



Machine Learning Approaches for Mapping Silica Sand Deposits Using Space-Borne Remote Sensing [†]

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Abstract

The Alappuzha district in Kerala, India, has large deposits of high-grade silica sand, which is mainly used for glass manufacturing. The primary objective of the study is to map these mineral deposits using multispectral satellite data and machine learning algorithms (MLAs). Moreover, detailed geochemical and structural characterisation was performed using Energy-Dispersive X-ray Fluorescence (ED-XRF) and X-ray diffraction (XRD), which confirmed the characteristics of the silica sand, with a SiO₂ content of 96.93–99.13%. The laboratory proximal spectra in the range of 400–2500 nm were processed and compiled as a reference spectrum for mapping using Landsat and ASTER remote sensing datasets. The support vector machine (SVM) outperforms other algorithms with an overall accuracy of 97.82%. Integrating remote sensing techniques, mineral characterization, and field data facilitates eco-friendly, sustainable mining of these strategic minerals.

Keywords: mineral mapping; silica sand; Landsat; ASTER; machine learning algorithms

1. Introduction

The distinct absorption features of minerals in the visible and infrared wavelength spectra enable rapid, non-invasive, and powerful remote sensing techniques for detecting minerals across challenging and inaccessible terrain [1]. Multi-spectral, moderate-resolution satellite remote sensing imagery, such as the Landsat series, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Sentinel, was used to identify strategic mineral occurrences [2,3]. A series of analytical techniques in digital image processing, spectral enhancement and spectral classification, such as Spectral angle mapper (SAM), Mixture tuned match filtering (MTMF), Principal component analysis (PCA), band rationing (BR), etc., proved to be effective in mapping various mineral occurrences and lithological units [4].

The advent of machine learning algorithms marked a significant breakthrough in data processing, providing robust, accurate classification of minerals and prediction of their concentrations [5]. ML models are data-driven algorithms developed from input data without relying on predefined rules. Since they offer an automated means of recognizing patterns in high-dimensional data, ML algorithms are widely used for image classification in remote sensing applications, where they easily handle large volumes of satellite data [6].



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Kerala in India is endowed with large deposits of high-grade silica sand, mainly used in glass manufacturing. Many investigations were carried out on silica sand in the Alappuzha district, Kerala, to evaluate their characterization for value addition [7]. Several silica sand mines and value-addition units work in the Alappuzha district, especially in Cherthala Taluk. During 2010–2011, the production of silica sand from the Alappuzha district was about 66,389 tonnes. So, cost-effective and eco-friendly indigenous technologies are necessary to derive potential targets for mining silica sand deposits. Even though advanced remote sensing techniques incorporating machine learning-based computational models have proven useful for mineral mapping, they have rarely been used to explore silica sand deposits and dunes in particular. Compared with other minerals, quartz-rich silica minerals are difficult to distinguish in the visible-near-infrared (VNIR) and shortwave infrared (SWIR) spectral regions due to the lack of strong absorption features [8]. The machine learning models showed potential to overcome this issue of weak spectral signatures and spectral similarities to extract mineral abundances, such as silica deposits [5]. Conventional remote sensing approaches like maximum likelihood classification, band ratio (BR), and Constrained Energy Minimization (CEM) were utilised for mapping silica deposits and sand dunes from Sentinel-2, ASTER, Landsat, and EO-1 Hyperion datasets [9–12]. Moreover, the potential of ALOS PALSAR data was used to map silica abundances using its characteristic electrical properties [13]. We evaluated multiple machine learning models to map beach sand minerals using multispectral and hyperspectral remote sensing datasets and laboratory-measured spectral signatures, achieving very good accuracy and producing classified maps showing mineral abundances. It reveals the potential of machine learning approaches for identifying silica sands, a topic that remains underexplored. So, as a follow-up to our previous study on beach sediments [2,14], we here explore ML-based mineral identification and mapping of inland silica deposits. Overall, the major objective of this study is to investigate potential silica targets in Cherthala, Alappuzha district, Kerala, India, using multispectral remote sensing datasets such as Landsat 8 and ASTER, using laboratory-measured spectral signatures as the reference. Moreover, an attempt has been made to compare the performance of four machine learning algorithms, such as Random Forest Classifier, Support Vector Machine, Maximum Likelihood Classifier, and Artificial Neural Network, with the conventional classification approach, like spectral angle mapper (SAM), for mapping the silica sand deposits.

2. Materials and Methods

A detailed flowchart showing the proposed methodology for mapping the silica sand deposits in the study area is shown in Figure 1.

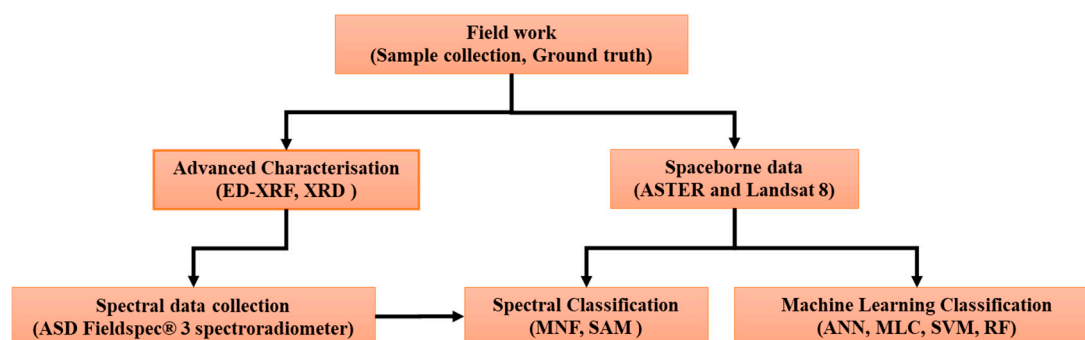


Figure 1. Flow diagram of the proposed methodology.

The workflow includes (i) Study area and field work, (ii) Laboratory analysis and spectral data collection, (iii) Advanced Spectral Classification, and (iv) Machine Learning classification.

2.1. Study Area and Field Work

A narrow stretch of land extending over 32 km from Arookutti to Cherthala, sandwiched by Vembanad Lake on one side and the Lakshadweep Sea on the other and situated in the Alappuzha district in Kerala, India, is endowed with large reserves of silica sand deposits that are generally flat to gently dipping (Figure 2). The geographic location of the study area is $9^{\circ}53'23.50''$ N– $9^{\circ}34'52.29''$ N latitudes and $76^{\circ}16'15.12''$ E– $76^{\circ}23'55.50''$ E longitudes. The Palaeo-beach ridges extend from Alappuzha to Nirkunnam and contain a high concentration of white silica sands, which form the Cherthala sand deposits of 8–9 km in length and 1–2 km in width [15]. Detailed fieldwork was carried out in the study area. Surface samples collected at the sampling stations were used to build reference spectra for mapping silica mineral occurrences. The photographs of the silica sand deposits taken during the field survey are shown in Figure 3. A total of 21 locations (C1 to C15 and S1 to S6) distributed across the study area were selected for sample collection and model development. Five data points were collected from each location, for a total of 105 data points. The sampling locations C1 to C15 were used for model training, whereas S1 to S6 were utilised to validate the model's classification performance.

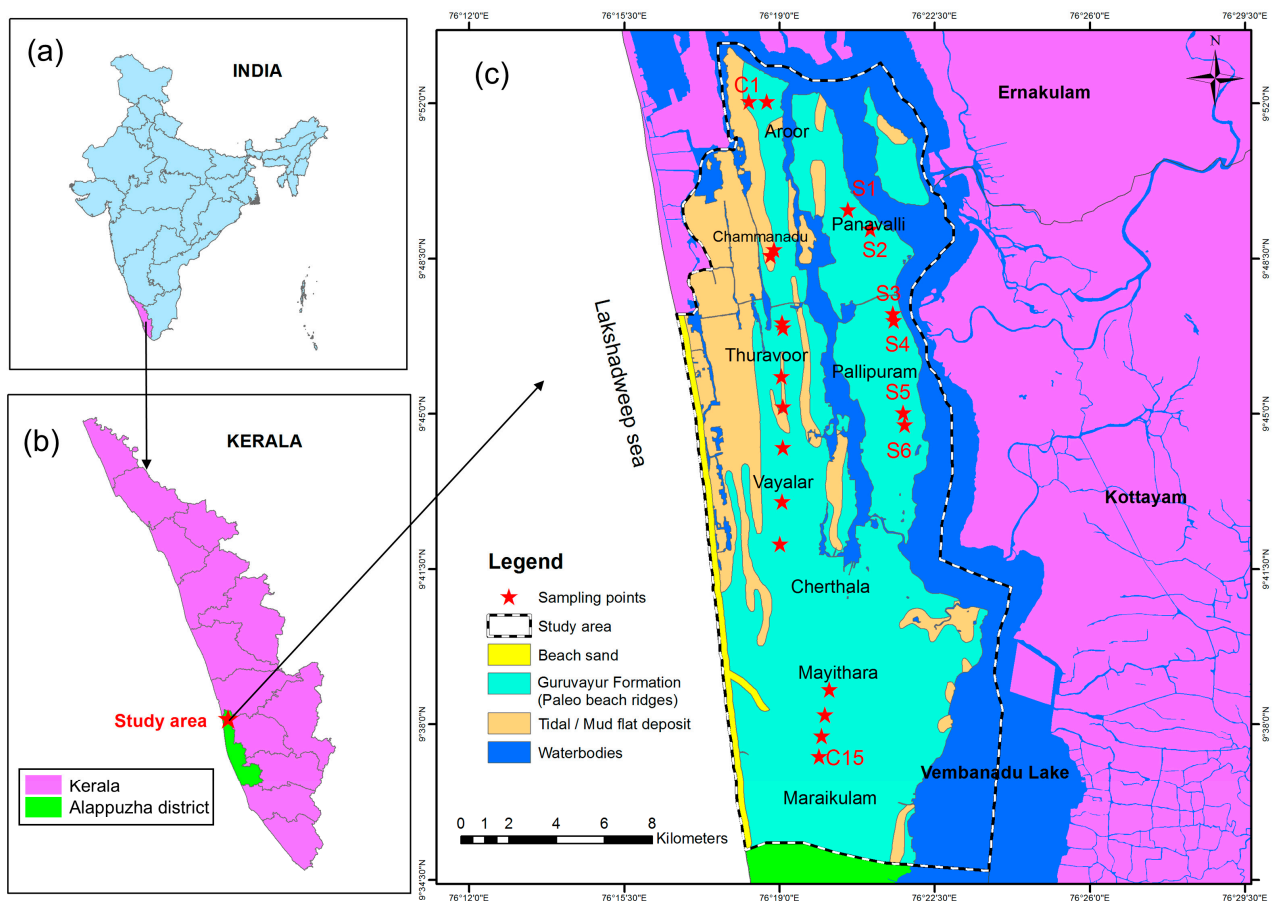


Figure 2. Study area map. (a,b) Location of study area in the Alappuzha district of Kerala, India. (c) Sampling points overlaid with the geological map of the study area.



Figure 3. Photographs of the silica sand deposits.

2.2. Laboratory Analysis and Spectral Data Collection

A portion of the bulk sample, approximately 100 g, was taken by coning and quartering for laboratory analysis. After pre-treatment, the heavy minerals were removed using bromoform, which has a specific gravity of 2.89 [16]. The weight percentage of silica sand present in each sample was computed. The SiO_2 content of silica sand was estimated using the Malvern PANalytical Epsilon 3 ED-XRF instrument with Omnian standard (Almelo, The Netherlands). The X-ray diffraction measurements were done using a PANalytical X'Pert Pro diffractometer (Almelo, The Netherlands).

The laboratory spectra of silica sand were measured using an ASD Fieldspec[®] 3 spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA). It measures the reflectance values in the visible-near-infrared (VNIR) (350–1000 nm) and short-wave infrared (SWIR) (1000–2500 nm) spectral regions at a sampling interval of 1.4 and 2 nm, respectively. The pre-processing steps applied to the collected spectra are (i) splice correction using ASD Viewspec ProTM (Analytical Spectral Devices Inc., Boulder, CO, USA), (ii) removal of spectral values measured in the wavelength range of 350 nm to 400 nm, and (iii) smoothing of spectra using the Savitzky–Golay algorithm with a 2nd order degree of polynomial and a window size of 15 [17,18].

2.3. Advanced Spectral Classification

Potential targets for silica sand exploration were identified using advanced image analysis, followed by Spectral Angle Mapper (SAM) classification of Landsat 8 and ASTER imagery. The study used two cloud-free ASTER L1B scenes acquired on 19 December 2017 and a Landsat 8 scene acquired on 18 January 2017. The advanced image analysis consists of the following processes such as (i) radiometric calibration and FLAASH atmospheric correction (Fast line-of-sight Atmospheric Analysis of Spectral Hypercubes), (ii) reduction in the spectral dimensionality and noise segregation using Minimum noise fraction (MNF), (iii) collecting pure pixels using Pixel purity index (PPI), (iv) target endmember extraction using n-D visualizer, (v) identification of mineral classes through spectral matching of endmember spectra with laboratory-derived spectra of silica sand using the scores obtained from Spectral Feature Fitting (SFF), Spectral Angle Mapping (SAM), and Binary Encoding (BE), and (vi) mineral mapping using Spectral Angle Mapping (SAM) classification algorithm [4]. All processes were performed using the Advanced Spectral Analysis (ASA) module in ENVI version 5.1.

2.4. Machine Learning Classification

Four machine learning algorithms, including Random Forest Classifier (RF), Support Vector Machine (SVM), Maximum Likelihood Classifier (MLC), and Artificial Neural

Network (ANN), were used to map inland silica sand deposits using multispectral Landsat 8 OLI imagery. The Random Forest classification was performed using EnMAP-Box, a free and open-source plugin for QGIS Desktop version 3.22.9, with 500 trees. For the SVM, the RBF kernel is selected with a penalty parameter of 100 and a gamma parameter of 0.167 [19]. A multilayer feed-forward ANN method was applied to Landsat 8 OLI data. The parameters used to execute the ANN include a logistic activation function, a training threshold of 0.9, a training rate of 0.2, a training momentum of 0.9, and a training root-mean-square (RMS) exit criterion of 0.1 [20]. The SVM, MLC, and ANN classification was performed using the ENVI version 5.3 image processing software. The overall accuracy and Kappa coefficient were used to evaluate ML algorithms.

3. Results

3.1. Characterisation of Silica Sand Deposits

The samples collected from sampling stations S1 to S6 show good silica concentrations ranging from 93.93% to 97.94%. The average silica sand content in the samples is 95.74%. The ED-XRF analysis of these samples yields an average SiO_2 content of 98.54%. The silica sand collected from all locations shows a high SiO_2 concentration, ranging from 96.93% to 99.13%. The XRD analysis of pre-processed samples, as shown in Figure 4a, shows diffraction peaks characteristic of highly crystalline quartz, confirming the presence of silica sand.

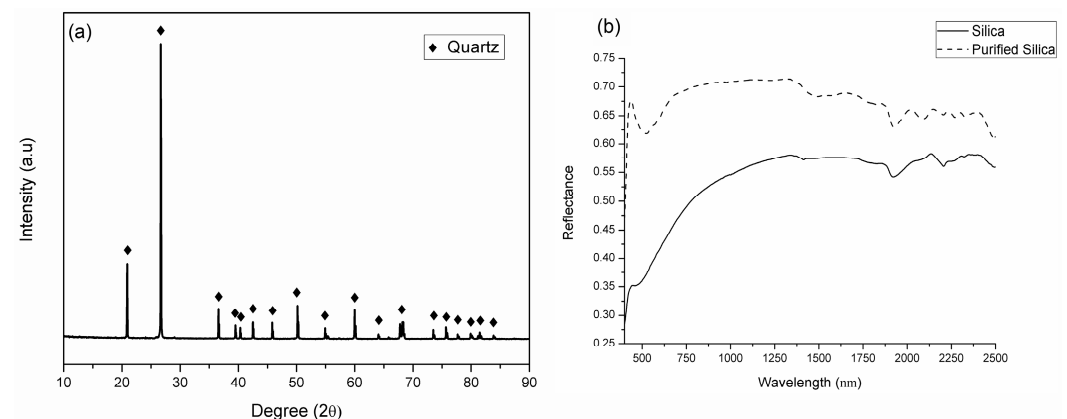


Figure 4. XRD pattern (a) and laboratory spectra (b) of the Silica sand.

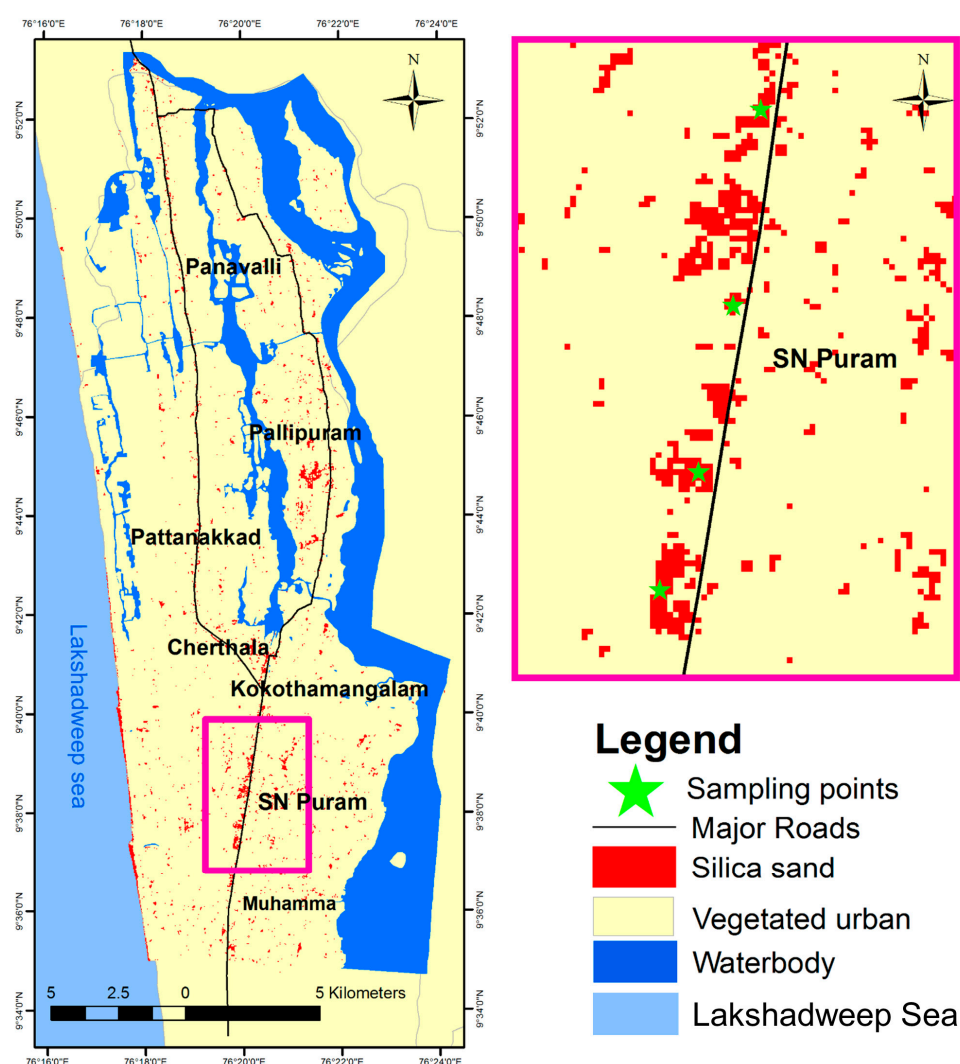
3.2. Mineral Mapping Using SAM Classifier

The mean spectrum of samples collected from the study area is used to develop the reference spectrum of silica sand, as shown in Figure 4b. The sensor's inherent errors, such as thermal drift, were corrected, followed by smoothing, yielding characteristic spectra of silica sand that are used to map potential silica sand targets. The noise-dominated, least-informative last bands were removed using the MNF transformation with appropriate thresholds. The PPI image showing spectrally extreme pixels as bright was generated using 100 iterations and a threshold of 3. Using spectral matching techniques, the endmember spectra of unique target materials identified using the 2D scatter plots were assessed with the reference spectra of silica sand. This results in the successful identification of true endmembers. The scores of SAM, SFF and BE are shown in Table 1.

Table 1. Results of spectral matching techniques for silica sand deposits.

Satellite Data	Date of Acquisition	Endmember	SAM	SFF	BE	Score
ASTER	19 December 2017 (Scene 1)	Silica	0.629	0.968	1	2.597
		Purified Silica	0.511	0.965	0.222	1.699
	19 December 2017 (Scene 2)	Silica	0.717	0.948	1	2.665
		Purified Silica	0.601	0.947	0.222	1.771
Landsat 8	18 January 2017	Silica	0.426	0.987	0.714	2.127
		Purified Silica	0.325	0.950	0.429	1.703

The Landsat data generate six endmembers, of which one has a maximum score of 2.127 and was used as the image spectrum for mapping silica sand occurrences. The ASTER scenes generated eight end members, corresponding to the top scores of 2.597 and 2.665, and were used as the training data for classification. In addition, end members representing water bodies, vegetation, and other common landforms and lithological structures were retrieved from the PPI images and excluded from further SAM classification. Figures 5 and 6 present SAM-classified images of silica sand abundance derived from the Landsat and ASTER datasets. The overall accuracy for the Landsat 8 OLI imagery is 90.48%, and for ASTER data it is 80.95%.

**Figure 5.** SAM classified image of the study area using Landsat 8.

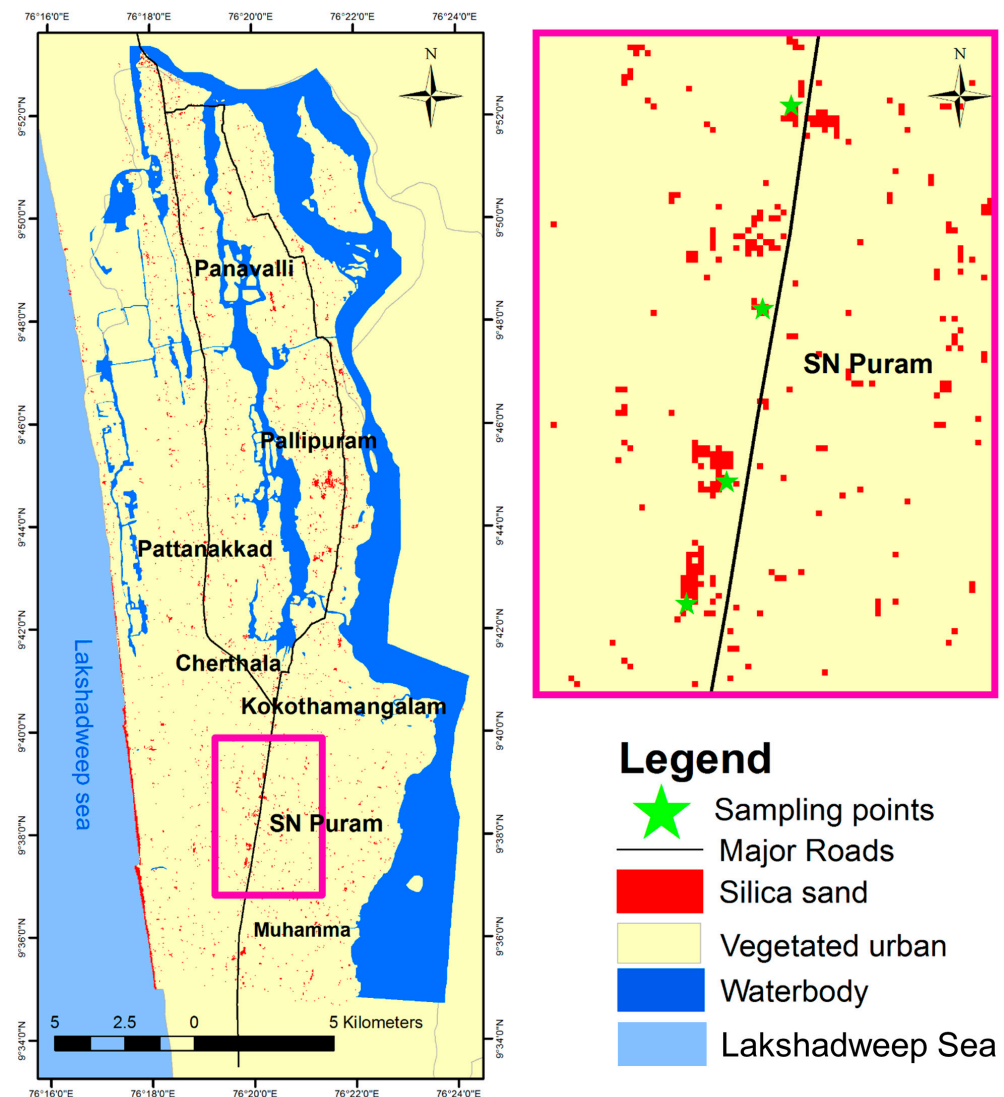


Figure 6. SAM classified image of the study area using ASTER data.

3.3. Comparison of Machine Learning Algorithms

The FLAASH-corrected Landsat 8 OLI imagery was used to map the silica sand deposits. The average spectra of training ROIs used to map the silica sand deposits in Cherthala are shown in Figure 7. The spectral similarities between inland and beach silica sands were carried out using Landsat multispectral imagery, as shown in Figure 7. They both exhibit a similar spectral signature, indicating comparable geochemistry and dominance of quartz. However, the higher reflectance of beach sands compared to inland sands may be due to their higher purity and better sorting. The beach sands are often exposed to continuous wave action, which causes removal of impurities, sorting and weathering. Apart from silica sand deposits, surface features such as vegetation, urban/settlement, and water bodies were also included in the classification process. The accuracy assessment indicates that all the ML algorithms perform well at mapping silica sand deposits, with average overall accuracy value of 97.07% and Kappa coefficient of 0.94%, respectively. Based on the results, we conclude that SVM outperforms the other algorithms, including RFC, ANN, and MLC. The SVM shows an overall accuracy of 97.8242% and a Kappa coefficient of 0.9574, followed by RFC with 97.76% and 0.96; ANN with 96.98% and 0.94; and, finally, MLC with the lowest accuracy at 95.71% and 0.92. The mineral classification map of inland silica sand deposits, generated using a Support Vector Machine (SVM), is shown in Figure 8. The mineral classification maps showing the distribution of silica sand

deposits in the Cherthala area, generated using different ML algorithms, are shown in Figure 9a–d.

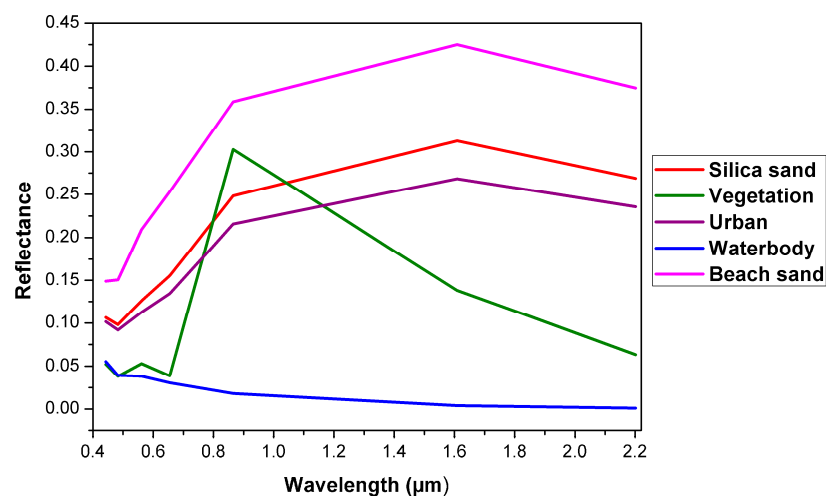


Figure 7. Average spectra of training ROIs collected for mapping inland silica sand.

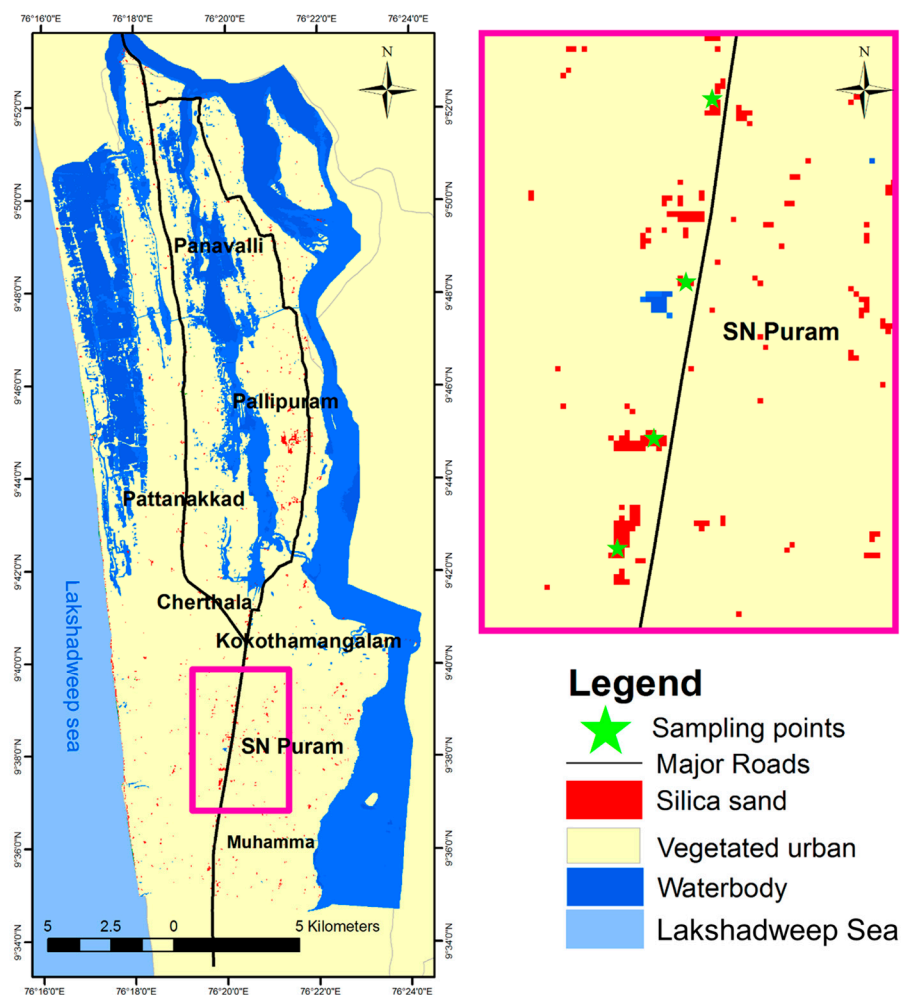


Figure 8. Mineral classification map showing the distribution of inland silica sand deposits using a support vector machine (SVM).

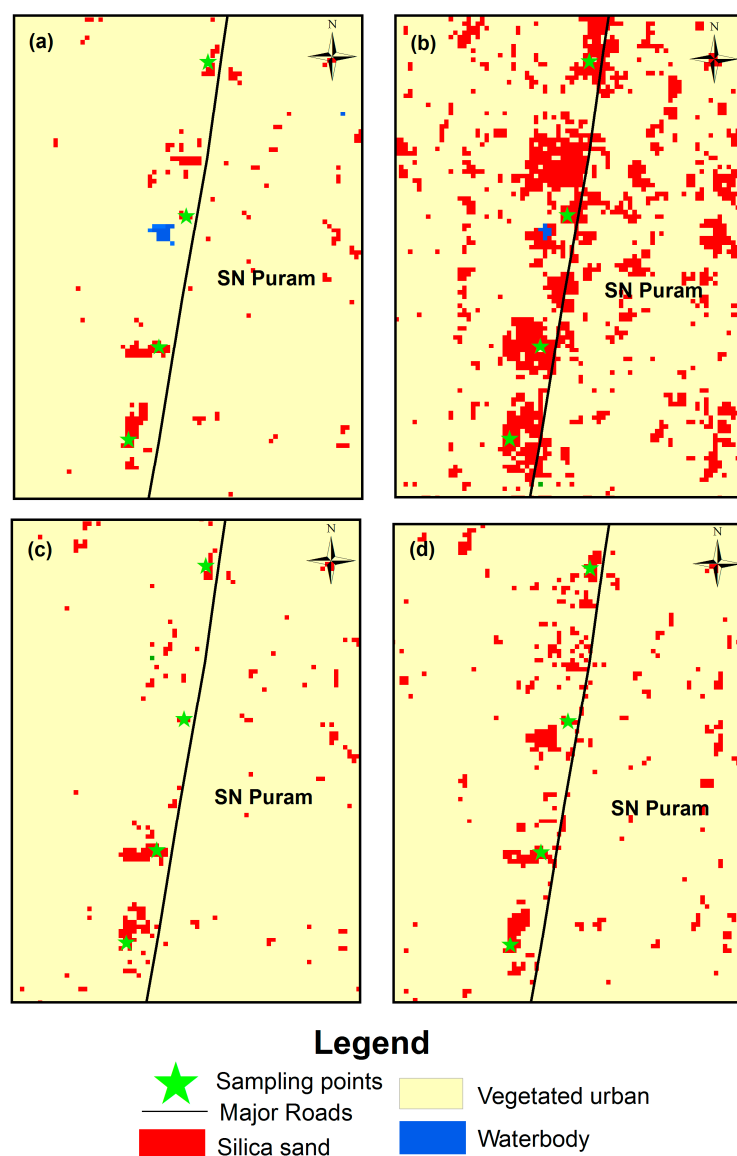


Figure 9. Mineral classification map showing the distribution of silica sand deposits in the Cherthala area using (a) SVM, (b) ANN, (c) RFC, and (d) MLC.

4. Discussion

Silica sand deposits were mapped successfully using two approaches applied to Landsat and ASTER remote sensing datasets. SAM is used successfully to compare image spectra with reference spectra and to perform per-pixel classification by measuring the spectral angle between the unit vectors representing the image and reference spectra [21]. In mineral exploration and mapping, SAM image classification was considered one of the primary techniques for generating “attribute maps” [22]. The SAM-classified maps can be considered “attribute maps” for silica sand explorations in the present study area.

Compared with other conventional remote sensing approaches, such as spectral indices, band combinations, and principal component analysis, the SAM has proved to be the best method for mapping minerals [22]. Generating reference spectra is essential for obtaining highly accurate SAM results. Using mean spectra from imagery to classify individual minerals yields low accuracy due to the limited spectral variability within each mineral [23]. The spectral signatures of the silica sand were generated with a spectroradiometer and used to map the mineral deposits using the SAM classification technique. The observed spectra are comparable with previously reported spectral signatures of silica sand deposits [9].

The increase in spectral reflectance of the silica samples after pre-processing is due to the removal of absorptive impurities, which enhances the brightness and intrinsic spectral properties of silica. Water absorption features were observed, particularly at 1400 nm and 1900 nm. The depth of the absorption is always proportional to the presence of the element or compound that triggered the absorption. The absorption around 0.9 to 1.2 μm and 1.4 to 1.9 μm may be due to the presence of iron oxides and hydroxide ions [9] trapped in the silicates, which is the major reason for characteristic spectral features. This approach, which maps minerals using spectral data for the minerals of interest, improves classification accuracy and thereby identifies the exact locations of mineral occurrences. Both Landsat 8 and ASTER have SAM classification accuracies of 90.48% and 80.95%, with slightly higher accuracy for Landsat 8. The Landsat 8 has a significantly higher signal-to-noise ratio, a uniform spatial resolution, and improved radiometric performance, which together contribute to its higher classification performance [24]. Moreover, the adopted MNF–PPI–SAM workflow introduces enhanced noise suppression and enables the selection of more representative endmembers for SAM classification. Higher classification accuracy for Landsat 8 than for ASTER was previously reported for lithological mapping [25].

The robustness of ML models in processing large volumes of remote sensing and in situ data, regardless of their noise and uncertainties, makes them a viable solution for remote sensing exploration of strategic minerals [5,26]. The best classification algorithms were selected based on accuracy measurements and misclassification counts. The accuracy of the classified mineral maps was assessed using the kappa index and overall accuracy (OA). The SVM outperformed other models by an overall accuracy of 97.82% and a Kappa coefficient of 0.96. A comparatively higher pixel misclassification rate is evident in the less accurate ANN-derived map (Figure 9b). The water body is not visible in the RFC and MLC (Figure 9c,d). Compared with other maps, the SVM map (Figure 9a) accurately locates silica sand deposits and other classes. The superior performance of SVM over ANN, MLC, and RF was also reported for mapping lithological units and alteration zones [19,27]. Upon verification with the geological map (Figure 2), the classified mineral abundances are consistent with geological formations and distribution patterns.

While hyperspectral remote sensing datasets deliver competitive results for mapping mineral deposits [28], we have attempted to apply hyperspectral techniques to multispectral data and machine learning models. Good prediction accuracy in the present study underscores the viability of using readily available multispectral datasets for mapping economically significant silica sand deposits. Further, it may be scaled up for other economically significant mineral deposits to adopt effective site-specific mineral exploration studies. Also, the present work will be extended to consider additional types of strategic mineral deposits, using advanced hyperspectral analyses and machine learning models applied to both multispectral and hyperspectral remote sensing datasets.

5. Conclusions

White silica sand deposits in the Cherthala region of Alappuzha district in Kerala, South India, are economically important for their use in the glass industry. Remote sensing exploration of silica sand deposits was successfully done using ASTER and Landsat satellite imagery. The SAM spectral classification technique generated an image depicting potential targets for mineral occurrences. Compared with the four widely used MLAs for mapping mineral sands, the SVM performs better at identifying potential zones of inland sand deposits. The high accuracy confirms MLAs' ability to map mineral sands using multispectral datasets, with the best hyperparameters and an accurate selection of training sites. This study facilitates accurate mapping with less time and fewer resources than conventional geological mapping in this field, enabling eco-friendly and sustainable mineral exploration.

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