Spectral similarity approach for mapping turbidity of an inland waterbody

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ABSTRACT
Turbidity is an important quality parameter of water from its optical property point of view. It varies spatio-temporally over large waterbodies and its well-distributed measurement on field is tedious and time consuming. Generally, normalized difference turbidity index (NDTI), or band ratio, or regression analysis between turbidity concentration and band reflectance, approaches have been adapted to retrieve turbidity using multispectral remote sensing data. These techniques usually provide qualitative rather than quantitative estimates of turbidity. However, in the present study, spectral similarity analysis, between the spectral characteristics of spaceborne hyperspectral remote sensing data and spectral library generated on field, was carried out to quantify turbidity in the part of Chilika Lake, Odisha, India. Spatial spectral contextual image analysis, spectral angle mapper (SAM) technique was evaluated for the same. The SAM spectral matching technique has been widely used in geological application (mineral mapping), however, the application of this kind of techniques is limited in water quality studies due to non-availability of reference spectral libraries. A spectral library was generated on field for the different concentrations of turbidity using well-calibrated instruments like field spectro-radiometer, turbidity meter and hand held global positioning system. The field spectra were classified into 7 classes of turbidity concentration as <5, 5–10, 10–15, 15–25, 25–45, 45–100 and >100 NTU for analysis. Analysis reveal that at each location in the lake under consideration, the field spectra matched with the image spectra with SAM score of 0.8 and more. The observed turbidity at each location was also very much falling in the estimated turbidity class range. It was observed that the spectral similarity approach provides more quantitative estimate of turbidity as compared to NDTI.

1. Introduction

The streams and rivers bring large amount of sediments along with them to inland surface or coastal waters, which in turn indicates erosion and related problems in the upstream river basin, worldwide (Amos and Mosher, 1985; Ritchie et al., 1987; Ritchie and Cooper, 1988; Choubey and Subramanian, 1992; Schiebe et al., 1992). More sediments and their deposition in waterbody may damage instruments installed in the hydraulic structures, reduce the useful life of the reservoir, increase the cost of water treatment (Bhargava and Mariam, 1990). Most importantly, the presence of sediments alter the inherent optical properties (IOPs) of the entire water column such as absorption, backscattering, downwelling irradiance and the angular distribution. This may affect the quantity and spectral quality of energy/light reflected from/absorbed by the water surface (Jerlov, 1976; Kirk, 1983; Ritchie et al., 2003; Cannizzaro and Carder, 2006; Wu et al., 2014). Moreover, the change in light attenuation by water column may deteriorate aquatic life and primary productivity, as well as the growth of aquatic vegetation (Ritchie et al., 2003; Wang et al., 2007; Birtwell et al., 2008; Zhang et al., 2010; Wu et al., 2014). Therefore, regular monitoring of surface waters is critical for maintaining and improving its quality. Hitherto, the water quality is being assessed by in-situ measurements and laboratory analysis of samples collected. These point measurements may be accurate for particular location at particular time, but, they do not provide spatio-temporal information needed for better assessment of water quality from management point of view. As remote sensing can easily detect the changes in the backscattering characteristics of the surface water and provide synoptic coverage, it has received widespread attention in the field of water quality.
monitoring (Quibell, 1991; Gitelson et al., 1993; Han and Rundquist, 1996; Ritchie et al., 2003; Zhang et al., 2010). The most common and optically sensitive water constituents namely turbidity and total suspended solids (TSS) have been usually estimated using remote sensing data (Hinton, 1991; Millie et al., 1995; Aguirre-Gomez, 2000; Kratzer et al., 2000; Doxaran et al., 2002; Tyler et al., 2006; Teodoro et al., 2008; Olmanson et al., 2013; Papouts et al., 2014).

Numerous studies have been carried out on water quality assessment and monitoring using remotely sensed data. These studies may be categorized into three types of models (i) the most simple empirical models, developed based on relationship between the backscattering characteristics of water surface and concentration of particular water quality parameter (Tassan, 1993; O’Reilly et al., 1998; Yuan et al., 2001; Deng and Li, 2003; Miller and McKee, 2004; Han et al., 2006; Zhou et al., 2006; Chen et al., 2007; Pavelsky and Smith, 2009; Chawira et al., 2013). For the development of these models, simple regression analysis to complex data driven models (Artificial Neural Networks) are being used. These models are easy to implement, but, they lack physics of the underlying process. Moreover, these developed models do not have general applicability as they are site specific in nature.

(ii) another similar class of model belongs to band ratio technique, in this approach, the most sensitive bands, with respect to particular water component, are identified and then ratio between the bands are being taken to enhance the satellite image for that particular component concentration. Normalized Difference Turbidity Index (NDTI) for example, has been used for qualitative estimates of turbidity in inland waterbodies around the globe (Lacaux et al., 2007; Gardelle et al., 2010). (iii) Another technique called the semi-analytical models, uses the IOPs of water are being assessed through radiative transfer theory or more sophisticated instruments and later, empirical relationships are being established between these IOPs and water component using simple regression or soft computing techniques (Doerffer and Fischer, 1994; Carder et al., 1999; Dekker et al., 2001; Warrick et al., 2002; Cannizzaro and Carder, 2006; Morel et al., 2007; Wang et al., 2007; Zhang et al., 2010). These techniques have extensively been used for coastal/marine waters, however, their application to inland surface waters is limited due to non-availability of high spatial and spectral resolution remote sensing data. Mostly, multi-spectral remote sensing data have been utilized in these models which results in reasonable accuracy. However, with the advancement in sensor technology and emergence of imaging spectroscopy (hyperspectral remote sensing), the results of these techniques improved, as the imaging spectro-radiometers acquire image data in many narrow contiguous spectral bands (Plaza et al., 2009). The technique enables the mapping of surface constituents having diagnostic absorption features of even 20–40 nm width (Van der Meer, 2006).

However, in the present study, an image classification technique, based on spectral similarity between continuous spectra of hyperspectral remote sensing image and field spectral library generated for different concentrations of turbidity using field spectro-radiometer, has been adopted for spatial quantification of the turbidity concentration in Chilika Lake, Odisha, India. This technique has been usually used to map minerals using hyperspectral remote sensing data (Van der Meer and de Jong, 2000; Van der Meer, 2006). Its application in the field of water quality studies is constrained by the availability of reference spectral library of different components with varying concentration (Mannheim et al., 2004; Osnis-Skatok et al., 2007; Santini et al., 2010; Yu et al., 2010; Zhu and Yu, 2013; Zhu et al., 2013; Wu et al., 2014; Kar et al., 2016). Here, an attempt has been made to develop a spectral library and its application on hyperspectral remote sensing data to classify water with regards to different concentrations of turbidity. The results of turbidity mapping are very encouraging as compared to NDTI band ratio approach. It was also realized that the developed spectral library may also be utilized for mapping the water quality of inland waterbody using hyperspectral remote sensing data of any date.

2. Study area

The coastal lagoons, located at the interface of rivers and sea, are one of the most productive, complex and dynamic ecosystems (Srichandan et al., 2015). Such ecosystems experience steep change in their bio-physical and chemical properties due to the mixing of fresh river water flow from one side and sea water intrusion from other (Srichandan et al., 2015). Chilika Lake, the largest coastal lagoon in India and the second largest lagoon in the world with width of 20 km and length of around 64 km has been selected as study site. It is a brackish water lagoon, spread over the Puri, Khurda and Ganjam districts of Odisha state on the east coast of India, covering an area of over 1,100 km² as shown in Fig. 1.

The frequent change in physico-chemical properties and their interaction with each other in Chilika Lake makes it a unique experimental site (Muduli et al., 2012, 2013). In 1981, Chilika Lake was designated as the first Indian wetland of international importance under the Ramsar Convention. At the northern end, tributaries of the Mahanadi River, such as Daya, Nuna and Bhargavi join the lagoon and are responsible for the large fresh water and sediment flux to the lagoon. The lagoon is separated from the Bay of Bengal by sand bar of 60 km length. The lagoon is connected to the Bay of Bengal through three inlet mouths, these are (i) the artificially dredged mouth near Sippakuda, (Satapara), (ii) naturally opened mouth just 2 km north of dredged mouth at Gabbakunda during August 2008 and (iii) through Palur canal in southern sector.

The climate of the region is tropical, with two dominant seasons defined in terms of wind patterns i.e., Southwest monsoon from June to September and Northeast monsoon from November to February; with an average annual rainfall of 1239 mm and 72 rainy days. The water quality of the lagoon changes widely with onset of different seasons and exhibits different ecological characteristics in localized pockets. The water of Daya, Bhargavi, Luna and Makara rivers contributes major portion (66%) of fresh water discharge (Muduli et al., 2013). The Chilika Development Authority’s (CDA) physico-chemical investigations indicate highly turbid water due to strong mixing of overlying water with sediments, the transparency values ranging between 8 and 117 cm (Mahapatro et al., 2012). It has been also reported that the total sediment load discharged into the lagoon has increased from 1.8 M tonnes in 1998 to 2.94 M tonnes in 2001 (Panigrahi et al., 2007). This highly productive ecosystem with its rich fishery resources sustains the livelihood of around 1.5 million fishermen who live in 132 villages on the shore and islands in the Lagoon (Ramesh et al., 2011).

3. Methodology

Considering the importance of the Chilika Lake, an attempt has been made to map its water quality with regard to turbidity using high spatial and spectral resolution hyperspectral remote sensing data. In the present analysis, to understand the capabilities of spectral similarity approach in the field of water quality studies, the Earth Observing – 1 (EO-1) Hyperion (Path: 140, Row: 46) hyperspectral remote sensing data of March 08, 2016 has been utilized. The Hyperion image consists of 220 spectral bands ranging from 400 to 2500 nm wavelength with a high spatial resolution of 30 m. A Hyperion image covers an area of 7.5 × 100 km, and provide detailed spectral mapping across all 220 channels at
approximately 10 nm spectral resolution with high radiometric accuracy (USGS: https://eo1.usgs.gov/sensors/hyperion).

Hyperion image was initially pre-processed using spectral subset technique and bad bands and columns were eliminated. The values of bad columns have been replaced by average radiance value of adjacent two columns. As water is sensitive in the spectral wavelength range of 400–1000 nm, the bands with wavelength over 1000 nm were removed to obtain 47 bands image for further analysis. The image was further atmospherically corrected using Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) which works on MODTRAN4 radiation transfer code. It corrects wavelengths in the visible through near-infrared and shortwave infrared regions, up to 3 μm (Adler-Golden et al., 1999) for better reflectance.

3.1. Normalized difference turbidity index approach

Initially, the common band ratio technique i.e. NDTI has been adapted to estimate the turbidity in this part of the lake. Following band combinations were used for calculation of NDTI as given in the Eq. (1).

\[
\text{NDTI} = \frac{\rho_{\text{red}} - \rho_{\text{green}}}{\rho_{\text{red}} + \rho_{\text{green}}}
\]

Fig. 1. Location of study area in India, Landsat 8 OLI image of January 04, 2016 showing location of sampling points and coverage of EO-1 Hyperion image.

Fig. 2. Instruments used to collect ground data, (a) field spectro-radiometer, (b) portable eco-sounder, (c) hand held GPS, (d) turbidity meter, (e) sun-photometer.
\(\rho_{\text{red}}\) and \(\rho_{\text{green}}\) are reflectance in red and green bands, respectively. It has been considered that the turbid water tends to behave like bare soil spectrally, with low reflectance in the green and high in the red wavelength (Lacaux et al., 2007; Gardelle et al., 2010). Generally, the NDTI values vary from \(-0.2\) to \(-0.0\) in the case of clear water, 0.0 to 0.2 for the moderately turbid water and >0.25 in case of highly turbid water. Therefore, more the NDTI value, more the turbidity. However, in the present study, the NDTI image has been classified based on its statistical properties: mean \(-\) standard deviation and mean + standard deviation as low and moderate turbid, respectively. More than moderate value has been regarded as highly turbid. It is to be noticed that this technique provides qualitative estimate of turbidity as low, moderate and high turbid concentration based on its NDTI values (Sharma et al., 2014).

3.2. Spectral library generation

A dedicated field campaign has been conducted during December 24–28, 2015 to collect the ground truth with regard to water quality parameters (in-situ), water samples (for laboratory analysis), depth, location and spectral characteristics. A number of calibrated instruments were used during the field campaign such as field spectro-radiometer, sun-photometer, portable eco-sounder, hand held GPS and turbidity meter; their arrangement is shown in Fig. 2.

A large number of field spectra have been collected from 48 randomly distributed locations (Fig. 1) in each north, central and south sector of the lake using SVC HR 1024 field spectro-radiometer. This field spectro-radiometer measures radiance/reflectance in spectral range of 350–2500 nm with spectral resolution of 1.5 nm between wavelength 350–1000 nm, 3.8 nm between wavelength 1000–1890 nm and 2.5 nm from wavelength 1890 nm onwards (SVC: http://www.spectravista.com/HR1024i.html). At each of these 48 locations, set of five spectra were collected, later, the average of these five spectra with specified turbidity had been regarded as representative spectra of that particular location. Care has been taken to avoid sun glint while taking measurements and the system was optimized every time by taking reference using white reference plate/spectralon for local conditions. As it was difficult to move entire spectro-radiometer at each location according to sun angle on boat, fiber optic cable has been used for aiming the target (water). Simultaneously, the water turbidity has been measured using turbidity meter on the spot. Turbidity meter is kind of opto-electronic meter in which an artificial light source emits a known

![Fig. 3. (a) FCC of EO-1 Hyperion image of March 08, 2016. (b) NDTI classified map of the part of Chilika Lake.](image-url)
intensity of light through a sample and the suspended particles in the water tend to scatter or absorb the light. The scattered light is then generally recorded at an angle of 90° on a photodetector. This measurement principle is known as nephelometry and the results are presented in Nephelometric Turbidity Unit (NTU). The location of each of these sampling points has been recorded using hand held GPS and water samples have been collected for laboratory analysis. Aerosol optical thickness was retrieved using sun-photometer and water depth was measured using portable eco-sounder at each location.

In this way, a field spectral library has been generated for different concentrations of turbidity in the lake in the spectral range of 400–2500 nm at very narrow bandwidth. However, as turbid water is sensitive mostly in visible and near infra red regions, the image has been subset in the range of 400–1000 nm at bandwidth of 10 nm and it was required to resample the generated spectral library correspond to Hyperion channels for spectral matching. It has been done by spectral library resampling tool in ENVI 5.0 (RSI, 2004).

### 3.3. Spectral similarity/matching analysis

In the field of imaging spectroscopy or hyperspectral remote sensing, the compositional information of the surface is usually obtained by comparing known field or library spectra and unknown image spectra statistically, which is commonly known...
as spectral matching or spectral similarity analysis (Van der Meer, 2006). This quantitative comparison of reflectance of imaging spectro-radiometer data with known field or library spectra is common for mineral mapping (Kruse et al., 1993; Van der Meer, 2006). Still, the development is going on to generate algorithms for object based image analysis and to classify hyperspectral remote sensing data by combining the spatial context of an image and spectral information (Stein et al., 1998; Van der Meer, 1999, 2006; de Jong and Van der Meer, 2004). A set of available spectral matching algorithms are being readily used in geological applications such as spectral correlation measure (Van der Meer and Bakker, 1997), spectral angle mapper (SAM) (Kruse et al., 1993), Euclidean distance measure and spectral information divergence (Chang, 2000). The further details of each of these algorithms may be found in Van der Meer (2006). In the present study, the most widely used SAM spectral matching algorithm has been adapted for mapping turbidity in Chilika Lake, India. SAM is a method for comparing image spectra to individual spectra or a spectral library. The algorithm determines the similarity between two spectra by calculating the “spectral angle (θ)” between them, treating them as vectors in a space with dimensionality equal to the number of bands (Kruse et al., 1993).

$$\cos \theta = \frac{\sum_{i=1}^{n} e_i r_i}{\sqrt{\sum_{i=1}^{n} e_i^2} \sqrt{\sum_{i=1}^{n} r_i^2}}$$

(2)

where, θ is spectral angle, e is given image spectra, r is reference spectra, n is number of classes. This method is insensitive to illumination since the SAM algorithm uses only the vector direction and not the vector length. The SAM classification has been done on the reflectance image with the help of generated field spectral library using the spectral tools available in ENVI 5.0. After the classification, similarity of both the spectra (field and image) has been analysed at different locations.

Fig. 5. Field spectra of points fall in each turbidity concentration class and its comparison with Ritchie et al. (1976) spectra along with field photo of different water.
4. Results and discussion

The sediments brought by flowing water increase the concentration of suspended material and hence turbidity, which in turn alters light attenuation by water. Subsequently, it changes the IOPs of water entirely, which further affects aquatic vegetation growth and life. It has been observed that with the increase in concentration of TSS/turbidity, the radiance emergent from water surface increases in the visible and near-infrared region (NIR) of electromagnetic (EM) spectrum and peak of spectra shifts towards red/NIR (Ritchie et al., 1976; Ritchie et al., 2003). As these changes in EM waves can easily be detected using multispectral satellite sensors, therefore an attempt has been made to map water quality of Chilika Lake using hyperspectral remote sensing data. Initially, the band ratio technique namely NDTI, has usually been applied for assessment of turbidity of surface water. In the present study, the Eq. (1) considering the Green band correspond to wavelength 548.9194 nm (Band 20) and Red band with wavelength 652.9015 nm (Band 21) for Chilika Lake has been used for estimation of turbidity.

![Image](image.png)

**Fig. 6.** (a) FCC of EO-1 Hyperion image of March 08, 2016, numbers over the image correspond to selected locations where field and image spectra with varying turbidity are matched (b) SAM classified image of the part of Chilika Lake.

<table>
<thead>
<tr>
<th>Turbidity class (NTU)</th>
<th>Location</th>
<th>Spectra of point matching</th>
<th>SAM similarity score</th>
<th>Absorption depth @ 660.85 nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;5</td>
<td>7</td>
<td>18</td>
<td>0.826</td>
<td>0.320</td>
</tr>
<tr>
<td>5–10</td>
<td>2</td>
<td>6</td>
<td>0.800</td>
<td>0.213</td>
</tr>
<tr>
<td>10–15</td>
<td>4</td>
<td>13</td>
<td>0.867</td>
<td>0.210</td>
</tr>
<tr>
<td>15–25</td>
<td>6</td>
<td>14</td>
<td>0.808</td>
<td>0.209</td>
</tr>
<tr>
<td>25–45</td>
<td>8</td>
<td>25</td>
<td>0.872</td>
<td>0.086</td>
</tr>
<tr>
<td>45–100</td>
<td>1</td>
<td>12</td>
<td>0.863</td>
<td>0.013</td>
</tr>
<tr>
<td>&gt;100</td>
<td>5</td>
<td>16</td>
<td>0.853</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 2: SAM spectral similarity results.
Fig. 7. Field and EO-1 Hyperion image spectra matching (continuum-removed spectra of selected locations for each class of turbidity).
650.6727 nm (Band 30) was used for NDTI calculation. The FCC of selected Hyperion image and the qualitative estimate of turbidity through NDTI technique are shown in Fig. 3(a & b), respectively.

These qualitative estimates may not serve the purpose of lake management and aquatic life studies. Therefore, in the present study, the spectral similarity approach has been attempted to estimate turbidity in the lake. In this regard, a field spectral library with varying turbidity concentration has been generated using sophisticated field instruments as discussed earlier and as shown in Fig. 4. It can be seen that with the increase in turbidity, the spectral response in the visible region especially green and red bands is increasing.

These field readings were further classified into number of classes based on their turbidity values in NTU as given in Table 1. Seven classes were defined <5 NTU, 5–10 NTU, 10–15 NTU, 15–25 NTU, 25–45 NTU, 45–100 NTU, >100 NTU as given in the table. Most number of locations found to fall in range from 10 to 25 NTU of turbidity. The high turbidity points mostly located in the northern sector of the lake, as the streams namely Daya, Nuna and Bhargavi which bring large sediment flux join the lake in this region. The turbidity concentration is less in the central and southern sector of the lake as compare to northern sector.

In a similar guideline, the field spectra of the locations falling in each category were separated and plotted as shown in Fig. 5 along with available pictures of the water of the same concentration. In this study also, it was observed that the reflectance increases with increase in the turbidity concentration (mainly sediments), in the red region of the EM spectrum. The field spectral library shown in figure are resampled spectra corresponding to selected (47) Hyperion bands at 10 nm bandwidth within wavelength range from 400 to 1000 nm. This library has further been used for spectral similarity analysis, the results are discussed in the section below.

In the SAM spectral similarity approach, entire spectral library of field collected spectra were matched with Hyperion image spectrum at each pixel and their spectral angle \(|\theta|\) has been measured. Wherever, the least angle between two spectra has been measured, the turbidity class of that field spectrum has been assigned to that particular pixel. In this way, entire image has been classified according to their turbidity concentration as shown in Fig. 6(b).

It is to be noted that SAM is not an identifier, it is only a similarity measure which indicate how similar the specific spectral features (absorption features) in field and image reflectance spectra (Green and Craig, 1985; Kruse et al., 1985; Yamaguchi and Lyon, 1986; Clark et al., 1987). For similarity analysis, it requires continuum removal, the spectra are normalized to a common reference (base line) and compared for individual absorption features as suggested by Kokaly (2001). Seven random points representing each turbidity class were selected (as shown in Fig. 6a) and their spectral similarity has been studied after removing the continuum as given in the Table 2.

The spectral similarity score of SAM spectral matching approach close to value of 1 indicates the closest match and higher confidence in the spectral similarity. At each location, the spectral similarity score found to be more than 0.8, which indicates better matching of two spectra (field and image). The continuum removed spectra of these locations are shown in the Fig. 7. These figures depict high similarity in both field and image spectra. The absorption depth in the red region has been analysed as with the increase of sediment concentration, the reflectance increases in this region. It was found that, with the increase in turbidity concentration (mainly suspended sediments), the absorption dip at 660.85 nm wavelength reduces; same has been reported in Table 2.

On comparing FCC of Hyperion image and SAM classified image (Fig. 6a & b) visually, it can be noticed that spectral similarity results are much better than NDTI (Fig. 3b). Moreover, it provides quantitative estimate (exact turbidity value range) of the turbidity rather than qualitative (low, moderate and high turbid). Using spectral similarity approach even minute spatial change in turbidity has been mapped. The CDA monitors the water quality of the lake regularly at their 30 monitoring sites. In order to validate the findings, the field data of the nearest date, i.e. February 17–20, 2016 from the date of pass of the satellite, for these stations (black triangle symbol in Fig. 6b) falling in the study region of the lake were procured and compared with the SAM classification results as given in Table 3. A very slight variation only in the location 20 was found, otherwise, at all other locations the field observed values are within the SAM classified turbidity range.

### 5. Conclusions

The water quality of Chilika Lake with regard to turbidity concentration has been studied using spectral similarity approach. For the analysis, the EO-1 Hyperion hyperspectral remote sensing image of March 08, 2016 has been used. The foot print of the data covers the central and northern part of the lake, where turbidity concentration is very dynamic. A spectral library, specific to Chilika Lake water quality parameters, has been generated using sophisticated instruments like field spectro-radiometer, turbidity meter and hand held GPS. The field spectral library has been resampled to Hyperion bandwidth and used for spectral similarity analysis adapting most widely used SAM approach. A very high similarity between the image spectrum and field spectrum was found at almost each pixel. At the selected locations the SAM similarity score was usually higher than 0.8. As, the field spectra were classified into 7 classes of turbidity concentration as <5, 5–10, 10–15, 15–25, 25–45, 45–100 and >100 NTU, SAM classified image resulted in these 7 classes of turbidity in the selected region of the lake. The SAM classification results were quantitative in nature as compare to simple NDTI approach which results in qualitative estimates of turbidity. Moreover, the observed turbidity concentration at different locations are well in the range of SAM classified results. The study shows usefulness of spectral library for water quality parameters and spectral similarity approach in water quality studies using imaging spectroscopy.

As the present study is an initial attempt in the direction of spectral library for water quality parameters and its application in spectral similarity analysis, a large number of recommendation needs to be followed in future research studies. The spectral library may further be improved by collecting field spectra in the different season with different conditions. The satellite image of same date of field campaign may improve the classification accuracy. The water quality assessment is a global issue, therefore, there is a need to set the protocols to develop standard spectral library with
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