ABSTRACT

OZEN, SIBEL. Use of Limited Data to Model Lake Water Clarity from Remote Sensed Data in Lake Mattamuskeet, NC. (Under the direction of Dr. Stacy A. C. Nelson and Dr. Siamak Khorram).

Water clarity is an important criteria for not only water quality monitoring but also the environmental management of a lake and surrounding watershed. This research focuses on the evaluation of Landsat 8 for the modeling water clarity in Lake Mattamuskeet, North Carolina. The main objectives of our study was to determine the relationship between remotely sensed data and secchi disk trancperancy (SDT) measurements in Lake Mattamuskeet using publically available SDT data and Landsat imagery. To adress this objective, the following quaestions were eximend in this study. Can *in-situ* SDT measurements be used to adequately model water clarity from remote sensed data despite non-extensive field sampling? Based on previous remote sensing studies, can comparable estimates of water clarity using Landsat 8 for the east and west sides of Lake Mattamuskeet, North Carolina be developed?

The east and west sides of Lake Mattamuskeet function bio-physically independent due to being bisected by NC Highway 94. Statistical relationships were developed to determine the ability to use remote sensing as a tool for water clarity monitoring. Although, Landsat 8 has been less use to establish relationships, this study includes one cloud-free Landsat 8 image within +/- 0 day of the 30 samples of SDT data is used for the development of linear regression models. Single bands and band combinations correlated with brightness value and SDT by using multiple and simple regression analysis. Backward elimination and Akaike`s information criteria (AIC) were used to select the best performing model for each

side of the lake. The results of this study showed that limited *in-situ* measurements can be used to model Lake Mattamuskeet water clarity from remote sensed data (R^2= 0.40-0.82, $P< 0.05$). However, increased frequencies of sampled field data is needed for matching temporal resolutions of satellite overflights. This research demonstrates a first attempt for analyzing of water clarity in Lake Mattamuskeet using available Landsat 8 data in an effort to increase capacities of monitoring agencies for assessing changes in lake water clarity.

Use of Limited Data to Model Lake Water Clarity from Remote Sensed Data in Lake Mattamuskeet, North Carolina

by
Sibel Ozen

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Forestry

Raleigh, North Carolina

2016

APPROVED BY:

_____	_____
Dr. Stacy A. C. Nelson	Dr. Siamak Khorram
Committee Co- Chair	Committee Co- Chair
_____	_____
Dr. Halil Cakir	Dr. Michelle Moorman

DEDICATION

I would like to dedicate this thesis to my family.

BIOGRAPHY

Sibel Ozen is originally from Arhavi from Turkey. She graduated from Black Sea Technical University with a Bachelor`s degree in Forestry Engineering in 2011, and 2014 she started the Master of science program in Department of Forestry and Environmental resources at North Carolina State University.

ACKNOWLEDGMENTS

I would like to thank Dr. Stacy Nelson, Dr. Siamak Khorram, Dr. Halil Cakir, and Dr. Michelle Moorman for their guidance, time, and helpful feedback. Special thanks to Dr. Stacy Nelson for putting extra effort helping me throughout my study at NCSU. I would also like to thank all my dear pack friends from NCSU for helping, guidance, and personal support.

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CHAPTER I

Literature Review

Water is one of the most fundamental natural resources not only the world, but also for the survival of life on the planet. Freshwater bodies, including rivers, reservoirs, wetlands, and lakes are important for human civilizations who are dependent on it. Increasing demand for human needs, including agriculture and industrial demands, has been known to cause continual stress on these freshwater resources, and the associated landscape is supporting these resources. In addition to various anthropogenic activities, these activities coupled also with natural disturbances need for continual environmental monitoring of water quality (see Butt et al. 2015a).

Lake water is an important freshwater resource and provides an essential life supporting system which includes fishing, transportation, agriculture, industry, recreation, and tourism for a society. Serious environmental concerns of Lake water-quality conditions include diminished water quality as a result of the rapid increases human population and development pressures (Duan et al. 2009). Monitoring and protecting water quality a significant concern for many federal and local government agencies (Duan et al., 2009; Olmanson et al. 2008).

Traditional approaches to monitoring water quality have included analyzing water samples for levels of nitrogen, phosphorus, total suspended solids, chlorophyll a, temperature, and dissolved oxygen. Although more traditional water clarity monitoring methods provide accurate estimates of water quality conditions, they require a continual

period of monitoring, and they are usually expensive and need more time because traditional methods requires extensive laboratory analysis (Li et al. 2004; Nas et al. 2010). On the other hand, Secchi disk transparency (SDT), which is an inexpensive tool, is widely used for analysis of water clarity and water quality (Dhillon et al. 2014). Hence, it is fundamental to find an efficient way to monitor and evaluate water quality in lakes (Duan et al. 2009).

The Secchi disk is a tool for measuring water clarity or transparency invented by Italian astronomer Pietro Angelo Secchi in 1865. The Secchi disk is a black and white metal circular disk 30cm (12in) in diameter. Since, the invention of the standard Secchi disk, a modified disk, smaller, 20cm (8in) diameter, has also been used (Dhillon et al. 2014). The measure is known as the Secchi depth, Secchi disk transparency, Secchi disk reading, and Secchi disk visibility. Additionally, SDT measurements have shown promising associations with remotely sensed spectral imagery collected from aircraft and satellite sensors (Kloiber et al. 2002; Kloiber, Brezonik, and Bauer 2002a).

Water clarity, which has used as a metric for water quality. Standardized measurements of water clarity indicate the ability of light to penetrate from the surface of the water to depth. The ability of light to penetrate to depth allows for the growth of macrophytes below the surface, which in turn may filter sediment or other contaminants from the water column. Additionally, increased plant growth in relationship to water clarity, may also provide important aquatic habitat benefits, by increasing available water column oxygen, habitat stability for aquatic fish and other organisms, as well as a food source for waterfowl. Water quality monitoring can be approach through *in situ* measurements of Secchi disk transparency (Duan et al. 2009; Heiskary et al. 1988).

While SDT measurements are relatively inexpensive and easy to perform, routine sampling is still limited by agency labor, access, geography, and budgets. This type of discontinuity in repetitive sampling may restrict remote sensing's ability to monitor water clarity effectively, as well as provide a spatial or temporal view of water clarity. Moreover, satellite technology has considerable potential as a cost-effective data source for ground-based monitoring programs (Kloiber et al. 2002).

Many investigators have effectively applied different remote sensing technologies for providing water quality analysis (e.g. IKONOS, Quick Bird, SPOT (Satellite Pour I'Observation de la Terre), SeaWIFS (Sea-viewing Wide Field-of-view Sensors), MERIS (Medium Resolution Imaging Spectrometer), MODIS (Moderate-resolution Imaging Spectrometer) and Landsat) (see Butt et al. 2015b; Coskun et al. 2006; He et al. 2012; Huiping et al. 2011; Kloiber et al. 2002; Kutser et al. 2015; Lai et al. 2011; Lathrop et al. 1992).

Among all of these satellite systems, the Landsat platforms have provided water quality monitoring from as early as the 1980s to present (Butt et al. 2015b). In 2008, all Landsat imagery became publicly available at no cost. As a result, these platforms that have been increasing in popularity in relating their acquired data source to various water quality parameters (see Butt et al. 2015b; Khorram, 1985; Kloiber et al., 2002; Li et al. 2004; Nas et al., 2010; Nelson et al., 2003; Pattiaratchi et al. 1994). Since the first Landsat platform became available in 1972, eight satellites in total have been launched. Currently, only two satellites are functional (i.e. Landsat 7 and Landsat 8) (see Figure1). Furthermore, Landsat 8 is similar to Landsat 7 (ETM+) except that the Landsat 8 has two additional spectral bands (see Figure 2). The advantage of Landsat platform is that it provides the largest running

historical inventory in the monitoring of the earth. It also performs 16 days revisit cycle (Lillesand et al. 1994).

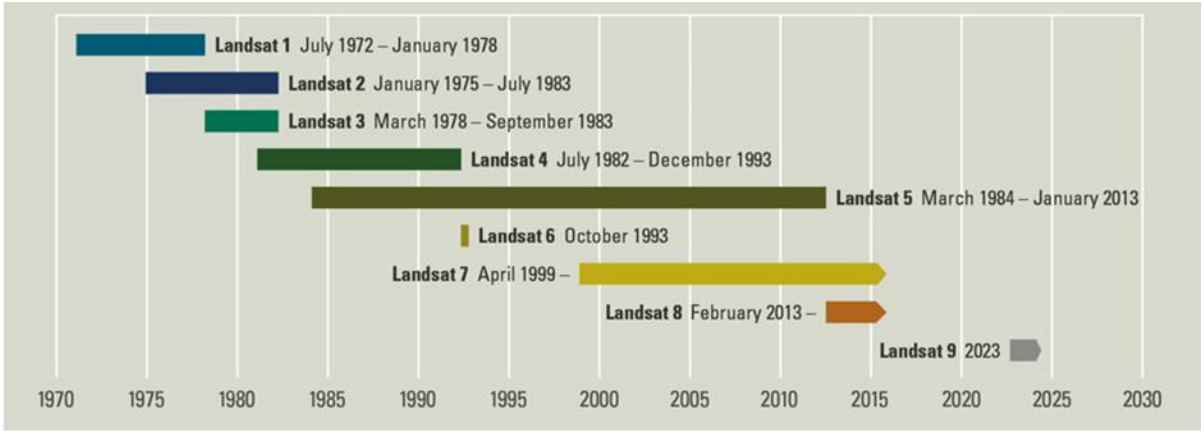

Figure 1: Time line of Landsat platforms (USGS, 2015)

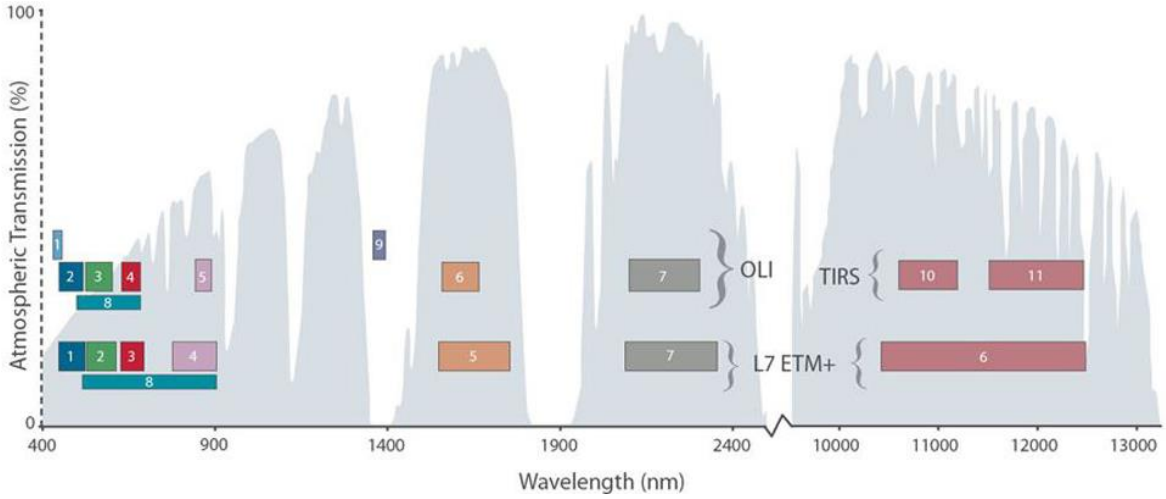

Figure 2: Platforms sensors and rectification (USGS, 2013)

Several investigators have studied the applicability of water clarity through Landsat sensors and ground sample data. For example Landsat (1-3) Multispectral Scanner (MSS), Landsat (4-5) Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) have been used to understand the relationship between water quality parameters of lakes and spectral reflectance as well as to determine the spatial distribution of some water quality parameters such as turbidity, Secchi Disk Transparency (SDT), suspended sediments (SS), and chlorophyll a (Chl-a) (Yip et al. 2015).

Many studies have also widely demonstrated strong relationships between standard lake water quality parameters and brightness data collected by satellite sensors (see Brezonik et al. 2005; Duan et al. 2007; Hellweger et al. 2004; Khorram, 1985; Lillesand et al. 1983; Nas et al., 2010). The relationship between water quality parameters (e.g. SDT, Turbidity, Chl-a) and spectral values of sensors (i.e. single band, band ratios, or combinations of bands)

have typically demonstrated through a statistical regression analysis. Larger R^2 values suggest higher correlations to the examined water quality parameter (Nas et al., 2010).

Early research, using Landsat 4-5 Thematic Mapper (TM) data, demonstrated strong relationships for water quality monitoring. Khorram and Cheshire (1991) used the Landsat 4 and Landsat 5 TM blue (band1), and green (band2) band to estimate Secchi Disk Transparency (SDT) in Augusta Bay, Sicily. In addition, they found band2 (green), to be consistent predictors of turbidity as a sediment analysis and band1 (blue) as a reliable indicator for chlorophyll-a analysis. Lathrop and Lillesand (1986) are also evaluated to Landsat 4 and Landsat 5 TM green band (band2) to estimate Secchi disk transparency (SDT) in Green Bay and central Lake Michigan. Pattiaratchi et al. (1994) assessed Landsat 4 and Landsat 5 TM data band1 and band3 for the monitoring of chlorophyll concentration and SDT for Cockburn Sound in Western Australia. Cox et al. (1998) investigated that satellite-based remote sensing, which was Landsat 4 and Landsat 5 TM, to assess water quality in 11 reservoirs of the Catawba River basin. In this study, the authors used the spectral band ratio consisting of green\ blue (Band3\ Band1) to estimate SDT. Kloiber et al. (2002) develop a relationship between SDT and Landsat TM data (Band1\Band3). Nelson et al. (2003) developed a relationship between Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and SDT, using blue\ green ratio (Band1\Band3) to estimate SDT from Landsat data in Michigan. Olmanson et al. (2008) brought together a 20-year comprehensive water clarity database from Landsat 4 and Landsat 5 TM and Landsat 7 ETM + for Minnesota lakes, larger than 8 ha surface area. This study contained data on more than 10,500 lakes at 5-year intervals over the period 1985-2005. Duan et al. (2009) evaluated Landsat 4 and Landsat 5 TM and SDT measurements in three lakes in northeast China, Lake Chagan, Lake Xinmiao, and Lake Kuli.

The result of this analysis was the discovery of a strong relationship between the sensor data and water clarity from field-collected SDT. Zhao et al. (2010) explored the ability to use Landsat 7 ETM+ and SDT for Taihu Lake. In this study, the brightness of the Landsat 7 ETM+ showed significant correlations with band1, band3, band1\band3. Nas et al. (2010) were able to estimate the relationship between spatial patterns using of Landsat 5 TM and water quality parameters such as SDT, Turbidity, chlorophyll-a, suspended sediment (SD) in Lake Beysehir, Turkey. The ratio of band1/band2 and band1 were in good agreement between Landsat 5 TM and SDT. Dhillon et al. (2013) examined by using SDT and Landsat 7 ETM + data. The results showed that brightness of the ETM + demonstrated significant relationships with a ratio of band1\band3. Yip et al. (2015) surveyed SDT and Chlorophyll-a concentration with Landsat 5 TM and 7 ETM + for Lake Diefenbaker Reservoir in Saskatchewan, Canada from 1984-2012. In this study, the authors used band1, band2, and band4 for assessing changes in SDT and Chl-a. According to Butt et al. (2015) results of this study SDT suggested a strong correlation with Landsat 7 ETM + and also band3 and band1/band3 were the good predictor of water quality monitoring (see Table 1). Furthermore, a few studies have demonstrated the relationship between ground-based data and Landsat 8. According to Hancock (2015), using Landsat 8 for monitoring water quality is utilized. The author discussed the relationship between SDT and Landsat 8 spectral bands and band ratios on her thesis and she found that band4, band3 and the ratios of band4\band3 as a reasonable model for determining the relationship between Landsat 8 and SDT.

There have observed declines in water quality Lake Mattamuskeet, North Carolina. The west side of the lake was dominated by phytoplankton and characterized by low transparency. On the other hand, east side of the lake was dominated phytoplankton biomass

and Submerged aquatic vegetation (SAV) (Waters et al. 2010a, 1249-1261). However, there is no longer a difference in SAV or water quality on east and west side of the lake. Both sides are becoming very similar and none of them provide SAV growth (Moorman M. et al. 2016). Lake Mattamuskeet has been routinely monitored by United States Fisheries and Wildlife Service since 2012. However, routine monitoring of SDT has been sporadic. In situ relationships developed from readily available remotely sensed data may provide an opportunity to assess lake water clarity, as well as this data, may be used to establish a protocol for more consistent water clarity monitoring. For that reason, it is important to understand the relationship between SDT measurements from Lake Mattamuskeet and remotely sensed data. Thus, the aim of this study is to establish a relationship between SDT and remotely sensed data acquired from Landsat 8. Through an examination of field collected data and available Landsat 8 spectral data from Lake Mattamuskeet, this study will develop statistical relationships to identify the ability to use remote sensing as a tool for consistent water clarity monitoring.

Table 1: Satellite measurements of water quality (Adapted from Nas et al., 2010)

Location	Sample size	Satellite Platforms	Parameter(s) R^2	Band or Band Combinations	References
Augusta Bay in Italy	42	Landsat 4-5 TM	SDT=0.83 TURB=0.52 CHLA=0.84	SDT= a+b x (band1)+ c X(band2) TURB= a+ b x (band2) CHLA= a+b x (Band1) + c x (band2)	Khorram et al. (1991)
Green Bay and central lake Michigan	15	Landsat 4-5 TM	SDT=0.98 CHLA = 96.4 Turbidity=98.8	SDT= a+b x (band2) CHLA= a + b x (band2) Turbidity= a + b x (band3)	Latrop et al. (1986)
Lake in Minnesota	~40	Landsat 4-5 TM Landsat 7 ETM + Landsat MSS	SDT= 0.71-0.92	SDT= a+ b x(Band1/ band3) + c x (band3)	Kloiber et al. (2002)
Lake Michigan	93	Landsat 7 ETM +	SDT=0.42	SDT= a+ b x (band1/band3)	Nelson et al. (2003)
10000 Lake is Minnesota	37	Landsat 4-5 TM Landsat 7 ETM + Landsat MSS	SDT= 0.77-0.80	SDT= a+ b x (band1/band3)+ c x (band1)	Olmanson et al. (2008)
Lake Beysehir Turkey	40	Landsat 5 TM	SDT= 0.60-0.71	SDT= a+ b x (band1/band3)	Nas et al. (2010)
Lake Chagan, Ximmia, and Kuli (China)	…	Landsat 7 ETM +	SDT= 0.72-0.98	SDT= a+ b x (band1/band3)	Duan et al. (2009)
Taihu lake in China	…	Landsat 7 ETM +	SDT=0.64	SDT= a+ b x (band1/band3)+ c x (band1)	Zhao et al. (2010)
Cordoba province Argentina	…	Landsat 7 ETM +	SDT=0.81	SDT= a+ b x (band1/band3)+ c x (band3)	Bonanse et al. (2015)
Rawal lake in Pakistan	20	Landsat 7 ETM +	SDT=0.73-0.79	SDT=a + b x (band3)	Butt et al. (2015)
Brookville reservoir Southeastern Indiana	30	Landsat 8	SDT=0.58	SDT= a+ b x (band4/band3)+c x (band4)	Hancock et al. (2015)

CHAPTER II

Use of Limited Data to Model Lake Water Clarity from Remote Sensed Data in Lake Mattamuskeet, NC

1.0 Introduction

Lakes are an important natural resource, not only for human beings but also serve as a vital ecosystem for several species fish, plants, and wildlife. Clean and sufficient fresh water provides many essential ecosystem services, such as transportation, fishing, agriculture, industry, recreation, drinking water supplies, and tourism. Rapid urbanization, industrialization and also human behavior lead to impairments of water quality. Critical global water issues rapid population growth, climate change, land use change, and rapid urbanizations may also cause lake water quality to degrade (Duan et al. 2009; Khan et al. 2005). Therefore, it is essential to have effective monitoring and management strategies in place for ensuring optimal water quality (Nelson et al. 2003; Olmanson, Bauer, and Brezonik 2008).

Secchi Disk measurement has been recognized as one of the easiest, fastest, and most economical ways to predict water clarity (Dhillon et al. 2014). Indeed, citizen-volunteer programs for collecting secchi disk transparency (SDT) have improved by state agencies in many areas across the U.S. (Nelson et al. 2003). However, frequent sampling and increasing volunteer SDT collection programs make ground-based monitoring conceivable and comparable to professionals measurements (Nelson et al. 2003).

Many studies have shown the use of satellite technology from space-based platforms provide essential information for monitoring and assessing lake water quality and also supply freely obtainable data (Duan et al. 2009; Lathrop et al. 1986). Several studies have also shown various remote-sensing sensors have been effective for monitoring lake water clarity (Butt et al. 2015; Yip et al. 2015; Khorram S. 1985; Lathrop et al. 1992; Olmanson, Bauer, and Brezonik 2002; Nelson et al. 2003). In addition, platforms such as Landsat have been widely used for establishing relationships between lake water clarity and spectral reflectance (Nas et al. 2010). For example, Lathrop and Lillesand (1986) evaluated relationship between Landsat 4-5 TM data and Secchi disk transparency, chlorophyll-a concentrations, turbidity level, and surface temperature. Band2 (green visible wavelengths) provided a significant relationship with SDT and Chlorophyll-a. Band3 (visible red wavelengths) was a good estimator for turbidity, and band6 was used for surface temperature. In addition, Khorram et al. (1991) used Landsat 4-5 TM data and water quality samples (SDT, Chlorophyll-a, temperature, and turbidity) from 42 sites. Band1 plus band2 was found to be the best predictor of the SDT. However, the best predictor of the turbidity was related to band2. For the temperature estimation, band6 was the reliable predictor. Several studies have found satellite systems are correlate strongly with SDT of lake (Nelson et al. 2002; Olmanson, Bauer, and Brezonik 2002; Sawaya et al. 2003a, 144-156; Woodruff et al. 1999, 41-52; Kloiber et al. 2002, 38-47; Kloiber, Brezonik, and Bauer 2002b, 4330-4340; Li and Li 2004, 893-901). Kloiber et al. (2001) used Landsat 4-5 TM imagery to predict SDT. He found that band1/band3+band1 had reasonable estimates of SDT. Nelson et al. (2003) evaluated band1/band3 for determining if Landsat 7 could be used to measure lake water clarity across multiple lakes. The authors discovered that the estimation of SDT and band1/band3 provided

significant statistical relationships. Moreover using band1/band3+band1 was a consistent predictor of SDT (Nas et al. 2010; Zhao et al. 2012).

For obtaining a reasonably accurate estimate of SDT, a recommended time window should be +/-1 day between SDT and satellite data (Kloiber et al. 2002). The length of the time window is important because it influences the strength and reliability of the ground overflight relationship for water clarity (Kloiber et al. 2002). In addition to this, ground observation data within +/-7 days of satellite image yielded significant statistical relationships (Kloiber et al. 2002; Kloiber, Brezonik, and Bauer 2002a; Butt and Nazeer 2015). Nelson et al. (2003) evaluated lake water clarity that was sampled within +/-7 days of the satellite imagery.

Landsat image and SDT relationships have largely been modeled through linear regression analyses (Nelson et al. 2003; Kloiber et al. 2002; Lathrop et al. 1986). Regression analyses have been used to show the statistically significant relationship of water clarity or water quality to remote sensed data based on extensive *in-situ* data, and closely couple with coincidental satellite overflights. What has less been explored is if non extensive SDT datasets, or even less frequently sample data, can be used to establish comparable relationships with remotely sensed imagery acquired at coincidental or near coincidental dates. However, previous studies routinely show using larger available SDT datasets, larger coefficient of determination (R^2) values have provided strong relationships between brightness values and *in-situ* measurement (ranging between R^2= 0.40- 0.82, $P< 0.05$). Landsat continues to provide a useful technique for analyzing and monitoring water quality. However, Landsat 8 has been less frequently used to establish water quality relationships.

Another advantage of Landsat technology is that the data is now available at no cost since on April 21, 2008.

The objective of this study was to assess the relationship between remotely sensed data and SDT measurements in Lake Mattamuskeet using publically available SDT data and Landsat imagery. To adress this objective, the following quaestions were eximend in this study. Can *in-situ* SDT measurements be used to adequately model water clarity from remote sensed data despite non-extensive field sampling? Based on previous remote sensing studies, can comparable estimates of water clarity using Landsat 8 for the east and west sides of Lake Mattamuskeet, North Carolina be developed?

2.0 Materials and Methods

2.1 Study area

Lake Mattamuskeet represents the largest natural lake in North Carolina, USA. The lake, located on the Albemarle-Pamlico peninsula in Hyde County, covers an area of (162 km^2), and is relatively shallow (mean depth = 1m; maximum depth = 1.75m), and low in elevation (0.15m) off the coast of NC (Fig 3) (Waters et al. 2010b; Waters et al. 2009).

Within the area surrounding the lake, there are four outflow canals, one on the west side and three on the east side that function to control water depth. These canals consist of water control structures that provide fresh water drainage during windy and rainy seasons. Furthermore, these canals prevent unwanted saltwater intrusions at other times (Waters et al. 2010b).

In 1850 European settlement began the construction of the first canal which connects the lake to the sea. Water level declined from 3m to the current depth of 1m due to this

construction. However, the most dramatic change occurred in 1915 due to the building of an extensive pumping system. This extensive pumping system caused 25% drain the southern part of the lake. After that in 1932 the lake was allowed to refill, and the lake became the Lake Mattamuskeet National Wildlife Refuge (Waters et al. 2010b). In 1940, the lake was divided into two basins by North carolina Highway 94. This division has effectively separeted the lake into two distinctive basins, making up an east and west side. Historically each side has shown differences in lake water clarity. According to Waters et al. (2008) the west side was dominated by phtoplankton and characterized by low transparency. In efforts to improve water clearity bentich fish were eliminated to decrease turbidity dating as far back in 1953. The east side of the lake was historically dominated by macrophytes and cracterized by clear water. However, recent observations since 2013, no longer report differences between each side of the lake (M. Moorman, personal communication, USFWS, 2015). Reduction of SAV and water clarity has observed in the east side of the lake (Moorman et al. 2016). Water quality of Lake Mattamuskeet has been observed by the U.S. Fish and Wildlife Service to be declining since the last decade. This agency has been periodically monitoring the lake since 2012; however routine monitoring of SDT has been infrequent. After surveying the available data from USFWS one data source was obtained for this analysis which matched statellite overflights. Furthermore, there are observed 10 years data gap between 2002 and 2012 in the Lake Mattamuskeet (M. Moorman, personal communication, USFWS, 2015).

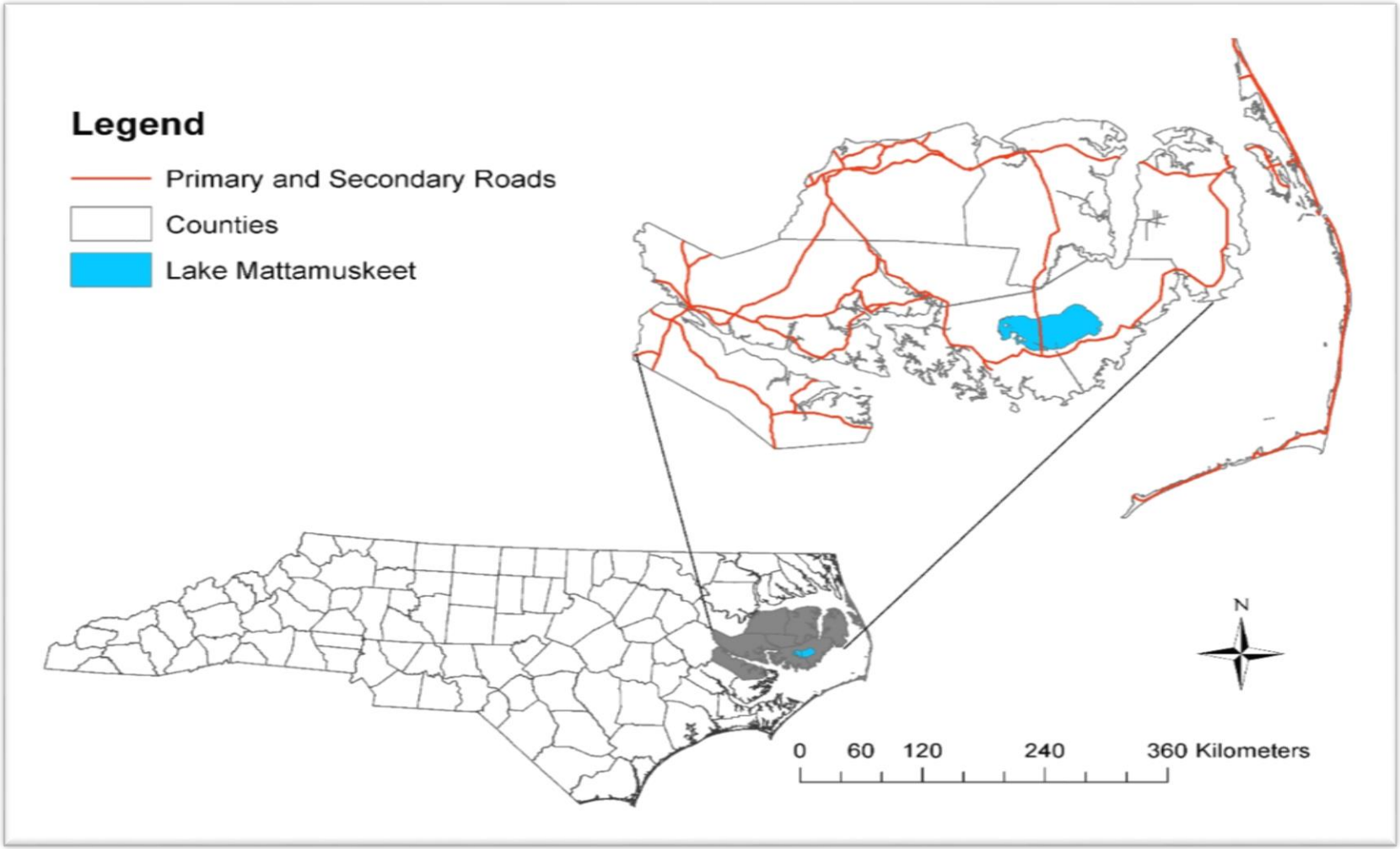

Figure 3: Lake Mattamuskeet

The U.S. Fish and Wildlife Service, in cooperation with the U.S. Geological Survey, maintains two automated water-quality monitoring stations of Lake Mattamuskeet (one in each basin) for continuous evaluation of the lake`s conditions. The U.S. Fish and Wildlife Service agency has regularly monitored the lake since 2012. Monitoring stations measure dissolved oxygen, temperature, pH, conductivity, salinity, water level, wind direction, turbidity, and light. However, routine monitoring of SDT has been less routine, with earliest reported SDT sampling dating back to 2007 (USGS, February 2, 2016, see table 2).

As recent as 2013, differences in water clarity conditions between the east side and west side of the lake were noticeable, with the east side repoted as being visibly less turbid and supporting macrophtes (M. Moorman, personal comminication, USFWS, 2015). According to M. Moorman (2015), the east side is presently characterized as being eutrophic and dominated by submerged aquatic vegetation (SAV). However, the west side of the lake was characterized as being hypereutrophic and dominated by algae, but recently the east side of the lake SAV has also shown a decline in water clarity and SAV (M. Moorman, personal communication, USFWS, 2015). Current conditions suggest both sides appeared to be similar in water quality with neither side being capable of providing SAV growth (M. Moorman, personal communication, USFES, 2015).

Lake Mattamuskeet presently supports several ecological, economic and recreational functions. The lake supplies transportation, recreation, and tourism resources for the surrounding communities. The lake’s strategic location is also of vital importance for waterfowl. Approximately 200,000 ducks, geese, and swans utilize the lake from November through February for over-wintering. Additionally, approximately 58,000 visitors use the

lake annually for hunting, fishing, and observing and taking a photograph (USFWS, November 17, 2014).

2.2 In-Situ Water Clarity

Water sampling and measurements were performed in April 2007, November 2011, June 2012, September 2012, April 2013, May 2014, and October 2014 (See Table 2) for the parameters of temperature, dissolved oxygen, conductivity, salinity, pH, and SDT. All data were obtained from U.S. Fish & Wildlife Service agency. Available data was compared to available Landsat 7 and Landsat 8 image data archives for matching dates, or +/- 7 days. Only SDT data collected on 13 April 2013 was found to match the corresponding available Landsat data.

The average of SDT was 0.105m for the east side for the 13 April 2013. However, the west side SDT average from 0.167m (See Table 3) for the 13 April 2013. The SDT data was collected from 30 different points in the lake. 15 samples were collected from the west side of the lake, and 15 samples were collected from the east side of the lake (See Figure 4).

Table 2: Available Water quality sampling measurements for Lake Mattamuskeet

Time	Field Data	Sample Size	Satellite Image	Used for Modelling
April 2007	Temp, Do, Conductivity, Salinity	6 West 4 East	Landsat 7 ETM+	No
November 2011	Temp, Do, Cond, pH, SDT, Salinity	6 West	Landsat 7 ETM+	No
June 2012	Temp, Do, Cond, pH	12 West 12 East	Landsat 7 ETM+	No
September 2012	Temp, Do, Cond, pH	15 west 15 east	Landsat 7 ETM+	No
April 2013	Temp, Do, Depth, SDT	15 West 15 East	Landsat 8	Yes
2014 May	Temp, Do, Cond, Salinity	8 West 8 East	Landsat 8	No
October 2014	Do, SDT	6 West 3 East	Landsat 8	No

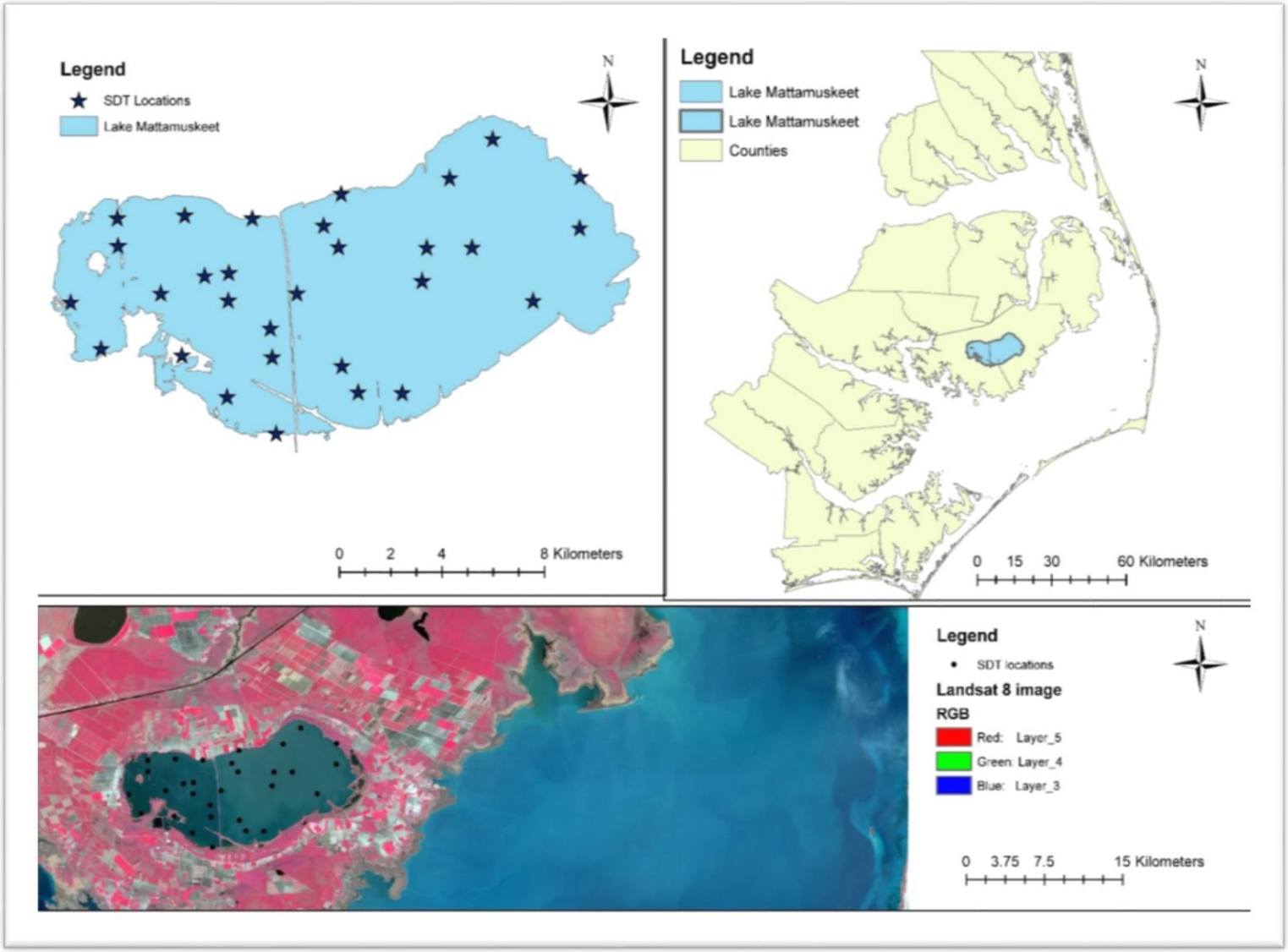

Figure 4: Location of SDT samples for the east and west basins of Lake Mattamuskeet

Table 3: SDT (m) values of Lake Mattamuskeet (13 April 2013)

	East Side	West Side
Average (m)	0.105	0.167
Min(m)	0.085	0.085
Max(m)	0.145	0.23

2.3 Remote Sensing Data-Set and Image Processing

Landsat 8 image data was obtained from the USGS Global Visualization Viewer (*http://glovis.usgs.gov/*). The Landsat 8 imagery contains data captured from two sensors, the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). OLI consists of nine bands (Table 4). The TIRS consists of the last two last bands which are band10 and band11 (USGS, January 15, 2016). Utilizing Landsat sensor's ability to differentiate earth features in different portion of the electromagnetic spectrum. Several studies have been shown that various bands have been effective for use in water quality analysis (Bonansea et al. 2015; Alparslan et al. 2010; Khorram et al. 1991; Kloiber et al. 2002). For instance, in Landsat 8 imagery, band2 represents shorter wavelength of light which penetrates water depth. Band3 is sensitive to water turbidity differences. Band4 senses strong chlorophyll absorption. Furthermore, band5 represents near IR, and is useful for water and terrestrial discrimination because near IR absorbs light reflecting from water bodies making these areas appear darker.

Table 4: Parameters of Landsat 8 Image (Adapted from USGS website)

Band	Type	Wavelength	Resolution
Band1	Coastal / Aerosol	0.43-0.45	30m
Band2	Visible blue	0.45-0.51	30m
Band3	Visible green	0.53-0.59	30m
Band4	Visible red	0.64-0.67	30m
Band5	Near-Infrared	0.85-0.88	30m
Band6	Short wavelength Infrared	1.57-1.65	30m
Band7	Short wavelength Infrared	2.11-2.29	60m
Band8	Panchromatic	0.50-0.68	15m
Band9	Cirrus	1.36-1.38	30m
Band10	Long wavelength Infrared	10.6-11.19	100m
Band11	Long wavelength Infrared	11.5-12.51	100m

14 April 2013 Landsat 8 data provided a coincidental image dataset that matched to *in-situ* SDT data. The image also contained 0% cloud cover, reducing the need for additional atmospheric correction. Additionally, Landsat 8 is comparable in band placement, temporal and spatial resolution to previous Landsat platforms. Thus, providing the possibility of comparable results shown in previous studies where demonstrated strong relationships in lake SDT water investigations.

Image analysis was performed using Erdas Imagine 2014 (Hexagon Geospatial, Inc. 2014) and ArcGIS 10.3.1 (Esri, Inc. 2015) software packages. The Landsat image was obtained as a geoTIFF data source and projected to Universal Transverse Mercator, North America Datum 1983 (NAD 83), and zone 18. Due to the large file size of the original image (228x 223 meters), the image was subset to an area containing the Lake Mattamuskeet study area (97x 57 meters). Spectral digital number (DN) values within the Landsat 8 imagery were extracted at SDT point locations matching the *in-situ* SDT sample locations. A 3 by 3 (9 pixel) area of interest (AOI) was formed for each of the sample locations due to the fact that a small cluster of pixels may provide the best correlation between satellite and field measurements (Krizanich et al. 2009; Kloiber et al. 2002; Nelson et al. 2003).

2.4 Statistical analyses

All statistical analyses were performed using SAS Enterprise Guide 6.1 software package (SAS, Inc. 2014). Simple linear and multiple (Backward) regression analyses were developed between the field samples data and spectral values extracted from the Landsat imagery. Akanke's information criteria (AIC) was used to select the best performing models. All regression models were developed separately for each side of the lake. Based on band

combinations obtained from reported literature values predicting SDT, 42 bands or band combinations were used for estimating the best performing model for Lake Mattamuskeet (Table 5). One outliers was removed from each side of lake based on a normality test. A linear regression utilizing the backward elimination method, which was used for prediction correlations, between SDT and Landsat 8 bands and applied band combinations. Moreover, the highest correlation coefficient (R) or coefficient determination (R^2), and the significance level of P=0.05 value was used for removing threshold. Also, Akaike`s Information Criterion (AIC) was used for estimating to select a best-performing model for Lake Mattamuskeet.

Table 5: Landsat 8 band and band combinations used for modelling SDT statistical relationships

Single Band	Band Ratios	Additional Band Combinations
band1	band2/band3	band2+band3+band4+band5
band2	band3/band2	band2+band3+band4
band3	band2/band4	band2+band3
band4	band4/band2	band2+band4
band5	band3/band4	band2+band5
band6	band4/band3	band2+band3+band5
band7	band5/band4	band3+band4+band5
	band4/band5	band3+band4
	band3/band5	band3+band5
	band5/band3	band4+band5
	band5/band2	(band2/band4)+band2
	band2/band5	(band4/band2)+band2
		(band2/band4)+band4
		(band4/band2)+band4
		(band2/band4)+band3
		(band5/band2)+band5
		(band2/band5)+band3
		(band2/band5)+band2
		(band5/band4)+band4
		(band2/band4)+band2+band5
		(band2/band4)+band4+band5
		(band4-band5/ band4+band5)
		(band3-band5/band3+band5)

3.0 Results

The linear relationship between SDT values and various Landsat 8 bands and band combinations was analyzed through regression analysis for each side of the Lake Mattamuskeet. Regression equations relating *in-situ* SDT to the corresponding Landsat 8 image for Lake Mattamuskeet are listed in Table 6, Table 7 (bivariate regression analysis) and Table 8, Table 9 (multivariate regression analysis). Akaike`s information criteria (AIC) was used to select the best performing model for each side of the lake. Each model seprately estimated SDT for the east and west side of the lake. The results of linear regression analysis for each side of lake indicate that the prediction of SDT data has a statistically significant relationship ($p < 0.05$) with Landsat 8 image. Results show that band2, band3, band4, band2/band4, and band4/band2 provided significant models for each side of the lake. Additional bands or band combinations that were examined and insignificant models were eliminated from further analysis. The linear regression of the east side of the lake produced 0.54 R^2 value ($p<0.05$) for band3 (see Table 6). However, the linear regression of the west side of the lake produced 0.56 R^2 value ($p<0.05$) for band2 (see Table 7). When comparing two linear regression models, the best performing model was band2 for the west side, and band3 for the east side of Lake (see Table 10).

Based on previous studies the prediction of SDT using Landsat 7 ETM+, (band1/band3) had a suitable agreement for regression anlayses (Nelson et al. 2003; Bonansea et al. 2015; Nas et al. 2010; Lathrop et al. 1992; Pattiaratchi et al. 1994; Kloiber et al. 2000). Also, Kloiber et al. (2002) evaluated (band1/band3) + band1 equation to correlate with Landsat data to water clarity. The fit between observed and estimated water clarity data

resulted in a high predictive value (R^2= 0.93). Our study showed that a relationship existed using Landsat 8, between SDT and band2/band4 (this corresponds to band1/band3 in Landsat 7), and also band2/band4 +band2 (this corresponds to band1/band3 +band1 in Landsat 7).

A pair-wise correlation was used to find the band or bands that were a more contributory in the multiple regression. Band2, band3, band4, and band5 were found to have a more significant relationship for estimating SDT in the multiple regression analysis. For both the east and west side of the lake, band2, band3, band4, and band5 and their combinations were selected for estimating the best-predicted model (See Table 8, 9). The backward elimination and ACI criteria were used to determine the best performing model. For the east side of the lake, band2 and band5 was found to be the best performing model. However, the combinations of band2, band3, and band5 suggested a suitable relationship for using regression equation for the west side of the lake (Table 11). The model results also showed very similar R^2, Adj R^2 and significant P values (See Table 8, 9).

To compare all multiple regression models, the R^2 values and Adj R^2 values the smallest AIC values, and P values were compared. All models were shown to be significant ($p<0.05$). However, the highest R^2 for the west side of the lake was 0.83 whithin the highest Adj R^2 and the smallest AIC value. However, for the east side of the lake, the highest R^2 value was 0.59 within the highest Adj R^2, and the smallest AIC value. Overall, the best performing model was band2 and band5 for the east side of the lake. For the west side of the lake, band2, band3, and band5 were the best performing models.

Table 6: East Side of Lake bivariate regression equations for water clarity parameter

East Side Simple Linear Regression					
In-Situ Data	Regression equations	R^2	P-value	Adjusted R^2	AIC
SDT	SDT= 1.254 - 0.00015 X (Band3)	0.54	0.004	0.5	-111.6355
	SDT= 0.881 - 0.00011 X (Band4)	0.51	0.006	0.47	-110.9373
	SDT= 1.162 - 0.00012 X (Band2)	0.49	0.008	0.45	-110.435
	SDT= -2.35 + 2.02 X (Band2 \ Band4)	0.49	0.008	0.44	-110.2656

Table 7: West Side of Lake bivariate regression equations for water clarity parameter

West Side Simple Linear Regression					
In-Situ Data	Regression equations	R^2	P-value	Adjusted R^2	AIC
SDT	SDT= 2.35 - 0.0003 x Band2	0.56	0.0031	0.52	-93.812
	SDT= 1.68 - 0.0002 x Band3	0.55	0.004	0.5	-93.284
	SDT= 1.42 - 0.00018 x Band4	0.5	0.0069	0.45	-92.053
	SDT= -2.65 + 2.26 x (Band2/ Band4)	0.4	0.0197	0.35	-89.759

Table 8: East Side of Lake multiple regression equations for water clarity parameter

East Side Simple Linear Regression					
In-Situ Data	Regression equations	R^2	P-value	Adjusted R^2	AIC
SDT	SDT= 1.14 - 0.00011 x Band2 - 0.000006 x Band5	0.59	0.0123	0.5	-111.05
	SDT= 1.92 - 0.00043 x Band2 + 0.00029 x Band4 - 0.000009 x Band5	0.61	0.0306	0.48	-109.89
	SDT= 0.85 - 0.0001 x Band4 - 0.000004 x Band5	0.56	0.0157	0.48	-110.42
	SDT= 3.75 - 0.0002 x Band2 - 0.000009 x Band5 -1.57 x (Band2/ Band4)	0.61	0.0321	0.47	-109.74
	SDT= 5.27 - 0.0002 x Band4 - 0.000009 x Band5 - 2.86 x (Band2/ Band4)	0.6	0.0336	0.47	-109.61
	SDT= 1.19 - 0.0002 x Band3 - 0.000002 x Band5	0.55	0.018	0.46	-110.08
	SDT= 0.52 - 0.00012 x Band3 + 0.43 x (Band2/ Band4)	0.54	0.0206	0.46	-109.73
	SDT= 1.11 - 0.00014 x Band2 + 0.00003 x Band3 - 0.000006 x Band5	0.59	0.0398	0.45	-109.09
	SDT= 1.19 - 0.00012 x Band3 - 0.000024 x Band4	0.54	0.0208	0.45	-109.7
	SDT= 1.26 - 0.00002 x Band2 - 0.00013 x Band3	0.54	0.021	0.45	-109.67
	SDT= 0.96 - 0.00004 x Band3 - 0.00007 x Band4 - 0.000004 x Band5	0.57	0.0482	0.42	-108.5
	SDT= -0.53 - 0.000007 x Band2 + 1.009 x (Band2/ Band4)	0.52	0.0264	0.42	-109.08
	SDT= 0.0044 - 0.00008 x Band4 + 0.56 x (Band2/ Band4)	0.52	0.0268	0.42	-109.04
	SDT= 0.72 + 0.00006 x Band2 - 0.002 x Band4	0.51	0.0272	0.42	-109
	SDT= 0.99 - 0.00013 x Band3 - 0.000002 x Band5 + 0.12 x (Bnad2/ Band4)	0.55	0.05	0.41	-108.09

Table 9: West side of Lake multiple regression equations for water clarity parameter

West Side Multiple Regression					
In-Situ Data	Regression equations	R^2	P-value	Adjusted R^2	AIC
SDT	SDT= 4.70 - 0.0001 x Band2 + 0.0003 x Band3 + 0.0004 x Band5	0.82	0.0012	0.75	-101.04
	SDT= 4.13 - 0.0009 x Band2 + 0.0003 x Band3 - 0.0002 x Band4 + 0.0005 x Band5	0.82	0.005	0.73	-99.199
	SDT= 5.29 - 0.001 x Band2 + 0.0005 x Band4 + 0.0002 x Band5	0.79	0.0023	0.72	-99.084
	SDT= 3.54 - 0.0006 x Band2 0.0003 x Band5	0.76	0.0008	0.71	-99.678
	SDT= 8.63 - 0.0007 x Band2 + 0.0002 x Band5 - 2.63 x (Band2/ Band4)	0.78	0.0023	0.71	-99.013
	SDT= 15.80 - 0.001 x Band4 + 0.0002 x Band5 - 8.23 x (Band2/ Band4)	0.78	0.0025	0.71	-98.833
	SDT= 1.02 + 0.0005 x Band3 - 0.0012 x Band4 + 0.0006 x Band5	0.76	0.0036	0.68	-97.77
	SDT= 6.42 - 0.002 x Band2 + 0.001 x Band4	0.7	0.0022	0.65	-96.903
	SDT=13.27 - 0.0007 x Band2 - 5.36 x (Band2/ Band4)	0.7	0.0024	0.64	-96.771
	SDT= 6.39 - 0.001 x Band2 - 0.0001 x Band3 + 0.001 x Band4	0.73	0.0064	0.64	-96.038
	SDT= 20.39 0.001 x Band4 -10.92 x (Band2/ Band4)	0.7	0.0025	0.64	-96.604
	SDT= 13.76 - 0.0006 x Band2 - 0.0001 x Band3 - 5.78 x (Band2/ Band4)	0.72	0.0069	0.63	-95.798
	SDT= 1.54 - 0.0005 x Band4 + 0.0003 x Band5	0.68	0.0032	0.62	-95.999
	SDT= 2.17 - 0.0002 x Band2 - 0.00007 x Band3	0.57	0.0149	0.48	-91.987
	SDT= 1.70 - 0.0003 x Band3 + 0.00006 x Band5	0.57	0.0155	0.48	-91.881

Table 10: Correlation of SDT and Band Combination

SDTeast = 1.254 - 0.00015 X (Band3)
SDTwest = 1.68 - 0.00020 X (Band2)

Table 11: Correlation of SDT and Band Combinations

SDT_{east} = 1.14 - 0.00011 x (Band2) - 0.0000055 x (Band5)
SDT_{west} = 4.70 - 0.001 x (Band2) + 0.00026 x (Band3) + 0.00034 x (Band5)

4.0 Discussion

This study represents an initial attempt at establishing a relationship between field collected SDT data and remotely sensed data. Although addition water quality parameters were available (Chlorophyll-a, turbidity, suspended sediment, and dissolve oxygen) only SDT data were used in this research due to data availability from the sampling agency. After surveying the available data from U.S. Fish and Wildlife Service one data set was found which matched the acceptable range in days +/- for Landsat satellite overflights.

Since 2012, the USFWS has maintained a water quality sampling program for Lake Mattamuskeet which included SDT. However, collection of these data proved to be sporadic and limited for comparison to the available Landsat data archive. Moreover, the available *in-situ* data was not matched to Landsat 7 due to atmospheric anomalies and incomplete SDT field measurements. Furthermore, there was a 10 years data collected gap between 2002 and 2012.

The 13 April 2013 field dataset closely matched the available 13 April 2013 Landsat 8 image (+/-0) days. The availability of results generated from only one SDT dataset, captured on a single date, further limited the ability to apply this study to other surrounding water bodies. Each side of Lake Mattamuskeet has different biophysical conditions. The study found statistically significant relationship between coincidental Landsat 8 imagery and SDT data for the east (R^2= 0.49- 0.59, $P < 0.05$) and the west (R^2= 0.40- 0.82, $P< 0.05$) sides of the lake. Differences in model results for the east and west sides of lake may have been a result of differences in lake depth. Average lake depth of the east side was 0.105 m. The average lake depth of the west side was 0.167 m. shallower depths have been shown the

increase bottom reflection in previous remote sensing analysis (Nelson et al. 2003). Additionally, both sides of the lake are surrounded by an agricultural watershed. Historically cotton represented the majority of the agricultural land cover surrounding the lake. Later agriculture practices converted cotton crops into corn. The agricultural fields surrounding the lake also have been chanalized, directly draining in the lake lake (M. Moorman, personal comminication, USFWS,2015). Thus, chanalized run off and transition of agricultureal practices may further limit water clarity and SAV growth depending on the proportion of land use surrounding each side of the lake.

Based on visual observations by the USFWS, poor water clarity within both sides of the lake may be a result of declining SAV (M. Moorman, personal communication, USFWS, 2015). Although the west side maintains a deeper basin than the east side of the lake, biologically neither size currently supports SAV development or growth (Tango and Batiuk 2013) (see Figure 5 and Table 3).

The U.S. Fish and Wildlife Service and U.S. Geological Survey two water quality monitoring stations on each side of Lake Mattamuskeet do not provide a spatial representation of data that lends itself to water clarity modelling with satellite remotely sensing. For better modelling of lake water clarity with available remote sensing data, a more spatially distributed and regular SDT monitoring approach is needed. Often natural resources and management agencies may be limited in personnel and budgets, to routinely monitor and collect lake water clarity and quality data (Nelson et al. 2003). However, the synchronization of field sampling routines to the availability of satellite data, provide the most beneficial use for the assessment of inland lakes with remotely sensed data (Kloiber, Brezonik, and Bauer 2002b; Nelson et al. 2003).

The role of remotely sensed data has the ability to augment data collection by management agencies, such as the U.S. Fish and Wildlife Service. Researchers have an advantage of using Landsat satellite data, which has a 16-day revisit cycle. This repetitive data cycle of satellite imagery provides an increased capacity and frequency to estimate SDT relationships and changes in lake water clarity. Optimal, field data collection should be synchronized with coincidental, or near-coincidental satellite overflights. Spectral relationship within visible, and perhaps near-infrared, spectral bands have been shown to provide consistent relationship to a number of water qaulity and clarity parameters (Kloiber et al. 2000; Kloiber, Brezonik, and Bauer 2002a; Olmanson, Bauer, and Brezonik 2008; Olmanson, Brezonik, and Bauer 2014).

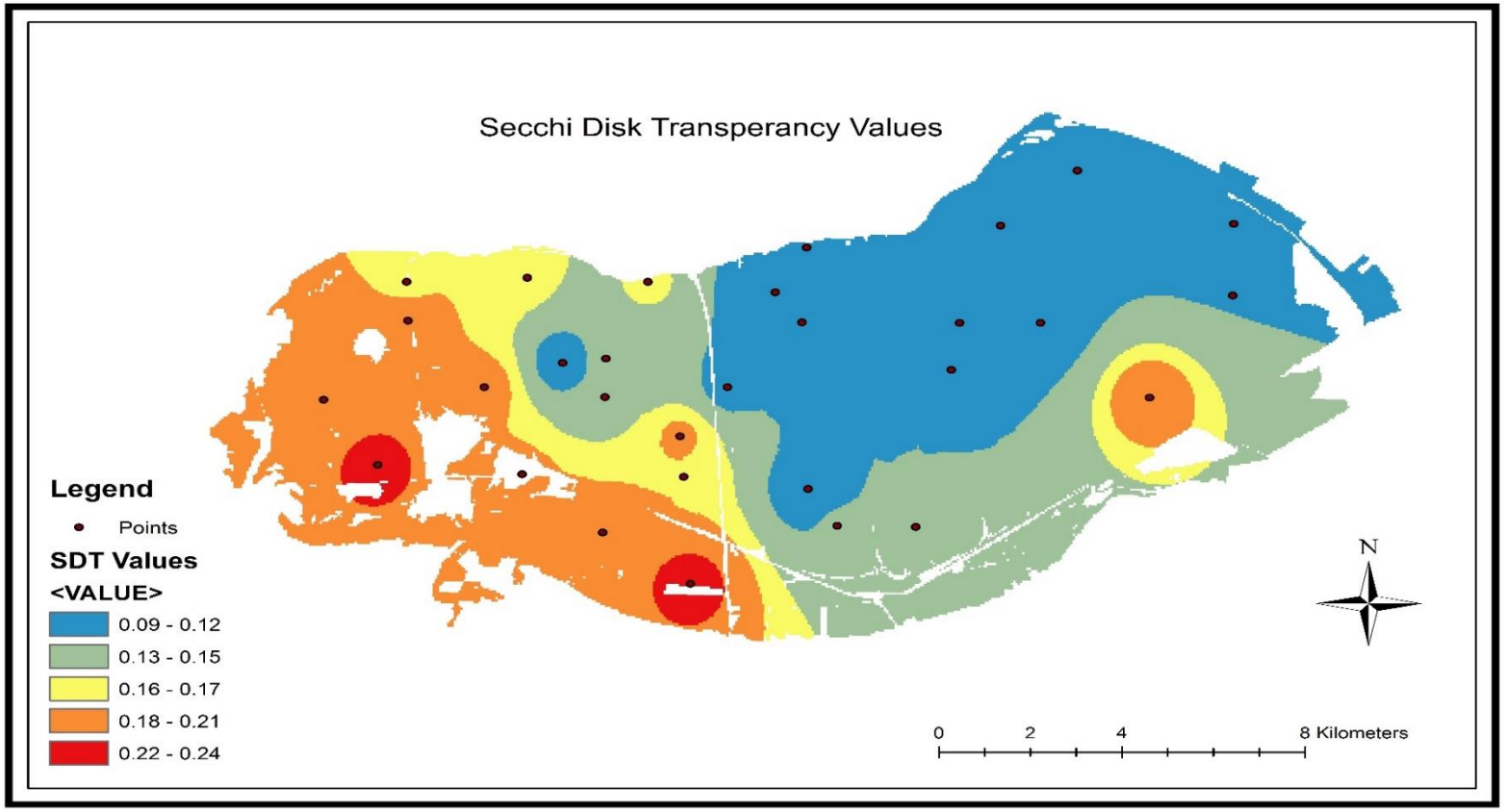

Figure 5: Secchi Disk Transparency

An additional advantage of using data obtained for Landsat sensors is that this information may also provide a retrospective analysis of water clarity back to the early 1970s, since Landsat was launched in July 23, 1972 (Bonansea et al. 2015). However, care should be taken to be ensure an appropriate field samples are collected on the ground for modeling the relationship to the imagery.

Despite the limited sample size of the available SDT data, statistical regression analyses developed between the SDT dataset and a single Landsat 8 image, showed good agreement for the west side $R^2 = 0.83$, $P<0.05$ and for the east side $R^2=0.59$, $P<0.05$. Furthermore, a comparison of multiple models used in this study suggest even with limited *in-situ* measurements Landsat 8 data can be used to model Lake Mattamuskeet water clarity ($R^2= 0.51- 0.82$, $p<0.05$). However, our model results would have benefited from a much larger sample size for the analyses data, as well more frequent historical SDT data that could be matched to corresponding Landsat imagery.

5.0 Conclusion

This study highlights the relationship between SDT and Landsat 8 remote sensing data. Regression results demonstrated statistically significant relationships between predicted SDT and *in-situ* data for the east and west side of Lake Mattamuskeet. Band3, band4, band2 and band2/band4 produced relationships ranging between R^2= 0.49 – 0.59 ($P<0.05$) for the east side, and R^2=0.40 -00.82 ($P< 0.05$) for the west side of the lake (see Table 6, Table 7, Table 8, and Table 9). However, band3 the produced the best performing model within a R^2= 0.56 for the east side of the lake. Band2 with a R^2= 0.54 was the best performing model for the west side of the lake (see Table 6, Table 7).

Using different bands, and band combinations, all models showed very similar R^2 values and significant p values (see Table 8, Table 9). However, multiple regression analyses for the west side of the lake showed, band2+band 3+band5 (R^2= 0.82) had good agreement for prediction of SDT. Band2+band5 (R^2= 0.59) suggested better agreement than other bands and combinations for the east side of the lake. This differences in model agreements may be due to differences in lake depth and lake bottom reflectance occurring on each side of the lake, as well as differing human impacts on each side of the lake. Our results suggests that band2+band3+band5 were better predictors than band2+band5 for the SDT estimation within R^2=0.59 and R^2= 0.82, respectively).Landsat 8, provided comparable estimates to previously reported literature values of water clarity for the east and west side of the Lake Mattamuskeet. Furthermore, it was found that having non-extensive data sets or even less-frequently sampled data can be used to establish those comparable relationships with remotely sensed imagery acquired at coincidental, or near-coincidental dates.

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CHAPTER III

1.0 General Conclusion and Discussion

Remote sensing is a vital technology for monitoring water clarity because it has many advantages. For instance, it reduces the cost, labor, and has a specific revisit cycle (Heiskary and Walker Jr 1988; Nelson et al. 2003). The main goal of this study was to investigate spatial patterns in water clarity in Mattamuskeet Lake. Secchi disk transparency was analyzed during this research. This research was able to build an empirical relationship between brightness value and ground observed data for predicting SDT during the time of 13 April of 2013. Results of this study showed that lake water clarity data extracted from Landsat 8 successfully. Band3 was the best performing model for the east side. On the other hand, band2 was the best performing model for the west side. Besides, band2 and band5 were a reliable predictor for the east side. For the west side band2, band3, and band5 were the consistent model. Furthermore, we can say that all the models produce a relationship based on limited data. Even though one data set is used for this analysis, the results showed very similar R^2 values. Moreover, backward elimination and Akaike`s Information Criteria (AIC) and Bootstrapping were used to select the best performing model for the each side of the lake (see Figure 6, Figure 7, Figure 8 and Figure 9).

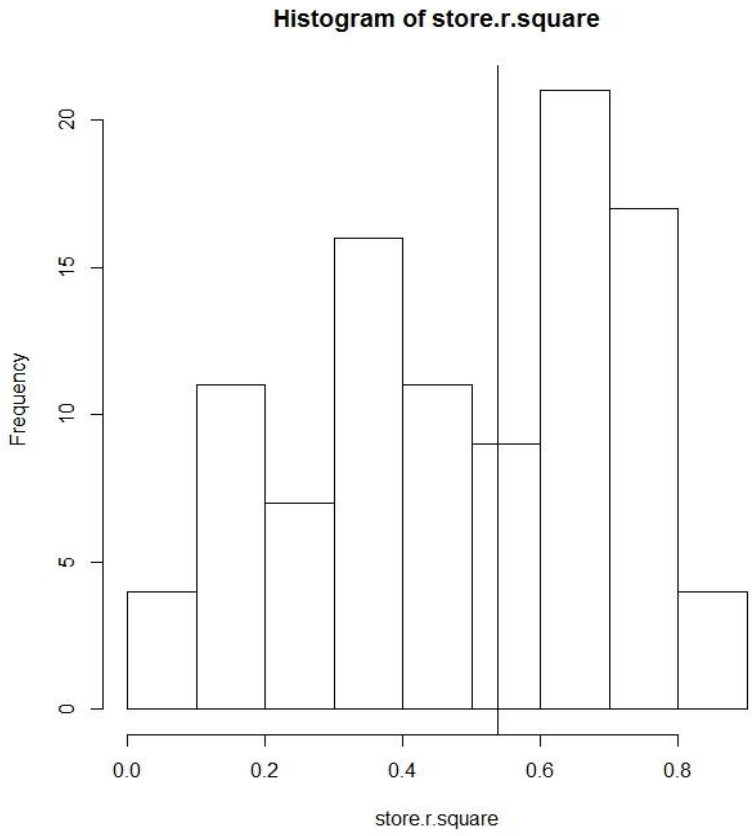

Figure 6: East side of the lake for band3

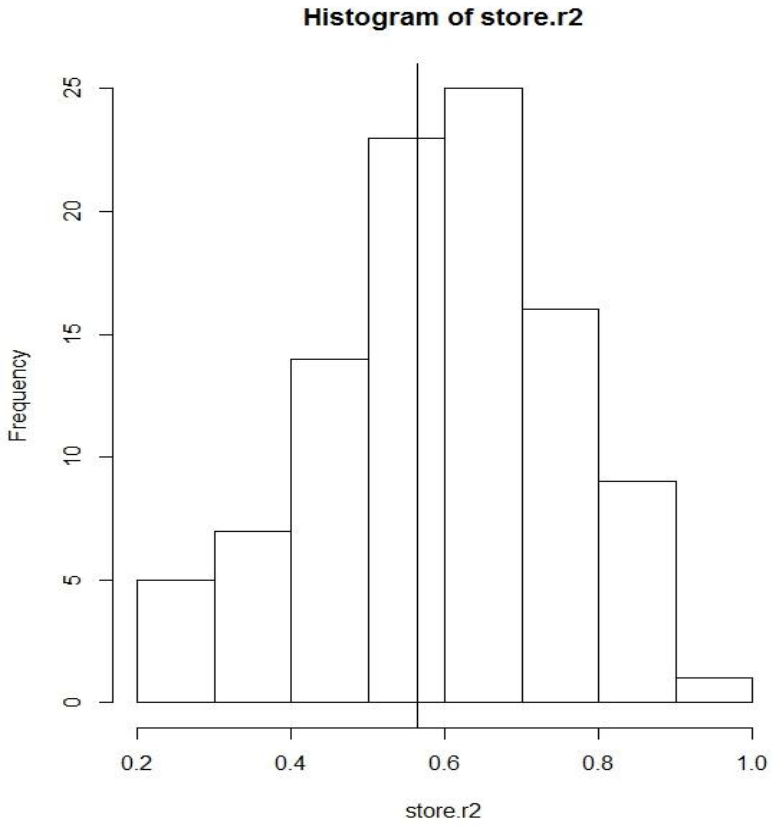

Figure 7: West side of the lake for band2

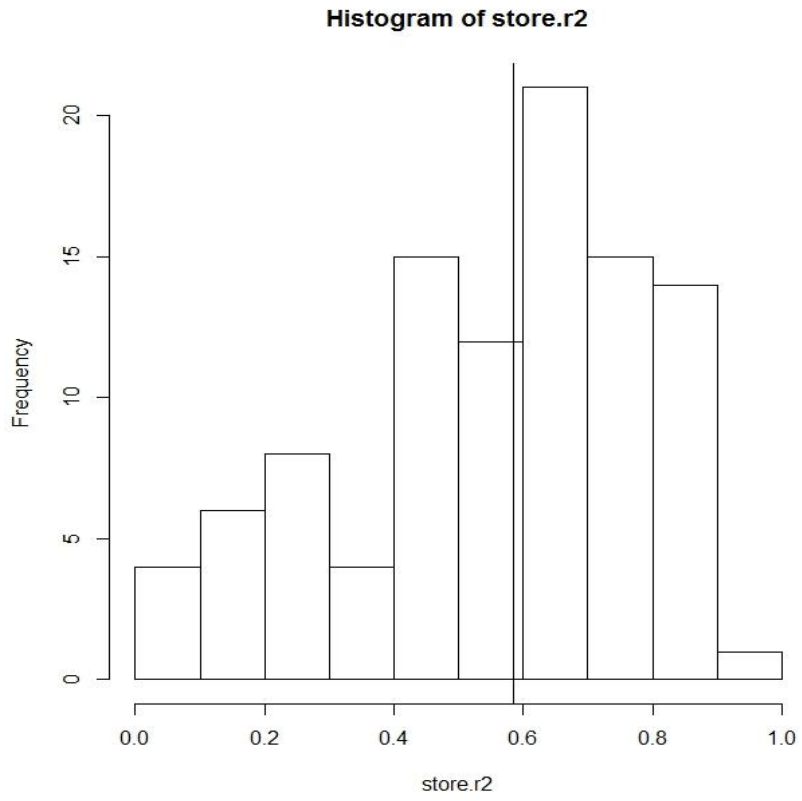

Figure 8: East side of the lake for band2+band5

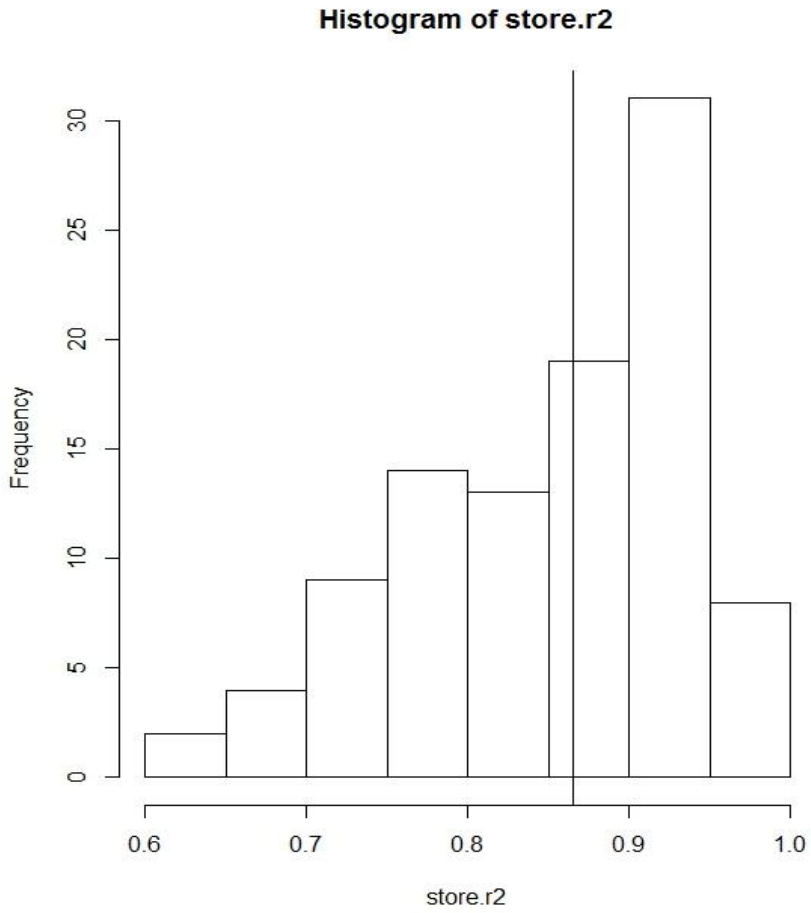

Figure 9: West side of the lake for band2+band3+band5

However, the models were not transportable between dates. For instance, we would not expect to get the same results if we use the same model on another date. This research is pilot analysis for Lake Mattamuskeet by using just one specific date set. Thus, the results showed that band2 and band5 had a reliable predictor for estimated SDT on the east side of the lake. However, band2, band3, and band5 were in a strong relationship between brightness value and SDT data on the west side of the lake.

Despite limited data, the results showed that the predicted SDT had a close agreement with in-situ data. Nevertheless, some limitations still exist in this research. Further research is needed to improve understanding of water clarity differences occurring within the lake. For instance, seasonal variability is significant for the analysis of water clarity. This research analyzed one seasonal data set, April 13, 2013. This time represented the submerged aquatic vegetation (SAV) growing season. However, the late summer growing may have provided an optimal time for accessing the relationship of water clarity to remote sensing. A study by Kloiber et al. (2001) found that reasonable results are yielded especially in late summer when water clarity is relatively constant.

Landsat 8 satellite data was used for this analysis. Landsat has been used to predict a relationship between brightness values and water clarity data, such as chlorophyll-a (CHL-a), turbidity, SDT (Nas et al. 2010; Butt and Nazeer 2015). On the other hand, there are many sensors that were used for successfully monitoring or evaluating the water quality or clarity (Butt and Nazeer 2015; Coskun, Gulergun, and Yilmaz 2006; Doron et al. 2011; He et al. 2012; Huiping, Hong, and Qinghua 2011; Kutser et al. 2015; Lai et al. 2011; Shanmugam, Ahn, and Ram 2008). For instance, Landsat and high-resolution IKONOS and QuickBird have similar spectral relationship towards lake water clarity and also the impervious surface

area. There is a great possibility to build on past research by using high-resolution satellite systems. Furthermore, the model relationship between Landsat and IKONOS or QuickBird is used to apply for analysis of water clarity or water quality (Sawaya et al. 2003b). Hence, it would be a great advantage to analyze water clarity with high-resolution satellite data in the future analysis of Lake Mattamuskeet.

SDT data was provided by US Fish and Wildlife service agent. This data showed that lake water clarity was now different from when it was observed in 2013. However, SDT values of 2013 demonstrated that the west side of the lake was clearer than the east side. This differences could be due to another external factor affecting the in-situ water clarity or could be different weather conditions. Thus, if we have more extensive field data, we can explain the variability of the changes in water clarity occurring through time.

Evaluating land use and land cover change would be perfect for further research in Lake Mattamuskeet. Human activities, construction, reclamation, residential developments, and urbanization have influenced land cover changes (Choi and Han 2013). These rapid changes impact on water quality and also watershed management. Water quality, ecosystem, and environmental deterioration of a watershed is affected by the land-use/land cover changes (LULCC). LULCC is a stressor towards them (Tang et al. 2005; Carpenter et al. 1992; Zhao et al. 2012). For that reason, LULCC changes provide valuable information between water quality data and the changing of the land use land cover. In further analysis it will be great to evaluate LULCC changes and impacts on Lake Mattamuskeet. Furthermore, remote sensing technology could be an efficient method for analyzing LULCC changes. We can use these results for predicting future water quality in the Lake Mattamuskeet.

As a result, this research can be improved by evaluation a variety of water quality parameters. Furthermore, various water quality parameters provide researchers with tools to estimate the relationship of LULC to *in-situ* water qaulity values. Moreover, there is a great capacity to have increased water quality samples if ground sample data is synchronized with overflights. These results are needed for implementing more frequent and cost-effective monitoring programs throughout many management agencies.

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