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REMOTE SENSING OF WATER COLOR TO ASSESS WATER QUALITY IN A CHANGING CLIMATE

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REMOTE SENSING OF WATER COLOR TO ASSESS WATER QUALITY IN A CHANGING CLIMATE

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ABSTRACT

Water is that basis of all life on this planet. Access to clean and safe freshwater provides the population with the basic means to live. Yet approximately one in seven people in the world do not have access to safe water. Water can become unsafe due to contamination by various organic and inorganic compounds. Organic contaminants such as phosphorus, nitrogen, or bacteria, disrupt the balance of the existing system. Metals like lead, fluoride, or mercury are inorganic and cannot be normally processed in a natural water system. These contaminants can come from industrial processes, agriculture, aging plumbing systems, etc. This study investigates commonly used GIS and Remote sensing technologies and approaches for assessing water quality using the unique spectral characteristics of water quality events such as algal blooms, acid mine drainage, and suspended sediment. Remote Sensing satellites and the vast amount of data collected from previous missions, make it possible to monitor for changes in quality and quantity of existing freshwater reserves. Synthesizing these findings will allow researchers to utilize, share, and embed this information into their own research on monitoring and tracking ever evolving water quality in target waterbodies.

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PREFACE

This thesis is submitted in Standard Format

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LIST OF ABBREVIATIONS

AMD	Acid Mine Drainage
Chl-a	Chlorophyll-a
CNN	Convolutional Neural Network
FLI	Floating Algal Index
HAB	Harmful Algal Bloom
HSI	Hyperspectral Imaging
MCI	Maximum Chlorophyll Index
MSI	Multispectral Image
MODIS	Moderate Resolution Imaging Spectroradiometer
NIR	Near Infrared
OLI	Operational Land Imager
PCRCNN	Point-Centered Regression Convolutional Neural Network
SSC	Suspended Sediment Concentration
SWIR	Short Wave Infrared
TDS	Total Dissolved Solids
TIR	Thermal Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
UAS	Unmanned Aerial System
VNIR	Visible Near Infrared

CHAPTER 1

INTRODUCTION

Earth's drinking water sources are finite. Less than one percent of earth's freshwater is actually accessible to the human population, by 2050 global demand for freshwater is expected to be one third greater than it is now (Denchak, 2018). Any changes to water quality could be detrimental, effecting aquatic habitats, recreation, drinking water, agriculture, etc. Water is a valuable natural resource that is essential to human and environmental health. Climate change is posing significant risks on water quality. Increasing temperatures and more intense storm events associated with climate change promote eutrophication and increased sediment and nutrient inputs, throwing of the balance of existing water systems (Stroming et. al. 2020). Water monitoring programs are thus essential to address consequences of the present and future threats of contamination to water resources (Usali and Ismail, 2010). Traditionally water quality parameters have been measured using in situ testing. Although they provide high accuracy, they can be expensive and labor intensive. In situ data collection is also limiting, only analyzing small areas of the water body. It does not allow for easy monitoring and forecasting of a large geographic area, and accuracy and precision can be questionable with sampling and lab errors (Gholizadeh et. al., 2016). Early detection and comprehensive monitoring of water quality is fundamental to effective management and mitigation of detrimental impacts.

Remote sensing techniques make it possible to monitor and identify large scale regions and waterbodies that suffer from qualitative problems more effectively and efficiently. NOAA describes remote sensing as the act of collecting data by detecting the energy that is reflected from the Earth. Sensors can be on satellites of mounted on aircrafts. First used in the Great Lakes in the 1970s, Landsat data explored and identified particulate contaminants, whiting events, and chlorophyll-a (Binding et. al., 2020). Since then, research on using remote sensing techniques for water quality monitoring has expanded. Benefits of remote sensing are numerous. It delivers synoptic water quality observations over large areas, frequent and consistent revisit times, time series analysis, event-based monitoring, and archived historical data allows for retrospective analysis dating back several decades (Binding et. al., 2020). However, optically complex waters can pose a challenge to the use of remote sensing data. It becomes important to select the correct sensor and algorithm for water quality analysis to retrieve the best results. Different sensors can capture radiation at various wavelengths reflected from the water's surface, measuring a variety of water quality indicators (Gholizadeh et. al., 2016).

In Binding et. al. (2020) the authors described the struggle of optically complex water when using Landsat data. However, found that the use of inverse modeling, an algorithm that exploits the red and near infrared portion of the spectrum, could be a useful technique when evaluating optically complex waters. Usali and Ismail (2010) analyzed six water quality parameters to find the best techniques for retrieving water quality data using remote sensing. For example, to measure suspended matter, Usali et. al (2010) found that wavelengths between 700 and 800nm have proved most useful for detecting suspended matter and that TM4 (Landsat) would be the most suitable satellite and band. For turbidity however, Usali et. al (2010) determined Landsat 5 TM Bands 3 and 2 to be most useful. Using this technology to document trends will help improve our understanding of water quality and better provide management action. This paper will provide further information to better narrow down which data retrieval methods are best suited per the water quality parameter in question.

A clear indicator of changes in water quality are changes in watercolor. Specific events can be correlated to specific colors of water. For example, algal blooms present a green-blue color (Binding et. al. 2020), acid mine drainage presents a red orange color (Yucel et. al. 2014), and suspended sediment presents a brown/tan color (Gholizadeh et. al. 2016). With the use of remote sensing these color changes can be documented and potentially be used for detecting and monitoring pollution events. Previous use of remote sensing has mostly been concentrated in documenting algal blooms, however monitoring acid mine drainage and suspended sediment should not be discounted as they pose an equal threat to human and environmental health and have distinct optical signatures.

Many states currently practice reactive harmful algal bloom (HAB) management strategies, sending teams out after events are reported (Stroming et. al, 2020).

While effective, human health is put at risk as it takes time for an algal bloom occurrence to be tested and reported. Remote sensing provides more nuanced decision making regarding harmful algal blooms and can provide forecasting and the necessary lead time before the occurrence of a HAB event. This not only will offer better protection of human health but will save the community money. Stroming et. al. (2020) conducted a study at Utah Lake and predicted that the difference between in situ testing and remote sensing would have saved the town nearly $370,000 in total medical expenses due to health outcomes in 2017.

Acid mine drainage and suspended sediment, while perhaps not as common of topics, have also been documented and monitored using remote sensing techniques. Acid mine drainage occurs because of abandoned mining sites. Debris and heavy metals leaching from there mines pollute streams with harmful discharge caused by minerals from mining, resulting in the notorious bright red-orange water. According to Yucel et. al. (2014), many studies were able to locate sources and monitor changes throughout the years using satellite remote sensing. In their own study, they were able to create a time series of physical and chemical changes in acid mine lakes in Turkey using Landsat, Quickbird, and Worldview satellite images. On the other hand, suspended sediment is a result of buildup from runoff or erosion of mud and clay. These conditions prevent penetration of sunlight into the water creating unsuitable conditions for aquatic life. Suspended sediments scatter light rather than absorbing it and transmitting it in straight lines, making it feasible to detect using remote sensing (Gholizadeh et. al, 2016).

As previously mentioned, this study will focus on compiling and synthesizing information regarding remote sensing techniques of color changing water quality events. Information will be compiled from various literature sources around the world where research has been conducted regarding the specific water quality parameter. Contextualize the analysis of this literature by: (1) summarizing information known about current remote sensing platforms and commonly used sensors, (2) providing an overview of the three core water quality events of focus, including algal blooms, acid mine drainage, and suspended sediment, and (3) discussing commonalities to present best practices for monitoring water quality events and potential future directions and considerations for the field.

CHAPTER 2

SATTELITE TECHNOLOGY

In remote sensing there are two categories based on the platform sensors are placed on. Airborne sensors are those that are mounted on platforms and reside within the Earth's atmosphere such as airplanes or drones. Spaceborne sensors are carried on satellites that orbit the Earth capturing images from outside the Earth's atmosphere (Gholizadeh et. al. 2016). Multi- and Hyperspectral airborne data provides a highly flexible approach to remote sensing. They have higher spectral and spatial resolution and sensors can be configured accordingly to the survey site (Jackisch et. al. 2018). Airborne data is good for water quality research because in situ testing can be easily coordinated with flyovers. However, Airborne remote sensing is complex and costly compared to spaceborne surveys. They require a great deal of planning in accordance with other air traffic, solar and weather conditions, and flight orientation (Gholizadeh et. al. 2016). They also cover smaller geographic areas at lower altitudes and data from these missions are not as publicly available as data from satellite remote sensors.

Spaceborne sensors are useful for multi-temporal studies and for monitoring trends and patterns of water quality in an area, image processing tends to be less complex than that of airborne sensors and data from these sensors tends to be free and available to the public. Compared to airborne sensors, spaceborne sensors tend to have courser spectral resolution, cloud cover can be limiting, and analyzing images may be more difficult resulting in over or underestimations of water quality parameters (Gholizadeh et. al. 2016). Despite these limitations, this study focuses on the use of satellite remotes sensing. Access to free, reliable, consistent data is valuable to researchers when monitoring water quality parameters and access to data around the world made satellite data attractive for this review. This study reviews a variety of sensors as applied to water quality however, there are three sensors that seemed to reoccur over most studies. Those sensors being Landsat 8, Sentinel-2 MultiSpectral Instrument (MSI), and Terra & Aqua MODIS.

Landsat is by far the most common satellite utilized. From the first recorded use of satellite remote sensing in the early 1970's, used to monitor particulate contaminants, whiting events, and chlorophyll-a, Landsat has offered the longest continuous global record of the Earth's surface (Binding et. al., 2020). It has been the most refined and possibly the most reliable with the main disadvantage being the long revisit time of 16 days compared to Sentinel's 5-day revisit time and MODIS at 2-3 days. The Landsat-8 satellite launched on February 11, 2013 and consists of two instruments, the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). These sensors provide seasonal coverage of the globe within the visible, near infrared (NIR), short wave infrared (SWIR), and thermal infrared (TIR) spectrum (NASA, 2021). Table 1 below describes the bands incorporated into the Landsat 8 satellite in terms of wavelength, spatial resolution, and applicability.

Table 1: Landsat 8 Bands

Landsat-8 Bands		
Band 1	30 m Coastal/Aerosol – shallow water and coral, and tracking dust/smoke	435 – 451 nm
Band 2	30m Blue	452 – 512 nm
Band 3	30m Green	533 – 590 nm
Band 4	30m Red	636 – 673 nm
Band 5	30m NIR	851 – 879 nm
Band 6	30m SWIR – 1 - Vegetation	1566 – 1651 nm
Band 7	30m SWIR – 2 - Vegetation	2107 – 2294 nm
Band 8	15 m Panchromatic	503 – 676 nm
Band 9	30 m Cirrus – atmospheric correction	1363 – 1384 nm
Band 10	100 m TIR – 1 – Surface temperature, crop water use	10606 – 11190 nm
Band 11	100 m TIR – 2 – Surface temperature, crop water use	11500 – 12510 nm

An adaptation from information provided on NASA.gov by B. Markham

Landsat 9 successfully launched on Monday September 27, 2021. Landsat 9 will work in tandem with Landsat 8 to collect images spanning the entire planet every 8 days. Imagery will help scientists make science-based decisions on key issues including water use, wildfire impacts, coral reef degradation, glacier and ice-shelf retreat, and tropical deforestation (Potter, 2021). This mission is an exciting and big step forward for data availability for Landsat, cutting its revisit time in half. This is expected to become a big asset in helping decision makers monitor overall health of the Earth and its natural resources.

Sentinel-2 launched on June 23, 2015, the satellite was equipped with an opto-electronic multispectral sensor for surveying in the visible, near infrared (VNIR), and short wave infrared (SWIR) spectral zones, including 13 spectral bands, ensuring the capture of differences in vegetation state, temporal changes, and minimizing impact of the atmosphere. The presence of two satellites in the mission allows for a revisit time of 5 days at the equator, 2-3 days at mid latitudes (EOA 2021). Table 2 goes into depth about the details of Band capabilities on Sentinel-2.

Table 2: Sentinal-2 Bands

Sentinel – 2 MSI Bands		
Band 1	60m Aerosols Correction	443 nm
Band 2	10m Blue – Aerosols Correction/Land Measurements	490 nm
Band 3	10m Green – Land Measurements	560 nm
Band 4	10m Yellow – Land Measurements	665 nm
Band 5	20m Vegetation Red Edge – Land Measurements	705 nm
Band 6	20m VNIR– Land Measurements	740 nm
Band 7	20m VNIR– Land Measurements	783 nm
Band 8	10m VNIR – SWIR – Water Vapor Correction – Land Measurements	842 nm
Band 8a	20m VNIR – SWIR – Water Vapor Correction – Land Measurements	865 nm
Band 9	60m VNIR - SWIR – Water Vapor Correction	940 nm
Band 10	60m SWIR – Circus detection	1375 nm
Band 11	20m SWIR – Land Measurements	1610 nm
Band 12	20m SWIR Aerosols Correction – Land Measurements	2190 nm

An adaptation from information provided on eoportal.org and sentinel.copernicus.eu

Moderate Resolution Imaging Spectroradiometer (MODIS) is a key instrument aboard the Terra and Aqua satellites. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths. With a larger spatial resolution of 250, 500, and 1000m, MODIS is better suited for larger waterbodies and is not as precise as Landsat and Sentinel datasets (Modis Web). However, the wide availability of bands and low revisit rates are valuable and have been used successfully in many studies. Table 3 describes the attributes of each of the 32 bands.

Table 3: Terra & Aqua MODIS Bands

Terra & Aqua MODIS Bands		
Band 1	250m Land/Cloud/Aerosols Boundaries	620 – 670 nm
Band 2	250m Land/Cloud/Aerosols Boundaries	841 – 876 nm
Band 3	500m Land/Cloud/Aerosol Properties	459 – 479 nm
Band 4	500m Land/Cloud/Aerosol Properties	545 – 565 nm
Band 5	500m Land/Cloud/Aerosol Properties	1230 – 1250 nm
Band 6	500m Land/Cloud/Aerosol Properties	1628 – 1652 nm
Band 7	500m Land/Cloud/Aerosol Properties	2105 – 2155 nm
Band 8	1000m Ocean Color/Phytoplankton/Biogeochemistry	405 – 420 nm
Band 9	1000m Ocean Color/Phytoplankton/Biogeochemistry	438 – 448 nm
Band 10	1000m Ocean Color/Phytoplankton/Biogeochemistry	438 – 493 nm
Band 11	1000m Ocean Color/Phytoplankton/Biogeochemistry	526 – 536 nm
Band 12	1000m Ocean Color/Phytoplankton/Biogeochemistry	546 – 556 nm
Band 13	1000m Ocean Color/Phytoplankton/Biogeochemistry	662 – 672 nm
Band 14	1000m Ocean Color/Phytoplankton/Biogeochemistry	673 – 683 nm
Band 15	1000m Ocean Color/Phytoplankton/Biogeochemistry	743 – 753 nm
Band 16	1000m Ocean Color/Phytoplankton/Biogeochemistry	862 – 877 nm
Band 17	1000m Atmospheric Water Vapor	890 – 920 nm
Band 18	1000m Atmospheric Water Vapor	931 – 941 nm
Band 19	1000m Atmospheric Water Vapor	915 – 965 nm

Band 20	1000m Surface Cloud Temperature	3929 – 3989 nm
Band 21	1000m Surface Cloud Temperature	3929 – 3989 nm
Band 22	1000m Surface Cloud Temperature	3929 – 3989 nm
Band 23	1000m Surface Cloud Temperature	4020 – 4080 nm
Band 24	1000m Atmospheric Temperature	4433 – 4498 nm
Band 25	1000m Atmospheric Temperature	4482 – 4549 nm
Band 26	1000m Cirrus Cloud Water Vapor	1360 – 1390 nm
Band 27	1000m Cirrus Cloud Water Vapor	6535 – 6895 nm
Band 28	1000m Cirrus Cloud Water Vapor	7175 – 7475 nm
Band 29	1000m Cloud Properties	8400 – 8700 nm
Band 30	1000m Ozone	9580 – 9880 nm
Band 31	1000m Surface/Cloud Temperature	10780 – 11280 nm
Band 32	1000m Surface/Cloud Temperature	11770 – 12270 nm
Band 33	1000m Cloud Top Altitude	13185 – 13485 nm
Band 34	1000m Cloud Top Altitude	13485 – 13785 nm
Band 35	1000m Cloud Top Altitude	13785 – 14085 nm
Band 36	1000m Cloud Top Altitude	14085 – 14385 nm

An adaptation from information provided by modis.gsfc.nasa.gov

Machine learning techniques are becoming a more popular avenue for water quality measurement. As of 2019 Aquasat has emerged as a useful tool in this sector as described in Kelvey (2021) This program uses machine learning to make accurate predictions of water quality at a global scale. Images taken by Landsat, 5, 7, and 8 over a 30 year period were correlated with in situ samples taken from the United States Water Quality Portal. The 600,000 matchups of remote sensing and sample data used for training allow for more reliable predictions of water quality based on Landsat images alone. For AquaSat, interest lied in chlorophyll-a as a measure of algae in water that turns it green, sediments yielding a tan color, dissolved carbon that darkens the water and indicates carbon leeched from the landscape, and Secchi disk depth as a measure of total water clarity. In the future, the design team is looking to incorporate more satellite datasets like MODIS to create an even more powerful tool for water quality assessment. This tool is one that could be essential across all the water quality events discussed in this paper and will be something to consider moving forward in future research.

CHAPTER 3

HARMFUL ALGAL BLOOMS

Harmful algal blooms (HABs) have emerged as one of the most prevalent and severe environmental problems of inland waterbodies (Hou et. al 2022). They are caused by microscopic, photosynthetic organisms that, like all other organisms, require sunlight and nutrients to grow. They are the foundation of food chains and webs in aquatic environments. When nutrient loading occurs from agricultural and urban runoff, the abundance of nutrients causes the concentrations of these bacteria to grow uncontrollably, resulting in HABs (Klemas 2012). Blooms typically occur in the spring when longer days provide stronger sunlight. Water warms and becomes less dense, allowing stratification. The upper stratified layer retains the bacteria where the sun is bright, and nutrients are plentiful. (Klemas 2012).

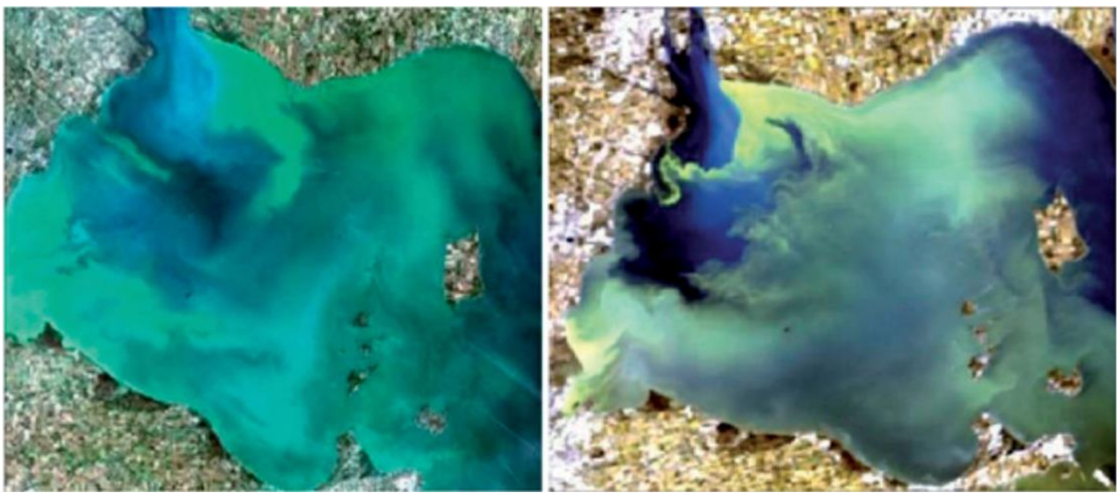
Figure 1: HABs on Lake Erie

Photo from NOAA Great Lakes Environmental Research Lab

Eutrophication is the process of excessive loading of nutrients. Eutrophication can disrupt the natural cycling and retention of essential nutrients in a water system. This imbalance promotes the formation of HABs, further degrading the aquatic system (Binding et. al. 2018). As the organisms grow, a thick layer of algae begins to form on the surface of the water. Sunlight is blocked from reaching lower levels of the waterbody inhibiting growth of benthic, photosynthetic organisms. In addition, when algae and bacteria from HABs die, the decomposition process uses up most of the surrounding oxygen. This results in "dead zones" where there is so little oxygen that aquatic life cannot survive (Denchak and Strum, 2019). Cyanobacteria is the most common type of freshwater HAB. About 60% of cyanobacteria samples contain toxins. Toxins released from HABs can quickly move through the food chain. One of the primary threats HABs pose to human health is contaminated drinking water and aquaculture (Stroming et.al. 2020). Not only do HABs pose a risk to human health, but they can also be costly and detrimental to economy. Decreasing tourism, recreation, and property values while increasing need for monitoring, testing, and water treatment. It is estimated that freshwater algal blooms cost the nation nearly $4.8 billion annually (Denchak and Strum, 2019).

Magnitude and frequency of these blooms is increasing globally (Klemas 2012). Early detection and comprehensive monitoring of HABs is fundamental to effective management and mitigation of detrimental impacts (Binding et.al. 2020). However, before effective mitigation techniques can be taken, spatial and temporal distribution of HABs must be understood. While some algae are able to move throughout the water column, remaining undetected, algae formed in calm weather on the surface, can be detected (Hou et. al. 2022). Chlorophyll-a (Chl-a) pigments act as an optical signatures of algal blooms. Chl-a mainly reflects green, absorbing energy from violet-blue and orange-red wavelengths (**Gholizadeh et. al. 2016).** Satellite measurements of reflectance can pick up on the green wavelengths, presenting an efficient way for monitoring HABs (Klemas 2012).

Figure 2: Images of Algal Blooms Captured by Sentinel Satellites



Images of Algal Blooms in Lake Erie, captured by Sentinel-2 (left) and Sentinel-3 (right). Photo from Pirasteh et. al. (2020) study.

Previously, in situ measurements of HABs have been limited both spatially and temporally due to time and cost. However, by utilizing satellite technology and its ability to pick up on optical signatures of water quality parameters, like the chlorophyll in HABs, alternative means of assessing HABs can be explored using remote sensing. It can be used to identify blooms and quantify abundance (Coffer et. al. 2020).

Previous Research

HABs are a pressing issue across the world in all types of waterbodies, and thus an extensive amount of research has been conducted by the scientific community on this topic. Remote Sensing was first documented in the Great Lakes in the 1970s, with Landsat data, to explore identification of particulate contaminants, whiting events, and chlorophyll-a (Binding et.al. 2020). Since then, various satellites and algorithms have been put into practice with various levels of strengths and weaknesses in detecting water quality related to HABs.

Landsat series has been used for bloom detection in the past however, with the launch of many new satellites, we have entered an era of unprecedented high resolution data availability with spectral bands specific for HABs detection. Chlorophyll retrieval algorithms are based on blue/green band ratios but can be difficult to detect in optically complex waters. Limitations of remote sensing (cloud cover, image frequency) are mitigated by the integration of hydrodynamic and ecological monitoring (Binding et. al. 2020). Studies like Hou et.al (2022), Gholizadeh et.al. (2016), and Klemas et. al. (2012) have relied solely on Landsat data and have received promising and reliable results. Hou et. al. 2022 used a color-based algorithm, with extensive validation the authors were able to prove the reliability of this system for HABs data retrieval. Gholizadeh et.al. (2016) stressed the importance of using more than one band to decern optical properties of chlorophyll-a with wavelengths residing near 675 nm and 700 nm.

Klemas et. al. (2012) used a threshold point, meaning that any readings above the threshold represented cyanobacteria in the water and anything on the lower side of the threshold represented clear waters. This method, while effective, is highly debated in other papers as it is unclear amongst researchers what that threshold number should be.

Other researchers have utilized different sensors in their studies like MODIS, Meris, and Sentinel datasets. Binding et.al. (2018) utilized MERIS maximum chlorophyll index (MCI) to quantify peak radiance near 700 nm, measured by Band 9. The HABs flag was raised on a pixel-by-pixel basis when chlorophyll-a measurements exceeded 10 micrograms^{-1}. The authors found that results of satellite data were skewed heavily by weather, specifically wind. The wind causes mixing and algae will mix into lower parts of the water column where it isn't detectable via satellite, resulting in lower readings. This however would not be a problem specifically related to MERIS; it likely will affects readings from other similar sensors as well.

Many recent studies have begun testing a multi-sensor approach for detecting HABs and are showing promising results. Coffer et. al (2020), Ma et. al. (2021), and Page et. al. (2018) are some such studies that recently tested multi sensor approaches. Coffer et. al. (2020) used MERIS and Sentinel-3A with a spectral shape algorithm. This approach is similar to that of Klemas et. al. (2012), if the fluorescence band of 681 nm fell below the threshold, this indicated that cyanobacteria was present in the water body. Again, this approach is highly debated by professionals in the field because of the disagreement of what the threshold should be. However, Ma et. al. (2021) and Page et. al (2018) had different approaches. Ma et. al (2021) used a combination of Terra/Aqua Modis, Landsat 8 OLI, and Sentinel-2A/B MSI. The struggle faced in this study was finding an algorithm that was appropriate for all three sensors. Researchers settled on a combination of the normalized difference vegetative index and chlorophyll reflection peak intensity index for this study to avoid misidentification of water and algal mixed pixels. The combination of these sensors provides monitoring up to three times per day, providing more efficient and accurate data. Page et. al. (2018) had a similar approach using Landsat 8 OLI and Sentinel-2A. Again, using a combination of different indexes and after adjusting calculations according to the different bands on each sensor, this study proved successful in utilizing a multi-sensor approach.

Recommended Practices

Given the vast expanse of knowledge and methods utilized across different studies, there is no clear best practice. However, there are key points that stand out across the reviewed literature. Which sensors have performed the best? What wavelengths best detect reflectance? How could a Multi-sensor approach be beneficial in future studies? Regardless of which sensor is used, it is stressed across all studies that more than one reference band should be utilized and these wavelengths should range between 550 and 700nm for peak reflectance. More specifically, one band around 665nm and another around 709 nm were most frequently used to retrieve chlorophyll reflectance data. Atmospheric correction is important for mitigating error in readings, and it is important to find the right algorithms to apply. The floating algae index (FLI) created for MODIS appears to be sensor independent, meaning it can be applied across a wide range of different satellites and can be used to calibrate other algorithms. Multi-sensor approach provides higher observation frequency and more detailed spatial information on algal blooms (Ma et. al. 2021). This practice could be incredibly beneficial moving forward, however will require more research to find algorithms that can be applied across various sensors. In situ testing is important for validating results and moving forward with remote sensing techniques.

CHAPTER 4

ACID MINE DRAINAGE

According to the US Environmental Protection Agency, environmental risks due to Acid Mine Drainage (AMD) are “second only to global warming and ozone depletion”. Mining activities across the world cause environmental damage and changes to the earth’s surface and underground. According to recent studies, approximately 19,300 km of streams and rivers and about 720 km^2 of lakes and reservoirs worldwide are affected by mine effluent (Blahwar et. al. 2012). In the US alone, thousands of abandon coal mines have been polluting rivers and streams for decades and only about ¼ of the damage has been cleaned up in the past 40 years (Phillis, 2021).

Figure 3: AMD in Belt Creek in Montana

This photo was adapted from Phillis (2021).

When water comes in contact with rocks that contain sulfate compounds, a chemical reaction occurs. This reaction causes waters to become highly acidic and encourages the dissolution of other heavy metals present in the mining area. The chemical equation for these reactions can be seen below:

$$4FeS_2 + 15O_2 + 14H_2O \rightarrow 4Fe(OH)_3 + 4SO_4^{-2} + 16H^+$$

The reactants of this equation are represented by pyrite, from mining activity (FeS_2) coming in contact with oxygen from the air (O_2) and water (H_2O). The reaction between these three elements produce ferric hydroxide $Fe(OH)_3$, sulfate (SO_4^{-2}), and hydrogen (H^+). Ferric hydroxide is the precipitate that contributes to the bright orange color of AMD. The increase in hydrogen ions is what contributes to the significant decrease in pH resulting in acidic waters (Acharya and Kharel 2020). The acidic water enhances dissolution of minerals from surrounding rocks and soils, leading to high levels of total dissolved solids (TDS) and metal contamination in mine discharge. The geochemical processes ultimately render stream water and sediments toxic, making the water unfit for drinking and recreation and adversely effects mining equipment and aquatic ecosystems (Phillis, 2021).

Treatment of AMD is often complex, costly, and challenging and may vary with site conditions, composition of acid mine water, and treatment methods (Acharya and Kharel 2020). In 2021 the Senate passed an infrastructure bill providing $11.3 billion for cleanup of defunct coal mines to be distributed over 15 years. The federal program funds cleanups in order of priority. Those that pose safety hazards to human health and pose risk to drinking water sources are at the top of the list. US officials are estimating $10.6 billion in construction costs will be needed to fix more than 20,000 problems nationwide. However, there is controversy about whether such resources will be enough (Phillis 2021). This presents an urgency to develop an efficient way of detecting priority waterbodies so action can be taken, and money is well spent. Remote sensing may prove to be a useful resource in this sense thanks to its accessibility, affordability, and wide spatial range.

Traditional remote sensing techniques use optical properties of watercolor to detect the presence of spectral variation in contaminated waters (Riaza et. al. 2015). The spectral characteristics of AMD are unique as the oxidized iron created a bright orange/red color in the water, which should be distinguishable using remote sensing techniques.

Figure 4: Satellite Image of AMD

This image was retrieved from earthexplorer.usgs.org

Earth remote sensing data (or “Earth Observations”) can substantially improve environmental monitoring of mining areas and image spectroscopy can be considered as a substantial addition or alternative to conventional methods and an efficient way to estimate AMD related contamination (Pyankov et. al. 2021). The following section will review previous studies and methods used to detect and measure AMD events in various waterbodies to determine which techniques presented the best results and what the recommended methods are for future research in detecting AMD using remote sensing technology.

Previous Research

In Davies and Calvin (2017), researchers performed lab scale simulation of AMD to study the unique spectral response of AMD from a lab setting to better interpret mine water bodies in remote sensing imagery. Researchers explored the potential use of visible to short wave infrared wavelengths to analyze water quality in pit lakes. They prepared solutions with increasing Fe^{+3} and Fe^{+2} concentrations to mimic the chemical properties of local AMD. The spectral response of synthetic and local AMD was measured using a field spectrometer and synthetic solutions were compared to local AMD for quantitative assessment. The results showed that the spectral signatures of Fe^{+3} were dominating and possessed distinct characteristics that may be used for diagnostic identification. Wavelengths between 350 and 625nm were especially useful in quantifying Fe^{+3} concentrations. Generally, reflectance was seen to decrease as ferric sulfate concentrations increased. Samples that were filtered before testing were found to have a lower total reflectance which is consistent with the idea that more particles in water will cause a greater scattering effect, thus increased reflectance. These results are very promising and suggest that water quality related to AMD may be qualitatively and quantitatively measured using remote sensing technology.

Methodology for studies that utilized remote sensing technology to detect AMD varied vastly. Some used satellites like Landsat and Sentinel datasets while others utilized unmanned aerial systems. Relationships between spectral characteristics of contaminated water, measured pH, and total Fe concentrations have been found. AMD as well as technogenic sediment formed during acidification had higher spectral reflectance in wavelength ranges of 650-750 nm than neutral waters (Pyankov et. al. 2021) These characteristics can be utilized by satellite imaging like Landsat and Sentinel. There are great benefits to utilizing these datasets, the data is free and available to the public, Sentinel satellites provide high temporal resolution (3-4 images per week in cloud free conditions), and the availability of 10 spectral bands in the visible near infrared region are all aspects that provide great potential for identifying AMD related water contamination (Kopackova, 2019). Blahwar et. al. (2012), Kopackova, (2019), and Seifi et. al. (2019) all used variations of satellites including Landsat, QuickBird, and Sentinel data for their research, producing promising results.

Blahwar et. al. (2012) utilized Landsat-7 ETM+ and hybrid false color composites using different combinations of band ratios and stacking with red, green, and blue filters. They found that the best image that highlighted iron precipitates on dry stream beds had the combination (B3/B1, B5/B4, B5/B7 =

red, green, blue, respectively). The ratio B3/B1 is suitable for detecting iron oxides, B5/B4 for ferrous minerals, and B5.B7 for clay minerals. Band ratios from Blahwar et. al. (2012) showed vegetation appearing blue and barren land appearing yellow and green. The riverbed appeared in shades of red-orange-yellow in the presence of iron in water/suspended sediments. In Kopackova (2019) study they introduced a new index for Sentinel-2 data, $D_{s\text{-}2(AMD)}$ allowing for mapping of AMD and differentiation between secondary minerals such as jarosite and other oxyhydroxides. The biggest spectral differences between the two groups of minerals were seen between 560 and 782 nm. The threshold value to differentiate between the two mineral groups was set using standard deviation method. Values higher than mean +1 were classified as oxy-hydroxides-dominating pixels and values higher than mean +2 were classified as Jarosite dominating pixels. The new index allowed for sufficient differentiation between the two groups and demonstrated Sentinel-2's ability to map seasonal variations in AMD.

Seifi et. al (2019) used Sentinel-2A and field data to identify and map iron bearing minerals to determine AMD production. The spectral angle parameter method was applied to Sentinel 2a images to identify AMD minerals and classify the study area. Fast line-of-sight atmospheric analysis of spectral hydrocubes algorithm was implemented on Sentinel 2a images to remove noise and obtain surface reflectance data. The produced map was verified with field surveys. Like Kopackova (2019), researchers in this study also looked to identify spectral differences in secondary AMD minerals such as, jarosite, goethite, and hematite. Sentinel 2a spectra presented absorption features in 430-480nm for all classes (band 1 for jarosite bearing classes and band 2 for all others), in 500-670 nm for hematite, goethite-hematite, goethite and jarosite-goethite classes (band 4 for hematite and goethite bearing classes), and in 850-940 nm for goethite-hematite and goethite classes (band 8 for goethite bearing classes). Overall accuracy of the mapping using the spectral angle mapper was 75%. Despite what may seem like positive results, there are limitations of using satellite datasets, course spatial resolutions and cloudiness can limit the reliability of satellite data.

More recently development of hyperspectral imaging has proved useful at expanding opportunities for remote sensing of AMD. Airborne hyperspectral data provides higher spatial and spectral resolution, which is crucial for identifying AMD (Kopackova, 2019). Sensors like HyMap, especially, can detect AMD minerals within the water, these measurements can serve as proxies for low pH, acid mine waters, and mine waste byproducts (Jackisch et. al. 2018). In the Jackisch et. al. (2018) study high resolution point clouds and DEMs were built from drone-borne RGB data using structure from motion multi-view stereo photogrammetry. The hyperspectral data was able to pick up on secondary AMD minerals, like jarosite and goethite with ease. Specific iron absorption bands in the unmanned aerial system (UAS)-hyperspectral image (HIS) data were identified and features were confirmed by in situ spectroscopy and in situ pH results validate UAS based mineral classification results. Evaluation of applied methods demonstrates drone surveying is a fast, non-invasive, inexpensive technique for multi-temporal environmental monitoring of post-mining landscape.

When using hyperspectral data, reference libraries can be utilized as in Riaza et. al. 2011 to ensure the output of a reasonable map when diagnosing spectra. Referencing spectral libraries are useful to assess oxidation or hydration stage of a mineral mixture. They also help establish statistical evaluations of scores produced by mineralogical diagnoses. For this study interpreter-oriented sequential spectral unmixing was applied, using standard algorithms, to extract features for thematic purposes, enabling the display of spatial patterns and spectral identification pixels within the scene as a map. Researchers of this study restricted the map area so that contaminated areas can easily be detected, and patterns could be assessed to interpret climate change trends, metal contamination and make AMD predictions. Again, while results of these studies seem strong, there are limitations of using airborne hyperspectral data. It can only be used in local areas as opposed to satellite earth observations, which can monitor large geographic areas.

Recommendation

Current research in the use of remote sensing data in detecting and monitoring mine-related water pollution impacts is limited, and methods are not uniform with some research focusing on using satellites and others using UAS. Clearly there are advantages and disadvantages to both methods however even within those two groups methods of data retrieval and algorithms vary. Once again there haven't been enough studies to provide a clear best practice. There is a need for more research for the effective use of remote sensing techniques in understanding coal mine production, gathering soil and water samples, and integrating hyperspectral images with field data. Which bands are ideal for detection of AMD? How and when might remote sensing measurements of AMD be skewed? There is a need for regular monitoring of acid mine drainage and water quality from overburden, rock dumps, refuse piles, mine tailings, and diffuse seeps to determine emerging problems, sought proper treatment designs, and reclaim mine sites for future use (Acharya and Kharel, 2020). However, from the research available some recommendations can be utilized across all platforms. Similar to measuring harmful algal blooms, influences such as vegetative material or the atmosphere must be accounted for and avoided as much as possible for reliable results. Reflectance peaks between 570 and 700 nm are found to be common across almost all studies. Thus, the red and red edge spectral bands are crucial in detecting AMD related contamination in separating pollute water from pure water. It is also important to note that across many studies, it was noted that in dry season metal contaminates seemed to increase and dilute in wet season. Perhaps measurements taken in dry spells may be more accurate when determining list of priority waterbodies.

CHAPTER 5

SUSPENDED SEDIMENT

Water transparency is an important indicator of water quality and ecosystem health, and directly indicates light transmittance of water bodies, a widely used parameter in water quality monitoring (Cui et. al. 2022). Suspended sediments are a dominant water constituent in inland and coastal waters and suspended sediment concentration (SSC) is a key parameter describing water transparency and hence, quality (Liu et. al. 2017). SSC includes a wide range of particulate material for the given water column. They can contain organic matter, inorganic matter, and microorganisms that are insoluble in water. Each of these constituents pose a significant impact on spatial and temporal aspects of the optical properties of a water body (Blix et. al. 2018). Researchers have shown that water clarity is correlated with a number of water quality variables, including, trophic state, hypolimnetic oxygen concentrations, along with suspended sediment concentrations.

Figure 5: Suspended Sediment in Tuscaloosa Lake

Photo Credit: City of Tuscaloosa via USGS

As the world continues to urbanize, populations in coastal areas are growing rapidly. This creates a growing need to monitor water quality in adjacent watersheds consisting of aquatic ecosystems like lakes, lagoons, and estuaries (Jally et. al. 2021). Human induced stresses are negatively affecting biological and physical processes in waterbodies. Pollution, sediment accumulation and introduction of exotic biology break the ecological balance of these ecosystems. Suspended sediments reduced storage capacity, minimizing flood control, and reduce light penetration to benthic aquatic communities (Li and Li 2004). Assessment of sediment influx is crucial to understanding processes that sustains water quality and geomorphic balance (Jally et. al. 2021). Degradation of lakes is gradual but can be nearly impossible to reverse (Li and Li, 2004). Regular monitoring of suspended solid fluctuations will be essential for understanding how they impact aquatic ecosystems, effects on communities, and how the problem can be mitigated.

In the past secchi disks have been relied on for measurements of water transparency in the field; however, this method is labor and cost intensive and has low sampling efficiency (Cui et. al. 2022). It is technically challenging to monitor SSC and distribution in large waterbodies let alone numerous systems across large scale region (Du et. al. 2022). However, SSC impacts light transmission. By using these characteristic absorption and scattering patterns of sunlight, remote sensing can be used to monitor fluctuations in suspended sediments. Intensity of the reflected signal can be used to determine particulate concentrations (Sydor et. al. 1978). Remote sensing techniques would make it possible to monitor and identify large scale regions and waterbodies that suffer from qualitative problems more effective and efficiently (Gholizadeh et. al. 2016).

Figure 6: Image of Suspended Sediment Captured by MODIS

Image of suspended sediments in the Great Lakes, captured by MODIS Terra Satellite. Photo accessed from NASA Earth Observatory.

Obtaining information on concentration at high spatiotemporal resolution is necessary for understanding water quality dynamics and identifying driving forces for further management and protection of aquatic ecosystems. Satellite remote sensing can provide synoptic observations from visible to near infrared spectral regions, which can be used to derive suspended sediment concentrations in water (Liu et. al. 2017). The following section will review previous research conducted using these techniques to evaluate which methods will be useful in future research monitoring suspended solids in varying aquatic systems.

Previous Research

The assessment of water’s optically active parameters relies on the knowledge of the behavior of light in waters. Molecular scattering of pure water follows a parabolic trend with higher values at short wavelengths, while absorption is highest in the red to infrared spectrum. Light scattering by suspended sediment strongly depends on the particle size, shape, and composition. The inorganic fraction of suspended sediments scatters light significantly while absorption is negligible (Giardino et. al. 2014**)**. Absorption and backscattering of light by suspended components influence the shape and magnitude of the water leaving reflectance, which is information that can be retrieved by remote sensing sensors (Giardino et. al. 2014**).** Secchi disk transparency has a strong correlation with satellite spectral-radiometric observation in lakes. Clearer water absorbs relatively little energy having wavelengths less than 600 nm, in the blue green portion of the spectrum. As turbidity changes, transmittance, and reflectance change, resulting in much higher visible light reflectance, lakes loaded with sediment reflect less blue and more red light. Overall, when the amount of blue light reflectance is high and red light reflectance is low, this indicated high water quality (Li and Li, 2004). Most studies have found that the red to near infrared spectra is most appropriate when monitoring suspended sediment concentrations. Red bands provide detailed information about horizontal distribution due to the effect of size, shape, and texture of particles (Jally et. al. 2021).

Most recently, in terms of satellite data, the most common sources for total suspended sediment concentration retrieval have been Landsat, specifically Landsat TM and OLI, followed closely by Sentinel-2 MSI. Beyond satellites, many highly suitable models have been developed in a variety of studies to accurately predict suspended sediment concentrations. Previous studies have shown the feasibility of using red spectra-based models to estimate water transparency and related parameters with good accuracy in moderately turbid lakes (Du et. al. 2022). However, more specific models are needed to be developed for more reliable results. Most recent research used Landsat to develop these models. In Du et. al. (2022), researchers developed a new algorithm for remotely estimating suspended solid concentrations. Necessity was based on the poor universality of the total suspended solids model developed for certain optically complex waters. This new algorithm was based on samples from lakes and reservoirs across the Eastern Plain Lake Zone in China. Although total suspended solids would be both over and underestimated, the logarithmic transformation linear model developed was satisfactory compared to previously reported studies

Jally et. al. used Landsat 8 OLI and in situ measurements to develop a site-specific algorithm for retrieval of suspended sediment concentration data. In this study algorithms were tested to establish a relationship between remote sensing reflectance of OLI2, OLI3, OLI4 and in situ observed suspended sediment concentrations. The model results show that the spatial distribution of satellite estimated SSC and in situ observed SSC follow a similar pattern. Landsat 8 OLI was also able to capture seasonal variability in all sectors of the lake. In some areas of the lake, bottom reflectance led to slight overestimations in SSC, but ultimately the SSC model developed in this study can be used as an essential tool to monitor SSC in study area and other similar lakes. Out of all the algorithms, multi band linear regression model with a new site-specific coefficient was found to be the most suitable for the estimation of SSC as compared to the single band linear regression model.

When using Sentinel-2 MSI, Liu et. al. (2017) researchers aimed to develop models for suspended solid concentration to compare with MODIS estimations and identify the appropriate spectral bands for suspended sediment concentration retrieval. Researchers of this study found that models based on B7 located at 783 nm appeared to be the most accurate retrieval method. Suspended sediment concentrations were generally consistent in spatial distribution and magnitude to those derived from MODIS. Specifically, the Sentinel-2 MSI B4, at 665 nm, was recommended for low loadings and B7, at

783 nm, was recommended for high loading. The high quality SWIR bands of Sentinel-2 MSI were important and vital to the success of suspended solid concentration retrieval because they facilitate the atmospheric correction over Case II waters.

Cui et. al. (2022) used a multi sensor approach. Data from both Landsat 8 OLI and Sentinel-2 MSI were used to provide a higher reoccurrence of data. Using the convolutional neural network (CNN) model water transparency data was retrieved to determine the best, most reliable methods. Before building the retrieval model, the digital numbers in images were converted into the water remote sensing reflectance and reflectance of Ultra, B, G, R, and NIR in the MSI and OLI sensors were used as inputs to the model. From there the point-centered regression convolutional neural network (PSRCNN) model was constructed and trained. This model used five consistent band reflectances and 20 band ratio combinations in Landsat OLI and Sentinel-2 MSI images as the input variables. Comparison with commonly used retrieval models such as band ratio, random forest, and support vector regression showed that the $PSRCNN_{opt}$ has the best performance with higher accuracy and robustness. However, it was comparatively less stable owing to the limitations of the available sample numbers as CNNs need high volumes of sample data to be accurate.

Recommendation

Overall, it is clear that regular monitoring of suspended sediment concentration using Landsat 8 OLI can be helpful for monitoring different environmental problems in lakes such as accumulation of sediment, effectiveness of dredging activities, areas with high probability of algal blooms, impact of sediment on sea grass habitats, overall water transparency, and productivity of the lake. Satellite data may also reduce the necessity of expensive and extensive fieldwork for collecting ground data. Use of remote sensing data will enhance in depth understanding of ecosystem responses against environmental changes in lake ecosystems (Jally et. al. 2021). However, further research will be needed in this field to develop algorithms so remote sensing data can be more heavily relied on. Machine learning may be a useful tool to look into for this due to limitations of empirical models in spatial and temporal scales. Providing an effective method to solve the nonlinear regression problem between water remote sensing reflectance and water transparency (Cui et. al. 2022). At the very least, using a multi-sensor approach would mitigate the problem of revisit frequency in Landsat data, combining data retrieved from Sentinel-2 and Landsat 8 would provide a revisit time of 2.9 days, improving the availability to retrieve water quality parameters.

Which sensors are ideal for monitoring suspended sediment concentrations? How can images of suspended sediment from satellites be reliable? Future research should focus on datasets from Landsat 8 OLI and Sentinel-2 MSI. Images selected for assessment should be high quality and cloud free.

Atmospheric correction is necessary as well as masking vegetative patches and areas where subsurface vegetation may skew results. The red to near infrared range is most suitable for detecting suspended solid concentrations, thus, bands that fall in the 700 to 800 nm range. To determine a well-fitting predictive relationship, an abundant number of ground-based measurements will need to be taken to validate data from remote sensing.

CHAPTER 6

DISSCUSSION

Water color is influenced greatly by suspended and dissolved particles and contaminants. Algal blooms appear green because of the chlorophyll content of the algae. Acid mine drainage appears red or orange due to the high concentration of heavy metals, and specifically the oxidation of sulfate compounds from the soil. Suspended sediments appear brown or tan from the natural dissolved organic matter. Generally, colored water is an indicator of poor water quality that can impart adverse effects on human health and aquatic environments. Typically, in situ measurements have been relied upon as an indicator of water quality however, this approach is limiting. In situ measurements are subject to error and are not reflective of conditions throughout the entire water body. Satellite remote sensing provides the opportunity for water quality to be monitored and quantified across the entire waterbody simultaneously. Historical data can be used to map trends and forecast future water quality events.

Across all three water quality events analyzed, algal blooms, acid mine drainage, and suspended sediments there seemed to be many commonalities in practices and techniques. One of the goals of this paper is to find reliable techniques for identifying and monitoring water quality events collectively and in a timely manner. Given this goal, satellite remote sensing seems to be the platform of choice giving the low cost and highly accessible nature of these datasets across all three events of focus. Most research studies provided promising results, weaknesses in data retrieval and image processing are being researched constantly and satellite technology is only getting better as time goes on. When utilizing satellite images there are areas of note. Overall, when amount of blue light reflectance is low and red light reflectance is high, this is indicative of poor water quality.

To retrieve reliable data, atmospheric correction is a vital aspect of data processing. In addition, vegetation can cause skewed results especially when measuring algal blooms given the importance of green reflectance. It is important to mask off heavily vegetative areas and utilize algorithms that remove vegetative influences in images such as the normalized difference vegetative index. As for datasets, Landsat and Sentinel appear to be the most reliable and frequently used. The main setback to Landsat is the infrequent revisit time of 16 days especially if a revisit coincides with cloudy conditions that result in unusable data. The launch of Landsat 9 should help this problem cutting revisit time down to 8 days. However, multi-sensor approaches also proved useful for mitigating this problem. For the time being, in situ measurements are vital for verifying results gathered from remote sensing. AquaSat provides a useful platform for this, correlating in situ data with data received from Landsat. With future plans to incorporate additional datasets like MODIS, AquaSat could prove to be a powerful tool moving forward in water quality analysis and is something future research should consider utilizing. Right now, building models and making water quality predictions require some coding skills, but the ultimate goal is to create a user-friendly interface that could be used by water quality and environmental professionals to make decisions about water resources.

Beyond general best practices for remote sensing there are specific bands and wavelengths that work best for detecting each water quality event. For remote sensing of algal blooms using more than one band is ideal with reflectance peaks targeted around 665 and 709 nm for retrieving chlorophyll reflectance data. For acid mine drainage related contamination red and red edge spectral bands are crucial. Wavelengths ranged between 570 and 700nm. For AMD it is important to note that metal contamination tends to increase in dry season when heavy metal contaminants are less diluted. Thus, dry season may provide the most reliable results when determining waterbodies of highest priority. Finally, for suspended sediments, the red to near infrared spectra is the best fit with wavelengths ranging between 700 and 800 nm, 650 nm for less severe cases.

Table 4: Corresponding Wavelengths for Water Quality Assessment

Event	**Reflectance Color/Spectra**	**Wavelengths**
Algal Blooms	Blue/Green	665 and 709 nm
Acid Mine Drainage	Orange/Red	570-700 nm
Suspended Sediments	Brown/Tan	700-800 nm

When monitoring water quality, there are two other important factors to consider in future studies. The first is water temperature. Water temperature is an important parameter for understanding the physical and biochemical processes occurring within a waterbody. It influences solubility, and thus availability of chemical constituents in water (Gholizadeh et. al 2016). This is important when considering concentration of heavy metals from AMD or suspended sediment concentrations. More importantly, water temperature has an indirect relationship with dissolved oxygen. Oxygen solubility decreases with increasing temperatures. Coupled with the algal blooms which thrive in warmer waters, this poses a detrimental effect on aquatic ecosystems. As algae grows thicker, the darker surface of the algae absorbs more sunlight resulting in even warmer waters and more algal growth (Denchak and Strum, 2019). Water temperature can be easily recorded with remote sensing using thermal infrared bands, located on most modern satellites. Derived from radiometric observations at wavelengths near 10,000 nm (Giardino et. al. 2014). It is a quick and easy thing to monitor and can be a very useful parameter to keep track of to understand spatial and temporal trends of water quality events.

The second factor to consider is the land use and land cover surrounding the waterbody. Land use plays a complex multi-faceted role in the hydrological cycle. Surface runoff is a major source of non-point source pollution and is responsible for the relationship between land use/cover and water quality.

Maillard and Santos (2008) study discusses how replacement of natural vegetation with agriculture and pastureland promotes surface runoff and sediment transport. Natural vegetation intercepts and reevaporates precipitation and influences other hydrological parameters such as percolation and surface runoff. When land is converted to impermeable surface or even just agricultural land, it promotes overland flow and erosion and prevents the replenishment of the water table. All these effects in turn influence water quality of nearby streams and rivers. Fertilizers can influence levels of phosphorus and nitrate and stock grazing may increase the presence of fecal bacteria resulting in contamination and algal blooms. Landscape patterns are everchanging and climate change is posing a serious threat to current landscapes. Quantifying these spatial patterns is not the end, but really the beginning to understanding ecological processes. If better understood and practiced, landscape patterns can play a useful role in understanding water quality causes and mitigation strategy (Li & Wu, 2004).

Although satellite remote sensing has been around and used thoroughly in water quality research since the 1970s, utilizing satellite earth observations and imagery for fairly regular water quality occurrences is simply not a common practice. As a part of Schaeffer et. al. (2013) study, researchers interviewed various stakeholders and environmental managers to determine why this was the case. The results mainly came down to cost, accuracy of data products in particular waterbodies, satellite mission continuity, and obtaining management approval for including satellite data in their work. As for cost, it was clear that it is not widely known that data from many reliable satellites such as Landsat, Sentinel, and MODIS can be accessed free of charge. Typical up-front costs may include hardware and required expertise to get started. Accuracy of data is another large challenge. Scientists do not yet trust the accuracy of remote sensing data. There is a widespread perception that traditional in situ samples represent ‘truth’ and less concern with the error that exists with in situ measurements not representing the entire waterbody. It needs to be stressed that the value of remote sensing is not always about absolute accuracy but synoptic and frequent coverage of numerous waterbodies and detecting relative changes and anomalous events in the observations. Some interviewees expressed concern about relying on a satellite that ends up going offline, a valid concern. However, satellites are necessary to provide future climate data, continuity in derived products will be of the utmost importance.

Future research in the field of remote sensing of water quality parameters should focus on the creation of tools to aid in monitoring and data collection techniques. A large limitation of remote sensing in the field is lack of knowledge. Stakeholders not knowing where to access remote sensing platforms or how to interpret the data. Using platforms such as Google Earth Engine to create tools that are easy to use will create a wider platform for remote sensing research to continue on. Eliminating the educational barrier that currently stands. There has been limited research in the field of acid mine drainage and using remote sensing as a monitoring technique. Creating a tool that can detect waterbodies across the United States that are suffering the effects will provide the necessary data to prioritize waterbodies for the allocation of federal funding for the next few years as these sites are cleaned up. By assembling this algorithm in the Google Earth Engine framework, researchers will be able to utilize, share, and embed findings into their own systems and seamlessly monitor and track acid mine drainage or other water quality parameters.

NASA has made significant progress in standardizing methods for successful missions. All in all, the use of satellite remote sensing comes down to interest in the workforce. Without people who know how to use it and are interested in implementing it, the interest is going to waste. Studies like Schaeffer et. al. (2013) are important and should be an area of focus. Identifying knowledge gaps will be crucial when trying to expand the field of remote sensing to include members of the public. Satellite remote sensing is too useful and readily available of a tool to be ignored. Ultimately, communication and education outreach are essential. There needs to be a push to inform the public about how they can integrate remote sensing techniques into their work. Providing workshops and engaging with environmental managers will prove useful in accomplishing this task. The water quality community needs to use remote sensing techniques and earth observation datasets in their own work to facilitate growth in the field, creating an environment where more research is gathered, and remote sensing of water quality becomes an even more reliable resource.

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