QUALITATIVE ASSESSMENT OF INLAND AND COASTAL WATERS BY USING REMOTELY SENSED DATA

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Abstract: The prime purpose of the research study was to elucidate the potential of remotely sensed data for estimation of water quality parameters (WQPs) in inland and coastal waters. The useful application of remotely sensed data for operational monitoring of water bodies demand for improved algorithms and methodology. The in situ hyperspectral Spectroradiometer data, water quality data and Airborne Imaging Spectroradiometer for Applications (AISA) data of Apalachicola Bay Florida, USA were collected. The data was analyzed to develop the models for assessment of total suspended sediment (TSS), chlorophyll-a (chl-a), and secchi depth. The analysis of collected spectral data reveals that a peak reflectance in red domain was well correlated with chlorophyll-a concentration. The optical depth is found to be strongly correlated with Chl-a and TSS. In order to examine the feasibility of multispectral data for water quality monitoring; AISA data was integrated into band widths of ALOS/AVNIR-2 sensor. The combination of three bands, band 2, 3 and band 4 was developed to correlate the remotely sensed data with TSS. The developed regression models showed good correlation with water quality parameters and may successfully applied for estimation of WQP in surface waters. The research work demonstrates an example for the successful application of remotely sensed data for monitoring the distribution of water quality parameters in water bodies.

1. INTRODUCTION

Assessment of water quality parameters in water bodies is one of the most scientifically relevant and commonly used application of remote sensing. Water quality monitoring requires regular and relevant observations which cannot be obtained by conventional field monitoring campaigns. Remotely sensed data with high spatial resolution and frequent acquisition frequency offer solution to monitor variability of water quality parameters up to several times per year. Application of remotely sensed data allows to discriminate between water quality parameters and to develop a better understanding of light, water and substances interactions. Hyperspectral remote sensing allows accurate and potential use of entire range of electromagnetic spectrum recorded in extremely narrow wavebands for monitoring water quality on multiple sites in water bodies. The operational monitoring and useful application of remote sensing in water bodies demands for improved methodology and sophisticated algorithms. Most of the satellite sensors record data in only a few broad spectral bands, the resolutions of which are too coarse to detect much of the spectral 'fine structure' associated with optically active substances in water (Goodin et al. 1993). The successful quantification of water quality parameters using remote sensing is affected not only by the type of waters under investigation, but also by the sensor used (Liu et al. 2003). The remotely sensed techniques for operational monitoring and management of water quality parameters (WQPs) depend on the substance being measured, its concentration, influencing environmental factors and the sensor characteristics. Effectiveness of remotely sensed data in water quality assessment of different water bodies has been examined by numerous researchers (Han, 2006; Dekker, 2001; Gitelson, 2007, etc.).

From the perspective of remote sensing, waters can generally be divided into two classes: case-I and case-II waters (Morel, 1977). Case-I waters are those dominated by phytoplankton (e.g. open oceans) whereas case-II waters containing not only phytoplankton, but also suspended sediments, dissolved organic matter, and anthropogenic substances for example some coastal and inland waters (Gin, 2003). Remote sensing in case II waters has been far less successful. Many scientists have pointed out that this is mainly due to the complex interactions of four optically active substances in case-II waters: phytoplankton (chl-a), suspended sediments, coloured dissolved organic matter (CDOM), and water (Novo et al., 1989; Quibell, 1991; Lodhi et al., 1997; Doxaran et al., 2002). The spectral characteristics of different water bodies and at different sampling points of the same water body are not same. Optically active components in the water bodies influence is qualitative and quantitative nature of the spectral signatures. The main components responsible for change in spectral signatures are yellow substance, phytoplankton pigments, and non living suspended matters and water itself. Remote sensing of water-constituent concentrations is based on the relationship between the remote-sensing reflectance, and the inherent optical properties, namely, the total absorption and the backscattering coefficients (e.g., Gordon et al., 1988). Chl-a concentration and total suspended solids (TSS) are two important water quality variables influencing the qualitative and quantitative nature of the spectral signatures.

The objective of present research is to develop relationships between water quality parameters (*WQPs*) and remotely sensed data (*RSD*) and to elucidate the spatial and temporal variation in chlorophyll-a concentration and TSS in Apalachicola Bay, Florida. The potential of simulated multispectral remote sensing data for delineation of WQPs was comprehensively examined.

2. STUDY AREA

The Apalachicola National Estuarine Research Reserve, 1 of 25 sites designated by the National Oceanic and Atmospheric Administration, covers approximately 246,766 acres (figure 1) and has an average depth of three meters The Bay is connected to the Gulf of Mexico through four major inlets: Indian Pass and West Pass at the western end, and East Pass and Lanark Reef at the eastern end. Most of the freshwater discharged into the Bay flows from the Apalachicola River (Wang et al. 2010). Water in the Bay is moderately stratified. The substrate of the Bay is predominately soft silt and clay with some sandy areas (Dardeau et al. 1992). Apalachicola Bay is a river-dominated, bar-built shallow estuary. It receives freshwater flows from the Apalachicola, Chattahoochee, and Flint River system (ACF), which drains over 60,000 km^2 of Georgia, Alabama, and Florida (Livingston 2006). Tides in Apalachicola Bay are mixed, with an uneven high and low tide and a range of 0.2 to 0.6 m (Huang et al. 2002). Water quality in estuarine ecosystems is affected by many natural and anthropogenic factors.

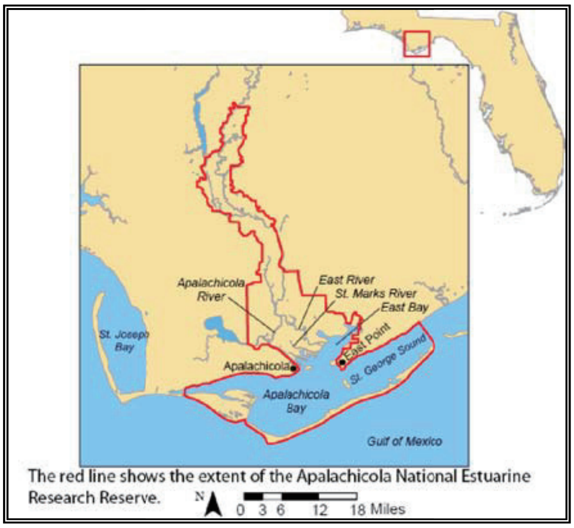

Figure 1. Map showing the research study Area: Apalachicola Bay, Florida

3. MATERIAL & METHOD

3.1 In situ measurements

Two independent in situ datasets were collected for model calibration and validation respectively. The ground truth data of Apalachicola Bay included water sampling for laboratory analysis (e.g. chl-a and seston), on-site measurements (e.g. Secchi depth, water depth), weather observations (e.g. wind speed and sky condition) and upwelling radiance and downwelling irradiance hyperspectral data.

Two pairs of Ocean Optics USB 2000 hyperspectral radiometers was used (the dual headed system, i.e., upward looking and downward looking Ocean Optics sensor) for acquiring upwelling radiance $L(\lambda)_u$ and downwelling irradiance $E(\lambda)_{inc}$ just above and below the water surface. The hyperspectral data was collected in the spectral range of 400 nm to 900 nm. To match their transfer functions, the inter-calibration of the radiometer was accomplished by measuring the upwelling radiance (L_{cal}) of a white Spectralon reflectance standard, simultaneously with incident irradiance (E_{cal}). Solar zenith angles ranged from approximately 20° to a maximum of 55°. Measurements were taken over optically deep water and an average of 10 consecutive spectra was used. The term reflectance is defined as the ratio between a reflected and an incident quantity of light. The ratio can consist of two radiances, two irradiances, or radiance and irradiance (Aas, 2009). Percentage spectral reflectance R(λ) was computed as:

$$\%R(\lambda) = [L(\lambda)_u / E(\lambda)_{inc}] \times [E(\lambda)_{cal} / L(\lambda)_{cal}] \times R(\lambda)_{cal} \times 100$$

$R(\lambda)_{cal}$ is the reflectance of the Spectralon panel linearly interpolated to match the band centers of each radiometer. At each station a standard set of water quality parameters was measured. Samples were filtered to estimate chlorophyll-a by spectrophotometric methods. TSS was determined gravimetrically using pre-ashed and tared filters. Filters and retained particulate matter were dried (60 °C for at least 24 h) and reweighed. The data was collected during field campaign carried out by the field crew of Center for Advanced Land Management Information Technologies (CALMIT), School of Natural Resources, University of Nebraska-Lincoln, USA.

Parameters	Min	Max	Med	Avg	SD
Chl-a (µg/l)	2.6	21.1	4.8	7.1	5.5
Seston (mg/l)	2.4	28.7	11.7	12.0	8.4
Secchi Depth (m)	0.35	0.35	0.9	0.8	0.3
Water Depth (m)	1	5.45	1.8	1.9	0.9

Table 1. Descriptive statistic (Minimum, Maximum, Median, Average, Standard Deviation) of measured water quality parameters

3.2 Airborne Imaging Spectroradiometer for Applications (AISA) Data

Visible to near infrared (NIR) hyperspectral airborne imaging Spectroradiometer is a valuable technology for remote sensing of the earth's surface because of its combination of good spatial and spectral resolution. Hyperspectral remotely sensed data was acquired by an aerial remote sensing platform. The instrument array included an AISA Eagle hyperspectral imager from Visible to Near Infrared (VNIR). The AISA Eagle is a solid-state, push-broom instrument that has the capability of collecting data with high spatial and spectral resolution. The spectral range of AISA eagle is 390 to 1000 nm in up to 512 bands. The sensor has an Inertial Navigation System (INS) and (Differential Global Positioning System) DGPS in order to provide spatially accurate data. The AISA Eagle pre-processing software provides for the automatic geometric correction, rectification, mosaicking, and calculation of at-platform radiance by applying calibration coefficients referenced to well-characterized spectroradiometric targets (Mishra, 2007). The algorithm uses the DGPS and attitude information from the INS to perform geometric, georeferencing and mosaicking operations (Makisara *et al*., 1994). AISA Eagle data used for the present study were acquired in the spectral range of 400 to 980 nanometer between 0330 and 0430 h (CST) on 3rd and 4th April 2006 when the solar zenith angle was close to 70^o. The sensor altitude was (2.073 km), and the image was acquired at nadir at a spatial resolution of 2 m and spectral resolution of 62 bands. Ground data indicated low wind (~ 3 m s^{-1}), high visibility (40 km), and clear skies. The site selected from flight lines covered an area of approximately 1.6 km^2 in the vicinity of Apalachicola Bay. The image data were converted to at-platform radiance by applying the calibration coefficients provided by AISA processing software 'Caligeo' for subsequent processing.

3.3 Atmospheric correction

The radiance received by a sensor, $L_t(\lambda_i)$, at the top of atmosphere (TOA) in a spectral band centered at a wavelength, λ_i can be divided into the following components (Gordon *et al.*, 1983):

$$L_t(\lambda_i) = L_r(\lambda_i) + L_a(\lambda_i) + T(\lambda_i)L_g(\lambda_i) + t(\lambda_i)L_w(\lambda_i)$$

Where $L_r(\lambda_i)$ and $L_a(\lambda_i)$ represents radiances generated along the optical path in the atmosphere by Rayleigh and aerosol scattering respectively; $L_g(\lambda_i)$ is contribution arising from the specular reflection of direct sunlight from the sea surface or the sun glint component; $L_w(\lambda_i)$is desired water leaving radiance; T is direct atmospheric transmittance; and t is diffuse atmospheric transmittance of the atmosphere.

The goal of atmospheric correction is to remove the contributions of scattering in the atmosphere and reflection from the water surface from the TOA radiances measured by a sensor in the visible region of the spectrum. AISA Eagle data were atmospherically corrected by using FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes), a first-principles atmospheric correction algorithm for visible to near infrared (NIR) hyperspectral data. FLAASH atmospheric correction uses MODTRAN code and typically consists of three steps (Matthew *et al.*, 2003). FLAASH uses the standard equation for spectral radiance at the sensor level, L, in the solar wavelength range (neglecting thermal emission) from a flat Lambertian surface or its equivalent (Vermote *et al.*, 1994).

$$L = \frac{A\ R}{(1 - R_e S)} + \frac{B\ R_e}{(1 - R_e S)} + L_a$$

Where R is pixel surface reflectance, R_e is surface reflectance averaged over the pixel and a surrounding region, S = the spherical albedo of the atmosphere, L_a = the radiance backscattered by the atmosphere, and A and B are the coefficients that depend on atmospheric and geometric conditions but not on the surface. Each of these variables depends on the spectral range of the selected channel; the wavelength index has been omitted for simplicity. The first term in above equation corresponds to radiance that is reflected from the surface and travels directly into the sensor. The second term corresponds to radiance from the surface that scattered by the atmosphere into the sensor, resulting in a spatial blending, or adjacency, effect. ENVI 4.3, digital image processing software, was used to process the AISA data. The image was first geometrically rectified to UTM (Universal Transverse Mercator) projection (Zone 16; Datum: WGS84). The geometrically and radiometrically corrected AISA image was used in the analysis.

4. MODEL DEVELOPMENT

The sub-surface spectral reflectance and atmospherically are depicted in figure 2 and figure 3 respectively. The acquired spectral data of the Apalachicola bay, USA represents first reflectance peak in the green domain near 550 nm and the second reflectance peak in the red domain showing turbid water with low CDOM. The peaks near 700 nm clearly proof the presence of chlorophyll in the bay. The field, laboratory and remotely sensed data were analyzed in a systematic manner. The collected spectrum shows that the qualitative nature of the acquired signals are same, however, the quantitative nature vary from point to point in the water body.

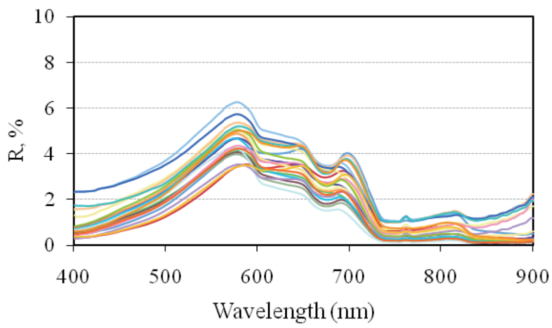

Figure 2. Sub-surface hyperspectral reflectance of Apalachicola Bay, USA

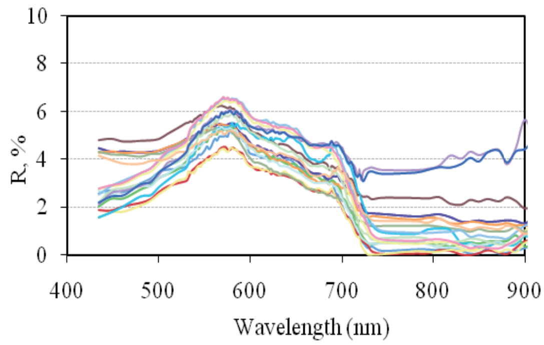

Figure 3. AISA reflectance of Apalachicola Bay, USA

The amount of TSS present in the water body defines the water category. Chlorophyll-a concentration and TSS were not correlated well (Figure 4) with the determination coefficient of linear relationship $R^2 < 0.33$. It depicts that chl-a was not the only characteristic controlling water quality, confirming that the waters belonged to typical case-II water group (Gitelson, 2008).

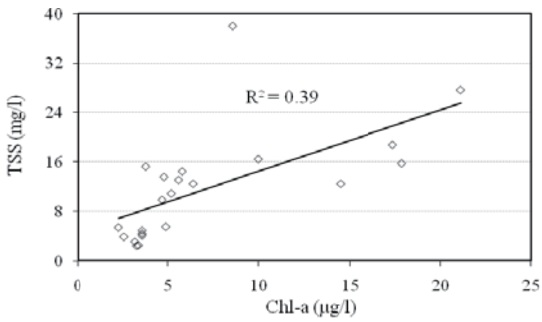

Figure 4. Correlation between chl-a and TSS

The ability to monitor water quality parameters in case II waters requires high resolution remotely sensed data and suitable techniques to examine the diverse nature of optical constituents present in the water body. Band ratio algorithms were developed to establish the relationship between the reflectance and selected water quality parameters. Band-ratioing did not universally give the best results but in many cases did; band ratioing has been suggested as the most appropriate approach elsewhere (Legleiter et al. 2005). In order to elucidate the potential of multispectral remote sensing for water quality monitoring, the AISA data is integrated in to band width of ALOS/AVNIR/2 sensor as follow;

$$Band\ 1 = \int_{420}^{500} R(\lambda)d\lambda \qquad Band\ 2 = \int_{520}^{600} R(\lambda)d\lambda$$

$$Band\ 3 = \int_{610}^{690} R(\lambda)d\lambda \qquad Band\ 4 = \int_{760}^{890} R(\lambda)d\lambda$$

4.1 Chlorophyll-a

In case I waters, concentrations of chlorophyll-a can be quite satisfactorily estimated with satellite images by using an empirical model and interpreting the received radiance at different wavelengths (Gordon and Morel 1983). However, in case II waters owing to complexity of the water constituents the retrieval of chl-a is difficult task and needs advance techniques and approaches. The pronounced scattering/absorption features of chlorophyll-a are: strong absorption between 450–475nm (blue) and at 670nm (red), and reflectance maximums at 550 nm (green) and near 700nm (Red Peak). A variety of algorithms have been developed for retrieving chl-a in turbid waters. All are based on the properties of the reflectance peak near 700 nm and the ratio of that reflectance peak to the reflectance at 670 nm (Gitelson et al., 2008). Gitelson, 1992 studied the behaviour of the reflectance peak near 700nm and concluded that the 700nm reflectance peak is important for the remote sensing of inland and coastal waters with regard to measuring chlorophyll. Han, 2005 pointed out that he spectral regions 630–645 nm, 660–670 nm, 680–687nm and 700– 735 nm were found to be potential regions where the first derivatives can be used to estimate chlorophyll concentration. Dekker, 1991 mentioned that the scattering and absorption characteristics of chlorophyll-a can be studied when more than one band is used. Hoogenboom et al., 1998 determined that a ratio using an Advanced Visible–Infrared Imaging Spectrometer (AVIRIS) band located near 713 nm with the band at 667nm was the most sensitive for chlorophyll retrieval for inland waters. A similar ratio (R_{674}/R_{705}) has been demonstrated to be optimal for inland lakes and rivers (Thiemann and Kaufmann, 2000). Three types of independent variables were tested: single spectral band, ratios of spectral bands, and combinations of multiple bands to develop linear regression equations and r^2 values were computed.

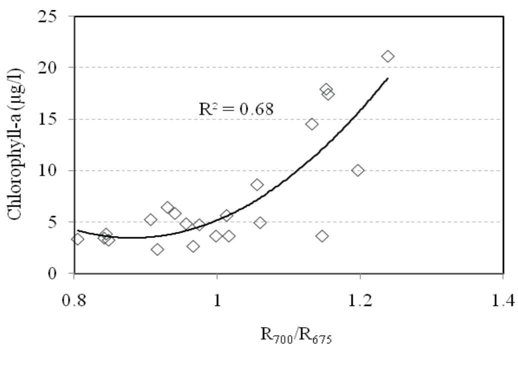

Figure 5. Relationship b/w chl-a and reflectance ratio

It was observed that the ratio of R_{700}/R_{675} is well correlated with chlorophyll-a concentration. The developed model is of the following form;

$Chl - a(\mu g/l) = m(R_{700}/R_{675})^2 + n(R_{700}/R_{675}) + l$; *where m, n and l are empirical coefficients.*

In case 2 waters, the presence of other optically active constituents (OACs) effect the nature of the signals and the discrimination in these constituents is complex. Dall'Olmo et al., 2003 provided evidence that a three band reflectance model, originally developed for estimating pigment contents in terrestrial vegetation (Gitelson et al., 2003), could also be used to assess chl-a in turbid waters. The model relates pigment concentration to reflectance $R(\lambda_i)$ in three spectral bands λ_i:
Pigment concentration = $R_{750}*(R_{670}^{-1}-R_{700}^{-1})$

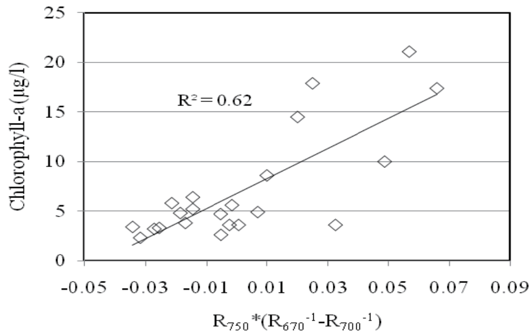

Figure 6. Relationship b/w chl-a and 3 band model

The developed model is of the following form;

$Chl - a(\mu g/l) = m[R_{750} * (R_{670}^{-1} - R_{700}^{-1})] + n$; *where m and n are empirical coefficients.*

The relationship between chl-a and AVNIR-2 ($Band_3/Band_1$) is demonstrated in figure 7.

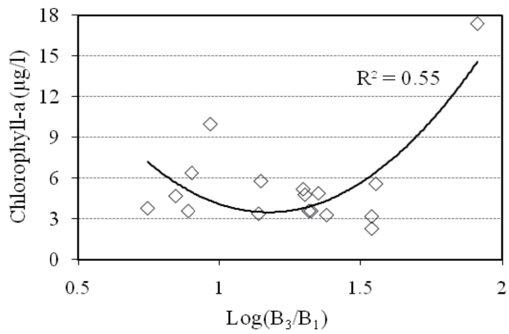

Figure 7. Relationship b/w chl-a and AVNIR-2 bands reflectance ratio

The developed model is of the following form;

$Chl - a(\mu g/l) = m[Log(B_3/B_1)]^2 + n[Log(B_3/B_1)] + l$;*where m, n and l are empirical coefficients.*

4.2 Total Suspended Matter (TSM)

TSS concentrations regulate light attenuation in inland and estuarine systems. In coastal waters, light scattering by suspended particles strongly affects light propagation in the water column (Lee et al., 2005), and determines to a large extent the magnitude of surface reflectance (Sathyendranath et al., 1989). Miller and McKee, 2004 demonstrated the application of MODIS (Terra) 250m data to quantify TSS using a linear regression model relationship established between MODIS band-1 (620–670nm) and in situ measurements of concentrations of inorganic-dominated TSS in the coastal northern Gulf of Mexico. Water colour associated with estuarine systems is typically characterized by high levels of total suspended solids (TSS), CDOM and chlorophyll, exhibiting a complex mixture of contributing colour constituents (Bukata et al., 1995). Total suspended matters *(or seston)* represent living organic matter (mainly Phytoplankton) and inorganic suspended solids (tripton). Tripton (Inorganic material & detritus) mainly contribute to scattering of light with low absorption. Absorption is normally neglected for the inorganic particles such as suspended sediments. Empirical relationships between spectral properties and total suspended matter showed good correlation with NIR/Green band ratio as illustrated in figure 8. The developed model is as follow;

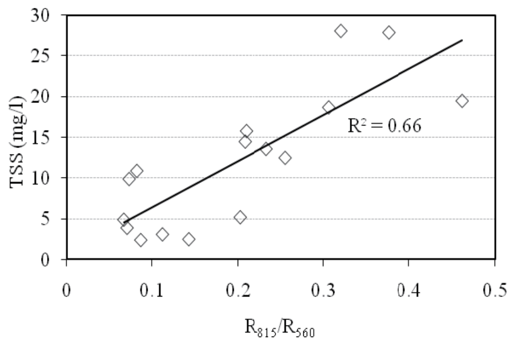

Figure 8. Relationship between TSS and reflectance ratio

$TSM\ (mg/l) = m(R_{815}/R_{560}) + n$; *Where m and n are empirical coefficients.*

The relationship between chl-a and AVNIR-2 ($Band_3/Band_1$) is demonstrated in figure 9 and the model is shown below.

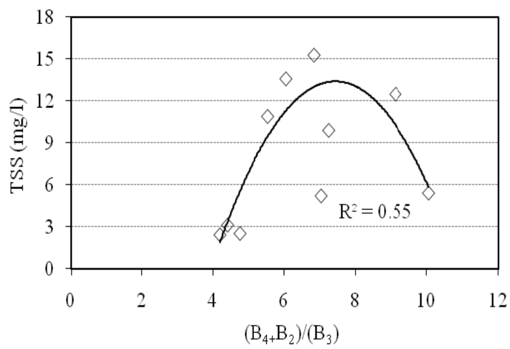

Figure 9. Relationship b/w TSS and ALOS/AVNIR-2 (3 band) reflectance ratio

$TSS(mg/l) = m[(B_4+B_2)/(B_3)]^2 + n[(B_4+B_2)/(B_3)] + l$; *where m, n and l are empirical coefficients.*

4.3 Secchi Depth (SD)

The measurement of water transparency has been attempted by various methods, most commonly based on light attenuation principles (Mobley 1994). The estimation of light attenuation in water bodies is not a trivial task, and therefore simpler methods have been proposed for the operational estimation of water transparency (Gomez, 2009). The best known is the Secchi disc, which is a black and white disc 20 cm in diameter that is used to estimate water transparency visually, by measuring the depth at which the disc is no longer visible. The main problem with estimating water transparency with the SD is the spatial significance of the samples, which are expensive to obtain and refer to single-point measurements. Remote sensing can be an ideal tool for monitoring water transparency. The secchi depth is found to be well correlated with reflectance ratio of R_{750}/R_{560} (NIR/Green). The simple band ratio technique is effective in monitoring SD by means of remotely sensed data.

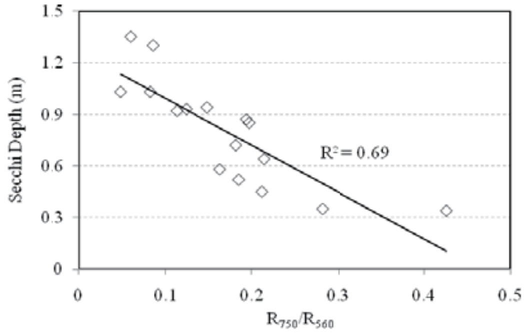

Figure 10. Relationship b/w secchi depth and reflectance ratio

$SD(m) = m(R_{750}/R_{560}) + n$; *where m and n are empirical coefficients.*

5. CONCLUDING REMARKS

Remote sensing is proposed as a useful tool for monitoring water quality parameters up to several times per year and offer valuable data on the seasonal variability of water quality. The research work demonstrates the feasibility of hyperspectral and multispectral remotely sensed data for monitoring the spatial and temporal variations of water quality parameters. The band ratio approach is effective for development of water quality algorithms and to minimize the effect of confounding environmental variables. It was found that the simple two band reflectance ratio R_{700}/R_{670} is well correlated with chl-a concentration. The three band model $R_{750}*(R_{670}^{-1}-R_{700}^{-1})$ is found to be predictor of chl-a concentration in case-II waters. The logarithmic ratio of ALOS/AVNIR-2 band 3 and band 1 was related with chl-a concentration in the study area. However, due to complexity of water and wide band width, the accuracy was not high. The ratio of NIR and green domain is best predictor of TSS. In case of multispectral remote sensing, the developed 3 band model including ALOS/AVNIR-2 band 4, band 3 and band 2 is well correlated with TSS. Empirical and semi-empirical algorithms are easy to use; however, the coefficients used in empirical algorithms are derived from data sets that do not necessarily represent all natural variations. The developed algorithms are based on the limited data set. More in situ water quality data, hyperspectral data and multispectral data is needed to calibrated and validated the models. Moreover, the spatial and temporal variability of water quality variables in the Apalachicola Bay needs investigation. It is important to incorporate water quality assessment as an integral part of water resources and environmental planning and management. Remotely sensed data is effective and efficient tool for monitoring the distributions of water quality parameters in inland and coastal waters and to support water management strategies.

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