MONITORING WATER QUALITY IN COMPLEX WETLAND ECOSYSTEMS USING REMOTE SENSING: A CASE STUDY OF THE PEACE-ATHABASCA DELTA

by

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THESIS ABSTRACT

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Earth's hydrology is made up of complex systems which are spatially varied and influence a number of ecosystem processes. Complex ecosystems, in this case, are defined as those involving multiple bodies of water and land masses which are seasonally connected to one another through various processes, resulting in an intricate aquatic and terrestrial relationship in a single area. There have been advances in how we study these environments, yet it remains important to determine the most efficient tools in order to accurately monitor ecosystem health in these regions. Monitoring water quality in freshwater-dominated, wetland systems is costly and often impractical due to the remote locations of areas of interest. By exploring the methods of analysis in which remotely sensed data can be used to monitor changes in the spatial patterns of water quality, it is possible to study these complex ecosystems in a more frequent and effective manner.

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CHAPTER I

INTRODUCTION

Earth's hydrology is made up of spatially varied, complex systems which influence a number of ecosystem processes. Complex ecosystems, in this case, are defined here as those involving multiple bodies of water and land masses which are seasonally connected to one another, resulting in an intricate aquatic-terrestrial relationship in a single area. There have been advances in the ways in which we study these environments, yet it remains important to determine the most efficient tools in order to accurately monitor ecosystem health in these regions. The process of monitoring water quality in freshwater-dominated, wetland systems is costly and often impractical due to the generally isolated locations of these areas of interest. By exploring the methods of analysis in which remotely sensed data such as satellite imagery can be used to monitor changes in the spatial patterns of water quality, it is possible to study these complex ecosystems in a more frequent and cost effective manner (Liu et al., 2003). Understanding how recent advances can aid in the monitoring of water resources in complex ecosystems will allow for a more comprehensive and systematic methodology which can be used to analyze water quality.

Monitoring water quality of water resources in complex ecosystems is paramount to the understanding of the natural dynamics of these systems. As aquatic ecosystems and water in general continues to be highly influenced by both human and environmental factors, methods for monitoring the quality of these resources have continued to develop. In remote and complex environments it is both "insufficient" and "impractical" to rely solely on in situ (or field collected) data when studying subjects such as water quality

(Long & Pavelsky, 2009). Limitations can arise from ground-based data collection surveys due to the isolated nature of some complex ecosystems. These limitations can in turn impact the overall data accuracy due to the inability of field measurements to capture heterogeneity of water quality measures throughout the extent of the study area as a whole (Liu et al., 2003). Satellite remote sensing can aid in the spatially unbiased approach to collecting water quality measures across broad regions as it can sample entire areas at once (Li & Li, 2004).

More recent interest in developing long term environmental monitoring projects has furthered the development of new techniques for remote sensing primarily because of its ability to provide a perspective not available through any other avenue (Liu et al., 2003). The shift towards the use of remotely sensed data for aquatic ecosystem monitoring has taken many forms including: analysis of hydrologic recharge, volumetric storage fluctuation rates, hydrologic connectivity, flow velocity of river systems and more (Long & Pavelsky, 2013; Pavelsky & Smith, 2008; Pavelsky & Smith, 2009; Smith & Pavelsky, 2008). The use of remotely sensed data has allowed for studies previously not feasible or practical due to inaccessibility of study areas.

Development of new, more advanced multi-spectral and hyper-spectral sensors has opened the door for more accurate and precise analysis of satellite imagery. As the demand for long-term monitoring of environmental change, the implementation of remotely sensed data into scientific research has continued to grow due to the ability of sensors to capture data for the same area over multiple time periods (Liu et al., 2003).

Although the field of remote sensing has continued to develop methods for monitoring various aspects of aquatic ecosystem health there is still a sizable gap in the literature related to the application of remote sensing techniques for studying water quality. A majority of previously published work focuses on single parameters in a single study area which was readily accessed through multiple field campaigns. While this approach is necessary for developing a new and innovative methodology, there has been limited application of these processes in complex ecosystems. It is necessary to apply these techniques to a variety of environments in order to understand how effective they are in monitoring water quality.

This research will work to determine the extent to which three specific water quality parameters can be measured through a coupling of in situ and satellite imagery. Landsat 4-5 TM data will be analyzed alongside in situ data collected during two field campaigns by researchers Colleen Long and Tamlin Pavelsky in 2010 and 2011 (results of their research published in 2013). Based on regression analysis of the field data and the results of the models, this study will identify how well current methods can accurately quantify various water quality parameters within the Peace-Athabasca Delta (PAD), Canada. The Peace-Athabasca Delta covers an area of about 5,600 km^2 and is a mixture of lakes, rivers, shallow marshes, and terrestrial ecosystems (Timoney 2013). This study aims to analyze the ways in which water quality can be monitored using remotely sensed imagery, specifically in complex wetland ecosystems such as the PAD. The results of this study will address how well current methods for quantifying colored dissolved organic matter (CDOM), chlorophyll-*a* and suspended sediment concentration (SSC) in Landsat imagery are for monitoring water quality in a complex, aquatic ecosystem. Additionally, it will seek to understand the distribution of these parameters throughout the spatial extent of the study area of the PAD. This thesis will present an evaluation of current methodological approaches to monitoring water quality in complex ecosystems by addressing the following research question:

How well can Landsat imagery be utilized to detect dissolved organic carbon, chlorophyll-a concentrations and suspended sediment content from high latitude lakes and rivers?

Ultimately, this study will work to contribute to the body of literature by applying previously developed methods to a unique and complex system with the intent of producing a methodology which can be applied to other complex ecosystems. If, for example, CDOM is able to be predicted from Landsat imagery in the PAD it might be possible to monitor in many other regions, and with historical imagery.

CHAPTER II

BACKGROUND

Monitoring Water Quality in Freshwater Systems

Traditional methods for monitoring and measuring water quality parameters typically require researchers to travel to the field location for water samples and other observations for analysis. This process can be not only be time consuming but also expensive and logistically challenging. Not only can the equipment be costly but the transportation can be as well. In complex wetland systems like the PAD, it is extremely difficult to navigate the entire study are due to the nature of the area. While the area is hydraulically linked through a series of smaller streams and lakes connecting the larger rivers and lake systems to one another, transporting researchers as well as the necessary equipment can be almost impossible in many portions of the PAD. In regions where water quality can be monitored and water can be sampled it is extremely costly to logistically travel to those locations. The expansion of technology such as remote sensing has allowed for changes in how water quality is monitored in freshwater ecosystems. Not only does remote sensing change the spatial and temporal scales which can be monitored, but it also elucidates the relationship between the hydrology, landscape and organisms within the ecosystem (Mertes, 2002). Integration of satellite-based monitoring of water bodies, coupled with traditional sampling methods, offers the most efficient way to analyze and monitor water quality data (Liu et al., 2010). Additionally, remote sensing allows for more effective analysis of the immense amount of variability throughout a landscape because of the spatial resolution of satellite based sensors. One of the advantages of utilizing this technology is that it can be used to apply similar methods to any imagery across the globe which might not otherwise be able to be monitored frequently or at all for one reason or another. These technologies can also potentially allow for the estimation of historical water quality values in regions where ground measurements were not recorded due to the extensive collection of archived Landsat data (Kulkarni, 2011). The implementation of remote sensing technology, coupled with traditional field measurements has the potential to improve not only the quality of water quality measurements but also the spatial extent and frequency of such monitoring activities.

Water Quality Parameters

Water quality is a measure of the biological, chemical and physical properties of water (Liu et al., 2003). To study these aspects of water, research is primarily conducted by collecting samples in the field and performing analysis in a laboratory setting. There are a number of parameters that describe freshwater quality including: suspended sediment, pH, microorganism composition, minerals, chlorophyll content, water temperature, salinity, and bathymetric properties. Dissolved elements are also of great importance when determining the overall quality of water. While the acceptable concentrations of these elements may vary depending on the intended use of the water, even small changes in their respective concentrations can have a significant negative impact on the health of both humans and aquatic organisms. CDOM, chlorophyll-a and SSC were selected as the water quality parameters in this study not only because of the role they play in determining general aquatic ecosystem health, but also because of their applicability to a variety of other regions.

The carbon cycle is based primarily on carbon dioxide which is fixed by plants through photosynthesis. For aquatic systems, carbon is important to monitor because of its role in photosynthesis and primary productivity (Spellman & Drinan, 2001). Studying Dissolved organic carbon (DOC) in aquatic ecosystems is significant in that wetlands and lakes act as sinks for atmospheric carbon and play a large role in carbon cycling at a global level (Cardille et al., 2013; Kutser et al., 2014). CDOM can be used as a proxy for monitoring DOC. Griffin et al. (2011) developed a simple algorithm for converting CDOM to DOC. Chlorophyll content is an indicator of primary productivity (particularly in regards to phytoplankton in aquatic ecosystems) and can be informative when monitoring eutrophication and algal blooms (Huang et al., 2014). Chlorophyll-a is a pigment that is found in almost all plants and is critical for photosynthesis to occur. Generally, concentrations of chlorophyll-a are used to determine the trophic status and water quality (Kulkarni, 2011; Huang et al., 2014). Water clarity is an important factor in ecosystem health in terms of light penetration and availability for both plant and animal species. This element of ecosystem health can be influenced by SSC which can block sunlight or limit the depth at which the light is able to penetrate a body of water. In the case of inland deltas like the PAD, sediment transport and deposition plays a large role in shaping the landscape and nutrient dynamics (Long & Pavelsky, 2013). These three water quality parameters are important in all freshwater systems, therefore analyzing these in particular will allow for the results of this study to be more widely applied.

Study Area

General

The PAD is composed of a mix of terrestrial and aquatic ecosystems which has a watershed spanning about 595,000 km^2 (Timoney, 2013). Within the extent of the PAD, there are numerous active deltas, rivers, and lakes which are connected to one another through a variety of small channels. This study will explore the ways in which remotely sensed data in combination with data collected in situ can be used to monitor changes in water quality. The Peace-Athabasca Delta is an ideal study area for this work because of the direct interaction between its terrestrial and aquatic ecosystems. This region displays a highly spatially heterogeneous pattern between its terrestrial and aquatic ecosystem processes, but has proven difficult to monitor using traditional field methods due to the heterogeneous and remote nature of the landscape. These characteristics make the PAD it an ideal study site for developing remote sensing methodologies because of the amount of variation in water bodies within a single area.

Located in the northeastern corner of Alberta, Canada, the Peace-Athabasca Delta is found within the Wood Buffalo National Park and is a UNESCO World Heritage Site. It was deemed a UNESCO World Heritage Site in 1983 based on its outstanding ecological and biological diversity. The PAD, which is located within the Wood Buffalo National Park, contains high concentrations of migratory wildlife and is one of the largest inland deltas in the world. In addition, it is the largest examples of the Great Plains-Boreal grassland ecosystem within North America (UNESCO World Heritage Centre, 2018). With a watershed of about 595,200 km^2, the Peace-Athabasca Delta (PAD) is the combination of two river deltas as the name suggests, the Peace and the Athabasca, that have formed in Lake Athabasca. The Peace Delta is considered inactive because the Peace River and the sediment it transports generally bypass the delta under present-day conditions. Currently, the Peace Delta is composed of a combination of marshes and mudflats which experience occasional flooding. In contrast, the Athabasca Delta is active as the Athabasca River drains through the delta and flows into Lake Athabasca (Timoney, 2013).

The largest lake connected with the PAD is Lake Athabasca, however only the western-most end where the Athabasca Delta is located is considered to be within the PAD for this study (Figure 1). The Athabasca Delta receives water from the Athabasca River. Lake Claire, located on the western edge of the PAD study area, is the second largest lake within this inland delta (Figure 1). Between Lake Claire and Lake Athabasca are a number of smaller lakes including Baril and Mamawi Lake. Within the wetland area between Lake Claire and Lake Athabasca are hundreds of channels, ponds and shallow lakes (defined as those that are less than 2m deep) which are not directly connected to surrounding rivers. These smaller hydrologic features are recharged at various times by other features and in some cases groundwater (Timoney, 2013). The PAD has high water tables which sometimes discharge groundwater at the surface. In areas where surface groundwater discharge occurs, it is either lost to evapotranspiration or diffused within surface waters.

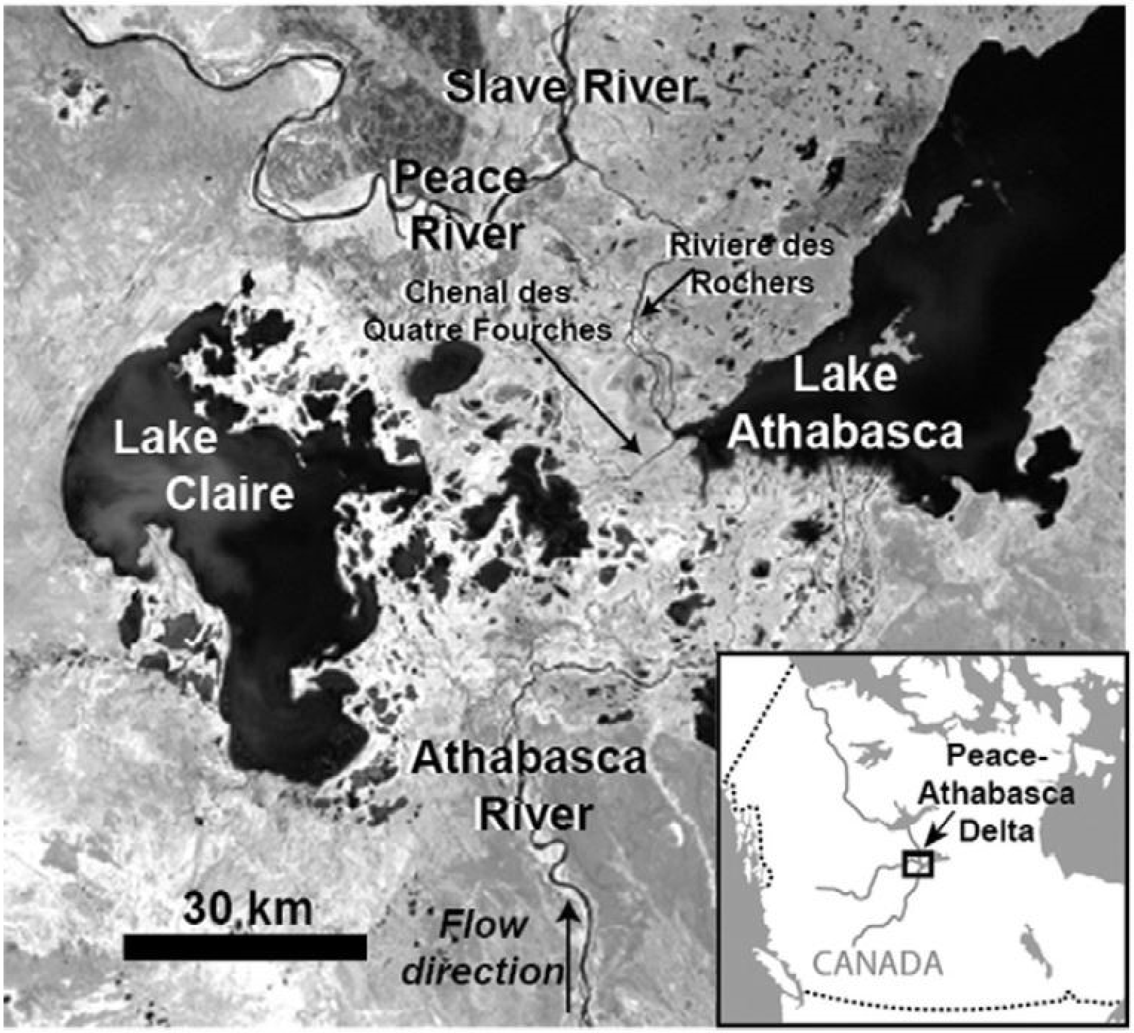
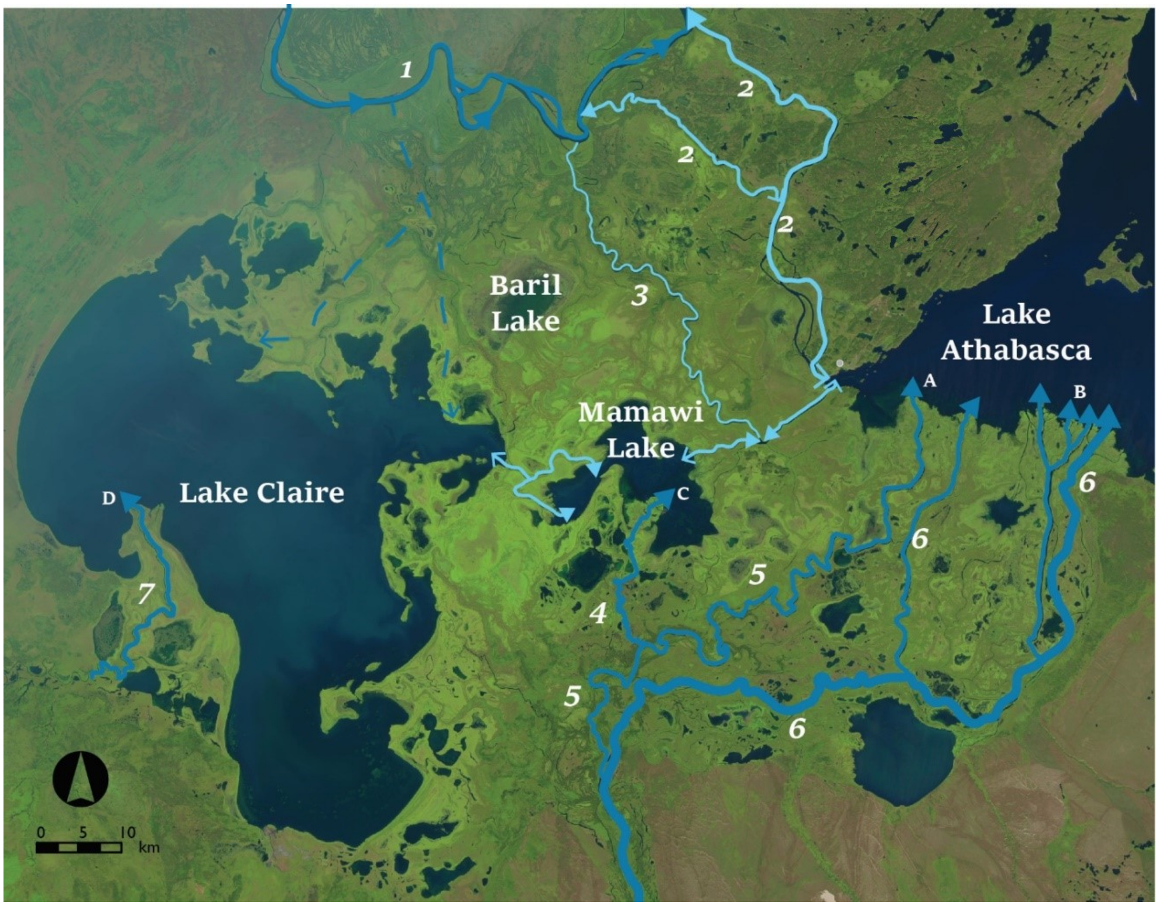


Figure 1: Landsat image of the PAD'S location within Canada (from Pavelsky & Smith, 2009).

Hydrology and Flow Patterns

About 90% of the PAD is composed of deltaic landforms with the other 10% being made up of nondeltaic features. Some key deltaic landforms include: active deltas, distributary channels, lakes, ponds, and mudflats. Nondeltaic features include: alluvial terraces, raised beaches, bedrock outcrops, and peatlands.

There are currently three main active deltas in the PAD, including the Athabasca River Delta, the Birch River Delta and the Cree/Mamawi Creek Delta (Figure 2). Despite being formed primarily by deltaic sediments, only about 5% of the total area of the PAD is currently experiencing active deltaic deposition. Since the PAD is made up of hundreds of interconnecting channels, shallow lakes and wetlands, the ecosystem is very dependent on hydrologic recharge (Pavelsky & Smith, 2008). The main source of water (represented as primary flow in Figure 2) and sediment input for the PAD is the Athabasca River. The Athabasca River flows north, entering the PAD from the south, where it ultimately reaches the Athabasca Delta and inputs water and sediment into Lake Athabasca (Figure 2). Mamawi Lake receives water through a variety of sources. Some water from the Athabasca River moves into the Embarras River which then flows into Mamawi Lake through the Cree/Mamawi Creek Delta (Figure 2). Lake Claire once received inputs from what are now inactive portions of the Peace and Athabasca Deltas, the only currently active delta which drains into Lake Claire is the Birch Delta (Figure 2). The complexity of this system speaks to the interconnectedness of a variety of hydrologic features within the PAD since water from one river can be transported across the rest of the region during certain flood conditions.



Legend

A & B – Athabasca Delta
C – Cree/ Mamawi Delta
D – Birch Creek Delta
1 – Peace River
2 – Rivere des Rochers
3 – Chenal Des Quatre Fourches
4 – Mamawi Creek
5 – Embarras River
6 – Athabasca River
7 – Birch River

Primary Flow Direction

Intermittent,
Small Channel Flow Direction

Potential Flow Direction

Figure 2: Map of flow patterns throughout the PAD including the three active deltas using Sentinel 2 imagery from 09/07/2017 using a RGB color scheme. In this image the green regions represent vegetation cover, blue illustrates bodies of water and the brown/pink tone shows bare earth. (Souces: PADEMP, USGS and Timoney, 2013)

Occasionally the Peace River will experience ice-jams which will lead to flow reversal of the river (Pavelsky & Smith, 2008). Due to the relatively flat nature of the PAD, many channels experience backflooding or even flow reversal (represented by potential flow in Figure 2) depending on the levels of Lakes Claire and Athabasca, as well as the Peace, Athabasca and Birch Rivers (Timoney, 2013). Smaller, closed drainage basins within the wetland areas rely on flooding events caused by ice-jams in the Peace River to recharge their water levels (Timoney, 2013). These closed-drainage basins are only connected to the major rivers during times of flooding and are too small to be included in Figure 2 (Timoney, 2013). Ice jams occur when ice blocks create a barrier somewhere along the Peace River and block the regular flow of water. These jams can last anywhere from a few minutes to multiple days and can be anywhere from a few hundred feet long to a few miles long (Beltaos et al., 2006). Major flooding events in the PAD occurred in 1972, 1974, 1996 and 1997, and have been attributed to ice jams that occurred along the Peace River (Beltaos et al., 2006). (The reach of the Peace Delta refers to the stretch of the Peace River which is displayed as intermittent, small channel flow in Figure 2). Some researchers came to the conclusion that there are a few particular conditions which must be met in order for ice-jam flooding to occur, including that the jam "must form within the delta reach of the Peace" (Beltaos et al., 2006). Additionally, during flooding events, flow reversal can occur, connecting a variety of features to one another which are generally separated (represented by the double-sided arrows in Figure 2). Sometimes the Peace River can flow south into Lake Claire, Baril Lake and Mamawi Lake due to ice-jams; other times simply due to high discharges represented as potential flow in Figure 2 by dashed lines (Timoney, 2013).

Geology and Formation

The PAD in its contemporary form began to develop around 10,000 years ago toward the end of the last glaciation; this exposed much of the modern delta's area, which was filled primarily with meltwater after the retreat of the Laurentide Ice Sheet (Bayrock & Root, 1972). Bedrock below the PAD is composed of gypsum, Athabasca Sandstone, Devonian limestone, gneisses and Canadian Shield granites (Bayrock & Root, 1972).

When the delta began to form it did not resemble the current complexity. The PAD was mostly formed during the Pleistocene and early Holocene when sediment was primarily transported by the Peace River through sandy braided deltas into Lake Claire and Mamawi Lake (Figure 3). Later in the Holocene, both the Peace River and Athabasca River began transporting silt-clay sediment into the PAD. Additionally, when this change occurred, silt-clay sediment began to enter the PAD from the Birch River. Today, there is only occasional sediment input from the Peace River during times of ice-jam flooding and less sediment transport from the Athabasca River than in the past. There are currently only three primary active distributary mouths (A & B, C, D in Figure 2) which input sand dominated sediment into Lake Athabasca, Lake Claire and occasionally Mamawi Lake (which is located between Lake Claire and Lake Athabasca as shown in Figure 2) (Timoney, 2013).

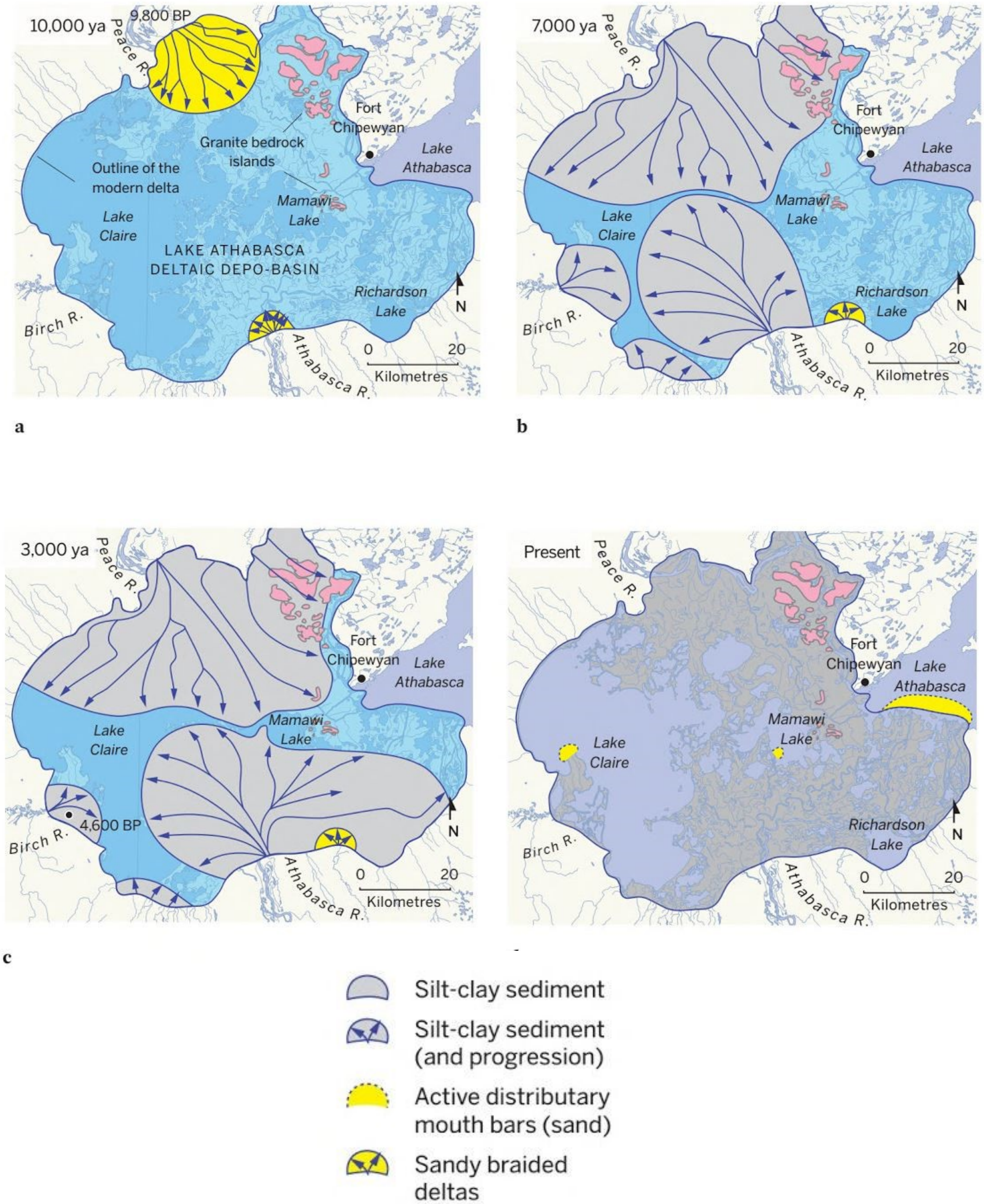


Figure 3: Model showing the evolution of the PAD throughout the Holocene from Timoney (2013).

Soil Composition

The surficial deposits of the PAD are described as "deltaic alluvium composed of bedded calcareous silt, sand and clay" (Timoney, 2013). The soil orders found in the PAD include poorly drained Regosolic, Gleysolic and Organic soils according to National Soil Database of Canada.

Regosols are rather immature soils with minimal profile development. Regosolic soils are also common in river floodplains with alluvial (fluvial) sediments as the parent material (Soils of Canada, 2016). In regions like the PAD, soils often experience prolonged water saturation within the upper horizons of the soil profile due the high water table in this area. This high degree of saturation results in gleysolic soils which often lack oxygen due to their high water content. Gleysols in the PAD are generally formed from regosols that have experienced prolonged waterlogging. The diagnostic characteristic of gleysols is the presence of gleyed features within the upper 50cm of the soil profile. The saturated condition of this soil order slows the process of organic matter transformation within gleysols. As a result, organic matter will not infiltrate gleysolic soils as quickly, leading to the formation of a layer of organic matter at the top of the profile. In landscapes where decomposition rates decrease, the organic matter input from plant life builds up around the surface of the soil profile. This layer of organic matter at the top of the gleysolic soils often leads to the formation of organic soils (Soils of Canada, 2016). The most dominant soils found within Canadian wetland landscapes are categorized within the organic soil order (Soils of Canada, 2016). Some areas within the PAD have a water table within 50cm of the land surface, and prolonged flooding events. As a result of the high water table, the soil profile is saturated for most of the year. This stagnant water becomes deoxygenated over time and is responsible for the soil becoming anaerobic which slows decomposition of organic material. The build-up of this organic material at the surface of the profile over time leads to the formation of organic soils (Soils of Canada, 2016).

CHAPTER III

METHODS

There are two main goals for the methods of this thesis. The first is to test existing models that relate the imaged intensity of reflectance from Landsat 5TM imagery to in situ measurements of water quality parameters. The second goal is to develop improved models that relate Landsat imagery to water quality parameters. While there are some similarities between the methods and data sources utilized in this study and those used in the work of Long and Pavelsky in 2013 as well as other researchers, this study will not be restricted by the model forms and Landsat bands used by previous researchers.

Data Acquisition

MODIS Aqua imagery would be ideal for monitoring water quality as it was developed to collect wavelength ranges most suitable for the analysis of water. However, it has a resolution which is too coarse (30m x 30m) and also is not available in scenes small enough to capture the Peace-Athabasca Delta. Landsat imagery is used because of its finer spatial resolution (15m x 15m), allowing for analysis of the relatively small area which the Peace-Athabasca Delta covers. The imagery for this study focuses on two Landsat 5 TM images obtained through USGS. Level-2 Landsat 5 TM surface reflectance imagery was available, therefore no additional preprocessing or atmospheric correction is necessary (USGS, 2015).

The in situ data used in this study was collected by researchers Colleen Long and Tamlin Pavelsky of the University of North Carolina at Chapel Hill in the summers of 2010 and 2011 (Figure 4). The data include a variety of parameters: temperature, turbidity, chlorophyll content, color dissolved organic matter (CDOM), suspended sediment concentration (SSC) secchi disc depth, surface flow velocity, and water depth. The 2010 dataset collected on June 23rd and July 5th, 2010 included a total of 177 data points, 72 collected from lakes and 105 collected from rivers. The 2011 dataset was collected on June 30th and July 3rd, 2011 included a total of 176 data points, 92 collected from lakes and 84 collected from rivers.

The first approach is using existing models to compare Landsat 5TM intensity to water quality using the aforementioned field data measurements and evaluating the existing models using indicators of fit. This approach will be detailed in the section "Application of Published Models" on page 23.

The second approach is creating new regression models to better fit the field data to the Landsat 5TM data. These new models will not be limited by the approaches and bands used by authors in previous studies, for example those used by Griffin et al., 2011, Topliss et al., 1990 and Huang et al., 2014.

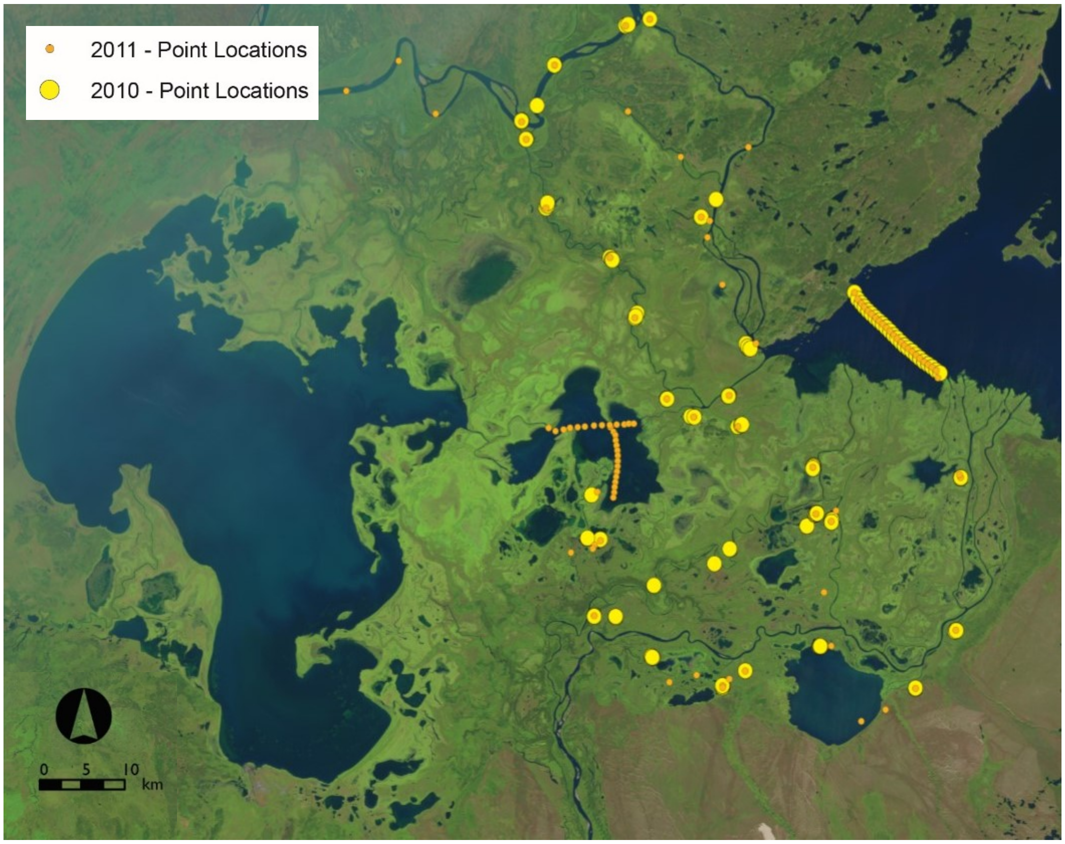


Figure 4: Map of in situ data points collected in 2010 & 2011 by Long & Pavelsky using the same background image as Figure 2. (Sources: USGS and Long & Pavelsky, 2013)

Models and Image Processing

Model Workflow

In order to test the accuracy of existing, published models for predicting CDOM, SSC and Chl-a, as well as produce new models to best fit the data, the in situ water quality data collected by Long & Pavelsky was split into a calibration set and a validation set. The first step in this process is to test the published models. To do so, the published models were applied to the 2010 Landsat imagery (collected on July 22, 2010) and compared to the 2010 in situ measurements. New models were created and calibrated using the 2010 imagery and in situ data based on the performance of the published models. Once created, the new models were applied to the 2011 imagery (collected on July 25, 2011) and, in order to determine how accurately the new models were able to predict CDOM, SSC and Chl-a, the results were compared with the 2011 in situ data (Figure 5).

1. **Initial Image Processing**
    a. Stack individual bands to create multiband raster images for 2010 and 2011
    b. Subset multiband raster images to include only the study area for the 2010 and 2011 imagery
2. **Application of Published Models**
    a. Apply the formulas for each of the water quality parameters to the 2010 imagery using ERDAS Imagine Model Maker
3. **Extracting Values from Output Rasters – Published Models**
    a. Extract raster values for each of the 2010 water quality raster outputs at the location of each of the 2010 in situ data points
    b. Compile all 2010 predicted values in a table to be compared with the 2010 in situ measurements
4. **Statistical Analysis – Published Models**
    a. Run regression analysis in R to determine the relationship between the in situ measurements and the remotely sensed measurements for each of the three water quality parameters for the 2010 in situ data and 2010 imagery
5. **Model Revisions - Creation of New Models**
    a. Based on the results of the regression analyses for each of the three water quality parameters, create new formulas for each parameter.
6. **Application of New Models**
    a. Apply the new formulas for each of the water quality parameters to the 2011 image only using ERDAS Imagine Model Maker
7. **Extracting Values from Output Rasters – New Models**
    a. Extract raster values for each of the water quality raster outputs at the location of each of the in situ data points
    b. Compile all raster values in a table to be compared with the in situ measurements
8. **Statistical Analysis – New Models**
    a. Run regression analysis in R to determine the relationship between the 2011 in situ measurements and the 2011 remotely sensed measurements each of the three water quality parameters

Figure 5: General workflow used in this study.

Application of Published Models

This study applies the methods outlined in Cardille et al. (2013) and Smith & Pavelsky (2009) to monitor water quality in the PAD. The three main indicators used for water quality measurement in this study are CDOM, chlorophyll and SSC. To quantify these factors, previously published models were first applied to the 2010 imagery. Although the published models used in this study were not created or tested specifically in the PAD, they were developed in highly turbid, hydraulically complex landscapes similar to the hydrology of the study area.

A model created by Griffin et al. in 2011 in East Siberia was utilized in order to quantify CDOM. When monitoring SSC variations generally the greatest distinction is found in the red portion of the electromagnetic spectrum (Smith & Pavelsky, 2009). In order to quantify SSC, an algorithm developed by Topliss et al. in 1990 developed in Bay of Fundy and Beaufort Sea was used. To monitor chlorophyll content this study employs methods from Huang et al. (2014), developed in "inland lakes in China", which utilizes a NIR-red two-band algorithm. (See Table 1 for formulas). Each of these authors used different measures of statistical significance and therefore it is difficult to directly compare the results of these models. The output of the published models were plotted against the 2010 in situ data values for each water quality parameter, once they were applied to the 2010 imagery.

Water Quality Parameter	Units	Published Models	Source
CDOM	ug/L	CDOM = ln(-1.145 + 26.529(TM3) + 0.603(TM2/TM1)	Griffin et al. 2011
SSC	cm/275mL	ln(SSC) = -6.2 * (TM1/TM2) + 1.4 * (TM1/TM2)^2 + 10.8	Topliss et al. 1990
Chl-a	ug/L	Chl-a = (1/TM1) * TM3	Huang et al. 2014

Table 1: Published models used to quantify CDOM, SSC and Chl-a using 2010 Landsat 5TM imagery. (Bands used in each formula are denoted by TM1 representing band 1 of Landsat 5TM, TM2 representing band 2 etc.)

Using the Model Maker tool in ERDAS IMAGINE 2016 the published models were applied to the 2010 Landsat imagery. The output of these model output raster datasets quantifying the amount of CDOM, SSC and Chl-a within the 2010 imagery. For each of the output raster datasets, the pixel values which correspond with the 2010 field sample points collected by Long and Pavelsky were extracted and compiled into a table containing both the field measurements for each water quality parameter and the model output for each point. Rather than using an average of surrounding pixels, the pixel values which were collected were assigned based on the pixel located closest to the point. To determine how well the published models statistically fit with the in situ data from 2010, regression analysis was conducted in the program R. These results helped to inform revisions to the published model in the next step of the process.

Creation of New Models

As a part of the new model creation portion of the study the performance of the published models was evaluated in order to ultimately answer the question of how effective they are for estimating chlorophyll-*a*, CDOM and SSC. New models were created due to the high p-values and low R^2 values resulting from the regression analysis of the published models and the in situ data. Ultimately the published models were reworked and new models were created based on these results.

The first step in creating the new models in this study is to create histograms to better understand the distribution of the 2010 in situ data for each of the three water quality parameters. Additionally, the in situ data points were reclassified based on the type of water body the sample was collected from, either lake or river. This allowed for three area distinctions to be made among the data including all samples taken, samples taken exclusively from rivers, and samples taken exclusively from lakes (these categories will be referred to as the "three spatial units" from here on). This led to the creation of a total of nine histograms: CDOM, Chl-a and SSC for all in situ collection points in the study area, CDOM, Chl-a and SSC for in situ collection points taken from rivers-only and CDOM, Chl-a and SSC for in situ collection points taken from lakes-only. By separating the in situ data points, it allows for a better understanding of how the data is statistically distributed throughout the study area and if there is any difference in the statistical distribution from data in all-water areas of the PAD versus those collected in lakes and rivers.

The frequency distributions of the field data were far from normal when all the data points were together, making regression problematic. As none of the histograms displayed normal distribution it is clear that the data need to be normalized before the new models were created. For each variable for each of the three spatial units, the Box-Cox Power Transformations was applied to normalize the in situ data (Box & Cox, 1964). To transform the value of the in situ data variable, the Box-Cox Power Transformation produces a value for lambda (λ) according to the following equation: $\frac{y^{\lambda} - 1}{\lambda}$. For each of the water quality parameters for each of the three spatial units this process of normalizing the data was conducted (Table 2). In order to normalize the histograms, the transformation equations were determined and are applied to each of the water quality parameters for each of the spatial unit datasets (Appendix: Histograms: Original & Normalized). In the Box-Cox Power Transformation, the lambda coefficient is a representation of transformation to normality, and Table 2 shows that the lakes and rivers have very different lambda values. Why might these be so different? The only reasonable answer is that there are different optical processing occurring in each of these environments, such as different water components or different mixing processes.

All Collection Points

Water Quality Parameter	*Lamda (λ)*	*Transformation Equation*
CDOM	1.2323	$\frac{y^{1.2323} - 1}{1.2323}$
SSC	0.2222	$\frac{y^{0.2222} - 1}{0.2222}$
Chl-a	0.7070	$\frac{y^{0.7070} - 1}{0.7070}$

River Collection Points

Water Quality Parameter	*Lamda (λ)*	*Transformation Equation*
CDOM	1.3131	$\frac{y^{1.3131} - 1}{1.3131}$
SSC	1.0707	$\frac{y^{1.0707} - 1}{1.0707}$
Chl-a	0.3434	$\frac{y^{0.3434} - 1}{0.3434}$

Lake Collection Points

Water Quality Parameter	*Lamda (λ)*	*Transformation Equation*
CDOM	0.7474	$\frac{y^{0.7474} - 1}{0.7474}$
SSC	0.1010	$\frac{y^{0.1010} - 1}{0.1010}$
Chl-a	-0.0606	$\frac{y^{-0.0606} - 1}{-0.0606}$

Table 2: Box-Cox Power Transformation equations for each of the water quality parameters for the three spatial units(including lamda values) which were used to normalize the datasets.

After the data were normalized, the next step in creating the new models was running a regression analysis in R to determine the equations for each water quality parameter within each of the spatial units. The normalized 2010 in situ data was plotted against the 2010 reflectance values from the 2010 Landsat 5TM imagery. It was necessary to determine the spectral bands (according to the Landsat 5TM sensor band distinctions) to be used in determining the relationship between the remotely sensed imagery and the water quality parameters in terms of R-squared and p-values once the linear equations were determined.

It is not explicitly known why certain model forms and bands were used in previously produced models, although it is likely they used some combination of theoretical and empirical reasoning. In this study, we may use different bands and band combinations compared to the previously published models. Based on research which found that the greatest amount of CDOM can be quantified based on wavelength ranges of 400-450 nm, Band 1 is used as it was decided to be the best for determining CDOM concentrations (Shi et al., 2017). It is suggested that for SSC the range of 700-750 nm demonstrates the most obvious relationship between reflectance and this water quality parameter, but the Landsat 5TM sensor does not collect this range. Based on this limitation, Band 3 is to be used for quantifying SSC because this band illustrates the most variation in reflectance as it corresponds with increasing SSC values and is in a wavelength range collected by the sensor used in this study (Qu, 2014). Finally, based on the absorption properties of chlorophyll-a the combination of Band 2/Band 1 is used to calculate Chl-a. This type of chlorophyll absorbs blue light around the 430-450 nm range corresponding to Landsat 5TM band 1 and displays the greatest reflectance around the

550 nm wavelength which corresponds with band 2 (Yu et al., 2010). In the use of a ratio of Band 2/Band 1, reflectance from band 2 should highlight chlorophyll-a while the reflectance in band 1 should normalize band 2 from the effects of atmospheric scattering.

For each of the water quality parameters the same spectral bands are used for each of the three spatial units (all water points, river points only and lake points only). The slope and intercept terms in the equations vary depending on the regression analysis conducted between the selected band value for each water quality parameter and the corresponding in situ water quality measurements.

Validation of New Models

Once the new equations were developed, they were validated using the 2011 imagery and 2011 in situ data. To ensure that the validation process of these new models is robust and accurate these data were not used in the calibration process. A masked version of the imagery that includes all bodies of water (both rivers and lakes) was applied to the equations for all collection points whereas masked images that include only the river or only the lakes were applied to the river and lake collection point formulas respectively. Once the equations were applied to the 2011 masked images, the pixel values which corresponded with the 2011 Long and Pavelsky field samples are extracted, leading to three sets of water quality parameter measurements (CDOM, SSC and Chl-a for each spatial unit). These values were then compiled into three tables for each of the spatial units and compared with the in situ data measurements within the same unit.

To determine the statistical strength of the relationship, the results for the predicted values (new model values) are plotted against the observed (in situ values). Since the histograms were normalized as part of the calibration process in order to determine the ultimate goodness of fit of each of the nine new models, the R-squared values are used validate the models.

CHAPTER IV

RESULTS

This chapter will illustrate the results of the published models as well as the new models to show the spatial distribution of CDOM, SSC and Chl-a throughout the study area of the PAD. In addition, it will explore the goodness of fit and validation of the new models to demonstrate how well the models performed.

Published Models Performance

In order to evaluate how well current methods are able to predict and quantify water quality parameters in complex environments such as the PAD the published models were applied to the 2010 imagery. R-squared and p-values are used to determine the statistical significance and goodness of fit of the published models (Table 3). Simply by looking at the graphs in Figure 6, it is clear that there is little to no relationship between the 2010 in situ data and the published model outputs from the 2010 imagery. The R-squared and p-values also show low correlation between the two datasets, suggesting that the published models do not accurately quantify CDOM, SSC and Chl-a from the Landsat imagery used in this study. Unfortunately it is not possible to directly compare these results with the values from the original study areas because they did not use the same measures of statistical fit. For instance, Griffin et al., 2011 used R-squared and p-values, Topliss et al., 1990 used Spearman's p and Huang et al., 2014 used RMSE.

Water Quality Parameter	R-Squared Value	p-value
CDOM	0.0014	0.265
SSC	-0.0023	0.4348
Chl-a	-0.0024	0.4504

Table 3: Statistical results of the published models based on the 2010 data.

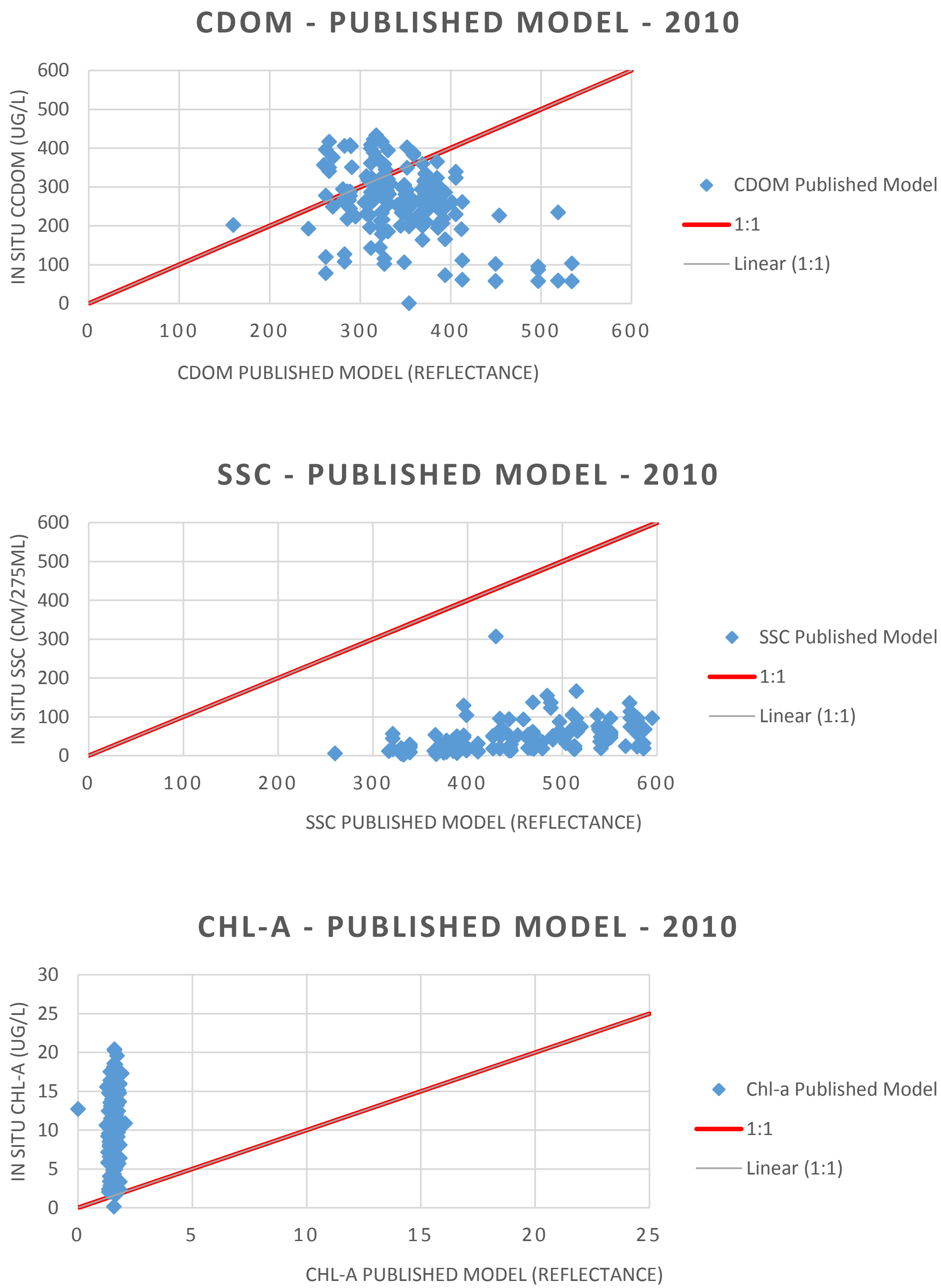


Figure 6: Graphs of results of the published models. (Red 1:1 line representing perfect model performance).

New Model Production

Once the various components are compiled, including the spectral bands as well as the slope and intercept terms for each water quality parameter for each of the spatial units, the equations can be formulated (Table 4). One immediately noticeable result of these models is in the case of the model predicting Chl-a in rivers and in lakes, the slopes of the equations are opposite for Chl-a. In the lake-only equation for Chl-a there is a negative relationship between green (band 2) and Chl-a; from an optical perspective, this is very unexpected. Chl-a should be strongly, positively related to green. The only reasonable hypothesis for why this inverse relationship exists is that there is some other material present in the water which covaries with Chl-a and has and inverse relationship with green. Unfortunately, it is unclear what is causing this relationship.

Equations for All Water Points	**Units**
CDOM_All = -1.6943(Band 1) + 1704.0828	ug/L
SSC_All = 0.012863(Band 3) – 0.334191	cm/275mL
Chl-a_All = 3.2371(Band 2/Band 1) + 0.4726	ug/L

Equations for River Points Only	**Units**
CDOM_Rivers = -1.2319(Band 1) + 1612.6339	ug/L
SSC_Rivers = 0.021325(Band 3) - 2.016857	cm/275mL
Chl-a_Rivers = 3.165(Band 2/Band 1) + 7.127	ug/L

Equations for Lake Points Only	**Units**
CDOM_Lakes = -0.25967(Band 1) + 173.36537	ug/L
SSC_Lakes = 0.0027862(Band 3) + 1.7630498	cm/275mL
Chl-a_Lakes = -0.1844(Band 2/Band 1) + 2.2562	ug/L

Table 4: New model equations for CDOM, SSC and Chl-a for each spatial unit.

New Model Performance

In order to understand the relationship between the output of the new models and the associated in situ data measurements the R-square and p-values were analyzed.

Additionally, the results of the statistical analysis conducted in R were graphed with a red 1:1 line representing perfect model performance where the outputs are equal to the measured in situ data (Figures 7-9).

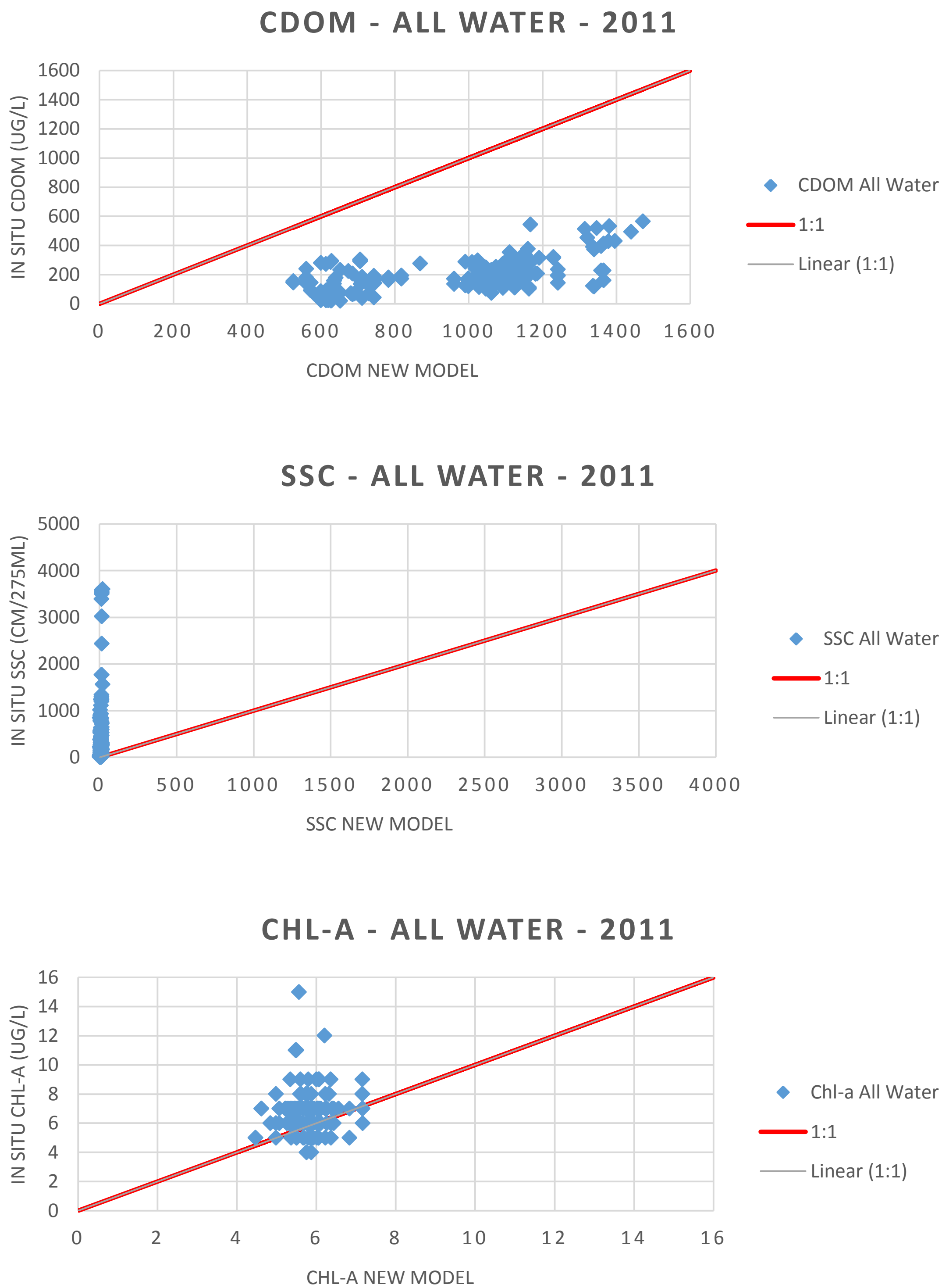
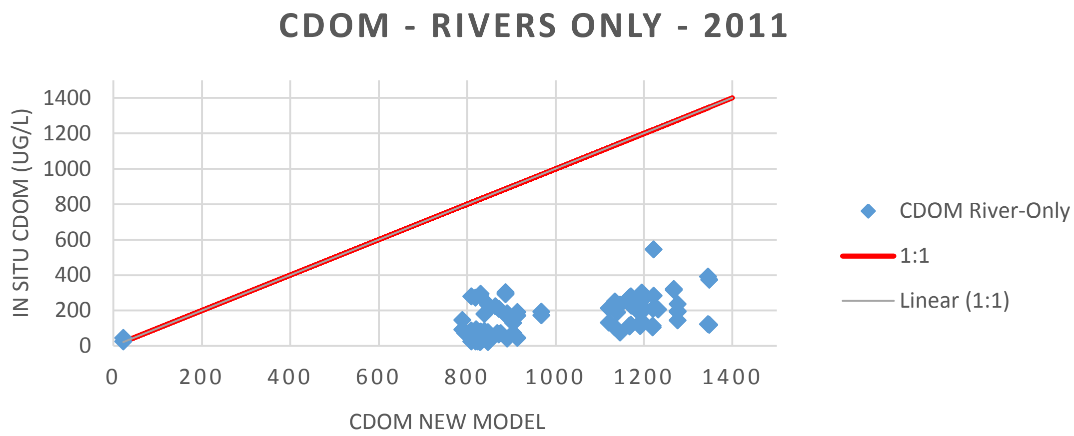
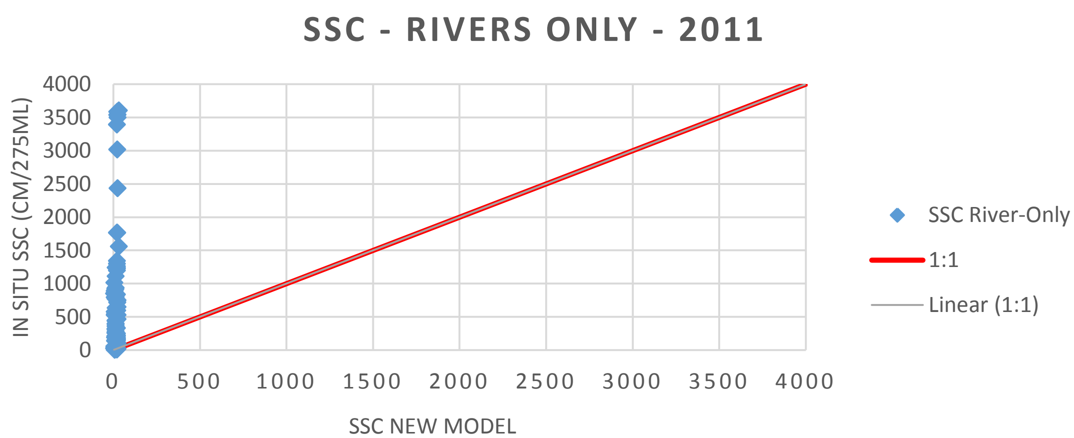


Figure 7: Results of the new models for predicting each of the three water quality parameters throughout all the water points within the study area. (Red 1:1 line representing perfect model performance).





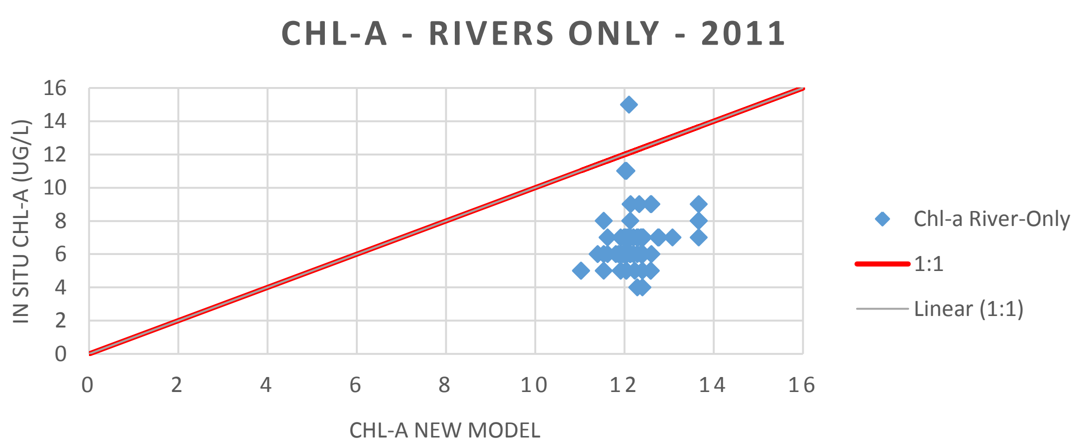
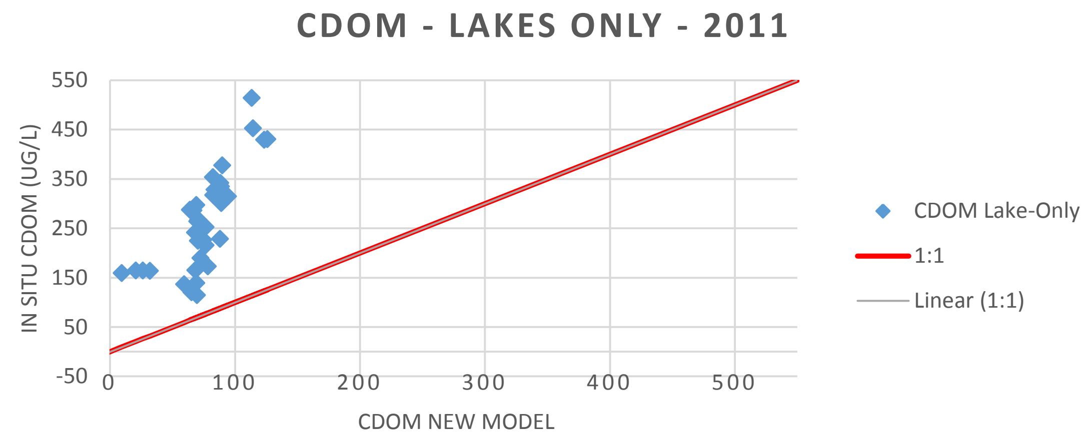
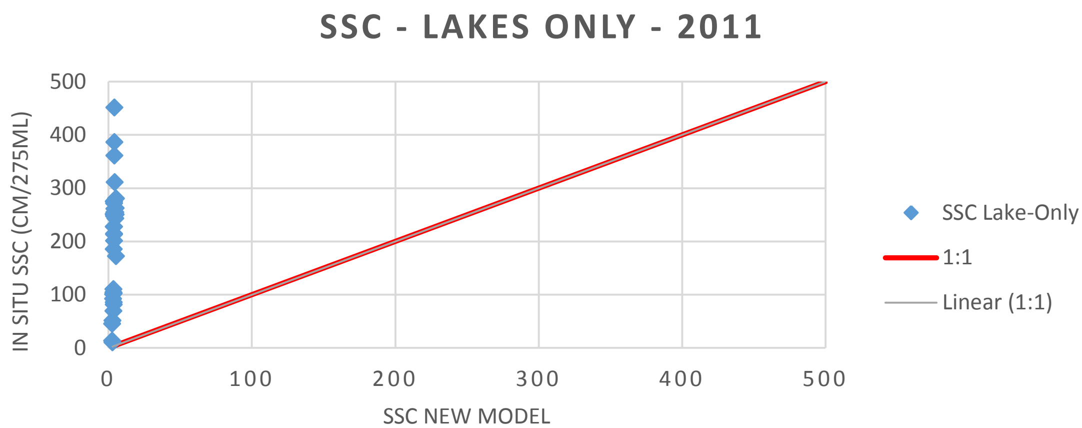


Figure 8: Results of the new models for predicting each of the three water quality parameters in the rivers within the study area. (Red 1:1 line representing perfect model performance).





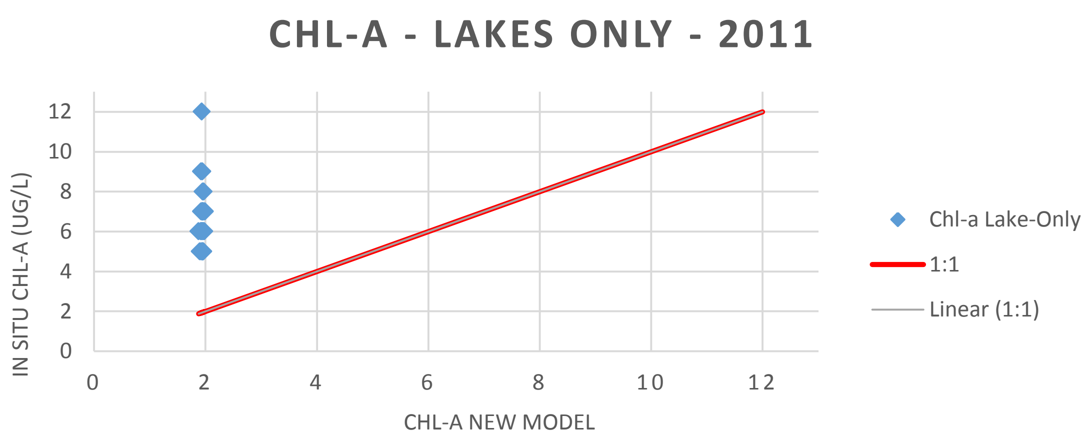


Figure 9: Results of the new models for predicting each of the three water quality parameters in the lakes within the study area. (Red 1:1 line representing perfect model performance).

Significant results for this study are considered to be R-squared values of greater than 0.2 and p-values of less than 0.05 (Table 5). The graphs as well as the R-squared and p-values strongly suggest that the new models performed better than the published models. All p-values for each of the nine new models suggested that the new models are more accurately able to quantify CDOM, SSC and Chl-a in all three of the spatial units. The models used for monitoring CDOM performed best, with R-squared values ranging from 0.2-0.3 which are quite a bit higher than any of the other models. The p-values associated with the CDOM models are also better than the other models which suggests that this water quality parameter can be quantified from remotely sensed imagery, such as Landsat 5TM, compared to other parameters. SSC performed second best with R-squared values ranging from 0.07-0.119 with p-values much less than 0.05. However, it is clear by looking at the graphs, the R-squared is not effectively representing the model performances. R-squared is mixing the offset and slope errors and clearly Figure 8 (SSC – Rivers Only – 2011) has a large slope error making the model actually perform worse than the R-squared suggests. The Chl-models did not perform very well. With R-squared values of less than 0.04 and p-values which are not all significant, the new models do not appear to quantify Chl-a very well, though the new models predicted Chl-a better than the published models.

All Water Points	R-Squared Value	p-value
CDOM_All	0.3132	6.009e-16
SSC_All	0.09033	2.851e-5
Chl-a_All	0.00513	0.1737

River Points Only	R-Squared Value	p-value
CDOM_Rivers	0.2034	1.118e-5
SSC_Rivers	0.119	0.0007177
Chl-a_Rivers	0.04005	0.0415

Lake Points Only	R-Squared Value	p-value
CDOM_Lakes	0.38	3.66e-11
SSC_Lakes	0.07553	0.004631
Chl-a_Lakes	-0.004713	-0.4456

Table 5: Statistical results from the 2011 validation analysis of the new models.

Overall, the new models performed better at quantifying the three water quality parameters compared to the published models although they are still not ideal for accurately predicting water quality from remotely sensed imagery.

Mapped Results of New Models

In order to validate the quality of each of the nine models which were developed in this portion of the study the new models were applied to the 2011 imagery. Depending on whether they were developed for all water within the study area, or only rivers or lakes each of the formulas were applied to the entirety of the 2011 imagery and masked accordingly. To compare the distribution of the particular water quality parameter quantified in each map, the results of the masked images were given the same color ramp; even though in some of the river-only images it does not appear to be much variation (Figures 10-18).

CDOM – New Model – 2011 – All Water

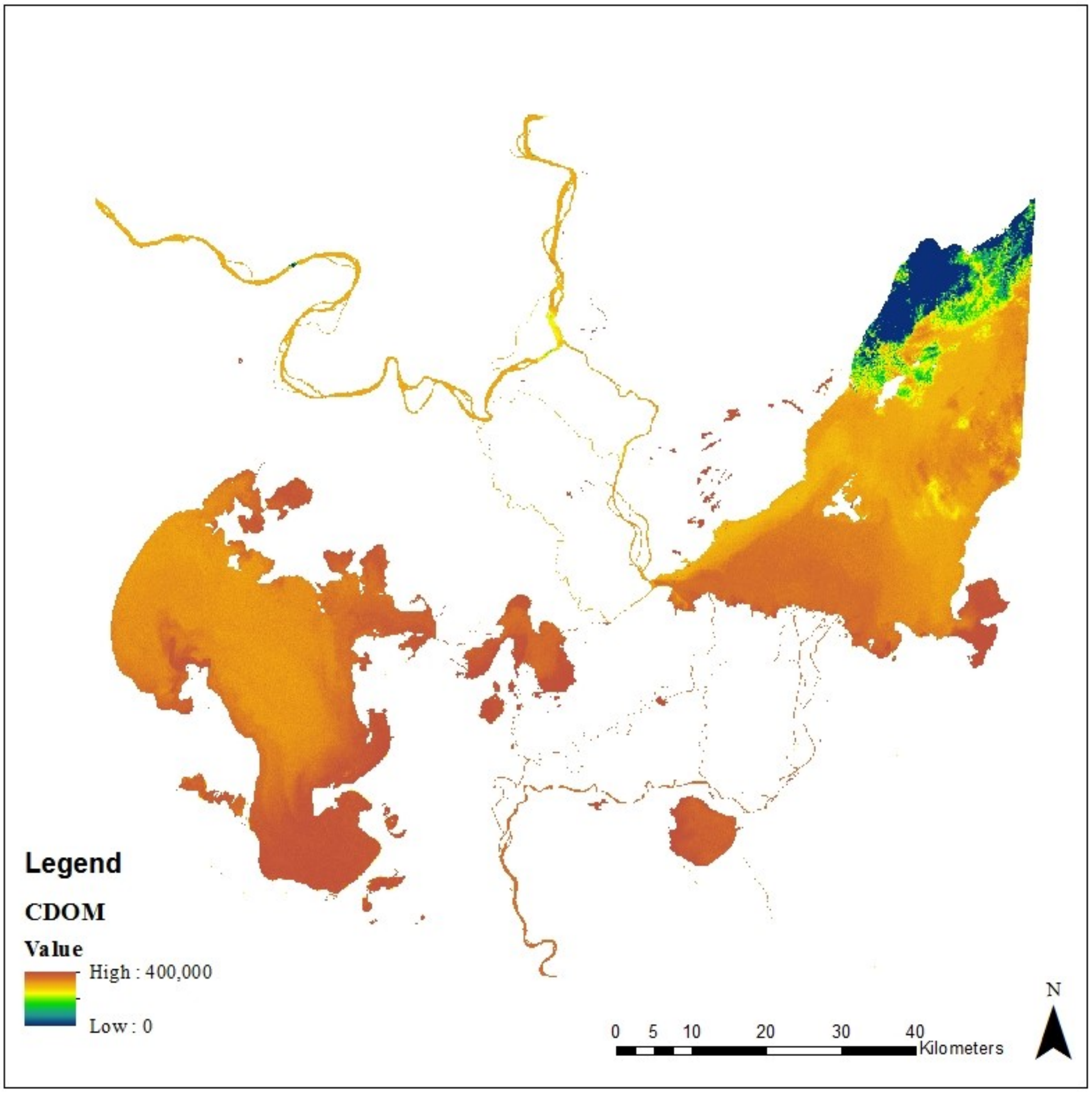


Figure 10: CDOM distribution for all water bodies in 2011 based on new model.

SSC – New Model – 2011 – All Water

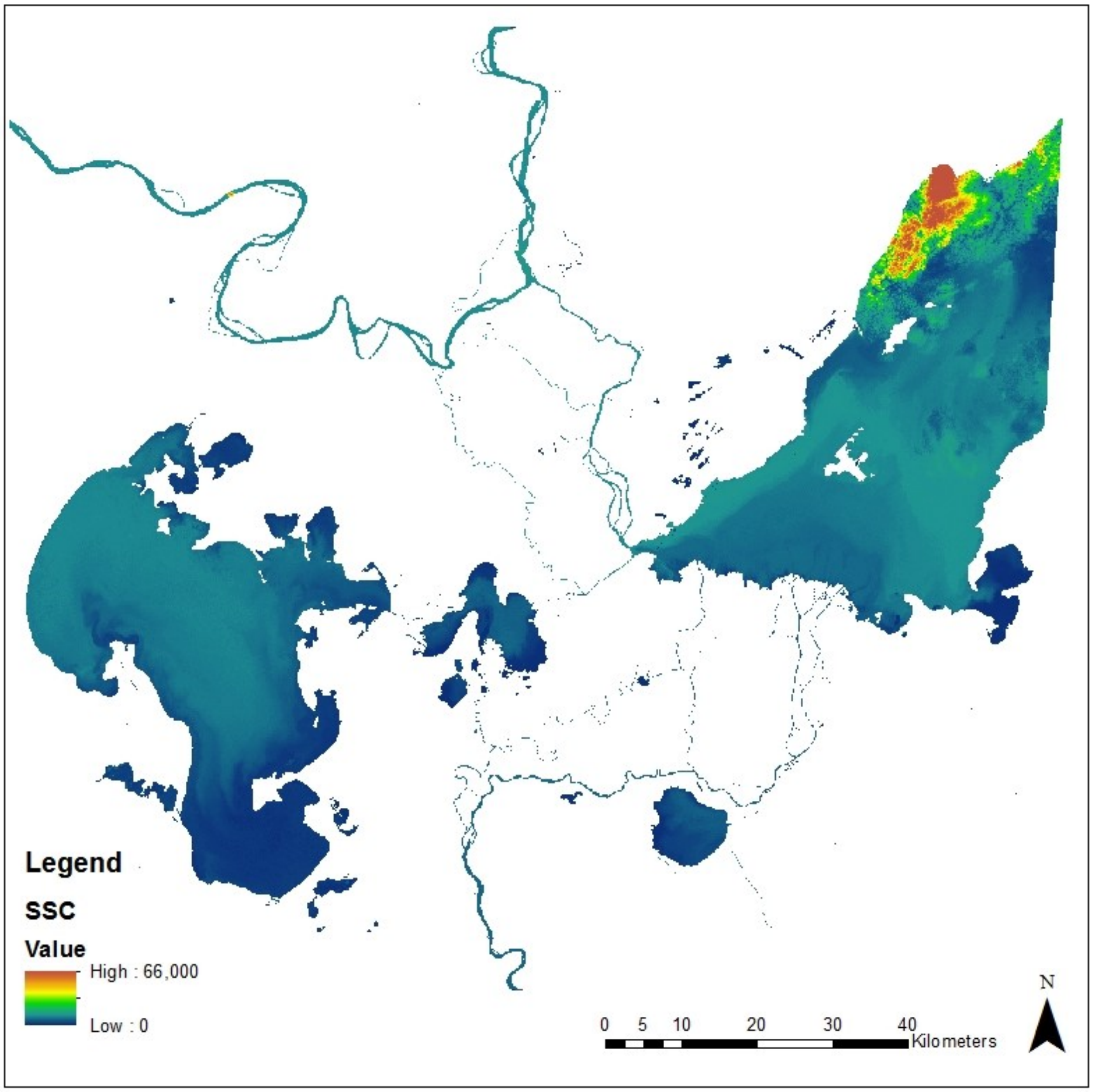


Figure 11: SSC distribution for all water bodies in 2011 based on new model.

Chl-a – New Model – 2011 – All Water

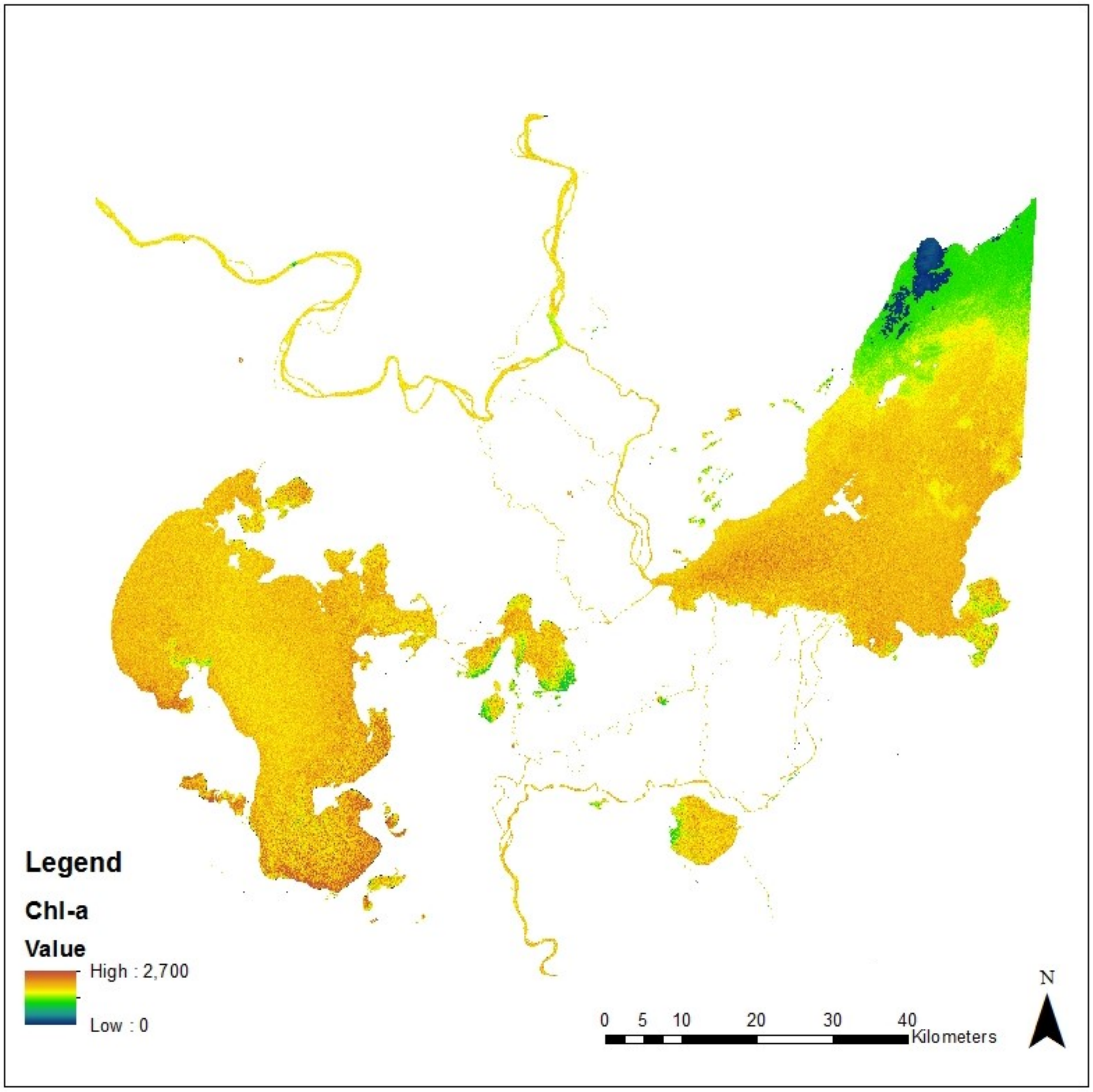


Figure 12: Chl-a distribution for all water bodies in 2011 based on new model.

CDOM – New Model – 2011 – Rivers

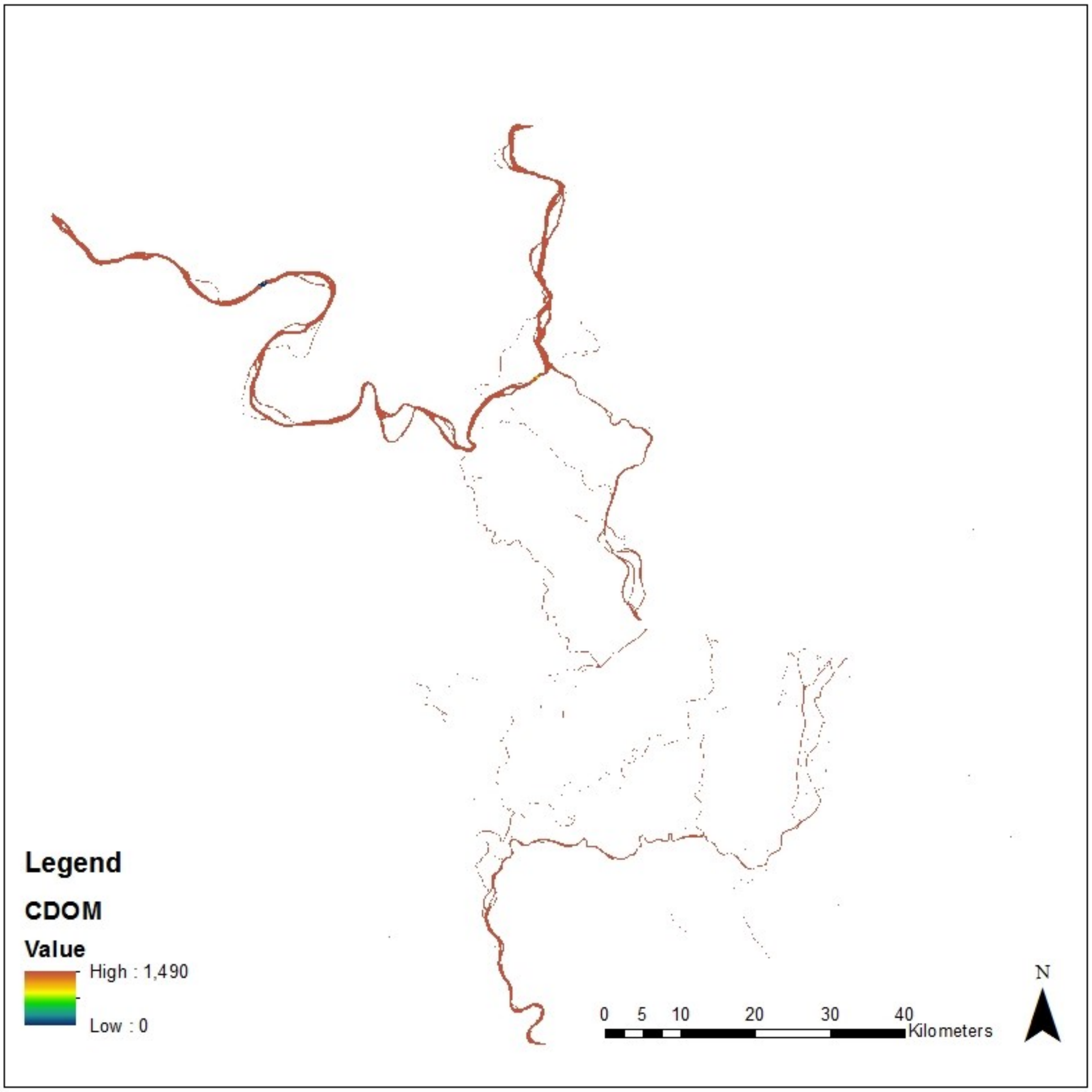


Figure 13: CDOM distribution for only river water bodies in 2011 based on new model.

SSC – New Model – 2011 – Rivers Only

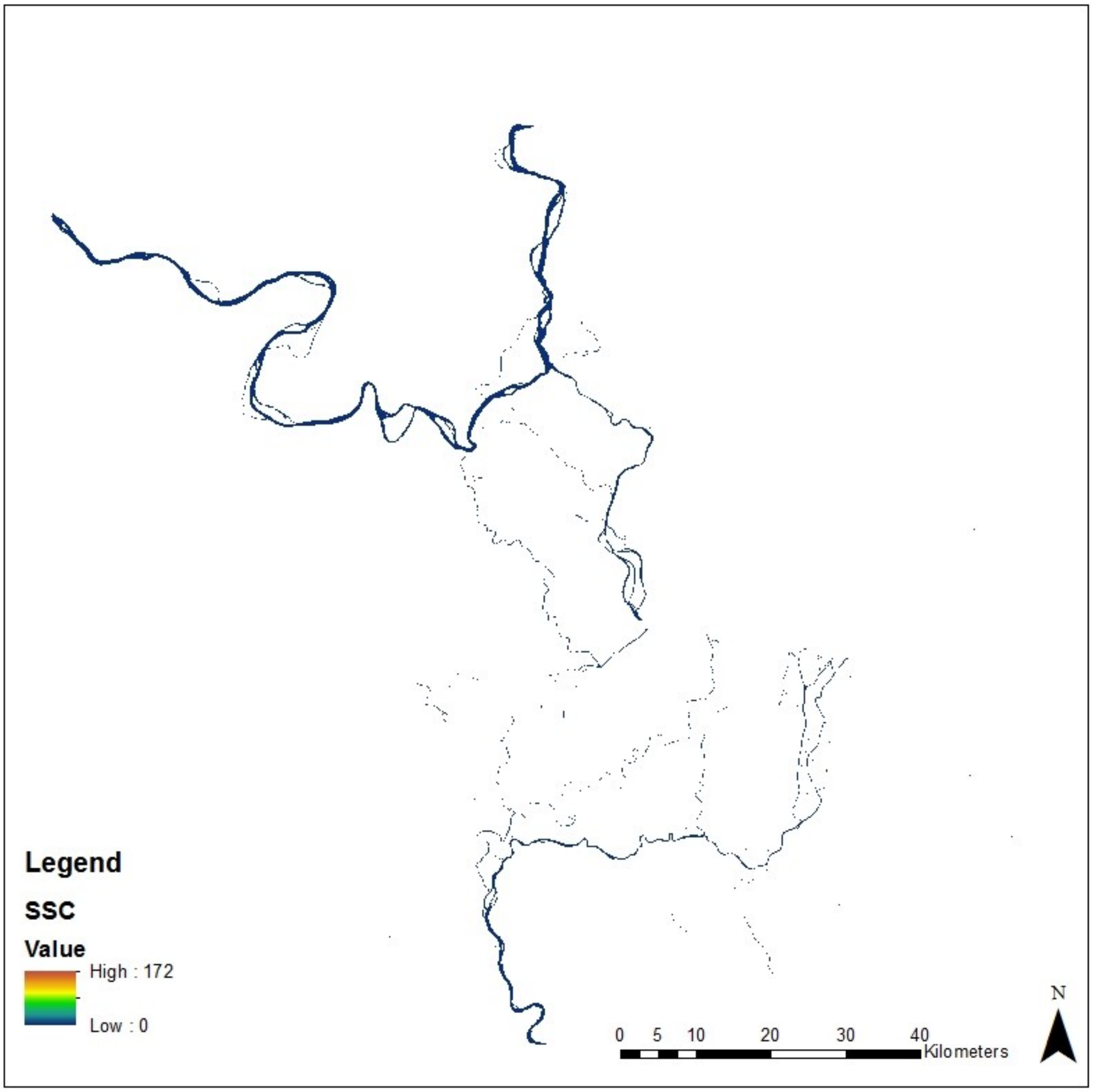


Figure 14: SSC distribution for only river water bodies in 2011 based on new model.

Chl-a – New Model – 2011 – Rivers Only

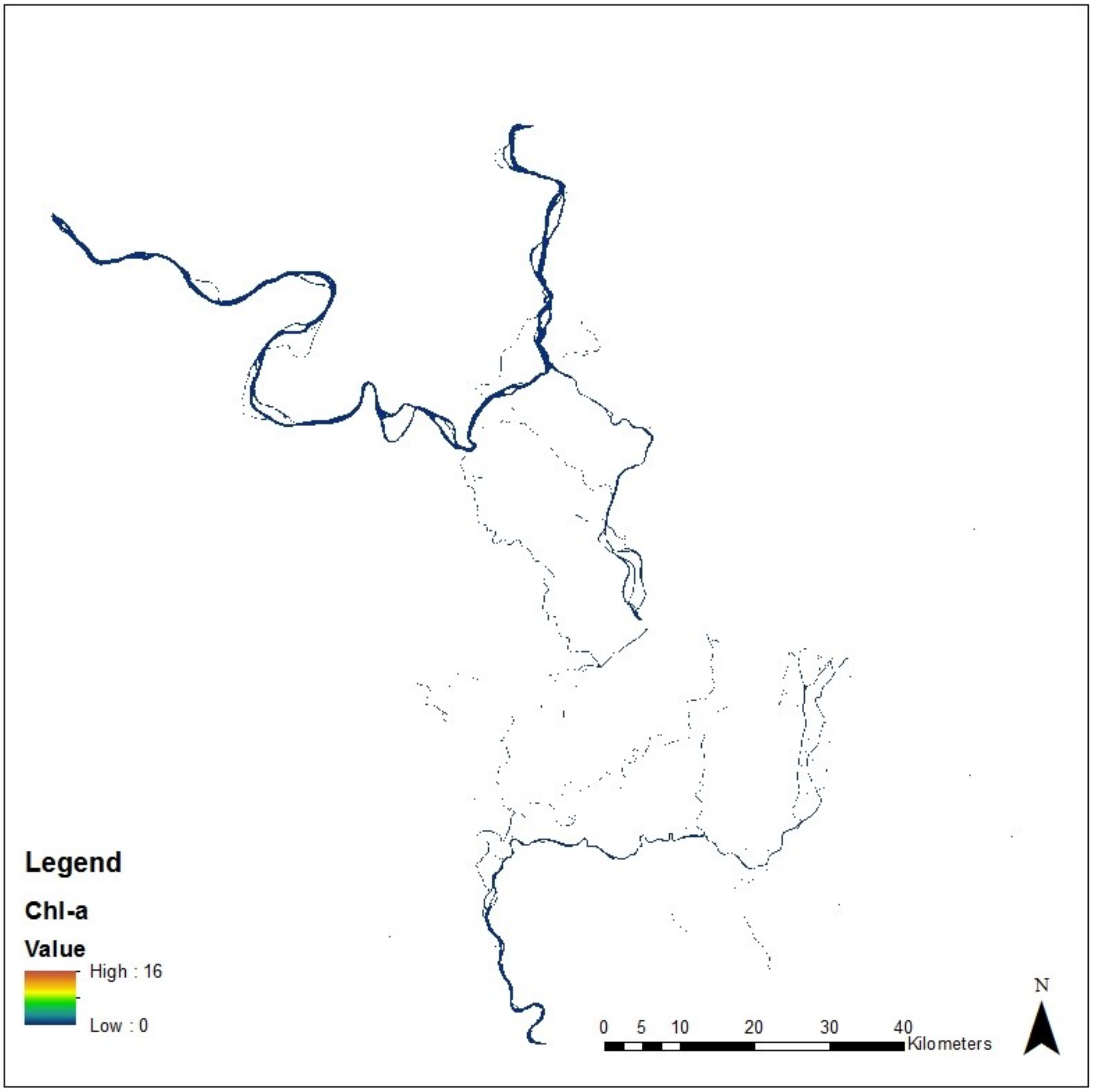


Figure 15: Chl-a distribution for only river water bodies in 2011 based on new model.

CDOM – New Model – 2011 – Lakes Only

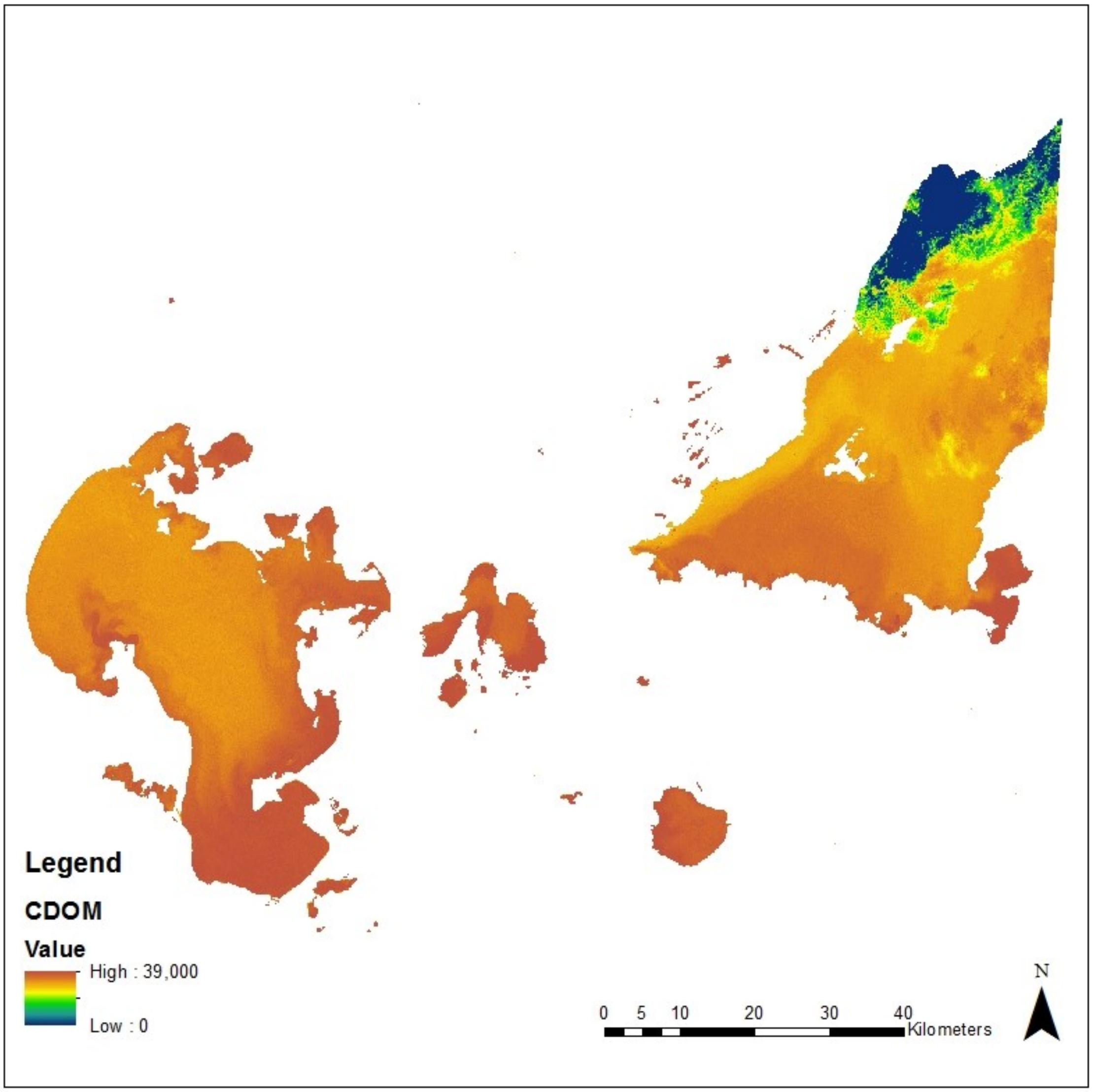


Figure 16: CDOM distribution for only lake water bodies in 2011 based on new model.

SSC – New Model – 2011 – Lakes Only

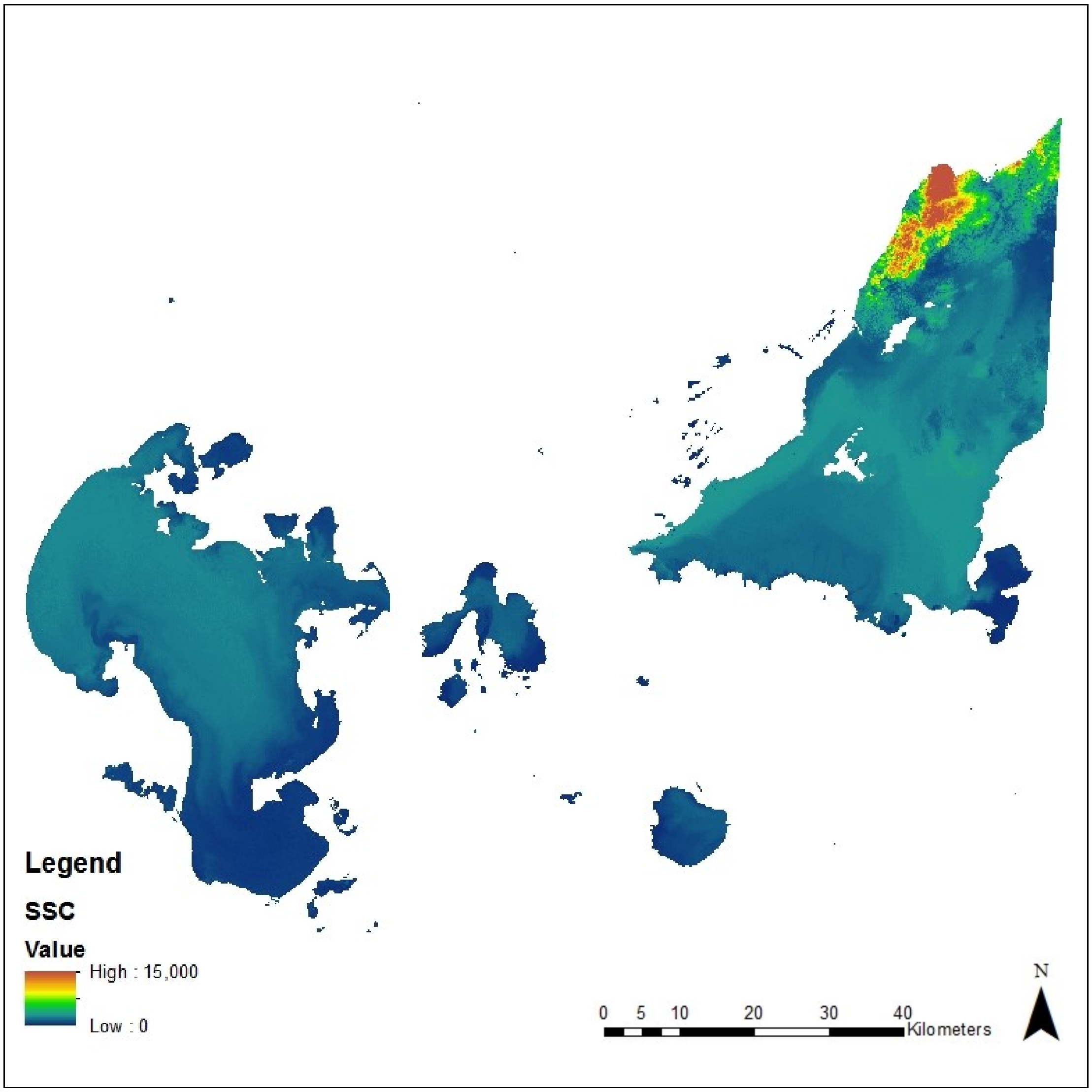


Figure 17: SSC distribution for only lake water bodies in 2011 based on new model.

Chl-a – New Model – 2011 – Lakes Only

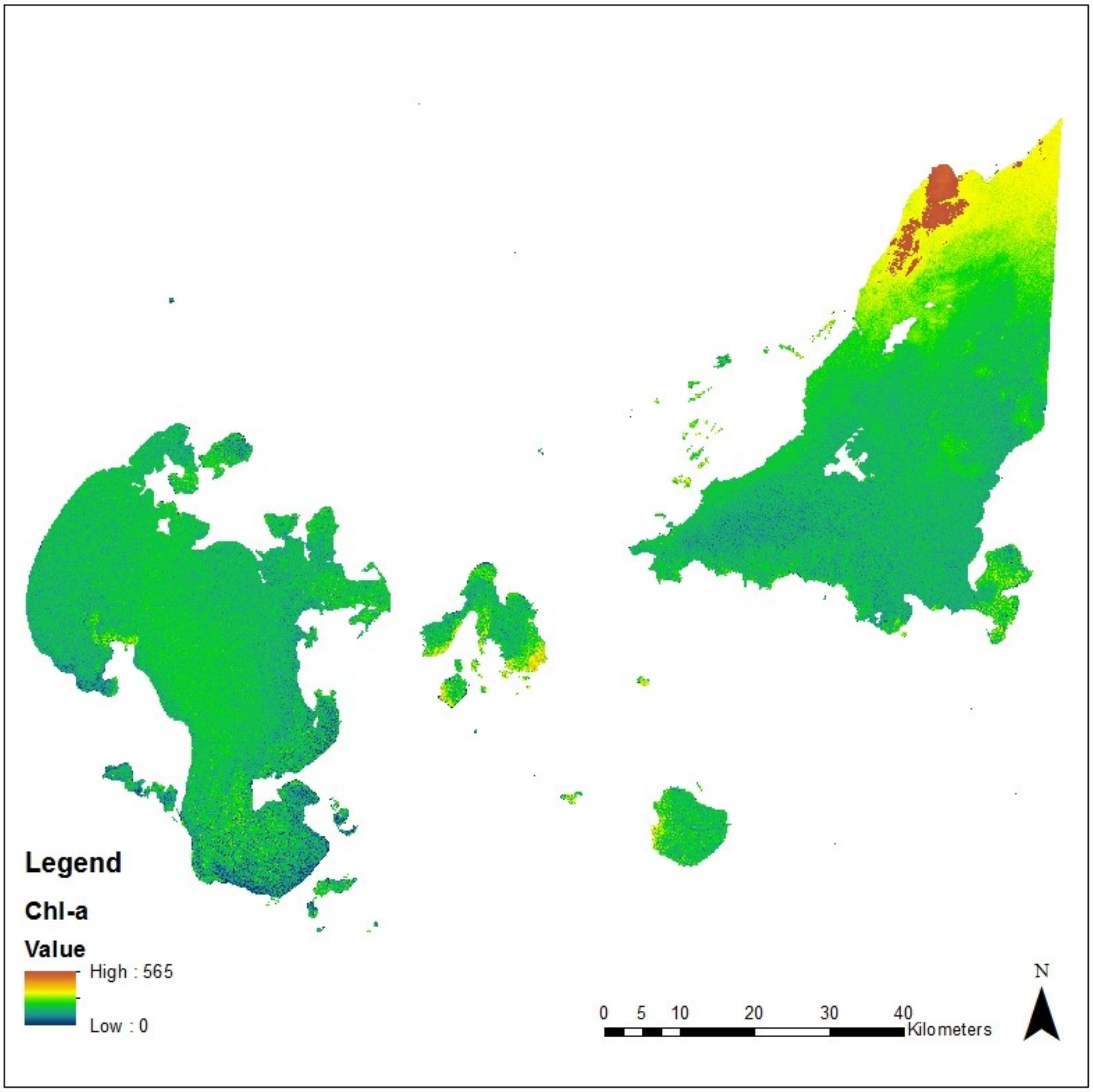


Figure 18: Chl-a distribution for only lake water bodies in 2011 based on new model.

CHAPTER V

DISCUSSION

This chapter explores the results examined in the previous chapter and includes an interpretation of these results. Additionally, this section discusses possible reasoning for why certain patterns are displayed and the overall accuracy of each of the twelve models used throughout this study. The original research question associated with this research will be analyzed along with methodological limitations and other considerations that were taken.

Data Acquisition

One significant difficulty with pursuing research in a study area as remote and complex as the PAD is the ability to conduct field work that directly coincides with satellite imagery collection. Ideally, in situ data measurements for each of the water quality parameters should be collected on the same day the Landsat sensor passed over the study area, however this is extremely hard to achieve logistically. Additionally, Landsat sensors (primarily those developed before Landsat 8) do not collect the wavelength ranges that are best for water quality monitoring. For these reasons, MODIS Aqua data is ideal for this type of remote sensing because it collects the smaller ranges of reflectance that are have been documented as being the primary wavelength for extracting water quality data. However, in this small study area MODIS imagery could not be used because of coarse resolution of the imagery (30 meters x 30 meters). Even the resolution of the Landsat 5TM imagery that was used is insufficiently fine at 15 meter x 15 meters and therefore there were cases of pixel mixing where there is both land and water in a number of pixels. There were no obvious cases of this mixing of pixels within the imagery, though mixing could have altered the results simply due to the limitations of the spatial resolution of the imagery.

The collection of in situ data may have also led to some possible errors in the overall results of this study. Since the PAD is such a complex environment it is extremely difficult to navigate, and was not necessarily possible for field measurements to be taken throughout the entirety of the study area. For instance, there were no water quality measurements collected in Lake Claire in 2010 or 2011 even though it is a major feature within the PAD. Additionally, not all sample locations that were sampled in 2010 were sampled again in 2011 which would have been ideal for this type of water quality study which divided the data by year for model calibration and validation. It is also possible there were errors with the actual water samples collected not being an accurate representation of the CDOM, SSC or Chl-a within a body of water because of the interconnectedness of this area. Since this methodology is being developed in hopes of applying the process to monitor water quality more frequently than a single month once a year, the ability of the models to predict these parameters accurately from a single image is of high importance. Although this type of inaccuracy is likely to occur mainly in the river systems, it is possible that it also impacts the lake samples as well. While this is no fault of the water sample collectors in the field, it is another difficulty which can arise when studying complex wetland ecosystems like the PAD.

Published Models

The use of previously published models to measure water quality parameters in a study area different from where the models were originally developed can be problematic and is often unsuccessful. Part of this study was to determine how well previously published models would perform in such situations, however precautions were taken when selecting the models. These precautions included the finding models which were created in environments similar to the PAD and using imagery from Landsat sensors. After applying the published models to the Landsat 5TM data and running a regression analysis between the output and the in situ water quality measurements, it became apparent that they did not accurately quantify CDOM, SSC and Chl-a within the study area. Both the R-squared and p-values for all the parameters suggest that the results were not significant. This shows that existing methods for monitoring water quality in complex wetland ecosystems are not sufficient and more research needs to be conducted in order to determine if there are models that can be applied to a variety of landscapes.

Model Development

The process used in this study to create the new models was empirically based and involved the splitting of the total in situ data so the 2010 in situ data and imagery was only used in the model calibration phase and the 2011 data was only used for validation of the models. The first step was to plot the in situ data in the form of a histogram, this proved to be informative because it showed that the raw data were not statistically normal. Without normal data, measuring the goodness of fit of the new models would have been inaccurate. Additionally, by analyzing the histograms, it became apparent that there were different patterns in the data based on what type of body of water the samples were collected from. This proved to be beneficial because the models performed differently depending on the spatial unit (all-water, river-only and lake-only). Ultimately the models developed for river-only points performed best, having the lowest p-values and highest R-squared values, followed by the all-water points and then lastly the lake-only points.

Model Performance

It is of interest that the river models are best at predicting the water quality parameters because of the coarse spatial resolution of the imagery, which makes it difficult to mask the small river features. The in situ data collection for river points was distributed throughout the entirety of the study area whereas the lake points were focused more on the eastern portion of the PAD. Therefore, it was not surprising to find that the lake models did not accurately predict the water quality parameters. The models created to quantify CDOM, SSC and Chl-a based on all the in situ data points (rivers and lakes) performed better than expected. It is clear that it is beneficial to create separate models for each water body type when monitoring water quality parameters. For instance, the SSC and Chl-a river models produced better p-values and R-squared values than the models which were created using all water features. Although as previously discussed in the results chapter, R-squared is not ideal in some cases as a performance measure. The only case where it did not appear beneficial to separate the in situ data points based on these spatial units was CDOM. All models predicting CDOM, including all water features, rivers and lakes performed best out of all of the other new models. By separating the data and creating these empirical models based on a variety of spatial units it was possible to see that some water quality parameters should have separate models depending on the body of water they are being measured in, while others do not.

Spatial Patterns of the Parameters

The spatial distribution of the water quality parameters shows the greatest variation at the mouths of the three active deltas where there are greater concentrations of CDOM, SSC and Chl-a entering the lakes and dispersing. In all of the imagery, there is a group of pixels limited to the northeastern portion of Lake Athabasca which appears to be caused by cloud cover in the original 2011 Landsat imagery.

CDOM displays a very similar spatial pattern between each of the three models. There are the highest values within the southern portion of Lake Claire and Lake Athabasca as well as generally high values within Mamawi Lake, although the values associated with CDOM do vary greatly between the models. The river model used to quantify CDOM displays the most variation throughout the systems of rivers compared to the other parameters, however the predicted CDOM within the rivers differs quite a bit between the all water and river-only models. Overall, CDOM displays the most consistent patterns between each of the three models suggesting that it is not necessary to create separate models for water body types when modeling this particular parameter.

Similar to the distribution of CDOM, SSC displays similar patterns in the outputs of the all water and lake-only models, however, SSC appears to disperse into the larger lakes shortly after passing through the mouths of the deltas. Additionally there is less variation in SSC throughout the larger water bodies with the main differences around river inputs and the banks. In general though the SSC values are very low, especially in the rivers-only model where they are almost at zero. These findings suggest that maybe Landsat 5TM band 3 might not be ideal for predicting SSC values.

The parameter which displays the greatest amount of variation in the results of the three models is Chl-a. The predicted values of Chl-a are extremely different between the all water and lakes-only models and in some cases the results seem to be opposite. For instance, at the mouth of the Birch Creek Delta in Lake Claire, the all-water model displays moderate to low Chl-a values while in the lakes-only model, the value is somewhat high. The rivers also display very different patterns between the all-water model and the rivers-only model. The rivers in the output of the all-water model for Chl-a shows moderate to high concentrations of Chl-a, whereas the rivers-only model displays very low values. It is unclear why this is the case but it may be attributed to the band combination used in these models (Landsat 5TM band 2/band 1), or there could be other unknown materials which could be effecting the optical properties of the water. Most models predicting Chl-a concentrations utilize NIR and red bands, however, there were studies that suggested using the blue band which is why it was used here. Overall, these results show that there is a great deal of error with the Chl-a models, something that can also be seen when analyzing the results of the regression analysis.

In order to improve upon these methods, a few developments need to be made. First, it would be necessary to develop sensors with higher resolution (less than 15m x 15m) and with a spectral resolution more similar that of MODIS Aqua. Additionally, there would need to be an extensive process for creating the models similar to this study but focused on a specific area of interest. Second, more intense surveying of the optical properties of the water to better understand the empirical relationships between the water quality parameters and apparent optical signatures. Finally, our models are primarily empirical and more physically-based modelling may be useful for better explaining and predicting these relationships. The results of this study do suggest, that it will be difficult to create models which can predict water quality parameters in any region without a great deal more investigation.

CHAPTER VI

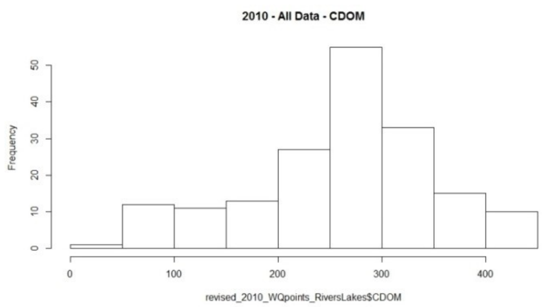
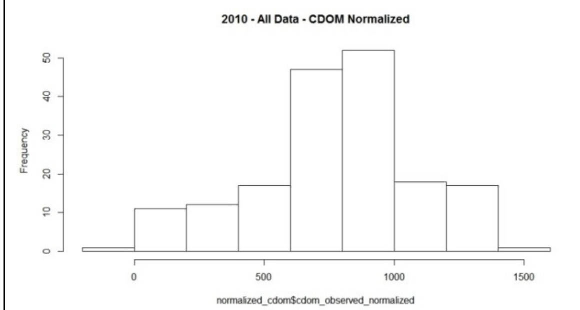
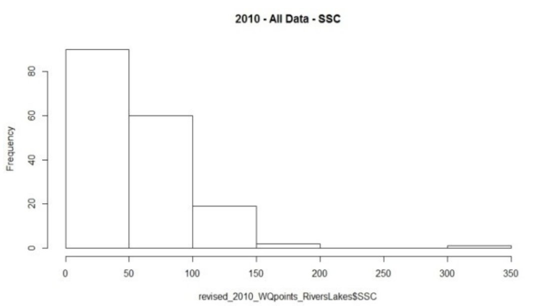
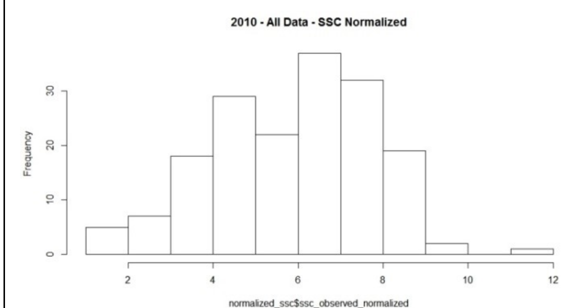
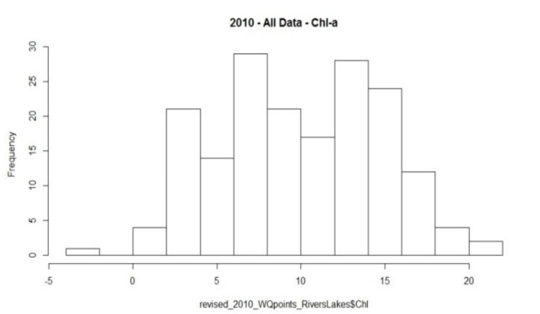
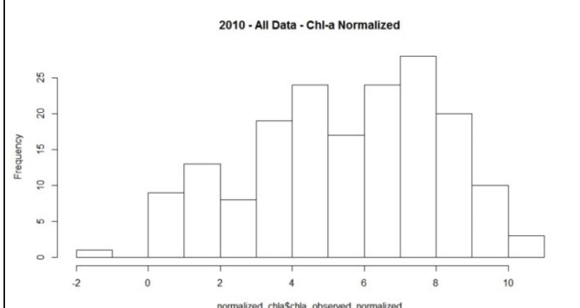
CONCLUSION

This study discusses the effectiveness of current methods for quantifying and monitoring water quality in complex wetland ecosystems such as the PAD. The results of this research show that the current, published models do not accurately predict CDOM, SSC and Chl-a in rivers and lakes at the scale of the PAD. Applying models developed in other locations were found to not be able to properly quantify these water quality parameters, however, models created specifically for this study area were much more effective. Additionally, models developed for particular water bodies, such as rivers and lakes, yielded some interesting results which suggest it may be beneficial to develop individual models for rivers and lakes even within the same study area to more accurately predict water quality.

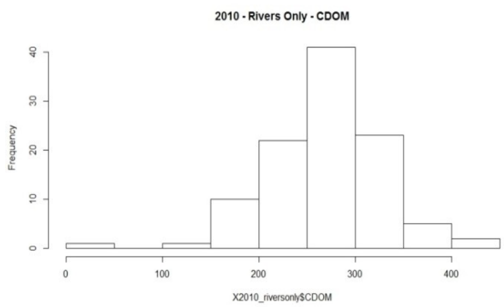
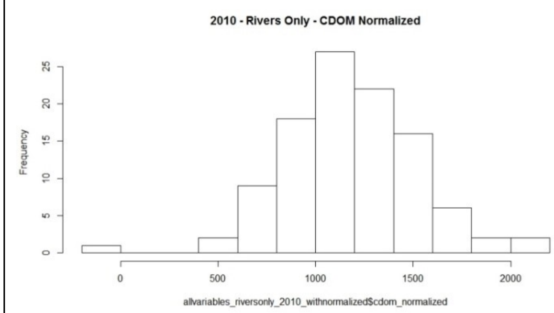
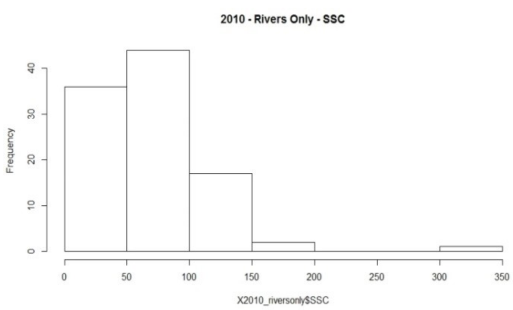
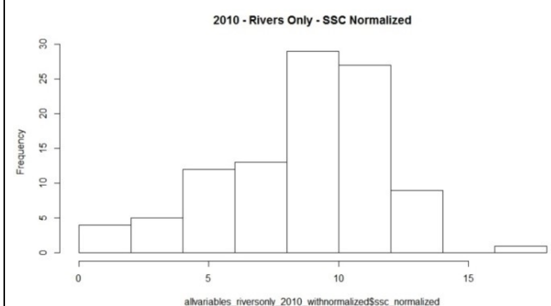
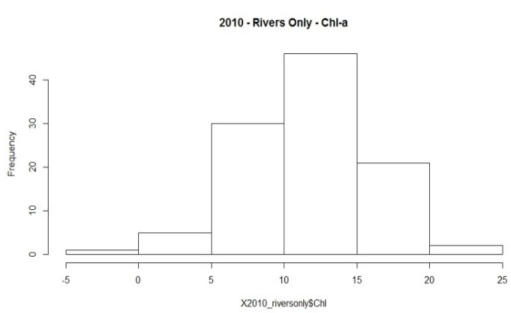
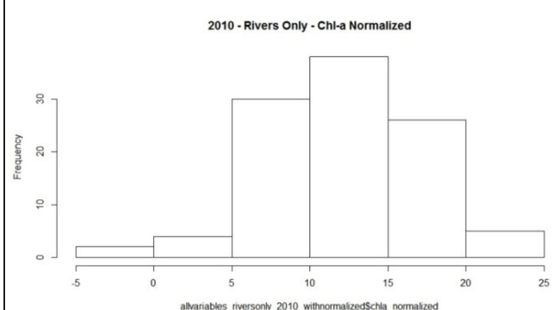
Throughout this research, it has become apparent there is a growing importance of developing models to extract water quality parameters from satellite imagery such as Landsat. Due to the increased difficulty of travel in complex wetland ecosystems like the PAD it is extremely challenging to rely solely on field measurements of water quality to monitor aquatic ecosystem health in these regions. The results of this study suggest a greater need for the development of models for estimating water quality parameters like CDOM, SSC and Chl-a which can be applied to a wider variety of locations. This might be done through more empirical modeling in different locations, use of different sensors, or better physics-based model development. In doing so, it would allow for more frequent monitoring of aquatic ecosystems with less need for field measurements and better, more informed management practices of complex ecosystems around the world.

APPENDIX
HISTOGRAMS: ORIGINAL & NORMALIZED

HISTOGRAMS FOR 2010: ALL POINTS

Original Histograms *(Side A)*	*Histograms after Box-Cox Transformation* *(Side B)*
 CDOM (ug/L)	 CDOM (ug/L)
 SSC (cm/275mL)	 SSC (cm/275mL)
 Chl-a (ug/L)	 Chl-a (ug/L)

HISTOGRAMS FOR 2010: RIVER POINTS ONLY

Original Histograms (Side A)	*Histograms after Box-Cox Transformation (Side B)*
 CDOM (ug/L)	 CDOM (ug/L)
 SSC (cm/275mL)	 SSC (cm/275mL)
 Chl-a (ug/L)	 Chl-a (ug/L)

HISTOGRAMS FOR 2010: LAKE POINTS ONLY

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(Side B)</th></tr>
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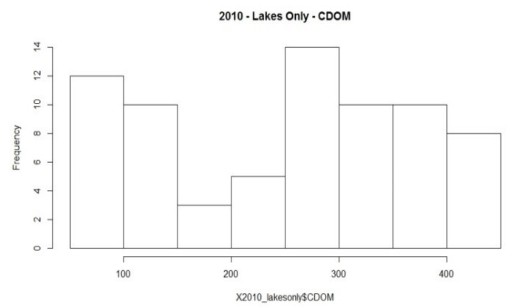

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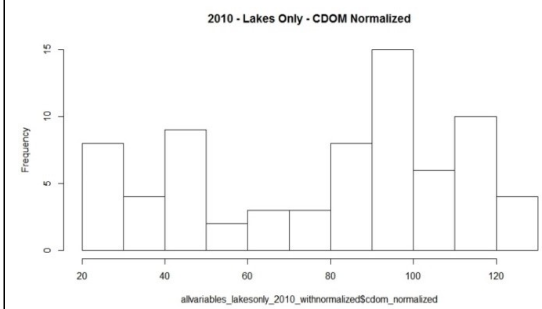

CDOM (ug/L)
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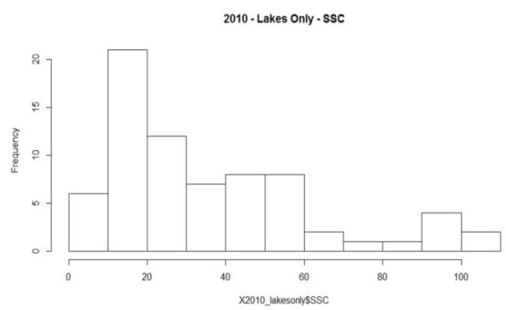

SSC (cm/275mL)
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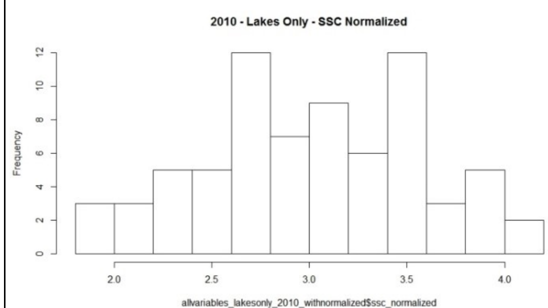

SSC (cm/275mL)
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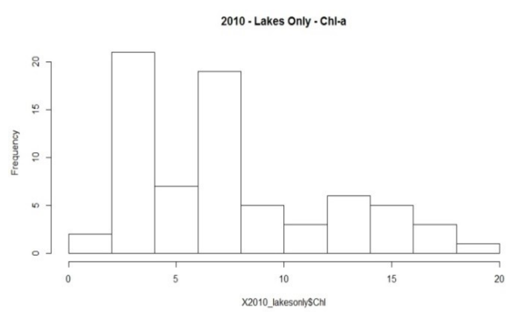

Chl-a (ug/L)
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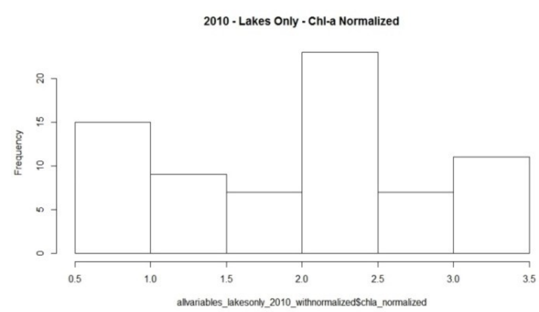

Chl-a (ug/L)
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REFERENCES CITED

Basu, Ben K., and Frances R. Pick. "Factors Regulating Phytoplankton and Zooplankton Biomass in Temperate Rivers." Limnology and Oceanography 41.7 (1996): 1572-77. Print.

Bayrock, L. A., and J. D. Root. Geology of the Peace-Athabasca River Delta Region, Alberta: Research Council of Alberta: Geology Division, 1972. Print.

Cardille, J. A., J. B. Leguet, and P. del Giorgio. "Remote Sensing of Lake Cdom Using Noncontemporaneous Field Data." Canadian Journal of Remote Sensing 39.2 (2013): 118-26. Print.

Griffin, Claire G., et al. "Spatial and Interannual Variability of Dissolved Organic Matter in the Kolyma River, East Siberia, Observed Using Satellite Imagery." Journal of Geophysical Research 116 (2011): G03018. Print.

Huang, C. C., et al. "Assessment of Nir-Red Algorithms for Observation of Chlorophyll-a in Highly Turbid Inland Waters in China." ISPRS Journal of Photogrammetry and Remote Sensing 93 (2014): 29-39. Print.

Kulkarni, Arun. "Water Quality Retrieval from Landsat Tm Imagery." Procedia Computer Science 6 (2011): 475-80. Print.

Kutser, T., et al. "Estimating Lake Carbon Fractions from Remote Sensing Data." Remote Sensing of Environment 157 (2015): 138-46. Print.

Liu, Y. S., M. A. Islam, and J. Gao. "Quantification of Shallow Water Quality Parameters by Means of Remote Sensing." Progress in Physical Geography 27.1 (2003): 24-43. Print.

Long, C. M., and T. M. Pavelsky. "Remote Sensing of Suspended Sediment Concentration and Hydrologic Connectivity in a Complex Wetland Environment." Remote Sensing of Environment 129 (2013): 197-209. Print.

Mertes, Leal A. K. "Remote Sensing of Riverine Landscapes." Freshwater Biology 47 (2002): 799-816. Print.

Pavelsky, T. M., and L. C. Smith. "Remote Sensing of Hydrologic Recharge in the Peace-Athabasca Delta, Canada." Geophysical Research Letters 35.8 (2008). Print.

Qu, Liqin. "Remote Sensing Suspended Sediment Concentration in the Yellow River." Doctoral Dissertation: University of Conneticut, 2014. 1-130. Print.

Variations in Spectral Absorption Properties of Phytoplankton, Non-Algal Particles and Chromophoric Dissolved Organic Matter in Lake Qiandaohu. Water, 2017.

Smith, L. C., and T. M. Pavelsky. "Remote Sensing of Volumetric Storage Changes in Lakes." Earth Surface Processes and Landforms 34.10 (2009): 1353-58. Print.

Spellman, Frank R., and Joanne Drinan. Stream Ecology and Self Purification: An Introduction. Second ed: CRC Press, 2001. Print.

Survey, Department of the Interior: U.S. Geological. "Landsat 4-5 Thematic Mapper (Tm) Level-2 Data Products - Surface Reflectance." U.S. Geological Survey 2015. Web2018.

Timoney, Kevin P. The Peace-Athabasca Delta: Portrait of a Dynamic Ecosystem. First ed. Edmonton, Alberta, Canada: The University of Alberta Press, 2013. Print.

Topliss, B. J., C. L. Almos, and P. R. Hill. "Algorithms for Remote Sensing of High Concentration, Inorganic Suspended Sediment." International Journal of Remote Sensing 11.6 (1990): 947-66. Print.

UNESCO World Heritage Centre. "Wood Buffalo National Park." UNESCO 2018. Web. 08/02/2018.

Van Gaelen, Nele, et al. "Identifying the Transport Pathways of Dissolved Organic Carbon in Contrasting Catchments." Vadose Zone.Special Section: Dissolved Organic Matter in Soil (2014): 1-14. Print.

Wassenaar, L. I., et al. "Controls on the Transport and Carbon Isotopic Composition of Dissolved Organic Carbon in a Shallow Groundwater System, Central Ontario, Canada." Chemical Geology (Isotope Geoscience Section) 87 (1991): 39-57. Print.

Yu, Qian, et al. "Functional Linear Analysis of in Situ Hyperspectral Data for Assessing Cdom in Rivers." Photogrammetric Engineering & Remote Sensing, 2010. 1147-58. Vol. 76. Print.