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Use of Hyperspectral Remote Sensing to Estimate Water Quality

Mbongowo Mbuh

Abstract

Approximating and forecasting water variables like phosphorus, nitrogen, chlorophyll, dissolved organic matter, and turbidity are of supreme importance due to their strong influence on water resource quality. This chapter is aimed at showing the practicability of merging water quality observations from remote sensing with water quality modeling for efficient and effective monitoring of water quality. We examine the spatial dynamics of water quality with hyperspectral remote sensing and present approaches that can be used to estimate water quality using hyperspectral images. The methods presented here have been embraced because the blue-green and green algae peak wavelengths reflectance are close together and make their distinction more challenging. It has also been established that hyperspectral imagers permit an improved recognition of chlorophyll and hereafter algae, due to acquired narrow spectral bands between 450 nm and 600 nm. We start by describing the practical application of hyperspectral remote sensing data in water quality modeling. The surface inherent optical properties of absorption and backscattering of chlorophyll a, colored dissolved organic matter (CDOM), and turbidity are estimated, and a detailed approach on analyzing ARCHER data for water quality estimation is presented.

Keywords: water quality, field spectroscopy, ARCHER, chlorophyll a, colored dissolved organic matter, turbidity, total phosphorus, nitrogen

1. Introduction

Water is one of the valuable and essential resources of life on earth. There is ever-increasing stress on water resources, and as population increases, there is an ever-increasing pressure placed on water resources [1–3]. Several nations depend on water resources for economic growth [4]. Water serves as a source of food, income, and livelihood for many [4, 5]. Equally, important information on resources that support life in an ecosystem is delivered by the quality of surface water [6]. An increase in water pollution deteriorates water quality and also threatens human health, aquatic ecosystem balance, economic development, and social prosperity [7, 8].

Supportable water resources management requires continuous and accurate monitoring. Satellite observations [1, 9] have provided data for such tracking for several years [10] and have served as a time- and cost-effective way to carry out large-scale monitoring [11, 12]. Water pollution is an important environmental issue, further limiting the availability of water for human and environmental use [1, 13]. Though nutrients are indispensable for plant and animal growth and

nourishment, an excess of some nutrients in water can disturb the river [1, 14, 15]. Excellent and clear water is imperative to the plants and animals that live in any watershed.

A significant difficulty in assessing surface water quality is identifying the sources of pollutants and the contribution of the parameters/variables that explain water quality variation [1, 6, 16–18]. Determining the conditions and parameters of water quality is one of the significant advantages of hyperspectral remote sensing technologies. Hyperspectral reflectance technology has been broadly used to examine and monitor the water quality conditions of many open water aquatic ecosystems [19, 20]. Hyperspectral remote sensing has been used to characterize algal blooms [21] and assess ammonia dynamics for wetland treatments [22, 23]. Tilley et al. [23] also developed remotely sensed hyperspectral signatures of macrophytes to monitor changes in wetland water quality predictors of total ammonia concentrations [24]. Hyperspectral remote sensing has similarly been used to determine water quality parameters like temperature, chlorophyll a, total suspended solids [25, 26], total phosphorus [27, 28], and turbidity; Lillesand et al. [29] and Lathrop and Lillesand [30] studied lakes and reservoirs, estuaries [31, 32], and tropical coastal areas [33, 34]. Other water quality studies on monitoring surface water bodies in different parts of the world (e.g., [35–40]) have all been interested in modeling and development of concentration distribution maps for different water quality parameters based on its reflectance characteristics. Algal concentrations in water through hyperspectral remote sensing images have been undertaken in the estimation of chlorophyll that is then used as an estimate for monitoring algal content and hence water quality. This approach has been adopted because wavelengths corresponding with the peak reflectance of blue-green and green algae are close together; it is harder to differentiate between them [19, 41, 42]. Hakvoorth et al. [43], however, demonstrate that hyperspectral imagers permit for improved detection of chlorophyll and hereafter algae, as a result of acquired narrow spectral bands between 450 nm and 600 nm [20, 44].

1.1 Remote sensing for water quality

The spectral signature changes in the water can be measured and relate them to empirical or analytical models to a water quality parameter through remote sensing techniques [25, 45]. Since the 1960s, the earth's resources have been monitored from space by the National Aeronautics and Space Administration (NASA) with multispectral scanners, which collect data sets in about 5–10 bands of relatively large bandwidths (70–400 nm) [10, 46]. The spectral resolution of data from the multispectral scanners was limited, inadequately evaluating water quality and starting in the mid-1980s. Hyperspectral remote sensing with a higher spectral resolution (i.e., 224 bands) and 30 meters in spatial resolution covering wavelengths from the 400–2500 nm “in the visible and near-infrared bands of the spectrum” (Field Assessment of a Fiber Optic Spectral Reflectance System <http://horttech.ashspublications.org/content/6/1/73.full.pdf>) became available for earth sciences including water quality monitoring. Some of these hyperspectral sensors include FTHSI on MightySat II, Hyperion on NASA EO-1, airborne visible/infrared imaging spectrometer (AVIRIS), Airborne real-time cueing hyperspectral enhanced reconnaissance (ARCHER), Hyperspectral Digital Imagery Collection Experiment (HYDICE), PROBE-1, Compact Airborne Spectrographic Imager (CASI), and HyMap. The ARCHER sensor, which is of interest to this research, is used to estimate the water quality parameters. The very high spectral resolution of hyperspectral sensors gives them the advantage over multispectral sensors in facilitating exceptional differentiation of objects based on their spectral response in the narrow

bands [10, 47]. This spectral information has made hyperspectral sensor data very useful in estimating dissolved organic matter, chlorophyll, and total suspended matter concentrations from optical remote sensing technologies [43, 48, 49]. Our objective is to review the literature of water quality as it relates to remote sensing, water quality modeling, and data fusion.

The application of hyperspectral remote sensing techniques to water resource problems is proving to be the most in-depth way of examining spatial, spectral, and temporal variations to derive more accurate estimates of information required for water resource applications [19]. This emergence offers the capability of covering large areas on a real-time scale to directly monitor and characterize environmental pollutants entering a body of water. Addressing the problem of colored dissolved organic matter (CDOM), Nelson and Guarda [50], in the South Atlantic Bight, and Vodacek et al. [51], in the Mid-Atlantic, examined the visible absorption spectra and characteristics of particulate and dissolved materials. Both studies demonstrated that colored dissolved organic matter comes mostly from riverine runoff, and it is also widespread and abundant in natural waters, which have a significant portion of the dissolved organic matter (10–90%), and influences water-leaving radiances [52]. Another chlorophyll retrieval study by Fell et al. [53] used chlorophyll algorithms to describe coastal properties in the Monterey Bay through hyperspectral remote sensing. Using a composite AVIRIS to examine marine environment changes, the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) algorithm was applied to derive chlorophyll information. The study showed the importance of high spatial resolution in representing the coastal ocean in the Monterey Bay, though additional research using higher hyperspectral resolution on the phytoplankton pigment spectral absorbance was recommended.

Kirkpatrick et al. [54] indicate that a considerable portion of the organic carbon in the oceans is found as dissolved organic matter (DOM) and a better understanding of the distribution and dynamics of DOM is necessary for understanding global carbon cycles. The authors also demonstrate that CDOM is often present in concentrations sufficient to affect the color of lakes, estuaries, and nearshore coastal waters, although other studies have shown that CDOM absorption does not correlate with chlorophyll *a* [55, 56]. Brando and Dekker [57] used spectroscopy to test for its capabilities over a range of water targets in eastern Australia using open ocean flushing and a combination of turbid and humic river inputs, to determine the water quality of the bay. Integrated atmospheric and hydro-optical radiative transfer models (MODTRAN-4, Hydrolight) were developed to estimate the underwater light field. A matrix inversion approach was used to retrieve chlorophyll *a*, dissolved organic matter, and suspended matter concentrations. The research demonstrated that Hyperion has enough sensitivity to map optical water quality concentrations of total suspended matter, dissolved organic matter, chlorophyll, and concurrently the complex waters of estuarine and coastal systems of the Moreton Bay. The results obtained from this retrieval were comparable to those estimated in the field campaigns, which were coincident with Hyperion overpasses. [38], in a similar study, collected three sets of remote sensing and ground-truth data to evaluate the correlations between reflection data and water quality analyses to develop optical indicators of water quality constituents. Imagery and field reflectance data and water quality samples were collected in the river in 1999 concurrently, and 2001, in southwest Ohio, and results showed a correlation between the spectral data and water quality parameters.

Brezonik et al. [36] used Landsat-based remote sensing to characterize chlorophyll *a*, total suspended sediments (TSS), turbidity, and Secchi disk transparency (SDT) of lake water quality. All three variables demonstrated a high correlation with each other, and all act as direct or indirect measures of algal abundance in

Minnesota lakes. This study also showed that chl-a and turbidity could be estimated from Landsat data if the near-contemporaneous ground measurements are available for calibration. Also, Kneubühler et al. [58], in evaluating total chlorophyll content (TCHL) concentration, used spectral reflectance data measured at 1 m above the water surface with a handheld field spectroradiometer and applied the semi-analytical algorithms. The results proved to be valuable for an enormous range of observed TCHL concentrations (0–460 $\mu\text{g/L}$), high r^2 , and low mean deviations. Dingtian et al. [59] used hyperspectral remote sensing images and field reflectance measurements with Field spec, to characterize chl-a and suspended solids in Taihu Lake, China. Their results showed the relationship between chl-a and wavelengths in Taihu Lake in different seasons, with an average correlation coefficient of more than 0.65. This research showed success in the application of hyperspectral remote sensing in retrieving chl-a and suspended solid concentrations.

Giardino et al. [60] used hyperspectral data to map chlorophyll a and tripton concentrations in Lake Garda based on the forward and inverse bio-optical modeling. The research demonstrated that Hyperion-derived levels were on average comparable to in situ data for chlorophyll a. The authors, however, mentioned that the same analysis was more complicated for tripton since some incompatibilities of methods occurred. This study demonstrated that the spatial and spectral resolutions of Hyperion and the capability of physics-based approaches were considered highly suitable, although more research was necessary to address the compatibilities of methods for monitoring waterbody features with a high rate of wind or wave-driven change. This study also showed that procedures used can be transferred to other water bodies if the optical characterization of the water body is known and information about atmospheric properties during the satellite overpass is accessible.

Equally, Giardino et al. [61] used satellite data and field spectrometer data to estimate chl-a as an indicator of the trophic level and CDOM in the Curonian Lagoon. A PANalytical handheld spectroradiometer in situ Rrs spectra can be used to parameterize a semi-empirical algorithm in retrieving chl-a concentrations and validate the performances of two atmospheric correction algorithms, to build a band ratio algorithm for chl-a and to validate MERIS-derived maps. Results from this combined in situ and calibration study confirmed the hypertrophic/dystrophic conditions of the Curonian Lagoon.

Santini et al. [62], to analyze colored dissolved organic matter, used hyperspectral remote sensing techniques ranging from empirical algorithm to complex physics-based models to retrieve water quality constituent. With the empirical approach, acceptable results for the CDOM concentrations were returned. The study also showed a correlation index of over 0.82, between the laboratory CDOM concentrations and model output. The study showed that the physical model could be used to retrieve simultaneously of chlorophyll and the total suspended matter concentrations. Another research studying the relationship between suspended sediments and reflectance has been demonstrated to rely on physical and optical characteristics of sediment type and sensor zenith angle [63], and the properties of scattering and absorption of sediment type affect water reflectance [64].

Xiao et al. [65] explored the potential of in situ hyperspectral remote sensing for estimating chlorophyll a and phycocyanin concentrations of a water body. In situ measurements of the lake surface reflectance at the five sites were examined using PANalytical FieldSpec3 spectroradiometer to investigate the relationship between PANalytical-based reflectance data and chlorophyll a and phycocyanin concentrations at different depths of water. The study shows significant correlations between lake surface reflectance and chlorophyll a and phycocyanin concentrations in upper mixed surface waters (0 to 1 m depth) at these five sites. Hommersom et al. [66] also used PANalytical field spec to carry out measurements in the central basin

of Lake Vänern, and matrix inversion algorithms were used to derive parameters such as the concentrations of chl-a and suspended particulate matter (SPM) and the absorption by colored dissolved organic matter at 440 nm. Maltese et al. [67] retrieved turbidity from MODIS data, and PANalytical handheld spectrometer was used to obtain underwater irradiances at 11 depths from just below the water's surface, up to 5.5 meters. In situ data, acquired during the spring and summer, were used to enhance the retrieval of water surface nephelometric turbidity locally through satellite images.

2. Remote sensing of water quality analysis approaches

2.1 Empirical approach and analytical methods

There exist two main approaches to examining water quality from remotely sensed data: the (semi-) empirical approach and the (semi-) analytical method [60, 68–72]. The most common are the semi-empirical and empirical approaches where water quality is determined by statistical relationships between measured spectral properties (reflectance) and the measured water quality parameter of interest [72]. Ocean color derivation algorithms for chlorophyll a concentration have applied this approach to high correlations between chl-a and the blue and green spectral regions (chl-a has absorption maxima at 430–450 nm and 660–680 nm (nanometers)) (Reif [73]). However, Dall'Olmo and Gitelson [74] have illustrated that these spectral regions typically do not work, and this problem has been fixed by subtracting the contributions of other factors on reflectance nearby the peak at 670 nm with a three-band reflectance model [75, 76].

With the use of empirical approaches, statistical regressions are recognized among reflectance values extracted from the image with synchronized in situ water quality measurements for correlation and validation well for retrieval of chl-a in waters with increased turbidity and overlapping absorption of dissolved organic matter and tripton [73, 76]. Using this method wavelengths are naturally evaluated and selected from regions in the spectrum in which absorption and reflectance are strongly impacted by the parameter of interest [68]. Band ratio algorithms between a reflectance peak near 700 nm and an absorption peak (red chl-a absorption band) around 670–680 nm have been developed for turbid water environments to retrieve chlorophyll [73]. Though the empirical approach has shown some success, it has the disadvantages that they require in situ samplings for testing and validation and they tend to be scene dependent, to apply locally to the explicit data from which they were derived [60, 68, 72, 77].

To solve this problem, analytically and semi-analytical approaches that mention modeling that is more complex where water parameter concentrations are related physically to the measured reflectance spectra by evaluating their absorption and scattering coefficients at multiple wavelengths are necessary to take care of the problems [73]. This method establishes sophisticated radiative transfer equations, relationships between water reflectance and the concentration of constituents and their specified inherent optical properties (SIOPS) [60, 68, 70, 72]. Using the analytical approach, the radiative transfer equation is inverted to determine water quality parameters, and several inversion procedures have been established for this purpose [78, 79] and have been revealed to optimize unknown parameters when measured input does not exist [60, 62, 78].

The inversion approach has been vital to separate bottom reflectance from water column spectra, in superficial waters where the water-leaving radiance/reflectance possibly encompasses some spectral evidence from the bottom reflectance and in

the water column [73, 80]. Using the simple methods like the empirical method, optically, shallow water can result in an overestimation of water column constituents caused by high reflectance values primarily from the bottom reflectance [81]. Comparing empirical and analytical approaches, it can be noted that analytical and semi-analytical methods are preferred for subsequent reasons: (1) they can be used to estimate both optically profound and shallow water optical properties, and the bottoms of optically shallow waters with physics-based modeling; (2) the approach does not require in situ water quality measurements to model, resulting in its independence; and (3) analytical and semi-analytical methods can be applied regionally in multiple lakes, reservoirs, and rivers with varied circumstances. Notwithstanding these benefits, nonetheless, they are computationally intensive and more expensive and difficult to use, thus requiring information of the inherent optical properties of the water body [73]. This research relies on the analytical approach to analyzing spectroscopic data.

2.2 Use of hyperspectral remote sensing methods and standard water quality approach in measuring the water quality parameters

Although the standard methods provide accurate measurement for a point in time and space, spatial or temporal view of water quality required for precise assessment of large water systems is usually not available [72]. It is necessary to integrate the use of calibrated image data with field spectral measurements to solve this problem, so as entirely to deploy the spatial and spectral information of hyperspectral remote sensing data. Hyperspectral images are critical for the water quality assessments where field data collection is planned to coincide with flight overpasses followed by the retrieval of the apparent and inherent optical properties of the basin or watershed of interest.

An in situ sampling water quality survey for nutrients is necessary at multiple sites in the study area, using the EPA-approved quality control/quality assurance procedures. A sample collected procedure is required, and we recommend 15 to 20 samples from each sampling area separated by at least 100 m from each other; using handheld spectrometer and paying particular attention to just the deep portions of the river for sample collection, above surface water reflectance was also measured. In situ data for chlorophyll a and other nutrients of interest can also be obtained from water quality databases, which contain data for fixed monitoring stations throughout the watershed of interest.

Using the handheld spectrometer to measure all the relevant quantities from above the surface, three types of measurements were carried out at each sampling site with the spectrometer: total upwelling radiance (LT), downwelling sky radiance (LSky), and “gray-card” radiance (LG, 3) reflected from a diffuse reflector (Spectralon®) [71]. All measurements were carried out at about 2:30 pm (local time), under clear skies, minor cloud cover, a wind speed of 4 m s⁻¹, and very calm water, at roughly 0.5 m above the water surface using a canoe. The above-water reflectance needs to be measured at 40° from the nadir and 90° from the azimuth and the sky reflectance measured in the same plane as the water, except for the angle from the zenith, which was 40°. To determine the downwelling irradiance, the Spectralon is assumed to have a Lambertian reflector in which, $E_d = \pi LG/R$, where LG is the average of the four grayscale scans and RG the reflectance of the diffuse reflector (~10%) [71].

2.3 Hyperspectral image processing

For the quantitative assessments of water quality parameters, detectable from hyperspectral data, data preprocessing is required by performing robust corrections

for atmospheric effects of adjacency effects and those effects occurring at the water surface level (sun glint, specular reflection of direct irradiance, and diffuse skylight).

Hyperspectral imagery requires an atmospheric correction to retrieve the surface reflectance from remotely sensed imagery by removing the atmospheric effects such as water vapor and other trace gasses. In an atmospheric correction, the radiance values are transformed into reflectance data to obtain water reflectance by removing surface reflectance [82], measuring the fraction of radiation reflected from the surface [83]. This procedure is particularly important for quantitative image analysis or change detection using hyperspectral data; image calibration is essential for remote sensing (**Figure 1**) to convert the instrument's digital numbers (DNs) to a substantial value to correct atmospheric instrument effect.

Image-driven empirical correction procedures have been suggested [57, 84, 85] for use with the Hyperspectral Imager for the Coastal Ocean (HICO), airborne visible/infrared imaging spectrometer (AVIRIS), Compact Airborne Spectrographic Imager (CASI-2), and Hyperion [86]. The empirical correction approach is based on the facts that clear ocean waters have water-leaving reflectance above 800 nm close to zero and sun glint and cirrus reflectance in the 400–1000 nm region. In this dissertation, we use the empirical line approach, which is an atmospheric correction method that serves as an alternative to radiative transfer modeling approaches [87]. This method calculates the empirical relation between radiance and reflectance using a dark and a bright target, well-characterized by field and image spectra. Our targets were measured in the area during data collection for optimal representation.

This method has been applied to correct both land and ocean data [88] and has shown great success with both coarser spatial resolution satellite sensor data and airborne data approaches [87]. This technique is only suitable for regional data correction where reflectance properties of bright and dark targets such as sand and water over uniform areas are measured coincidentally with the aircraft or airborne overpass [89].

A minimum of two known materials is required to use this method to carry out the calibration, and selecting one bright object and one dark object is also crucial for this exercise. This calibration method is recommended to use on two targets; however, using more targets will better estimate the relationship between target reflectance and at-sensor radiance [87, 88]. Using the image and field spectra, the two targets are regressed linearly against the reflectance spectra measured on the

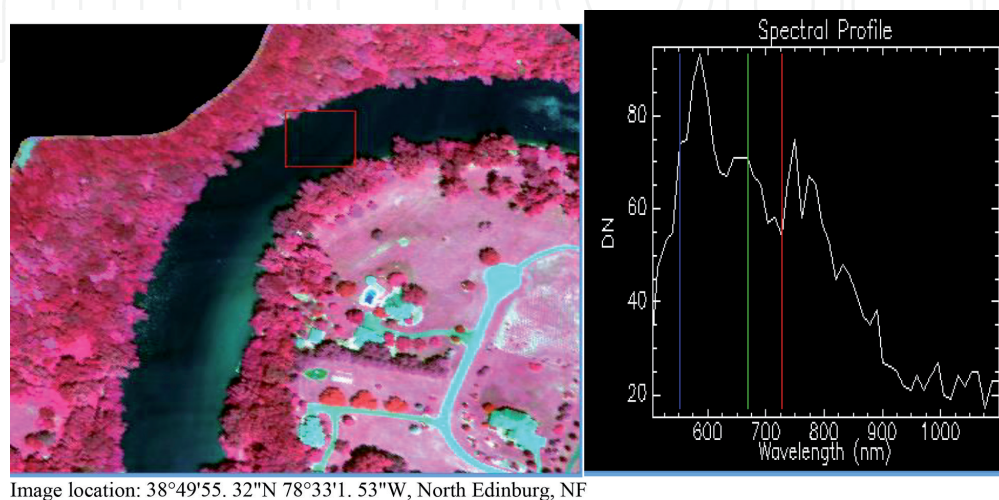


Figure 1. ARCHER color composite (RGB of 726 nm, 668 nm, and 551 nm) for areas around Edinburg, the North Fork of Shenandoah River in Virginia, USA. Image location: 38°49'55. 32"N 78°33'1. 53"W, North Edinburg, NF.

field to derive the gain and offset coefficients [88]. Once the gains and offsets are obtained, they are then applied to the entire image to derive surface reflectance, by producing reflectance values that are comparable to field measured values [88] (**Figures 1** and **2**). The empirical line method uses the following equation to calculate the gains and offsets:

$$\text{Reflectance (field spectrum)} = \text{gain} * \text{radiance (input data)} + \text{offset}.$$

Remote sensing data is also impeded by the effect of wave-induced sun glint [90], and this has become a limiting factor in estimating water quality efficiently from airborne data with high accuracy. The environmental and atmospheric effects resulting in inaccuracies in remote sensing classification results remain a growing concern in remote sensing classification [91]. For an adequate estimation of water quality with remote sensing data that is void of inaccuracies, the sun glint needs to be examined. After performing atmospheric correction on our image, sunglint removal was required to correct atmospheric effects on the visible wavelength region (0.45–0.69 μm). The sunglint is the specular reflection of sunlight directly transmitted from the air-water interfaces [92]. Under clear skies and irregular water surface, specular reflectance can result in sun glint on the image, which reduces the accuracy of retrievals [93]. The sunglint often occurs on an image when the orientation of the water surface is directly reflected toward the sensor as a function of the position of the sun, the viewing angle, and the state of the water surface [92].

These circumstances have resulted to the more excellent specular reflection of light from water “than the water-leaving radiance from the sub-surface features.” The necessity to remove the sun glint contribution for better image classification or information retrieval has been recognized by several researchers [90]. The approach adopted for this research estimates the amount of glint in the image by using data from the near-infrared (NIR), with the assumption that water-leaving radiance is negligible in this part of the spectrum, and any NIR signal left after atmospheric correction is undoubtedly from the sunglint. A relationship is established between the NIR and glint radiance while using the spectrum of the deep-water part of the image [92]. We use the shallow water sunglint removal approach that assumes that all the radiance from the NIR reaching the sensor is from atmospheric scattering and surface reflection, and any signal at the NIR after atmospheric correction is sunglint [92].

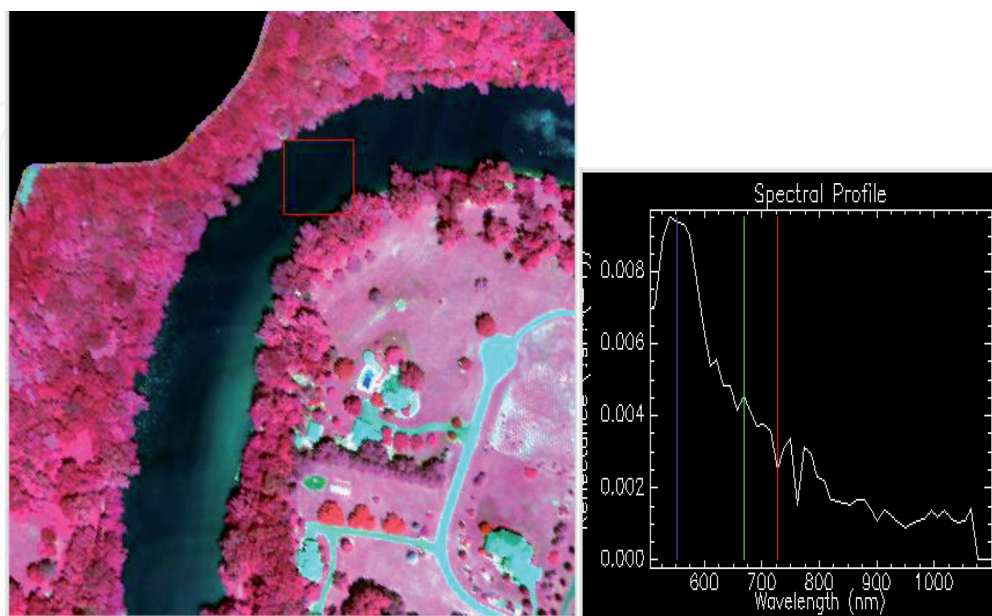


Figure 2. Atmospherically corrected ARCHER using empirical line calibration approach with a color composite of RGB 726 nm, 668 nm, and 551 nm for areas around Edinburg (above), for North Fork of the Shenandoah River taken on July 12, 2014. Image location: 38°49'55.32"N 78°33'1.53"W, North Edinburg, NF.

3. Sun glint background and removal approach

There are five critical processes through which a remote sensing detector receives radiance reaching it, as shown in **Figure 3** from Kay et al. [92].

Several approaches have been proposed for glint correction for estimating the contribution of glint to the “the sensor reaching radiance, and then subtract it from the received signal” [92]. Hochberg et al. [94] proposed a sunglint removal method, which assumed that the NIR brightness is only made up of sunglint and a spatially constant ambient NIR component. This method also believes that the sunglint present in the visible band is linearly related to the brightness of the NIR band. However, all two assumptions were proven weak because the first assumption models a constant ambient NIR brightness, which is removed from all pixels during analysis, and secondly, only two pixels are used to establish a linear relationship assumption. Selecting only one bright and one dark pixel could result to a bright pixel chosen from the land, which necessitated masking for results from this method to be efficient, and, this makes it very difficult and time-consuming. Thus, the difficulty of being able to identify an appropriate bright pixel can result in significant errors, which undermine the effectiveness of the method proposed by Hochberg et al. [94].

Hedley et al. [95], after acknowledging how sensitive this approach was to outlier pixel, proposed a revised method in which glint intensity is obtained using several pixels rather than two to establish a linear relationship between regression between the NIR and visible bands to allow sunglint contribution removal [90]. Hedley et al. [93] proposes using single or several regions on the image where sunglint is evident with consistent spectral brightness. The linear regression uses NIR brightness (x-axis) against the visible band’s intensity (**Figure 4**) of all the selected pixels.

As recommended by Hedley et al. [93], the first step is to select the minimum NIR brightness NIR Min deep-water pixels having a variety of glint intensities from which a sample is calculated. The next step in deglinting the image is to use each visible spectrum (VIS) Band *i* and perform a linear regression on the NIR pixel

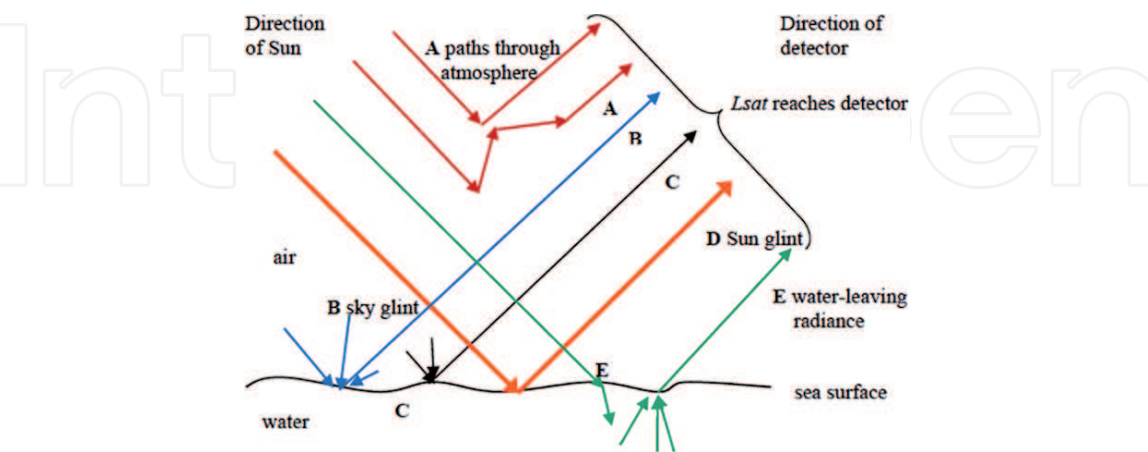


Figure 3.
Diagram showing routes by which light can arrive at a remote sensing detector from Kay et al. (2005).
→ (A) Molecules or aerosols scattering in the atmosphere, which is either single or multiple.
→ (B) Surface-water scattering from the atmosphere followed by reflection to the detector—known as “sky glint.”
→ (C) Whitecaps reflections from the sea surface.
→ (D) Surface-water specular reflection directly transmitted from the sun to the atmosphere to the surface and from the surface to the detector—also called “sun glint.”
→ (E) Atmosphere and air-water interface transmission, which is followed by reflection or scattering below the water surface and transfer back to the detector through the atmosphere.

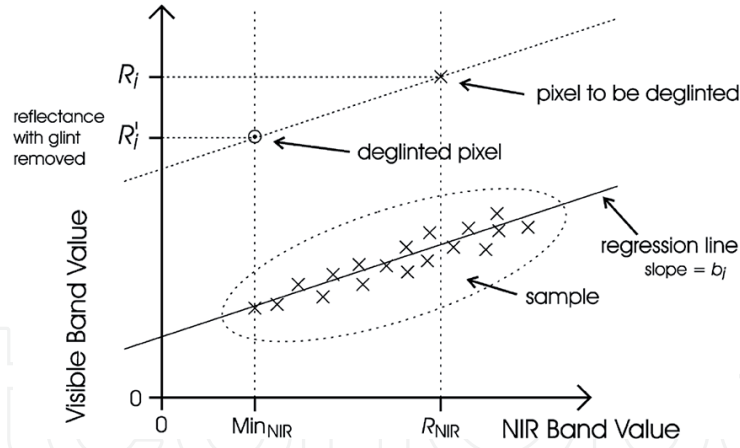


Figure 4.
Graphical interpretation of sunglint correction method from Hedley et al. [93].

brightness R_{NIR} against the pixel value of VIS band R_i . A user-based selection process is used to collect the samples, and land or cloud masking is not necessary. The product of slope b_i and R_{NIR} minus Min_{NIR} is subtracted from R_i to obtain the pixel R'_i with glint removed using the following equation:

$$R'_i = R_i - b_i(R_{NIR} - Min_{NIR}) \quad (1)$$

where b_i is the regression slope.

R_i is the visible band.

R_{NIR} is the NIR pixel value.

Min_{NIR} is the ambient NIR value, which is NIR pixel with no sunglint, which is either estimated from the figure above or from the entire image, and it is less prone to outliers caused by nonoptically deep pixels.

The result of the sunglint corrects brightness in band i , by minimizing outlier effects caused by surface objects [92]. This approach can be applied on either before or after atmospheric correction since it works entirely on the relative magnitude of values, and the pixel units are not very necessary for image deglinting. We initially corrected out the image with the empirical line method before removing the sunglint. It should, however, be mentioned that, if there are variations in the atmosphere properties, this will also affect the regression slope, thus making glint effect to be confounded [92]. As outlined by Hedley et al. [93], this approach is attained in four steps:

Step-by-step implementation

1. Image is radiometrically corrected.
2. Area of the image displaying a range of sun glint, with a more or less homogeneous surface, is selected. The minimum NIR brightness value is determined.
3. The newly created region of interest is used as a subset to create a new image with only the glare pixel subset and all image bands saved individually in ASCII. A linear regression of NIR brightness (x-axis) against the visible band (y-axis) is performed using the selected pixels in Excel to remove the sunglint from each band. The output of interest from the linear regression analysis for each band is the slope, which is called b_i in the equation above.
4. To individually glint each band i or all pixels in the image, the product of b_i and NIR brightness of the pixel (minus Min_{MIN}) subtracted the pixel value in band i as illustrated in Eq. (1).

4. Conclusion

The combination of several hundred spectral bands in a single acquisition has been made feasible by hyperspectral systems, which produce more detailed spectral data. Before advances in hyperspectral remote sensing, the multispectral imagery was the only data source in land and water observational remote sensing from airborne and spacecraft operations since the 1960s [10]. However, multispectral remote sensing data were only collected in three to six spectral bands in a single observation from the visible near-infrared and shortwave infrared regions of the electromagnetic spectrum, making it challenging to examine water quality from this data source. The present chapter covered hyperspectral remote sensing data analysis using field spectrometer data and remote sensing of water quality. Research has shown that remote sensing, GIS, and hydrological models can be integrated to solve hydrological problems [96, 97]. Here we review relevant literature on research in hyperspectral remote sensing that examines water quality parameters like suspended sediments, turbidity, chlorophyll a, and total phosphorus as investigated by numerous researchers. Unique characteristics of hyperspectral remote sensing data are introduced. This chapter shows that field observations/ spectroscopy, and water quality modeling is very instrumental in the accuracy of remote sensing analysis. We also presented the methodology for the study of visible to infrared hyperspectral remote sensing data from ARCHER aircraft and data collected with a handheld field portable spectroradiometer, to retrieve and establish a relationship between water quality parameters like chlorophyll a, colored dissolved organic matter, turbidity, phosphorus, and nitrogen in the Shenandoah River Basin.

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