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Original paper

Detection of surface coal mining areas from remote sensing data based on the Google Earth Engine cloud computing platform

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Abstract: Surface Coal Mining Areas (SCMAs) refer to regions affected by open-pit coal mining activities, including extraction sites and associated waste disposal zones. This study proposes the methodology for SCMA detecting in Cam Pha and Ha Long regions (Quang Ninh province, northern Vietnam) from remote sensing data based on Google Earth Engine (GEE) cloud computing platform. The remote sensing data used in this study consists of multispectral satellite images from Landsat 8 OLI_TIRS. Processing remote sensing data to detect SCMA includes the following steps: image segmentation using SNIC algorithm (Simple Non-Iterative Clustering), spectral index calculation from Landsat images, threshold-based classification, and spatial analysis to delineate extracting areas (EA) and stripped/dumping areas (SA-DA). The results indicate that Cam Pha has a larger EA (11.98 km^2) and SA-DA (17.09 km^2) compared to Ha Long (6.36 km^2 and 3.59 km^2), respectively. In contrast, Ha Long exhibits a higher EA/SA-DA ratio (1.77), suggesting more land reclamation, while Cam Pha has extensive mining waste accumulation (0.70). These findings highlight the severe environmental degradation caused by coal mining, emphasizing the need for sustainable land management. The SCMA detection approach in GEE provides an efficient, scalable method for real-time monitoring, long-term change detection, and environmental restoration planning in mining regions.

Keywords: Vietnam, remote sensing, GEE, surface coal mining areas (SCMA)

1. Introduction

In recent years, the global demand for energy has been steadily increasing, leading to a rise in mineral resource extraction activities, particularly coal mining (Carvalho, 2017; Song et al., 2025). Coal is one of the most important natural resources; however, its extraction comes with numerous negative environmental impacts, including soil degradation, air and water pollution, and the destruction of natural ecosystems (Finkelman et al., 2021; Tasev et al., 2025). Therefore, monitoring and managing coal mining areas is critical to mitigating these harmful effects on the environment and surrounding communities (Şalap et al., 2009; Wang et al., 2021).

Traditional methods of detecting and monitoring coal mining areas often require direct intervention and can be costly and time-consuming (Tong et al., 2015; Fernández-Lozano et al., 2018). However, with the rapid development of remote sensing technology, particularly the use of satellite imagery, this process has become more efficient and cost-effective. Satellite imagery provides vast, high-resolution, and frequent data, allowing for real-time monitoring of changes in mining areas, which supports decision-making and environmental protection planning by managers and authorities (Paradella et al., 2015; Kimijima and Nagai, 2023).

Currently, several methods are used to detect SCMAs from satellite imagery (Mukherjee et al., 2019). These methods include spectral index-based and machine learning-based detection. Indices are commonly employed to differentiate mining areas from other land types. These indices help identify areas lacking vegetation, barren land, or surfaces impacted by mining activities (Fernández-Manso et al., 2012; Zeng et al., 2017). However, they are often limited in distinguishing complex land cover types, particularly in heterogeneous mining environments. Recent studies have also explored multi-index approaches that integrate several spectral indices simultaneously, aiming to improve discrimination accuracy in complex mining landscapes (Zeng et al., 2018). Such multi-index approaches can leverage the complementary strengths of different indices, enhancing robustness against spectral confusion and environmental variability. In addition, machine learning techniques such as Random Forest (RF) (Chen et al., 2017; Yu et al., 2022), Support Vector Machine (SVM) (Karan and Samadder, 2016; Chen et al., 2019), and Artificial Neural Networks (ANN) (Yilmaz et al., 2018; Abaidoo et al., 2019) have been applied to classify mining areas. Nevertheless, these methods typically require extensive ground truth data and careful parameter tuning, which may not always be available or feasible in large-scale applications. Therefore, there is a trade-off between simplicity and accuracy in previous approaches, highlighting the need for a more balanced method that is both effective and scalable.

One of the powerful tools for processing and analyzing satellite imagery today is the Google Earth Engine (GEE) platform. GEE offers the ability to process large-scale remote sensing data rapidly, allowing users to access an enormous satellite image database, including images from various satellites such as Landsat, Sentinel, and MODIS (GEE, 2025b). Leveraging GEE's advanced computational capacity, studies on coal mining monitoring can perform spatial analysis, calculate spectral indices, classify, and identify mining areas effectively, thus supporting resource and environmental monitoring.

This study aims to detect surface coal mining areas in Cam Pha and Ha Long, Vietnam, by integrating Landsat image and spectral indices including NDVI, NDCI, and BAI. The proposed method employs the SNIC (Simple Non-Iterative Clustering) algorithm for image segmentation, as it efficiently produces compact and uniform super pixels while preserving object boundaries, thereby enhancing the accuracy of subsequent threshold-based classification used to delineate extracting and stripped/dumping areas. The entire workflow is implemented on GEE to take advantage of its large-scale data processing capabilities. This setup is intended to support a scalable and efficient framework for environmental monitoring in mining regions and is expected to provide new insights into the spatial distribution and extent of mining impacts, as demonstrated in subsequent analyses.

2. Materials and methodology

2.1. Study area

Ha Long and Cam Pha, located in Quang Ninh province in northeastern Vietnam, feature a diverse terrain consisting of coastal areas, islands, mountains, and mining zones (Dang et al., 2021). Ha Long city primarily develops along the coastline, with gradually sloping terrain extending into the bay, where thousands of limestone islands create the unique landscape of Ha Long Bay. In contrast, Cam Pha, situated to the east, is predominantly mountainous and heavily fragmented by large-scale coal mining operations. This area contains numerous mining waste dumps and land that has been altered due to mineral extraction, significantly impacting the environment and coastal ecosystems. The combination of coastal and mining landscapes creates a stark contrast between the two cities and poses significant challenges for sustainable development (Nguyen et al., 2022).

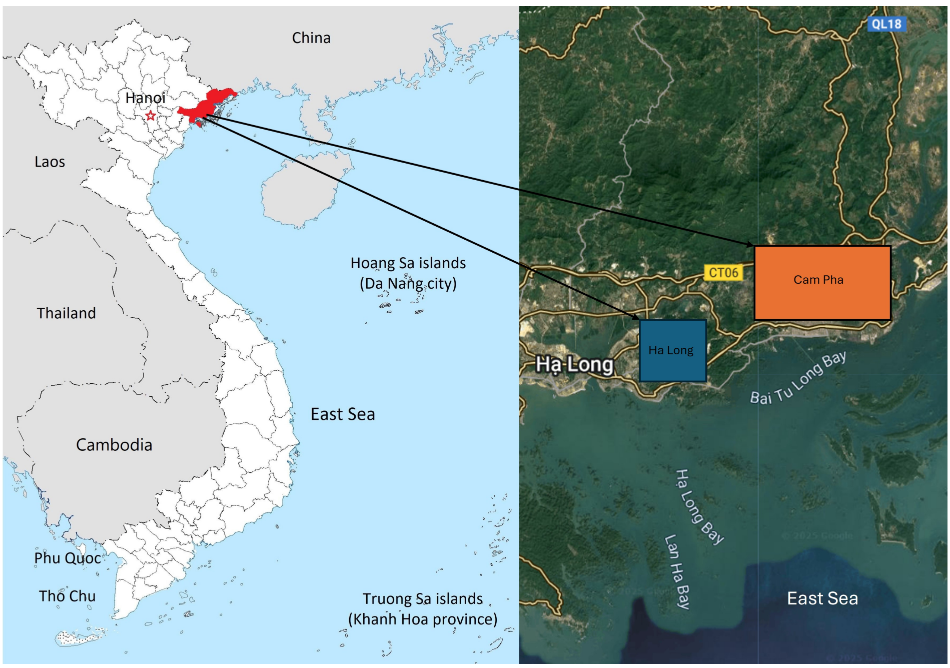

Fig. 1. Location of the study area

Ha Long and Cam Pha exhibit a distinct distribution of EA, SA, and DA, where large open-pit coal mines dominate. EA zones are concentrated in major mining sites such as Mong Duong, Coc Sau, and Cao Son, where high-intensity coal extraction takes place (Van Pham et al., 2021). Surrounding the EA zones, SA and DA areas consist of stripped vegetation zones and coal waste dumps, which significantly affect soil quality, water sources, and air pollution levels. Sediment deposition and pollution from coal waste pose threats to coastal ecosystems, especially in Ha Long Bay and its surroundings.

2.2. Data

Landsat data is a collection of satellite imagery gathered since 1972 through a collaboration between NASA and the U.S. Geological Survey (USGS), aiming to provide detailed information about Earth's surface (NASA, 2025; USGS, 2025b). These images assist in environmental monitoring, natural resource management, and climate change research. Landsat satellites offer data with a spatial resolution of 30 meters and a global revisit cycle of 16 days. In this study, Landsat 8 imagery acquired on November 7, 2024 was used to support analysis. Landsat data is freely accessible through platforms like Google Earth Engine and USGS Earth Explorer (GEE, 2025b; USGS, 2025a).

2.3. Methodology

The study proposes a robust method for detecting SCMAs from Landsat imagery by integrating advanced image processing techniques. This methodology encompasses segmentation using the SNIC algorithm, calculation of relevant spectral indices and classification based on predefined thresholds. Landsat 8 imagery acquired on November 7, 2024 was used for this analysis. The entire process is implemented on the GEE platform, which offers powerful tools for processing and analyzing large-scale satellite imagery and geographic data. The subsequent sections delineate each step of this approach, from image acquisition to the generation of the final spatial distribution of SCMA.

Step 1. Collect Landsat images based on the research area

The first step in this research method is to collect Landsat satellite image for the research area. Landsat satellites provide medium-resolution images (30 m), which are highly suitable for monitoring mining activities on a large scale (Petropoulos et al., 2013). Landsat data is particularly useful for detecting surface changes over time, which is essential for tracking mining areas (Townsend et al., 2009; Hemati et al., 2021). Image from Landsat can be collected from different seasons to minimize the impact of weather conditions such as clouds or fog, which could obscure mining areas in the images (Zhu et al., 2018). The correct selection of Landsat image forms the basis for the subsequent steps in the research, allowing for accurate analysis of mining areas and their conditions.

Step 2. Segmentation using the SNIC algorithm

After obtaining the satellite images, the next step is to apply the SNIC algorithm for image segmentation (Khadka and Zhang, 2023; Karakuş, 2024). Segmentation is the process of dividing an image into homogeneous regions based on spectral and spatial similarities, which makes classification easier (Blaschke et al., 2004; He et al., 2016). The

SNIC algorithm is effective in segmenting an image into smaller regions that share similar characteristics such as color, texture, or other spectral properties (Achanta and Susstrunk, 2017). Unlike traditional clustering algorithms, SNIC provides high-quality segmentation without requiring iterative processes, which results in more accurate segmentation (Tassi and Vizzari, 2020; Zhong et al., 2024). In this study, the SNIC algorithm was implemented in GEE with the following parameter settings: size: 100, compactness: 0.2, connectivity: 8, neighborhoodSize: 128. These values were chosen after several experimental runs to balance between over- and under-segmentation, ensuring that the mining and coal dumping areas can be clearly delineated while minimizing spectral noise.

Step 3. Calculate NDCI, BAI, and NDVI indices

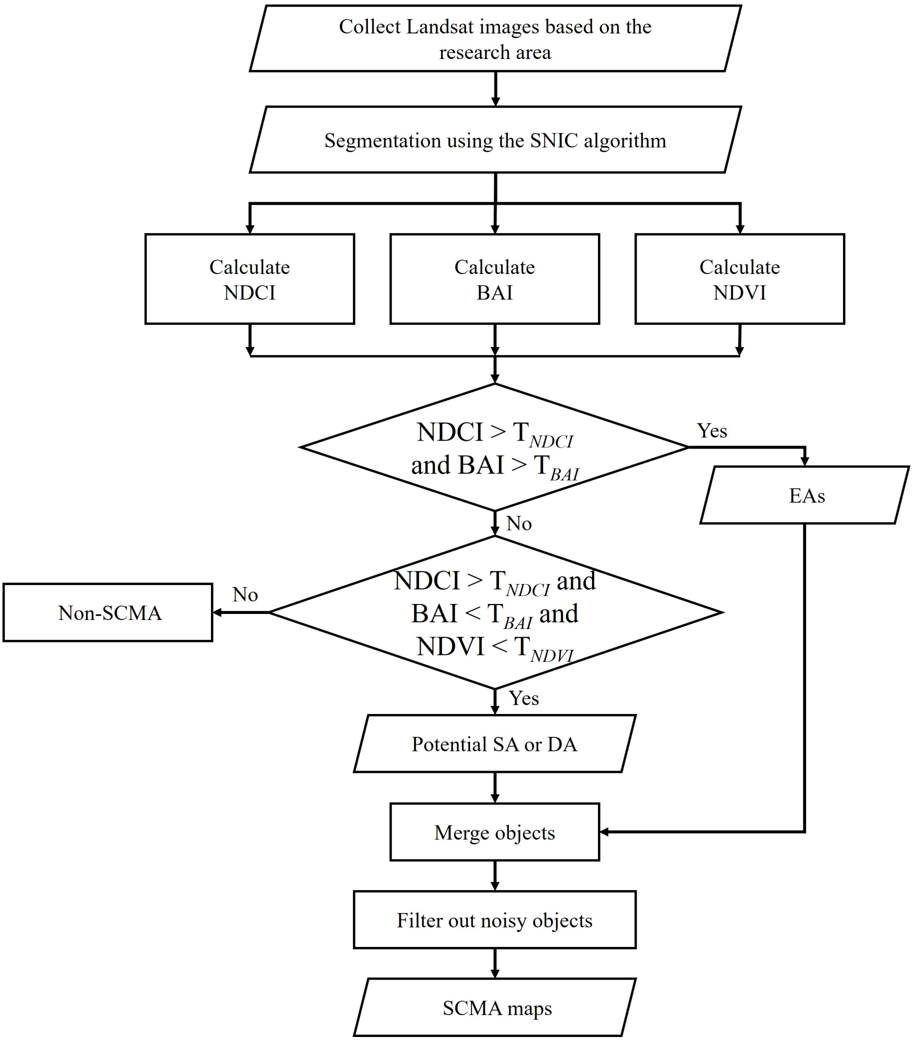

Fig. 2. Flow chart of remote sensing image processing method

Once segmentation is complete, the next step is to calculate the NDCI, BAI, and NDVI indices from the Landsat data. These indices are crucial for classifying mining areas because they reflect the spectral characteristics of mining land:

– *NDCI* (Normalized Difference Coal Index): is a specialized index designed to detect mining areas. This index helps distinguish coal mining areas from other types of land due to the specific spectral reflectance properties of disturbed soil and mining activities (Mao et al., 2014). *NDCI* is calculated according to the formula:

$$NDCI = \frac{SWIR1 - NIR}{SWIR1 + NIR}; \tag{1}$$

– *BAI* (Built-Up Area Index): is a spectral index that distinguishes urban areas from other land types. BAI's effectiveness comes from its sensitivity to the reflective properties of man-made surfaces. In the context of coal mine detection, *BAI* can help identify areas where mining activities are taking place. The combination of this index increases the accuracy of classification and delineation of coal mining areas, making it a powerful tool for environmental monitoring and resource management. The formula of *BAI* is calculated as follows (Zeng et al., 2017):

$$BAI = \frac{Blue - NIR}{Blue + NIR}; \tag{2}$$

– *NDVI* (Normalized Difference Vegetation Index): is a widely used index to distinguish between vegetated land and bare land. Mining areas typically lack vegetation, so *NDVI* helps to eliminate areas with healthy vegetation and identify those devoid of plant cover. *NDVI* is calculated as (Myneni et al., 1995):

$$NDVI = \frac{NIR - Red}{NIR + Red}, \tag{3}$$

where *Blue*, *Red*, *NIR*, *SWIR1* denote Band 2, Band 4, Band 5, and Band 6 in the Landsat-8 OLI image, respectively.

Step 4. Classification based on thresholds

After calculating the *NDCI*, *BAI*, and *NDVI* indices, the next step is to classify regions based on predefined thresholds (T_{NDCI}, T_{BAI}, T_{NDVI}). The classification process proceeds as follows (Zeng et al., 2017):

– If NDCI exceeds the threshold and BAI also exceeds the threshold, the area is classified as an Extracting Area (EAs), where active coal mining is occurring;
– If the above condition is not met, further comparisons are made with *NDCI* greater than the threshold, *BAI* less than the threshold, and *NDVI* also less than the threshold, leading to classification as Stripped Area (SA) or Dumping Area (DA);
– Areas that do not meet any of these conditions are classified as Non-SCMA (Non-Surface Coal Mining Area).

Step 5. Merging objects

After classification, the next step is to merge fragmented objects into larger regions. During segmentation, small or disconnected objects may be identified, which can reduce the accuracy of classification. By merging adjacent objects with similar spectral and spatial properties, larger and more meaningful mining areas are created. This merging process improves the quality of the final map, ensuring that mining areas are represented as continuous regions and can be more easily analyzed.

Step 6. Filter out noisy objects

The next step involves filtering out noisy or irrelevant objects, typically small, isolated regions that do not meet the size or shape criteria of actual mining areas. A minimum area threshold filter is applied, whereby all objects with an area smaller than 1 hectare and independent are removed. This is implemented using the function in GEE to calculate object size and filter out features below the threshold. This step enhances the classification accuracy by excluding artifacts, shadows, or scattered pixels that may otherwise be misclassified as mining features.

Step 7. Generate final spatial distribution of SCMAs

After completing the detection and filtering steps, the final step is to generate final spatial distribution of SCMAs. These distributions will show the locations of coal mining areas, barren lands, and dumping areas. This is the final output of the process and provides an overview of the distribution of mining areas within the research area. These distributions can be used for further studies to monitor changes in mining areas over time, assess environmental impacts, and support resource management.

3. Results and discussion

Figure 3 presents the Landsat 8 OLI image acquired on November 7, 2024, covering Cam Pha (left) and Ha Long (right), displayed in natural color composite. Cam Pha is characterized by extensive open-pit coal mines and waste dumps, appearing as gray/white regions, while green areas indicate the presence of remaining vegetation. As a major coal mining hub in Quang Ninh province, this area has significant environmental impacts. In addition, Ha Long with its coastal and urban landscape, experiences less direct mining activity but still contains waste dumps in proximity to residential areas.

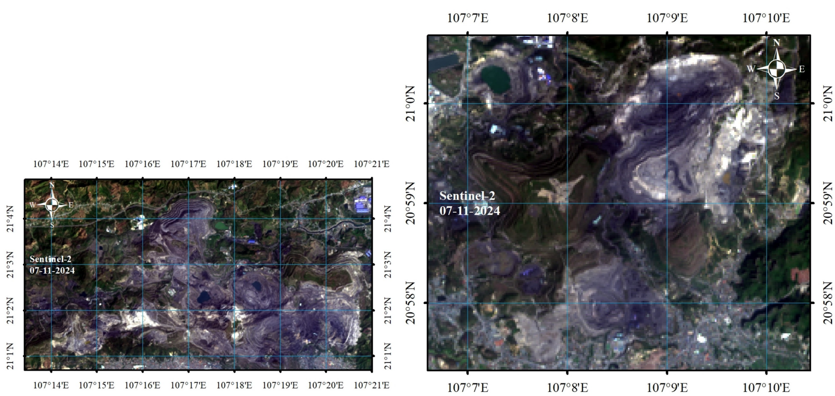

Fig. 3. Landsat 8 image of the study area: Cam Pha (left) and Ha Long (right)

Figure 4 presents the *NDVI*, *NDCI*, *BAI*, and SCMA of the Cam Pha area, providing insights into the environmental impacts of coal mining. *NDVI* reflects vegetation cover, with low values concentrated in mining areas due to vegetation loss, while *NDCI* identifies surface coal deposits, mainly in active mining sites. *BAI* indicates land surface disturbance, with brighter areas representing stripped or heavily impacted regions. The spatial distribution of SCMA clearly delineates EA and SA-DA. EA zones (red) are concentrated in the central and northern parts of Cam Pha, where large open-pit coal mines are located. Meanwhile, SA-DA zones (blue) are primarily distributed in the western and southeastern areas, representing waste dumps or stripped lands. This distribution highlights the significant deforestation and land degradation caused by coal mining activities.

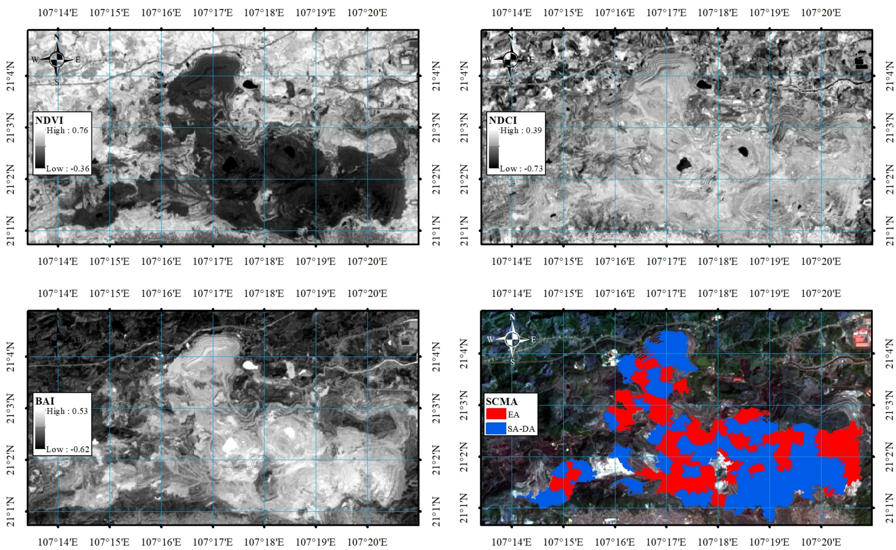

Fig. 4. NDVI, NDCI, BAI and SCMA of Cam Pha area

Figure 5 displays the *NDVI, NDCI, BAI*, and SCMA of the Ha Long area, reflecting the environmental impacts of coal mining. *NDVI* ranges from -0.33 to 0.75, with low values concentrated in mining areas due to vegetation loss. *NDCI*, ranging from –0.68 to 0.34, identifies surface coal deposits, primarily in open-pit mines. In addition, *BAI*, varying from –0.59 to 0.48, highlights areas with significant land surface alterations, often associated with soil stripping. The spatial distribution of SCMA reveals that EA are concentrated in the southern and central parts of Ha Long, where large-scale coal mining operations take place, while SA-DA are scattered around EA zones, particularly in the northern and along mining site boundaries.

Table 1 presents the area of EA and SA-DA in Cam Pha and Ha Long. Cam Pha has an EA area of 11.98 km^2, significantly larger than Ha Long's area of 6.36 km^2, reflecting more intensive coal mining activities due to the presence of large open-pit mines. Regarding SA-DA, Cam Pha covers 17.09 km^2, substantially exceeding Ha Long's 3.59 km^2, indicating a larger extent of mining waste disposal in Cam Pha as a result of

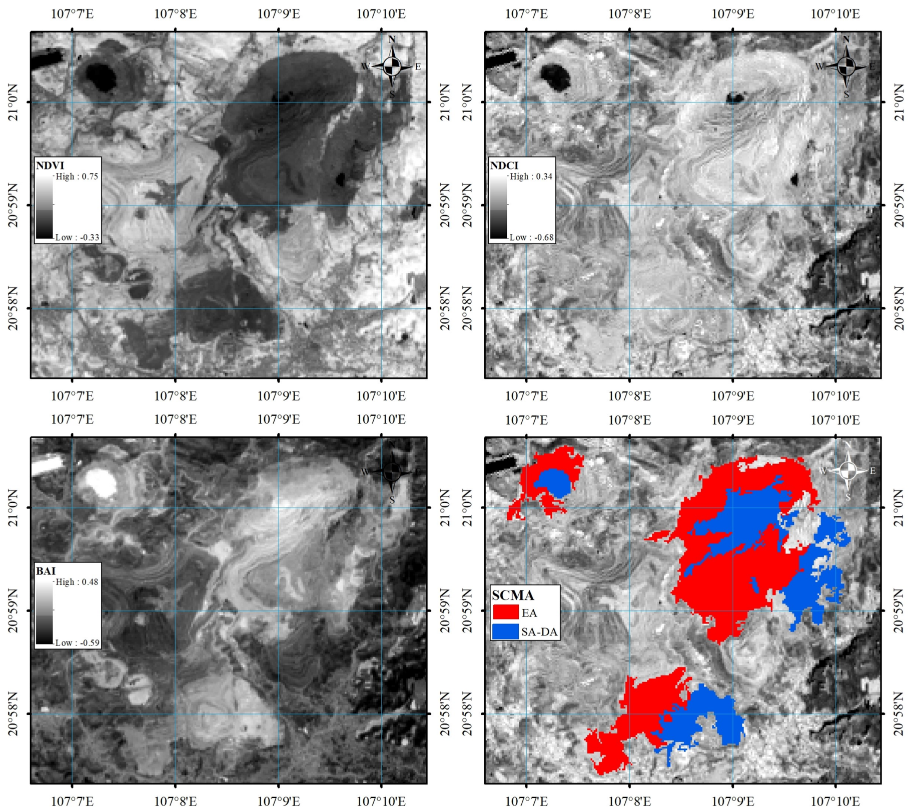

Fig. 5. NDVI, NDCI, BAI and SCMA of Ha Long area

Table 1. Area of objects in the study areas

Area (km^2) Region	Extracting areas (EA)	Stripped/dumping areas SA-DA
Cam Pha	11.98	17.09
Ha Long	6.36	3.59

prolonged extraction. The total affected area (EA + SA-DA) in Cam Pha is 29.07 km^2, whereas Ha Long accounts for only 9.95 km^2, demonstrating that Cam Pha experiences more severe environmental impacts. The EA/SA-DA ratio in Cam Pha is 0.70, meaning the waste disposal areas exceed the actual extraction sites, while Ha Long exhibits a ratio of 1.77, indicating that extraction areas are nearly twice the size of waste disposal zones. This difference suggests that Cam Pha remains a primary coal mining hub, whereas Ha Long has undergone more land reclamation efforts to preserve its tourism landscape.

Our approach was validated using ground truth pixels interpreted from high-resolution imagery (Fig. 6), providing quantitative evidence to support the reliability of the classification results (54/58 ~93.10% for EA and 53/59 ~89.83% for SA-DA). Compared to previous studies, this research confirms the effectiveness of spectral indices in detecting mining areas, consistent with Zeng et al. (2017). Mukherjee et al. (2019) also highlighted the value of tailored coal indices. Overall, the findings from existing studies consistently demonstrate the strong potential of spectral indices for accurate and efficient mapping of mining activities. Unlike pixel-based or machine learning methods, our approach integrates SNIC segmentation to enhance spatial coherence, offering a practical balance between accuracy and simplicity for SCMA detection. In addition, these findings underscore the necessity of continuous environmental monitoring and restoration measures in coal mining regions.

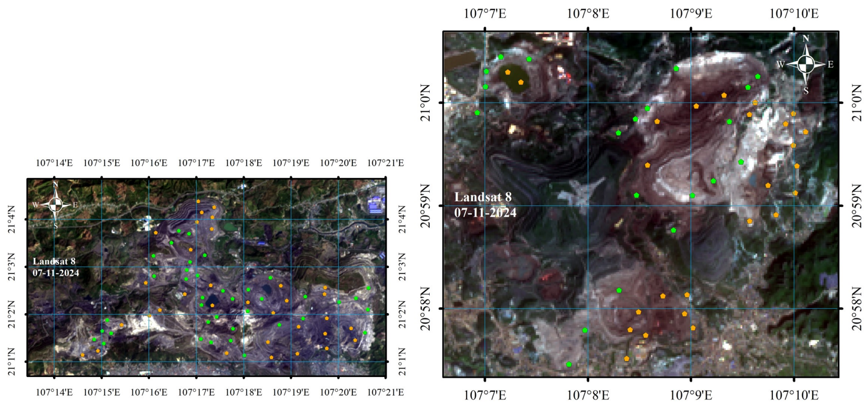

Fig. 6. The locations of the accuracy assessment points were collected using Google Earth: EA (green), SA-DA (orange)

4. Conclusion

This study demonstrates the effectiveness of remote sensing techniques in detecting surface coal mining areas (SCMAs) and assessing their environmental impacts in Cam Pha and Ha Long. The results show that Cam Pha exhibits more extensive land degradation, with an extracting area (EA) of 11.98 km^2 and a stripped/dumping area (SA-DA) of 17.09 km^2. In contrast, Ha Long has a smaller EA of 6.36 km^2 and SA-DA of 3.59 km^2, reflecting a lower level of mining-related disturbance and a higher rate of land reclamation. The application of *NDCI*, *NDVI*, and *BAI* indices, in combination with the SNIC algorithm, enables accurate detection and delineation of mining zones, offering critical insights into mining-induced land use changes. Validation using ground truth pixels interpreted from high-resolution imagery showed a classification accuracy of 93.10% for EA and 89.83% for SA-DA, indicating the robustness and reliability of the proposed method. Notably, the EA/SA-DA ratio in Cam Pha is 0.70, indicating that waste disposal areas exceed the size of active extraction zones, while in Ha Long, the ratio is 1.77, suggesting more active land recovery. These findings highlight the urgent need for sustainable land reclamation and targeted environmental management policies in heavily affected mining regions. Future research should focus on integrating multi-temporal satellite imagery for long-term monitoring of mining impacts and applying machine learning algorithms to enhance classification performance. Additionally, expanding the study to larger geographic regions could help validate the scalability of the proposed method and support the development of an automated SCMA monitoring system.

Author contributions

Conceptualization: V.P.L., L.H.T.; methodology: V.P.L., L.H.T.; formal analysis and investigation: L.H.T., V.P.L.; writing – original draft preparation: V.P.L.; writing – review and editing: V.P.L.; supervision: L.H.T.

Data availability statement

The datasets used during the current study are available from the corresponding author on reasonable request.

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