

OPEN-PIT LIMESTONE MINING AREAS MAPPING AND ASSESSMENT USING RANDOM FOREST ALGORITHM FOR SUSTAINABLE DEVELOPMENT

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Received: September 19, 2023; Revised: May 29, 2024; Accepted: August 13, 2024

Abstract

Limestone excavation is prone to land use/cover change, which impacts the ecosystem. The objective of this paper is to use a remote sensing dataset and the Quantum Geographic Information System (QGIS) to map and assess active captive limestone mining sites at the Yerraguntla in the YSR Kadapa district, Andhra Pradesh, India, for the year 2019. In this paper, the Limestone mining area was assessed as 379.57 ha with an overall accuracy of 95.79%, user accuracy of 97.25%, producer accuracy of 99.18%, and kappa coefficient of 0.957 by analyzing Sentinel-2A imagery dataset with Random Forest (RF) classifier. The findings were assessed in 2019 using very high-resolution (<1m) Google Earth images (486.47 ha) from Google Earth Pro and industrial field survey reports (487.10 ha). This research helps Limestone mine owners and Environmental engineers implement eco-friendly mining operations and monitor mining progress at low cost with less human efforts for sustainable development.

Keywords: Classification; Google Earth Image; Limestone mine; RF Classifier; satellite Imagery

Introduction

Limestone is a non-metallic mineral made up of calcium carbonate (CaCO_3). Limestone also contains trace components like clay, feldspar, pyrite, quartz, and iron carbonate (<https://geology.com/>). Limestone is a principal raw material in the cement manufacturing industry and construction sector (www.mines.ap.gov.in). India is

affluent in high-quality Limestone reserves. The total Limestone reserve in India in 2015 was 2,03,224 million tonnes (MT), of which 16,336 MT (8%) are classified as reserves and 1,86,889 MT (92%) as resources, according to National Mineral Inventory (NMI) data based on the United Nations Framework Classification (UNFC) system (Soni and Nema, 2021).

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The study region has broad Limestone deposits covering an area of 2477.55 ha, with an active mining area of 487.10 ha in 2019 (YSR Kadapa District Survey Report, 2021). The environmental deterioration induced by Limestone mining in the form of dust and noise produces geomorphic hazards, significantly impacting human civilization and local life (Sudhakar and Reddy, 2023a). Hence, it is important to monitor mining areas periodically to mitigate environmental impacts for the industry's long-term sustainability (Hoy *et al.*, 2024). Monitoring mines just through in-situ assessment may not be scalable, and there is also a risk of failing to detect associated corruption when rent-seeking public inspectors are aligned with both legitimate and illicit mining enterprises. The study objective is to locate, delineate, and evaluate Limestone mines and land-use changes in and near mining areas using open-source remote sensing data from satellite systems and machine learning techniques.

Machine Learning (ML) in remote sensing applications is an emerging discipline that is progressively gaining consideration from scientists, industry eminent persons, and researchers (Shirmard *et al.*, 2022) due to the abundance of available remote sensing datasets. Spatial remote sensing offers many advantages over conventional geological mapping methods regarding coverage area, speed, and cost (Sudhakar and Reddy, 2022a). ML in remote sensing applications includes challenges such as the unavailability of up-to-date datasets, the production and evaluation of training datasets, and algorithm design uncertainty. The research objectives include mapping and evaluating the limestone mining area from space, implementing a machine learning algorithm, and validating the area with information from field surveys of businesses.

Previous research has demonstrated that supervised machine learning algorithms can be used to locate mining sites (Maus *et al.*, 2020). These places are characterized by visible characteristics such as contour cuts, tailing dams, water storage systems, roadways, and buildings (Werner *et al.*, 2019). Support vector machines (SVM) and random forests (RF) machine-learning models are created on publicly available satellite data to monitor the extent of coal mines, as well as land use and land cover classification (Mehta *et al.*, 2024). Landsat images was used to train 11 land use land cover classes, comprising a mine class, using the maximum likelihood classifier in India's Dhanbad district (Singh *et al.*, 2018). Open-pit mine were mapped at Turkey's Goynuk using an SVM classifier and high-resolution satellite images (1m) from the Ikonos and

Quickbird systems (Demirel *et al.*, 2011). Geophysical, Geotechnical, and Electrical Resistivity Tomography were used to characterize the waste dump materials and ground water conditions at Thailand's open-pit coal mines (Hoy *et al.*, 2024).

This research paper is organized as follows: Section 1 introduces the study, Section 2 contains resources, Section 3 contains methodologies related to mapping and assessing limestone mining areas, Section 4 contains the results and discussion, and Section 5 contains the paper's conclusions.

Materials

Study area

The research is carried out at the cement industrial region illustrated in Figure 1. The study region includes four cement plants and its open-pit captive Limestone mines (coromandel, Niduzuvvi, Zuari, and Bharati cement Limestone (CLM) mines) and Kadapa black Limestone mines in the premises of Yerraguntla town, which is located 47 km west of the YSR Kadapa district headquarters in Andhra Pradesh, India. The town of Yerraguntla is located at 14.63°N Latitude and 78.53°E Longitude, with an elevation of 164 m on average (Sudhakar *et al.*, 2022a; Sudhakar and Reddy, 2023b).

Limestone mines

The Kadapa district has mineral resources such as barites, asbestos, and Kadapa stone. According to the geological survey of India's 1983 survey, the district has a total resource of 4078 million tonnes of limestone in all categories. Kadapa is well-known for its stone known as Kadapa stone, which is utilized in building construction and slabs, particularly in southern India (Sudhakar and Reddy, 2019). In total, 11 mining leases cover a total area of 3375.38 ha in the Kadapa district. Cement-grade Limestone resources can be found in the mandals of Yerraguntla, Jammalamadugu, Kamalapuram, and Mydukur (YSR Kadapa District Survey Report, 2021).

Cement Grade limestone mines

Major cement producers recommended that limestone with CaO 42% (min), Fe₂O₃ 1- 2%, Al₂O₃ 1-2%, SiO₂ 12-16%, and MgO 4% (max) be used in cement production. Four cement plants with an annual capacity of 9.58 MTPA have been erected in Yerraguntla town in the YSR Kadapa region. Table 1 provides a basic description of captive open-pit Limestone mines (Sudhakar *et al.*, 2022b).

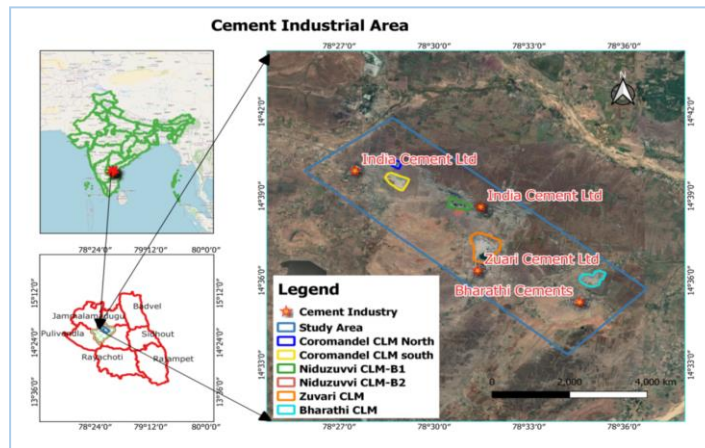


Figure 1. Limestone mining areas at the Yerraguntla cement industrial area

Table 1. Cement-grade limestone mines summary at the study area

	Coromandel Limestone Mine	Niduzuvvi Limestone Mine	Zuari cement Limestone Mine	Bharati cements Limestone Mine
Cement Industry	ICL, Chilamkur	ICL, Yerraguntla	ZCL, Yerraguntla	BCCPL, Nallalingayapalli
Cement production Capacity (MTPA)	1.38	0.61	4.30	3.3
Commenced Year	1982	1979	1984	2006
Mine Lease Area (ha)	602.137	335.06	656.68	632.28
Active Mining Area (ha)	112.37	66.17	241.0	67.56
Limestone Production rate	2 to 5.5 (MTPA)	1.0 (MTPA)	7.0 (MTPA)	5.0 (MTPA)
Cement Production grades	PPC and OPC	PPC and OPC	OPC and PPC	OPC, PPC & PSC
Cement production capacity (MTPA)	1.485	1.38	4.6	5.0
Limestone Mine lease ends	2031(year)	2034(year)	2041(year)	2038(year)
Mineral reserves/ resources (MT)	276.06	82.98	178.856	330.186
Geographic Coordinates	14° 38' 51.0"N to 14° 40' 31.1"N	14°37'48.8" N to 14°39'19.9" N	14°36'10" N to 14°38'30" N	14°34'02" N to 14°36'28" N
Geographic Coordinates	78° 27' 55.4"E to 78° 29' 40.4"E	78°29'23.4"E to 78°31'14.2" E	78°31'24"E to 78°33'30"E	78°33'35" E to 78°36'51" E

Methods

Limestone mining area assessment

The performance evaluation of the Machine Learning Classifier (RF classifier) for the cement grade active Limestone mining area mapping and assessment has been divided into four phases; the 1st phase involved dataset collection, pre-processing, and extracting the sentinel-2A images to the area of interest. The 2nd stage entails collecting training and testing samples. The classification of spectral images for mining area mapping and assessment is the 3rd phase. The 4th phase included evaluating classifier accuracy, area computation, and validation, with the area determined using Google Earth images and an industrial field survey report. The workflow used in this research study is depicted in Figure 2.

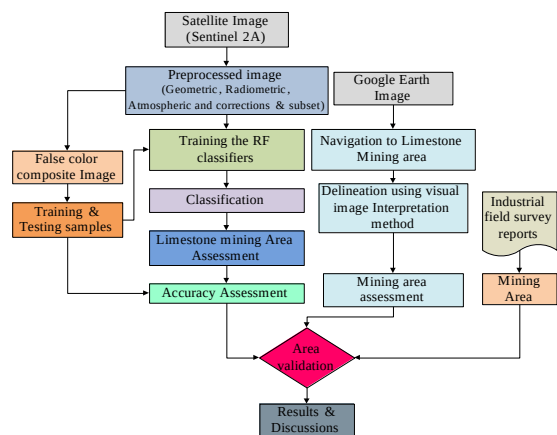


Figure 2. Limestone mining area mapping and assessment

Google Earth Images

Google Earth images have the benefit of displaying the most up-to-date satellite images with a spatial resolution ranging from 15m to 15cm (less than one meter). Most common satellite image processing software, such as ERDAS IMAGINE, ENVI, ArcGIS, QGIS, and others, has recently introduced tools to import and visualize Google Earth (GE) images. Google Earth provides images for the different periods since 1972, which would be helpful in the study of the Limestone mining area change assessment (Sudhakar and Reddy, 2022b). The limestone mining area mapping and assessment algorithm using Google Earth imagery is described below.

Algorithm for Limestone mining area Assessment using Google Earth image

- Determine the locations of Limestone mining areas from industrial reports
- Open the Google Earth image in the Google Earth Pro software tool.
- Navigate to the mining location.

- Delineate limestone mines by visual interpretation, considering topography, tone, texture, and light using a polygon place marker tool and labelling them.
- Measure the area of a created polygon using the measurement tab.
- Complete area measurement by double-clicking on the last point, or click done and save the file as Keyhole Markup Language (.kml) file.
- Repeat the steps (c) to (f) for all Limestone mine classes of interest.

Table 2. Limestone mining area from Google Earth images

S. No.	Name of the Limestone mine	Mining Area (ha) in 2019
1.	Coromandel Limestone Mine North	21.00
2.	Coromandel Limestone Mine South	90.90
3.	Niduzuvvi Limestone Mine block-2	08.51
4.	Niduzuvvi Limestone Mine block-1	57.50
5.	Zuvari Cements limestone mine	241.0
6.	Bharati Cements Limestone mine	67.56
Total Area		486.47

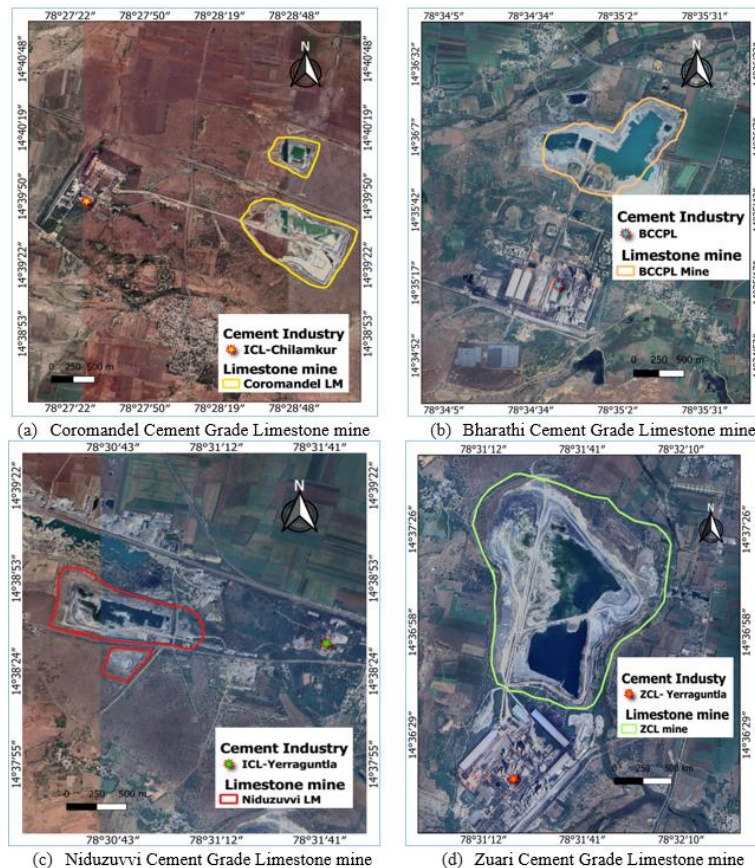


Figure 3. Cement Grade captive Limestone mining area

Random Forest classifier

The Limestone mining area and assessment were carried out in three stages. The first included data collection, pre-processing, layer stacking, and cutting of sentinel-2A imagery to the study region. The collection of training and testing samples, as well as training the Random Forest (RF) model, is provided in the second phase. The third phase corresponds to the mining area mapping and assessment. The fourth phase consists of classifier accuracy evaluation, followed by area comparison.

Imagery Dataset collection

In this research article, we used Sentinel-2A (Level-2A product) Multispectral Instrument (MSI) sensor dataset for the date March 25, 2019, from the (<https://earthexplorer.usgs.gov/>) USGS Earth Explorer (EE). Sentinel-2A satellite covering 13 spectral bands (4-Bands at 10 m, 6-Bands at 20m, and 3-Bands at 60m spatial resolution) with central wavelengths ranging from 0.443 μ m to 2.190 μ m (Main-Knorn *et al.*, 2017). Sentinel-2A is a wide-swath (290km) imaging mission that provides a geospatial dataset on land use/cover change.

Pre-processing

The dataset from Sentinel-2A is analyzed using the SCP in QGIS software to map and assess the Limestone mining area in 2019. For that, the 10m and 20m spatial resolution bands are corrected geometrically and projected to the universal Coordinate Reference System (CRS) EPSG: 32644-WGS84/UTM Zone 44N, subsequently an atmospheric correction performed using Dark Object Subtraction1 (DOS1) method to eradicate atmospheric scattering from the image (Das and Angadi, 2020). In the Radiometric calibration image pixel digital number (DN) converted into Top of Atmospheric (Reflectance) (Sudhakar and Reddy, 2023a). The pre-processed images are layer stacked (group of nine bands), and clipped the imagery dataset to the study area of interest (Deliry *et al.*, 2021) as shown in Figure 4. The Figure 4(a) depicts a pre-processed Sentinel-2A True color composite (TCC) image, in which white color indicates a Limestone mining area, blue indicates barren lands, and dark brown indicates the fallow lands.

To map the captive open-pit Limestone mining area, ground control points (GCPs) were obtained from Sentinel-2A False Color Composite (FCC) image (Figure 4 (b)) generated from the band combination 7-3-2 (Somvanshi and Kumari, 2020). A total of 1,28,795 pixels (140 points) were randomly selected over the mining region, with a minimum of 21,466 pixels (20 points) for each land use/cover class. The points were divided as 80%

(1, 03,036 pixels) for training and 20% (25,759 pixels) for testing.

The training data samples are used to train the model, while the testing data sample points are utilized to assess its accuracy. Using the visual interpretation method in the FCC of Sentinel-2A image, the sample points were classified into six land use/cover types (barren land, built-up, fallow land, limestone mine, vegetation, and water body). The yellow color represents barren lands, the red mixed white region represents the built-up areas, the dark brown part means fallow lands, the white color represents the Limestone mining regions, and the red represents the vegetation regions.

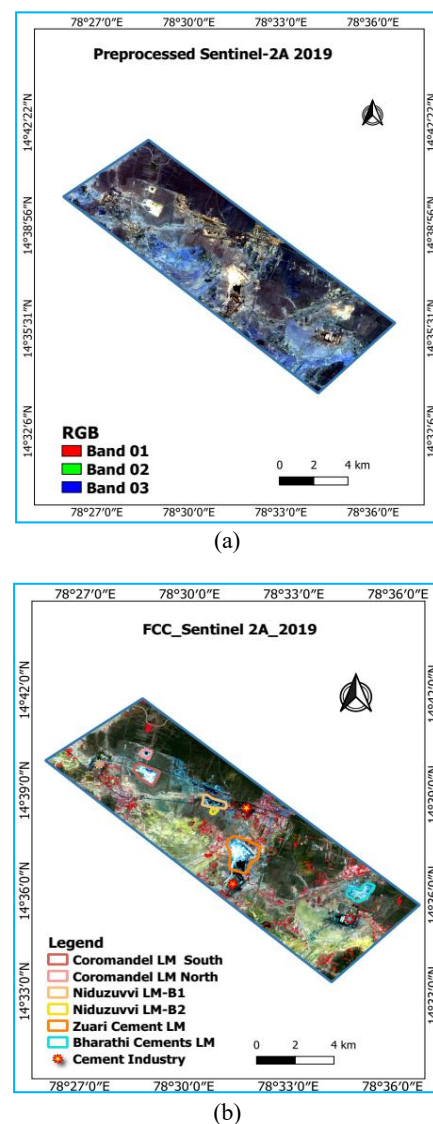


Figure 4. Pre-processed sentinel-2A images in the year 2019

Random Forest (RF) algorithm

The RF classifier is an ensemble method, it is widely used in classification and regression problems. Compared to k-Nearest Neighbour (KNN) and support vector machine (SVM) algorithms, it takes less training time. It handles missing values and has the ability to work on a large data set with higher accuracy and prevents the problem of over-fitting. The RF algorithm consists of two phases. In the training phase, multiple decision trees are constructed using bootstrap samples and random feature subsets. In Testing phase predictions are aggregated across all trees with majority vote for classification (Alshari and Gawali, 2022). The RF algorithm is implemented with default parameters (Table 3) on the high-resolution Sentinel-2A imagery using the 'dzetsaka' classification tool in the QGIS software (Maxwell *et al.*, 2018; Han *et al.*, 2020). Figure 5 illustrates the study area. The land use land cover image is determined using a random forest algorithm in that the Limestone mining area is mapped in red color.

Table 3. RF algorithm process parameters

S.No.	Input parameter	Value/ Selection
1.	Reference data points (RDP)	140 points (1, 28,795 pixels)
2.	Training data samples (N)	80% of RDP
3.	Testing data samples	20% of RDP
4.	Number of Iterations (K)	06
5.	Instances (n)	3000
6.	Number of classifiers (B)	10
7.	Features (p)	36

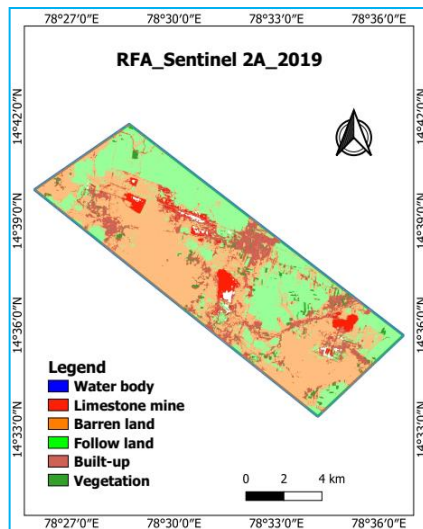


Figure 5. Captive Limestone mining area

Random Forest algorithm

Training Phase:

Given:

B: The number of classifiers in RF

K: The number of classes in the target variable

N: Training data samples with n-instances, p-features, and target variable

Steps:

For sample $b = 1$ to B

(a) From the training data, generate the bootstrapped sample Z_b^* of size N.

(b) Construct an RF tree C_b to the bootstrapped data Z_b^* , by recursively repeating the steps (i) - (iii) for each terminal node of the tree t, until the node size n_{min} is reached.

(i) From the p variables, choose m variables at random ($m = \sqrt{p}$).

(ii) Among the m variable, find the best split/cut points.

(iii) Using the best split/cut points, divide the node into two daughter nodes.

(c) Out put the ensemble of trees C_b

Testing Phase:

Accumulate the B Trained classifiers by utilizing a simple majority vote. The anticipated class label from classifiers C_B for a test instance, x, is:

$$C_B(x) = \operatorname{argmax}_j \sum_{b=1}^B I(C_b(x) = j), \text{ for } j=1, 2, \dots, K$$

Results and Discussions

Performance evaluation

A confusion matrix is frequently used to estimate the performance of classification models. In this research paper (Sudhakar and Reddy, 2023a), we used the confusion matrix to compare the categorized and validation pixels. The confusion matrix's rows represent instances in classified class pixels, while the columns represent instances in the ground truth pixels (reference data). The diagonal represents the correctly classified image pixels for each class. The confusion matrix was generated using the Semi-Automatic Classification Plugin (SCP) for the QGIS software tool. Statistical indicators such as overall accuracy, user accuracy, producer's accuracy, and Kappa hat are estimated using Equations (1-4) (Sudhakar *et al.*, 2022a).

Producer's accuracy (PA)

$$= \frac{\text{Number of correctly classified pixels in given a class}}{\text{producer's sum in that column}} \times 100$$

(1)

$$\text{User's accuracy (UA)} = \frac{\text{Number of correctly classified pixels in a given class}}{\text{user's sum in that row}} \times 100 \quad (2)$$

$$\text{Overall accuracy (OA)} = \frac{\text{Total number of correctly categorized pixels}}{\text{Total number of pixels used for accuracy assessment (N)}} \times 100 \quad (3)$$

$$\text{Kappa hat (K)} = \frac{N \sum_{i=1}^r Y_{ii} - \sum_{i=1}^r (Y_{i+} * Y_{+j})}{N^2 - \sum_{i=1}^r (Y_{i+} * Y_{+j})} \quad (4)$$

Where r is the number of rows in the matrix, Y_{ii} is the number of observations (pixels) in rows i and column i , Y_{i+} and Y_{+j} are the total land classes in row i and column j , respectively, and N is the total number of observations included in matrix

Table 4 shows the highest and lowest producer (PA) and user (UA) accuracies across the six-land use/cover classifications. The producer accuracy of the limestone mine is 99.18%, while the users' accuracy is 97.25%; when these two are compared, the producer accuracy is higher. This indicates that RF results are more reliable in Limestone area mapping. To explain this miss classification, consider the pixels that are collected in the Limestone mining field is 7,135 from Table 4. However, in the determined image, there are a total of 7,277 pixels, of which 63 correspond to a water body, 14 to barren land, and 123 to vegetation area. So, basically, categorization errors occurred here. Similarly remaining classes accuracies are were compared.

Mining area validation

Table 5 shows the assessment findings of the mining area acquired as 380.19 ha with user accuracy (UA) of 97.25%, Producer accuracy (PA) of 99.18%, overall accuracy (OA) of 95.79%, and Kappa hat of 0.957 using the Random Forest method implemented in the 'r.report' processing

tool in QGIS. The obtained area is compared to the area of 487.1 ha determined by the industry using a conventional field survey method, and the area is derived from a high-definition Google Earth image (486.47 ha). The RF classifier-derived mining area is less than industrial survey reports due to the RF classifier separating water bodies from the mining area.

Table 5. Limestone Mining Area Comparison

S. No.	Method(s)	Limestone mining area (ha)
1.	Random Forest	380.19
2.	Google Earth Image	486.47
3.	Industrial data	487.10

Conclusions

This research article evaluates the Random Forest algorithm's effectiveness in mapping and assessment of Limestone mining area and land use and Land cover classifications. The 'dzetsaka classification tool' was used to implement the RF algorithms in QGIS. The Random Forest algorithm produces the land use and Land cover map, with an overall accuracy (OA) of 95.79% and a kappa hat (K) of 0.957. The assessed Limestone mining area using RF method is 379.57 ha, it is less in comparison to the industrial field survey area of 487.10 ha. This is due to the RF classifier separated the water body from the mining area. In future work include very high spatial resolution (<1 m) Multispectral/Hyperspectral satellite imagery classification using Deep Learning Methods can be used to more precisely evaluate Limestone mining area, determine mining depth from the ground surface, and assess environmental damages using satellite imagery.

Table 4. Confusion matrix of the Land use/cover class using RF classifier

		> Reference data (Ground Truth pixels)						User's Sum (CCD)	UA (%)
Land use/cover class		Water Body	Limestone Mine	Barren Land	Fallow Land	Built-up Area	Vegetation Area		
Classified class data	Water Body	1193	32	0	31	0	0	1256	97.38
	Limestone Mine	63	7077	14	0	0	123	7277	97.25
	Barren land	6	12	59053	1129	31	499	60730	97.23
	Fallow Land	0	0	1359	48251	6	596	50212	96.09
	Built-up Area	0	0	0	52	1475	288	1815	81.12
	Vegetation Area	0	14	87	792	285	6327	7505	84.30
	Producer's Sum (GTP)	1262	7135	60513	50255	1797	7833	128795 (N)	
PA (%)		94.53	99.18	97.58	96.01	82.08	80.77		
overall accuracy (%) = 95.79									
kappa hat = 0.957									

Author Contribution statement

The authors affirm the following contributions to the paper: G. Umamaheswara Reddy and N. Usha Rani devised the research approach; C. Venkata Sudhakar gathered, analysed, interpreted, and developed the manuscript. The writers read and approved the article.

Conflict of interest statement

The authors have indicated that they have no conflicts of interest. All co-authors have seen and approved the paper, and there is no financial interest to disclose. The authors certify that their contribution is original and has not been considered by any other publications.

Funding

The authors state that no funds or grants were obtained to carry out this research or prepare this work.

Acknowledgments

The authors would like to thank the Geology and Mining department of Andhra Pradesh for providing field data on captive Limestone mines.

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