SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I12P102

Volume 12 Issue 12, 11-21, December 2025


*Original Article*

# Communication of Surface Water Turbidity Estimation via Segmented PCA and Machine Learning on Landsat 8 Data

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Received: 02 October 2025 Revised: 04 November 2025 Accepted: 03 December 2025 Published: 27 December 2025

***Abstract*** *- The second-largest brackish water Lagoon in India is Pulicat Lake, with an area of approximately 759 km². It is being supported by inland river systems and opened to the Bay of Bengal, creating a dynamic interface between freshwater and marine environments. The lake also hosts an abundant flora and fauna; this is very crucial in ensuring the balance of the ecosystem and is also a critical habitat for the birds. The use of turbidity as a measure of water quality, ecosystem, and land cover dynamics is relevant to monitoring turbidity in Pulicat Lake. Remote sensing would be an efficient technique for elucidating both spatial and temporal changes in turbidity. This research indicates that a hybrid mix of Segmented Principal Component Analysis (SPCA) and the machine learning process will be used to enhance the performance of predicting the level of turbidity by applying Landsat 8 images. The suggested SPCA-based system considerably improves the classification accuracy, reaching the general accuracy of 99.2664 percent and a Kappa coefficient of 0.9896, which is higher than the traditional approaches. Precisely, the NDTI/Random Forest model gave an overall accuracy of 88.0189% and a Kappa coefficient of 0.8313, whereas the Band 4/Random Forest model gave an overall accuracy of 98.8656% and a Kappa coefficient of 0.9839. All these findings indicate the efficiency and durability of the SPCA-bound method of monitoring turbidity in ecologically very sensitive areas such as the Pulicat Lake.*

***Keywords*** *- Pulicat Lake, Landsat – 8, Turbidity, Principal Component Analysis (PCA), NDTI, Random Forest Algorithm.*

## 1. Introduction

Lakes are important ecological resources that sustain human activity and biodiversity as a multifunctional ecosystem. They also provide fresh water to the human population, irrigation agriculture, and serve as an essential habitat to various aquatic life and migratory species of birds. Lakes are described ecologically as complex socio-ecological systems, which have diverse features across lakes and even within the same lake as a result of space and time variation. The major contributors to lake biodiversity are, among others, the physicochemical properties and turbidity level, the land use near the lake, and climatic conditions [1]. Residing in some of the leading lakes in India, the country is identified with high instances of natural diversity, including Chilika, Dal, Shivajisagar, Kolleru, and Pulicat. These lakes can be categorized as freshwater, salt, natural, and artificial lakes in regard to their origin and the salt concentration [2]. Pulicat Lake is found in the Coromandel Coast along the Bay of Bengal. This salty water lagoon separates the Andhra Pradesh and Tamil Nadu states. About 96 percent of the lake is located in Andhra Pradesh; the other part, stretching to the lake mouth, is located in Tamil Nadu [3].

Scientific aquaculture and fishing have continued to put additional strain on the ecosystem of the Pulicat Lake, which has gradually resulted in reduced water quality [4]. The remote sensing technologies have provided viable solutions to monitoring and management of such aquatic environments. The most popular field is the identification and analysis of spatial changes and measuring the area of water dispersal in lakes via satellite images and Geographic Information System (GIS) [5]. Digital image analysis is significantly associated with image classification, which identifies all the image pixels to specific land cover or water quality classes and classifications [6]. The classification techniques are divided into pixel-based and object-based techniques.

The dataset comprising the Landsat 8 Operational Land Imager (OLI) offers an abundant supply of spectral modes, yet due to a high level of correlation within a feature, set redundancy emerges, and it becomes difficult to classify the features. To handle this issue, dimensionality reduction methods such as PCA are utilized to remove redundant data and maintain high variance in the data [7]. This paper proposes a new conceptualization of turbidity monitoring in Pulicat Lake, utilizing key turbidity-related spectral features. The classification mechanism will be effective in differentiating the levels of turbidity in water using remotely sensed data.

## 2. Literature Survey

Water quality measurement, more specifically, turbidity, is very instrumental in aquatic ecosystem monitoring and biodiversity conservation. Turbidity has become a potent medium through which several techniques have been investigated over the years, and remote sensing has proven useful [8]. Remote sensing offers a complete and effective method of assessing water quality at a large scale, as it can provide both spatial and temporal data. Satellite imagery, especially from the Landsat missions, has been extensively utilized in the literature of water quality monitoring because space photography can cover larger areas and longer durations [9].

Visibility or the ecological balance of water depends on the turbidity indicators to reveal the presence of suspended particles in the water, thus affecting the amount of light penetration and disturbing aquatic organisms. Some research efforts have highlighted the significance of turbidity as an indicator of ecological conditions at the lake, river, and coastal levels [10]. Conventionally, the magnitude of turbidity was determined in situ, which is also constrained in terms of space. The improvement in remote sensing, however, has silenced this concern by providing a mechanism to gauge turbidity in remote and, in most cases, unreachable areas [11].

Several methods are recommended for gauging turbidity using remote sensing data, including band ratios, NDTI, and PCA. The success of band ratios (the combination of green and blue) in distinguishing between water bodies and land has been extensively employed, although it is not always the most effective band ratio in capturing subtle information about turbidity variations [12]. Applications of NDTI have been promising in enhancing turbidity estimation based on the multi-range of reflectance values in electromagnetic spectra. Nevertheless, these techniques are usually restrictive regarding the accuracy and generalization to various water bodies whose properties vary [13].

The PCA has been predominantly used to reduce the dimensions of remote sensing data and identify meaningful components. Although it is observed that PCA has been valuable in various environmental monitoring contexts, it occasionally fails to distinctly distinguish the level of turbidity, particularly in complex and dynamic environments such as lakes under brackish conditions. The current developments have led to the use of SPCA, which achieves better classification accuracy than classifying the data into discrete spatial units followed by applying PCA [14]. It has been found that SPCA is especially effective in settings where a major phenomenon, such as fluctuating water quality and level of turbidity, is observed across the areas. The methods that have been expanding in their application to remote sensing in civil applications include machine learning algorithms such as SVM and Random Forest. The approaches are sensitive to non-linear feature-feature relationship and can significantly contribute to the improvement of turbidity estimation models [15].

Multiple studies have demonstrated that the use of machine learning, both alone and in conjunction with remote sensing data, is more effective than traditional theory in terms of prediction and strength, particularly when applied to complex ecosystems under diverse environmental conditions [16].

Elementary studies have been conducted to determine turbidity within brackish water ecosystems, including Pulicat Lake; nonetheless, the use of sophisticated remote sensing and machine learning technologies to monitor water quality in this environment has been encouraging [17].

It has been revealed that machine learning algorithms have been capable of significantly improving the accuracy of turbidity level predictions through the use of SPCA, which forms an effective field of assessment for ecologically sensitive ecosystems [18].

Such a combination of methods is a step in the right direction of ecological surveillance that will allow the management and conservation of the most vital water reserves.

## 3. Materials and Methods

### *3.1. Study Area and Data*

One of the 17 coastal lagoons is Pulicat, found on the east coast. The lagoon extends across the border into the states of Tamil Nadu and Andhra Pradesh on the Coromandel Coast of South India. The lake falls within the latitude of 13 ° 33 ' 57 in degrees, and 80 ° 10 ' 29 in longitude, respectively. The data sets of Landsat 8, comprising 142 rows and row 51, to be used in the investigation, are available on the United States Geological Survey Earth Explorer site [8].

**Table 1. Landsat – 8 OLI dataset**

| | |
|---|---|
| **Acquired Image Dates** | 11-06-2024 |
| **Path/Row** | 142/51 |
| **Datum** | EPSG:32644 |
| **Projection** | UTM |
| **Spatial Resolution** | 30mm |
| **File Format of Acquired Images** | Geo – TIFF |
| **Total number of bands** | 11 |
| **Type of sensor** | OLI |

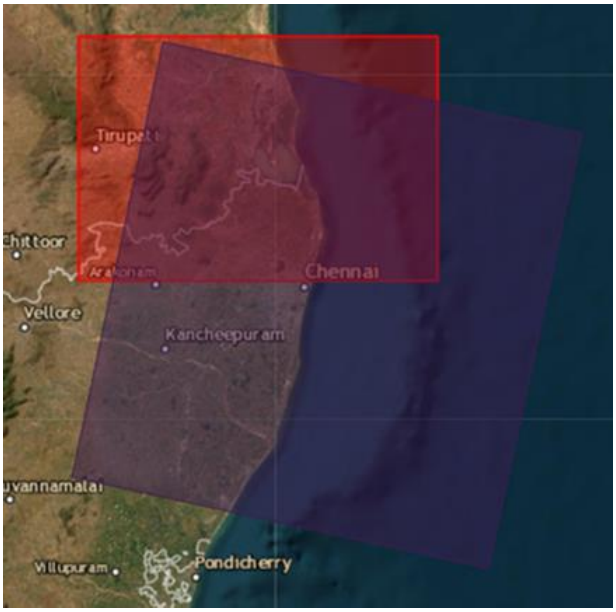


**Fig. 1(a) Foot print of ROI in Landsat 8 OLI**

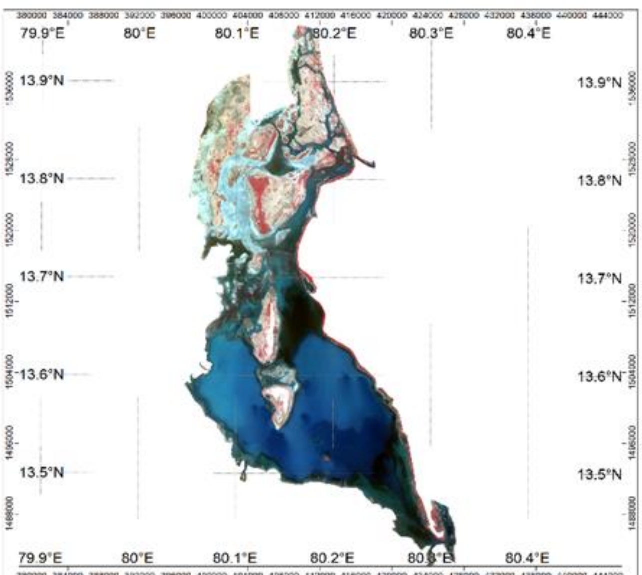


**Fig. 1(b) Layer-Stacked Image of Pulicat Lake**

## 4. Proposed Method

Figure 2 describes the proposed methodology based on Landsat 8 imagery in the lagoon area as the main source of data to determine turbidity. The first step in the workflow is data preprocessing in the form of Digital Numbers (DN) as Top of Atmosphere (TOA) reflectance. All bands are then subjected to PCA to reduce the dimensionality of the data, allowing the extraction of meaningful features [19]. The first two largest principal components are classified by binary classification using the random forest algorithm on the factors used due to their maximum variance, as this process classifies the areas of water and non-water into one water mask, which represents the lagoon. Pairs of bands are then broken down using spectrally segmented PCA, namely, 3, 4, and 5. PC1 in the segmented PCA, and the water mask generated, is subsequently input with a second Random Forest classification [20]. The classification is based on three levels of turbidity: Low Turbid, Medium Turbid, and High Turbid water. A confusion matrix is used to determine the accuracy of the results of the classification and to validate the workability of the proposed approach.

### *4.1. Pre- Pre-Processing of Data*

Preprocessing is a crucial stage in preparing remote sensing data for operational analysis and precise classification. The Landsat 8 Operational Land Imager (OLI) data employed in this research were preprocessed with the help of the information derived.

From the metadata file that comes along with it [21]. The first process was to first transform the unprocessed values of the Digital Number (DN) to Top of Atmosphere (TOA) reflectance, which standardizes solar angle and radiometric effect differences [22].

After radiometric correction, raster clipping was performed to cut the dataset into an ROI, specifically Pulicat Lake. The resulting composite image, in layer format, of the ROI is shown in Figure 1(b).

### *4.2. Conversion of DNS to Top of Atmosphere (TOA) Reflectance*

Conversion of satellite image digital number values to TOA reflectance values. TOA reflectance is obtained using Equation (2).

$$\rho\lambda' = M^{\rho} * Qcal + A^{\rho} \tag{1}$$

$$P\lambda = \frac{\rho\lambda'}{\sin(\theta SE)} = \frac{\rho\lambda'}{\cos(\theta SZ)} \tag{2}$$

Where

$\rho\lambda'$ =Top-of-Atmosphere Planetary Spectral Reflectance, without correction for solar angle.

$M^{\rho}$= Reflectance multiplicative scaling factor for the band.

$A^{\rho}$=Reflectance additive scaling factor for the band.

Qcal=Level-1 pixel value in DN.

$P\lambda$=Top-of-Atmosphere Planetary Reflectance.

$\theta SZ$=Solar Zenith Angle.

$\theta SE$=Solar Elevation Angle.

## 5. Principal Component Analysis (PCA)

Principal component analysis is an effective feature extraction and dimensionality reduction method that can be used to classify data properly. Mappings of high-dimensional information in receiving sensing are burdensome, particularly with the type of data classes inherent in Pulicat Lake. PCA pays attention to the reduction of dimensionality, wherein the high-dimensional data is reduced to low-dimensional data.

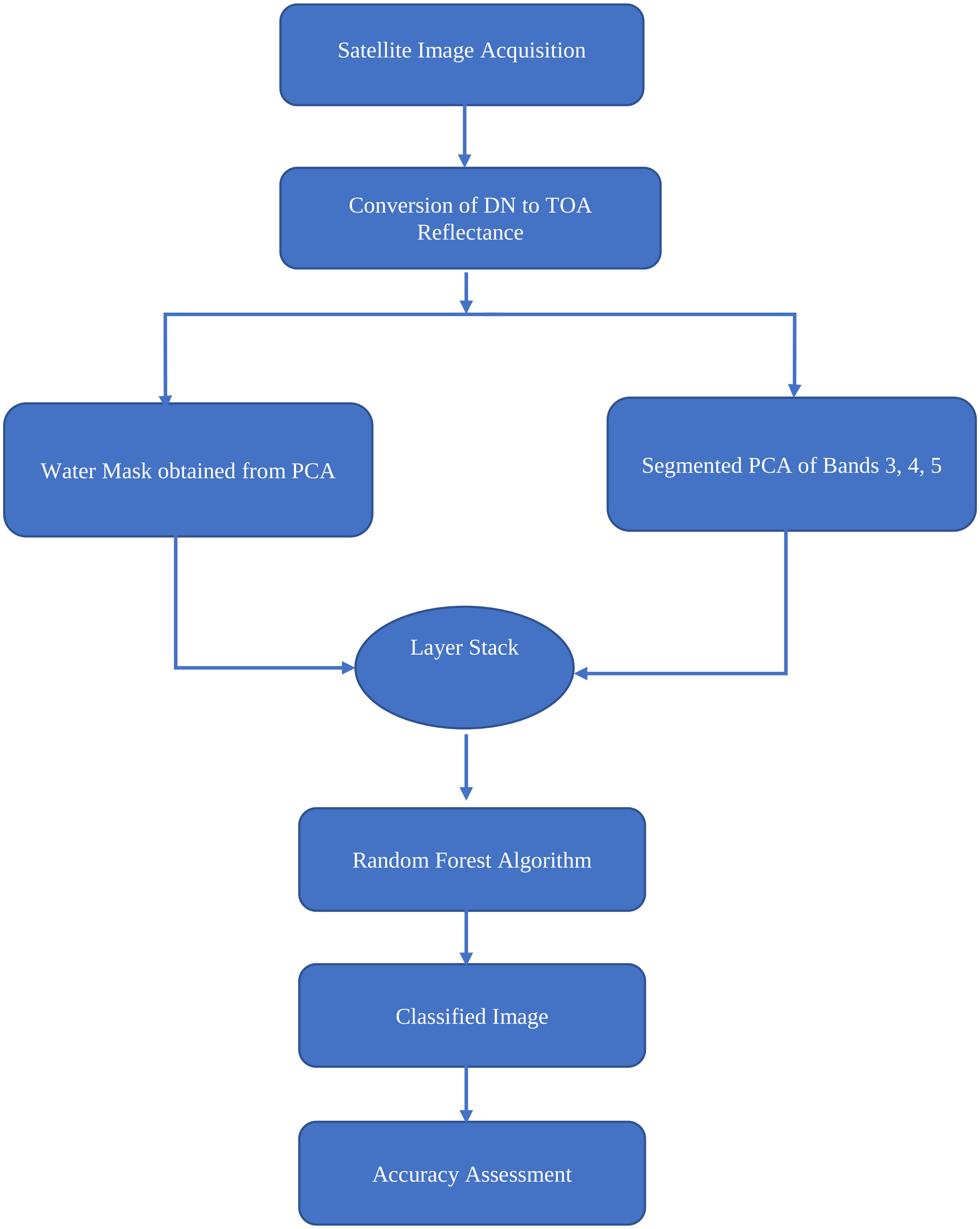


**Fig. 2 Workflow for proposed method**

It makes the interpretations more interpretable, but at the same time retains the most significant data [23]. It does this through the identification of new axes. These novel axes are referred to as principal components, which are orthogonal, meaning that they are non-persistent and hence an effective tool of dimensionality reduction. Figure 3 Visualization of PCA data points distribution in the two-dimensional space. PC-1, or the leading principal component, is the direction of greatest variance in the data set. The next highest variance is PC-2, which is orthogonal to PC-1. PCA would help in converting correlated variables into a collection of uncorrelated components by use of a series of optimum linear combinations, which would assist in dimension reduction and improvement of data meaning.

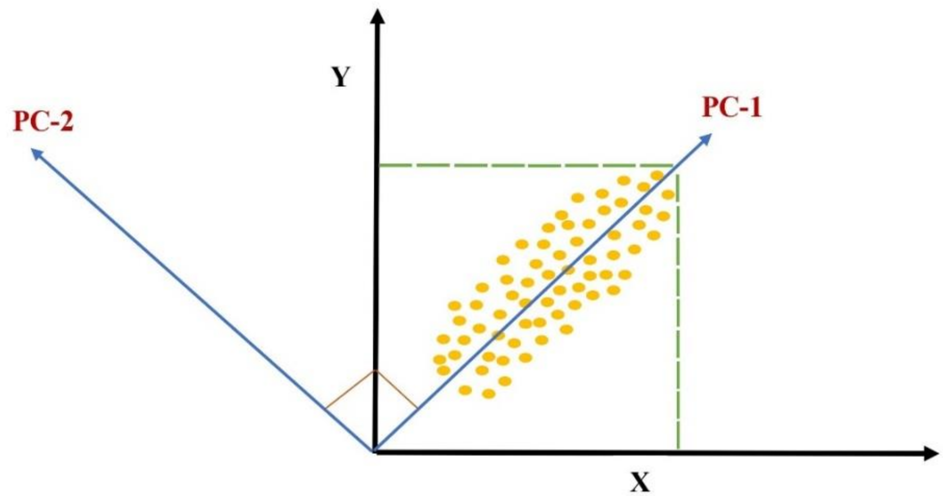


**Fig. 3 Principal Component Analysis (PCA) for a Two-Dimensional data set**

### *5.1. Eigen Vectors for PCA*

The results of the Land satellite 8 give high-dimensional information; it can make the classification tasks in the Pulicat Lake area quite challenging. PCA can provide a solution to this as it can reduce the dimensions of the data to a form that is lower-dimensional and therefore amenable to efficient classification in the ROI. Using this method, a Unique Principal Component (PC1) obtained as a result of a segmented PCA of three bands (3, 4, and 5) is chosen to extract the turbidity feature in water, as it has the highest variance among the components.

The suggested approach with principal components that collectively explain more than 90 percent of the cumulative variance increases the performance of the suggested method in producing more accurate classification results.

**Table 2. Eigen vector matrices for SPCA**

| | PC 1 | PC 2 | PC 3 |
|---|---|---|---|
| **Band 3** | -0.233 | 0.6706 | -0.7043 |
| **Band 4** | -0.4283 | 0.5795 | 0.6934 |
| **Band 5** | -0.8731 | -0.4632 | -0.1522 |

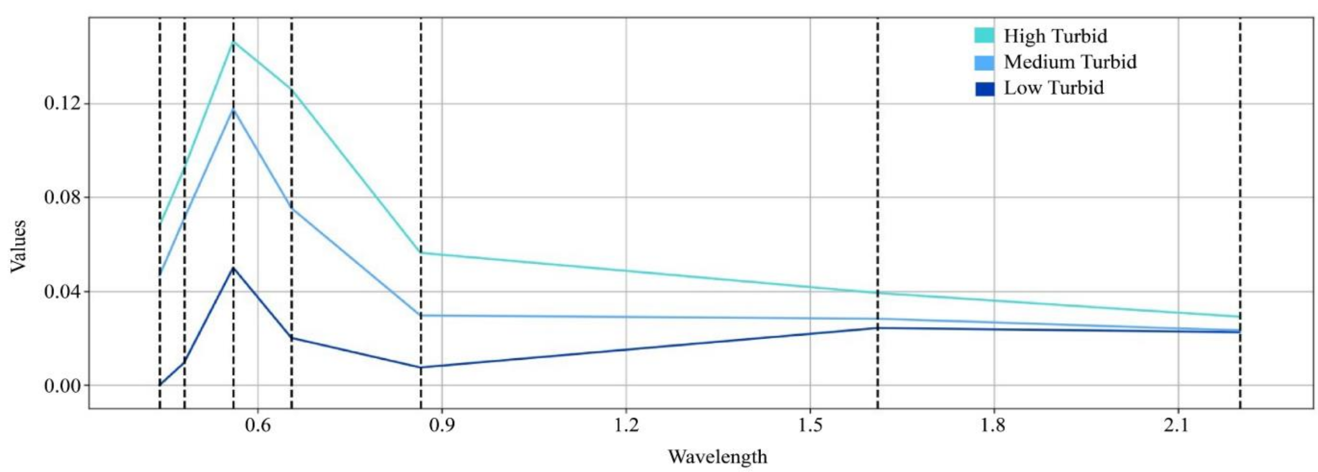


**Fig. 4 Spectral reflectance profile**

The results of spectral reflectance according to the three turbidity classes of Low Turbid Water, Medium Turbid Water, and High Turbid Water are shown in Figure 4. A distinct division of the classes is observed in Bands 3, 4, and 5, where a vertebrate marking is evident between the high and low turbidity levels. This spectral difference provides a crucial understanding of the optimal band combination for accurate turbidity classification.

### *5.2. Random Forest Algorithm*

The algorithm is an ensemble learning method known as the Random Forest algorithm, which involves building a forest of Decision trees. During the training process, it generates several Decision trees. The trees are built on a random sample of the dataset to extract features in every partition [11]. This noise makes a diverse set of trees, minimizing the threat of overfitting and enhancing the overall forecast result [12]. The decision trees are generated based on various subsets of the provided data set. This algorithm generates several decision trees from a training set, and the predictions of each tree are combined to produce an output. Random forest algorithms have three primary hyperparameters: node size, the number of trees, and the sample size of features [16]. During this research, the RF classifier is set with an intermediate 10 trees and a default split feature of 2. This setup was discovered to strike a balance between the accuracy of the classification method and the efficiency of computation in the turbidity mapping problem of the Pulicat Lake area.

### *5.3. Normalized Difference Turbidity Index (NDTI)*

The spectral reflectance values of the concerned pixels of the Region of Interest are used to estimate the turbidity of the water bodies using the NDTI. NDTI works with the Red (Band 4) and Green (Band 3) reflectance bands [13]. Sumanta Bid [14] states that the turbidity index rises when the red band reflectance exceeds the green band reflectance.

The NDTI is obtained using Equation (3).

$$\mathrm{NDTI} = \frac{Red - Green}{Red + Green} \tag{3}$$

The NDTI is performed to determine the turbidity of various classes present in the image. The mean of NDTI is considered for identifying different turbid classes [14].

### *5.4. Accuracy Assessment*

A confusion matrix is used to evaluate the classification. The measures that are taken into account in the assessment are User Accuracy, Producer Accuracy, the Overall Accuracy, and the Kappa Coefficient.

**Table 3. The description of turbidity classes in Pulicat Lake**

| Class Names | Description |
|---|---|
| Low Turbid Water | Clear water bodies, such as rivers and lakes, with minimal suspended particles. Indicates low turbidity and stable water conditions. |
| Medium Turbid Water | Water bodies consisting of moderate levels of suspended matter and often influenced by surrounding vegetation, aquatic plant growth, and proximity to human habitation. The NDTI mean value for this class is 0.1357, indicating an intermediate turbidity condition. |
| High Turbid Water | Water bodies with high sediment content due to inflows and runoff. Characterized by a mean NDTI value of -0.0673, indicating elevated turbidity levels. |

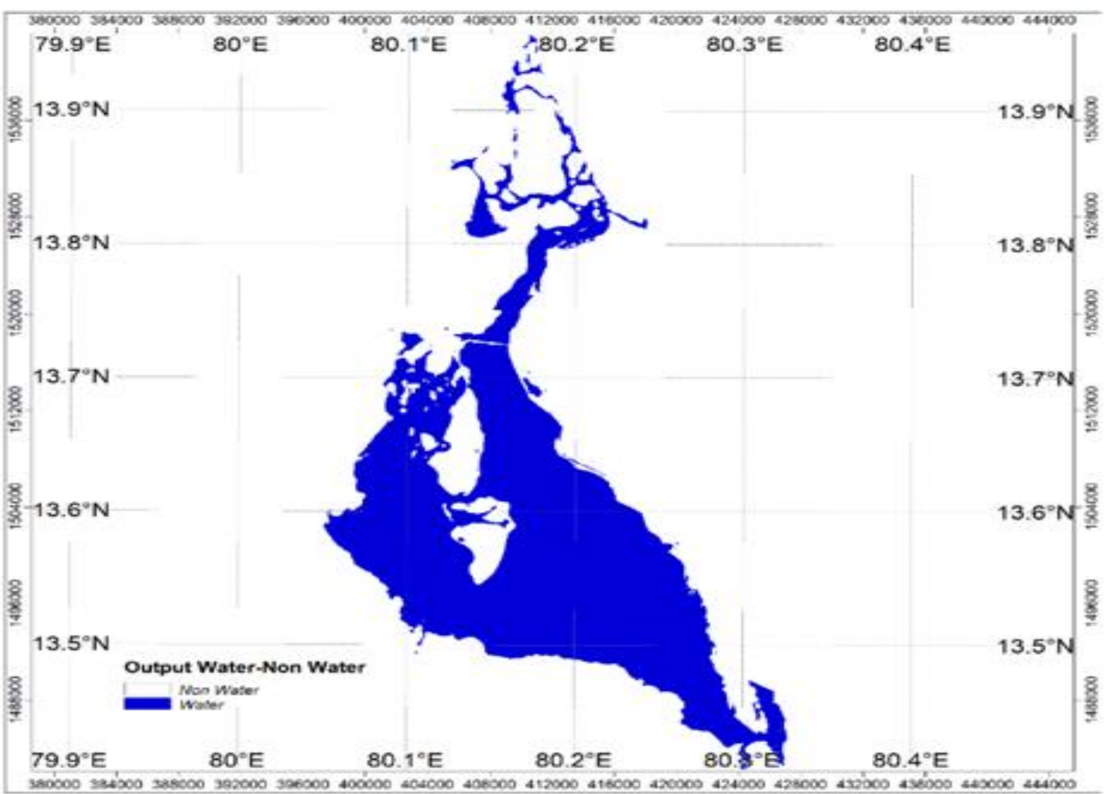


**Fig. 5 Water mask using PCA and Random Forest Algorithm**

## 6. Results

Figure 5 shows the classification of the water bodies to design a water mask with the help of the Random Forest algorithm. Figure 6 shows the index of NDTI, whereas Figure 7 shows the index of turbidity using NDTI and the Random Forest Algorithm. It is a turbidity classification measure that is represented through Band 4 and the random forest algorithm, as indicated in Figure 8. Figure 9 illustrates the proposed method, which relies on the PC1 of SPCA for Bands 3, 4, and 5, combined with the Random Forest Algorithm. The process of classification helps define the turbidity of water, resulting in three classes named: Low Turbid Water, Medium Turbid Water, and High Turbid Water. The procedure that was created in the given study had a greater classification performance, with the overall accuracy being 99.26 per cent and the Kappa coefficient 0.9896.

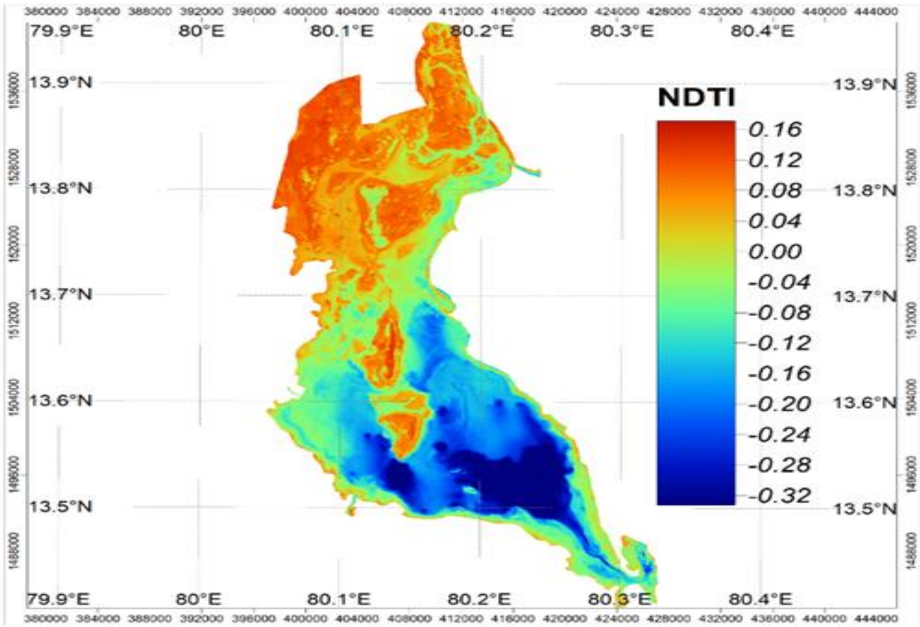


**Fig. 6 NDTI**

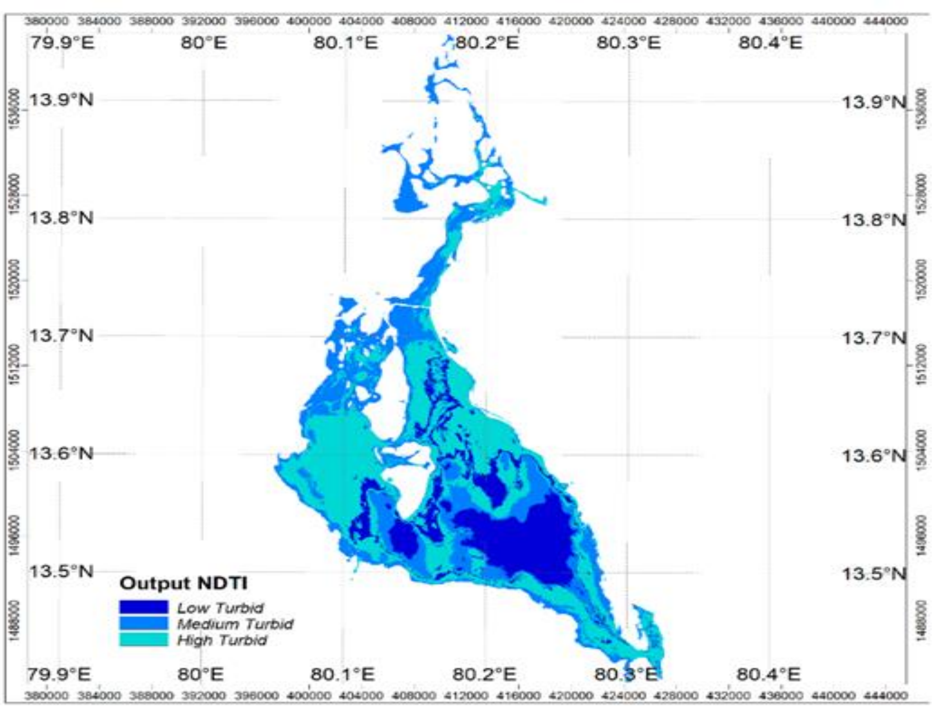


**Fig. 7 Classification of Turbidity using NDTI/RF**

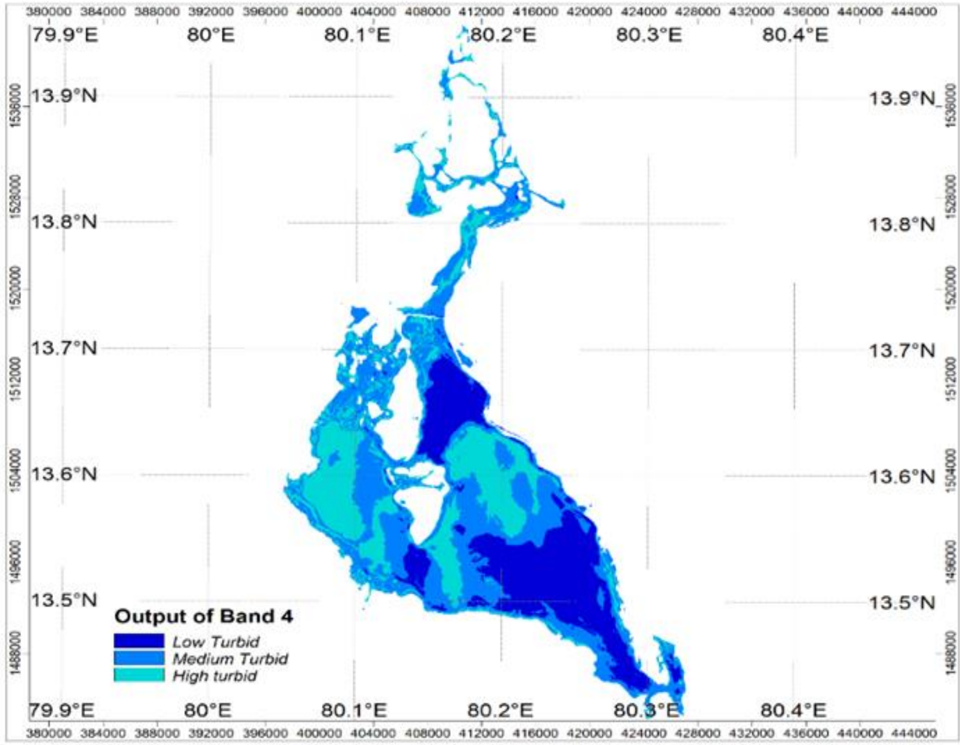


**Fig. 8 Classification of Turbidity using Band 4/RF**

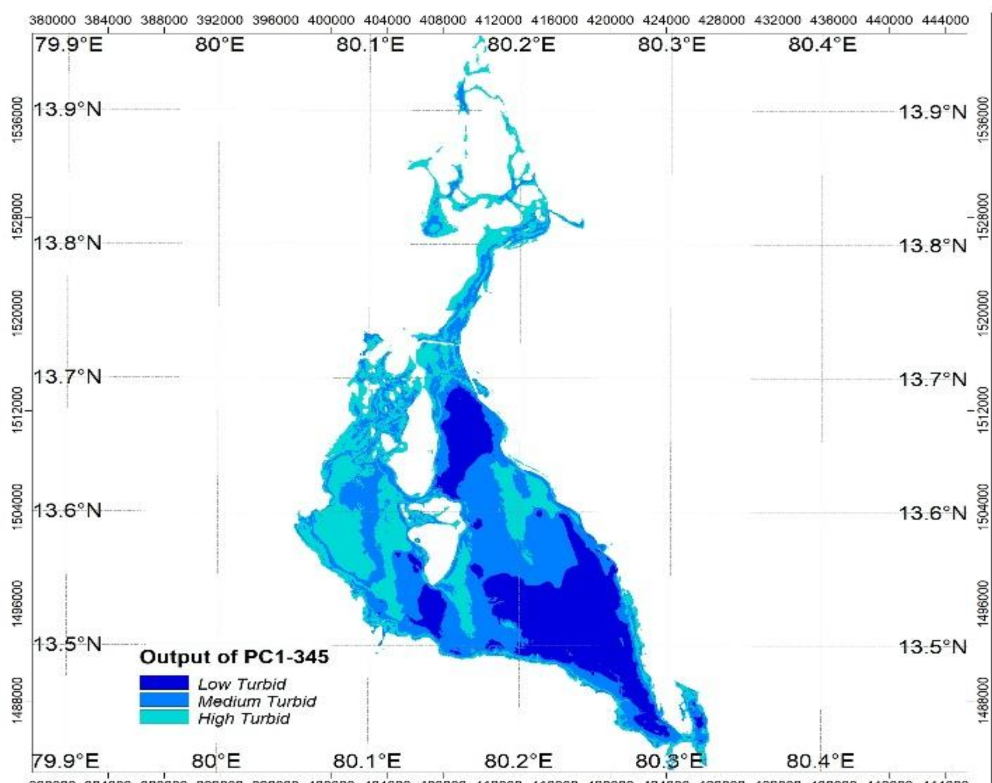


**Fig. 9 Classification of Turbidity using SPCA/RF**

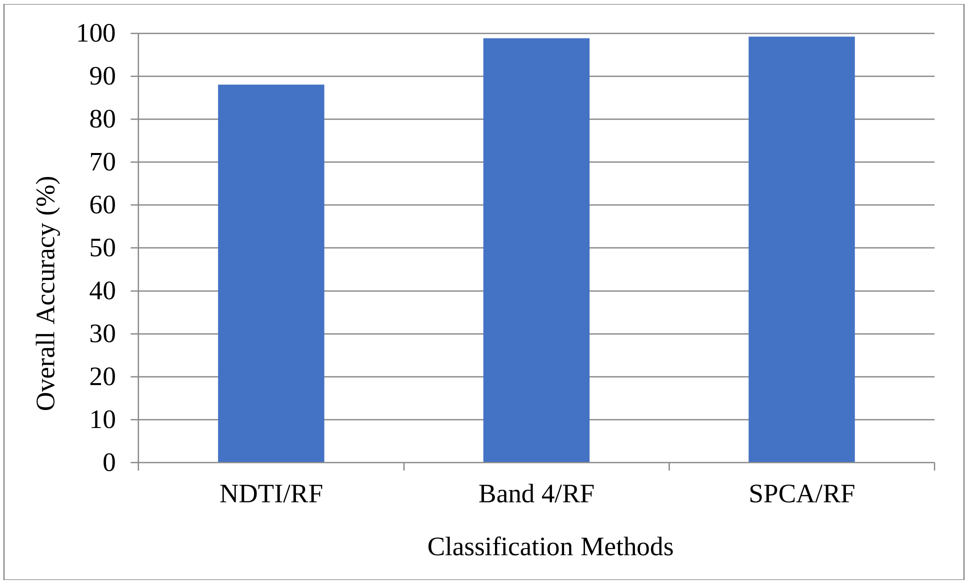


**Fig. 10 Overall accuracy comparison**

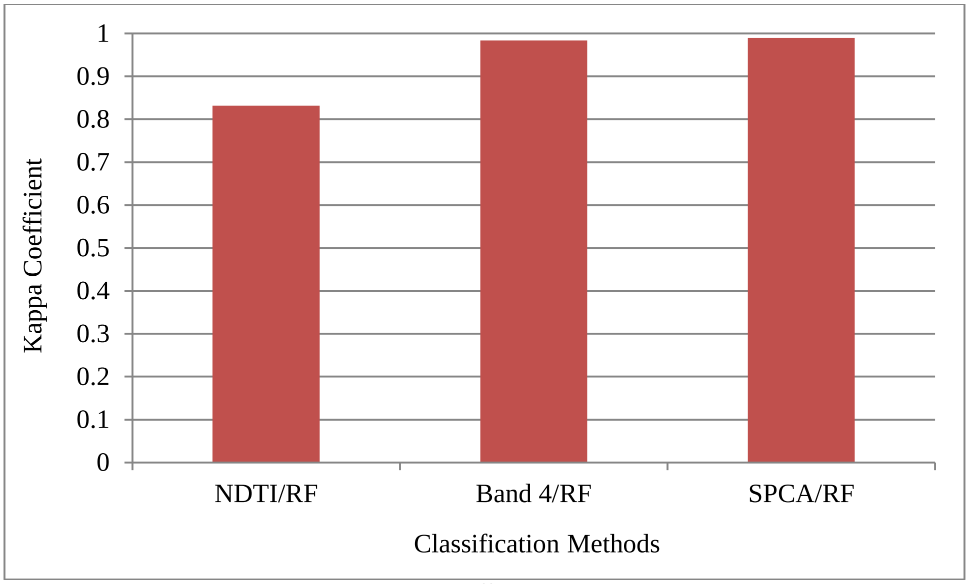


**Fig. 11 Kappa coefficient comparison**

**Table 4. Table for overall accuracy and Kappa Coefficient**

| Classification | Overall Accuracy | Kappa Coefficient | User Accuracy (%) | Producer Accuracy (%) |
|---|---|---|---|---|
| **NDTI/RF** | 88.0189 | 0.8313 | 100 | 92.6256 |
| **Band 4/RF** | 98.8656 | 0.9839 | 92.500 | 100 |
| **SPCA/RF (Proposed Method)** | 99.2664 | 0.9896 | 97.3684 | 100 |

## 7. Discussion

The Pulicat Lake also has variable levels of turbidity, which indicates the level of biodiversity present in the lake, as well as the health of the ecosystem. The turbidity in the lake also affects the ecological features of the area, where the land cover is more diverse. More specifically, the bio-score of the ecosystem is closely associated with turbidity in the area of the lagoon, which is an important measure of the quality of the environment. The proposed approach aims to determine the level of turbidity in the water bodies of Pulicat Lake using satellite data and a classification process. The water class is found to be more vulnerable to the changes in turbidity than the vegetation and the soil classes. A random forest algorithm coupled with the proposed SPCA beats the two approaches, NDTI and Band 4. Table 4 gives a relative summary of the research findings of the three methods applied in this study.

## 8. Conclusion

This paper aims to provide a novel method for efficient turbidity monitoring in the Pulicat Lagoon area. The measurement of turbidity would be important in tracking the spatial and temporal change in the bio-score, which is a major measure of the health status of the ecosystem. Three techniques for extracting turbidity features, which include the segmented Principal Component Analysis (PCA) Bands 3, 4, 5, and 6, titled Normalized Difference Turbidity Index (NDTI), and Band 4 (red band) of Landsat 8 OLI, were used to extract turbidity features by one algorithm, namely the Random Forest algorithm. These extracted features were compared in terms of performance to determine the performance in classification. The turbidity characteristics calculated using the SPCA demonstrated good performance in classification relative to either the NDTI or band 4. It means that the given method is more efficient and useful for monitoring turbidity in the Pulicat Lake ecosystem.

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