and diversity of ASM activities, (2) how ASM's unique characteristics influence the choice of RS methods, and (3) which RS approaches are the most accurate and cost-effective. We found current studies disproportionately focused on ASM regions in Africa, which highlights the need to extend the research to other regions with unique ASM characteristics, such as coal and sand mining in India and China. The selection of RS approaches is heavily influenced by local ASM contexts, the

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scale of analysis, and resource constraints such as funding for high-resolution imagery and validation data availability. We argue that accurate regional-scale ASM mapping (>100,000 km2) requires innovative combinations of data and methods to overcome data management and storage challenges. Local community participation, including miners, is vital for on-ground mapping and monitoring capacity. We outline a research agenda needed to develop a range of approaches for mapping and monitoring ASM in under-studied regions. By synthesizing effective methods, we provide a foundation for generating accurate and comprehensive spatial data, addressing the issues of inaccurate and incomplete data that global ASM platforms aim to resolve. This spatial data can guide policymakers, NGOs, and businesses in making informed decisions and targeted interventions to improve ASM sector safety, sustainability, and efficiency. Leveraging cloud-based geoprocessing platforms, with regularly updated global satellite image archives, combined with crowd-sourced on-ground information offers a potential solution for sustained regional-scale monitoring.

1. Introduction

Artisanal and small-scale mining (ASM) represents a labour-intensive extraction process from small (<5 ha) or marginal mineral deposits using rudimentary tools, predominantly occurring in lower to middle-income countries (Cooke et al., 2019; Zvarivadza, 2018). While ASM significantly contributes to socio-economic benefits such as employment generation, poverty alleviation, and foreign exchange, it is also associated with unregulated environmental degradation, child labor, and localized disruptions with potential regional impacts (Fritz et al., 2018; Rustad et al., 2016; Schwartz et al., 2021; Zvarivadza, 2018).

One of the central debates surrounding ASM revolves around its formalization, which involves integrating ASM into the formal economy, subjecting it to legal and regulatory frameworks, and providing miners with access to support services and markets (Hilson et al., 2022). Proponents argue that formalization can improve working conditions, enhance environmental stewardship, and increase government revenue (Jiménez et al., 2024). Additionally, ASM often serves as a coping strategy for poverty alleviation and livelihood diversification (Hilson and Maconachie, 2020). In rural areas, ASM and farming are intertwined, with ASM providing supplementary income during agricultural off-seasons and farming acting as a fallback during periods of low mineral prices or resource depletion (Bryceson and Jønsson, 2010).

Policymakers and donors face the challenge of balancing the economic benefits of ASM with addressing its negative impacts. Effective policies should promote responsible ASM practices, provide alternative livelihoods, and tackle the root causes of poverty and marginalization (Hilson, 2024). Conflicts between large-scale mining (LSM) and ASM often emerge, as LSM operations encroach on ASM areas causing displacement and environmental degradation, while ASM activities can result in illegal mining within LSM concessions, leading to environmental damage and security concerns. (Hilson et al., 2020; Kemp and Owen, 2019). Therefore, it is important to understand the spatial dimensions and geographical distribution of ASM activities. Analyzing spatial data can inform targeted interventions, identify overlaps with biodiversity hotspots, and support sustainable initiatives. It also aids in legalizing and supporting artisanal miners through targeted monetary interventions. Comprehensive spatial data also helps resolve conflicts between LSM and ASM by delineating designated areas, preventing encroachment, and identifying feasible coexistence zones. This information supports sustainable and equitable resource-sharing strategies and policies, ensuring both sectors thrive without conflicts.

To date, a broad range of RS approaches have been applied to detect and monitor ASM in diverse local contexts. Artisanal and small-scale gold mining (ASGM), for instance, typically occurring near river streams, creates distinct surface footprints such as irregular lunar-shaped pits, tailings, and pit-lakes spanning areas of <5 ha but sometimes extending to over 100 ha due to feature merging. These features are usually detectable by medium-resolution (5–30 m pixels) airborne or satellite images, provided the pixel size is less than a quarter of the mining pit (Jensen, 2009). The global coverages and regular acquisitions (every 5–16 days) of the Landsat and Sentinels programs offered opportunity for researchers, such as Barenblitt et al. (2021) and DeWitt et al. (2022), to detect ASM areas as small as 5 ha, facilitating methodological trials for ASM mapping.

The mapping of rudimentary mineshafts associated with lode deposits, such as gemstones, demands the precision of pricier high spatial-resolution imagery (<5 m pixels), due to their limited surface footprints (< 1 ha). While such imagery provides greater accuracy and detail, cost and data volume restrictions often confine its use to localized studies (Ahmed et al., 2021; Chirico and DeWitt, 2017). Unoccupied aerial systems (UAS) provide even finer resolution, but their limited coverage limits their optimal suitability to project-specific applications or targeted sampling strategies. (Carreiras et al., 2012).

There is limited published work successfully mapping ASM beyond the local scales, e.g., for whole countries, continents, or globally. Studies such as Maus et al. (2022) and Tang and Werner (2023) have endeavoured to spatially capture the global extent of various mining activities, including both industrial mining and ASM. However, these datasets do not comprehensively represent ASM activities and thus hold limited utility in many regions.

Scaling-up ASM mapping would enrich our understanding of ASM's immediate and cumulative impacts (De Haan et al., 2020; Hilson, 2020; Hilson and Maconachie, 2020). In practice, this would require converting a local-scale workflow to regional, national, and global scales consistently. However, while the RS literature and the case studies to date demonstrate that a range of data and techniques can be used to detect and monitor ASM, the applicability of those specific methods tested locally to other locations or their scalability to regional or global levels remains uncertain.

This paper reviews RS approaches employed for mapping ASM to date to provide the basis for then developing a regional (100 − 500 k km^2) to continental (> 500 k km^2) scale mapping and monitoring programs. We sought to identify areas where additional research could provide the most valuable insights by filling knowledge gaps, building and understanding the role of local factors in choosing appropriate RS approaches enabling the transferability of methods developed in one study to other contexts and identifying cost-effective methods for further application, and where RS could address current limitations of field-based approaches to monitoring ASM in some contexts. Specifically, we were motivated by three research questions:

(1) To what extent do current RS studies represent the geographical distribution and diversity of ASM activities globally?
(2) How do the unique characteristics of ASM operations and the specific local contexts influence the selection of RS approaches for mapping ASM?
(3) Based on an evaluation of RS approaches employed in ASM studies thus far, which methods exhibit the highest levels of accuracy and cost-efficiency?

2. Methodology

2.1. Collating peer-reviewed research papers

We identified 150 papers using Google Scholar with the following key phrases: "artisanal small-scale mining remote sensing", "artisanal small-scale mapping", and "small-scale mining identification and mapping", as of October 2022. We identified an additional eight papers in Scopus and the Web of Science (WoS) using the following query string: "TI/AB = ('artisanal' AND 'small-scale mining' AND ('remote sensing' OR 'satellite' OR 'earth observation' OR 'identification' OR 'monitoring' OR 'spatial analysis'))".

Our search string focused on studies using RS as the primary tool for detecting and mapping ASM, as our review aims to synthesize literature specifically on remote sensing techniques. Broader terms like 'identification' or 'monitoring' would have included studies not prioritizing remote sensing. We excluded papers using GIS modeling, spatial analysis, or other non-RS methods, as they do not meet our objective of evaluating remote sensing's effectiveness in ASM contexts.

The lead author screened titles, abstracts, and full papers, removing duplicates manually. This narrative review focuses on synthesizing literature specific to RS applications in ASM detection and mapping. Given that ASM is loosely defined in the academic literature, for the initial search, we accepted the definition provided by the authors and then followed a three-step process to collate papers for our final review. First, we examined the abstracts of all papers ($n = 158$) to assess their relevance to any ASM detection, mapping, or monitoring attempts using various RS approaches. Only those addressing ASM activities distinct from industrial large-scale mining (LSM) and applying RS as a main or auxiliary tool were deemed relevant. Second, we thoroughly read all pertinent papers ($n = 85$) to further select those that (1) employed an RS approach to identify and map ASM sites or proxy indicators of ASM, and (2) defined ASM and outlined a method for mapping ASM distinct from the identification of any LSM activity. Lastly, we applied snowball literature sampling on the identified papers ($n = 55$) to incorporate any additional relevant articles meeting the criteria, resulting in 57 papers which hereafter we refer to as 'study'. This review may have biases: language bias from only English papers, selection bias from specific criteria, snowballing bias from key studies, and database bias excluding niche journals. We also excluded grey literature like technical reports, white papers, theses, and conference proceedings.

2.2. Data compilation and categorization

We compiled a database to summarize key variables related to the location and the scope and methodology of the studies. This includes ASM commodity, mining or extraction method, the average size of the mining site, features used for identification, sensors (type of RS imagery or data), and the recognition method (Table 1).

We documented the 'commodities' mined to identify the predominant resources extracted by ASM. We classified studies that reported the extraction of more than two commodities into two distinct categories: "Metalliferous" for studies reporting the mining of various metals and "Crystalline" for those associated with the mining of crystal resources (McKenna et al., 2020). Furthermore, we recorded the type of extraction method or "mining methods". This included a broad spectrum of techniques such as open-pit mining, dredging, sluicing, shaft mining, underground mining, and a category termed "mixed method." The mixed method category encompasses studies that report a combination of extraction techniques for different commodities within a single investigation.

Following the categorization by McKenna et al. (2020), we classified RS sensors used by reviewed studies into five groups. For studies employing optical satellite imagery, we classified the sensors as follows: "EO High" represents Earth observation with high spatial resolution (<5 m); "EO Medium" denotes Earth observation with medium spatial resolution (5–30 m); and "EO Low" signifies Earth observation with low spatial resolution (>30 m). The remaining two sensor categories encompass "SAR" for satellite synthetic aperture radar and "UAS" for high-resolution imagery obtained via unoccupied aerial systems.

We classified the average size of ASM sites as either smaller or larger than 5 ha. This distinction was based on an estimation of the minimal mining site size that can easily be identified, with minimal errors, by optical satellite imagery with medium to low spatial resolution using a pixel-based classification technique (Smith et al., 2019). Furthermore, the "identification" of mining areas was categorized based on whether they were directly discerned from the surface footprint (e.g., mining pit, sluicing area, and tailings) or inferred from proxy indicators (e.g., nightlights and water siltation).

The "Recognition Method" encompasses both the identification of surface features (detection) and the categorization of these features (classification), which we classified into seven categories. "Pixel-based" methods assess the similarity of pixels for specific land cover types, while "Subpixel-based" techniques analyze the blend of land cover present within each pixel. In contrast, "Object-based" and

Table 1
Variables used to categorize the scope and methodology of each study in this review.

Variables				
Commodity	Mining method	Identification feature	RS imagery	Recognition method
Metalliferous	Dredging	Mining site	EO Low (> 30 m)	Advanced classification techniques
			EO Medium (5–30 m)	
– Nickel	– Underwater excavation of placer deposit.	– Mining pit	EO High (< 5 m)	Digitization
– Tin	Sluicing	– Mining sluicing area	SAR (Synthetic Aperture Radar)	Interferometry
– Iron		– Tailing facilities		Pixel-based
– Gold	– Gold-bearing gravels are washed down by sprayed jets of water.	– Mining dredging area	UAS (Unoccupied Aerial System)	Subpixel-based
– Copper		Proxy indicator		Segmentation-based
– Coltan	Shaft			Object-based (GEOBIA)
– Manganese		– Nightlights		
– Bauxite	– Ores and minerals were excavated using vertical shafts.	– Greenness and moisture index		
	Underground			
Crystalline		– Water siltation		
	– Extraction of ores and minerals from underground deposit veins.	– Backscatter changes		
– Amethyst		– Surface soil displacement		
– Diamond	Open-pit			
– Cassiterite				
– Monazite	– Extract ores and minerals from an open pit after top-soil removal.			
– Tantalite				
– Tourmaline	Mixed mining methods			
Crocidolite				
Cobalt				
Emerald				
Limestone				

"Segmentation-based" approaches focus on detecting objects and segments rather than individual pixels. "Interferometry" is applied to SAR images. Studies that manually mapped and digitized ASM from RS imagery without utilizing the aforementioned methods were categorized as "Digitization." The term "Advanced classification techniques" refers to detection and classification methods that employ more complex algorithms, such as deep learning models (e.g., Convolutional Neural Networks).

2.3. Data analysis

To assess the global distribution of ASM mapping studies (Question 1), we extracted the country of origin for each paper based on the reported study location. We subsequently mapped the distribution of studies using QGIS (ver. 3.20.0) and the ASM-dependent population map derived from Dorner et al. (2012). We quantified the count of each categorical variable and compiled the reported accuracy results. The average size of ASM target studies was calculated from the average extent of mining sites reported in the papers to elucidate the impact of satellite image selection on the extent of detectable ASM. We used the "ggalluvial" package (Brunson and Read, 2020) to create alluvial charts, illustrating the proportions and interconnectedness of data within and between variables (Question 2).

Furthermore, we compiled the accuracy levels reported in the studies, sorted them into the "recognition method" categories and the RS sensors used, and then calculated minimum, maximum, and average values (Question 3). It is essential to note that we collected accuracy levels reported by authors from the collated studies, each employing different validation approaches, and then averaged these values within their respective 'recognition method' groups. However, data training and test distribution, specific environmental, local biophysical factors, particular ASM types, and other site-specific factors that might influence the accuracy of the methods were not considered (Lyons et al., 2018; Morales-Barquero et al., 2019).

3. Results and discussion

3.1. Geographical distribution and commodity focus of RS-based ASM mapping

Our analysis shows a significant research focus on RS-based ASM mapping in central-western African countries, specifically Congo and Ghana, with gold, cassiterite, and diamonds as the main mined commodities (e.g., Barenblitt et al. (2021), Kranz et al. (2017), and Snapir et al. (2017)). This observation is substantiated by the 15 and 19 publications generated in these countries on the subject, underscoring the growing interest in ASM monitoring within the region (Fig. 1). However, of the 72 countries with a large ASM-dependent population (Dorner et al., 2012), only 15 countries have been the subject of active, peer-reviewed RS-based studies aimed at monitoring ASM.

Consequently, the current RS efforts inadequately reflect the global geographical distribution of ASM activities, given the considerable research gap for countries with a large ASM-dependent population, such as the Central African Republic (CAR), Niger, Sierra Leone, and Zimbabwe (Fig. 2). The call to extend RS to these lesser-studied regions, rich in minerals such as nickel, copper, and diamond, is clear (Hilson et al., 2019; Jaillon and De Brier, 2019; Maconachie, 2009). Such diversification would not only aim in an effort to manage this sector for environmental and social benefits, but it would also offer a much more holistic global view of ASM. Enhanced datasets are instrumental in devising effective policies (McQuilken and Hilson, 2016).

Several factors, ranging from site accessibility and data availability to policy priorities, shape this research bias. Remote regions with ASM activities pose significant research challenges, due to infrastructure

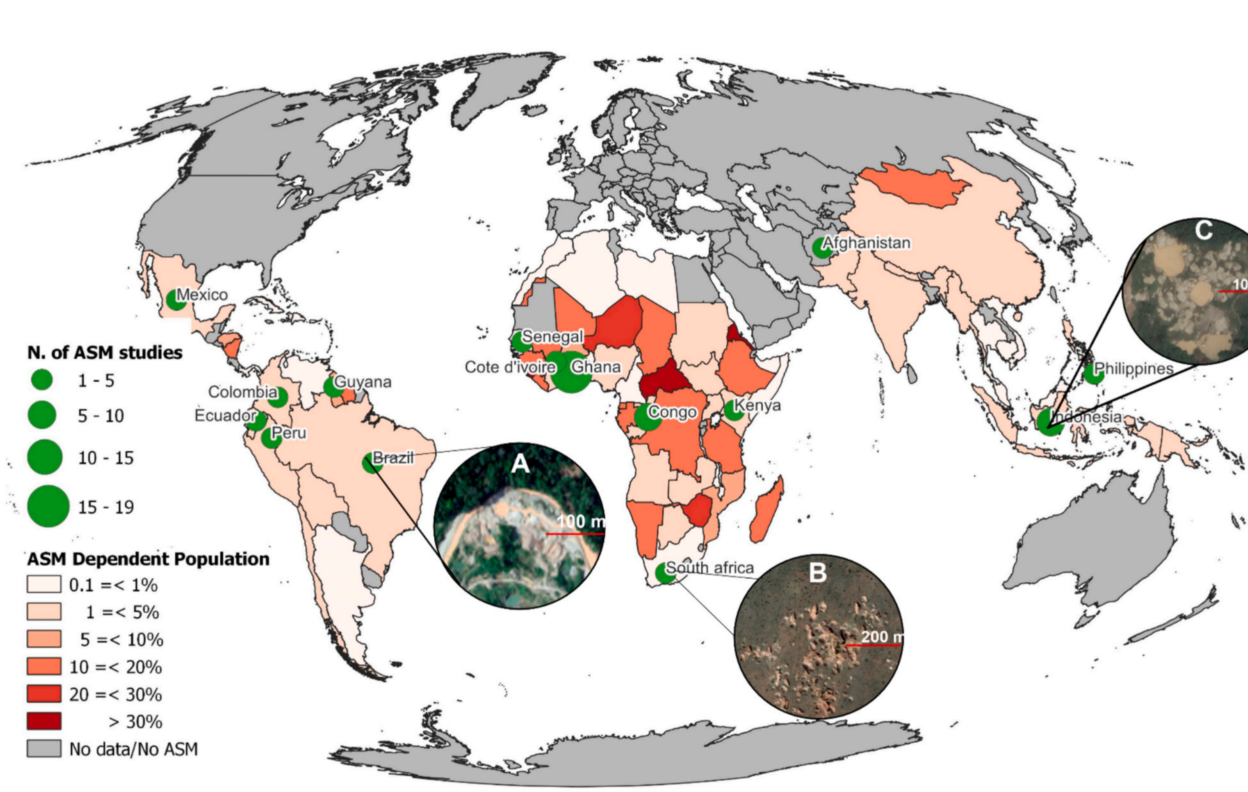

Fig. 1. Geographic distribution of the studies, percentage population that depends on ASM (World-Bank-Group, 2019), and the example of ASM surface footprint (Google Earth 2023 imageries). A. Small-scale gold mining in Amazon Forest Brazil; B. Crocidolite mining in Prieska town, South Africa; C. Small-scale gold mining in West-Kalimantan, Indonesia.

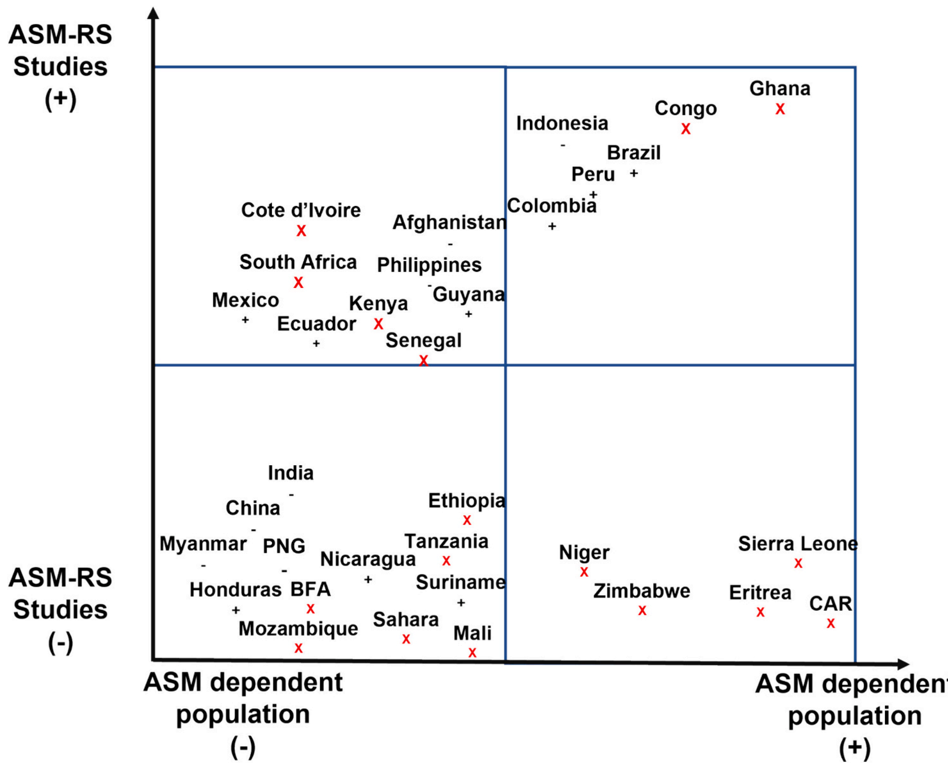

Fig. 2. A schematic representation depicts the relationship between selected countries' population dependency on ASM and the intensity of ASM RS studies, ranging from nonexistence to the highest recorded number of peer-reviewed studies. The axis represents a spectrum with non-quantitative units. The countries featured in this figure address both legal and illicit ASM concerns. Symbols denote regional categorization: (x) represents African nations, (−) corresponds to Asian nations, and (+) signifies American nations.

deficits, security threats, and logistical hurdles, hampering field research and vital ground data acquisition (Wagner and Hunter, 2020). Furthermore, the availability of publicly accessible, open-access satellite imagery data also varies regionally, with certain areas having better coverage. For example, high cloud coverage and frequency in wet-tropical regions limit usable optical satellite imagery availability

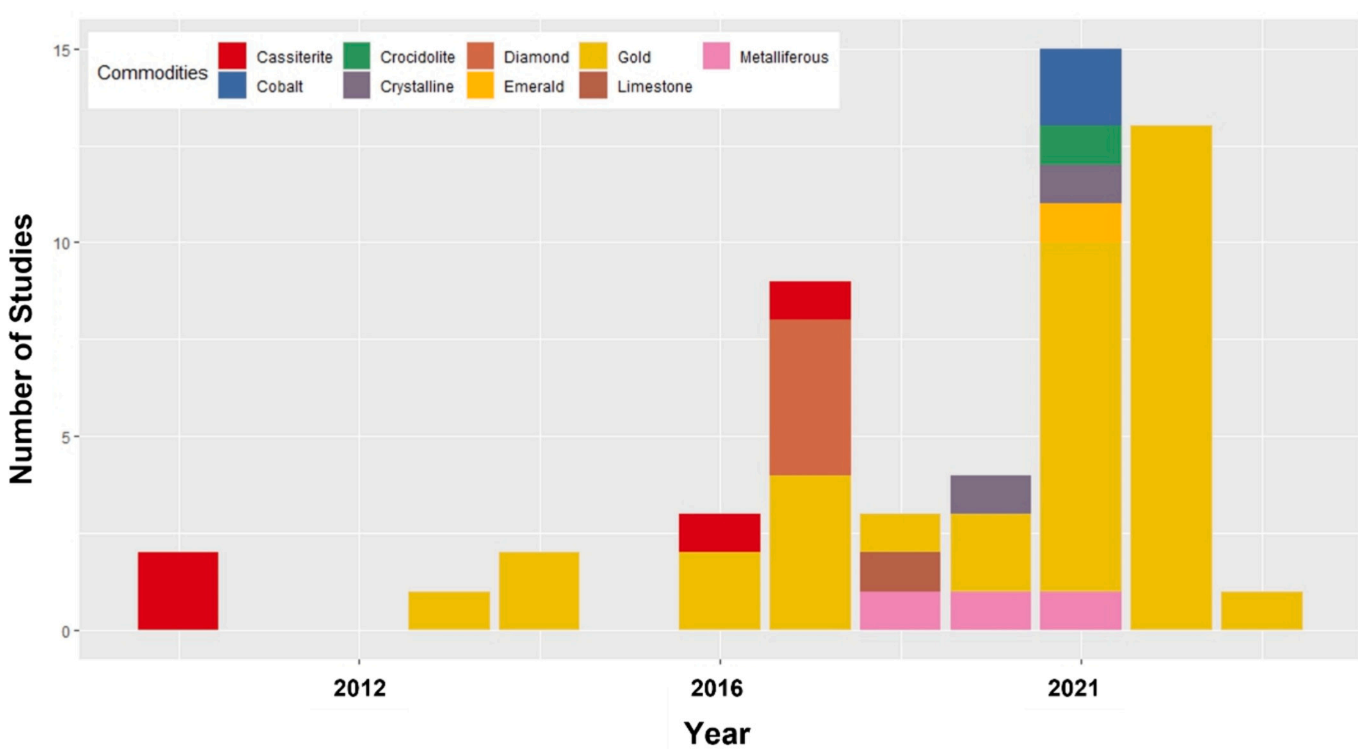

Fig. 3. Stacked bar charts of the publication numbers for each year, according to the mined commodity.

compared to drier environments (Laborde et al., 2017).

Policy priorities and funding allocation also influence research focus in ASM mapping. Certain countries or regions may receive more attention due to political, economic, or environmental considerations (Hilson, 2002; Hilson and McQuilken, 2014). Furthermore, the dearth of knowledge regarding the complexity of ASM-related impacts, lack of clarity in the policy framework, and resource limitations contribute to the monitoring approaches deployed by the countries hosting ASM problems (Hentschel et al., 2002; Miserendino et al., 2013). These factors collectively contribute to the observed biases in RS-based ASM mapping, highlighting the need for a more comprehensive and inclusive approach to address the global distribution of ASM activities and their associated environmental impacts.

Published RS-based mapping studies to date focused on gold as the most extensively investigated commodity, followed by diamond, cassiterite, and a variety of metalliferous materials (Fig. 3: e.g., Ibrahim et al. (2020), Ngom et al. (2020), and Obodai et al. (2019)). However, a comprehensive global picture of ASM commodities, including coal and sand, remains scarce. This bias may arise from the global prevalence of ASGM, attributed to its simple extraction process and easy market access (Schwartz et al., 2021; Seccatore et al., 2014). Broadening RS research, especially in areas like China and India where coal and sand ASM are common (Deb et al., 2008; Shen and Gunson, 2006), is crucial. Such expansion would contribute to determining the suitable RS mapping strategies for these distinct environmental settings.

3.2. Context-dependent selection of RS data and recognition methods for ASM mapping

The alluvial chart (Fig. 4) illustrates the distribution and interrelationships among variables and categories in RS studies of ASM. Each category, represented by a bar (nodes), represents the proportion of related publications. Our findings show a focus on open-pit ASM, being the most studied extraction method (27 studies). This type of ASM, typically clustered and easily identifiable, is mostly mapped using EO Medium and well-established pixel-based or sub-pixel-based methods (e.g., Kumi-Boateng and Stemn (2020) and Elmes et al. (2014)). These activities often occur near rivers, producing distinct surface footprints, such as interconnected irregular pits, tailings, and pit-lakes.

Contrary to clustered ASM, some mining sites are more dispersed, covering areas of <5 ha and utilizing less discernible techniques like panning and dredging. These methods may not be readily identifiable through lower-resolution imagery. Such types of ASM can be mapped using high-resolution imagery, employing object-based, segmentation-based, and digitization approaches (e.g., Aggrey et al. (2021), Bona et al. (2018), and Janse van Rensburg and Kemp (2022)).

We also found that studies were often conducted in regions with mixed ASM extraction methods, which encompass a range of extraction techniques for different commodities within a single investigation (e.g., open-pit mining, sluicing, and panning). These studies exhibit a similar inclination toward sensor type selection based on the average ASM sizes within the studied area (e.g., Isidro et al. (2017) and Nyamekye et al. (2021)), Sentinel-2 for clustered ASM sites with an extent of >10km^2. They focus on identifying easily recognizable features such as lunar-shaped pits, pit-lakes, sluicing machines, or clusters of miner tents in alluvial areas.

Research on mapping underground ASM, such as cobalt tunnel mines in the DRC, is limited to 5 papers. Detecting underground mining features, such as tunnel openings, excavated materials, semi-permanent buildings, and pathways associated with underground mining, requires costly EO High imagery with a resolution of <1 m, such as Worldview-2 and UAS (DeWitt et al., 2022). More cost-effective alternatives such as open-access SAR data can be used for surface deformation and subsidence analysis cover (e.g., Ammirati et al. (2020) and Brown et al. (2020)), overcoming the EO Medium limitations (Moreira et al., 2013).

3.3. Accuracy and cost-effectiveness of RS approaches in ASM mapping

Evaluating the effectiveness of RS mapping methods revealed varying accuracy levels, influenced by the mining operation's context and scale. We do note that accuracy estimates for one study may not be

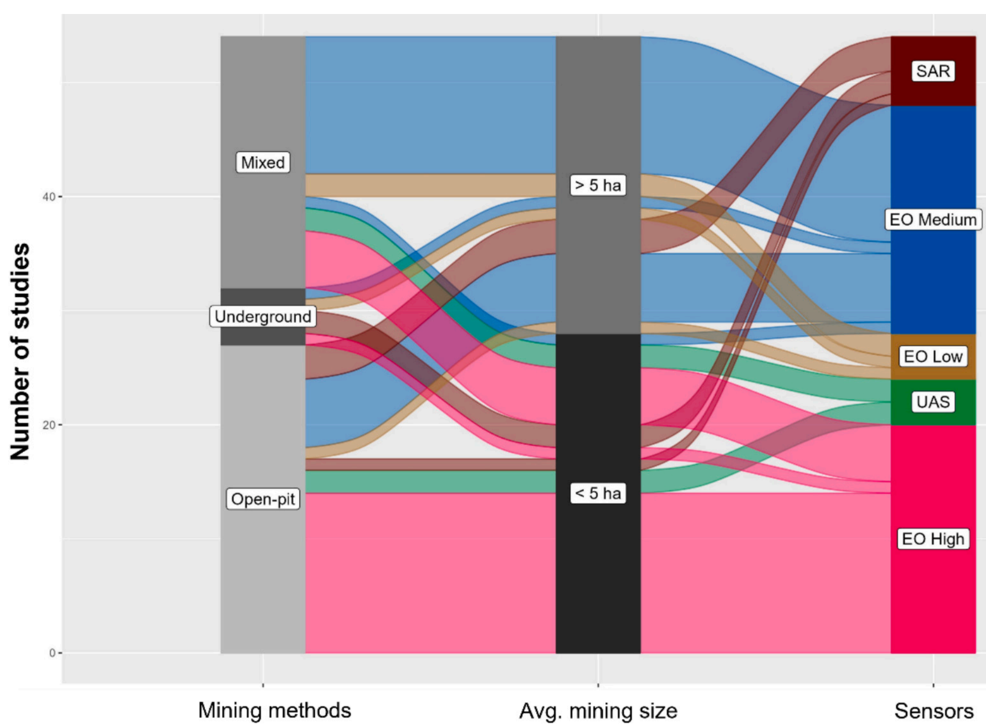

Fig. 4. Alluvial diagram demonstrating the proportions within variables and the correlation between variables of ASM mapping efforts using RS technologies and methods.

suitable for comparison with those of another – as the studies used widely varying types of error and accuracy assessment approaches, with large variations in critical factors such as the number and distribution of validation or reference data (Lyons et al., 2018; Morales-Barquero et al., 2019). The manual digitization method, predominantly utilizing EO High, reported the highest average accuracy (97 %; Table 2) and appeared most effective for monitoring ASM sites smaller than 5 ha, informally regulated mining sites, and even underground mining, enabling detailed assessments and precise spatial records (e.g., Ahmed et al. (2021) and DeWitt et al. (2022)). Object-based and segmentation-based approaches, also mainly applied to EO High, achieved relatively high average accuracies of 87.6 % and 87.1 %, respectively. These methods were capable of mapping small ASM sites (<5 ha) albeit limited to site-specific or local-scale investigations (e.g., Schoepfer et al. (2010) and Stoll et al. (2022)).

The pixel-based approach using EO medium was the most common and reliable method for congregated ASM sites (Fig. 5), with an average reported accuracy of 89.6 % (e.g., Hausermann et al. (2018)). To map in forested areas where there is mixed spectral information per pixel, the sub-pixel-based classification utilizing low- to medium-spatial resolution imagery can produce high accuracy (average of 93.3 % in Asner et al. (2013) and Elmes et al. (2014). More advanced classification techniques, such as deep learning algorithms, have achieved 95.8 % accuracy for mapping open-pit ASM (e.g., Camalan et al. (2022) and Kimijima et al. (2022)).

The recent use of interferometry from SAR imagery shows promise in mapping both open-pit and underground ASM through surface deformation and subsidence analysis (Monserrat et al., 2014). However, interferometry is sensitive to vegetation coverage, temporal decorrelation, and temporal phase aliasing, affecting the accuracy of this approach and restricting its applicability to specific environmental contexts such as sparsely vegetated areas and not forests (Manconi, 2019; Rocca et al., 2000).

Taken together, the selection of an appropriate recognition method for ASM mapping depends on the specific characteristics of ASM activities (size, above or below ground), available data sources, context (forests versus sparse vegetation), and the spatial and temporal detail required. There is a diverse range of approaches with strengths and limitations, and decisions also depend on skills capacity and computational resources.

In the context of mapping ASM using RS, cost-effectiveness analysis illuminates the trade-offs between the detail of maps, spatial resolution, and financial requirements. Among the methods examined in this review, employing EO Medium imagery stands out as the most cost-effective option, striking a balance between cost and accuracy (Table 3). This is due to most EO medium images being freely accessible, and expenses may primarily arise from fieldwork or software procurement.

Table 2
Summary of overall map accuracies taken from studies in the review that quantified overall map accuracies.

Recognition method	Sensor (Avg[min-Max]: N)				
	EO Low	EO Medium	EO High	SAR	UAS
Advanced Classiffcation Techniques		95.8 [92–99.6]:2		79 [76–82.1]:2	
Digitization	93:1		94.6 [83.3–99]:8		
Interferometry				85.1 [83–89.6]:4	
Object-based		88:1	87.2 [84–93]:8		96.5:1
Pixel-based	92 [85.1–99]:2	89.6 [72.6–98]:2	95 [92–98]:2		90.9:1
Segmentation-based			87 [85–89]:2		
Subpixel-based	86:1	93.3 [87–99]:2			

While EO High images provide greater detail and superior accuracy, they come at higher costs, making them more applicable for site-specific or local investigations. Similarly, UAS offers higher resolution than satellite imagery, yet is only optimal for site-specific studies (e.g., Chirico and DeWitt (2017)). High costs notwithstanding, detailed high-spatial-resolution data is crucial for handling individual, informally regulated, or conflict-associated ASM sites (Kranz et al., 2016; Schoepfer et al., 2010).Finally, SAR imagery offers a unique advantage in detecting changes in surface topography related to mining activities and remains relatively unaffected by cloud coverage (Moreira et al., 2013). However, the cost-effectiveness of acquiring commercially high-resolution SAR data should be considered, despite the current availability of cost-free, medium-resolution SAR.

3.4. Future research directions and RS advances needed to map ASM beyond the local scale

Scaling up ASM mapping requires rigorous methodologies, robust data resources, and advanced processing capabilities. Mapping ASM in lesser-explored regions offers a unique opportunity to assess various methodologies in diverse contexts. Integrating open-source, multi-type RS data with cloud-based platforms like Google Earth Engine (GEE) is crucial due to GEE's exemplary storage and computational capabilities. This approach provides access to global, consistently collected datasets. Enhancing these datasets requires building local capacity, particularly in collecting ground-validated ASM spatial data and interpreting proxy data as foundational or supplementary resources.

The effectiveness of ASM mapping beyond the local scale is constrained by the quality of satellite imagery. Common challenges with multispectral products include cloud cover and forest canopy obstructions (Isidro et al., 2017; Lobo et al., 2016). While SAR images are less affected by these issues, speckle issues can compromise classification accuracies (Maghsoudi et al., 2012). The integration of multispectral and SAR datasets, known as data fusion, can offset the limitations of each type individually. While multispectral-SAR data fusion offers the potential for enhanced ASM mapping accuracy, challenges related to data storage and processing persist (Moomen et al., 2022). Nevertheless, leveraging cloud-based geoprocessing platforms may mitigate these challenges (Mutanga and Kumar, 2019). This combined approach provides a promising, cost-effective solution for efficient and sustained ASM monitoring at a regional scale, especially vital for developing nations addressing ASM-related issues.

Effective ASM monitoring also requires ample training and test data, acknowledging that data collection is often labour-intensive and resource-demanding. When ground-checked data is scarce, alternative avenues to source reliable spatial data are needed. These options may include (1) manual interpretation of free EO High imagery like Google Earth, (2) utilization of global digitized mining datasets, such as Allan et al. (2023), Maus et al. (2022), or Tang and Werner (2023), or (3) reports from governmental and non-governmental organizations documenting confirmed ASM sites. Additionally, diving deeper into proxy data sources—from RS-analyzed social media feeds to citizen science insights and environmental markers like tainted vegetation, soil anomalies, and nightlight patterns—can shed light on the more informal ASM operations although with some limitations (e.g., Kyba et al. (2019); Kimijima et al. (2021); Levin et al. (2020); Kimijima et al. (2022); and (Allan et al., 2023)).

Furthermore, to enhance training and validation efforts, we propose establishing localized training programs in collaboration with local universities and research institutions. These programs will build capacity in remote sensing techniques specific to ASM detection and

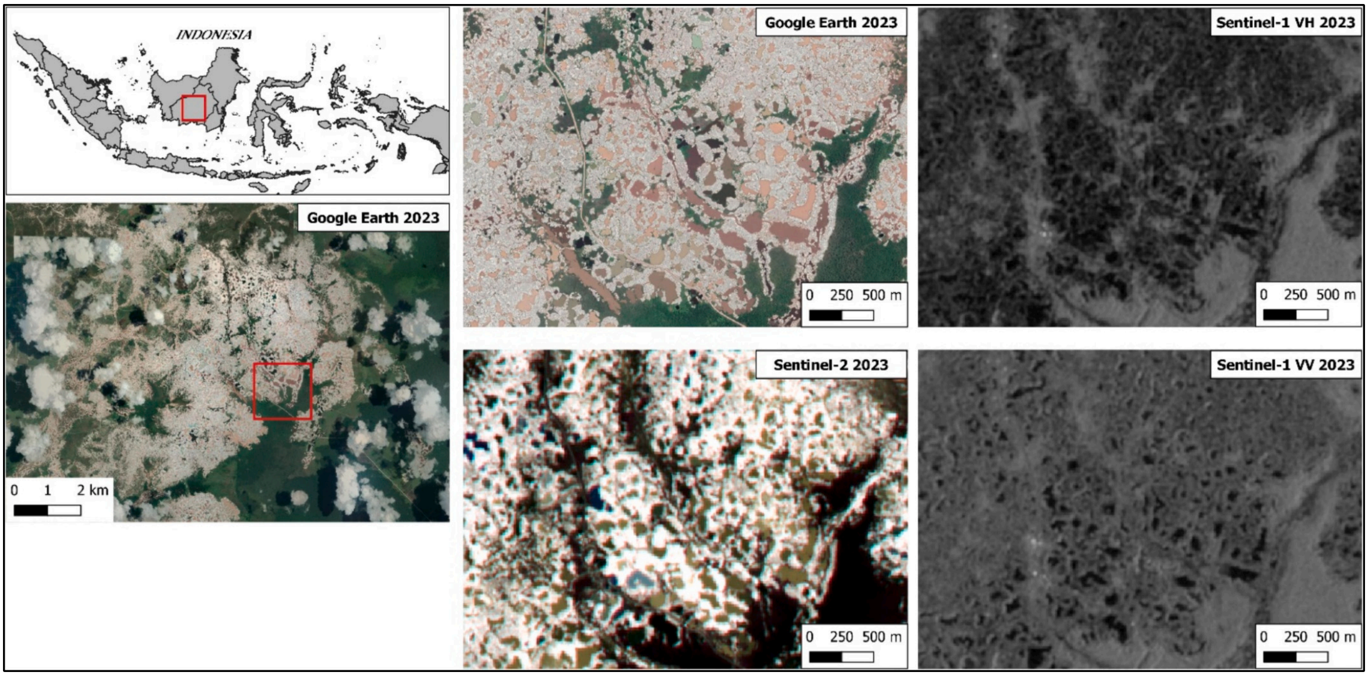

Fig. 5. Illustration of surface features in a congregated artisanal small-scale gold mining area in Kalimantan, Indonesia, depicted using multispectral Google and Sentinel-2 imagery (5–4-3 bands composite; 10 m pixel resolution), as well as Sentinel-1 SAR with VV (vertical-vertical) and VH (vertical-horizontal) polarizations (10 m pixel resolution).

monitoring adapted to local conditions and needs. In regions with significant security and logistical challenges, such as Central African Repulic and Niger, remote training modules and virtual collaboration tools can provide ongoing support and capacity building, including online courses, webinars, and workshops. Partnering with local NGOs already working in these regions can support and facilitate on-the-ground implementation.

Transitioning from research to application, local governments should proactively incorporate RS approaches into ASM mapping and monitoring strategies rather than relying solely on external research. We encourage personnel from mining regulatory agencies or related public sectors to invest strategically in enhancing their RS expertise. Collaboration with the scientific community and local universities to foster capacity-building and consultation efforts may also yield benefits (Moomen et al., 2019). International organizations and funding agencies should actively engage in discussions and dissemination of RS opportunities, especially for monitoring ASM activities in remote regions (Moomen et al., 2022). Strengthening local stakeholder capacity, including researchers, officials, community representatives, and miners, is crucial for a participatory approach in ASM monitoring. Organizing regional workshops and conferences in safer neighboring countries, like Ghana or Senegal, and creating regional hubs with existing centers of excellence in remote sensing and mining research will foster cross-sector partnerships. Formal collaborations with international research organizations and leveraging China's technological infrastructure through partnerships with institutions like the Chinese Academy of Sciences can pilot advanced remote sensing techniques for ASM detection and monitoring, ensuring integration of cutting-edge methodologies.

When extended beyond local scales, spatial data offers new tools to understand the socioeconomic and environmental complexities of ASM activities, providing insights into formalization, cultural shifts, livelihoods, infrastructure, and community welfare (Ang et al., 2023; Hilson et al., 2022). Unlike traditional non-spatial or field-based methodologies, this approach visualizes connections between causative factors and mining consequences, as demonstrated by case studies on land-use conflicts and social acceptance (Malone et al., 2023; Rustad et al., 2016). Integrating various socio-economic and environmental metrics, spatial data emphasizes collaboration and knowledge-sharing platforms like DELVE (https://delvedatabase.org/) for disseminating spatial data and best practices. These platforms facilitate information exchange among stakeholders, supporting effective policy development and interventions.

4. Conclusion

ASM mapping encounters challenges due to the site-specific nature of ASM issues, including the diverse nature of this activity, and limitations to map and monitor it with RS. However, opportunities for rapid studies persist in regions heavily dependent on ASM and where extensive extraction of ASM commodities occurs. Adapting RS techniques to the unique features of ASM, whether they are congregated or dispersed informal mining sites, using appropriate imagery and analysis methods, can significantly enhance detection and monitoring capabilities. Nevertheless, it is essential to emphasize that further research is still needed to address existing knowledge gaps in mapping underground ASM and to explore more cost-effective mapping approaches.

Another pivotal aspect in scaling up ASM mapping is the intricate balance between the level of detail, spatial resolution, and budgetary constraints. Cloud-based geoprocessing platforms with vast satellite archives emerge as promising tools for scalable ASM mapping. Additionally, the fusion of multispectral and imaging radar data can leverage the strengths of both RS data types while mitigating their individual limitations. Crucially, ensuring a thorough gathering of training and validation data is critical for dependable analysis. Collaborations with local communities and a deeper grasp of proxy data can bolster data acquisition, especially in data-scarce regions. By crafting bespoke mapping systems that engage local stakeholders and incorporate additional data such as social media insights, a more inclusive and partnership-driven ASM mapping approach emerges. Harnessing cloud platforms to amalgamate these elements fosters a cooperative framework, simplifying RS processing available online and enabling regular updates—paving the way for a cooperative regional or even global ASM mapping and monitoring initiative.

Accurate mapping of ASM can reveal its true contribution to

Table 3
Key characteristics and appropriate mapping applications for selected examples of active and passive RS imagery in ASM studies.

EO programs (sensors)	Cost	No. of Studies	Features	ASM mapping application
UAS (Drone)	Very high (Hired services start from USD1,400/ 100 ha)	3	These products achieve a very high spatial resolution of up to centimetres and provide varied multispectral data types depending on the attached sensor.	Appropriate only for mapping local scale mining sites, including small sites (<5 ha) and underground mining sites, as well as the equipment used by miners.
Geoeye-1	Very high (USD10.00/ Km^2)	2	These products achieve a very high spatial resolution of 40 cm for panchromatic and 1.65 m for multispectral imagery, which includes RGB and Near InfraRed-NIR bands. Additionally, it has a high temporal resolution of 2–9 days and a sufficient footprint width of 15.2 km.	Suitable for local-scale mapping to a larger extent than drones and potentially lower cost per square kilometre. It is capable of mapping very small mining sites (<5 ha), including underground mining sites.
Sentinel-2	Freely available	14	These products have a medium to coarse spatial resolution ranging from 10 m to 60 m and 12 bands, including the SWIR band, with a radiometric resolution of 16 bits. It also offers a decent temporal resolution of 5 days and can cover an area of 170 × 185 km per scene.	Suitable for regional to global-scale mapping, this program is capable of mapping individual mining sites with an extent of >5 ha. However, it is incapable of mapping smaller mining sites, including underground mining. The program has a higher temporal resolution than the Landsat program, which increases the accuracy of temporal analysis.
Sentinel-1	Freely available	5	Sentinel-1 is a Synthetic Aperture Radar (SAR) satellite that provides high-resolution (up to 5 m) images with a wide swath (up to 400 km) and all-weather, day-and-night imaging capabilities.	Sentinel-1 is capable of regional to global-scale mapping and can effectively map mining sites with an extent of less than 5 ha, including underground mining, with a higher temporal resolution than the Landsat program, thereby increasing the accuracy of temporal analysis.

Note: The current estimated prices are based on the rates for services found on the internet as of 16/05/2023.

development and counter negative narratives about the sector. We emphasize the importance of standardized remote sensing methods facilitating better data sharing and aggregation among stakeholders for more effective collaboration and knowledge exchange. Global platforms for ASM data, which aim to address issues of inaccurate and incomplete data, can benefit significantly from these improved remote sensing methods.

CRediT authorship contribution statement

Ilyas Nursamsi: Conceptualization, Data curation, Methodology, Writing – original draft. **Stuart R. Phinn:** Writing – review & editing. **Noam Levin:** Writing – review & editing. **Matthew Scott Luskin:** Writing – review & editing. **Laura Jane Sonter:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Consent to participate

All authors consented to participate in the research and the elaboration of the manuscript.

Consent for publication

All authors have approved the contents of the manuscript and agreed with its submission.

Ethical approval

Not applicable.

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