ASSESSMENT OF SPATIAL AND TEMPORAL LAKE WATER QUALITY TRENDS AND EFFECTS OF LAND USE/LAND COVER IN MAINE

Presented to the Graduate Council of
Texas State University-San Marcos
in Partial Fulfillment
Of the Requirements

for the Degree

Master of SCIENCE

by

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San Marcos, Texas
December 2012

ASSESSMENT OF SPATIAL AND TEMPORAL LAKE WATER QUALITY TRENDS

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ACKNOWLEDGEMENTS

I would like to thank my family, especially my husband Dane Courville, for their encouragement and support throughout my enrollment in graduate school. I would also like to thank my thesis advisor, Dr. Jennifer Jensen, and my committee members, Dr. Mark Fonstad and Dr. Richard Dixon, for their contributions to both my graduate studies and my thesis.

This manuscript was submitted on October 8, 2012.

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1.0 INTRODUCTION

1.1 Background

The concept of “man and land” or “society and environment” has been a consistent theme within the field of geography for the past 100 years. During this time, the scale of human impacts on natural resources has increased while time and space, two fundamental concepts in geographic inquiry, have continued to present some of the most challenging issues for geographers (Wolman 2004). More recently, the importance and complexity of Land Use/Land Cover (LULC) change has been recognized (Lambin et al. 2001); however the temporal and spatial impacts of LULC change on freshwater lakes are rarely studied despite the known value of lake systems.

Lakes are a valuable resource throughout the world; they contain large reservoirs of freshwater and play host to diverse ecosystems (Bronmark and Hansson 2005; O’Sullivan 2005). The quality of surface water within lakes is evaluated based on multiple parameters, including water temperature and clarity (US EPA 2003). Water temperature within a lake can affect the solubility of dissolved oxygen, the metabolism and respiration of plants and animals, and the toxicity of pollutants (Stefan et al. 1998). Water clarity is an important indicator of the general health of a lake system including the amount of sediment present, algal biomass, and the trophic condition of the lake (Bronmark and Hansson 2005; Dodson 2005).

The most common way of measuring lake water temperature and clarity is with *in situ* measurements. While *in situ* measurements are accurate for a single point and time, they do not give a spatial or temporal view of water quality (Ritchie 2003), specifically water temperature and clarity. Satellite remote sensing allows for assessment of large areas and greater temporal coverage of lake water temperature and clarity, making it possible to assess multiple water bodies effectively, efficiently, and at a lower cost than *in situ* assessments.

1.2 Problem Statement

While satellite platforms have been used to evaluate lake water temperature and clarity at many locations around the globe, these studies rarely include both water temperature and clarity and studies of water temperature seldom address both the large spatial scale and long-term temporal scale that is necessary to identify systematic changes. Additionally, past research has not thoroughly addressed the impact of LULC on lake water temperature and clarity. If LULC patterns and/or changes have an impact on lake water temperature and clarity, the effects can likely be identified with the use of approximately 25 years of satellite imagery covering a large spatial scale.

1.3 Objectives

The intent of this study was to use approximately 25 years of satellite imagery to determine if water quality variables, specifically water temperature and water clarity, in east-central Maine change over time and whether the change is associated with the spatial scale of analysis and/or temporal patterns of LULC. Specifically, individual objectives were as follows:

1. Is there a relationship between land use/land cover within a lake catchment and lake surface water temperature and clarity?
2. Do lake surface water temperature and clarity display a systematic change over time either as a whole (i.e. all lakes in a given region) or within individual lakes?
3. If a systematic change in water temperature and/or clarity is identified, is there a relationship with land use/land cover change?

1.4 Justification

This assessment of water temperature and clarity for the study area, including identification of significant trends or changes in water temperature and clarity, can be used to help guide monitoring and management decisions for the region. The assessment may also prove to be valuable for directing future research initiatives within the study area or identifying lakes that could benefit from more intensive assessments. Additionally, the identification of significant relationships between water quality and LULC, including LULC changes, may be applicable at a larger scale, including areas outside of the study area and the State of Maine. The results of this research could potentially be used to establish or improve land management practices aimed at protecting water quality within lake catchments as well as at regional scales.

1.5 Literature Review

1.5.1 Water Quality Overview

Freshwater lakes support diverse biological communities (Bronmark and Hansson 2005) and are a valuable resource for humans. Lakes provide recreational opportunities, support fishery operations, and are reservoirs of freshwater for drinking water and crop irrigation (O'Sullivan 2005). Recognizing the value of not only lakes, but of all surface waters of the United States, the United States government has taken regulatory action to protect surface water quality. United States water quality regulations were enacted in 1948 as the Federal Water Pollution Control Act (FWPCA) (US EPA 1972) and amended in 1972. The 1972 and subsequent amendments are collectively known as the Clean Water Act (CWA). The CWA set standards and goals that have become the driving force behind implementation of water quality assessments in the United States. Two of the core water quality assessment parameters identified by the Environmental Protection Agency (EPA) are water temperature and clarity (US EPA 2003).

Water temperature is a key factor in freshwater ecosystems. It impacts behavior, distribution, and metabolic rates of freshwater species. Water temperature also impacts dissolved oxygen levels since the amount of oxygen water can hold in solution decreases as water temperature increases. Decreased oxygen further impacts freshwater species by increasing their oxygen demand. Water clarity is also referred to as secchi disk depth due to the instrument that is most often used to measure it. Water clarity, or secchi disk depth, is an estimate of light penetration which is mainly affected by the amount of dissolved and suspended substances in the water (Bronmark and Hansson 2005). Since light penetration affects the distribution of algae and aquatic plants, water clarity is also an indicator of the trophic state of a lake (Dodson 2005). In addition to ecological value, lake water quality can also impact economic values. A study of lakefront property values in Maine compared with lake water clarity found that lakefront property values significantly increase with increased water clarity (Michael et al. 1996).

1.5.2 Traditional Methods to Assess Water Quality

In situ water quality measurements are commonly used to measure lake water quality (Ritchie et al. 2003). When using *in situ* measurements, select lakes are often chosen to represent an entire region. As part of a study to assess lake sampling programs, Wagner et al. (2008) found that there can be biases when selecting representative lakes for a region, resulting in areas with certain types of LULC, such as lakes in urban areas, being sampled more often than lakes in areas with other types of LULC, such as lakes in agricultural areas. This can result in many lakes being sampled infrequently or never at all, resulting in no accurate assessments of water quality for many lakes (McCullough et al. 2012). Additionally, while *in situ* water quality measurements are accurate for a given point and time, they do not provide the spatial or temporal coverage that is many times necessary for accurate lake assessment and management (Ritchie et al. 2003).

1.5.3 Remote Sensing Methods to Assess Water Quality

Assessment of water quality parameters using satellite remote sensing can provide “spatially unbiased” and long-term temporal information regarding select water quality parameters. Monitoring lake water quality using satellite remote sensing also has the ability to be retrospective and investigate the relationship between the landscape (i.e. LULC) and lake water quality (Kloiber et al. 2002b).

The ability of satellite remote sensing to assess water quality parameters relies on both the properties of the water body and the abilities of the remote sensing platform. Two water quality parameters that can be measured using satellite remote sensing are water temperature and clarity. In terms of water temperature, various remote sensing platforms have been used to successfully monitor water temperature including the Moderate Resolution Imaging Spectroradiometer (MODIS) (Crosman and Horel 2009) and NASA's Earth Observing System (EOS) Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Becker and Daw 2005). Despite the successes of these and other satellite platforms, they lack either the resolution necessary to monitor smaller bodies of water or the long-term temporal data necessary to detect changes over time.

The Landsat-5 Thematic Mapper (Landsat-5) provides higher spatial resolution thermal infrared images with coverage available since the early 1980s. Early use of data extracted from Landsat-5 images to assess lake surface water temperature indicated the potential utility of Landsat-5 thermal data; however, it was determined that further calibration was necessary to compensate for error (Ritchie et al. 1990). Due to the need for calibration, many studies using Landsat-5 data to assess surface water temperature have focused on calibration and atmospheric correction methods. Planck's Black Body Equation, or Planck's Law, is often used for calibration of the Landsat-5 thermal band (Schneider and Mauser 1996; Mustard et al. 1999; Giardino et al. 2001). Planck's Black Body Equation "defines the relationship between the radiance emitted from an object at a certain wavelength and its absolute temperature" (Mustard et al. 1999). For atmospheric correction, measured atmospheric data such as radiosonde data are often used. Using calibrated data, studies have found differences between satellite-derived water temperatures and *in situ* measurements of -0.06 °C (Schneider and Mauser 1996) and root mean square error differences of 0.328 °C (Giardino et al. 2001).

An assessment of on-orbit calibration for Landsat-5 imagery indicated that the Landsat-5 thermal band has had varied calibration results since the launch of the satellite platform; however, some of the error may have been caused by earlier processing systems that have since been replaced. Further analysis of the Landsat-5 thermal band found that the current processing system, when correlated with ground truth data from lakes in the United States, has an offset error of -0.7 °C (Barsi et al. 2003). Despite the results of these and other researchers that show error in measurements derived from the Landsat-5 thermal band, the use of Landsat-5 imagery has proven successful in monitoring lake surface water temperature, especially when assessing spatial distributions.

Using Landsat-5 thermal data, Giardino et al. (2001) identified surface water temperature distributions within a single lake in Italy. Landsat-5 thermal data have also been successfully used to determine the distribution of thermal pollution within estuary environments in Rhode Island through the assessment of seasonal and temporal surface water dynamics (Mustard et al. 1999). The ability of Landsat-5 thermal data to identify spatial distribution of surface water temperature was also used to identify groundwater discharge areas by assessing groundwater-surface water interactions in shallow groundwater dominated lakes in Nebraska (Tcherepanov et al. 2005). These studies reflect the utility of Landsat-5 thermal data to identify spatial distribution patterns of surface water temperatures; however studies using Landsat-5 thermal data often work under the assumption that atmospheric conditions remain the same across a single

Landsat image (Mustard et al. 1999; Tcherepanov et al. 2005; Handcock et al. 2006; Oesch et al. 2008). As previously indicated, the assessment of temporal surface water trends has not been the focus of research using Landsat-5; instead, researchers often use other satellite platforms for temporal surface water studies.

In terms of water clarity, the use of remote sensing imagery, including imagery provided by Landsat-5 and its earlier predecessors, has been well studied, especially in the Upper Midwest region of the United States. While various satellite platforms have been used to monitor inland lake water clarity, the long-term temporal coverage, spatial resolution, and data availability provided by Landsat makes it particularly useful. Early studies proved Landsat imagery can be successfully used to classify lakes within a predefined trophic class (Scarpace et al. 1979) and predict secchi disk depths (Lillesand et al. 1983). More recent studies have confirmed the utility of Landsat imagery for monitoring lake water clarity. Unlike assessments of surface water temperature, studies of water clarity often cover large spatial scales as well as long-term temporal scales.

A study of approximately 500 lakes in the Minneapolis and St. Paul, Minnesota area using Landsat imagery from 1973 through 1998 found “excellent agreement between satellite-estimated and ground-observed [secchi disk transparencies] can be achieved” (Kloiber et al. 2002b). An assessment of lake water clarity in Wisconsin using Landsat imagery was used to develop a database of lake transparencies for the entire state (Chipman et al. 2004), and a 20 year assessment of the more than 10,000 lakes in Minnesota using Landsat imagery found a consistently strong relationship between water clarity values derived from Landsat images and field-measured secchi disk values (Olmanson et al. 2008).

The use of Landsat imagery to determine water clarity values relies on the existence of *in situ* measurements for calibration. As described in the study of lakes in the Minneapolis and St. Paul, Minnesota area (Kloiber et al. 2002a), average spectral brightness values for a given Landsat image can be compared with ground observations of secchi disk transparency values within a selected time frame and then Pearson correlation coefficients and step-wise multiple regression analysis can be used to identify the Landsat spectral bands best correlated with secchi disk transparency values. The necessity of *in situ* measurements for calibration can limit the ability to determine water clarity values using Landsat imagery. Additional limitations include cloud cover and haze in the atmosphere as well as the availability of high-resolution, low cost, satellite imagery (McCullough et al. 2012). These limitations exist when assessing both water clarity and water temperature.

1.5.4 Changes in Lake Water Quality and Effects of LULC

As stated by Bruhn and Soranno (2005), “the total sum of anthropogenic stressors can increase or decrease over time, and water quality may also be expected to change over time.” It is these changes that are at the heart of many water quality assessments. Various studies have documented changes in lake water temperature over time, especially within individual large lakes. Lake Zurich in Switzerland was found to have experienced a significant warming trend between 1947 and 1998 with the uppermost 20 meters of the lake warming at a rate of approximately 0.24 °C per decade (Livingstone 2003). Between 1979 and 2006, surface water temperatures of Lake Superior in the United States were found to have increased approximately 2.5 °C (Austin and Colman 2007), and an assessment of Lake Tahoe on the border of California and Nevada found an overall warming trend of 0.015 °C per year since 1970 (Coats et al. 2006). Additionally, a regional assessment of six lakes in California and Nevada, including Lake Tahoe, using 17 years of data from Along Track Scanning Radiometer (ATSR) series and MODIS series sensors concluded that all 6 lakes exhibited a surface water warming trend of approximately 0.11 °C per year with respect to summer nighttime water temperatures (Schneider et al. 2009).

Multiple studies of spatial and temporal trends in lake water clarity have been completed, primarily in the Upper Midwest region of the United States. A study of 71 lakes in Michigan from 1974 through 2001 using *in situ* data found an overall trend of stable or increased water clarity with 63 percent of the lakes exhibiting no significant trend, 31 percent significantly increasing in water clarity, and 6 percent significantly decreasing in water clarity during the study period (Bruhn and Soranno 2005). A separate analysis using Landsat imagery of approximately 500 lakes in Minnesota found that lake water clarity primarily remained stable during a 25 year study period with only 10 percent (49) of the assessed lakes exhibited significant temporal trends in water clarity and 34 of the 49 lakes exhibited a significant increase in water clarity while the remaining 15 lakes exhibited a significant decrease in water clarity (Kloiber et al. 2002a). A statewide assessment of over 10,000 lakes in Minnesota using Landsat imagery had similar findings to the previous study in Minnesota with a general trend of stable water clarity over a 20 year study period (Olmanson et al. 2008).

In contrast to the other findings, a study of Wisconsin lakes using over 30 years of Landsat imagery and *in situ* measurements found a general trend of increasing lake water clarity; however a few instances of decreasing lake water clarity were also noted

(Peckham and Lillesand 2006). Outside of the Upper Midwest, a study of 127 lakes in Florida using *in situ* assessments from a 30 year period found that there was no significant change in water clarity; however, the researchers excluded from the study lakes with known management changes that may have impacted water quality (Terrell et al. 2000).

One factor that may influence water quality parameters such as water temperature and clarity is LULC. Land use/land cover changes within the United States, in particular within the eastern United States between 1973 and 2000, have been documented by the United States Geological Survey (USGS) and EPA Land Cover Trends Project (Loveland and Acevedo 2006). The effects of LULC on lake water temperature have not been well researched; however studies have shown that LULC can impact stream and river water temperature. Removal or alteration of riparian vegetation has been found to alter stream water temperature primarily through changes in insulation which shades waterways and controls air circulation near the water surface (Poole and Berman 2001).

A study in Maine found that, following timber harvesting operations, streams where no forested buffer was left had the greatest increase in mean weekly maximum water temperatures (approximately 1.4 to 4.4 °C) (Wilkerson et al. 2006). Changes from forested land cover to urban development can also increase stream water temperature. A runoff model for a small river basin found that by changing 50 percent of the land cover from forest to pavement, overall stream water temperature rose in the summer and fell in the winter. This indicates that forest area, when compared to an urbanized area, has the effect of moderating the range of annual water temperature variation (Ozaki et al. 2008). Also on a watershed scale, an analysis of select watersheds in Kentucky found that stream water temperature was significantly higher in urban and mixed use watersheds than in agricultural watersheds (Coulter et al. 2004). From these studies it can be inferred that LULC may impact lake water temperature either directly and/or indirectly as a result of the in-flow from hydrologically connected streams and rivers.

Some of the previously referenced water clarity studies in the Upper Midwest have also analyzed trends in water clarity based on different LULC classifications. The study of over 10,000 lakes in Minnesota (Olmanson et al. 2008) found that there were differences in lake water clarity between ecoregions within the State; however with the exception of general trends from north to south and general LULC associated with an ecoregion, the study did not specifically identify water clarity trends based on LULC. Similarly, the study by Peckham and Lillesand (2006) in Wisconsin identified spatial trends by ecoregion. One ecoregion in particular, the Northern Lakes and Forest Ecoregion, was identified as having a significant temporal trend of increasing water clarity. The reason for this trend, along with the overall trend of increasing water clarity in Wisconsin, was hypothesized to be related to changes in land use, zoning, or stream and lake vegetation buffers. Other non-anthropogenic causes of the trend of increasing water clarity were also hypothesized, such as changes in phytoplankton density as a result of climate or atmosphere changes.

One of the studies of water clarity in the Upper Midwest included an analysis of the relationship between LULC and lake water clarity (Bruhn and Soranno 2005). The study found that there was a correlation between increased water clarity and residential land use within 100 meters of lakes in the study area as well as a relationship between decreased water clarity and the presence of wetland cover within 500 meters of lakes in the study area. Another trend noted in the study was increased average lake water clarity in northern Michigan where there is more forested land cover, in contrast to southern Michigan where there is more agricultural land use. Despite these noted correlations with LULC, the study by Bruhn and Soranno (2005) found that, overall, there were few strong relationships between LULC and water clarity. The authors indicated one reason for this lack of strong relationships may be their chosen method of buffering the lakes within the study area as opposed to using lake watersheds or catchments to correlate LULC to water clarity. When developing a model to predict water clarity values for lakes in Maine using both Landsat data and physical lake characteristics and landscape features, McCullough et al. (2012) used wetland area as a proxy for watershed disturbance since wetlands "help [regulate] lake clarity and inversely [indicate] land potentially available for development." The relationship between wetland area and water clarity noted by McCullough et al. (2012) supports the findings by Bruhn and Soranno (2005).

1.6 Broader Impact/Implications

Monitoring and maintaining lake water quality is a concern for government agencies as well as private organizations and citizens (Olmanson et al. 2008). An effective lake management and water quality monitoring program should include both temporal and spatial coverage of water quality parameters; however due to high costs and complex logistics, lake water quality monitoring programs often sacrifice spatial coverage of many lakes and instead focus on frequent monitoring of only a few lakes (Kloiber et al. 2002b). The use of satellite imagery allows for both regional scale assessments of water quality as well as extraction of retrospective temporal data (Olmanson et al. 2008). Water quality data from lake monitoring and assessments can be used to investigate relationships between landscapes and water quality, determine regional differences, and identify ranges of water quality within a region. This information can then be used to set water quality guidelines and make management decisions (Kloiber et al. 2002b). Using research on spatial and temporal water quality data derived from satellite imagery, trends in water quality can be better assessed and more accurate guidelines and management decisions can be made for a specific lake, area, or region. In order to better guide water quality management, further research is needed regarding spatial and temporal lake water quality changes or trends as well as the impact of LULC and LULC changes on water quality, specifically water temperature and clarity.

2.0 MATERIALS AND METHODS

2.1 Study Area

The State of Maine is the northeasternmost state in the United States. Maine is a cold-temperate climate where winters are typically long and cold and summers are typically short and warm (McCullough et al. 2012). Glacial movements and deposits approximately 12,000 years ago are primarily responsible for the creation of the almost 6,000 lakes in Maine. Of the nearly 6,000 lakes, 90 percent are drainage lakes where the majority of water flowing into and out of the lake is surface water (Hasbrouck 1995). Maine has the greatest total area of inland surface water for all states east of the Great Lakes (Davis et al. 1978). Lakes in Maine are well distributed geographically and vary in size from less than 2.47 acres to greater than 75,000 acres. Since monitoring began in 1970 through 2009, the average secchi disk depth for lakes in Maine has consistently been between four and six meters (McCullough et al. 2012). Within Maine, the study area was limited to one Landsat-5 image (approximately 32,000 square kilometers) with coverage of eastern and central Maine (Figure 1). This area is located primarily within EPA Ecoregion 82 which is identified as the Laurentian Plains and Hills, a region where glacial processes created numerous lakes and wetlands. The USGS and EPA Land Cover Trends Project found that there was a 9.5 percent change in the region’s land cover between 1972 and 2000 with forest cover continuously being the largest land cover classification and timber harvesting being one of the most significant activities in the ecoregion (Moreland [no date]).

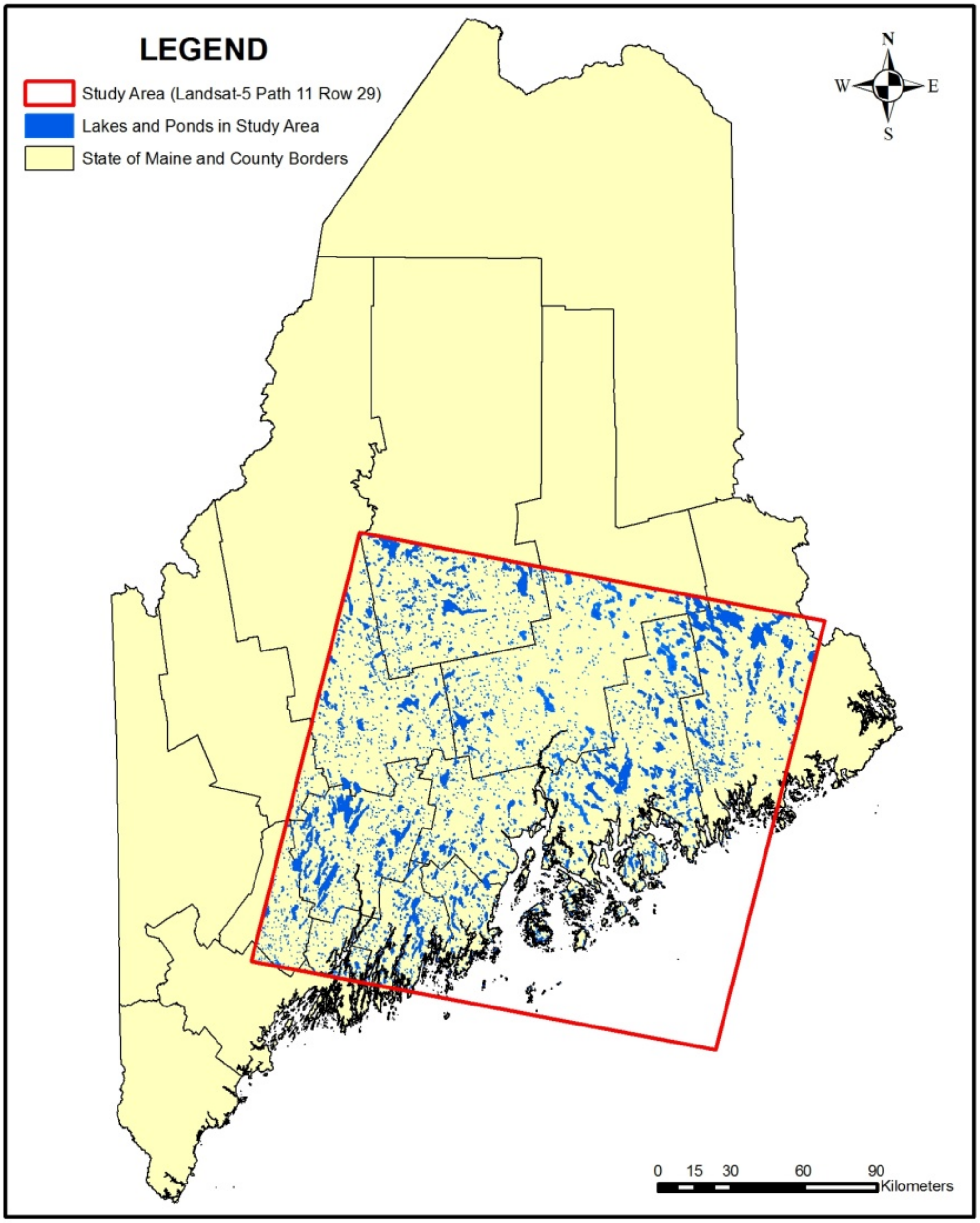

Figure 1: Location of the study area showing all lakes within the study area**.**

2.2 Remote Sensing Datasets and Image Processing

Landsat-5 images are available at no cost from the U.S. Geological Survey (USGS) via their Global Visualization Viewer (GloVis). Use of GloVis enabled the acquisition of Landsat-5 images of the study area (identified as Landsat-5 Path 11 Row 29) for the entire study period (1984 through 2011). Based on previous research regarding lake water clarity in the Upper Midwest, the target annual index period for image acquisition was July 15th through September 15th with a preference for August (Olmanson et al. 2008). Multiple Landsat-5 images were available for each annual index period; however cloud cover and haze limited the number of usable images and eliminated many years within the study period. Ultimately, only six images without excessive cloud cover were available for use. McCullough et al. (2012) found that the coastal nature of Landsat Path 11 in Maine resulted in less consistent cloud-free imagery when compared to adjacent Landsat Path 12 that provides coverage of more inland western Maine. Image selection within the index period was also based on the availability of *in situ* lake water clarity data for a given year. Correlation between Landsat-5 images and *in situ* lake water clarity data is further addressed later in this section. Refer to Table 1 for a list of Landsat-5 images included as part of this study.

Table 1: List of Landsat-5 images included in the study.

Year	Date	Cloud Cover*
1986	August 5	10%
1995	August 14	2%
1999	August 25	0%
2000	July 26	0%
2005	August 9	15%
2008	July 16	0%

*As reported by USGS GloVis

Following image acquisition, the images were processed to convert digital numbers to top of atmosphere reflectance using the techniques described by Chander et al. (2009). Initial attempts to correct for atmospheric effects using the 6S (second simulation of satellite signal in the solar spectrum) algorithm for Landsat-5 bands 1 through 5 and 7 did not provide data that could be used to extract water quality data or accurately classify and compare LULC due to over-correction (creation of negative reflectance values), especially in Landsat-5 band 1. While use of atmospheric correction could have potentially aided in the analyses performed as part of this study, previous research has proven that conversion to top of atmosphere reflectance can be used for image analysis (i.e., Goetz et al. 2003; Homer et al. 2004; Giri et al. 2011) and that a full atmospheric correction is not necessary. Additionally, atmospheric correction is not required for extraction of water clarity values since data extracted from satellite images is calibrated to ground data. Atmospheric correction was not completed (or attempted) for Landsat-5 band 6 (the thermal band) due to additional data requirements such as radiosonde data that were not readily available for the study region over the study period; however, ongoing analysis has indicated that band 6 is accurate to within 1 °C (Chander and Markham 2003). As such, the thermal band was converted to at-sensor apparent temperature following methods described by Chander et al. (2009). Final image processing included identification of areas with cloud cover or visible haze. Areas with cloud cover were identified as part of the LULC classification (refer to Section 2.3) as well as by visual inspection of each image. Areas of haze were identified by visual inspection using multiple band combinations to assist in haze identification. A combination of Landsat-5 bands 1, 5, and 7 was primarily used to aid in the identification of haze. Due to the focus on lake catchments and buffer areas surrounding lakes, if cloud cover or haze was identified in a lake catchment or buffer area, the lake was removed from further analysis.

2.3 LULC Classification of Landsat-5 Datasets

The image pre-processing described above allowed the completion of a LULC classification for each of the six years analyzed in this study. To maintain consistency with nationally-recognized data, the LULC classification system used by the Multi-Resolution Land Characteristics Consortium (MRLC) 2001 National Land Cover Dataset (NLCD) was used for this study. The MRLC 2001 NLCD classification system is described by Homer et al. (2004). Only primary (i.e., Level 1) classes present within the study area were used. The LULC classes identified for each image included water (identified as open water), developed land, barren land, forest areas, planted/cultivated areas, wetlands, and clouds. The “cloud” classification was used to aid in identification of areas affected by cloud cover; these areas were not used in subsequent analyses of water quality. The LULC classes for each image were defined using a supervised classification method.

Supervised classification requires training or calibration sites in order to determine the spectral signature of each LULC class. Training sites were identified using high resolution aerial imagery from 2003 through 2005 and USGS Digital Ortho Quarter Quads (DOQQs) from 1996 through 1998 available for the study area from the Maine Office of GIS as well as imagery provided by Google Earth™. Pixels were assigned to a class using the maximum likelihood method. Validation of LULC classifications using a combination of the original satellite imagery and aerial imagery along with randomly generated validation points enabled verification of LULC classification accuracy as well as identified necessary modifications to the supervised classification. A stratified random sampling framework was used to generate validation points. Supervised classification was performed separately for each image. For the supervised classification, training sites were verified for each image and new/additional training sites were selected as determined to be necessary.

For the LULC supervised classification, a Normalized Difference Built-up Index (NDBI) (Zha et al. 2003) was used to improve separability between wetland and developed areas. Additionally, Landsat-5 bands 5 and 6 were not used in the classification process since they were not found to aid in the accuracy of the classification. The supervised classifications were performed using ERDAS Imagine remote sensing processing software.

2.4 Identification of Drainage Catchments for Analysis

In addition to identification of areas of different land use or land cover, the designation of open water as part of the LULC classification facilitated the creation of lake polygons and areas-of-interest (AOIs) for each lake within the study area. For each of the lakes included in the study, the immediate drainage catchments were identified using existing drainage divide polygons available from the Maine Office of GIS (USGS and MGS 1994). The immediate drainage catchment was used as opposed to an entire drainage catchment since lakes in Maine are often drainage lakes that connect to other lakes through a series of rivers or streams. The connection between multiple lakes creates overlapping drainage catchments for lakes within the region. By using only the immediate drainage catchments, as identified by the dataset from the Maine Office of

GIS, each lake included in the study had a unique drainage catchment. If the catchment of a lake did not fall entirely within the study area, the lake was eliminated from further analysis.

Buffers of 100 and 500 meters were created around each lake for analysis of potential relationships between LULC within the buffer areas and water temperature and/or clarity. The 100 meter and 500 meter buffers were selected based on buffer areas used in a previous study by Bruhn and Soranno (2005) (refer to Section 1.5.4). Buffers were created using ArcGIS analysis tools which enabled the creation of a dataset with a unique buffer for each lake.

2.5 Identification of Areas of Interest for Analysis

Identification of AOIs within each lake allowed for consistent and accurate extraction of water temperature and clarity values from the satellite images. To eliminate the possibility of selecting open water pixels influenced by land or vegetation (i.e., mixed pixels), the first step to select the AOIs was to offset the AOIs inward from the edge of each lake polygon by the width of one thermal pixel (120 meters). An unsupervised classification using the ISODATA algorithm was then implemented to identify spectral signatures for the open water areas and eliminate shallow water areas where sediment and/or the presence of aquatic plants may affect the spectral response (Olmanson et al. 2001) and thus influence water clarity values. The unsupervised classification method allowed for the identification of areas that have an increased spectral response in the near infrared band (Landsat-5 band 4). An example of ten different spectral responses created through an unsupervised classification of the 2008 image open water areas is provided as Figure 2. In this example, classes eight and ten were removed from further use in terms of selection of AOIs for each lake. It was also found that this method was effective in eliminating areas that appeared to have surface reflectance influenced by the angle of the sun (e.g., specular reflection) and/or a rough (wavy) water surface. These areas visibly appeared to have a glare on the water surface in the Landsat-5 image. The area remaining within a given lake polygon, after creating the 120 meter offset and eliminating areas based on the unsupervised classification results, was identified as the area from which to extract the AOI for a lake. Because of the use of the unsupervised classification method, the AOIs for each lake varied between years since each year was represented by a separate Landsat-5 image. In other words, the size of the AOI depended on the size of the lake and the results of the unsupervised classification method. Kloiber et al. (2002a) used a slightly different procedure for identifying an AOI for each lake within their study area in Minnesota, but the results were similar with AOIs ranging from just a few pixels for small lakes up to 1,000 pixels for larger lakes.

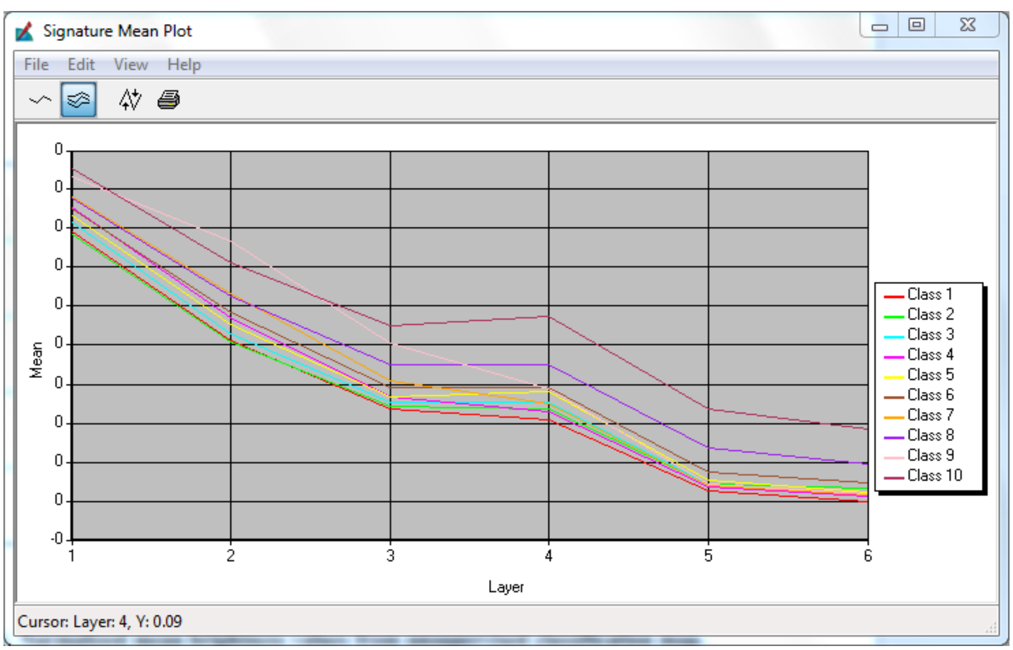

Figure 2: Example of spectral response of unsupervised classifications used for AOI selection for 2008 image.

A maximum AOI size of 1,000 pixels was selected based on previous research (Kloiber et al. 2002a). In order to eliminate the creation of AOIs larger than 1,000 pixels in size, an additional criteria used in the selection of AOIs was lake depth. Information regarding lake depth for most lakes within the study area was available from the Maine Office of GIS in the form a GIS dataset that provided the lake depth at multiple points throughout each lake (MEDEP and MEIFW 2011). The deepest point for each lake was selected and a buffer of 535 meters (the area required to select a maximum of 1,000 pixels) was created around the deepest point. The intersection of this buffer area and the area selected by offsetting 120 meters from the edge of the lake combined with the area identified using the unsupervised classification resulted in the final determination of the AOI for each lake. For lakes where information regarding lake depth was not available, the approximate center of the lake was used. Lakes with an AOI less than 120 meters in width or length were eliminated from further study as well as lakes with an AOI of less than nine pixels (Kloiber et al. 2002b). A series of images that illustrate the process of AOI selection for a single lake are provided in Figure 3. An example of a single lake within the study area, the lake catchment, the 100 and 500 meter buffer areas around the lake perimeter, LULC classifications, and the lake AOI is provided as Figure 4.

Great Pond, Hancock County

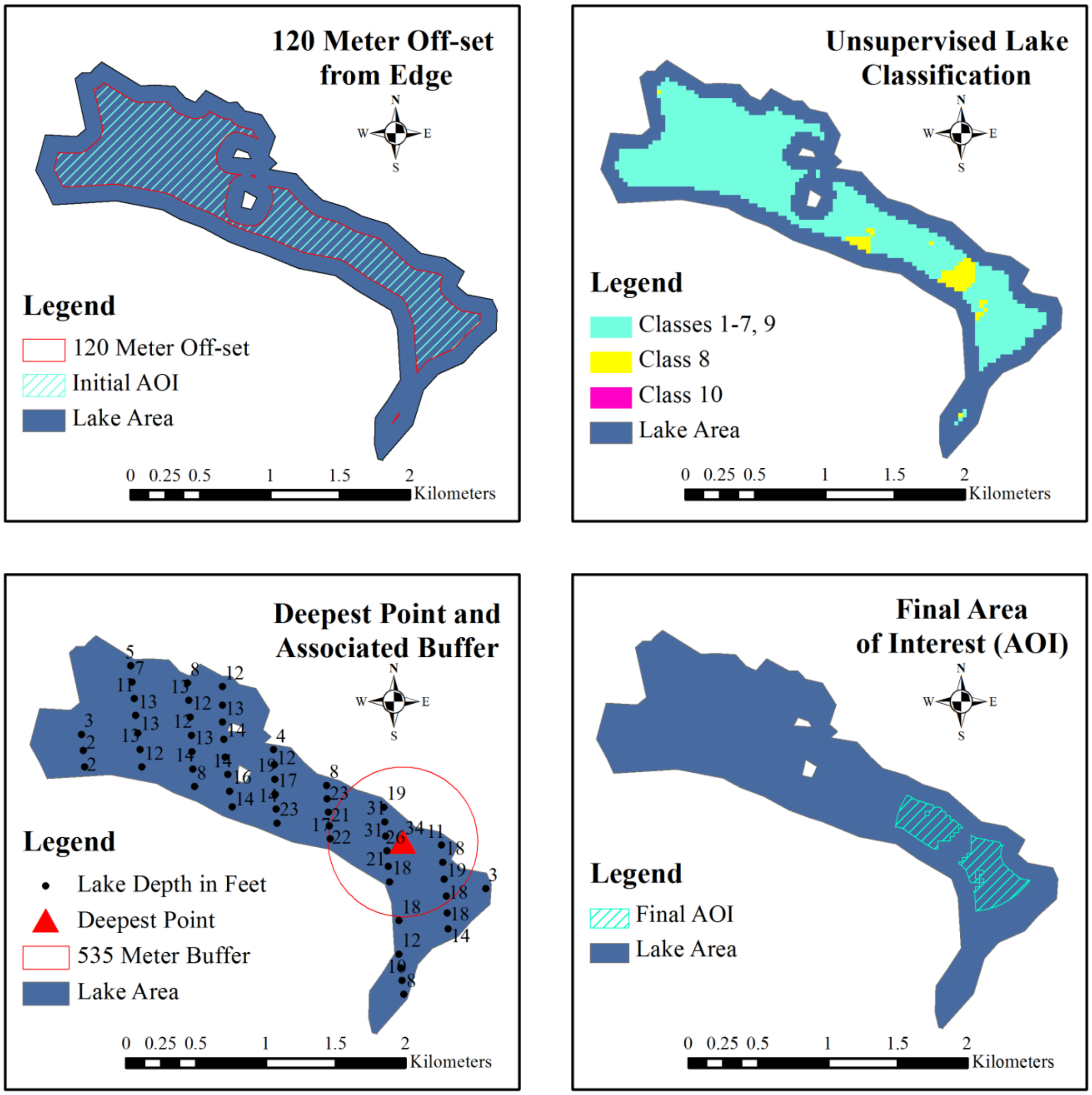

Figure 3: Images illustrating the process of AOI selection for a single lake.

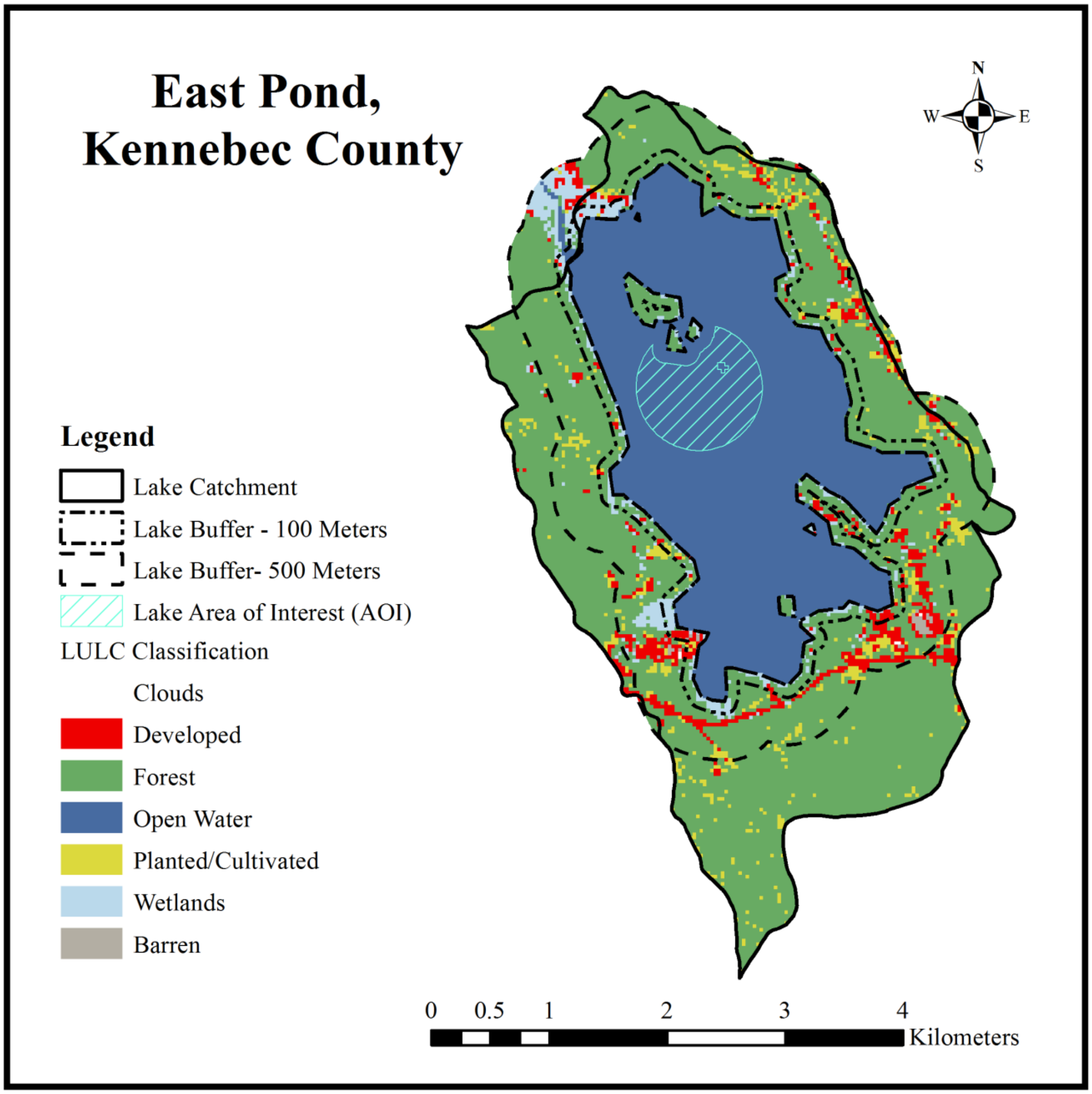

Figure 4: Example of a single lake within the study area, the lake catchment, the 100 and 500 meter buffer areas around the lake perimeter, LULC classifications, and the lake AOI.

2.6 Extraction of Water Quality Values

The lake AOIs were used to extract water temperature and clarity values from the Landsat-5 images for each lake within each study year. It should be noted that when referring to water temperature extracted from satellite imagery, the temperature is the surface water apparent temperature, and that all water temperature and clarity values referenced in this and subsequent sections are based on the values extracted from the lake AOIs. For water temperature, the radiance measurements for Landsat-5 thermal band 6 were used to derive water temperature using Planck's Black Body Equation which "defines the relationship between the radiance emitted from an object at a certain wavelength and its absolute temperature" (Mustard et al. 1999). Conversion to black body temperature was completed using the methods described by Chander et al. (2009). This method converts Landsat-5 band 6 to effective at-sensor brightness temperature which provides the temperature in Kelvins. The mean at-sensor brightness temperature was extracted from each lake AOI for each image. Mean at-sensor brightness temperatures were then converted from Kelvins to degrees Celsius for subsequent analyses.

The AOIs identified in Section 2.5 were also used to extract water clarity values (identified as secchi disk depths) for each lake and within each study year. *In situ* water clarity data for more than 800 lakes in Maine from 1952 through 2008 (availability varies by lake and year) has been compiled by the University of Maine George J. Mitchell Center for Environmental and Water Research (2011). Use of these data allowed water clarity values to be determined for all lakes within each Landsat-5 image, with the exception of any lakes affected by cloud cover or haze.

Following methods described by Kloiber et al. (2002a), Landsat-5 spectral bands best correlated with *in situ* secchi disk depth values were identified through use of Pearson correlation coefficients and stepwise multiple regression analysis. A technical document, *Image Processing Protocol for Regional Assessments of Lake Water Quality* (Olmanson et al. 2001), provided additional information and step-by-step guidelines for Landsat image processing to extract lake water clarity values. The methods described by Olmanson et al. (2001) are not as robust as those used by Kloiber et al. (2002a) in terms of selection of spectral bands and image calibration; however the step-by-step instructions were used to guide image processing for extraction of lake water clarity values.

Lakes with *in situ* water clarity values within +/- 7 days of each Landsat-5 image date were initially selected for each study year. Past research has determined that *in situ* data collected within seven days of a satellite overpass are generally acceptable for determining lake water clarity values and that data collected within ten days of overpass may be used (Kloiber et al. 2002a; Olmanson et al. 2008). The use of *in situ* data collected closer to the time of satellite overpass reduces error when estimating water clarity values; however, a greater time frame can increase the sample size of *in situ* data as well as the geographical area from which the data were collected (McCullough et al. 2012). In accordance with the previous research, when possible (based on the amount of available data) a narrower timeframe was used. The timeframe used for each study year is included in Table 2. A natural log data transformation was performed on the *in situ* data before the data were entered into statistical processing software in order to identify the equation or model that, based on the *in situ* data, could be used to best predict water clarity values for all lakes covered by the same Landsat-5 image. Landsat-5 bands 1 through 5 and 7 mean spectral responses (top of atmosphere reflectance) for the AOIs associated with each lake were extracted for lakes with existing *in situ* data in order to perform the analysis. For this and subsequent analyses, SPSS statistical analysis software was used for statistical data analysis.

Previous research (Olmanson et al. 2001) indicated that a combination of a Landsat-5 band 1 to band 3 ratio (B1:B3) and Landsat-5 band 3 (B3) may provide a best-fit model for extraction of water clarity data from Landsat-5 imagery. For the Landsat-5 images included in this study, it was found that the best-fit model produced by SPSS always included B1:B3 and band 7 (B7) as opposed to B3 as reported in Olmanson et al. (2001). For select years an additional predictor value of B3 or B1 was also included. Refer to Table 2 for the best-fit model equations; *R*-squared values associated with each equation; number of lakes with *in situ* data (n) used to create the best-fit model; and timeframe (based on days before or after the Landsat-5 image date) for each image (year). Refer to Figure 5 for scatter plots of the *in situ* water clarity values and estimated water clarity values.

Table 2: Summary of best-fit model equations for estimation of lake water clarity values using Landsat-5 spectral data.

Year	Equation	R^2	n	Days
1986	-2.669+4.199(B1:B3)+217.813(B7)+88.686(B3)	0.73	56	+/- 5
1995	-4.931+2.309(B1:B3)+157.857(B7)	0.81	71	+/- 5
1999	-5.858+2.666(B1:B3)+380.539(B7)	0.83	64	+/- 3
2000	0.936+1.564(B1:B3)+8.380(B7)-45.608(B1)	0.70	46	+/- 3
2005	-16.044+4.133(B1:B3)+194.081(B7)+80.070(B1)	0.81	24	+/- 7
2008	-4.064+1.961(B1:B3)+ 166.400(B7)	0.89	55	+/- 5

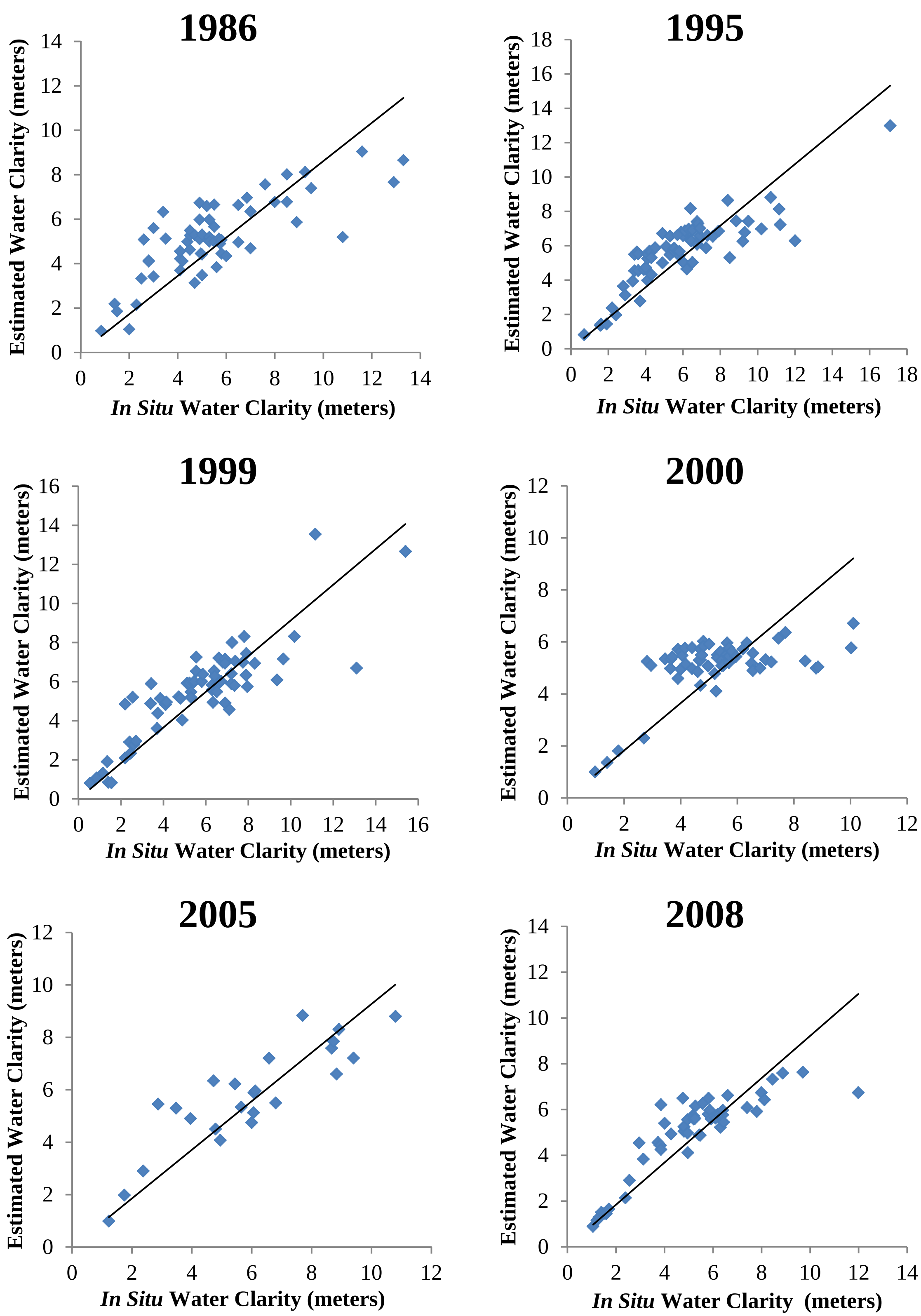

Figure 5: Scatter plots showing the *in situ* (observed) water clarity values measured as secchi disk depths and the secchi disk depth water quality values estimated based on Landsat-5 imagery.

In their image processing protocol, Olmanson et al. (2001) used *R*-squared values of approximately 0.80 for images within the July 15 to September 15 index periods. As can be seen in Table 2, an *R*-squared value of 0.80 or greater was achieved for four of the six years; however, for the remaining two years (1986 and 2000) the *R*-squared values were 0.70 and 0.73, respectively. The best-fit equations were also evaluated to ensure that multicollinearity was not present among the independent variables (the Landsat-5 spectral values). Multicollinearity was primarily a concern when B1 and B3 were used as predictor values in addition to the B1:B3 ratio. Multicollinearity was evaluated by examination of Variance Inflation Factor (VIF) values, where VIFs greater than ten are considered to be problematic and indicators of multicollinearity among model covariates (Meyers et al. 2006; Shieh 2011). Variance inflation factor values associated with the predictor equations used to create the best-fit models for water clarity values ranged from 1.01 to 7.47, well below the threshold value of ten.

2.7 Data Analysis

2.7.1 Evaluation of Relationship between LULC and Water Quality

Data from the most recent study year, 2008, were used to evaluate the relationship between LULC and water temperature and clarity. The 2008 image was selected to evaluate the relationship between LULC and water quality because it was the most recent year in the study period with acceptable levels of both cloud cover and water quality data. Based on Landsat-5 imagery from July 16, 2008, 337 lakes in the study area were used to evaluate the relationship. Data for LULC analyses were extracted from the LULC image for 2008 (refer to Section 2.3). From the 2008 classified image, the percentage of each LULC class (open water, developed land, barren land, forest, planted/cultivated land, and wetland) within the immediate catchment area as well as within 100 meters and 500 meters of each lake (buffer areas) was determined using pixel counts calculated using the ArcGIS spatial analyst zonal tools. Pixel counts were then converted to percent cover for each lake catchment as well as each buffer area. For open water, the area of the lake itself was excluded from the analysis area. Water quality data were extracted from the Landsat-5 image as described in Section 2.6.

Prior to evaluation of the relationship between the water quality variables and LULC, the 2008 water quality data were evaluated for normality. An analysis of the data distribution for the 2008 water temperature values indicated that both the skewness and kurtosis values (-1.24 and 1.70, respectively) fell outside the range of +/- 1 suggested by Meyers, et al. (2006). Additionally, the results of a Kolmogorov-Smirnov test ($p < 0.05$) indicated that there was a possible normality violation (Meyers et al. 2006). In order to correct for the possible normality violations, a reflect and logarithm data transformation was applied to the water temperature values. Following the data transformation, both skewness and kurtosis values (0.32 and -0.11, respectively) were within the suggested +/- 1 range and the results of the Kolmogorov-Smirnov test ($p > 0.50$) indicated that there was not a normality violation. The transformed water temperature values were used for the analysis regarding the relationship between water temperature and LULC.

An analysis of the data distribution for water clarity values indicated that the data displayed skewness within the suggested range of +/- 1 (Meyers et al. 2006); however, at 2.71, the data were found to display what may be considered an unacceptable value for kurtosis. Despite the high kurtosis value, the results of a Kolmogorov-Smirnov test ($p > 0.05$) indicated that there was not a normality violation (Meyers et al. 2006).

Water temperature and clarity values for study year 2008 were entered into a data matrix with the LULC percentages for each LULC class. Separate data matrixes were created for the lake catchments, the 100 meter buffer areas, and the 500 meter buffer areas. To determine if there was a significant relationship between lake water temperature and/or clarity and one or more of the LULC classes, multivariate regression analyses were performed with lake water temperature and clarity values as the dependent variables and the LULC classes as independent variables. Multivariate regression analyses were performed for both water quality variable and for each LULC area (catchments and buffer areas) with all LULC classes. Based on the results of the initial multivariate regression analyses, additional regression analyses were run with only the LULC classes that were identified by the initial multivariate regression analyses as statistically significant classes ($p \leq 0.05$). The results of the subsequent multivariate regression analyses identified the LULC classes that had a significant relationship with water temperature or clarity for lake catchments and/or buffer areas.

2.7.2 Evaluation of Water Quality Change

In order to evaluate water quality change over time, water temperature and clarity values were extracted from the Landsat-5 images for each study year following the methods described in Section 2.6. Multivariate regression analyses, with water temperature and clarity as the dependent variables and time as the independent variable, were used to determine if there has been a systematic, statistically significant ($p \leq 0.05$), change over time in water temperature and/or clarity. These analyses were completed using all lakes in the study area that had data for all study years (data availability based on cloud/haze free coverage). First, regression analyses were performed for individual lakes to determine if the water temperature or clarity for any given lake had exhibited a systematic, statistically significant change during the study period. Next, similar analyses were performed using the average water temperature and clarity values for all lakes within each study year to determine if there was a statistically significant change over time in the region as a whole for either water temperature or clarity values.

2.7.3 Evaluation of Effect of LULC on Water Quality Change

For lakes that were identified as exhibiting a significant temporal trend in water temperature or clarity (refer to Section 2.7.2), the dominant LULC class was identified for the entire lake catchment and within the 100 and 500 meter buffer areas. The dominant LULC class was determined based on percent cover in 1986, the earliest study year and base year for change detection. For the dominant LULC class, pixel counts calculated by ArcGIS spatial analyst zonal tools were converted to percent cover within each lake catchment and buffer area for each study year. Following calculation of percent cover, regression analysis was used to determine if there was a statistically significant ($p \leq 0.05$) relationship between the change in the percent of the dominant LULC class and the water temperature or clarity values. In addition to evaluation of changes in the dominant LULC class, analyses of changes in other LULC classes and their relationship with water temperature and/or clarity values were also completed for LULC classes that were identified as potentially having a relationship with water quality values. The identification of LULC classes that potentially have a relationship with the water quality values was based on the previously described analysis/evaluation of the relationship between LULC and water quality (refer to Section 2.7.1).

A second evaluation was completed to further identify significant relationships between changes in LULC and water temperature or clarity. Following the methods described above, for lakes that were identified as having exhibited a statistically significant change in water temperature or clarity, the percent of each LULC class was identified within each lake catchment and the 100 and 500 meter buffers for each study year. Regression analyses with time as the independent variable and each LULC class as a dependent variable were used to identify if any of the lakes with a statistically significant change in water temperature or clarity during the study period had also exhibited a statistically significant change in one or more LULC class within the same time period. Completion of separate regressions for each lake and each LULC class enabled the identification of lakes and their associated catchment and or/buffer area(s) that exhibited both a significant change in water quality and a significant change in percent cover of one or more LULC class over the study period.

For lakes identified as exhibiting both a statistically significant change in water quality and a statistically significant change in one or more LULC class, a final regression analysis was used to determine if there was a statistically significant relationship between the percent change in the LULC class and the identified changes in water temperature and/or clarity values. Again, these regression analyses were only completed for lakes that exhibited a significant change in water temperature or clarity and the LULC class for that lake's catchment or buffer area that also exhibited a significant change.

3.0 RESULTS

3.1 LULC Classification of Landsat-5 Datasets

In order to evaluate the relationship between LULC and water quality, the entire Landsat-5 image for study year 2008 was classified. An accuracy assessment for the 2008 classified image was performed using a stratified random sampling framework. Following methods outlined by Jensen (2005), a sample size based on a multinomial distribution with an 85 percent confidence interval was used. Based on this method, 529 points were initially generated for the 2008 classified image; however points that fell along the edge of the image were eliminated from use as part of the accuracy assessment. Ultimately, 483 accuracy assessment points were used with a minimum of 30 points within each class. The number of accuracy assessment points per class ranged from 33 to 121 such that land cover classes with a smaller footprint on the ground (i.e., barren land), had fewer points than land cover classes with a larger footprint on the ground (i.e., forest). An accuracy assessment error matrix for 2008 is provided in Table 3.

Table 3: Accuracy assessment error matrix for the supervised classification of the 2008 Landsat-5 image. Assessment includes areas influenced by cloud cover. Classification image data are reported as columns and reference image data are reported as rows.

	Water	Developed Land	Barren Land	Forest	Planted/ Cultivated	Wetland	Cloud	Total	Producer Accuracy
Water	78	0	0	0	0	0	1	79	0.99
Developed Land	0	33	9	10	2	4	20	78	0.42
Barren Land	0	5	23	0	2	0	3	33	0.70
Forest	0	1	0	83	8	5	9	106	0.78
Planted/Cultivated	0	2	1	13	33	2	3	54	0.61
Wetlands	0	1	0	12	0	35	15	63	0.56
Clouds	0	0	0	0	0	0	70	79	1.00
Total	78	42	33	118	45	46	121	483	
User Accuracy	1.00	0.79	0.70	0.70	0.73	0.76	0.58		

Overall Accuracy	**0.73**
Kappa Statistic	**0.69**

Based on the values in Table 3, the supervised classification was least accurate in identification of cloud areas. This was primarily due to variability in cloud opacity, which created mixed spectral responses that did not necessarily correspond to either the cloud or the ground cover beneath the cloud. This finding reinforced the need for manual removal of areas affected by clouds or haze. After excluding points that fell within any areas affected by clouds or haze, 362 accuracy assessment points were used for validation. When areas with clouds were not included in the accuracy assessment, the overall accuracy improved from 73 to 79 percent with a Kappa statistic value of 0.74 in contrast to 0.69. An error matrix excluding areas identified as/affected by clouds is provided in Table 4.

Table 4: Accuracy assessment error matrix for the supervised classification of the 2008 Landsat-5 image. Assessment excludes areas influenced by cloud cover. Classification image data are reported as columns and reference image data are reported as rows.

	Water	**Developed Land**	**Barren Land**	**Forest**	**Planted/ Cultivated**	**Wetland**	**Total**	**Producer Accuracy**
Water	78	0	0	0	0	0	78	1.00
Developed Land	0	33	9	10	2	4	58	0.57
Barren Land	0	5	23	0	2	0	30	0.77
Forest	0	1	0	83	8	5	97	0.86
Planted/Cultivated	0	2	1	13	33	2	51	0.65
Wetlands	0	1	0	12	0	35	48	0.73
Total	78	42	33	118	45	46	362	
User Accuracy	1.00	0.79	0.70	0.70	0.73	0.76		
Overall Accuracy	**0.79**							
Kappa Statistic	**0.74**							

The remainder of the study years were classified after the 2008 classification was completed. In order to eliminate the need to classify the entire image, only areas that fell within a catchment or buffer zone for a lake that had water quality data for at least one of the study years were used. A map showing these areas is provided as Figure 6. Because of the inability for the classification method to accurately identify areas influenced by cloud cover, accuracy assessments for the remaining study years did not include points that fell within areas influenced by clouds or haze. For consistency with the 2008 image accuracy assessment, for each year a total of 362 accuracy assessment points were randomly generated with a minimum of 30 points per class. For the five image years prior to 2008, the overall accuracies associated with the supervised classifications ranged from

83 to 85 percent with Kappa statistic values of 0.77 to 0.80. A summary of the accuracy assessment results for study years prior to 2008 is provided in Table 5.

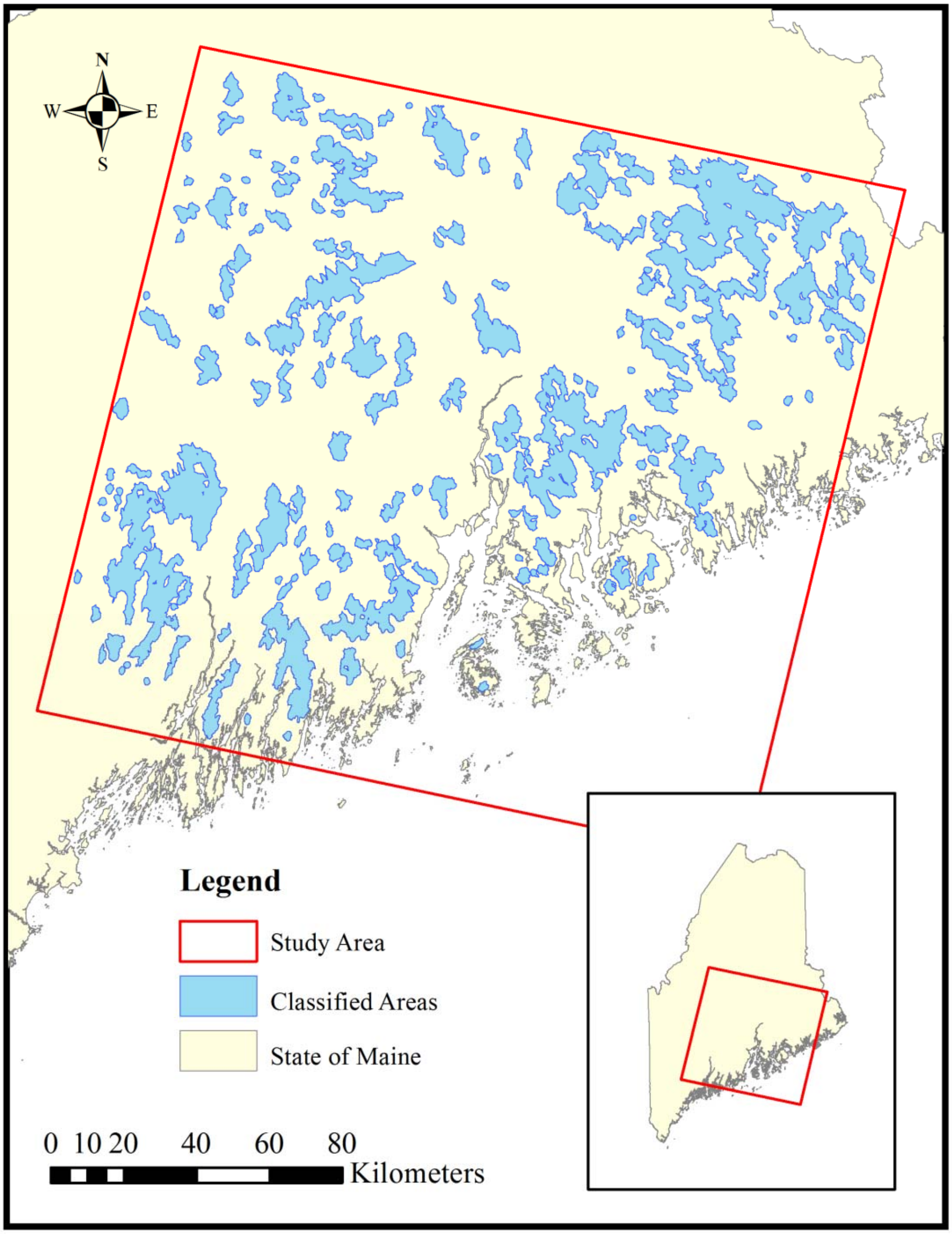

Figure 6: Lake catchment and buffer areas for lakes that have water quality data for at least one of the study years.

Table 5: Summary of supervised LULC classification accuracy assessments for 1986, 1995, 1999, 2000, and 2005 images.

LULC Class	1986 Image		1995 Image		1999 Image		2000 Image		2005 Image	
	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy
Water	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Developed	0.66	0.85	0.63	0.87	0.67	0.85	0.69	0.86	0.75	0.96
Barren Land	0.77	0.96	0.93	0.90	0.63	0.90	0.60	0.82	0.83	0.65
Forest	0.96	0.83	0.94	0.83	0.88	0.84	0.86	0.87	0.88	0.89
Planted/cultivated	0.59	0.69	0.64	0.84	0.72	0.79	0.79	0.77	0.68	0.93
Wetland	0.55	0.64	0.61	0.66	0.69	0.52	0.74	0.49	0.67	0.53
Overall	0.84		0.85		0.83		0.83		0.84	
Kappa	0.78		0.80		0.77		0.77		0.79	

3.2 Relationship between Water Quality and LULC

Based on Landsat-5 imagery from July 16, 2008, the most recent study year, 337 lakes in the study area were used to evaluate the relationship between LULC and water temperature and clarity using multivariate regression analyses. Results associated with changes in water temperature, clarity, or LULC, and relationships between water quality variables and LULC are considered to be statistically significant (significant) if $p \leq 0.05$, unless otherwise noted.

For water temperature and LULC classes within the lake catchments, the results of the multivariate regression analysis indicate that two LULC classes contribute to the weighted combination of independent variables (LULC classes) that produces the best estimates of water temperature. The two LULC classes that contribute to the model are the percent of the immediate lake catchment identified as developed land and the percent of the immediate lake catchment identified as open water. The multiple correlation coefficient or *R* value for the model identified as the best predictor of water temperature is 0.21 and the *R*-squared coefficient of multiple determination is 0.04. The multiple correlation coefficient (*R)* value is a measure of the association or strength of the linear relationship between the dependent variable and the combination of independent variables, while the coefficient of multiple determination (*R*-squared) quantifies the percent variance of the dependent variable accounted for by the combination of the independent variables used in the model (Cohen and Cohen 1983; Meyers et al. 2006). The results of the multivariate regression analysis indicate that a significant relationship exists between water temperature and the percent of developed land and open water within the lake catchment. The standardized coefficient (beta weight) produced for the independent variable percent developed land (beta weight of -0.16) has a negative relationship with lake surface water temperature, indicating that as the percent of developed land within a lake catchment increases, water temperature decreases. The beta weight associated with the independent variable percent open water (beta weight of 0.14) has a positive relationship with water temperature, indicating that as the percent open water within the lake catchment increases, water temperature increases. Further assessment of the multivariate regression analysis indicates that multicollinearity is not present between the independent variables (VIF value of 1.00).

For water temperature and LULC classes within 100 meters of a lake, the results of the multivariate regression analysis indicate that only one LULC class, planted/cultivated land, contributes to the model that is the best predictor of water temperature. The *R* value for the model identified as the best predictor of water temperature is 0.30 and the *R*-squared value is 0.09. The results of the multivariate regression analysis indicate that a significant relationship exists between water temperature and the percent of the area within 100 meters of a lake identified as planted/cultivated land. The beta weight produced for the independent variable indicates that percent planted/cultivated land (beta weight of -0.30) has a negative relationship with water temperature, indicating that as the percent of planted/cultivated land within 100 meters of a lake increases, lake surface water temperature decreases.

For water temperature and LULC classes within 500 meters of a lake, the results of the multivariate regression analysis indicate that only one LULC class, developed land, contributes to the model that is the best predictor of water temperature. The *R* value for the model identified as the best predictor of water temperature is 0.28 and the *R*-squared value is 0.08. The results of the multivariate regression analysis indicate that a significant relationship exists between water temperature and the percent of the area within 500 meters of a lake identified as developed land. The beta weight produced for the independent variable indicates that percent developed land (beta weight of -0.28) has a negative relationship with water temperature, indicating that as the percent of developed land within 500 meters of a lake increases, lake surface water temperature decreases. Results of the analyses regarding the relationship between water temperature and LULC are summarized in Table 6.

Table 6: Summary of relationship between water quality variables and LULC.

LULC Area	Predictors (significant independent variables)	Relationship with Water Quality Variable	Partial Correlation Coefficient (Squared)	Model *R*-Squared
Water Temperature				
Lake Catchment	Developed land	Negative	0.02	0.04
	Open water	Positive	0.02	
Within 100 Meters of Lake	Planted/Cultivated	Negative	0.09	0.09
Within 500 Meters of Lake	Developed	Negative	0.08	0.08
Water Clarity				
Lake Catchment	Planted/cultivated	Negative	0.01	0.12
	Developed	Negative	0.05	
Within 100 Meters of Lake	Planted/cultivated	Negative	0.07	0.09
	Wetland	Negative	0.02	
Within 500 Meters of Lake	Planted/cultivated	Negative	0.04	0.12
	Wetland	Negative	0.02	
	Developed	Negative	0.03	

For water clarity within the lake catchment, the results of the analysis indicate that a combination of two LULC classes contribute to the model that is the best predictor of water clarity. The two LULC classes that contribute to the model are the percent of the lake catchment identified as planted/cultivated land and the percent of the lake catchment identified as developed land. The *R* value for the model identified as the best predictor of water clarity is 0.34 and the *R*-squared value is 0.12. The results of the multivariate regression analysis indicate that a significant relationship exists between water clarity and the weighted linear composite of the percent of planted/cultivated land and developed land within the lake catchment. The beta weights produced for the independent variables indicate that percent planted/cultivated land and percent developed land (beta weights of -0.13 and -0.26, respectively) have negative relationships with water clarity, indicating that as the percent of each of these variables increases within a lake catchment, water clarity decreases. Further assessment of the multivariate regression analysis indicates that multicollinearity is not present between the independent variables (VIF value of 1.35).

For water clarity and LULC classes within 100 meters of a lake, the results of the multivariate regression analysis indicate that a combination of two LULC classes contribute to the weighted combination of independent variables that produces a model that is the best predictor of water clarity. The two LULC classes that contribute to the model are the percent of the area within 100 meters of a lake identified as planted/cultivated land and the percent of the area within 100 meters of a lake identified as wetland. The *R* value for the model identified as the best predictor of water clarity is 0.30 and the *R*-squared value is 0.09. The results of the multivariate regression analysis indicate that a significant relationship exists between water clarity and the weighted linear composite of the percent of planted/cultivated land and wetland within 100 meters of a lake. The beta weights produced for the independent variables indicate that percent planted/cultivated land and percent wetland (beta weights of -0.27 and -0.14, respectively) have negative relationships with water clarity, indicating that as the percent of each of these variables increases within 100 miles of a lake, water clarity decreases. Further assessment of the multivariate regression analysis indicates that multicollinearity is not present between the independent variables (VIF value of 1.00).

For water clarity and LULC classes within 500 meters of a lake, the results of a multivariate regression analysis indicate that a combination of three LULC classes contribute to the weighted combination of independent variables that produces a model that is the best predictor of water clarity. The three LULC classes that contribute to the model are the percent of the area within 500 meters of a lake identified as planted/cultivated land, the percent of the area within 500 meters of a lake identified as wetland, and the percent of the area within 500 meters of the lake identified as developed land. The *R* value for the model identified as the best predictor of water clarity is 0.35 and the *R*-squared value is 0.12. The results of the multivariate regression analysis indicate that a significant relationship exists between water clarity and the weighted linear composite of the percent of planted/cultivated land, wetland, and developed land within 500 meters of a lake. The beta weights produced for the independent variables indicate that percent planted/cultivated land, percent wetland, and percent developed land (beta weights of -0.22, -0.14, and -0.18, respectively) have negative relationships with lake water clarity, indicating that as the percent of each of these variables increases within 500 miles of a lake, water clarity decreases. Further assessment of the multivariate regression analysis indicates that multicollinearity is not present among the independent variables (VIF values of 1.12 to 1.49). Results of the analyses regarding the relationship between water clarity and LULC are summarized in Table 6.

3.3 Water Quality Change

After elimination of all lakes affected by clouds and/or haze, there were 40 lakes available with data for all six study years. Water quality data were extracted from all 40 of the lakes for each study year. The results of the linear regression analysis with time as the independent variable and water quality as the dependent variable for each of the 40 lakes found that, for water temperature, 21 of the 40 lakes exhibited a significant change in water temperature over the study period. For the 21 lakes that exhibited a significant change in water temperature, the water temperature values for each lake increased over the duration of the study period with an overall average increase for all 21 lakes of 3.42° Celsius. Frequently, the highest water temperature value for any given lake was found to have occurred in study year 2005. For water clarity, only one lake exhibited a significant change in water clarity over the study period. For this lake, overall water clarity decreased 1.21 meters over the study period. When all lakes in the study year were evaluated together, the average change in water temperature was significant with an overall warming trend of 3.11° Celsius; however, the average change in water clarity was not found to be significant. Refer to Figure 7 for a map showing the locations of lakes that had a statistically significant change in water temperature and/or clarity based on data from all six of the study years.

To increase the sample size, an analysis was also run without data from 2005 included in the analysis. The year 2005 was chosen for removal because availability of water quality data in 2005 was identified as the most limited due to an extensive presence of cloud cover and haze in the Landsat-5 image from 2005. With data from 2005 removed from the analysis, the sample size (i.e. the number of lakes with water quality data available for all years) increased from 40 to 99. A linear regression was again run for each of the lakes with time as the independent variable and water quality as the dependent variable. For water temperature, 35 of the 99 lakes exhibited a significant change in water temperature over the study period with an overall average increase for all 35 lakes of 3.07° Celsius. For the 35 lakes that exhibited a significant change in water temperature, all lakes were identified as having experienced an overall increase in water temperature. For water clarity, only 2 of the 99 lakes exhibited a significant change in water clarity over the study period. Both of the lakes that exhibited a significant change in water clarity were identified as having experienced an increase in water clarity; one lake with an overall increase of 1.47 meters and another lake with an overall increase of 2.61 meters over the study period. The average water temperature and clarity values for the 99 lakes did not exhibit a significant change over the study period. Refer to Figure 8 for a map showing the locations of lakes that had a statistically significant change in water clarity and/or surface water temperature when study year 2005 was excluded from the data.

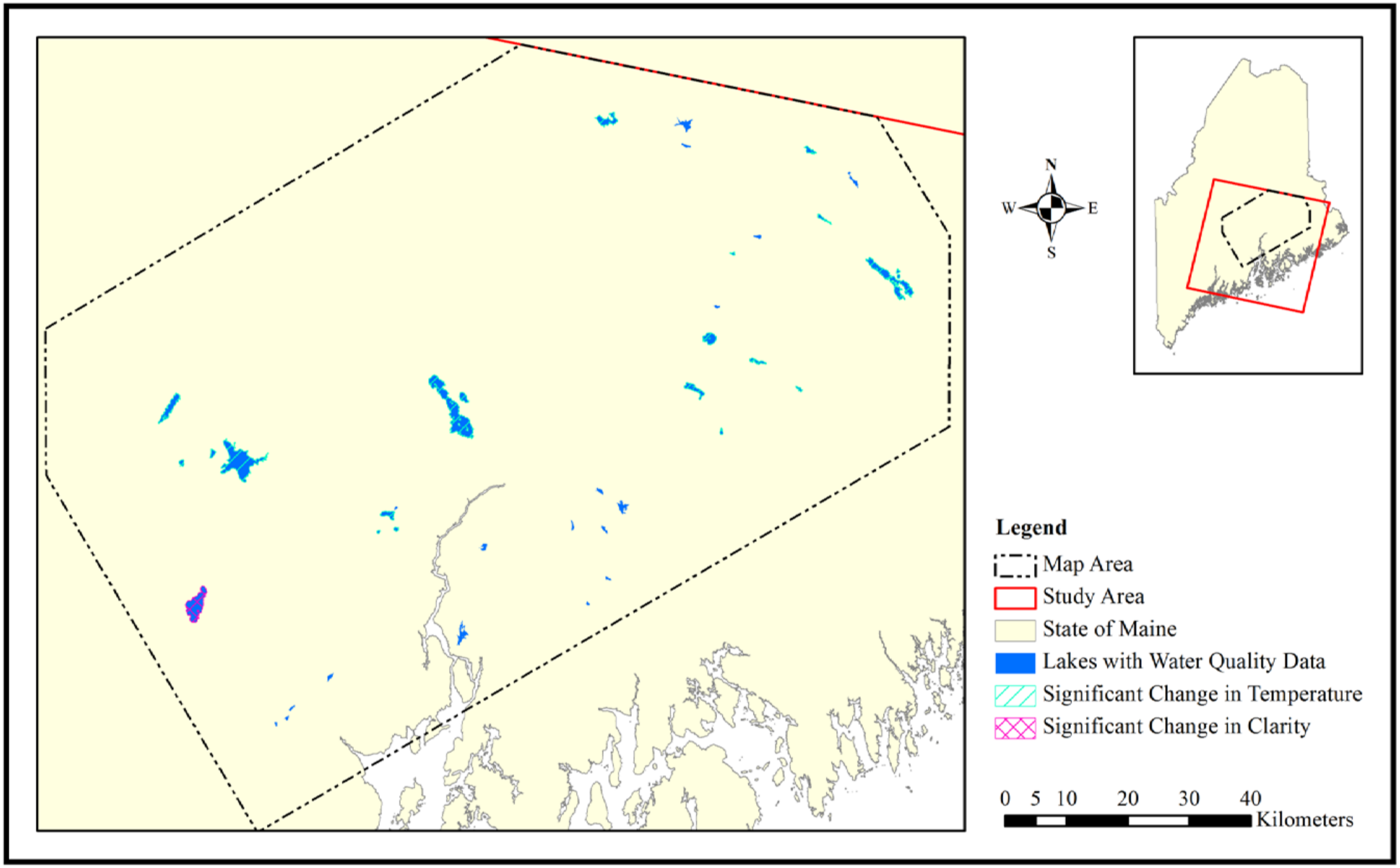

Figure 7: Lakes that exhibited a statistically significant change in water temperature and/or clarity based on data from all six of the study years.

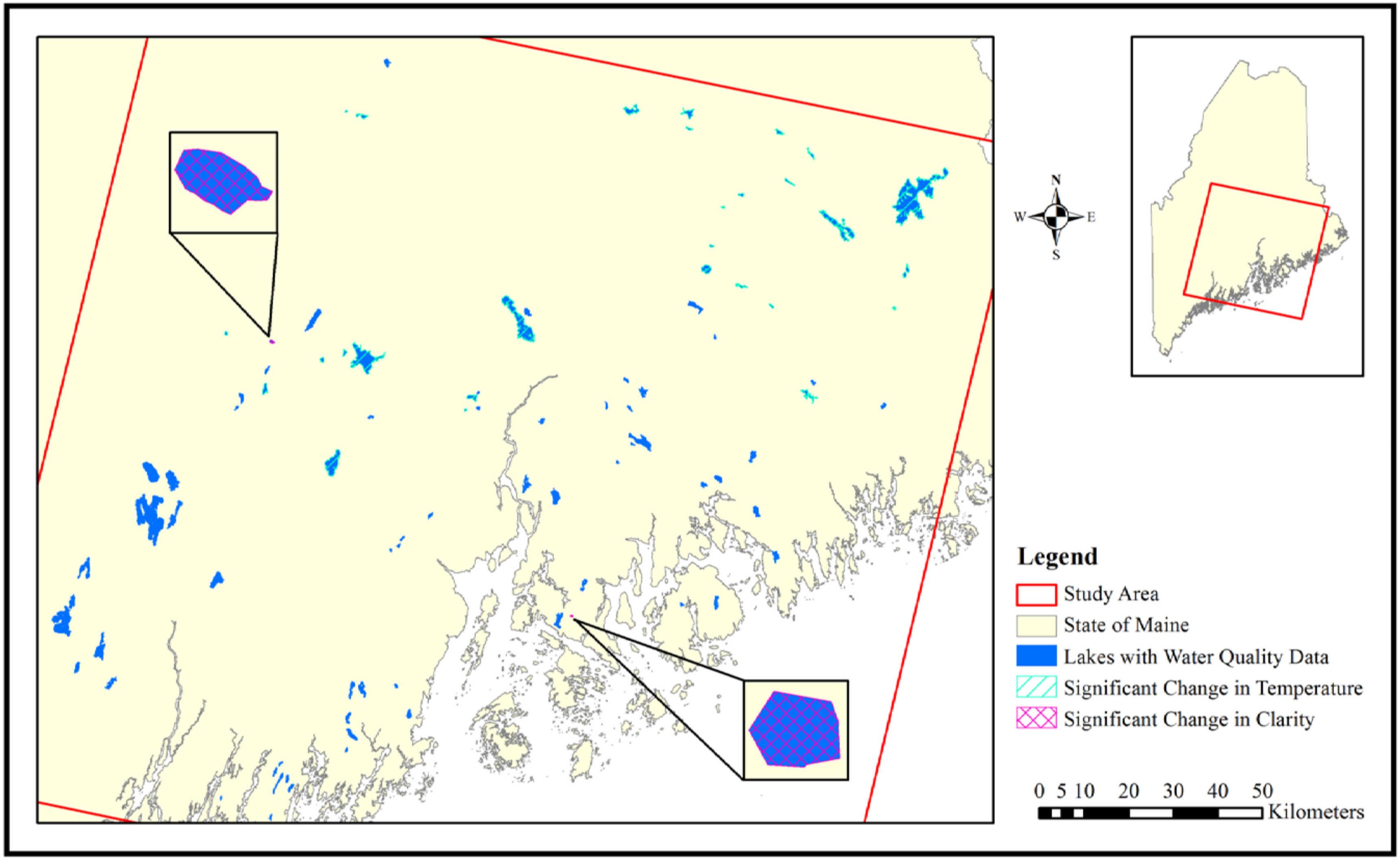

Figure 8: Lakes that exhibited a statistically significant change in water temperature and/or clarity based on data excluding study year 2005.

3.4 Relationship between Water Quality and LULC Change

For lakes that exhibited a significant temporal trend in water temperature or clarity, a regression analysis was completed to determine if there was a statistically significant relationship between changes in the dominant LULC class and changes in water temperature and/or clarity over the study period. The analysis was completed for each lake and the dominant LULC class in each catchment and buffer area. As previously indicated, there were 21 lakes identified that exhibited a significant change in water temperature and only 1 lake that exhibited a significant change in water clarity. For all of the lakes with an identified significant change in water temperature or clarity, the dominant LULC class in all catchments and buffer areas was identified as forest.

For water temperature, the results of the regression analysis indicated that there were no lake catchments, one 100 meter buffer area, and one 500 meter buffer area with a significant relationship between changes in percent forest cover and changes in water temperature during the study period. The 100 meter and 500 meter buffer areas identified as having a significant relationship with water temperature were associated with two separate lakes, but both exhibited an overall increase in percent forest cover over the study period and the associated lakes exhibited an overall increase in water temperature. For water clarity, there were no significant relationships identified between changes in the percent cover of the dominant LULC class (forest) and changes in water clarity over the study period; however, as previously noted, this analysis included only the one lake that exhibited a significant change in water clarity over the study period.

As with previous assessments, the analysis between changes in the percent cover of the dominant LULC class and changes in water temperature and clarity was also completed after removing data from study year 2005. For water temperature, this increased the sample size to 35 and for water clarity this increased the sample size to 2. Again, the dominant LULC class for all lake catchments and buffer areas was identified as forest. For water temperature, the results of the regression analysis with data from study year 2005 removed indicated that there was one lake catchment, no 100 meter buffer areas, and no 500 meter buffer areas with significant relationships between changes in percent forest cover and changes in water temperature during the study period. The one lake catchment with a significant relationship between water temperature and forest cover exhibited an overall decrease in forest cover and the associated lake exhibited an overall increase in water temperature. For water clarity, there were no significant relationships identified between changes in the percent forest cover and changes in water clarity over the study period; however, as previously noted, this analysis only included the two lakes that exhibited a significant change in water clarity over the study period.

An analysis was also completed to evaluate the relationship between water quality and LULC classes that were identified as potentially having a relationship with water temperature or water clarity. The identification of these LULC classes was completed using the methods described in Section 2.7.1. The LULC classes identified as having a statistically significant relationship with either water temperature or clarity are identified in Section 3.2 and summarized in Table 6. The identified LULC classes varied by water quality parameter and catchment/buffer area. For water temperature and lake catchment, the identified LULC classes were developed land and open water. The results of regression analyses for all 21 lakes with a significant change in water temperature indicated that there were no lakes with a significant relationship between changes in water temperature and changes in either percent cover of developed land or open water. For 100 meter buffer areas, the identified LULC class with a potential influence on water temperature was developed land. The results of regression analyses identified one lake with a significant relationship between changes in water temperature and changes in percent cover of developed land within the 100 meter buffer areas. Over the study period, this 100 meter buffer area exhibited an overall increase in developed land and the associated lake exhibited an overall increase in water temperature. For 500 meter buffer areas, the identified LULC class with a potential influence on water temperature was planted/cultivated land. The results of the regression analyses identified one lake with a significant relationship between changes in water temperature and changes in percent cover of planted/cultivated land within the 500 meter buffer areas. Over the study period, this 500 meter buffer area exhibited an overall decrease in planted/cultivated land and the associated lake exhibited an overall increase in water temperature.

For water clarity, LULC classes identified as having a potential influence on water clarity were planted/cultivated land for lake catchments, 100 meter buffer areas, and 500 meter buffer areas; developed land for lake catchments and 500 meter buffers areas; and wetland areas for 100 meter and 500 meter buffer areas. The results of regression analyses for the one lake with an identified significant change in water clarity indicated that there were no significant relationships between changes in water clarity and changes in percent cover of planted/cultivated land, developed land (lake catchment and 500 meter buffer), or wetland areas (100 and 500 meter buffers).

The analysis of the relationship between changes in water quality values and LULC identified as potentially having a relationship with water quality was repeated with data from 2005 removed from the analysis. This again increased the sample size for water temperature to 35 and the sample size for water clarity to 2. For water temperature, the results of the regression analyses indicated that there was one lake catchment with a significant relationship between changes in water temperature and changes in percent cover of developed land and no lake catchments with significant relationships between changes in water temperature and changes in percent cover of open water. Over the study period, the lake catchment identified as having a significant relationship between water temperature and developed land exhibited an overall increase in developed land and the associated lake exhibited an overall increase in water temperature. There were two 100 meter buffer areas identified as having a significant relationship between changes in water temperature and changes in percent cover of developed land, and there was one 500 meter buffer area identified as having a significant relationship between changes in water temperate and changes in percent cover of planted/cultivated land. Over the study period, both 100 meter buffer areas exhibited an overall increase in developed land and the 500 meter buffer area exhibited an overall increase in planted/cultivated land; all three associated lakes exhibited an overall increase in water temperature over the study period.

For water clarity, when 2005 data were removed from the analysis there were no significant relationships identified between changes in water clarity and changes in percent cover of planted/cultivated land or developed land within the lake catchments. For 100 meter buffer areas, there was one lake with an identified significant relationship between changes in water clarity and changes in percent cover of planted/cultivated land, but there were no identified significant relationships between changes in water clarity and changes in percent cover of wetland areas. Over the study period, the 100 meter buffer area identified as having a significant relationship with water clarity exhibited an overall decrease in planted/cultivated land and the associated lake exhibited an overall increase in water clarity. Additionally, for the 500 meter buffer areas, there were no significant relationships identified between changes in water clarity and changes in percent cover of developed land, planted/cultivated land, or wetland areas.

The results of the analysis regarding the relationship between lakes with significant changes in water quality and select LULC classes are summarized in Table 7. The summary table combines results from analyses both with and without data from study year 2005.

Table 7: Summary of lakes with a significant relationship between changes in water quality and changes in select LULC classes.

<table>
<tr><th>Water Quality Variable</th><th>Water Quality Variable Increase/Decrease</th><th>LULC Class</th><th>LULC Increase/Decrease</th><th>Area</th><th>Sample Size (Lakes)</th></tr>
<tr><td>Temp.</td><td>Increase</td><td rowspan="3">Forest</td><td>Decrease</td><td>Catchment</td><td>1</td></tr>
<tr><td rowspan="2">Temp.</td><td>Increase</td><td>Increase</td><td>100 m. Buffer</td><td>1</td></tr>
<tr><td>Increase</td><td>Increase</td><td>500 m. Buffer</td><td>1</td></tr>
<tr><td>Temp.</td><td>Increase</td><td rowspan="2">Developed Land</td><td>Increase</td><td>Catchment</td><td>1</td></tr>
<tr><td>Temp.</td><td>Increase</td><td>Increase</td><td>100 m. Buffer</td><td>3</td></tr>
<tr><td>Temp.</td><td>Increase</td><td rowspan="3">Planted/ cultivated</td><td>Decrease</td><td>500 m. Buffer</td><td>1</td></tr>
<tr><td>Temp.</td><td>Increase</td><td>Increase</td><td>500 m. Buffer</td><td>1</td></tr>
<tr><td>Clarity</td><td>Increase</td><td>Decrease</td><td>100 m. Buffer</td><td>1</td></tr>
</table>

For the 21 lakes that exhibited a significant increase in surface water temperature over the study period, linear regression analyses with time as the independent variable and percent cover of each LULC class as the dependent variable was completed. A significant change in the percent cover of at least one LULC class was identified in four lake catchments, four 100 meter buffer areas, and seven 500 meter buffer areas. The identified changes were associated with 9 of the 21 lakes that exhibited a significant increase in water temperature over the study period. A summary of the significant changes in the percent cover of LULC classes is provided in Table 8.

Table 8: Summary of the significant changes in LULC for lakes that have data for all years and have exhibited a significant change in water temperature. Numbers in the table indicate the number of lake catchments/buffer areas that exhibited a significant change in a given LULC class.

Area	LULC Change	Barren	Developed	Forest	Open Water	Planted/ Cultivated	Wetland
Lake Catchment	Increase	0	0	1	0	0	0
	Decrease	0	2	0	0	2	1
100 Meter Buffer	Increase	0	1	1	0	0	0
	Decrease	0	1	0	1	3	0
500 Meter Buffer	Increase	0	0	2	0	0	0
	Decrease	1	1	1	0	3	0

A linear regression between water clarity and percent cover of each LULC class was also completed for the one lake that exhibited a significant decrease in water clarity over the study period. The results of the regression analyses indicated that none of the LULC classes exhibited a significant change over the study period when looking at the lake catchment; however, a significant increase in the percent cover of developed land within the 100 meter buffer area and a significant decrease in percent cover of open water within both the 100 meter and 500 meter buffer areas were identified.

The analysis regarding changes in LULC was also performed for lakes that exhibited a significant change in water temperature and/or clarity when study year 2005 was excluded from the data. Again, this increased the sample size for lakes that exhibited a significant change in water temperature from 21 to 35 and from 1 to 2 for water clarity. For the 35 lakes that exhibited a significant increase in water temperature over the study period (excluding data from 2005), a significant change in percent cover of at least one LULC class was identified in five lake catchments, seven 100 meter buffer areas, and three 500 meter buffer areas. The identified changes were associated with 12 of the 35 lakes that exhibited a significant increase in water temperature over the study period. A summary of the significant changes in the percent cover of LULC classes is provided in Table 9.

Table 9: Summary of the significant changes in LULC for lakes that have data for all years excluding 2005 and exhibited a significant change in water temperature. Numbers in the table indicate the number of lake catchments/buffer areas that exhibited a significant change in a given LULC class.

Area	LULC Change	Barren	Developed	Forest	Open Water	Planted/ Cultivated	Wetland
Lake Catchment	Increase	0	0	1	0	1	0
	Decrease	0	1	2	0	3	0
100 Meter Buffer	Increase	0	2	1	0	0	0
	Decrease	0	1	1	1	3	2
500 Meter Buffer	Increase	0	0	0	0	0	0
	Decrease	0	1	1	0	1	0

For the two lakes that exhibited a significant increase in water clarity when data from 2005 was excluded, only one significant change in LULC was identified: one of the two lakes exhibited a significant decrease in the percent cover of planted/cultivated land within 100 meters of the lake. This lake was identified as having experienced an overall increase in water clarity over the study period.

To further evaluate the relationship between changes in LULC and changes in water quality over the study period, another regression analysis between water quality values and LULC classes was run. This analysis included only lakes that exhibited a significant change in water temperature or clarity and the LULC class for that lake's catchment or buffer area that also exhibited a significant change. For water temperature, results indicated that there was one lake with a significant relationship between changes in water temperature and changes in percent forest cover within a 100 meter buffer area. Additionally, there was one lake identified as having a significant relationship between changes in water temperature and changes in percent cover of planted/cultivated land within a 500 meter buffer area. Both lakes identified as having significant relationships exhibited an overall increase in water temperature over the study period. The lake with the identified relationship with percent forest cover exhibited an overall increase in percent forest cover over the study period while the lake with the identified relationship with percent planted/cultivated land exhibited an overall decrease in percent planted/cultivated land over the study period. No other significant relationships were identified between water temperature and LULC for lakes that exhibited a significant change in water temperature as well as a significant change in one or more LULC classes within either the lake catchments or buffer areas.

For water clarity, results indicated that there were no significant relationships between changes in water clarity and changes in LULC for the one lake that exhibited a significant change in water clarity as well as significant changes in LULC classes.

An analysis to identify significant relationships for lakes that exhibited both a significant change in water quality and a significant change in one or more LULC class was also run with data from 2005 removed from the analysis. Results indicated that, for one lake, there was a significant relationship between changes in water temperature and changes in percent cover of forest and planted/cultivated land within the lake catchment. Over the study period, this lake exhibited an overall increase in water temperature and the lake catchment exhibited an overall decrease in both forest cover and planted/cultivated land. One other lake was also identified as having a significant relationship between changes in water temperature and changes in percent cover of planted/cultivated land within the lake catchment. Over the study period, this lake exhibited an overall increase in water temperature and the lake catchment exhibited an overall increase in planted/cultivated land. There were no other statistically significant relationships identified.

For water clarity, when 2005 data was excluded from the study, one lake was identified as having a significant relationship between changes in water clarity and changes in percent cover of planted/cultivated land within the 100 meter buffer area. This lake exhibited an overall increase in water clarity and the 100 meter buffer area exhibited an overall decrease in percent cover of planted/cultivated land. There were no other statistically significant relationships identified.

The results of the analyses regarding the relationship between lakes with significant changes in water quality and significant changes in one or more LULC class are summarized in Table 10. The table combines results from analyses run with data from all six study years as well as results from analyses run with data that excluded study year 2005.

Table 10: Summary of lakes with a significant relationship between significant changes in water quality and significant changes in at least one LULC class.

Water Quality Variable	Water Quality Variable Increase/Decrease	LULC Class	LULC Increase/Decrease	Area	Sample Size (Lakes)
Temp.	Increase	Forest	Increase	100 m. Buffer	1
Temp.	Increase		Decrease	Catchment	1
Temp.	Increase	Planted/ cultivated	Decrease	500 m. Buffer	1
Temp.	Increase		Decrease	Catchment	1
Temp.	Increase		Increase	Catchment	1
Clarity	Increase		Decrease	100 m. Buffer	1

4.0 DISCUSSION

Comprehensive assessments of lake water quality (specifically water temperature and clarity) are necessary to help maintain both biological and economic systems associated with lakes. Results of this study show that lake water clarity and surface water temperature values can successfully be extracted from Landsat-5 imagery. The extraction of surface water temperature from Landsat imagery can be completed without the use of ground or *in situ* data; however, accuracy relies entirely on satellite calibration. Future research using water temperature extracted from Landsat imagery could benefit from more ground studies that measure lake surface water temperature at the time of satellite overpass.

Unlike extraction of water temperature data from Landsat imagery, the extraction of water clarity values is dependent on the availability of *in situ* data and thus is not independent of field work; however, as is the case with Maine, many states have established volunteer programs to aid in the collection of *in situ* data. The existence of *in situ* data near the date of satellite overpass makes extraction of water clarity data from Landsat imagery possible, but can also become a limiting factor in water clarity research using satellite imagery. For this study, the availability of additional *in situ* data collected at or near the time of satellite overpass would have increased the sample size for water clarity model development, allowing data from some lakes to be removed from model development and used instead for model verification. Due to a limited amount of *in situ* data, model verification was not performed as part of this study. The clarity values used in this study were based on the best fit models developed for each study year. The *R*-squared values associated with the models ranged from 0.70 to 0.89, indicating that the models create values that do not exactly mimic *in situ* values, potentially adding some error into the analyses completed using water clarity values; however the *R*-squared values of the models used in this study are consistent with those reported by other researchers when modeling water clarity values based on Landsat imagery (Kloiber et al. 2002b; McCullough et al. 2012). Despite these and other limiting factors, this study supports past research that demonstrates the usefulness of Landsat imagery in lake water quality studies, specifically focusing on lake surface water temperature and water clarity. The results of this study indicate that, for the study region, there is a significant relationship between select LULC classes and both water temperature and clarity. The relationship varies based on the area (lake catchment, 100 meter buffer, or 500 meter buffer) used for analysis, thus, selection of an analysis area is important in the context of interpreting results. For water temperature, a combination of select LULC classes within 100 meters of a lake was found to explain more variation in water temperature than LULC classes within a lake catchment or 500 meters of a lake. For water clarity, a combination of select LULC classes within a lake catchment and within 500 meters of a lake was found to explain more variation in water clarity than LULC classes within 100 meters of a lake. This indicates that water temperature may be more affected by LULC immediately surrounding a lake while water clarity may be more affected by LULC further inland (i.e., further away from the edge of a lake).

The three LULC classes that were found to have a significant relationship with water temperature are developed land, open water, and planted/cultivated land. Developed land and planted/cultivated land both were found to have a negative relationship with water temperature, indicating that as the percent cover of one of these LULC classes increases, surface water temperature decreases. Open water within a lake catchment (excluding the area of the lake itself) was found to have a positive relationship with water temperature, indicating that as the percent cover of open water increases, so does surface water temperature. Previous research does not directly address the relationship between lake surface water temperature and LULC and the purpose of this study was not to identify the reasons why such relationships might exist, but solely to identify that the relationships do exist.

For water clarity, the three LULC classes that have a significant relationship with water clarity are developed land, wetland, and planted/cultivated land. All of these LULC classes have a negative relationship with water clarity, indicating that as the percent cover of one of these classes increases, water clarity decreases. This finding supports previous research (Bruhn and Soranno 2005; McCullough et al. 2012) in regards to the relationship between water clarity and wetland area, but does not support the findings of Bruhn and Soranno (2005) that water clarity increases with increased residential or developed land. While the reasons regarding the relationship between water clarity and the select LULC classes could be hypothesized (such as increased disturbance from developed and planted/cultivated land adds more sediment to surface water), as with water temperature, the reasoning for the relationships was not the focus of this study.

Despite the existence of significant relationships between water temperature and water clarity and select LULC classes, evaluation of *R*-squared values produced by the multivariate regression analyses shows that LULC only explains a small amount, less than 12 percent, of the total variation in water temperature or clarity. This finding indicates that, while evaluations of the relationship between LULC and water temperature and clarity should be continued, there may be other variables that explain a greater percentage of the variation in water temperature and/or clarity. These variables could include lake characteristics such as lake area, shape, and depth, or geomorphologic characteristics of a lake catchment frequently used in hydrologic modeling such as flow or stream length, catchment shape (i.e., circularity ratio, compactness ratio, basin elongation), relief characteristics (such as maximum relief, relief ratio, relative relief), and elevation (Apaydin et al. 2006).

While future research should include other variables such as lake and lake catchment physical/geomorphologic characteristics, it is important to remember that many, if not most, lake and catchment physical characteristics cannot be controlled by land owners and natural resource managers. Land use and land cover are characteristics that are frequently determined by human activity and thus can be managed. For this reason, the findings of studies such as this one are important in identifying the effect that different LULC classes have on water temperature and clarity, even where LULC only explains a small percentage of the variation in the water quality parameters. It should also be noted that the findings of this study identify a relationship between LULC and water quality, but this relationship does not necessarily identify a causal relationship.

Out of 40 lakes with data for all six study years, 21 exhibited a significant change in water temperature and only 1 exhibited a significant change in water clarity. When study year 2005 was removed from the analysis, there were a total of 99 lakes with data for the remaining five study years. Of the 99 lakes, 35 exhibited a significant change in water temperature and 2 exhibited a significant change in water clarity. Overall, a significant change over the study period in water temperature for all lakes in the region was identified when using the average value from the 40 lakes that had data for all six years; however when data from 2005 were excluded from the analysis and the sample size was increased to 99, the change in water temperature over the study period was not found to be significant. Additionally, analyses with and without data from 2005 identified 21 and 35 lakes, respectively, that exhibited a significant change in water temperature over the study period. The reasoning for the significant changes in water temperature is unknown; however, the findings of this study indicate that future research should attempt to identify the reasons for the identified surface water temperature increases in the region. Specifically, it is recommended that future research focus on determining if the identified changes are due to external factors that may influence temperatures extracted from satellite imagery (addressed below) or if surface water temperatures in the region are actually increasing at the significant rates identified by this study.

In terms of water clarity for lakes in the region, the findings of this study indicate that, overall, water clarity has remained relatively constant since 1986 with few lakes experiencing a significant increase or decrease in water clarity. Previous research in other regions supports the finding of overall stable water clarity values when assessing multiple lakes within a region (Terrell et al. 2000; Kloiber et al. 2002a; Bruhn and Soranno 2005; Olmanson et al. 2008).

Based on the lakes that exhibited a significant change in water temperature as well as other lakes included in this study, there is a clear pattern that shows increases in water temperature values extracted from the Landsat-5 images for the study area over the study period. The overall increase in lake surface water temperature is supported by previous research on lakes both within the United States and worldwide (Livingstone 2003; Coats et al. 2006; Austin and Colman 2007; Schneider et al. 2009); however the rate of change is greater than rates of change reported by the previous studies. The focus of this study was not only to identify if a change had occurred, but also whether or not there was a relationship between that change and LULC change. This relationship between water temperature and LULC change is addressed later within this Section; however it must also be recognized that there are other potential reasons for the identified increase in water temperature. One explanation for the changes in temperature could potentially be due to the need for additional calibration of the Landsat-5 thermal band. Previous assessments indicate that the Landsat-5 thermal band has had varied calibration results since it launched; however, early processing systems have been replaced and recent analysis has found that the current Landsat-5 processing system, when correlated with ground truth data from lakes in the United States, has an offset error of only -0.7 °C (Barsi et al. 2003). The conversion of digital number to at-sensor brightness temperatures is based on prelaunch calibration constants (Chander 2009); however, Chander (2009) does not indicate the need for time-dependent calibration constants. Another explanation for the increases in water temperature could be the influence of climatic changes and the influence of air temperatures in the region. Data from the U.S. National Weather Service Climate Prediction Center (2005) show that events such as El Niño and La Niña can influence air temperatures with July, August, and September air temperatures in the region generally being cooler during El Niño years and more variable during La Niña years.

The two years in the study period with the overall highest water temperatures were 2005 and 2008. While it can be hypothesized that El Niño and La Niña events may influence water temperature or that the air temperature associated with these events may influence values extracted from satellite imagery, there is no clear relationship between the increased water temperatures and El Niño or La Niña events since 2005 and 2008 are both considered to be “neutral years” that were not directly influenced by El Niño or La Niña climate patterns (FSU COAPS 2012). Concerns with calibration and changes in climatic conditions are only two potential reasons for the identified increase in water temperature within the study period. Further research focused on water temperature values extracted from Landsat-5 imagery and the potential reasons for increases in water temperature is necessary to determine the reason for the identified water temperature changes within the region over the study period.

Of the lakes that were identified as having a significant increase in water temperature over the study period (including the results of analyses both with and without data from 2005), three lakes were identified as having a significant relationship with changes in the dominant LULC (forest). One lake had a significant relationship with a lake catchment that had decreasing forest cover; one lake had a significant relationship with a 100 meter buffer area that had increasing forest cover; and one lake had a significant relationship with a 500 meter buffer area that had increasing forest cover. Further evaluations of the relationship between water temperature and additional (select) LULC classes also identified minimal significant relationships. For analyses completed between water temperature and developed land, one lake had a significant relationship with a lake catchment that had increasing developed land and three lakes had a significant relationship with 100 meter buffer areas that had increasing developed land. For analyses completed between water temperature and planted/cultivated land, one lake had a significant relationship with a 500 meter buffer area that had increasing planted/cultivated land and one lake had a significant relationship with a 500 meter buffer area that had decreasing planted/cultivated land.

For water clarity, when looking at changes both in the dominant LULC class and other LULC classes that potentially have a relationship with water clarity and including both data with and without study year 2005, the only significant relationship identified was for one lake with increasing water clarity and decreasing planted/cultivated land within a 100 meter buffer area.

Of the 21 lakes with a significant change in water temperature, 9 lakes were identified as having a significant change in one or more LULC classes over the study period. With data from 2005 removed, of the 35 lakes with a significant change in water temperature, 12 were identified as having a significant change in one or more LULC class over the study period. When looking solely at water quality/LULC classes that had a significant change over the study period (both with and without data from study year 2005), the only identified significant relationships were between changes in water quality and changes in forest and planted/cultivated land over the study period. For water temperature, one lake with an overall increase in water temperature had a significant relationship with an increase in forest area within 100 meters while another lake with an increase in water temperature had a significant relationship with a decrease in forest area within the lake catchment. Similarly, two lakes had an overall significant increase in water temperature and a decrease in planted/cultivated land (one within a lake catchment and one within a 500 meter buffer area) while another lake with a significant increase in water temperature had an increase in planted/cultivated land within the lake catchment. For water clarity, there was one lake identified with an identified significant relationship between a significant increase in water clarity and a significant decrease in planted/cultivated land within a 100 meter buffer area.

As can be seen be the results summarized above, the findings of this study regarding the relationship between lakes with a significant change in water temperature or clarity and LULC changes are limited and sometimes contradictory. These results indicate that, based on this study, no clear relationship between changes in water temperature or clarity and changes in LULC can be identified. One of the reasons for the limited results could be due to the fact that, specifically for water clarity, very few lakes in the region with a significant change in water quality were identified. Future research may benefit from a focus specifically on additional lakes with known changes in water temperature or clarity to see if a consistent relationship with LULC change is able to be determined. Alternately, when evaluating the relationship between LULC changes and water quality, lakes without significant changes in water quality could be included, this would increase the sample size and determine if there are areas where significant changes in LULC have occurred and water quality has not been affected.

Focusing on fewer lakes with known changes in either water quality or LULC could potentially allow for a more detailed LULC classification if the overall area classified was smaller. For this study, the lakes and their associated lake catchments and buffer areas stretched across an entire Landsat-5 image which covers approximately 32,000 square kilometers. Even when the area was limited to only lake catchments and buffer areas associated with lakes with water quality data, the area of classification covered approximately 6,500 square kilometers.

The overall accuracy of the supervised classifications varied from 79 to 85 percent over the six study years with Kappa statistic values associated with the overall accuracy ranging from 0.74 to 0.80. When evaluating the accuracy of a single LULC class between years, the accuracy varied even more and was sometimes lower than the overall accuracy as can be seen when looking at both the producer and user accuracy values summarized in Tables 4 and 5 in Section 3.1. The variations in accuracy between images inherently add some error to any analysis that compares changes in LULC between years (i.e., classified images). If future assessments focused specifically on lakes with known changes in water quality or on lake catchments/buffer areas with known changes in LULC, the accuracy of the LULC classification may be able to be improved, especially if the area being classified was smaller with less varied terrain; however, a more focused, smaller study area would eliminate the large spatial pictures that studies such as this one can provide.

Overall, examination of the relationship between changes in water quality and changes in LULC did not identify any clear, consistent, or potentially causal relationships. For water temperature, this indicates that there may be other factors influencing water temperature within the region. For water clarity, the sample size for lakes that exhibited a significant change in water clarity was not large enough to indicate a clear, consistent, relationship with LULC change. As previously stated, future research regarding the effect of LULC change on water temperature and clarity would likely benefit from focusing on lakes or lake catchments/buffer areas with known changes.

5.0 CONCLUSION

This study evaluated lake surface water temperature and water clarity for lakes in east-central Maine covered by a single Landsat-5 image with a footprint of approximately 32,000 square kilometers. Using surface water temperature and clarity values extracted from six Landsat-5 images between 1986 and 2008, the relationship between the water quality variables and LULC was evaluated. Additionally, temporal trends in both the water quality variables and LULC and the relationship between changes in the water quality variables and LULC were analyzed. Data from 337 lakes within the study area were used to evaluate the relationship between the water quality variables and LULC. Results of this analysis indicated that, for the study region, there is a significant relationship between both water quality variables and select LULC classes; however the relationship varies based on the area used for the analysis (i.e., lake catchment, 100 meter buffer, or 500 meter buffer) and only explains a small amount of the variation in surface water temperature and water clarity. Two different datasets, one with 40 lakes and six years of data and one with 99 lakes and five years of data, were used to evaluate temporal trends in the water quality variables as well as the relationship between temporal changes in the water quality variables and LULC. The dataset with 40 lakes identified 21 lakes with a significant increase in water temperature and one lake with a significant decrease in water clarity. The dataset with 99 lakes identified 35 lakes with a significant increase in water temperature and two lakes with a significant increase in water clarity. Analyses regarding the relationship between temporal changes in the water quality variables and LULC identified some statistically significant relationships; however, the overall results of these analyses did not identify any clear, consistent, relationships between changes in the water quality variables and LULC.

Combined, the results of this study aid in the identification of the relationship between water quality and LULC as well as identify temporal changes in water quality and point towards directions for future research. Additionally, the findings of this study support previous research in proving the ability of satellite imagery to be used in assessments of water quality, enabling the evaluation of larger spatial scales and longer temporal scales than assessments that rely solely on the existence of *in situ* data.

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