A REVIEW OF METHODS AND REGRESSION MODELS USING SATELLITE IMAGERIES ON PHYTOPLANKTON'S WATER QUALITY PARAMETERS ESTIMATION

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Commission IV, WG 7

KEYWORDS: Geospatial Analysis, Phytoplankton, Water Quality, Remote Sensing

ABSTRACT:

Water quality monitoring is compulsory to maintain and preserve aquatic ecosystem health, especially for the phytoplankton community. Phytoplankton abundance relies greatly on the condition of water, it is important to assess the water quality parameter (WQP) to estimate the abundance of PP. However, obtaining WQP using conventional methods (water sampling and laboratory assessment) requires more time and cost of operation. Therefore, Geographical Information System (GIS) and remote sensing (RS) approaches are becoming popular methods of measuring water quality parameters (turbidity, total suspended solids (TSS), temperature, pH, etc). This paper aims to review the assessment of WQP in relation to PP abundance and other interchangeable factors from the recent studies and efforts on WQP assessment using geospatial technologies approaches. Methods, algorithms, and accuracies established from the GIS and RS techniques are discussed. From ten (10) extended review research articles, it is revealed that most WQP has an indirect and direct effect on human activities, seasonal changes, fish production, water pollution, and especially PP abundance. In addition, about nine (9) previous research articles revealed the use of various satellite image sensors to estimate WQP from Landsat 8 is the most common, to Landsat 7 ETM+, 5, Sentinel MSI, and the least used is RapidEye. Further research also finds that the three most common types of WQP estimated via the geospatial analysis method are turbidity, pH, and Secchi depth with the highest R^2 value equal to 0.810,0.947, and 0.990 respectively.

1. INTRODUCTION

Phytoplankton (PP) is a prokaryotic or eukaryotic species of plankton that normally comes in a form of a single cell, colony, chain or in a form of filamentous that is usually recognized as an element of the marine food cycle in nature, as well as a native source of food and oxygen for humans (Shams et al., 2012). Their abundance composition can be utilised to evaluate the ecological integrity of aquatic habitats. Their primary function in the biological clock is serving as an essential source of livestock to a range of aquatic animals, including molluscs, herbivorous fish, crustacean larvae, and zooplankton. The phytoplankton abundance is commonly found in almost every waterbody including fresh water, salt water and even in brackish water. As a result of the highly dynamic nature of the estuarine environment, phytoplankton production and species traits may vary significantly (da Costa Santana et al., 2018). As a bio-indicator of its surrounding environment, PP relies greatly on its habitat which is the quality of the water body itself.

The physio-chemical characteristics of the water and the productivity of the coral reef depend on the plankton density and variety (Payra et al., 2013). Prior research founds that the concentration of phytoplankton decreased as the salinity rose (Harris, 2012). Not only that, because the phytoplankton is aquatic flora that performs photosynthetic processes and serves as a source of dissolved oxygen (DO) in the waters, there is mutual interaction between DO and phytoplankton (Veronica, 2014). Numerous factors were found to be significant in evaluating the quality of water including temperature, nitrate, electrical conductivity (EC), phosphorus, DO and potassium (Bhateria & Jain, 2016). However, a few common WQPs often used by researchers to relate to phytoplankton abundance are water depth, turbidity, pH, temperature, chlorophyll-a (chl-a), and EC (Nkwuda, 2018; Veronica, 2014; Wang et al., 2017).

The most common practice for water assessment is using in-situ sampling and laboratory testing. However, a large-scale waterbody may not be sufficiently examined by laboratory methods based on sampling points since they are frequently labour-intensive, expensive, and time-consuming (Gholizadeh et al., 2016; Ouma et al., 2020). This is because each of the WQPs (turbidity, dissolved oxygen, temperature, pH) needs a specific instrument in assessing and collecting data via in-situ sampling. For instance, a mercury thermometer is used to measure water surface temperature, a refractometer is used to measure salinity and a pH meter to measure the pH level of water (Shoaib et al., 2017). Thus, the water quality assessment is required with the integration of the latest technologies (GIS and RS) to overcome time-consuming and high-cost issues when dealing with ground sampling.

In the last decade, the use of geospatial technologies (GIS and RS) has been used to find out the capability of the methods in WQP prediction in relation to the phytoplankton (Gernez, 2017;

González-márquez et al., 2018; Hasab et al., 2015). The most common methods for data acquisition are via satellite imagery with the integration of the GIS platform (Avdan et al., 2019; Gong et al., 2014; Shoaib et al., 2017). With a variety type of sensors such as Landsat-7 (TM/ETM+), Landsat-8 (OLI), Sentinel, Interferometric Synthetic Aperture Radar (IFSAR), RapidEye, and Moderate Resolution Imaging Spectroradiometer

(MODIS) where each sensor has a specific algorithm for WQP estimation. For example, statistical equation models for Landsat-8 were used to estimate salinity by integrating ground sampling salinity data with the normalized difference vegetation index (NDVI) (Hasab et al., 2015). Landsat 8 OLI/TIRS and Sentinel MSI are often preferred among researchers for WQP estimation because of their wide range of hyperspectral bands as compared to other lower spectral resolution images. On top of being open access data, both Landsat-8 and Sentinel-2 satellite imageries have the ability to give an estimation for quite a few of the WQP such as water surface temperature, turbidity, pH salinity, chl-a and suspended particular matter (SPM) (Gernez, 2017; Hasab et al., 2015; Ouma et al., 2020)

Hence, this study will discuss the RS approaches and regression equation models used to acquire and estimate the phytoplankton’s WQP relates to the other interchangeable factors from about 19 of the previous review articles. This study will benefit the researchers in assessing and estimating the several WQP using geospatial technologies with or without water sampling.

2. MATERIALS AND METHODS

This review paper uses a total of 19 gathered previous research papers as a reference from online scientific publications. Some of the keywords that were used to search for related papers are ‘Phytoplankton’, ‘water quality’, ‘Remote Sensing’ and ‘GIS’. Each publication then was reviewed and discussed to find similarities and correlations with each keyword.

3. DISCUSSIONS

3.1 PP Abundance and Interchangeable Factors in Relation with WQP

The ever-changing state of the WQP mainly depends on seasonal change, weather conditions, tides, anthropogenic activities and marine pollution (El Gammal et al., 2017; Gupta et al., 2005; Rosa et al., 2022). Table 1 shows five (5) different factors that were almost consistently mentioned by prior research papers which are an abundance of PP, seasonal changes, human activities, fish production, and water pollution. With PP being the most consistent factor related to the WQP, it is indisputable how crucial their roles are in affecting WQP. Recent correlation studies found that 63.8% of phytoplankton occurrence is influenced by pH, DO, salinity, total phosphate (PO_3), nitrate (NO_3), and Ammonia (NH_3), while the remaining 36.2% is influenced by other variables (Veronica, 2014). Aside from that, seasonal changes are the second strong relation with WQP. About 7 out 0f 10 of the reviewed previous papers have acquired WQP sampling and analysed the biochemical of water quality based on different seasons (Harris, 2012; Nkwuda, 2018). This is because the water temperature of tropical rivers can fluctuate as much as almost 10˚C in between seasons (rainy season and dry season). The temperature was recorded to be from 25.5˚C during the rainy season to 34.3˚ C during the dry season (Nkwuda, 2018). On top of that, the water quality index of lake water is more impacted during the summer than it is during the winter which might be a result of the fact that cold temperatures inhibit microbial activity, maintaining the DO level in a fairly good range throughout the entire winter season (Bhateria & Jain, 2016). Hence, seasonal research on water quality in relation to phytoplankton abundance is crucial to comprehend the pollution and stressed environmental conditions, which will ultimately be useful for gaining information about fishery production. The least related factors mentioned but cannot be ignored by previous papers are the effects of human activities, fish production, and water pollution on the WQP.

Due to a variety of anthropogenic activities, water quality had deteriorated in modern times (Bhateria & Jain, 2016). Not only that, certain types of land use (mangroves, industries, mooring activities, ponds, settlements, and intensive ponds have the potential to negatively impact the dynamics of the current ecosystem and influence river flow (Guntur et al, 2018). These listed human activities often affect the condition of WQP and can indirectly affect the PP abundance. As a cause of effect, the differential impact of hydrographical conditions on PP species causes its distribution to exhibit significant spatio-temporal fluctuations. Not to mention that they are extremely useful indicators of water quality, including pollution (Payra et al., 2013).

Author/ Year	Interchangeable factors that relate to WQP				
	PP	Seasons	Human activities	Fish production	Water pollution
(Medupin, 2011)	/	/	/		
(Harris 2012)	/	/			/
(Payra et al., 2013)	/	/		/	
(Veronica, 2014)	/	/	/	/	
(He et al., 2016)	/	/			
(Bhateria & Jain, 2016)	/	/	/	/	/
(El Gammal et al., 2017)	/		/		
(Guntur et al, 2018)	/		/		/
(Nkwuda, 2018)	/	/	/		/
(Udeme Jonah, 2020)	/		/		/

Table 1. Interchangeable factors in relation to WQP based on prior studies.

3.2 Geographical Information System and Remote Sensing in Estimating WQP

Satellite imageries can be access through open-source website such as United States Geological Survey (USGS) https://www.usgs.gov/, and Copernicus, *https://www.copernicus.eu/en* makes it stand out from the other data collecting approaches. These websites provide numerous satellite imageries obtained from many types of sensors from all over the world such as MODIS, Landsat, Sentinel and IFSAR. Resolutions for each type of sensor have been categorized into spatial, spectral, temporal, radiometric, and geometric resolutions. These four resolutions are correspondingly important in estimating WQP. However, images with hyperspectral resolution are often in favour by researchers because its wide range of different bands allows us to estimate more than one WQP at once. Table 2 shows several satellite imageries that frequently used in water quality assessment are Sentinel MSI and Landsat-8 OLI/TIRS due to its capability of estimating PO_3, EC, TSS, turbidity, chl-a, Secchi depth, salinity and water pH (González-márquez et al., 2018; Hasab et al., 2015; Shoaib et al., 2017) while only a few researchers use Landsat-7 ETM+ on assessing SSM, chlorophyll-a, pH, Secchi depth and total PO3 (Alparslan & Aydöner, 2014; Pereira et al., 2020). Another driven factor of varying sensor preferability in estimating types of WQP is the temporal resolution. As mentioned before, WQP strongly relates to seasonal changes (Harris, 2012; Medupin, 2011; Payra et al., 2013). Hence the variability in time difference is often sought after in assessing WQP.

Satellite image pre-processing is the initial step in image processing that deals with removing radiometric, atmospheric, and geometric distortions that are present in the raw image data. these terms can also be defined as radiometric, atmospheric, and geometric corrections (Ratnaparkhi, 2020). The sole purpose of radiometric correction is to convert the relative values of the digital number or the image’s pixels to an absolute measurement of reflectance. While the atmospheric correction is done to remove the atmospheric effects and convert the radiometric data into radiation or surface reflectance (González-márquez et al., 2018). These corrections were applied by several prior researchers during the pre-processing phase before extracting the WQP (Gernez, 2017; Ouma et al., 2020; Pizani et al., 2020). With that, it is safe to say that these corrections are compulsory initial steps before extracting WQP from any satellite images. In some occasional cases, some researchers use Dark Object Subtraction (DOS) during the atmospheric correction for Landsat 8 OLI and sentinel-2B images (Siregar et al., 2019). The DOS serves as a measure in a "clean-up" procedure that also accounts for air dispersion, or haze (Chavez, 1998).

Table 2 shows that turbidity is the most common WQP extracted across several types of satellite images (Alparslan & Aydöner, 2014; Avdan et al., 2019; González-márquez et al., 2018; Ouma et al., 2020; Shoaib et al., 2017). In assessing the turbidity, only required a wavelength ranging between 0.45 to 0.69 micrometres which are commonly had in every satellite image. This certain wavelength is used in bands 2 and 3 in Landsat-8 OLI and bands 3 and 4 in Sentinel MSI (Ouma et al., 2020). The only drawbacks of using the GIS and RS methods are the limitation to extracting other biological properties of WQP such as Ammonia, nutrients, nitrogen and dissolved oxygen. These other parameters can’t be overlooked in predicting the abundance of PP since it has a strong correlation with the total of ammonia and nitrogen as per conducted in previous research (Wang et al., 2022).

3.3 Regression Models to Extract Water Quality Parameter from Sensor

The estimation regression models were often created by the statistical approach that measures the correlation between dependent and independent variables. The essential step in creating a regression is to assess the correlation by using a statistical approach which includes the Pearson correlation coefficient (R) and coefficient of determination (R^2). The value of R2 uses to express the linear relationship between variables (Schober & Schwarte, 2018). Table 3 shows five (5) different classes of R^2 values (Bazgeer et al., 2012; Yang et al., 2011). In Numerous studies have been established to identify the significance of regression in assessing the WQP.

Table 4 indicates several numbers of equation regression models in linear or multiple regression which are established to estimate WQP relates to the band of satellite imageries and ground sampling datasets. The regression indicates the conditions and distribution of water quality of the site survey which will reduce the water sampling procedures if the R and R^2 present in a good relationship. In 2008, Mokhtar and Mohd (2008) has introduced estimating WQPs (turbidity and Total Suspended Solids (TSS)) using digital camera bands in different resolution. Alparslan & Aydöner (2014) estimates WQP using four (4) different bands of Landsat-7 images. The value of WQP was derived by using regression analysis. The estimated WQP was then compared with in-situ sampling WQP. The highest R2 is at 0.955 which is a correlation between Total Suspended Solid (TSS) and band 6 of Landsat-8 OLI (González-márquez et al., 2018) using MATLAB software. A publication by Hasab et al. (2015) found a relation between salinity and the normalized difference vegetation index (NDVI) (Equation 1) of a Landsat 8 using the SPSS software. Not limited to salinity, Gernez (2017) focused on chl-a and SPM with ground sampling data to the Sentinel MSI images. Research has been extended by applying the RapidEye sensor to retrieve WQP using Pearson’s correlation coefficient (Avdan et al., 2019). Multiple linear regression (SMLR) has been tested on using Landsat TM, Landsat 7 ETM+, and Landsat 8 OLI (Pereira et al., 2020). A comparison of the capability of the Landsat sensor and Sentinel sensor has been tested on WQP determination (Pizani et al., 2020; Ouma et al., 2020).

$$NDVI = (Band5-Band4) / (Band5+Band4) \tag{1}$$

Author/Year	WQP	Sensor
(Alparslan & Aydöner, 2014)	SPM, chl-a, Secchi depth, turbidity and total phosphate (TP)	Landsat-7 ETM
(Hasab et al., 2015)	Salinity	Landsat-8 (OLI/TIRS)
(Avdan et al., 2019)	EC, total dissolved soils (TDS), suspended particular matter, water transparency, water turbidity, depth and chl-a	RapidEye
(Gernez, 2017)	Turbidity and chl-a	Sentinel MSI
(Pereira et al., 2020)	Water pH	Landsat 5 TM, 7 ETM+, and 8 OLI
(Ouma et al., 2020)	Chl-a, total suspended solids, and turbidity	Sentinel-2A MSI and Landsat-8 OLI
Shoaib et al., 2017)	Chl-a, turbidity, Secchi disk depth and temperature	Landsat-8 OLI, Sentinel-2 MSI and Landsat-8 TIR
(González-márquez et al., 2018)	Conductivity, total suspended solids, turbidity, and water pH	Landsat-8 OLI

Table 2. Types of sensors and list of extracted WQP from previous research.

R^2	Interpretation
0 - ±0.10	Negligible correlation
±0.11 - ±0.39	Weak correlation
±0.40 - ±0.69	Moderate correlation
±0.70 - ±0.89	Strong correlation
±0.90 - ±1.00	Very strong correlation

Table 3. Correlation of Coefficient and its interpretation (Schober & Schwarte, 2018)

Author/ Year	**Type of sensor/ data acquisition**	**Parameter**	**Regression**	**Coefficients of Determination (R^2) and Accuracy**
Mokhtar and Mohd (2008)	Digital Camera, Water sampling	Turbidity, TSS	Turbidity = 3.364(TSS) – 33.320 TSS = $a_0 + a_1R + a_2G + a_3B + a_4(R/G)^2 + a_5(R/B)^2 + a_6(G/B)$ Where; a0, a1, a2...... - Correlation Coefficient R, G, B - DN of Red, Green and Blue bands	 TSS regression: $R^2 = 0.955$ RMSE ± 7.942
(Alparslan & Aydöner, 2014)	Landsat- 7 ETM+, Water sampling	SPM, chl-a, secchi depth, turbidity and total phosphorus (TP)	Regression: 1. Chl-a = 44.7869 − 0.2908(x1) − 0.6905(x2) + 0.1019(x3) + 0.4843(x4) 2. TP = 6662.498 − 65.7467(x1) − 65.3952(x2) + 1.8(x3) + 96.2487(x4) 3. SPM = 42.2672 − 0.8694(x1) − 0.3716(x2) + 1.05(x3) + 0.1247(x4) 4. Secchi depth = −10.408 + 0.0542(x1) + 0.2703(x2) + 0.01(x3) − 0.3093(x4) Where, X1 = Band 1, X2 = Band 2, X3 = Band 3 X4 = Band 4	Chl-a regression: $R^2 = 0.91$ SE = 0.4885 TP regression: $R^2 = 0.99$ SE = 21.3537 SPM regression: $R^2 = 0.99$ SE = 0.0085 Secchi depth regression: $R^2 = 0.99$ SE = 0.0155
(Hasab et al., 2015)	Landsat-8 (OLI/TIRS)	Salinity	Regressions: 1. Linear = 17159 x (NDVI) - 42.57 ± SE 2. Power = 7578.7 x (NDVI) 0.672 ± SE 3. Exponential = 507.7 x $(e)^{10.176 *(NDVI)}$ ± SE Where; NDVI = (Band5-Band4) / (Band5+Band4) SE = Standard Error of observed salinity.	Linear regression: $R^2 = 0.7343$ SE = 94.33 Power regression: $R^2 = 0.6975$ SE = 71.56 Exponential regression: $R^2 = 0.8524$ SE = 51.25
(Gernez, 2017)	Sentinel MSI, Water sampling	SPM and chl-a	Regressions: 1. Est chl-a = 1.02(chl-a sampling) – 0.07 2. Est SPM = 0.93(SPM sampling) + 0.32	Chl-a and water sampling: $R^2 = 0.92$ RMSE = 3.05 SPM and water sampling: $R^2 = 0.96$ RMSE = 56.26
(González-márquez et al., 2018)	Landsat- 8 OLI, Water sampling within 3 different season (May 2015, December 2015, and June 2016)	Phosphate (PO), EC, TSS, turbidity, and water pH	Regressions: 1. Log (PO) = − 14.383 + 107.32 x Log(B5) − 36.249 x Log(B6) − 82.972 x Log(B7) + 33.252 x (Log(B5))2 − 34.867 x $(Log(B7))^2$ 2. TSS = 276.44 − 18960 x B6 3. Log (Turbidity + 15) = 1.4562 + 42.333 x (B4 − B2) + 1527.6 x $(B4 − B2)^2$ 4. pH = 7.4059 + 0:25376 x (B1/B5) 5. EC = 52.412 + 157.56 x (B1 − B2) + 0.0044809 x (1/ (B1 − B3)) − 0.36922 x ((B1 − B6) / (B1 − B3)) − 2.2498 x ((B2 − B3) / (B2 − B5)) Where, B1, B2, …, B7 is number of bands in Landsat 8.	PO regression: $R^2 = 0.755$ RMSE = 0.060 TSS regression: $R^2 = 0.955$ RMSE = 3.480 Turbidity regression: $R^2 = 0.784$ RMSE = 0.108 pH regression: $R^2 = 0.947$ RMSE = 0.037 EC regression: $R^2 = 0.884$ RMSE = 0.445
(Avdan et al., 2019)	RapidEye,	EC, TDS, SPM,	Regression (top 3):	I8 regression: $R^2 = 0.88$

	Water sampling	turbidity, depth and chl-a	1. I8 = 0.46(turbidity sampling)^2 – 1(turbidity sampling) + 0.24 2. I4 = -0.01(depth sampling)^2 + 0.14 (depth sampling) + 1.28 3. I7 = 0.19(turbidity sampling) + 0.53 Where; I4, I8, and I7 is types if indices used in retrieving WQP from RapidEye sensor.	I4 regression: $R^2 = 0.85$ I7 regression: $R^2 = 0.84$
(Pereira et al., 2020)	Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI Water sampling	pH	Regressions: 1. GP pH = 0.9471(pH) + 0.2957 2. SMLR pH = 0.8752(pH) +0.8272 Where; GP (genetic programming) and SMLR (stepwise multiple linear regression) is an analysis method to establish regressions.	GP Ph regression: $R^2 = 0.85$ RMSE = 0.55 SMLR pH regression: $R^2 = 0.74$ RMSE = 0.85
(Ouma et al., 2020)	Landsat-8/OLI and Sentinel-2A/MSI (S2A)	Chl-a, total suspended solid (TSS), and turbidity	Regressions (sentinel): 1. Chl-a = 395763(B3-B11)^2 – 44991(B3-B11) + 1288.2 2. TSS = 93011((B4 + (B8/B4))/2)^2 − 82773((B4 + (B8/B4))/2) + 18442 3. Turbidity = 367.82(B2/B3)^2 – 976.42(B2/B3) + 649.13 Regression (Landsat 8): 1. Chl-a = 4050.2(B3) − 170:43 2. TSS = 2454.1(B3/B2) – 1584.4 3. Turbidity = 102.56 (B3+B4) – 5.5003 where, B2 = Band 2, B3 = Band 3, B4 = Band 4, B8 = Band 8, B11 = Band 11	Chl-a regression: Sentinel $R^2 = 0.7015$ RMSE = 12.8408 Landsat-8 $R^2 = 0.8581$ RMSE = 2.5596 TSS regression: Sentinel $R^2 = 0.6133$ RMSE = 8.3845 Landsat-8 $R^2 = 0.9249$ RMSE = 0.0349 Turbidity regression: Sentinel $R^2 = 0.8004$ RMSE = 0.0349 Landsat-8 $R^2 = 0.8125$ RMSE = 0.4024
(Pizani et al., 2020)	Sentinel-2 MSI and Landsat-8 OLI	Chl-a, turbidity, secchi disk depth and temperature	Regressions top 2(sentinel-2 MSI): 1. pH = 12.2621 + (-246.4698 x B1) + (29.4987 x B3) + (300.0727 x B6) + (-140.2648 x B8) 2. Secchi depth = 396.3 x (22408.6 x B1) + (-16290.6 x B3) Regressions top 2(Landsat-8 OLI): 1. Secchi depth = 511.9 + (21335 x B1) + (-17343.6 x B3) 2. $R^2 = 0.81$ 3. Turbidity = 0.2294 + (-59.2739 x B1) + (48.0012 x B3) 4. $R^2 = 0.80$	pH regression: Sentinel $R^2 = 0.89$ RMSE = 0.04 Secchi Depth regression: Sentinel $R^2 = 0.84$ RMSE = 49.48 Landsat-8 $R^2 = 0.81$ RMSE = 54.15 Turbidity regression: Sentinel $R^2 = 0.8004$ RMSE = 42.9 Landsat-8 $R^2 = 0.80$ RMSE = 42.7

Table 4. Method and Regressions to acquired WQP from multiple Satellite Imageries Sensors

4. CONCLUSIONS

From the extended review of the previous related research papers, the three main sensors often used by researchers to estimate WQP are Landsat 8 OLI/TIRS, Sentinel MSI and Landsat 7. The most common WQP that were managed to be extracted from the listed sensors are turbidity, pH, and secchi depth. Although geospatial analysis and RS approaches on estimating WQP is only limited to a few selected WQP, it is undeniably cost less time and money as compared to in-situ sampling method. From this research, it is beyond doubt how the development of regression models helps us in seeing how much each spectral band of each sensor are correlates with the WQP and most importantly enabling us researchers to estimate the WQP itself. However, each regression cannot be use for an accuracy assessment of WQP since there are still other factors that may affected its credibility such as the abundance of PP, changes of weather, places, type of water bodies etc.

ACKNOWLEDGEMENT

This project was sponsored by Universiti Teknologi MARA (600-RMC/LESTARI SDG-166 T 5/3 (104/2019)).

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