Retrieval of water quality parameters of South Andaman coral Islands using remotely operated underwater vehicle

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ABSTRACT

Remotely operated underwater vehicle (ROV)-based spectral irradiance measurements at South Andaman coral reef islands are used to derive water quality parameters (chlorophyll-a, total-suspended sediments, turbidity, salinity, Secchi disk depth, diffuse attenuation coefficient) at different depths of the water column. Different combination of standard formula is used to extract the water quality information from the sub-surface reflectance measurement and compared with the data derived from satellite images and conventional water sample analyses. Water quality data derived from ROV-based irradiance measurement and satellite sensor (Landsat data) correlate well to the extent of 0.85 ($R^2$). Results from spectral radiance measurements up to 20 m water depth using the ROV along with high-definition images of coral reef biodiversity can be effectively used to understand the habitats’ diversity and also to derive different water quality parameters in spatio-temporal scale.

Introduction

Based on the principles of penetration of the solar radiation into the ocean basins, remote sensing techniques have been extensively used for water quality studies. The fundamental principle is that different wavelengths of light will penetrate water with varying degrees of intensity. Red light attenuates rapidly in water and therefore does not penetrate further than a meter or so, in contrast to blue light which penetrates much further. In clear water, the seabed can reflect enough light to be detected by a satellite sensor even when the depth of water approaches 30 m (Anbazhagan, Subramanian, & Yang, 2011; Lee, 2010). The depth of light penetration is also dependent on the turbidity of the water, suspended sediment particles, phytoplankton and dissolved organic compounds which may scatter or absorb light.

Conventionally, water quality studies have been carried out by collecting water samples from the field and then analyzing it in the laboratory. The samples at a point location are the sole representatives of the entire or a part of the region being studied. Though in-situ measurements provide high accuracy information, the area coverage of the analysis is confined to the sample location point. To cover a larger area at an instance, remote sensing techniques have been evolved both spectrally and spatially.

It is often difficult to get the synoptic information on water quality at a regular interval from the field monitoring networks. This results in the usage of remotely sensed data for hydrodynamic and biogeochemical models to estimate the water quality parameters. However, remote sensing techniques have limitations when it comes to observation beneath the water.

The seabed reflectance signal reaching a sensor on any platform (satellite, aircraft, ship or ROV) is distorted by the water column and penetration of light plays a major role while measuring the reflectance from the water. The water quality conditions differ depending on the estuarine, coastal or riverine origin. Pure water absorbs red to near-infrared portions of the signal, but natural seawater contains compounds such as phytoplankton, suspended sediments, and colored dissolved organic matter that differentially absorb and scatter portions of the visible spectrum altering the signal detected by the sensor remotely (Randolph, Dierssen, Twardowski, Cifuentes-Lorenzen, & Zappa, 2013).

For the past few decades, water quality parameters were derived by developing different combination of algorithms and applied to different types of satellite sensors such as Landsat, SPOT, SeaWiFs (Doxaran, Froidefond, & Castaing, 2003), MERIS (Xi & Zhang, 2011), IRS P4 OCM (Pravin, 2008) etc. Gholizadeh, Melesse, and Reddi (2016) have provided a comprehensive review of the sensors used to derive the water quality parameters and their optical dependence.

The diffuse attenuation coefficient ($K_d$) of the spectral downward irradiance plays a critical role in oceanographic and water quality studies. Many studies were carried out to determine the diffuse...
attenuation coefficient from the downwelling irradiance (Gordon et al., 1988), from water-leaving radiances within the blue-green spectral region (Morel, 1988), from two-step empirical algorithm with Chlorophyll as an intermediate link (Morel, 1988; Morel & Maritorena, 2001; O’Reilly et al., 1998), from the concept of apparent and inherent optical properties and radiative transfer theory (Gordon et al., 1988; Lee et al., 2005).

The estimation of other water quality parameters depends directly or indirectly on the diffuse attenuation coefficient which can be derived from the field-measured irradiance data at varying depths. However, the diffuse attenuation coefficient is the combination of optical properties of various other factors such as partial attenuation due to pure water, colored dissolved organic matter, suspended sediments and chlorophyll (Kirk, 1986). Many studies use K_d as a direct measure of chlorophyll estimation (Al Kaabi et al. 2016; Devlin, Barry, Painting, & Best, 2009). Similar approach by correlation of Secchi disk depth and K_d has been carried out by Al Kaabi et al. (2016).

The estimation of chlorophyll has been done using various approaches such as Bio-Optical Model-Based tool from Remote sensing images (BOMBER) (Giardino et al., 2014), two-step optimization procedure for turbid waters (Santini, Alberotanza, Cavalli, & Pignatti, 2010), OC4, OC3M, GSM, GIOP Algorithm (Hu, Lee, & Franz, 2012; O’Reilly et al., 1998), correlation between bands (Allan, Hamilton, Hicks, & Brabyn, 2011; Lim & Choi, 2015) and band ratio methods (Bhatti, Nasu, Takagi, & Nojiri, 2008).

Studies on deriving total-suspended sediments which is also a factor of water clarity has been derived from band ratio techniques (Chen, Huang, Chen, & Chen, 2011; Doxaran et al., 2003; Sokoltsky, Xianping, & Shen, 2014), from band correlation methods using surface reflectance measured at 645nm and/or 855nm (Miller & McKee, 2004; Ondrussek et al., 2012) and from the diffuse attenuation coefficient (Devlin et al., 2009)

The empirical relationship between the reflectance and water quality parameter such as chlorophyll-a, total-suspended sediments, and colored dissolved organic matter has been tested with various algorithms by Ligi et al. (2017). Devlin et al. (2009) derived an empirical relationship between colored dissolved organic matter, suspended particulate matter and diffuse attenuation coefficient for UK marine waters. A review on the available empirical relationship of various remote sensors with inland and transitional water quality parameters has been listed by (Mark, 2011).

Field measured spectro-radiometer and water quality data were analyzed to bring out the relation between each water quality parameter and measured irradiance (Arthi & Shanmugam, 2016; Mishra, Narumalani, & Rundquist, 2005).

Remotely Operated Vehicles are emerging as highly precise underwater platform which houses intended sensors to explore underwater world in spatio-temporal scale with underwater positioning devices and depth information while recording the sensor-based measurement. In the present study, downwelling irradiance measured at various depths using ROV with its precise underwater position and depth in the coral reef islands of South Andaman is considered as a direct measure of reflectance to derive the water quality parameters. Hence, this paper attempts to compare South Andaman Islands water quality data derived by applying standard formula using field measured irradiance data with ROV and from the satellite images and also from the analyses of water samples.

**Study area**

The study area includes parts of South Andaman Islands viz. Chidiyatapu, Red Skin and Wandoor (Figure 1). The principal streams flow along north–south oriented structural trend of the Andaman ridge and take an eastwards swing before merging into the Andaman Sea. Dhanikhari Nala flows from south to north for about 15 km from Chidiyatapu to Flat Bay in South Andaman Island before entering the sea (Bandopadhay & Carter, 2017).

Beaches on the Wandoor and Chidiyatapu coast show discontinuous 10–20 cm thick lenses of gently seaward dipping (10°) sheet-like sandstones, whereas beach rock is made up of ~50 cm thick units of weakly indurated and parallel laminated sandstone beds. Coral and shell-bearing conglomerates have been recognized along the coastline of Paget Island. Chidiyatapu beach rocks are older with an age of 4410–3900 years BP than Wandoor beach rocks of 1540–1350 years BP (Bandopadhay & Carter, 2017).

South Andaman is rich in biodiversity and all the reefs are having small reef flat and gradual reef slope with good luminosity, covered with coral live cover along with dead corals, rubbles, etc. (Raghuraman, Sreraj, Raghunathan, & Venkataraman, 2012). Water quality parameters drive the coral reef biodiversity and its sustainability. The study regions at South Islands were not affected by the anthropogenic activities. Continuous measurement of such parameters is critical for sustainable management and to understand the healthiness of coral reef ecosystem.

**Methodology**

ROV is a remotely operated underwater vehicle developed at National Institute of Ocean Technology and named as PROVe (Polar cum Shallow water Remotely Operated Vehicle). It has
4 degrees of freedom for exploration and mapping of shallow water habitat up to 500 m depth and polar ice shelf and lakes (Ramesh et al., 2017). The ROV is mounted with spectral radiance and irradiance sensor, scanning sonar, water temperature, and salinity sensors apart from a navigation sensor suite comprising of MEMS-based Inertial Navigation System, DVL (Doppler Velocity Log), Compass (Magnetic based), and a Depth Sensor for precise navigation of the underwater vehicle. The spectral sensors measure the downwelling radiance above the sea surface mounted in the ship and the downwelling irradiance at varying depths using ROV. The mounting arrangement of spectral sensors at the ship and ROV assembly interface details is shown in Figure 2. The specification of ROV is provided in Table 1.

Using the vertical thruster, ROV was driven to deeper depths and maneuvered with feedback sensors for its position, depth, and heading. All scientific sensor data such as water temperature, salinity, dissolved oxygen, and downwelling irradiance are logged continuously during the movement of ROV in spatio-temporal scale along with time stamping and position tag with depth. To understand the status of coral reef at the study region, apart from the irradiance and other sensor data acquisition, underwater images were acquired using high-resolution High-density underwater camera devices. For the present study, the water quality derived from the reflectance from Landsat 8 OLI and the irradiance data collected by the ROV-mounted RAMSES makes spectro-radiometer has been compared for the same season when the ROV is deployed. The sensor specification of the
Landsat 8 OLI and ROV-mounted spectroradiometer is provided in Table 2.

**Table 2. Sensor specification.**

| Parameters                  | ROV                                      | Landsat OLI                                      |
|-----------------------------|------------------------------------------|--------------------------------------------------|
| Spatial resolution (m)      | 0.30 ~ 0.90                              | 15 ~ 30                                          |
| Spectral resolution (nm)    | 3.5                                      | 15 ~ 180                                         |
| Spectral range (nm)         | 319–950                                  | 440–2190                                         |
| No. of bands                | 190                                      | 11                                               |
| Depth                       | 500m                                     | Surface                                          |
| Swath (Km)                  | Narrow & continuous                      | 290                                              |
| Date of Acquisition         | 6 April 2016- Red Skin                   | 21 April 2016                                    |
|                             | 3 April 2016- Chidiyatappu               |                                                  |

Data processing and analysis

Data processing and analysis flow chart used in this study is shown in Figure 3. Measured data from ROV-mounted irradiance sensor and the reflectance data from the Landsat image have been used to derive the water quality parameters. The spatial resolution of the Landsat 8 OLI is 30 m and the resolution of the ROV-based measurement is <1 m. The water quality result from Landsat data and the field measured water quality data are used to compare the water quality parameters derived from the irradiance data measured from ROV.

Data pre-processing

The ROV measured irradiance and the satellite sensor measured radiance are pre-processed to remove the errors due to factors such as atmosphere, water column, sun glint effects, and depth. By pre-processing, the data measured at first point and the last point are calibrated to remove the errors mentioned above.

Since the sensor keeps moving in this observation from one position to another position with varying depth, normalization of the data is carried out from the irradiance data measured. The positional and temporal variation causes change in the solar illumination leading to variations in the incident surface irradiance, $E_s(z_1, \lambda)$ measured at a given time $t(z)$. In the present study, $E_s(t(z_m), \lambda)$ refers to the incident spectral irradiance measured from the sea surface at time $t(z_m)$, and $E_d(z_m, \lambda)$ refers to the downwelling irradiance at water depth. The change in solar illumination due to cloud cover at each scan can be normalized to a specific scan in order to quantify the variation in the obtained downwelling irradiance spectra (Mueller, 2000) by applying the following formula in Equation (1) (Mishra et al., 2005)

$$\text{Normalization factor} (z_m, \lambda) = \frac{E_s(t(z_1), \lambda)}{E_d(t(z_m), \lambda)}$$

where $E_s(t(z_1), \lambda)$ is downwelling irradiance measured at time $t(z_1)$. A sample spectral irradiance before and after normalization is shown in Figure 4.
Analysis of water quality parameters

Diffuse attenuation co-efficient

Diffuse attenuation coefficient ($K_d$) is the measure of the light availability at different depths. The spectral measure of $K_d$ can provide information on the relative contribution of the algal pigments, suspended matter and colored dissolved organic matter to photosynthesis. Algae absorb the light through their harvesting pigments and through their other cell material. Some algal species have a highly scattering cell material. Dead organic matter scatters light is usually brown-colored and thus absorbs blue to blue-green light effectively. Mineral matter is usually light-colored and is a strong scatterer (Brando, Dekker, Marks, Qin, & Oubelkheir, 2006). Knowing the importance of the scattering, reflection, and absorption of the light for the different components of water, each water quality parameters can be extracted. From the ROV-based irradiance measurements at varying depths ($z$), $K_{dis}$ calculated based on Equation (2)

$$K_d(z, \lambda) = -\frac{1}{E_d\lambda} \times \frac{dE_d}{dz} \quad (2)$$

Where $K_d(z, \lambda)$- diffuse attenuation coefficient (m$^{-1}$); $E_d\lambda$ - downwelling irradiance (W m$^{-2}$); and $dz$ - thickness of the medium (m)

Estimating the diffuse attenuation coefficient from the satellite images is different from the measured values with ROV. $K_d$ measured from Equation (2) involves irradiance data measured at varying depths, whereas the diffuse attenuation coefficient at 470nm and 560nm is used for estimating the surface reflectance of the satellite images. Mueller (2000) framed a standard formula for estimating $K_d$ values for MODIS imagery using Rrs 555 and Rrs 490 as given in Equation (3). Based on the $K_d$, the value of water leaving radiance is calculated using Equation (4).

$$K_d(490) = 0.016 + 0.1565 \times \frac{Lw(490)}{Lw(555)} \quad (3)$$

$$Lw(\lambda) = Rrs(\lambda) \times E_d(\lambda) \quad (4)$$

where Lw ($\lambda$) is water-leaving radiance at wavelength $\lambda$, Ed ($\lambda$) is the downwelling irradiance just above the sea surface, Rrs ($\lambda$) is the remote sensing reflectance at wavelength $\lambda$ and $E_d(490)/E_d(555)$ is around 1.03 and varies slightly for different sun angles (Lee et al., 2005).

$$K_d(490) = 0.016 + 0.1565 \times \frac{Rrs_{490}}{Rrs_{555}} \quad (5)$$

$$K_d = 0.016 + 0.1565 \times \frac{B2}{B3} \quad (6)$$

By following the same procedure, diffuse attenuation coefficient is derived using Equation (6) at a wavelength of 490nm.

Absorption and scattering coefficient

The scattering and absorption processes of the light in the water column and reflectance by the substrate determine the color of natural waters. The resultant radiances leaving the water are masked by the direct reflection of the sun and skylight at the water surface, and interrupted by the light absorption and scattering processes in the atmosphere. Thus, substantial processing of the satellite image data is required to derive the valid water quality parameters that are corrected for all the undesirable light contributions. An understanding of the radiative transfer in the atmosphere to and through the air–water interface and into the water column is a prerequisite for the testing of...
existing algorithms, as well as for the development of new algorithms for retrieving the concentrations of the selected water constituents. Therefore, the relationship between the optical properties of light absorption, scattering, and the concentration of these constituents has to be known for the water column, as well as the reflectance properties of the substrate for substrate mapping. An analytical model for water quality retrieval relates the subsurface irradiance reflectance \( R(0-) \), to the water constituent concentrations. Several models for coastal and inland waters were investigated as summarized by Dekker et al. (2001). Model outputs are very similar to an analytical solution of the irradiance transfer equations given by Aas (1987):

\[
R(0-) = f \times \frac{b_b}{a + b_b} \tag{7}
\]

where \( a \) is the total absorption coefficient, \( b_b \) is the total backscattering coefficient and \( f \) is the anisotropy factor of the downwelling light field (allowing for varying sun angles and sun and sky light relative distribution of incoming light). However, in this study, the measured downwelling irradiance data and the diffuse attenuation coefficient can be used to calculate the absorption and backscattering coefficients as given in Equations (8) and (9).

\[
a = K_d \times 0.8795 \left( \frac{\text{Irradiance after normalisation}(\lambda)}{0.094} \right) + 1 \times 1.0395
\tag{8}
\]

\[
b_b = \frac{K_d \times 0.8795 \left( \frac{\text{Irradiance after normalisation}(\lambda)}{0.094} \right)}{X}\tag{9}
\]

**Chlorophyll-a**

Chlorophyll-a is one of the important water quality parameters to understand the biodiversity linkages as it is an indicator of the phytoplankton abundance and biomass in the coastal waters (Jamshidi & AbuBakar, 2011). Chlorophyll containing organisms is the primary producer in most of the marine process and associated food chains. In this paper, for estimation of the chlorophyll concentration from the irradiance data and its relationship with diffuse attenuation coefficient (empirical relationship proposed by Morel & Maritorena, 2001) has been used Equation (10).

\[
K_d(490) = K_w(490) + x(490) \times Cht(490) \tag{10}
\]

where empirical constants \( K_w(490) \), \( x(490) \), \( e(490) \) equals to 0.0166 m \(^{-1}\), 0.07242, and 0.68955, respectively (Al Kaabi et al., 2016).

For the estimation of chlorophyll from the satellite data, the ratio of reflectance (OC4 algorithm) has been used Equation (11).

\[
\log_{10}(chl_a) = a_0 + \sum_{i=1}^{4} \left( \log_{10} \left( \frac{Rrs(\text{blue})}{Rrs(\text{green})} \right) \right)^i	ag{11}
\]

where \( Rrs(\text{blue}) \) is 443 > 490 > 510, \( Rrs(\text{green}) \) is 555, \( a_0 = 0.3272, a_1 = -2.9940, a_2 = 2.7218, a_3 = -1.2259, a_4 = -0.5683 \).

**Total suspended sediments**

Total suspended sediment (TSS) concentration throws light on the suspended load dynamism at the study site and the characteristics of the seafloor. The suspended sediment composes of the algae (pigments and cell material), dead organic matter and mineral matter. Suspended sediments sourced from the land erosion processes, biological and microbial activities are deposited on the seafloor by recording the source characteristics. Numerous models (Chen et al., 2015; Miller & McKee, 2004; Tassan, 1994) were used to derive TSS from the remotely sensed data (ocean color imageries) by the polar orbiting satellites. These models have been developed based on the remote sensing reflectance at different wavelengths. Tassan (1994) model provided in Equations (12)-(13) has been used to derive TSS in this study.

\[
X_i = Rrs560 + Rrs665 \times \left( \frac{Rrs560}{Rrs490} \right)^{0.5}
\tag{12}
\]

\[
\log \text{TSS} = 1.830 + 1.26 \times \log X_i
\tag{13}
\]

The TSS is estimated from the underwater irradiance data using diffuse attenuation coefficient. The diffusion of light along the water column is influenced by Chlorophyll-a, TSS and CDOM (Kirk, 1986).

**Colored dissolved organic matters (CDOM)**

The CDOM includes naturally occurring water-soluble biogenic and heterogeneous organic substances that are yellow to brown in color. The absorbance spectra often overlap with the spectra of chlorophyll (Aiken, McKnight, Wershaw, & MacCarthy, 1985). However, Strömbeck and Pierson (2001) reported that the absorbance of red light spectrum can be significant. CDOM can be used as an indirect measure of the dissolved organic carbon (DOC) and salinity. In this study, the relation between \( Kd \), TSS, and CDOM provided by Devlin et al. (2009) shown in Equation (14) has been used to derive the CDOM values as S.FLU. – standar-ized fluorescence units.

\[
\text{CDOM} = \frac{Kd + 0.1155 - 0.0654 \times \text{TSS}}{0.5639}
\tag{14}
\]

**Total phosphorus**

Total phosphorus (TP) consists of the measurement of all inorganic, organic and dissolved forms of
phosphorus. Phosphates are the plant nutrients helps plants and algae to grow quickly. Wu et al. (2010) have attempted to derive total phosphorus from Quiantang River at China using Landsat images. To estimate TP, reflectance measured at 560nm and 665nm is used as provided in Equation (15).

\[
TP = 0.12 \times \log \left( \frac{R_{560}}{R_{665}} \right) + 1.3 \quad (15)
\]

The source of phosphates in seawater is contributed by the dead plant materials, dead reef rock, crushed coral substrates that settle on the bottom seafloor (Larned, 1998). Hence, the total phosphorus can also be directly related to chlorophyll-a concentration and indirectly related to the transparency or water clarity, which is estimated by Secchi depth.

**Secchi disk depth**

Secchi disk depth is a direct measure of transparency of water. This measure acts as a proxy to determine the underwater visibility under various geometric illumination conditions (Anuj & Shanmugam, 2015). Gordon and McCluney (1975) have provided relation between irradiance and the depth of penetration of light for different water types. Based on the inverse relation with diffuse attenuation coefficient, Equation (16) has been used in this study to derive Secchi disk depth. Similar relation between SDD and \(K_d\) has been used by Lee et al. (2015).

\[
Secchi \text{ Disk Depth} = 1.04 \times K_d^{-0.82} \quad (16)
\]

Secchi disk depth has been derived from the diffuse attenuation coefficient.

**Results and discussions**

In the present study spectral measurements from ROV and satellite images are used to derive the water quality parameters. Figure 8(a) shows the diffuse attenuation coefficient map at 490nm which is derived from the satellite image of South Andaman Islands covering Chidiyatappu, Red Skin and Wandoor Creek. From the map, it is inferred that the diffuse attenuation varies from 0.09 to 0.16 (m\(^{-1}\)). The map also provides the overview on the penetration of sunlight spatially over the region. It can be noticed that shallower regions have higher attenuation coefficient than in the deeper ocean. However, satellite image cannot provide the variation of the diffuse attenuation coefficient over the depth. This can be achieved from the ROV data which measures the spectral irradiance at varying water depths. The graph of the diffuse attenuation coefficient with respect to depth at Red Skin and Chidiyatapu islands is shown in Figure 5(a,b).

The diffuse attenuation coefficient calculated from the ROV data ranges from 0.05 to 1.09 (m\(^{-1}\)) while from the satellite data it ranges from 0.09 to 0.16 (m\(^{-1}\)). This significant difference in the maximum limit measured using two different inputs (ROV-based irradiance data and satellite image data) is due to the fact that the satellite image considers the reflectance measured from the penetrable water column (ie. the diffuse attenuation coefficient is the average of the water column), while the ROV spectral irradiance measurements range from 0.06 to 16.35 m of water depth.

From the determined diffuse attenuation coefficient, the inherent optical properties (IOPs) such as absorption and scattering coefficient have been derived. This is used to identify the optical
properties of the medium through which the light is propagating. The absorption and scattering coefficient at different wavelengths such as 400 nm, 490 nm, and 500 nm have been derived using irradiance and diffuse attenuation coefficients for Red skin (Figure 6(a,c)) and Chidiyatapu islands (Figure 6(b,d)). For the two different datasets, this study uses two methods to estimate the chlorophyll-a. ROV data using the estimated diffuse attenuation coefficient to calculate the chlorophyll-a availability at varying water depths as shown in Figure 7(b,c). The OCM4 algorithm has been used to estimate the chlorophyll distribution map for the South Andaman coast (Figure 7(a)). The OCM4 algorithm uses the ratio of blue and green bands in the satellite images. From the map, it can be inferred that the closed waters shows higher chlorophyll content and deeper water shows less chlorophyll.

Figure 6. Absorption and Scattering co-efficient at wavelengths 400 nm, 490 nm, and 555 nm at (a) & (c) at Red Skin, (b) & (d) at Chidiyatapu of Andaman Islands.

Figure 7. (a) Chlorophyll-a (chl-a) map of South Andaman Islands and Graph of Chlorophyll for varying depth of (b) Red Skin Island, (c) Chidiyatapu Island.
content. This may be due to the penetration of light and reflectance measurement from the shallow depth measured by the satellite sensor. The chlorophyll content measured from satellite images ranges from 0.8 mg l$^{-1}$ to 2.53 mg l$^{-1}$, whereas the chlorophyll calculated using irradiance data ranges from 0.001 to 1.29 mg l$^{-1}$ measured at varying depth.

From Figure 7(c), it can be noticed that there is a sudden increase in the chlorophyll values, this may be due to the fact that the waters of Chidiyatapu consist of sponges apart from the corals. Around 18 species of sponges are present at Chidiyatapu Island and these sponges depend on the photosynthetic activity of the associated algae for the translocation of nutrients (Kirubasankar et al., 2016).

The result of the total-suspended sediment map of South Andaman Island derived from the satellite image is provided in Figure 10(a) and the results from the ROV data are provided in Figure 8(b). The map shows higher suspended sediments near the coast where there is shallow depth while the graph depicts the higher suspended sediments at higher depth reducing toward the surface. This indicates the clarity of water that enables the light to penetrate to the depth. The suspended sediments map derived from satellite image is the average of the suspended sediments between the water columns from the sea surface to the bottom. The reflectance of the corals beneath the water surface may be misled to higher suspended sediments at some regions. The TSS derived from satellite image ranges from 5.25 mg l$^{-1}$ to 60 mg l$^{-1}$ while the one calculated from the ROV irradiance ranges from 0.28 mg l$^{-1}$ to 58.69 mg l$^{-1}$ at varying depth.

Figure 9(a) shows the CDOM map of the South Andaman Island ranging from 0.59 S.Fl.U. to 0.66 S.Fl.U. and Figure 9(b,c) shows the CDOM variation with respect to the water depth at Redskin and Chidiyatapu Islands.

The range of CDOM varies largely at Redskin Island at shallower depth and gradually reduces to 0.11S.Fl.U,
while at Chidiyatapu, the CDOM range confines within 0.5 S.Fl.U. This result also indicates that the waters of Chidiyatapu are clearer than in the Red Skin Islands which is corroborated with the underwater visuals with rich reef growth in these regions at a depth of 5 m (Ramesh et al., 2017).

From Figure 10(a), it can be noticed that the shallower region around the island shows higher phosphate content ranging from 1.29 µmol l$^{-1}$ to 1.38 µmol l$^{-1}$. Figure 10(b,c) indicates the total phosphorus variation with respect to depth ranging from 1.28 µmol l$^{-1}$ to 1.67 µmol l$^{-1}$ and it shows an increase of total phosphate with respect to depth.

From Figure 11(a), it can be inferred that the deeper oceans shows the maximum SDD, while the shallower water shows varying depth from 4.32 to 7.31 m. Figure 11(b,c) shows the graph of SDD with varying water depths. SDD measures at Chidiyatapu (Figure 11(c)) have an alternative decreasing and increasing trend due to hindrance due to the light attenuation by the corals at different depths. Such hindrance can be visualized using underwater high-definition camera mounted on the ROV. Figure 12 shows the screenshots of the underwater images during the maneuvering at different depths at Chidiyatapu and Red Skin Islands.

Validation of the applied formula for deriving the different water quality parameters in the present study using ROV measured irradiance data and satellite imagery-based derived data is carried out by comparing the field measured water quality data (Jha et al., 2015) and measurement by Andaman and Nicobar Center for Ocean Science and Technology (ANCOST), NIOT, Port Blair. The Comparison table (Minimum-Maximum statistics) of the water quality parameters is given in Table 3.

The regression coefficient ($R^2$) of the derived water quality parameters from the ROV irradiance and water quality data derived from satellite imageries with an accuracy of 0.85 (Number of samples (N) = 13) (Figure 13(a)) and matching to 0.93 (N = 11) (Figure

Figure 10. (a) Total phosphorus map of South Andaman Islands and Graph of TP for varying depth at (b) Red Skin Island, (c) Chidiyatapu Island.

Figure 11. (a) Secchi Disk Depth map of South Andaman Islands and Graph of SDD for varying depth at (b) Red Skin Island, (c) Chidiyatapu Island.
13(b)) with the field measured water quality data indicating the validation of the applied formula for deriving the parameters in this work and this methodology may be adopted to any biodiversity, satellite data validation with precise site-specific measurement with ROV.

**Conclusions**

The water quality parameter was derived for the first time using the ROV-mounted underwater irradiance measurement for the Andaman coral reef islands and compared with the satellite and field measured data for the same time period. Water quality parameters such as Kd, Chlorophyll-a, TSS, Total Phosphate, salinity, CDOM, and SDD were derived using the standard equations and compared with the irradiance measurement by the ROV and from the satellite images for the same time period of data acquisition. Validation of data sets shows correlation coefficient of 0.85 for the water quality parameters derived from the ROV with satellite images, and correlation coefficient 0.93 for the ROV with field measured water quality parameters. Apart from the spatial derivation of the water quality parameters, the study also brought out the changes in the vertical profile of the derived parameters, which is of much usage to compare and validate the satellite image derived water quality parameters and its depth limitations for spatial mapping and assessment of water quality degradation or improvement. The outcome of the present study will be a valuable addition to the research community to utilize the application of the underwater technology for the spectral data processing and validate the satellite data limitations with reference to the depth.

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**Table 3.** Derived water quality parameters comparison with published field data for validation.

| Parameters     | Field/Published data | Estimated from Satellite image | Estimated from ROV mounted irradiance measurement |
|----------------|----------------------|--------------------------------|--------------------------------------------------|
|                | Min                  | Max                            | Min                 | Max             | Min            | Max             |
| Chl-a (mg L⁻¹) | 0.5                  | 3.9                           | 0.8                 | 2.53            | 0.8            | 1.22            |
| TSS (mg L⁻¹)  | 21                   | 59                            | 5.25               | 60              | 3.03           | 58.6            |
| TP (µmol L⁻¹) | 0.5                  | 2.2                           | 1.2                | 1.45            | 1.27           | 1.30            |
| Salinity (PSU)| 31                   | 33                            | 30                 | 39              | 28             | 34.6            |
| CDOM (S.FLU)  | -                    | -                             | 58                 | 347             | 50             | 167             |
| SDD (m)       | -                    | -                             | 4                  | 7.3             | 0.5            | 5.8             |
| Kd (m⁻¹)      | -                    | -                             | 0.09               | 0.16            | 0.05           | 1.09            |

**Figure 12.** ROV-based image captured at (a) Red Skin Island (b) Chidiyatapu Island.

**Figure 13.** Correlation regression of water quality parameters from (a) ROV vs Satellite-derived water quality measurements (b) ROV vs *insitu* data.
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