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Monitoring Secchi disk transparency of Warasgaon reservoir of Pune by using LISS III sensor

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ABSTRACT

Secchi disk transparency (SDT) is the simplest and the most efficient measure to monitor water quality of the reservoir. The nutrients from the agriculture fields, sewage from human settlements and industries drain into reservoirs and lakes. It contributes to the increasing level of suspended particles, algal growth and coloring of water and reduces transparency of water. These changes can be detectable by remote sensors. In this study LISS III sensor of Resourcesat-2 used to model SDT of Warasgaon reservoir, Pune. The green ($r = 0.75$), red ($r = 0.79$) and NIR ($r = 0.75$) bands of LISS III showed good correlation with observed SDT, while band ratios Red/NIR ($r = 0.81$) and NIR/SWIR ($r = 0.81$) showed significant correlations. Several linear and multiple linear regression models developed from the in-situ measurements of SDT and the radiance value of LISS III image. The multiple linear regression model based on green, red, NIR and red/SWIR found to be the best fit ($r = 0.88$) to the in-situ data. The results showed that the Warasgaon reservoir was oligotrophic in condition during the December 2012.

Keywords: Secchi disk transparency (SDT), Liss III, regression model.

1. Introduction

Surface water is an essential natural resource to the living beings. Its quality directly affects the ecosystems, human health, and economic activities. Lakes, reservoirs, rivers and ocean are the main sources of surface water. Generally, reservoirs are built to store massive amount of surface water for drinking, irrigation and generate electric energy. The nutrients from the agriculture fields, sewage from human settlements and industries drain into reservoirs and lakes. It contributes to the increasing level of suspended particles, algae growth, and coloring of water and reduces dissolved oxygen levels that deplete the quality of water and threat the ecosystem of the water body. The increased level of suspended particles and growth of Algae reduces the sunlight penetration into the water (Choubey 1994). The sunlight penetration into the water can be measured in terms of transparency. It decreases with the increase of turbidity and biological activity in the water. Therefore, transparency of the water can be used as a measure to monitor the water quality of the reservoir. Secchi disk is a simple and economic device used to measure the transparency of water. It is made of a circular metal disk of 8 inch in diameter painted black and white in alternating quadrants and attached to a measurement thread. The disk is slowly lowered into the water until it is no longer visible. The depth of the water where the disk disappeared is termed as Secchi Disk Transparency (SDT), A reservoir can be classified into four categories (Table 1), i.e, oligotrophic, mesotrophic, eutrophic and hyper-eutrophic based on SDT values (Carlson and Simpson 1996). The nutrient levels in the water increases from oligotrophic to hyper-eutrophic, while the water quality and transparency decreases. The aquatic plants and algae presence are abounded in the eutrophic and hyper eutrophic reservoirs.

Table 1: Lake tropic states and classification range for SDT (Carlson and Simpson 1996)

Classification	SDT (m)	Water Calrity
Oligotrophic	>8 - 4	Clear water, Salmonid Fisheries dominate
Mesotrophic	4 - 2	Moderate clear water
Eutrophic	2 - 0.5	Less Clear water, Warm water fisheries dominates, Nuisance macrophytes, algal scums
Hypereutrophic	0.5 - 0.25 >	Dense algae and macrophytes

SDT sampling requires in-situ measurements. These in-situ measurements are accurate, and require a lot of time and money to enumerate the entire reservoir. Remote sensing can be used as a contemporary tool to overcome this difficulty. Several researchers used remote seining sensors in combination of in-situ measurements of SDT to monitor the water quality of lakes (Choubey 1994; Harris et al. 1976; Sheela et al. 2011; Thiemann and Kaufmann 2000). Regression equation based on observed SDT and radiance values of satellite imagery often used to estimate SDT at un-sampled locations (Baban 1993; Olmanson et al. 2001). Landsat Multi Spectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) data was widely used to estimate the SDT of water bodies (Baban 1993; Giardino et al. 2001; Harris et al. 1976; Olmanson et al. 2008). Indian remote sensing sensors viz., LISS-I, III and IV are also used to estimate the water quality of the reservoirs (Choubey 1994; Mabwoga et al. 2010; Sheela et al. 2011; Thiemann and Kaufmann 2000). In this study Resourcesat-2's LISS III (Linear Imaging Self Scanner) imagery acquired from National Remote Sensing Centre (NRSC) of India used to monitor the SDT of Warasgaon reservoir.

2. Material and methods

2.1 Study area

Warasgaon reservoir on Mose River is situated south west to the Pune city. Also, it is known as Veer Pasalkar dam. The reservoir extended approximately 20 km in length from west to east and about 5 km wide in north to south direction. The reservoir was constructed to cope up with drinking water needs of the Pune city. The reservoir water is used also for recreation, fishing and irrigation. Warasgaon reservoir (Figure 1) bounded between coordinates 18° 21' to 18° 25' north of equator and 73° 25' to 73° 37' east of Greenwich meridian.

2.2 Secchi disk measurements

Secchi disk transparency (SDT) is a commonly used, economic parameter measures the water quality (Guan et al., 2011). SDT values measured at 24 sampling locations on 24-Dec-2012 and selected on the basis of systematic random sampling nearly 500 meters apart (figure 2), In order to avoid the reflection from the surrounding vegetation classes the sample locations are selected along the central cross section of the reservoir. The location of each sampling point is measured by using Garmin 24 channel hand held GPS.

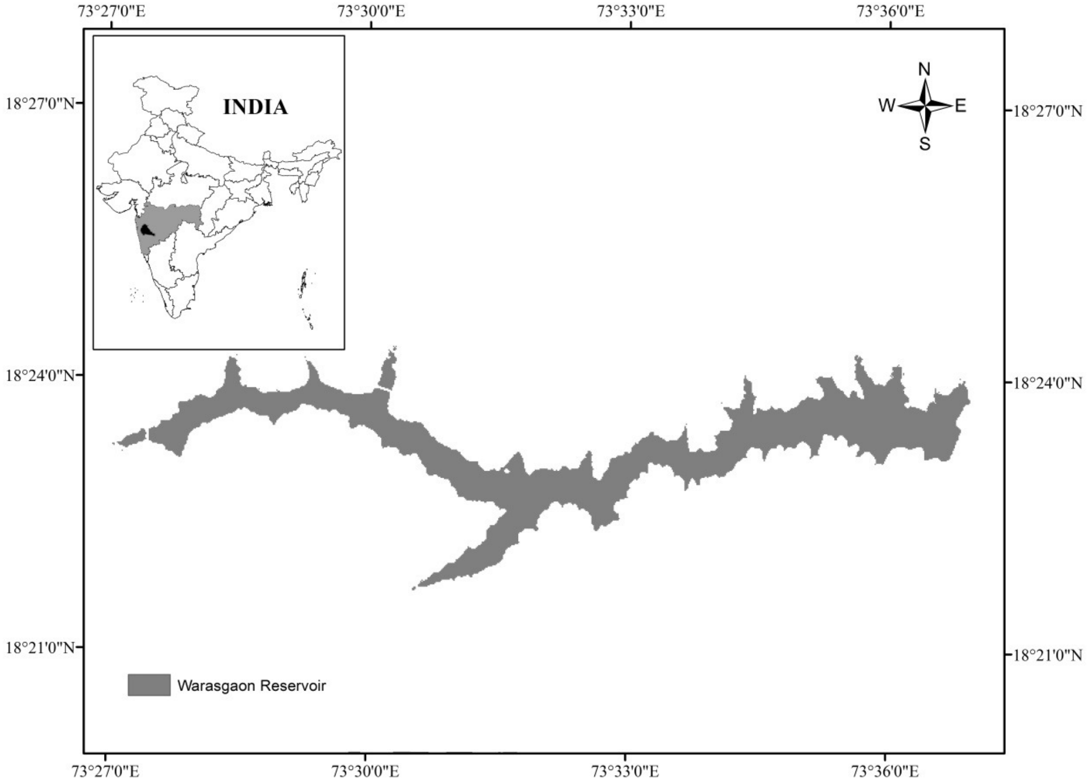

Figure1: Location map of the Warasgoan reservoir

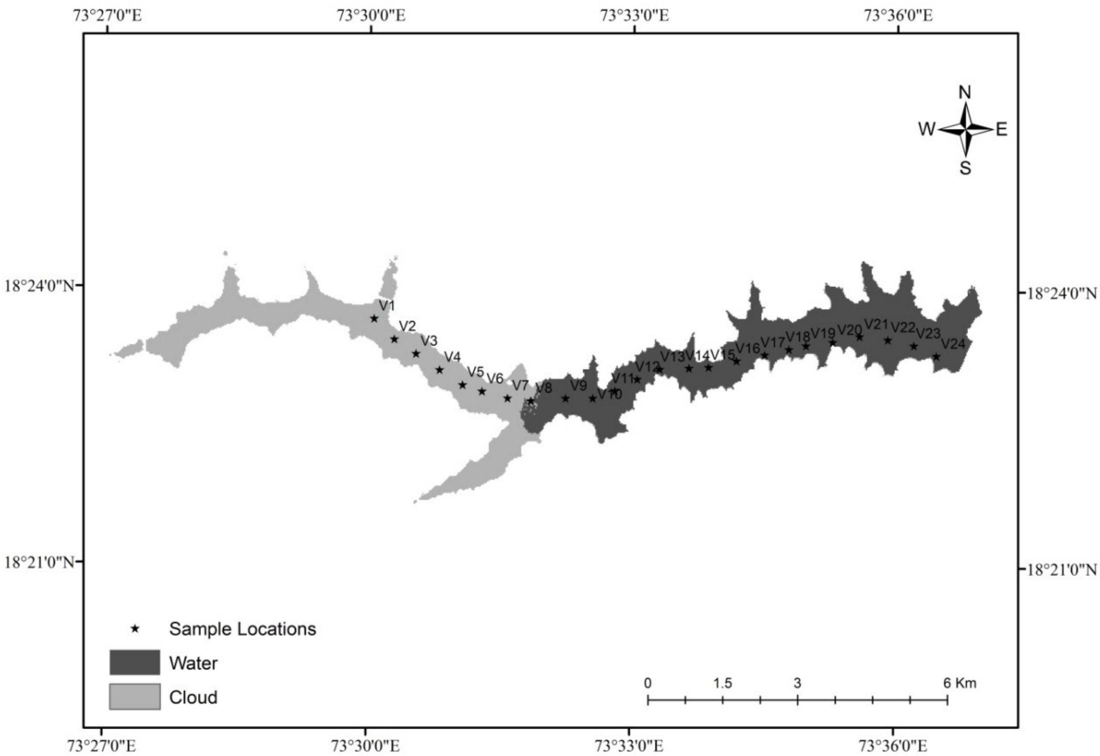

Figure 2: Map showing sampling location and water affected by cloud over the reservoir.

3. Satellite image processing

The clear water allows high transmittance and less absorption of wavelength below 0.6 µm and large amount of suspended sediments from soil erosion contributes to the reflectance of higher wavelength in visible range (Li and Li 2004). The increasing level of nutrients in water causes growth of algae and increases the water reflectance in green wavelength. Further, the transmittance of water decreases with the increase of sediments and algae growth. The level suspended sediments are strongly correlated with the Near Infra-Red (NIR) radiation (Mabwoga et al. 2010; Onderka and Pekárová 2008). These optical properties of water can be detectable by the satellite sensors. Once the relationship established between the observed SDT values with corresponding radiance values in satellite image, one can estimate the SDT at unsampled locations. Therefore, remote sensing data provides a contemporary solution to overcome the difficulty to predict water quality of unsampled location (Fuller et al. 2004). This study used NRSC's LISS-III sensor dated 20-Dec-2012 to monitor the water clarity of the study area. Table 2 presents the specification of LISS III sensor boarded on Resourcesat-2. The acquired satellite imagery was geo-referenced with the help of Survey of India's Open Series Map (OSM) toposheets E43H11 and E43H07 to UTM 43N projection on WGS 84 datum.

Table 2: Specification of LISS III sensor boarded on Resourcesat-2

IGFOV (across track) (m)	23.5
Spectral Bands (microns)	B2(Green): 0.52 - 0.59 B3(Red): 0.62 - 0.68 B4(NIR): 0.77 - 0.86 B5(SWIR): 1.55 - 1.70
Swath (km)	141
Bands Saturation radiance (mW cm^{-2} sr^{-1} μm^{-1})	B2: 50.0973, B3: 46.79, B4: 31.5, B5:5.9862
Quantizationb(bits)	10 (7bit data is transmitted to BDH after DPCM)
No. of gains	Single

Source: RESOURCESAT-2 Data Users' Handbook, December 2011, NRSC and Meta data file

Water only image is necessary to prepare the pixel level map of SDT based on the best fitted regression model. An unsupervised classification method used to extract the water only image from the satellite data. ISODATA clustering algorithm implemented on the LISS-III image to classify into 150 landcover classes. Due to the presence of cloud over the westren part of the reservoir, first land cover class has been identified as water not effected by cloud and from second to fifth land cover classes have been identified as water under cloud. The water land cover image of the reservoir used as mask to extract the water only image from the satellite data. In order to avoid ambiguity in the regression, the water not under fog has been used for analysis (figure 2), The Digital Numbers (DN) of each pixel in each band of water only satellite image converted to their corresponding physical measures, i.e., radiance values by using the following formulae (Markham and Barker 1987).

$$L(\lambda) = \frac{L(\lambda)_{max} - L(\lambda)_{min}}{DN_{max}} * DN(\lambda) + L(\lambda)_{min} \quad \dots (1)$$

$L(\lambda)$ = spectral radiance (mW cm^{-2} sr^{-1} μm^{-1})
$L(\lambda)_{max}$ = maximum spectral radiance
$L(\lambda)_{min}$ = minimum spectral radiance
DN_{max} = maximum digital number
$DN(\lambda)$ = digital number

The maximum and minimum spectral radiance values of the LISS III sensor of Resourcesat-2 can be found in metadata file supplied by the data provider. The values used for the conversion of DN to the radiance are presented in table 3.

Table 3: Maximum and minimum spectral radiance and DN_{max} values of Resourcesat-2's LISS-III image.

BAND	$L(\lambda)_{min}$	$L(\lambda)_{max}$	DN_{max}
B2: Green	52	0	1023
B3: Red	47	0	1023
B4: NIR	31.5	0	1023
B5: SWIR	7.5	0	1023

4. Regression analysis

The relationship between remotely sensed imagery and water quality parameters are usually examined through linear regression of the in-situ measurements and the spectral radiance values retrieved from the sensor (Kloiber et al. 2002; Nelson et al. 2003; Onderka and Pekárová 2008). Regression analysis is a statistical method used to investigate the relationship between two or more variables. It is generally used to understand or predict a dependent variable with the help of independent variables. Simple linear regression predicts the value of a dependent variable based on one independent variable, whereas multiple liner regression predicts the value of a dependent variable based on several independent variables. In this study, SDT of sampling locations is treated as dependent variable and the average radiance value of 3*3 window of image bands and band ratios of the corresponding locations used as independent variables. Data analysis extension of Microsoft excel has been used to perform linear and multi linear regressions.

Table4: List of good fitted regression models with observed SDT.

S. No.	Regression Model	Correlation coefficient (r) and Coefficient of Determination (r^2)	Signification (P)
1	SDT = - 5.047 + 3.107(B3/B5)	r = 0.81 and r^2 = 0.66	p = 0.0002
2	SDT = 27.424 – 6.444 (B2) + 6.299 (B3) + 7.516 (B4) – 38.936 (B5)	r = 0.88 and r^2 = 0.77	p = 0.003
3	SDT = 7.503 – 6.388 (B2) – 5.915 (B3) +7.490 (B4) + 6.201 (B3/B5)	r = 0.88 and r^2 = 0.78	p = 0.003
4	SDT = 4.510 – 5.087 (B2) – 4.344 (B4) + 3.831 (B3/B5)	r = 0.86 and r^2 = 0.75	p = 0.001

The radiance values of band 2: Green (r = 0.75), band 3: Red (r = 0.79) and band 4: NIR (r = 0.75) were correlated well with the SDT observations, while the band ratios B3/B5 (r = 0.81) and B4/B5 (r = 0.81) are shown a significant correlation with SDT observations of 24-Dec-2012. Several regression models, including linear regression and multiple linear regression were developed using SDT as dependent variable and band radiance or/and Band ratios as independent variables. Table 4 shows the best fitted linear and multiple regression models. From the table, one can conclude that, the regression model with radiance values of band 2, 3, 4 and band ratio of 3 to 5 is the best fitted model. Therefore, it was used to estimate the SDT of un-sampled locations to prepare a pixel level SDT map of Warasgaon reservoir (figure 3),

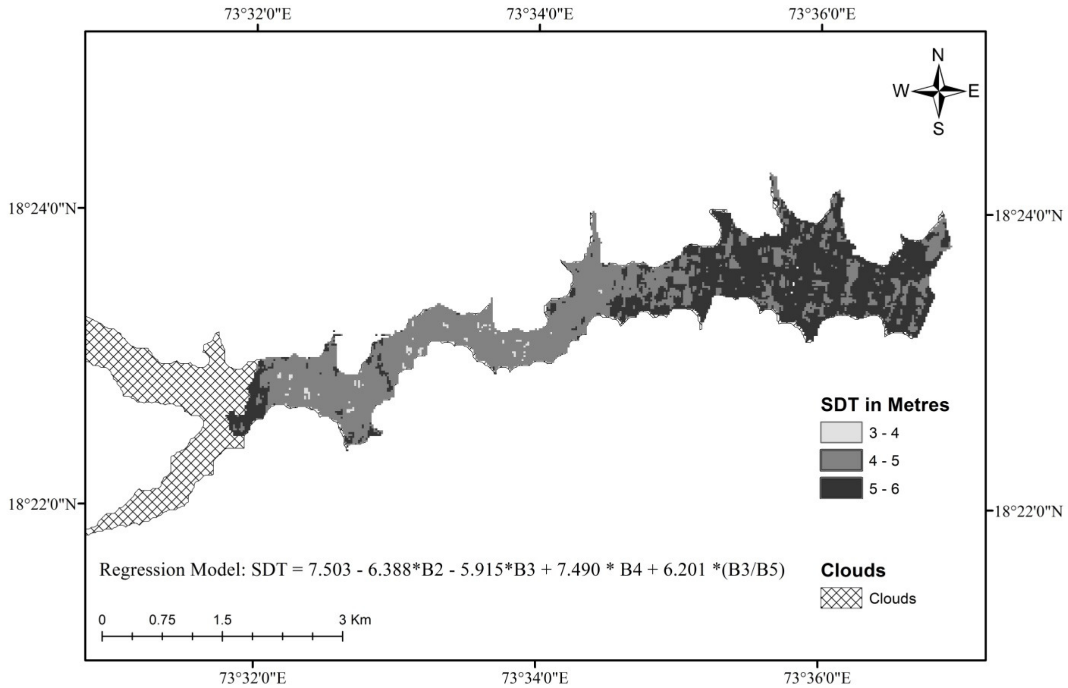

Figure 3: Map showing the modeled SDT based on the best fitted regression model of Warasgoan reservoir.

5. Results and conclusion

The map of modelled SDT based remote sensing and in-situ measurements revealed that most of the part of Warasgaon reservoir comes under Oligotrophic condition in the month of December 2012. This shows the quality of water in the reservoir was good with less nutrient levels. Since the cloud over western part of the reservoir, the study not accounted the spatial variation SDT in western part of the reservoir. However, it was observed the water transparency increased from west to east in direction. All bands of LISS III expect SWIR band shown good correlation and band ratios B3/B5 and B4/5 shown significant correlation with in-situ SDT observations. The multiple linear regression model based on B2, B3, B4 and B3/B5 found best fitted model of SDT of Warasgaon reservoir. The study revealed the use of LISS III sensor to model the spatial distribution of water transparency of the reservoirs. The absence of the blue wavelength band might be a drawback of LISS III sensor to monitor the water clarity, because clear water reflects most of the incident radiation in blue wavelength. This study showed the potential use of remote sensing to monitor the water quality of the reservoir with minimum number of in-situ observations. The method is cost effective and easy to adapt to other inland water bodies. The study showed LISS III sensor data can be used to model and monitor the water quality of the study area.

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