A Review on Remote Sensing Approaches on Coastal Aquatic Systems

P. J. E. Delina

Department of Agricultural Engineering, Faculty of Agriculture, Eastern University, Sri Lanka
delinap[at]esn.ac.lk

Abstract: ***Coastal ecosystems are the natural systems with high biotic production ranging from coral reefs to seagrass meadows, sand dunes, mangroves, salt marshes, tidal flats, lagoons and estuaries. The most common form of detections and monitoring of coastal aquatic systems are water quality, Chlorophyll –a, biomass of aquatic vegetation and Phytoplankton, which include in - situ sampling and laboratory analysis. Historical water quality data are seldom available in many instances. To overcome these limitations, remote sensing in coastal aquatic resources can be a helpful tool. It can be used in a more effective and efficient manner to monitor and identify large - scale regions and water bodies that suffer from qualitative problems. The remote sensed data in the digital form helps to carry out the digital spatial analytical process. Remote sensing approaches combined with the Geographic Information System have been extensively used for terrestrial and aquatic ecosystems monitoring. This review summarizes the basic concepts and remote sensing applications in coastal water bodies, with special reference to water quality and chlorophyll - a detection.***

Keywords: Chlorophyll –a, multispectral remote sensing, satellites, thermal infra - red remote sensing, water quality

1. Introduction

"A remote sensing instrument collects information about an object or phenomenon with the instantaneous –field - of - view (IFOV) of the sensor system without being in direct physical contact with it [1]". In the early 1920s, the remote sensing of the coastal environment relied on aerial photographs [2] mainly used to map mangroves [3] and changes in the coastline. The major drawback of aerial photography is its limited area of coverage and high cost [4]. However, the launch of Landsat in 1972 triggered the remote sensing applications of coastal regions [2]. Since then, remote sensing has been widely used to detect changes in coastal environments and for environmental sensitivity mapping such as mangroves distribution, algal/phytoplankton mapping, surface water quality monitoring, aquatic vegetation monitoring, etc. [1]. The applications of coastal remote sensing have been made using different satellites covering areas of interest at regional scale with different spatial, spectral and temporal resolutions such as Landsat series (2 - 8) (MSS/ TM/ ETM+ and OLI), SPOT (1 - 4), IKONOS, Sentinel 1 - 2, etc.

The following table 1 summarizes the non - commercial earth observation (EO) satellites and their characters used in the environmental mapping.

Although *in - situ* measurement offers high accuracy, it is a labour intensive and time consuming process and only able to represent a restricted level of point estimations. Obtaining spatial and temporal variations of quality in large water bodies is almost impossible. Due to its topographic situation, monitoring, forecasting and managing entire water bodies might be inaccessible in *in - situ* measurements. The accuracy and precision of collected *in - situ* data can be questionable due to field sampling and laboratory errors [6].

Kallio *et al*. [7] has indicated that applying remote sensing in along with other monitoring programs benefit a synoptic view of the entire water body for more effective monitoring of the spatial and temporal variation, able to synchronize view of the quality parameters in a group of water bodies over a vast region, provides a comprehensive historical record of missing information in an area and represents trends over time through historical archives of satellite imagery and prioritizes sampling locations and field surveying times.

The applications of remote sensing in coastal environments have limitations. The most common problem is cloud infestation in the images and the Turbidity of the coastal waters.

Table 1: A comprehensive summary of non - commercial EO satellites and sensors visit

Satellite (Agency)	Sensor	# of Channels	Spectral range	Spatial Resolution (m)	Swath Width (km)	Image Archive
ALOS (JAXA, Japan)	AVNIR-2	4	Optical	10	70	2006–2011
	PALSAR	1	L-band SAR	7–100	40–350	2006–2011
	PRISM	1	Panchromatic/Stereo	2.5	70	2006–2011
TIROS/AVHRR (NOAA, USA)	AVHRR	6	Optical/thermal	1,100	~2700	1978–present
Landsat (NASA/USGS,USA)	MSS	5	Optical/thermal	68 _ 83	185	1972–1997
	TM/ETM+	7	Optical/thermal	30/120	185	1987–2011
	OLI/TIRS	11	Panchromatic/optical/thermal	15/30/100	185	2014–present
Terra and Aqua (NASA, USA)	MODIS	36	Optical/thermal	250/500/1,000	2330	2000–present
Quickbird (Digital Globe, USA)	Quickbird	5	Panchromatic/optical	0.55/2.16 (at 400 km altitude)	14.9(at 400 km altitude)	2001–2015
SPOT (Airbus DS, France 46)	SPOT PANSPOT MS	5	Panchromatic/optical/stereo	1.5/6	60	1986–present
Geoeye	Geoimage	5	Panchromatic/optical	0.41/1.65	15.2	2008–present

(Extracted from [5] Earth Observation: Data, Processing and Applications)

In the past, the cost of obtaining multiple sets of imagery was high, but Landsat and Sentinel imagery are freely available. Most early studies used Landsat images with a medium spatial resolution that gave satisfactory results. Still, more recently, images with a high spatial resolution (i. e., WV - 2 and IKONOS) for coastal environments are yielding good results in mapping [8, 9]. However, the suitability depends on the nature of the research problem [2].

2. Overview of multispectral remote sensing methods on coastal water bodies

Multispectral remote sensing is the technique that uses radiometers and spectroradiometers to record several broad channels in optical wavelengths [1, 5]. Multispectral scanners (MSS) are the devices that sense and digitally record radiation in multiple defined wavelength regions of the visible and infrared parts of the electromagnetic spectrum using imaging radiometers or imaging spectroradiometers.

Multispectral scanners can be divided into sub - categories based on their spatial resolution as low resolution (> 80 m), medium resolution (10–80 m), high resolution (< 10 m) and very high resolution (< 1m) [5]. Most optical radiation intercepted by water surfaces is absorbed or transmitted rather than reflected (Figure 1). Water bodies generally reflect 1–15% of the downwelling radiation, with most only reflecting 2–6% [10]. Water bodies include inland water (dams, rivers, lakes, and reservoirs) and maritime waters (estuaries, lagoons and oceans). In water bodies, reflectance generally decreases with increasing water depth, although for some substrata, such as dark seagrasses, the reverse relationship may occur. The strong absorption of NIR energy in the first few centimeters of water clearly defines land/water boundaries in EO imagery, in contrast to the high reflectance of soil and vegetation at this wavelength [11]. The reflectance properties of the water column are determined by the water colour, the water column and the water depth. Both suspended sediments and dissolved matter determine water colour. These constituents can be organic (such as Phytoplankton or dead and/or decaying particulate matter) or inorganic (such as minerals). In optically shallow water, the reflective properties of the substratum are also relevant to the observed reflectance from the surface of a water body [11].

The presence of suspended particles in water is typically indicated by an increase in reflectance in visible and NIR wavelengths (depending on the colour of the solids). Organic constituents, such as coloured dissolved organic matter (CDOM), Chlorophyll, and phycocyanins, also display distinctive spectral absorption characteristics. Characteristics of the water surface, that is, the air/water interface, also impact reflectance from water bodies. Water texture, sunglint and sky glint, floating layers (such as algal blooms and pollutants) and foam all change the spectral characteristics of surface waters. These attributes can complicate EO studies focused on the water column and substratum but are used in some applications to determine water movement and quality.

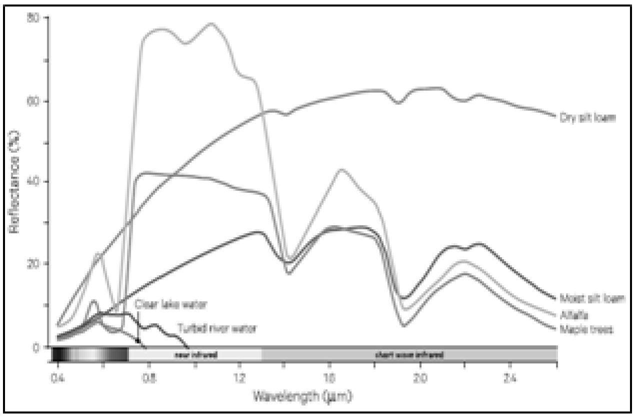

Figure 1: Idealized spectral signatures (Source: [11])

Therefore, various models have been developed to exploit the relationship between water reflectance properties and water body variables such as [12] Chlorophyll —indicator for phytoplankton biomass, trophic and nutrient status, Cyano - phycocyanin and cyano - phycoerythrin —

indicators for cyanobacterial biomass common in harmful and toxic algal blooms in inland and marine waters, Coloured dissolved organic matter (CDOM) for optically measurable component of dissolved organic matter in the water column and Total suspended matter (TSM) and non - algal particulate matter (NAP) for assessing water quality and a significant factor controlling the light environment of aquatic environments. These EO methods have been used to map water quality, create global ocean colour maps, monitor ocean productivity and map chlorophyll concentration in the ocean and inland water bodies.

3. Overview of thermal infrared (TIR) remote sensing on coastal water bodies

Thermal infrared remote sensing is the technique that the radiometers record a few broad channels in middle and thermal infrared wavelengths. Thermal infrared radiometers detect energy emitted from the Earth's surface in a 3–15 mm wavelength range. It should be noted that EO thermal sensors record emittance from the upper layer of the Earth's surface, possibly as thin as 50 mm, which may or may not be characteristic of the thermal properties of the observed features [13]. TIR imagery can be acquired at any time of the day or night.

TIR imagery is used for a wide range of engineering and environmental applications, including assessing heat loss, thermal efficiency and insulation effectiveness in residential, commercial and industrial buildings, thermal water pollution, dam seepage and fire hotspots. Since thermal emissions are closely related to moisture content, TIR imagery is also valuable for mapping soil moisture, evapotranspiration, surface temperature and vegetation stress. TIR remote sensing has particular value for a variety of geological applications, including sediment transport, volcanic landform interpretation, lithological mapping and surface roughness [14, 15]. Different surface materials can vary markedly in terms of their thermal behaviour. Water, for example, retains heat, cools slowly at night and warms gradually during the day, whereas rocks and soils absorb heat quickly during the day and release heat rapidly at night. The thermal behaviour of Earth surface materials is influenced by many factors, including Sun angle variations, topography, rainfall, climatic conditions, and the composition, texture and density of each material [16].

The following table 2 mentions the thermal imaging sensors that are used in the TIR remote sensing in assessing coastal aquatic bodies. The thermal wavelengths that can be used to estimate surface temperature are limited by atmospheric absorption to various ranges; 3–5 µm—measures peak emissions from bushfires, 3–4 µm - mine fires and power stations, 8–14 µm—measures peak emissions from land, waterbodies (including thermal water pollution) and 9–10 µm urban infrastructure.

Table 2: Commonly used thermal imaging sensors

Instrument	Mission(s)	Agency	Number of thermal bands in (3–5 mm)	Number of thermal bands in (8–14 mm)	Ground resolution (m)
HCMR	HCMM	NASA	0	1 (10.5–12.5)	600
TIMS	Airborne	NASA/JPL/Daedalus	0	6 (8.2–12.2)	50 (at 20,000 m)
ATLAS	Airborne	NASA	1 (3.35–4.20 mm)	6(8.2–12.2)	10 (at 5,000 m)
Daedalus AMS	Airborne	Daedalus	1 (3.0–5.4 mm)	1 (8.5–12.5)	Selectable
TM	Landsat-4 Landsat-5	NASA/USGS	0	1 (10.4–12.5)	120
ETM+	Landsat-7	NASA/USGS	0	1 (10.4–12.5 mm)	60
TIRS	Landsat-8	NASA/USGS	0	2 (10.6–11.2;11.5–12.5)	100
ASTER	Terra	NASA/USGS	0	5 (8.125–11.65)	90
MODIS	Terra/Aqua	NASA/USGS	7(3.66–4.549)	8(8.4–14.385)	1000
Imager	GOES	NOAA	1(3.8–4.0)	2 (10.2–11.2; 11.5–12.5	4000 8000
AVHRR	TIROS-N to NOAA-19	NOAA	1 (3.55–3.93)	2 (10.3–11.3; 11.5–12.5)	1100 (LAC)4000 (GAC)

(Extracted from [5] Earth Observation: Data, Processing and Applications)

Estimation and modeling surface temperature at global scales is relevant to a wide range of climate and environmental studies. A number of processing methods have been developed to calibrate TIR data to indicate apparent surface temperature. This technique is commonly used for inland water temperature, sea surface temperature (SST) mapping, land surface temperature (LST) and meteorological applications.

4. Discussions

1) Remote sensing applications on estimating water quality of the coastal aquatic system

The term water quality indicates the physical, chemical and biological characteristics of the water, including temperature, Chlorophyll, Turbidity, total suspended and dissolved solids (TSS & TDS), nutrients (Total and Ortho Phosphate, Total Nitrogen, Ammonium Nitrogen), coloured dissolved organic matter (CDOM), dissolved oxygen (including BOD & COD), pH, total organic carbon, salinity, etc. [6]. Multispectral imagery collected by space - borne satellite platforms have provided a valuable tool for rapidly assessing the spatial variability of inland and coastal water quality parameters over synoptic scales [17].

In remote sensing, water quality parameters are estimated by measuring changes in the optical properties of water caused by the presence of the contaminants. Therefore, optical remote sensing has been commonly used to calculate the optically active water quality parameters, which depends on whether it belongs to Case 1 or Case 2 waters [18]. According to the definitions by [19] Case 1 waters are those "waters whose optical properties are determined primarily by phytoplankton and related coloured dissolved organic matter (CDOM) and detritus degradation products" and Case 2 waters are "everything else, namely waters whose optical properties are significantly influenced by other constituents such as mineral particles, CDOM, or microbubbles, whose concentrations do not covary with the phytoplankton concentration. " These types highly define the bio - optical state [18] of the Chlorophyll and water quality parameters in remote sensed studies.

The monitoring of inland and coastal aquatic systems can be highly affected by inappropriate satellite sensors [20]. Ocean colour sensors like the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Medium Resolution Imagining Spectrometer (MERIS) have frequent revisit time (1–3 days) and sufficient radiometric resolution (12 - bit) needed for dark objects like water bodies. However, the spatial resolution of these sensors (300–1000 m) was suitable only for large aquatic systems while, the majority of the water bodies on Earth are small [21, 22]. Toming *et al.* [23] mention that Landsat series (Landsat 1–7) satellites had good spatial resolution (30–79 m) but the limited radiometric resolution (6–8 bits) being used to a certain extent for mapping water quality parameters of lagoons/lakes. However, compared to the other medium resolution satellites, Landsat 8 has a higher spatial resolution of 30 m and radiometric resolution is 12 - bit compared to Landsat 5 TM and Landsat 7 ETM+ (8 bits). It is suitable for remote sensing of even dark (CDOM - rich) lakes and coastal sediment concentrations at high resolution and accuracy due to its higher signal - to - noise ratio (S/N) compared to previous Landsat images [22, 23].

Perivolioti *et al*. [24] used a series of 30 years Landsat images to develop water Quality Element (QE) of Lake Koronia and compared it against *in - situ* data, specifically for the determination of water Temperature and pH. The temperature was estimated from all Landsat images, using the respective thermal bands and standard calibration followed by linear regression analysis for the complete, unified time series of the temperatures of Lake Koronia. Several remote sensing studies have been devoted to retrieving total suspended solids (TSS) and Turbidity in the aquatic system [25]. From the study by [22], spatiotemporal variation of Turbidity at Cam Ranh Bay and Thuy Trieu Lagoon was assessed using remote sensing data (Landsat 8). The algorithm for turbidity retrieval was developed based on the correlation between *in - situ* measurements and the red band of Landsat 8 OLI showed the correlation of $R^2 = 0.84$ ($p < 0.05$).

The Multispectral Imager (MSI) of Sentinel 2A (S2A) contains channels useful for water quality monitoring. S2A MSI and LS8 OLI sensor specifications in terms of spectral band - centers are very similar. The improved spatial resolution of the MSI sensor (10, 20 m) regarding OLI (30 m) allows for a better separation of small - scale features. It enables the observation of smaller river inlets and ponds [26]. The resampling technique helps the MSI match OLI 30 m spatial resolution to examine the spectral patterns retrieved by these two sensors, which can be cross - calibrated to increase the temporal resolution for more frequent monitoring of water quality parameters [23]. For example, findings from the study of Toming *et al.* [23] indicates that a good correlation was obtained between band ratio algorithms calculated from Sentinel - 2 MSI data and lake water parameters like Chl a ($R^2 = 0.83$), CDOM ($R^2 = 0.72$) and DOC ($R^2 = 0.92$) concentrations as well as water colour ($R^2 = 0.52$) from the mapping of nine small and two large lakes.

Another study conducted by Nhamo *et al.* [27] indicates the use of multispectral satellite images with a digital elevation model (DEM) to delineate wetland extent and the seasonal variations of the flooded area were assessed through an analysis of monthly water indices derived from the NDWI from Landsat and MODIS for the period of 2000 - 2015. The study of water quality seasonal variability (2000 to 2015) in Yangtze River Estuary and its adjacent coastal area was carried out by using MODIS/Terra and MODIS/Aqua satellite sensors to map the Suspended sediment concentration (SSC) and to calculate the Diffuse attenuation coefficient at 490 nm (Kd_{490}) where the values were seemed to be higher during the dry season than during the flood season [28].

A similar study was conducted at Florida Bay [29], investigating the spatial and temporal changes of biophysical parameters associated with water quality, including Turbidity, chl - a, total phosphate (TP) and total nitrogen (TN) using the application of integrated remote sensing, GIS and statistical techniques. Landsat TM and Landsat 8/OLI were used to assess temporal and spatial patterns and the results were validated with *in - situ* measurements. The findings show a good correlation in the multiple linear regression models both in dry and wet season (R^2=0.86 for chl - a, R^2=0.84 for Turbidity, R^2=0.74 for TP and R^2=0.82 TN in dry season) and (R^2=0.66 for chl - a, R^2=0.63 for Turbidity, R^2=0.69 for TP and R2=0.82 for TN in wet season) which can be used as a prediction model for the spatiotemporal variations of the selected water quality parameters in Florida Bay. The findings by Markogianni *et al*. [30] also emphasize the utilization of Landsat 8 images on the temporal studies of chlorophyll - a, CDOM and nutrient concentrations (nitrate, nitrite, phosphate and total nitrogen) of Trichonis Lake (Greece) for 2013/2014. The multiple linear regressions among reflectance measures and in - situ measurements of the above quality parameters indicate an excellent correlation to develop prediction models.

2) Remote sensing applications on Chlorophyll –a detection on coastal aquatic system

Algal blooms in both fresh and brackish water systems are directly related to chl - a concentration [6]. Chl - a is the primary indicator of trophic state because it acts as a link between nutrient concentration, particularly phosphorus and algal production. Chl - a mainly reflects green and absorbs most energy from wavelengths of violet - blue and orange - red light. Thus, many researchers frequently use the visible and near - infrared bands in their investigations to obtain strong correlations between water column reflection and chlorophyll concentration (Phytoplankton) in different water bodies [31, 32]. However, the determination of chl - a concentration is much more complex and less accurate in Case 2 waters due to the complexity of the constituents in water and requires advanced approaches and techniques.

Various visual spectral bands (Blue (0.40–0.50 µm), Red (0.60–0.70 µm)) and Green (0.50–0.60 µm)) and their ratios (Green (0.50–0.60 µm) and Red (0.60–0.70 µm), NIR and Red, Green and Blue, Blue (0.40–0.50 µm) and Red (0.60–0.70 µm)) are widely used to quantify chl - a [6]. Spectral band ratios can reduce irradiance, atmospheric and air - water surface influences in the remotely sensed signal [12, 33]. The prominent scattering - absorption features of chl - a include strong absorption between 450–475 nm (blue) and at 670 nm (red) and reflectance reaches to peak at 550 nm (green) and near 700 nm (NIR) [6]. Moses *et al*. [34] indicate that the reflectance peak near 700 nm and its ratio to the reflectance at 670 nm have been used to develop a variety of algorithms to retrieve chl - a in turbid waters and concluded that the 700 nm reflectance peak was necessary for the remote sensing of inland and coastal waters, especially for measuring chlorophyll concentration.

The review by Gholizadeh *et al*. [6] further elaborates that measured concentration of chl - a using all bands of Landsat - 5 TM and Band 1 (445–530 nm), Band 2 (520–610 nm), Band 3 (640–720 nm) and Band 4 (770–880 nm) of IKONOS data to estimate chl - a concentration in Istanbul, Turkey and Chl - a presented a good correlation with both Landsat 8/OLI bands and band ratio, with calculated R values for Bands 2, 3, 4 and band ratio (Band 5/Band 3) as 0.66, 0.70, 0.64 and 0.64, respectively, at a significance level of $p < 0.01$. Zhang and Han [35] found that OLI bands 1 to 4 and their combinations had a good correlation with chl - a concentration, while Band 2, Band 5 and a ratio of Band 2/Band 4 to measure chl - a concentration. However, it revealed that the Landsat TM seems to be more appropriate and widely used for chl - a assessment. Temporal coverage and spatial resolution of TM and its easy accessibility can be the main reasons for selecting this sensor [30]. Two decadal trends of chlorophyll - a concentration (Chl - a) in Negombo estuary, Sri Lanka, were analyzed with satellite optical sensor (Landsat, MODIS Ocean Colour 3 and ASTER) data observed from 1987 to 2011 and *in - situ* measurements to generate 30m resolution and 15m resolution Chl - a distribution maps which could be used as chlorophyll prediction model [36].

Furthermore, MODIS, SeaWiFS, MERIS, and RapidEye to estimate chl - a concentration in turbid waters using two - band and three - band models based on band ratios such as Red and NIR bands. While Moses *et al*. [34] compared MODIS and MERIS to estimate the concentration of chlorophyll - a in reservoirs related to Dnieper River and the Sea of Azov (Case 2 waters) using two - band and three - band models. Several algal bloom indices were used to distinguish the algal bloom waters from non - bloom waters and to develop new empirical chl - a algorithms for the large aquatic systems such as (1) normalized Rayleigh - corrected reflectance (Rrc) data with concurrent MODIS and field measurements (2) normalized green - red difference index (NGRDI) and atmospherically - corrected MERIS data (3) Normalized Difference Vegetation Index (NDVI), Chlorophyll Spectral Index (CSI), Floating Algae Index and the Normalized Difference algal Bloom Index (NDBI) in a shallow eutrophic lake, Lake Chaohu along with *in - situ* remote sensing reflectance (Rrs) and MODIS Rayleigh - corrected reflectance (Rrc) data in combination with data of local wind speed [37].

However, multispectral sensors like SeaWiFS, Landsat ETM+, MODIS, ALI do not provide the resolution for distinguishing cyanobacteria from other algal species as these sensors cannot detect Phycocyanin (PC) pigment [38]. But, MERIS bands 6 and 7 allow detecting PC features only if the concentration of cyanobacteria is sufficiently high [39].

The Multispectral Imager (MSI) of Sentinel 2A (S2A) contains channels useful for water quality models developed to quantify Chl - a concentrations such as the floating algal index (FAI) [40] and normalized difference chlorophyll index (NDCI). For example, Ha *et al*. [41] used field measurements and concurrent Sentinel 2A MSI imagery (S2A) over Lake Ba Be, in Vietnam to estimate Chl - a. The study further elaborates that S2A green - red band ratio (band 3 versus band 4) showed a strong positive correlation of corresponded field measured reflectance ratio with Chl - a by an exponential curve ($r^2 = 0.68$). Chlorophyll - a were found using the two - band algorithm based on Sentinel - 2/MSI and Sentinel - 3/OLCI also indicates a promising application on remotely estimate chlorophyll - a for coming decades in turbid inland waters [42].

5. Summary and Conclusions

Remote sensing can be combined with other geographic information sciences (GIScience), including Cartography, Surveying and GIS. The field has unique overlapping knowledge and intellectual activity areas as they are used in physical, biological and social science research. The majority of remotely sensed data collected for earth resource application results from sensors that record EM energy. The appropriate sensor selection for coastal remote sensing depends on factors relating to spatial, spectral and temporal resolution.

References

[1] Jensen, J. R. (2007). Introductory to Digital Image Processing: A Remote Sensing Perspective. Prentice - Hall Series in Geographic Information Science. **In:** Mbolambi. C. (2016). Assessment of Coastal Vegetation Degradation Using Remote Sensing in False Bay, South Africa. Ph. D. thesis, Stellenbosch University. pp.1 - 93. [Accessed on 02.03.2018]. Available at https: //scholar. sun. ac. za/bitstream/handle/. . .1/. . . /mbolambi_assessment_2016. pdf

[2] Edwards, A. J., Green, E. P., Mumby, P. J. and Clark, C. D. (2000). Remote Sensing Handbook for Tropical Coastal Management. France: United Nations Educational, Scientific and Cultural Organisation (UNESCO). **In:** Mbolambi, C. (2016). Assessment of Coastal Vegetation Degradation Using Remote Sensing in False Bay, South Africa. Thesis submitted in fulfilment of the requirements for the degree Masters of Science in Geography and Environmental Studies in the faculty of Science at Stellenbosch University. Fischer, W. A., Hemphill, W. R. and Kover, A. (1976). Progress in remote sensing. Journal of Photogrammetric. Vol.32. (2). Pp.33 - 72. [Accessed on 28.07.2021]. Available at https: //core. ac. uk/download/pdf/188223856. pdf

[3] Reark, P. and Ross, P. S. (1975). Mangrove vegetation stratification using Salyut 7 photographs and satellite images. *Geo - carto International*. Vol.3. Pp.31 - 47. **In:** Mbolambi, C. (2016). Assessment of Coastal Vegetation Degradation Using Remote Sensing in False Bay, South Africa. Thesis submitted in fulfilment of the requirements for the degree Masters of Science in Geography and Environmental Studies in the faculty of Science at Stellenbosch University. [Accessed on 28.06.2020]. Available at https: //core. ac. uk/download/pdf/188223856. pdf

[4] Friel, C. and Haddad, K. (1992). GIS manages marine resources. GIS World. Vol.5. Pp.33 - 36. **In:** Mbolambi, C. (2016). Assessment of Coastal Vegetation Degradation Using Remote Sensing in False Bay, South Africa. Thesis submitted in fulfilment of the requirements for the degree Masters of Science in Geography and Environmental Studies in the faculty of Science at Stellenbosch University. [Accessed on 28.06.2020]. Available at https: //core. ac. uk/download/pdf/188223856. pdf

[5] CRCSI. (2016). Earth Observation: Data, Processing and Applications. Volume 1A: Data—Basics and Acquisition. Harrison, B. A., Jupp, D. L. B., Lewis, M. M., Forster, B., Mueller, N., Smith, C., Phinn, S., Hudson, D., Grant, I., Coppa, I. (Eds.). CRCSI, Melbourne. [online]. [Accessed on 30.04.2018]. Available at https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[6] Gholizadeh, M. H., Melesse, A. M. and Reddi, L. (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors 2016*.16 (1298): 2 - 43. [Accessed on 03.03.2018]. Available at http: //citeseerx. ist. psu. edu/viewdoc/download?doi=10.1.1.633.1491&rep=rep1&type=pdf doi: 10.3390/s16081298.

[7] Kallio, K., Kutser, T., Hannonen, T., Koponen, S., Pulliainen, J., Vepsäläinen, J. and Pyhälahti, T. (2001). Retrieval of water quality from airborne imaging spectrometry of various lake types in different seasons. Sci. Total Environ. Vol.268. Pp.59–77. **In:** Toming, K. Kutser, T., Laas, A., Sepp, M., Paavel, B. and Nõges, T. (2016). First Experiences in Mapping LakeWater Quality Parameters with Sentinel - 2 MSI Imagery. Remote Sens.2016. Vol.8. (640). Pp.2 - 14. [Accessed on 28.06.2020]. DOI: 10.3390/rs8080640.

[8] Wang, J. J. and Lu, X. (2010). Estimation of suspended sediment concentrations using terra Modis: An example from the lower Yangtze River, China. Sci. Total Environ.2010. Vol.408. Pp.1131–1138. **In:** Liu, X., Zhang, Y., Shi, K., Zhou, Y., Tang, X., Zhu, G. and Qin, B. (2015). Mapping Aquatic Vegetation in a Large, Shallow Eutrophic Lake: A Frequency - Based Approach Using Multiple Years of MODIS Data. ISSN 2072 - 4292. Remote Sens.2015. Vol.7. Pp.10295 - 1032. [Accessed on 28.06.2020]. DOI: 10.3390/rs70810295.

[9] McCarthy, M. J. and Halls, J. N. (2014). Habitat mapping and change assessment of coastal environments: an examination of WorldView - 2, Quick Bird and IKONOS satellite imagery and airborne island habitats. *International Journal of Geo - Informatics.* Vol.3. Pp.297 - 325. **In:** Mbolambi, C. (2016). Assessment of Coastal Vegetation Degradation Using Remote Sensing in False Bay, South Africa. Thesis submitted in fulfilment of the requirements for the degree Masters of Science in Geography and Environmental Studies in the faculty of Science at Stellenbosch University. [Accessed on 28.06.2020]. Available at https: //core. ac. uk/download/pdf/188223856. pdf

[10] Phinn, S. R., and Dekker, A. G. (2004). An Integrated Remote Sensing Approach for Adaptive Management of Complex Coastal Waters. The Moreton Bay Case Study. Moreton Bay Remote Sensing Tasks (MR2). CRC for Coastal Zone, Estuary and Waterway Management, Brisbane. **In:** CRCSI (2017) Earth Observation: Data, Processing and Applications. Volume 1B: Data—Image Interpretation. (Eds. Harrison, B. A., Jupp, D. L. B., Lewis, M. L., Forster, B. C., Coppa, I., Mueller, N., Hudson, D., Phinn, S., Smith, C., Anstee, J., Grant, I., Dekker, A. G., Ong, C., and Lau, I.) CRCSI, Melbourne. [Accessed on 30.04.2020]. Available at https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[11] CRCSI. (2017). Earth Observation: Data, Processing and Applications. Volume 1B: Data—Image Interpretation. Harrison, B. A., Jupp, D. L. B., Lewis, M. L., Forster, B. C., Coppa, I., Mueller, N., Hudson, D., Phinn, S., Smith, C., Anstee, J., Grant, I., Dekker, A. G., Ong, C., and Lau, I. (Eds.). CRCSI, Melbourne. Australia and New Zealand CRC for Spatial Information. [Accessed on 30.04.2018]. Available at

https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[12] Dekker, A. G., and Hestir, E. L. (2012). Evaluating the feasibility of systematic inland water quality monitoring with satellite remote sensing. *CSIRO: Water for a Healthy Country National Research Flagship*. **In:** CRCSI (2016) Earth Observation: Data, Processing and Applications. Volume 1A: Data—Basics and Acquisition. Harrison, B. A., Jupp, D. L. B., Lewis, M. M., Forster, B., Mueller, N., Smith, C., Phinn, S., Hudson, D., Grant, I., Coppa, I. (Eds.) CRCSI, Melbourne. [online]. [Accessed on 30.04.2018]. Available at https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[13] Campbell, J. B. and Wynne, R. H. (2011). Introduction to Remote Sensing (5th Ed.). The Guilford Press. P.667. **In:** Smith, R. B. (2012). Introduction to Remote Sensing of Environment (RSE). Micro - Images, Inc., 2001–2012. [Accessed on 30.04.2020]. Available at http: //www.microimages. com.

[14] Ramsey, M. S. (2004). Quantitative geological surface processes extracted from infrared spectroscopy and remote sensing. Paper presented at the Mineralogical Association of Canada Thermal Infrared Spectroscopy Workshop, London, Ontario, Canada. http: //www.pitt. edu/~mramsey/papers/GAC1. pdf. **In:** CRCSI (2017) Earth Observation: Data, Processing and Applications. Volume 1B: Data—Image Interpretation. (Eds. Harrison, B. A., Jupp, D. L. B., Lewis, M. L., Forster, B. C., Coppa, I., Mueller, N., Hudson, D., Phinn, S., Smith, C., Anstee, J., Grant, I., Dekker, A. G., Ong, C., and Lau, I.) CRCSI, Melbourne. [Accessed on 30.04.2020]. Available at https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[15] Carter, A. J., Ramsey, M. S., Durant, A. J., Skilling, I. P., and Wolfe, A. (2009). Micron - scale roughness of volcanic surfaces from thermal infrared spectroscopy and scanning electron microscopy. *Journal of Geophysical Research - Solid Earth*. Vol.114. doi: http: //dx. doi. org/10.1029/2008jb005632. **In:** CRCSI (2017) Earth Observation: Data, Processing and Applications. Volume 1B: Data—Image Interpretation. (Eds. Harrison, B. A., Jupp, D. L. B., Lewis, M. L., Forster, B. C., Coppa, I., Mueller, N., Hudson, D., Phinn, S., Smith, C., Anstee, J., Grant, I., Dekker, A. G., Ong, C., and Lau, I.) CRCSI, Melbourne. [Accessed on 25.10.2020]. Available at https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[16] Elachi, C., and van Zyl, J. (2006). Introduction to the Physics and Techniques of Remote Sensing, Second Edn. Wiley Inter - science, New Jersey. **In:** CRCSI (2016) Earth Observation: Data, Processing and Applications. Volume 1A: Data—Basics and Acquisition. (Eds. Harrison, B. A., Jupp, D. L. B., Lewis, M. M., Forster, B., Mueller, N., Smith, C., Phinn, S., Hudson, D., Grant, I., Coppa, I.) CRCSI, Melbourne. [Accessed on 12.06.2021]. Available at https: //www.crcsi. com. au/assets/. . . and. . . /Earth - Observation. . . /Vol1A - low - res - 27MB. pdf

[17] Gould Jr, R. W. and Arnone, R. A. (1997). Remote sensing estimates of inherent optical properties in a coastal environment, Remote Sensing of Environment, Vol.61. (2). Pp.290 - 301. **In:** Benjamin Page. (2017). A Multi - Satellite Based Technique for the Phenological Assessment of Cyanobacterial Algal Blooms across Inland Waters. The University of Georgia. (Thesis). Pp.1 - 76. [Accessed on 12.06.2021]. DOI: 10.13140/RG.2.2.16485.29920.

[18] Mobley, C. D., Stramski, D., Bissett, W. P. and Boss, E. (2004). Optical Modeling of Ocean Water. Is the Case 1 - Case 2 Classification Still Useful? *Coastal Ocean Optics and Dynamics*. pp.61 - 67. [Accessed on 25.11.2018]. Available at https: //tos. org/oceanography/article/optical - modeling - of - ocean - waters - is - the - case - 1 - case - 2 - classification - still -

[19] Morel, A. (1988). Optical modeling of the upper ocean in relation to its biogenesis matter content (Case 1 waters). J. Geophys. Res. Vol.93 (C9). Pp.10749 - 10768. **In:** Mobley, C. D., Stramski, D., Bissett, W. P. and Boss, E. (2004). Optical Modeling of Ocean Wate. Is the Case 1 - Case 2 Classification Still Useful? Coastal Ocean Optics and Dynamics. [Accessed on 12.06.2021]. Available at https: //core. ac. uk/download/pdf/346216188. pdf

[20] Palmer, S. C. J., Kutser, T. and Hunter, P. D. (2015). Remote sensing of inland waters: Challenges, progress and future directions. *Remote Sens. Environ.2015*. Vol.157. Pp.1–8. **In:** Ha, N. T. T., Thao, N. T. P., Koike, K. and Nhuan, M. T. (2017). Selecting the Best Band Ratio to Estimate Chlorophyll - a Concentration in a Tropical Freshwater Lake Using Sentinel 2A Images from a Case Study of Lake Ba Be (Northern Vietnam). ISPRS International Journal of Geo - Information. Vol.6. (290).15 pages. [Accessed on 12.06.2021]. DOI: 10.3390/ijgi6090290.

[21] Verpoorter, C., Kutser, T., Seekel, D. and Tranvik, L. J. (2014). A global inventory of lakes based on high - resolution satellite imagery. Geophys. Res. Lett.2014. Vol.41. Pp.639–642. **In:** Toming, K. Kutser, T., Laas, A., Sepp, M., Paavel, B. and Nõges, T. (2016). First Experiences in Mapping LakeWater Quality Parameters with Sentinel - 2 MSI Imagery. Remote Sens.2016. Vol.8. (640). Pp.2 - 14. [Accessed on 12.06.2021]. DOI: 10.3390/rs8080640.

[22] Quang, N. H., Sasaki, J., Higa, H. and Huan, N. H. (2017). Spatiotemporal variation of Turbidity based on Landsat 8 OLI in Cam Ranh Bay and Thuy Trieu Lagoon, Vietnam. *Water*.9 (570): 1 - 25. [Accessed on 19.11.2017]. Available at http: //citeseerx. ist. psu. edu/viewdoc/download?doi=10.1.1.633.1491&rep=rep1&type=pdf DOI: 10.3390/w9080570.

[23] Toming, K., Kutser, T., Laas, A., Sepp, M., Paavel., B. and Nõges, T. (2016). First experiences in mapping lake water quality parameters with Sentinel - 2 MSI Imagery. *Remote Sensing*.8: 640 - 654. [Accessed on 21.03.2018]. Available at http: //www.mdpi. com/journal/remotesensing/2072 - 4292/8/8/640 doi: 10.3390/rs8080640

[24] Perivolioti, T. M., Mouratidis, A., Bobori, D., Doxani, G. and Terzopoulos, D. (2017). Monitoring water quality parameters of Lake Koronia by means of long

time - series multispectral satellite images. *AUC Geographica*. pp.1 - 13. [Accessed on 23.01.2018]. Available at https: //www.researchgate. net/publication/319911534 DOI: 10.14712/23361980.2017.14

[25] Dogliotti, A. I., Ruddick, K. G., Nechad, B., Doxaran, D. and Knaeps, E. (2015). A single algorithm to retrieve Turbidity from remotely - sensed data in all coastal and estuarine waters, Remote Sensing of Environment, 156. Pp.157 - 168. **In:** Benjamin Page. (2017). A Multi - Satellite Based Technique for the Phenological Assessment of Cyanobacterial Algal Blooms across Inland Waters. The University of Georgia. (Thesis). Pp.1 - 76. [Accessed on 12.06.2021]. DOI: 10.13140/RG.2.2.16485.29920.

[26] Vanhellemont, Q. and Ruddick, K. (2016). ACOLYTE for Sentinel - 2: Aquatic Applications of MSI Imagery. *Proceedings of the ESA Living Planet Symposium, Prague, Czech Republic*. pp.9–13. **In:** Ha, N. T. T., Thao, N. T. P., Koike., K. and Nhuan, M. T. (2017). Selecting the best band ratio to estimate Chlorophyll - a concentration in a tropical freshwater lake using Sentinel 2A images from a case study of Lake Ba Be (Northern Vietnam). *ISPRS International Journal of Geo - Information.6*: 290 - 305. [Accessed on 02.03.2018]. Available at https: //www.mdpi. com/journal/ijgi DOI: 10.3390/ijgi6090290

[27] Nhamo, L., Magidi, J. and Dickens, C. (2017). Determining wetland spatial extent and seasonal variations of the inundated area using multispectral remote sensing. *Water*.43 (4): 543 - 552. [Accessed on 23.01.2018]. Available at https: //cgspace. cgiar. org/handle/10568/91314

[28] Yang, X., Sokoletsky, L. and Wu, H. (2017). Water quality seasonal variability (2000 to 2015) in Yangtze River estuary and its adjacent coastal area. *Journal of Remote Sensing & GIS.6* (4): 1 - 10. [Accessed on 10.12.2017]. Available at https: //www.omicsonline. org/open - access/water - quality - seasonal - variability - 2000 - to - 2015 - in - yangtze - river - estuary - and - its - adjacent - coastal - area - 2469 - 4134 - 1000216 - 97197. html DOI: 10.4172/2469 - 4134.1000216.

[29] Gholizadeh, M. H. and Melesse, A. M. (2017). Study on spatiotemporal variability of water quality parameters in Florida Bay using remote sensing. *Journal of Remote Sensing & GIS.6* (3): 2 - 11. [Accessed on 03.03.2018]. Available at https: //www.mdpi. com/1424 - 8220/16/8/1298 DOI: 10.4172/2469 - 4134.1000207

[30] Markogianni, V., Kalivas, D., Petropoulos, G. and Dimitriou, E. (2017). Analysis on the feasibility of Landsat 8 imagery for water quality parameters assessment in an oligotrophic Mediterranean Lake. *Conference Proceedings, Rome Italy.19* (9) Part XII: 1517 - 1525. [Accessed on 03.03.2018]. Available at https: //www.researchgate. net/publication/320322956

[31] Hadjimitsis, D. G. and Clayton, C. (2009). Assessment of temporal variations of water quality in inland water bodies using atmospheric corrected satellite remotely sensed image data. Environ. Monit. Assess. Vol.159. Pp.281–292. **In:** Gholizadeh, M. H., Melesse, A. M. and Reddi, L. (2016). A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques. Sensors 2016. Vol.16. (1298). Pp.2 - 43. [Accessed on 12.01.2021]. DOI: 10.3390/s16081298.

[32] Giardino, C., Bresciani, M., Cazzaniga, I., Schenk, K., Rieger, P., Braga, F., Matta, E. and Brando, V. E. (2014). Evaluation of multi - resolution satellite sensors for assessing water quality and bottom depth of Lake Garda. Sensors 14. Pp.24116–24131. **In:** Bresciani, M., Cazzaniga, I., Austoni, M., Sforzi, T., Buzzi, F., Morabito, G. and Giardino, C. (2018). Mapping phytoplankton blooms in deep subalpine lakes from Sentinel - 2A and Landsat - 8. Hydrobiologia. [Accessed on 15.08.2020]. Available at https: //doi. org/10.1007/s10750 - 017 - 3462 - 2.

[33] Lillesand, T. M., Kiefer, R. W. and Chipman, J. W. (2008). Remote sensing and image interpretation.6th ed. Hoboken (NJ): Wiley. **In:** Mbolambi, C. (2016). Assessment of Coastal Vegetation Degradation Using Remote Sensing in False Bay, South Africa. Thesis submitted in fulfilment of the requirements for the degree Masters of Science in Geography and Environmental Studies in the faculty of Science at Stellenbosch University. [Accessed on 04.05.2021]. Available at https: //core. ac. uk/download/pdf/188223856. pdf

[34] Moses W, Gitelson A, Berdnikov S and Povazhnyy V. (2009). Satellite estimation of chlorophyll - a concentration using the red and NIR bands of MERIS—the Azov Sea case study IEEE Geosci. Remote Sens. Lett. at press. **In:** Moses, W. J., Gitelson, A. A., Berdnikov, S. and Povazhnyy, V. (2009). Estimation of chlorophyll - a concentration in case II waters using MODIS and MERIS data—successes and challenges. Papers in Natural Resources.285. Environ. Res. Lett. Vol.4 (2009) 045005. [Accessed on 12.01.2021]. DOI: 10.1109/LGRS.2009.2026657

[35] Zhang, F., Wang, J. and Wang, X. (2018). Recognizing the relationship between spatial patterns in water quality and land - use/cover types: A case study of the Jinghe Oasis in Xinjiang, China. *Water* 10 (646): 1 - 17. [Accessed on 15.07.2018]. Available at https: //www.mdpi. com/2073 - 4441/10/5/646/pdf - vor

[36] Dahanayaka, D. D. G. L., Hideyuki Tonooka1, Wijeyaratne, M. J. S., Atsushi Minato and Ozawa, S. (2013). Two decadal trends of surface Chlorophyll - a concentrations in tropical lagoon environments in Sri Lanka using satellite and *in - situ* data. *Asian Journal of Geo - informatics*.13 (3): 7 - 16. [Accessed on 22.06.2017]. Available at www.geoinfo. ait. ac. th/ajg/index. php/journal/article/viewFile/105/69

[37] Xue, K., Zhang, Y., Duan, H., Ma, R., Loiselle, S. and Zhang, M. (2015). A remote sensing approach to estimate vertical profile classes of Phytoplankton in a eutrophic lake. *Remote Sensing.7*: 14403 - 14427. [Accessed on 28.02.2018]. Available at https: //pdfs. semanticscholar. org/65ab/020d54ccefeaddeabaca72b42fe94bb83f6b. pdf DOI: 10.3390/rs71114403

[38] Teta, R., Romano, V., Sala, G. D., Picchio, S., Sterlich, C. D., Mangoni, A., Tullio, G. D., Costantino. V. and Lega, M. (2017). Cyanobacteria as indicators of water

quality in Campania coasts, Italy: a monitoring strategy combining remote/proximal sensing and in situ data. Environ. Res. Lett.024001. Vol.12. Pp.1 - 12. [Accessed on 15.06.2021]. DOI: 10.1088/1748 - 9326/aa5649.

[39] Kutser, T., Metsamaa, L., Vahtmae, E. and Strombek, N. (2006) Suitability of MODIS 250m resolution band data for quantitative mapping of cyano - bacterial blooms *Proc. Estonian Acad. Sci. Biol. Ecol*. Vol.55. Pp.318–28. **In:** Teta, R., Romano, V., Sala, G. D., Picchio, S., Sterlich, C. D., Mangoni, A., Tullio, G. D., Costantino. V. and Lega, M. (2017). Cyanobacteria as indicators of water quality in Campania coasts, Italy: a monitoring strategy combining remote/proximal sensing and in situ data. Environ. Res. Lett.024001. Vol.12. Pp.1 - 12. [Accessed on 22.06.2020]. DOI: 10.1088/1748 - 9326/aa5649.

[40] Hu, C. A (2009). Novel Ocean Color Index to detect floating algae in the global oceans. *Remote Sensing of Environment.1*13: 2118–2129. **In:** Liu, X., Zhang, Y., Shi, K., Zhou, Y., Tang, X., Zhu, G. and Qin, B. (2015). Mapping aquatic vegetation in a large, shallow eutrophic lake: A frequency - based approach using multiple years of MODIS Data. *Remote Sensing*.7: 10295 - 1032. [Accessed on 01.03.2018]. Available at https: //pdfs. semanticscholar. org/7fae/518bea821cf66cf33f6f170ac845ba23f9ce. pdf DOI: 10.3390/rs70810295

[41] Ha, N. T. T., Thao, N. T. P., Koike., K. and Nhuan, M. T. (2017). Selecting the best band ratio to estimate Chlorophyll - a concentration in a tropical freshwater lake using Sentinel 2A images from a case study of Lake Ba Be (Northern Vietnam). *ISPRS International Journal of Geo - Information*.6: 290 - 305. [Accessed on 02.03.2018]. Available at https: //www.mdpi. com/journal/ijgi doi: 10.3390/ijgi6090290

[42] Lins, R. C., Martinez, J. M., Marques, D. M., Cirilo, J. A. and Fragoso Jr, C. R. (2017). Assessment of Chlorophyll - a remote sensing algorithms in a productive tropical Estuarine - Lagoon System. *Remote Sensing*.9 (516): 1 - 19. [Accessed on 22.06.2017]. Available at https: //www.mdpi. com/2072 - 4292/9/6/516/htm doi: 10.3390/rs9060516

Author Profile

E. Delina J. Prince, Senior Lecturer, Department of Agricultural Engineering, Faculty of Agriculture, Eastern University, Sri Lanka. The author was graduated from the Faculty of Agriculture, Eastern University Sri Lanka in 2009 and serving as Lecturer at the Department of Agricultural Engineering since 2012. She has completed MSc. in Integrated Water Resource Management and MPhil. in Geo - informatics at Postgraduate Institute of Agriculture, University of Peradeniya, Sri Lanka. She has published articles in International Journals and Conference Proceedings related to Agriculture and Water Resource Management.