MODELING THE IMAPACTS OF LAKE LEVEL CONTROL STRUCTURE MANAGEMENT SCENARIOS ON AQUATIC VEGETATION DISTRIBUTIONS IN HIGGINS LAKE, MICHIGAN

by

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Abstract

Initiated by riparian homeowners concerned with increased shoreline erosion due to artificially high managed lake levels, this study of the potential ecological impacts of changing lake level management strategies on Higgins Lake was funded by the Muskegon River Watershed Assembly via the Michigan Department of Natural Resource's Fisheries Division Habitat Improvement Fund and the Higgins Lake Property Owners Association. The focus of this thesis was the development of bathymetric, substrate and vegetation maps from sonar surveys (conducted July-August, 2012) to assess the extents and distribution of submersed aquatic vegetation (SAV), a key component of fisheries habitat, and to develop a predictive model to quantify how changes to lake level management might impact those extents and distributions.

The observed percent cover of SAV on Higgins Lake was 11.1% (approximately 1,138 acres) and was largely restricted to depths between 3 and 15 meters. The average observed depth of SAV was 6.03 m and the most frequent depth of SAV occurrence was 4.32 m; emergent vegetation was not observed during the survey. The maximum recorded height of SAV was 2.09 m. Average SAV height was 0.27 m (+/- 0.20 m) and the most frequently occurring SAV height was 0.13 m.

The logistic regression model (R-squared = 0.397; covariates: depth, % light remaining at depth, slope and fetch) successfully predicted occurrence of SAV at a rate of 82.5% when compared to the observed data. The lake level management scenarios explored had a range of water surface elevations of 350.89 – 351.80 meters above mean sea level. Under these scenarios the predicted areal extent of SAV ranged from 1,276 acres at the lowest water surface elevation, to 1,416 acres at the highest. The baseline model scenario (same water

surface elevation as during the survey) over-predicted SAV extents by 267 acres. The predicted depth range of SAV shifted in conjunction with changes to water surface elevation. Overall, the model did not predict significant changes to SAV extents or distributions under the lake level management scenarios in question and the potential changes are likely insufficient to measurably impact fisheries habitat on the lake.

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Introduction

Lake levels have been legally established by courts on many inland lakes in the state of Michigan and throughout the Midwest. Court regulated lake levels generally include a high water level during the open water season (summer) and a lower level during periods of ice-cover. The high levels are set so that residents have easier boating access in the open water season, and the low levels help prevent ice damage to docks and shorelines (O'Neal & Soulliere, 2006). These managed water levels are generally achieved via actively managed lake-level control structures (i.e. dams).

The control of lake-levels can have significant effects on whole lake ecosystems, particularly in relation to community diversity, fish spawning, fish movements and plant and animal production (Wilcox & Meeker, 1992). Dams alter natural water level fluctuations which can be important for maintaining diverse plant communities; and this in turn impacts rearing habitat for fish, mammals and water fowl. Furthermore, they typically restrict the passage of fish species between lakes and downstream systems, which can adversely affect seasonal and spawning migrations. Artificially high water levels can increase shoreline erosion as well, a result that often leads to the construction of seawalls by lake-residents. Seawalls in turn reduce the presence of shoreline and emergent vegetation, restrict the movement amphibians and mammals, and increase shoreline erosion adjacent to the seawall (O'Neal & Soulliere, 2006).

On Higgins Lake, local controversies about water level fluctuations related to the management of the outlet control structure have persisted for years and more recently become a heated topic of debate (Reznich, 2012). Due to concerns associated with high rates of erosion in parts of the lake, the Higgins Lake Property Owners Association (HLPOA) requested help in 2010 from the Michigan Department of Natural Resources (MDNR) Fisheries Division with evaluating erosion, habitat, and passage issues relating to future management options of the Higgins Lake water-level outlet control structure. In order to better inform citizens, MDNR Fisheries Division acting through the Muskegon River Watershed Assembly (MWRA) funded a study in 2012 using Michigan's Habitat Improvement Fund. The purpose of the study was to evaluate potential impacts to Higgins Lake and its outlet river (the Cut River) of altering the current court imposed lake-level management regimes, including as a potential scenario the for the sake argument the potential removal of the outlet control structure.

The study consisted of a hydrologic and hydraulic evaluation of the study system by Michigan State University's (MSU) Hydrogeology Lab as well as extensive hydro-acoustic surveys by both MSU and University of Michigan to evaluate existing fish habitat conditions and predict how future alterations in water level might affect those conditions (University of Michigan). My goal in this thesis research was (1) to collect and use hydroacoustic data from several different sonar systems to evaluate the bathymetry and spatial distribution of submerged aquatic vegetation (SAV) on Higgins Lake, as aquatic vegetation is a key aspect of fish habitat (Stuber et al., 1982; Wiley et al., 1984, Krieger et al., 1984; McMahon et al., 1984) ; and (2) to generate a predictive SAV model that could be used to quantify how areal extents of vegetation might change in response to changes in lake-level management.

Methods

Study Site

Higgins Lake is an intermorainal lake in deep glacial drift deposits in Roscommon County Michigan and is the tenth largest and fifth deepest inland lake in Michigan. The maximum recorded depth from this survey was 41.05 m (134.69 ft) and the average depth was calculated to be 15.86 m (52.03 ft). The lake area varies seasonally with water level and was calculated to be 10,252 acres at the time of this survey (summer 2012). The volume of the lake was estimated at 20 billion cubic feet (Jones, 1991) and has a hydrologic retention time of 12.4 years (Minnerick, 2001). The shoal region (less than 3 m depth) makes up approximately 27% of the total lake area.

Higgins Lake and its watershed form the headwaters of the Muskegon River; it has a catchment area of approximately 28,738 acres (Huron Pines, 2007) and is primarily groundwater fed. About 51.3% of the water input comes from groundwater, 43% is derived from direct rainfall, and two small inlet streams (Big and Little Creek) contribute 4.3% and 1.4%, respectively (Limno-Tech, 1992). The only outflow of the lake is the Cut River, which passes through Marl Lake just downstream of Higgins and joins with the Backus Creek system before entering Houghton Lake.

A lake-level control structure located at the Cut River outlet is used to manage water levels at Higgins Lake. It is a low-head dam that can alter the water surface elevation by approximately +/-18 inches. The first outlet control structure was built in 1936, with repairs and additions in 1950. In 1982 a Roscommon County Circuit Court order confirmed the summer legal lake level at 1154.11 feet above sea level and a winter legal lake level of 1153.61 feet above sea level (Huron Pines, 2007). The authority responsible for operating the dam to maintain the legal lake levels is the Roscommon County Board of Commissioners.

Higgins Lake is an oligotrophic lake and due to its depth and high groundwater inputs, supports a number of cool and coldwater fish species including Rainbow Trout, Lake Trout, Brown Trout, Rainbow Smelt, Yellow Perch and Lake Whitefish. Other popular game species include Rock Bass, Walleye and Pike. As a result, angler use of the lake is substantial; the Michigan Department of Natural Resources (MDNR) estimates that anglers annually take over 60,000 trips, logging over 250,000 hours on Higgins. The annual economic value of this fishery to the local economy is approximately $1.6 million and the two state parks on the lake bring in over 600,000 visitors to Higgins Lake every year (Huron Pines, 2007).

SONAR Units Employed

The following acoustic range finding units were employed in this study: a 200 kHz depth sounder, a 455 kHz down-facing linear transducer, a tow-behind side scan unit, and an Acoustic Doppler Current Profiler (ADCP).

The 200 kHz (20^o cone angle) and 455 kHz (1.1^o cone angle) transducers were a part of Navitronic's Lowrance HDS-8 recreational sonar and navigation unit with integrated WAAS enabled GPS. Transducers were mounted on adjustable rigging at the stern of the vessel.

The tow-behind side scan sonar unit employed was a triple-frequency Imagenex Yellowfin with an integrated differential ready GPS. For this survey, an operating frequency of 330-kHz and a range of 200 meters (400 meter total swath coverage) was employed. Cable-out was recorded to assess the unit's layback position relative to the vessel.

The ADCP unit was a Sontek River Surveyor S5 (1 Hz sample rate) with integrated GPS. This unit was installed on an adjustable mount approximately about half-way between midship and stern at the region of the vessel least affected by wave motion.

Bathymetric Mapping – Field Data Collection Methods

Bathymetric mapping was performed collaboratively with researchers from MSU. Higgins Lake's unusual morphology governed our field data collection strategy. The team from MSU collected depth soundings on the broad shallow near-shore shelf around the margins of the lake. They used a "warp and weft" sampling pattern; three warp survey lines following the 0.5 meter, 1.5 and 3 meter depth contours and a weft survey line which runs between. I performed the offshore bathymetric survey (3 m and deeper) which consisted of a 400 meter spaced grid, "painting" of significant features ("sunken islands") smaller than the 400 m grid, and concentrated zig-zag coverage of the drop-off region encompassing the lake. The survey was designed so that coverage by both crews would overlap at 3 meters depth. Both survey crews maintained survey speeds at approximately 5 knots. The initial survey by both crews occurred from July 30th 2012 to August 17th 2012.

The 200 kHz transducer was used to collect ranging data for the offshore and drop-off bathymetry. The unit also recorded depth-corrected signal return intensity, evaluated as a relative measure of substrate hardness and thus a proxy for sediment type. Substrate maps were then developed from these data, and a 1936 MDNR winter lake-survey was used to delineate the substrate classes. The tow-behind side scan sonar unit was a triple-frequency Imagenex Yellowfin with an integrated differential ready GPS.

Bathymetric Mapping – Data Processing Methods

Unless otherwise noted, all GIS (Geographic Information Systems) processing and outputs were completed using the Esri ArcGIS® software, ArcMap™ version 10 and will hereto be referred to in the text as ArcGIS or ArcMap. The bathymetric surface was the first data-product to be generated, and a number of corrections had to be applied to the sounding records to correct for systematic errors, including the position of the transducers relative to the GPS receiver, physical variables associated with the lake conditions (i.e. lake-level changes during survey dates, wave size and frequency), skews in acoustic return signal at varying angles of incidence (i.e. surveying across steep bed slopes), depth related anomalies (i.e. lack of bottom detection in deep water or multiple echo returns in shallow water), and survey unit misidentification of SAV canopy or fish schools as lake-bottom. To account for these errors, a number of corrections were applied to the sonar data before import into GIS software for map generation.

(1) The transducer offsets relative to the GPS antennae and average depth of the transducers below the water surface during normal survey speed were applied to location information using commercial survey software (DrDepth).

(2) Due to the complexity of potential errors, automated correction methods did not greatly improve accuracy and thus visual examination of the sonogram was necessary. Visual inspection and correction of errors resulting from wave-action, signal return

inconsistencies, and misidentification of true lake bottom were also performed using DrDepth.

DrDepth includes a tool for visually displaying the sounding sonogram and applying corrections either manually or via correction algorithms (Figure 1). DrDepth provides ‘Refine,’ ‘Smooth,’ and ‘Manual draw’ tools to correct errors. The ‘Refine’ tool performs a local depth estimator around the current estimate on a ping by ping basis. The ‘Smooth’ tool uses a band pass filter to attenuate amplitudes of depth-soundings, resulting in a smoothing of any wave action present in the data. The ‘Manual draw’ allows the user to digitize a new estimate of lake-bottom which is ideal for correcting false bottom detections.

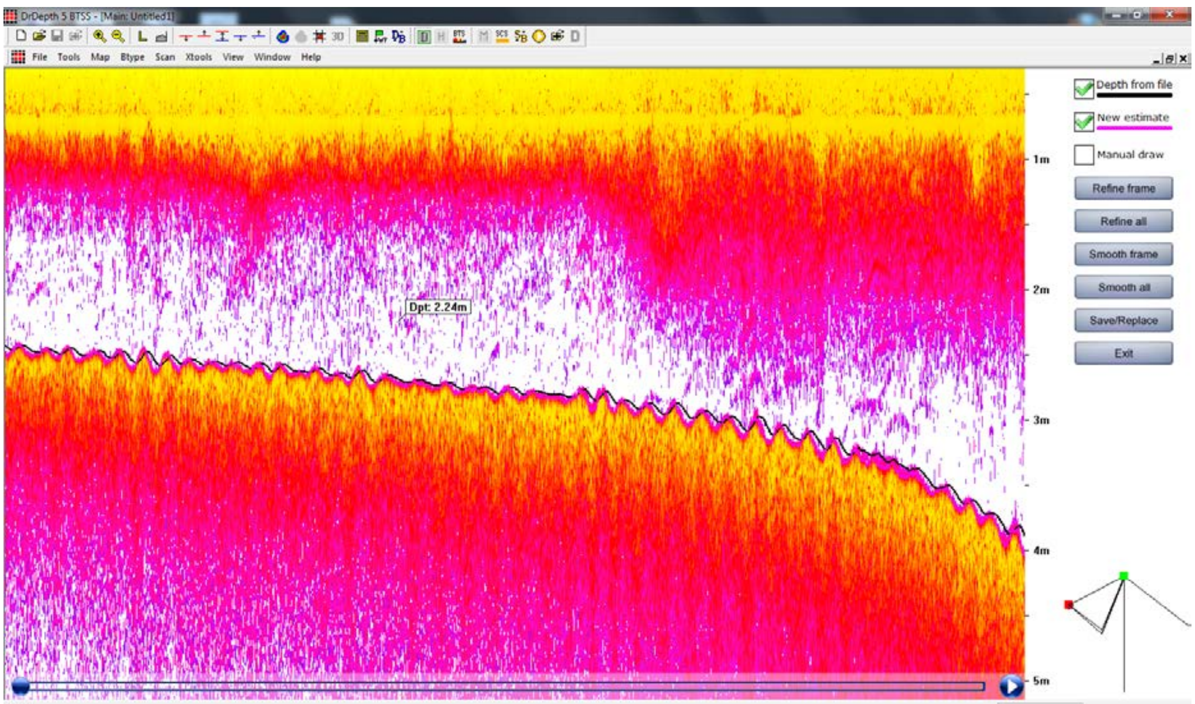

Figure 1. DrDepth sonogram display; this is a color-scaled representation of echo backscattering strength, with brightest colors indicating highest return intensity. Depth in meters is displayed on the right axis. The bright yellow at the top of the sonogram is the result of water surface echo return, as well as interference from propeller turbulence and epilimnetic organisms (phytoplankton). The lake floor is represented by the black line and the data below this is non-real and represents attenuated signal return.

(3) The Lowrance data with above noted offsets and corrections were then exported from DrDepth as comma delimited files ASCII text consisting of latitude and longitude in World Geodetic System (WGS) 1984, depth in feet, time offset in milliseconds from the start of recording, and relative hardness.

(4) A final review of each file consisted of sorting the depth data to remove any outliers (any negative depths and depths greater than 41 meters, the maximum known depth of the lake).

(5) Finally, mean daily USGS lake level gauge information was applied for each sample date to correct for changes in depth due to changing water level during survey dates to ensure accuracy of lake-bottom elevations. Daily lake level information was obtained from the United States Geological Survey (USGS) Higgins Lake gauge (station number 442805084411001).

The shoreline elevation (the selected zero-depth for used throughout this project) was established as the average daily lake level at the date of aerial imagery collection (July 2, 2012), which was just slightly before our survey. This elevation (351.773 meters AMSL), which is also the current summer legal lake level (SLL), was linked to the water's edge of Higgins Lake via digitization of the shoreline using ArcMap. Aerial imagery was obtained via the United States Department of Agriculture National Farm Service Agency Aerial Imagery Program ortho-rectified aerial imagery database (www.fsa.usda.gov/FSA/). The georeferenced bottom elevations were imported and a bathymetric surface interpolated via the ArcGIS Geostatistical Wizard. To produce the bathymetric raster surface, ordinary kriging with no detrending was employed (Oliver, 1990; Stein, 1999). The semivariogram model was optimized to minimize mean square error, and the interpolation search neighborhood was set to a four sector 45^{o} offset with a maximum of five and minimum of two neighbors.

Aquatic Vegetation Mapping – Field Data Collection Methods

Conventional manual techniques for delineating aquatic vegetation are typically very labor intensive and result in observations over limited spatial extents. Although optical techniques such as aerial photography can be useful to delineate spatial patterns in shallow or clear water, they are limited by light attenuation in the water column, surface roughness and cloud cover. Hydroacoustic surveys however, can overcome many of these obstacles (Winfield et al., 2007). To determine extents and heights of submerged aquatic vegetation, a sidescan towfish unit and the Lowrance 455 kHz down-facing linear transducer were used. Due to the higher operating frequency and characteristics of the 455 kHz linear acoustic beam, it produces a higher resolution image when compared to the 200 kHz conical depth-sounder (Figure 2). As discussed in more detail below, the sidecan data were processed, but deemed insufficient to accurately delineate SAV on Higgins.

Aquatic Vegetation Mapping – Data Processing Methods

To delineate submerged aquatic vegetation on Higgins Lake, a number of techniques were explored and used. As side scanning techniques have been found to be effective for delineated seagrass beds (Lee Long et al., 1998; Moreno et al., 1998), I first attempted to map vegetation using the Imagenex Yellowfin side-scan data (sensor depth and cable layback offsets applied, turns clipped, georeferenced) using Chesapeake Technology's SonarWiz 5. The SAV beds on Higgins however, were difficult to distinguish on the resulting sidescan mosaic imagery for two main reasons. One, because the unit was set to its maximum range, the resulting mosaic images were of lower resolution making it difficult to visually distinguish SAV. Two, sidescan mapping is best utilized on flat terrain; on Higgins, much of the SAV exists along the drop off regions in the lake, and the rapid changes in topography negatively impacted the output imagery. Thus ultimately image processing was performed on only the outputs from the Lowrance StructureScan 455 kHz down-facing linear transducer (Lowrance's DownScan Imaging™) to determine the extents and height of SAV in Higgins Lake.

The Lowrance file formats (SL2) were then processed with a commercial sonar software package (SonarTRX, Leraand Engineering Inc.). This software program converted the Lowrance SL2 sonar files into piecewise images at a user-specified number of pings per image and applied speed corrections for these images (i.e. when traveling at faster speeds the image was stretched to account for the increased distance between pings). SonarTRX also produced a Google Earth KML (Keyhole Markup Language) file for each SL2 file processed, which contained the geospatial information that was later used to map the SAV data in ArcGIS. A series of image analysis algorithms were then developed in MATLAB to extract vegetation information.

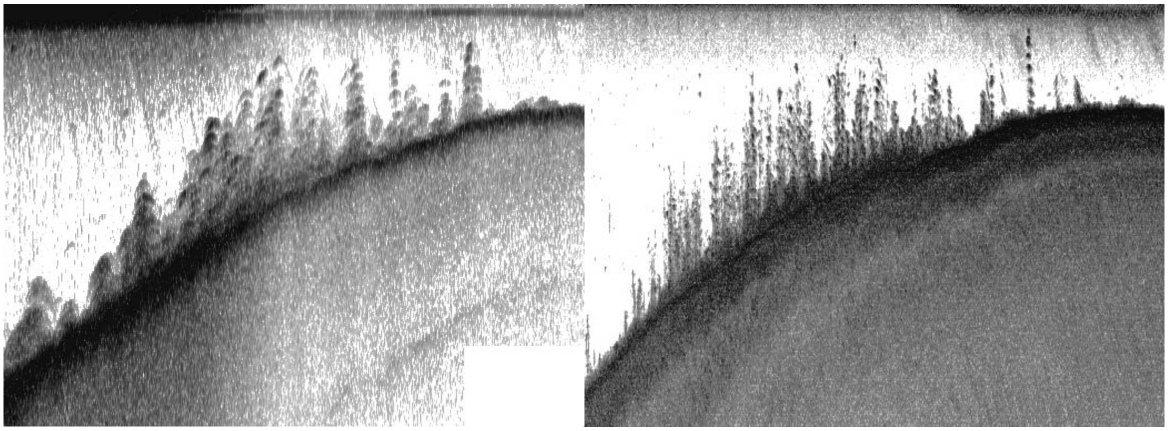

Figure 2. A comparison of two sonar outputs from the same stand of submerged aquatic vegetation. The image on the left was collected with the 200-kHz conical transducer and the image on the right was collected with the 455-kHz linear transducer. Note the increased level of detail in the SAV stands in the image on the right.

The steps in my MATLAB-based image analysis which were performed on each sonar image (See Appendix B for the MATLAB image-analysis scripts) included:

(1) Each image was imported as an 8-bit grayscale intensity image and treated as a matrix array with a value range of 0-255 for each element. This scaled intensity represents the echo backscatter strength at any location with low values representing little echo return (unpopulated water column) and high values representing strong echo returns. A series of “cleaning” and preparation steps followed.

(2) The next step was the application of a mask. This masking replaced approximately the top twenty percent of the image with zero values to eliminate surface return interference from entering into latter SAV detection steps.

(3) Then, a median filter was applied (five by five pixel window) to reduce random intensity and overall “noise” in the sonar image (i.e. gaseous bubbles in the water column).

(4) Next, each column in the image was normalized by the maximum value in that column to bring the values in each column to a normalized continuous scale of zero to one. These normalized values were then multiplied by 255 and rounded to return the values to an 8-bit integer array.

The next step involved the application of logical decision rules to draw distinctions between the water column, any potential SAV and the lake bottom in each image. My primary assumptions were: (a) the maximum value in each column represented the strongest signal return which is indicative of lake-bottom; (b) all sufficiently low pixel values represented open water column; (c) pixel values of intermediate intensity, that were directly adjacent to the bottom represent SAV. Processing steps consisted of identifying the maximum value in each column and evaluating the pixel values directly above that maximum value location as either SAV or water column. After four continuous pixels of water column were detected above the lake bottom or vegetation, the remainder of the pixels above were classed as water column.

Down-scan image quality varied throughout the data set due to factors such as wave action, the angle of incidence between the acoustic beam and the lake bed, speed of the vessel, and distance to lake-bottom. Manually adjusting key parameters in the cleaning steps (mask size, median filter neighborhood, pixel values determining SAV and bottom) was necessary for approximately twenty percent of the data set (5,400 of 27,000 images). The images requiring additional user input were most typically associated with one of the following conditions: survey locations in deep water (over 30 meters) where signal loss occurred; survey locations in shallow water (less than 3 meters) where surface return signals encompassed a majority of the water column; or survey locations which ran perpendicular to steep angle drop-off where a higher proportion of the sonar signal was reflected away from the transducer.

Other issues encountered included: returns from fish schools being interpreted as SAV; the non-detection of SAV in shallow water due to the masking step described above; and inaccuracy in SAV heights, particularly macrophyte stands where gaps between interspersed leafs resulted in labeling the remainder of rows in the column as water. These issues were corrected manually during a final intensive quality control review.

The result of delineation via the MATLAB image analysis steps (Figure 3) was a trinary image consisting of bottom (pixel value = 255), potential SAV (pixel value = 128), and water column (pixel value = 0) for each image. These trinary outputs were then written to comma-delimited text files where the following data from each column in the image was reported as follows: the number of pixels from the water's surface to the detected bottom, the number of pixels to the top of the vegetation (if present), percent SAV (as pixels) of water column, and a binary indicator of vegetation presence/absence.

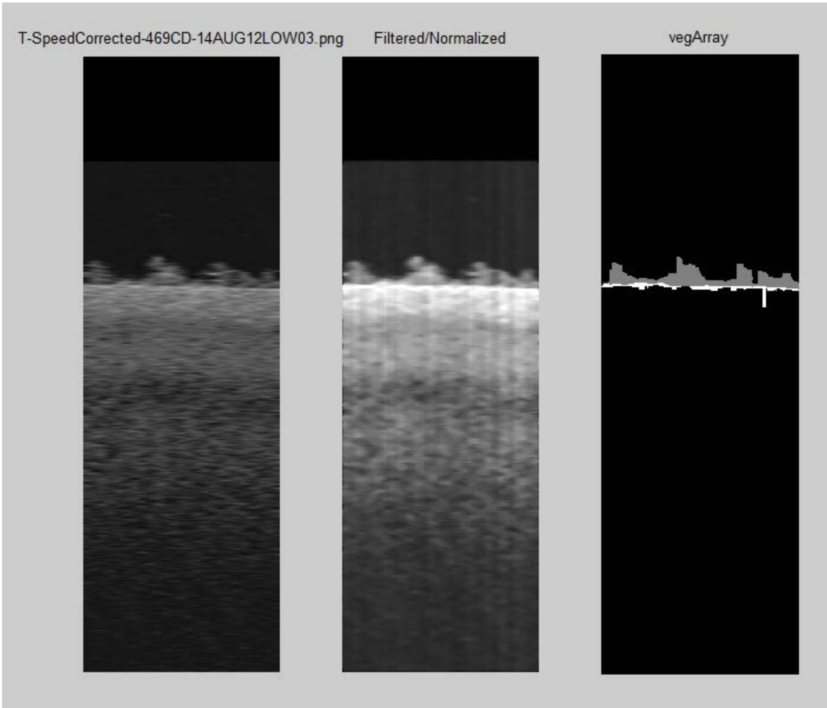

Figure 3. Results of MATLAB image processing on sonar imagery. The image on the left is the raw data input with mask applied. The middle image is after the application of a median filter and column by column normalization by maximum column value. The right image is the trinary output with the white representing the lake-bottom, gray representing SAV, and black above SAV representing the water column.

The quality control review consisted of visually scanning through the output images from each sonar record to identify for which images the MATLAB processing steps would likely produce inaccurate SAV detections. Generally, sonar images which were problematic were very easy to recognize. These problematic images were then re-processed individually by the user in MATLAB to determine if manual corrections were necessary. If the image analysis output was inaccurate, the pixel counts were directly edited in the text file to more accurately reflect presence/absence of vegetation and/or height of vegetation present in the sonar image (approximately 3.5% of the data required this step).

At this stage, the text files containing SAV information were not geocoded: however each sonar image output via SonarTRX had an associated Google Earth KML file which included spatial reference data. To georeference the SAV text files for import into GIS software, a Python script was developed to parse the text of the KML file and extract the start and end latitude and longitude of each image. Then, using MATLAB, the start and end latitude and longitude were inserted at the beginning and end of each SAV text file and a derivation of the Haversine formula (Robusto, 1957) was employed to calculate the latitude and longitude for all intermediary records in each file such that every column of every speed-corrected image had been converted to a spatially referenced record that could be imported into GIS software where each record serves as a point observation.

Upon importing the georeferenced SAV data into ArcGIS, as series of processing steps were required before a continuous interpolated surface could be generated. First, depth information from the bathymetric surface was added to the SAV data set. The height of vegetation at each sample location was then calculated using the percent height (pixel height of SAV in the image divided by the pixel height of water column) of SAV.

Due to the number of records (over 7.4 million) the SAV data, every 10th record was selected as a subsample. During reviews of original sonar imagery, the tallest noted vegetation was approximately 2.1 m in height, so all samples with vegetation heights greater than 2.2 m were eliminated. Also during the image review stage, the greatest depth noted for standing algal biomass (likely stonewort, family Characeae) was approximately 14 meters, so all SAV data with vegetation detected at a depth of 15 meters or greater was eliminated. Additionally, due to limits associated with the resolution of the sonar imagery and the image-processing techniques, any detected vegetation which was less than one percent of the water column or less than 10 cm in height was removed.

Supplemental Aerial imagery and SAV Map Generation

There were portions of the lake that were not captured in my hydroacoustic survey. These areas included the shallow shelf (surveyed by MSU) as well as areas that were in between my survey tracks. To supplement the SAV point data derived from the sonar survey, the following GIS processing steps were performed:

(1) Using aerial imagery (July 2, 2012), polygons were digitized around all visible SAV beds and all shallow regions (and thus good visibility on the aerial imagery) of the lake.

(2) If sonar survey data points were present within the SAV polygons, the information from these survey points was used to assign an average vegetation height for that polygon. Otherwise, the nearest available survey point data at a similar depth were used.

(3) A point grid was generated (100 meter spacing) across the lake and depth information was added to each point. Each point was then assigned vegetation information (i.e. presence/absence of SAV, height of SAV if present) based on the polygon it fell within.

(4) All points greater than 15 m deep was assigned an absence value for vegetation.

(5) The 100 m spaced point grid was combined with the sonar survey point data to form the final data set for subsequent mapping and modeling.

Using the final combined data set described above, ordinary kriging was performed (ArcGIS Geospatial Wizard) to generate a continuous surface representing SAV heights across Higgins Lake (Figure 9). No detrending was employed and the semivariogram model was optimized to minimize the mean square error. Following the same 10 cm cutoff used to account for limitations in image processing methods, a binary presence/absence map was generated from the SAV height map where all values greater than 10 cm were considered SAV (Figure 11).

SAV Mapping Validation

To assess the accuracy of the SAV point observations derived from image analysis steps, the SAV data were validated against a Eurasian watermilfoil (*Myriophyllum spicatum*) survey of Higgins Lake conducted by the Huron Pines Resource Conservation & Development Area Council, Inc. in 2002 (Huron Pines, 2002) with updates in 2003 and 2005. Their effort consisted of a boat-based survey of the shoals and drop off regions, using glass-bottom buckets to identify milfoil beds; each recorded survey point was a confirmed milfoil bed. In ArcGIS, a 30m buffer was generated around each Huron Pines survey location and all image-analysis derived SAV observations intersecting this buffer were validated. Additionally, because of the clarity of the lake, aerial imagery could be used to qualitatively confirm the success of the code output in shallow shoal areas.

Predicting Aquatic Vegetation – An Empirical Model

Important factors effecting the occurrence and distribution of aquatic vegetation include light, substrate texture, substrate stability, wave disturbance, and hydrostatic pressure (Figure 3). I developed a conceptual model to link these factors with variables (highlighted in blue) that I measured with sonar or could be derived from my sonar-based surveys. I then developed an empirical model using a binary logistic regression (King,

2008) reflecting the causal structure illustrated in my diagram. Note that in Figure 4 depth is connected to almost every other factor related to aquatic vegetation occurrence and is likely therefore be a key driving factor in any statistical model.

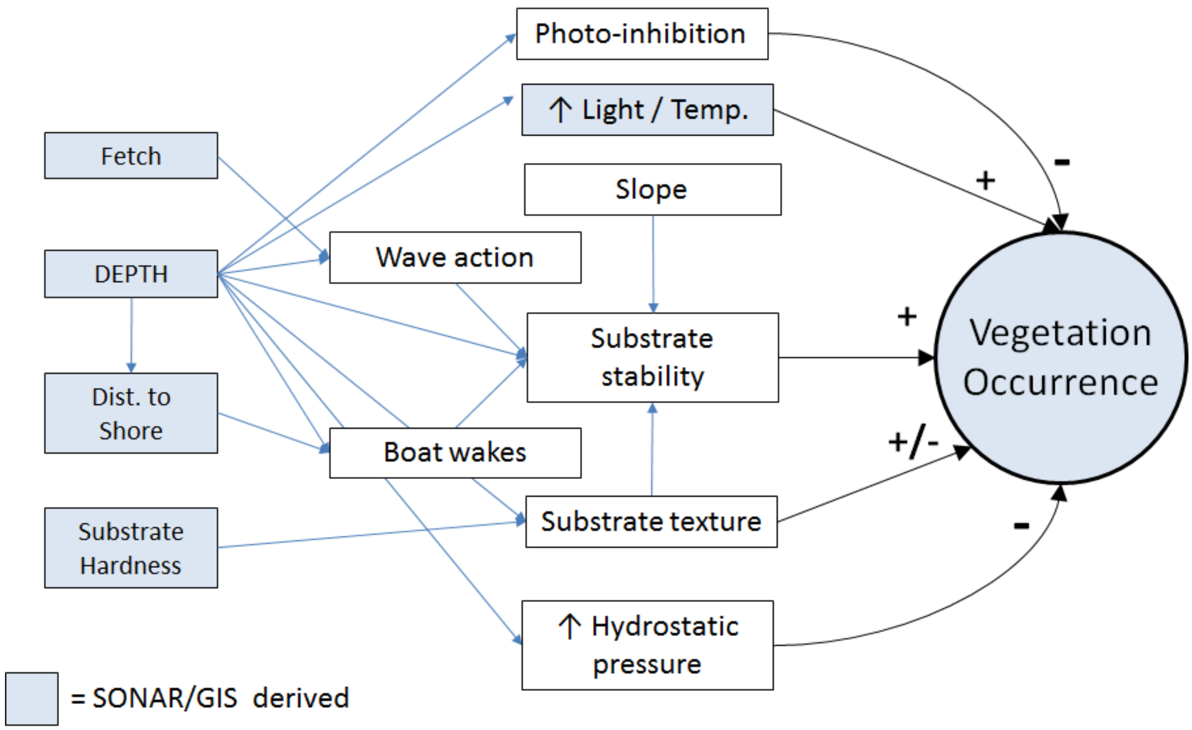

Figure 4. Conceptual model linking factors influencing the occurrence and distribution of aquatic vegetation to measureable/calculable variables.

Solar radiation intensities which are too high can inhibit growth and survival of many species (Powles, 1984). Below inhibiting levels, however, photosynthesis is light dependent. During thermal stratification, vertical distributions of temperature and light are correlated in lentic systems; both decreasing with depth. Substrate conditions can also influence SAV distributions. A number of factors including wave action (energy dissipation per unit depth), substrate texture (grain size) and bottom slope influence substrate stability. If the sediments are unstable, vascular plants are more likely to be dislodged, and less likely to become established. Sediment texture can independently influence likelihood of occurrence of aquatic vegetation; for example, a cobble bed may be particularly stable and suitable for attached algae but does not allow penetration of vascular rooting structures. It has also been shown that increasing hydrostatic pressure also negatively impacts aquatic plant growth and survival (Wetzel, 2001).

Binary logistic regression was used to produce a statistical model to predict the distribution of SAV in response to changes to lake-level arising from different management scenarios. Following a similar model developed for bays and estuaries of Lake Superior (Angradi et al., 2013), I explored the following variables as potential predictors: water depth, slope, directionally-weighted fetch, substrate hardness, and percent light remaining at depth, plus all 2-way interactions between predictors. A log base 10 transformation was applied to the substrate hardness data.

Models were fit using DataDesk 6.3 (Data Description, Inc.). Due to the large sample size ($n = 551{,}162$), all of the predictors noted above were statistically significant ($p<0.0001$) predictors and a manual step-wise selection of all possible combinations and 2-way interactions was tested. The combination with the highest resulting R-squared value and the highest accuracy in predicted presence and absence relative to observed (contingency table analysis) was selected.

For the purposes of interpretation I assigned modeled probabilities in a binary fashion assigning predicted values $< 0.3675 = 0$, and predicted values $> 0.3675 = 1$. This binary assignment was selected to produce symmetrically assessed accuracies when compared to the observed data. That is, the model was designed to produce true positives and true negatives in equal proportion as no advantage could be determined for a model that favored one type of error over the other. Once model symmetry was achieved, Pearson product-moment correlation coefficient and R-squared values were calculated for each combination of predicting variables and interaction terms. The final model was selected based on highest assessed accuracy and R-squared values. The best-fit model was entered into the raster calculator in ArcGIS to develop predicted SAV output maps. Water level change scenarios were then explored by adding or subtracting the desired value to the depth components in the regression equation. For lower water level scenarios, a raster mask was applied to exclude what would be newly exposed shoal area from the analysis. Because no on-shore elevation data were collected however, the analysis of raised water level scenarios (i.e. reporting % cover of SAV) used extrapolated lake-surface areas via a linear regression of lake area versus changes in depth based on the lower elevation scenarios.

Management Scenarios

In consultation with the Muskegon River Watershed Council and MDNR, the research team developed a series of lake-level change scenarios (Table 1) to be evaluated in modeling studies. Each scenario was named by reference to change in depth (in inches) from the summer legal level (351.77 m above mean sea level). I added an extreme high and an extreme low scenario to help clarify responses in model sensitivity tests.

Scenario Name	Scenario Description	WSE (m AMSL)	WSE Change (m)	Aprox. Change in Inches
SLL +60	Extreme high (sensitivity test)	353.04	1.50	+60
SLL +1	Highest level without dam modification	351.80	0.03	+1
SLL	Summer legal level	351.77	0.00	0
SLL -9	Proposed new low level	351.54	-0.23	-9
SLL -18	All dam gates open	351.09	-0.46	-18
SLL -26	Dam removal	350.89	-0.66	-26
SLL -60	Extreme low (sensitivity test)	350.04	-1.50	-60

Table 1. Scenario names and descriptions of lake-level change scenarios to be modeled. Note that the scenario names are approximations in inches of the lake level change scenario, as the management of the dam by stakeholders is conducted in English units.

The SLL +1 scenario represents the highest achievable water level given the current capacity of the Higgins Lake outlet structure, where all flop gates are in the up position and all stop logs are in place. The SLL -9 scenario represents a potential lower lake level suggested by some stakeholders. The SLL -18 scenario represents the lowest achievable lake-level (all-gates open) without modifications to the dam structure itself. The SLL -26 scenario represents the best estimate of WSE elevation were the outlet control structure to be removed. As noted above, the SLL +60 and SLL -60 scenarios are used to assess model sensitivity to extreme high and low water elevations.

Aquatic Vegetation Modeling – Ancillary Data

A series of ancillary data products were produced as input variables for the lake-wide vegetation model. These included maps of fetch, slope, and substrate hardness. Additionally, surface water quality data was collected and explored for spatial trends, although no spatial trends were observed and will not be discussed further. Methods employed to develop these maps are described briefly below:

Fetch- Historical weather data were obtained for the nearby Roscommon County station at Houghton Lake (Houghton, MI). One year of daily average wind direction data was sampled at approximately five year intervals from 1963-2013 and the statistical frequency of wind direction was determined along the four cardinal axes. The directionally-weighted fetch was then computed in MATLAB at a 100 m by 100 m grid resolution, where the value at each location is equal to the sum of the distance to shore in each cardinal direction weighted by the frequency of wind direction across the meteorological record. These grid data were then imported into ArcGIS and an exact inverse-distance weighting interpolator was applied to generate a continuous raster surface.

Bathymetric slope- A slope raster surface was generated in ArcGIS as the first derivative of the bathymetric surface. Due to the low density of sample data in offshore regions of the lake, however, any interpolation method employed on this data would result in increasingly irregular artifacts as distance from the sampled data increases. When kriging the bathymetric surface the interpolator generated artificial “ridges” or spider-webbing in the offshore areas that extended along the sector edges of the search neighborhoods. These ridges were artificially higher than the surrounding area, resulting in an un-realistic derived slope surface. To produce a more realistic slope map, a 50 m point grid was introduced and surface information from the bathymetric map was added to these points. This allowed the production of a secondary “smoothed” bathymetric surface from which the slope surface was derived.

Substrate- To delineate substrate types in Higgins Lake, the depth-corrected signal attenuation of the 200 kHz sonar data was interpreted as a relative measure of substrate hardness and served in my vegetation model as a proxy for sediment texture. Signal attenuation values were subsequently classed as sediment types (i.e., organic depositional, clay, marl, sand, gravel/hardpan/vegetation) based on a 1936 MDNR substrate survey map of Higgins Lake and on visual assessment during our survey. These hardness data were imported into ArcGIS. Sonar data were again supplemented with a 100 m regular spaced point grid using average interpreted hardness values and visual classification. For example, an average hardness value for the sandy shoals was estimated from sonar samples and used to assign a hardness value for all grid points in the shoals. The survey data and 100 m grid points were joined into a single data set and then interpolated by ordinary kriging following the same methods used for the bathymetric surface.

Percent light remaining at depth- This was calculated using the equation:

$\% \, Light\ remaining\ at\ depth = 100 * e^{-0.05 * Z}$ where Z is the depth in feet. The light extinction coefficient value (-0.05) was estimated from 20 years of vertical profile monitoring in Higgins Lake by the Higgins Lake Property Owners Association. No significant difference in light penetration was found between the North and South basins.

Results

Bathymetric Mapping

The bathymetric surface reflects the unique morphological characteristics of Higgins Lake: a large shallow shoal surrounding a series of deep basins. The maximum recorded depth was 41.05 m (134.69 ft), mean depth was 15.86 m (52.03 ft), and the mode was 1.52 m (4.99 ft). The shoal region (less than 3 m depth) made up approximately 27.1% of the total area. The average and maximum depth of the North basin was 15.94 m and 41.05 m, respectively. The average and maximum depth of the South basin was 15.42 m and 30.88 m, respectively. The hypsometric curve (Figure 6) shows depth on the horizontal axis and a cumulative percent of lake area as a percent on the vertical axis. Important physical and ecological values are noted along the horizontal axis, including depth (28.07 m) of phototrophic zone (the depth at which only 1% of surface light remains), the average depth of the thermocline (approximately between 9 and 14 m), the terminus of the shoal shelf (approximately 3 m), and the zone of vegetation.

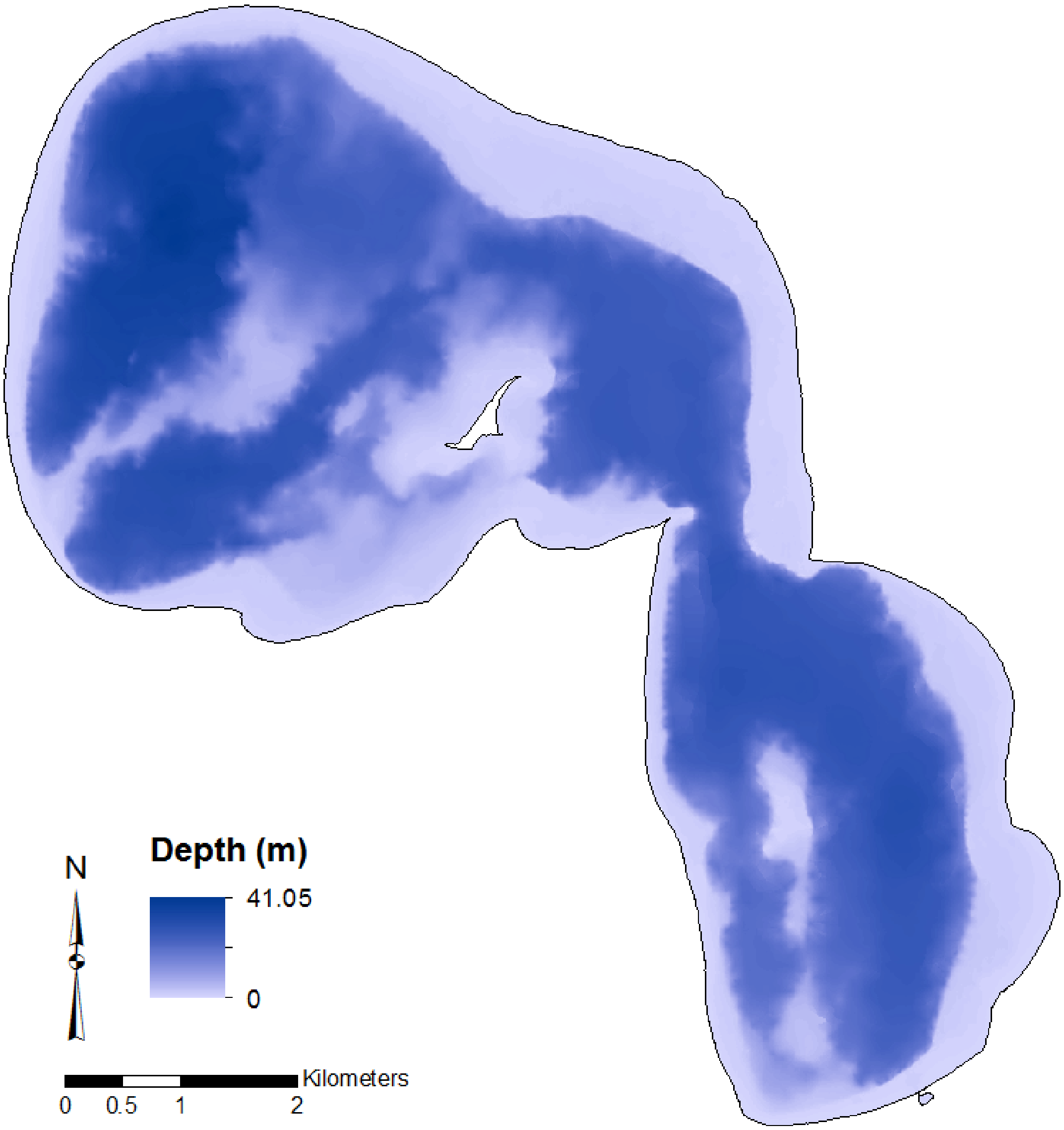

Figure 5. Interpolated bathymetric surface of Higgins Lake.

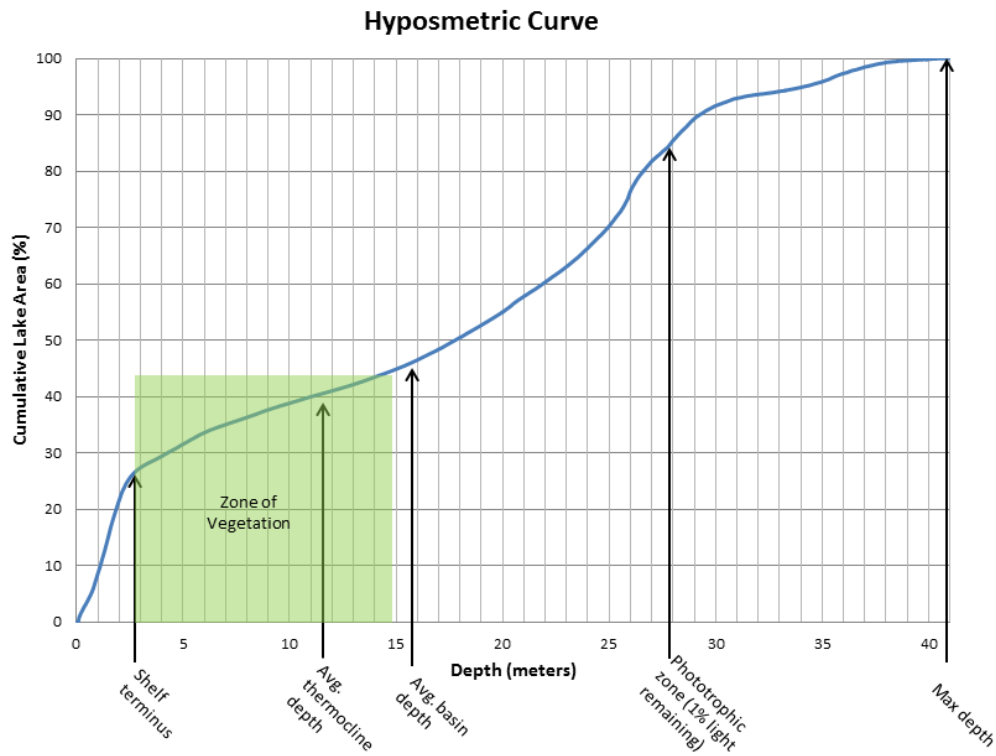

Figure 6. Hypsometric curve for Higgins Lake.

Aquatic Vegetation Mapping

Submersed vegetation covered approximately 11.1% of the lake basin, or 1,138 acres (Figure 9). SAV was largely restricted to depths between 3 and 15 meters (Figure 6, 8). The average observed depth of SAV was 6.03 m and the most frequent depth of SAV occurrence was 4.32 m. Emergent vegetation was not observed during the survey. During the image review stage, the greatest depth noted for standing algal biomass was approximately 14 m. The maximum mapped SAV height was 1.37 m (Figure 7), although the maximum recorded SAV height before interpolation was 2.09 m. Kriging produces an inexact estimated surface, so these taller macrophytic stands were lost in the interpolation step. Average SAV height was 0.27 m and the most frequently occurring SAV height was 0.13 m. The range of heights was considered to be 0.10 – 2.09 m with a standard deviation of 0.20 m.

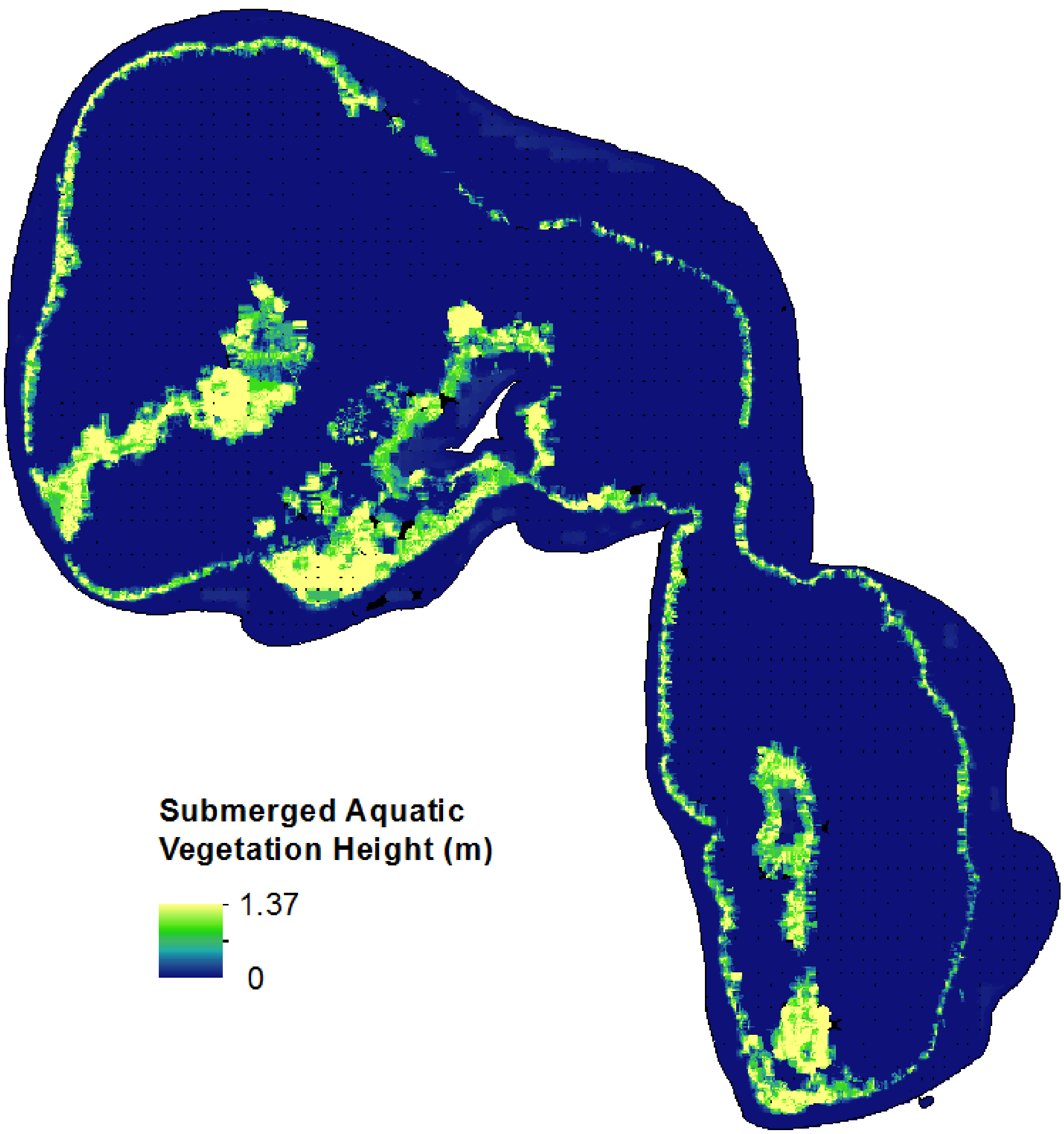

Figure 7. Height and location of submerged aquatic vegetation on Higgins Lake (Summer, 2012).

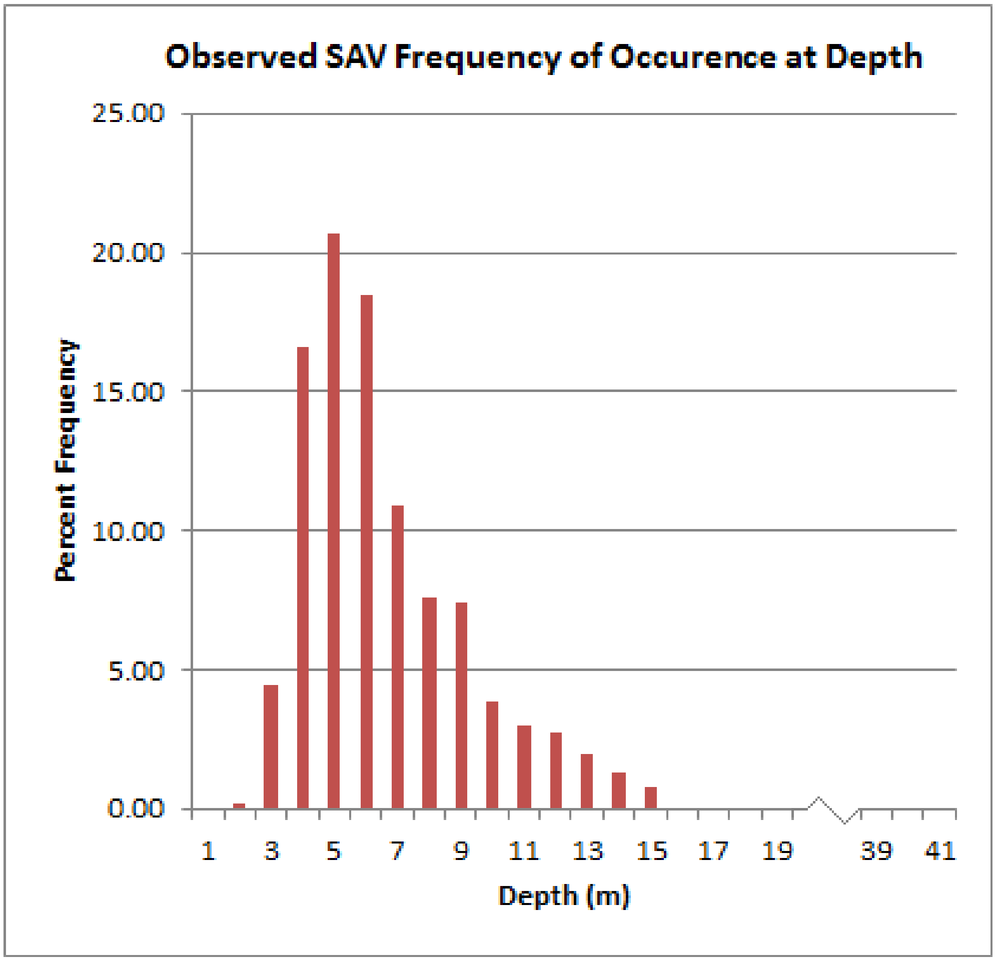

Figure 8. Frequency distribution of observed submerged aquatic vegetation occurrence at depth.

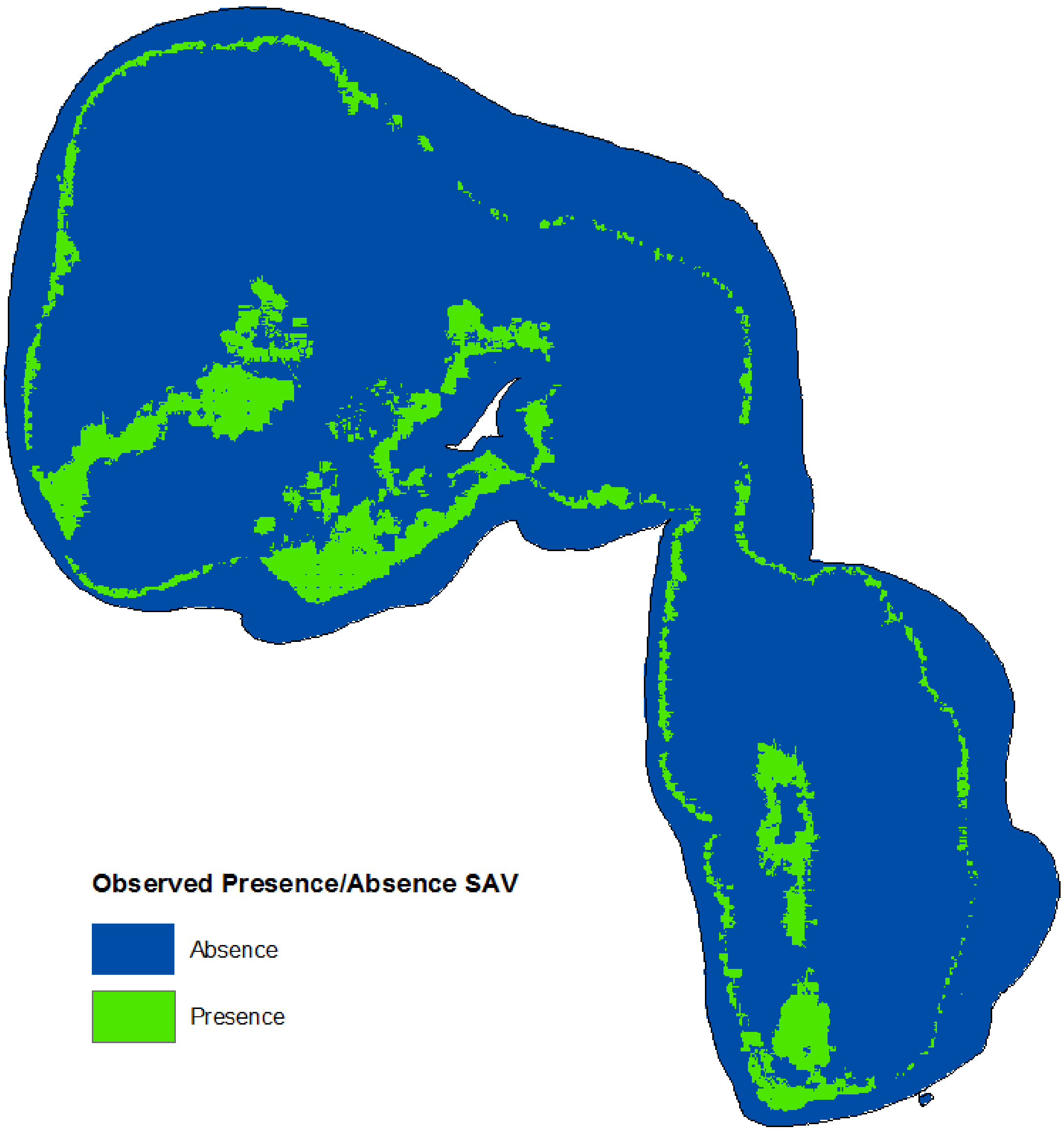

Figure 9. Observed presence/absence map of submerged aquatic vegetation on Higgins Lake.

Vegetation Mapping Validation

To assess the accuracy of the MATLAB-based sonar image analysis to delineate SAV in Higgins, a 30 m buffer was generated around each Huron Pines survey location and all image-analysis derived SAV observations intersecting this buffer were validated. The

Huron Pines surveys identified 78 as having Eurasian water milfoil present and of these 78 sites, 22 had SAV point data derived from the image analysis within the buffer zone. Of these 22 locations, 21 had observation points with SAV presence detected, 89.1% of which were positive for SAV.

Ancillary Data Maps

Maps of substrate hardness and wind fetch were produced for use in the SAV modeling (Figures 10,11). The substrate map (Figure 10) shows sandy shoals surrounding the mainly clay basins, with some significant areas designated as marl. A single class is assigned for regions of high acoustic return intensity (hardpan\gravel\vegetation).

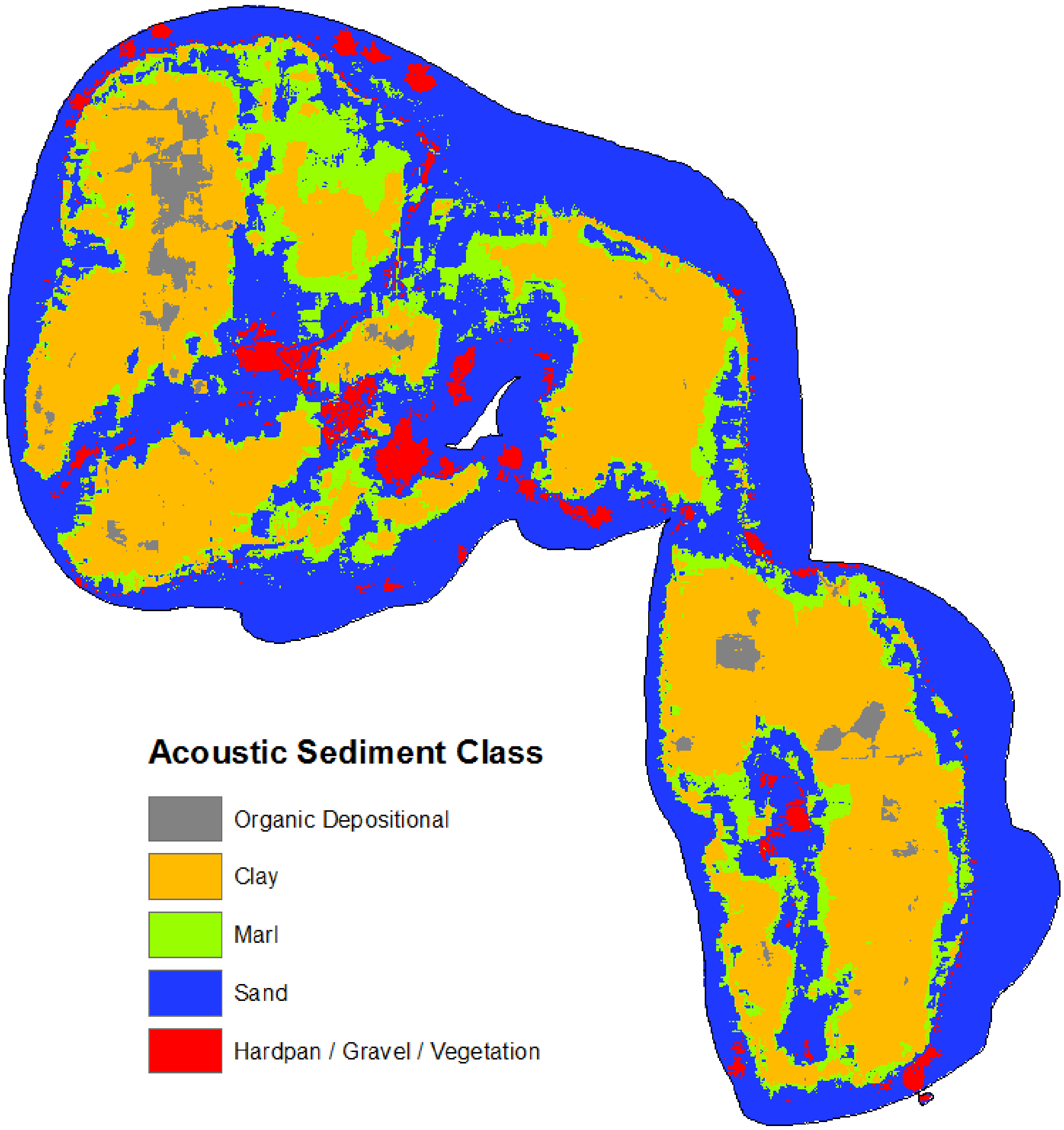

Figure 10. Acoustically derived sediment classification map.

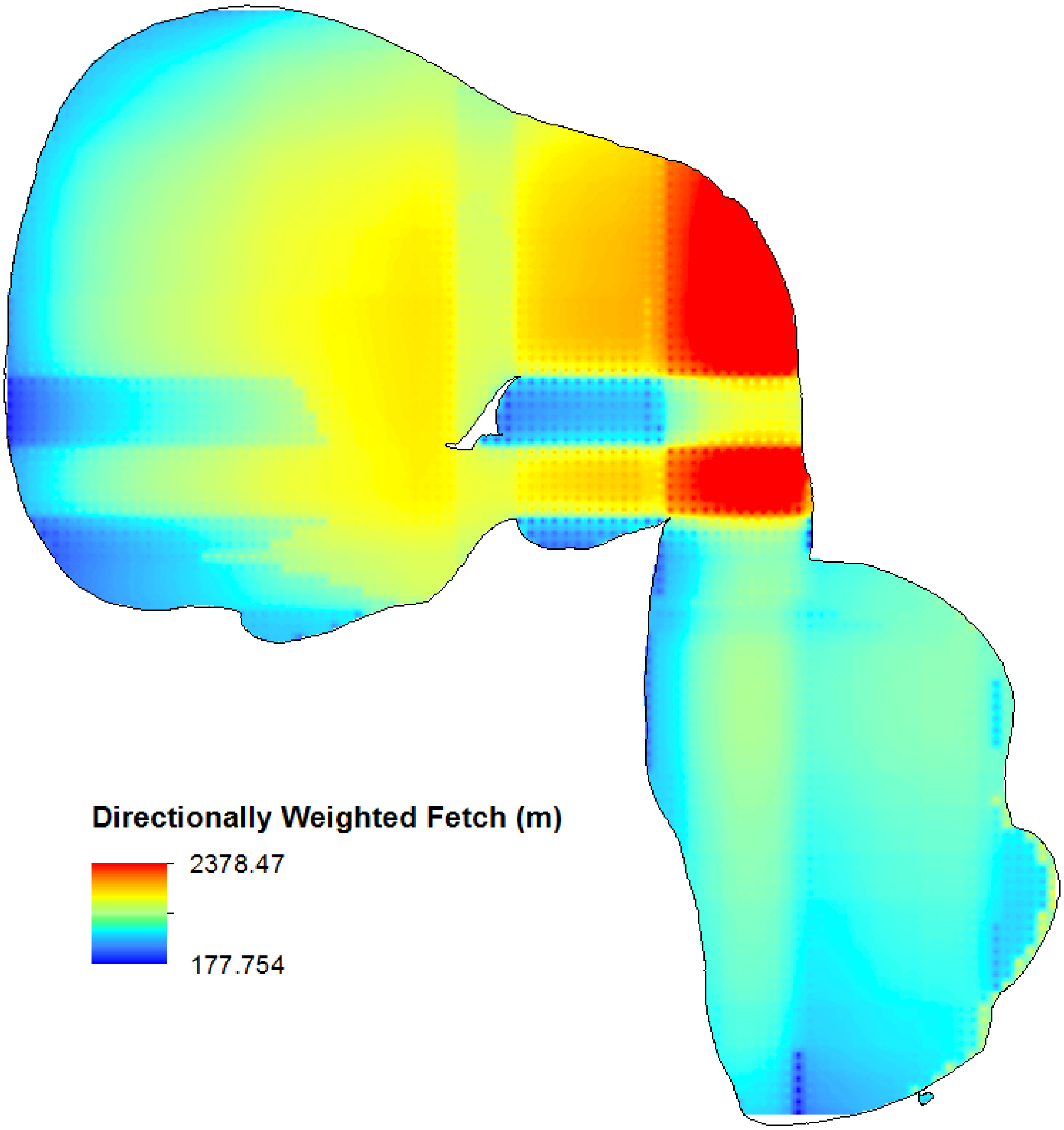

Figure 11. Fetch map, weighted by wind direction over the four cardinal axes and interpolated with inverse distance weighting.

The fetch map (Figure 11) showed that the highest fetch regions are in the northeast region of Higgins Lake. This is a region with high levels of active shoreline erosion reported by riparian homeowners. The fetch values serve as a correlate for wind-driven wave energy which at shallow depths, results in bottom disturbance which impacts SAV distribution (Koch, 2001).

Below is the frequency distribution of wind direction for a sub-sample of meteorological data collected from 1964-2013 at the Houghton Lake station. The predominant wind direction is a westerly wind.

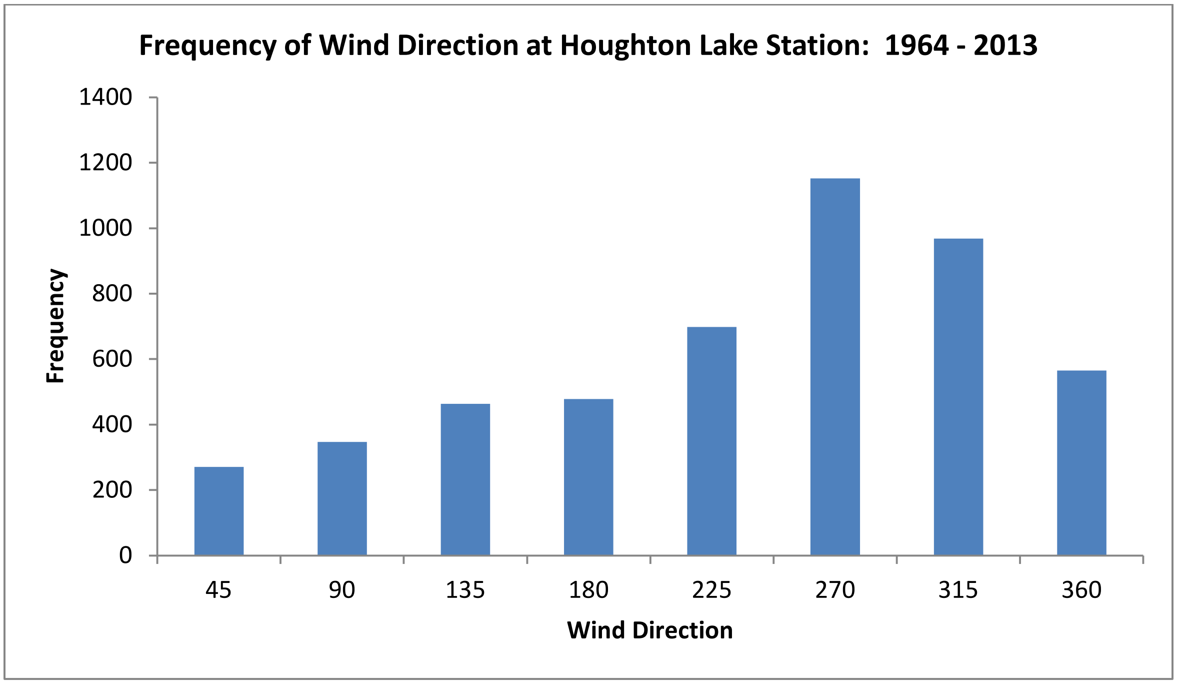

Figure 12. Frequency distribution of wind direction at the Houghton Lake station from 1964 -2013. Note that at 270^{o}, the wind direction is from the west, at 360^{o} the wind direction is from the north, etc.

Logistic modeling of SAV

The best performing logistic model of submersed aquatic vegetation had the following form:

$$ln\frac{p}{1-p} = 19.03 - 1.187 * Depth - 0.2086 * \%light + 0.0201 * \%slope - 0.00196 * fetch$$

Where p is the probability that the dependent variable (aquatic vegetation) is present, depth is water depth in meters, %light is percent of surface light intensity,% slope is percent slope of the bathymetric surface, and fetch is directionally weighted mean fetch in meters (R-squared = 0.3969, n = 551,162).

A threshold value of 0.3675 was used to classify the linear output of the logistic equation into binary presence/absence predictions. This corresponds to a threshold probability of 0.591. The classification accuracy of the categorical model with respect to the input data was about 82.5% (Table 2), and the classification error rate was 17.5%. The Chi-squared for the contingency test was 218,700 ($p<0.0001$), indicating statistically significant difference between observed and predicted occurrences, despite the 17.5% error rate. This is due to the very large sample size and as such we were willing to accept the high error rate.

		Observed	
		0	1
Predicted	0	82.5%	17.5%
	1	17.5%	82.5%

Table 2. Contingency analysis of observed SAV versus model predicted SAV.

Evaluation of Management Scenarios

Increasing water surface elevations led to increases in the areal extent of submersed vegetation and vice-versa (Table 3). However, lake surface area and water surface elevation (WSE) were also highly correlated (R-squared = 0.984; Figure 13). Consequently, within the range of WSE levels envisioned in the management scenarios, little change in percent of surface with submersed vegetation coverage was predicted by my model (Table 3). The overall relationship observed between WSE and SAV as a percentage of lake surface area cover was somewhat parabolic, particularly when the extreme scenarios were included. In general though, increases in surface elevations above SLL -26 (the lowest realistic lake level) led to increases in vegetation cover (Figure 14, Table 3). These increases were modest for the realistic scenarios, but more substantial in the extreme case. Median depth for the vegetation declined with increasing WSE (Figure 14) as might be expected.

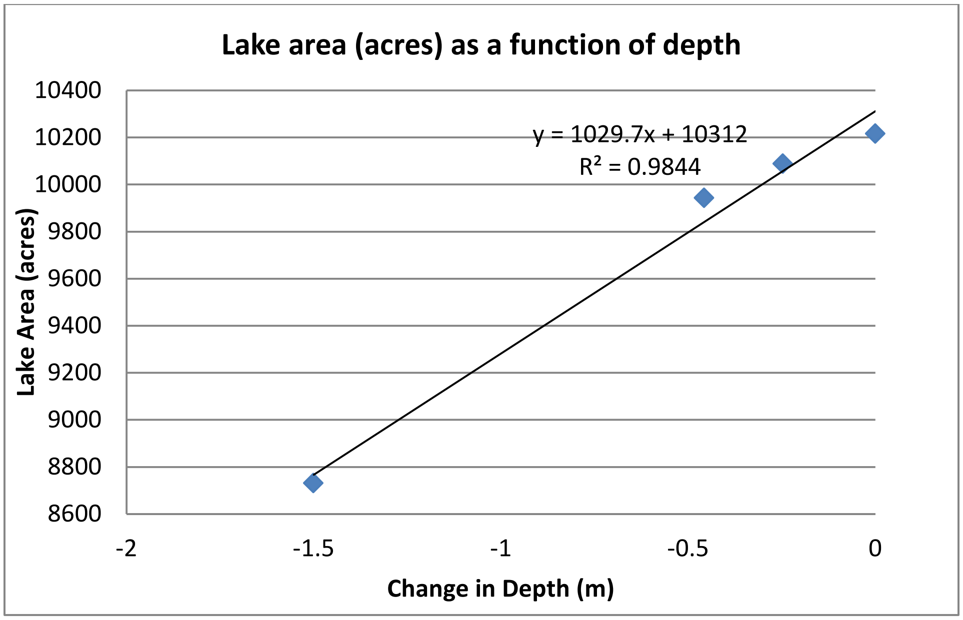

Figure 13. Regression of lake area as a function of depth derived by raster analysis and used to predict lake area at raised water level scenarios for percent SAV cover estimations.

Scenario Name	WSE (m AMSL)	WSE Change (m)	Lake Area (acres)	% Cover SAV	Acres SAV
SLL +60	353.04	1.5	11856	21.67	2569
SLL +1	351.8	0.03	10340	13.69	1416
SLL	351.77	0	10216	13.75	1405
SLL -9	351.54	-0.23	10097	13.28	1341
SLL -18	351.09	-0.46	9943	13.08	1301
SLL -26	350.89	-0.66	9801	13.02	1276
SLL -60	350.04	-1.5	8731	13.61	1188

Table 3. Summary of predicted lake areas and lake-wide percent cover of SAV under model scenarios.

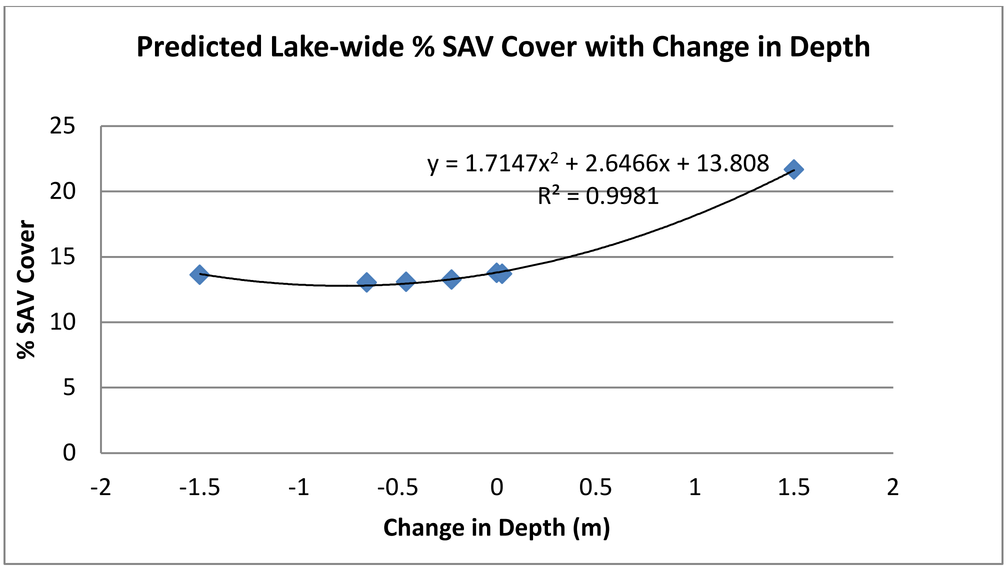

Figure 14. Predicted lake-wide percent cover versus changes in depth (m).

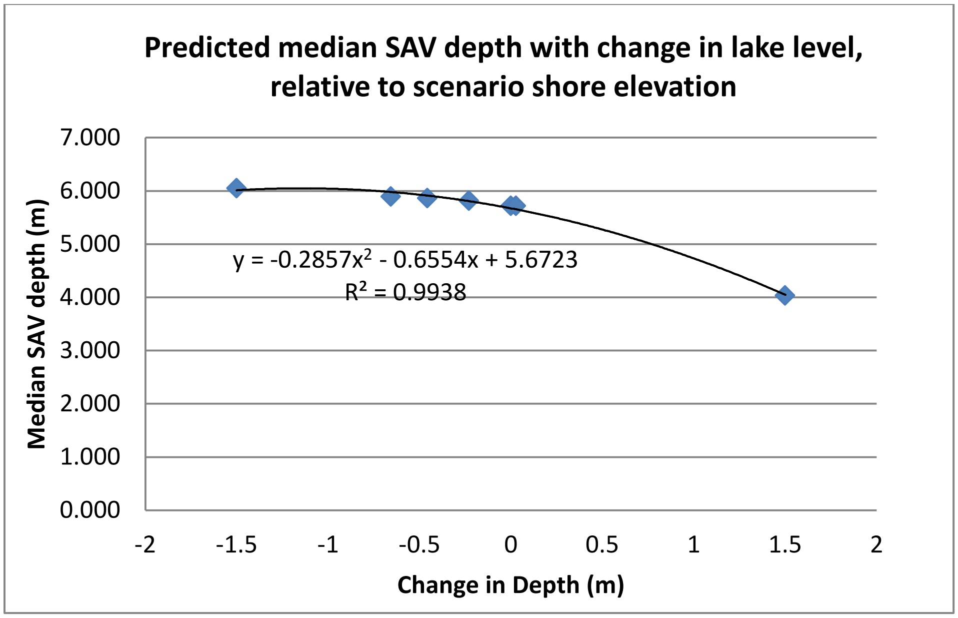

Figure 15. Predicted median depth (m) of SAV versus lake level change. The median depth is corrected for the associated change in lake-level for each scenario.

The mapped baseline SAV model output is displayed in Figure 15. Maps of all modeled SAV scenarios can be found in Appendix A.

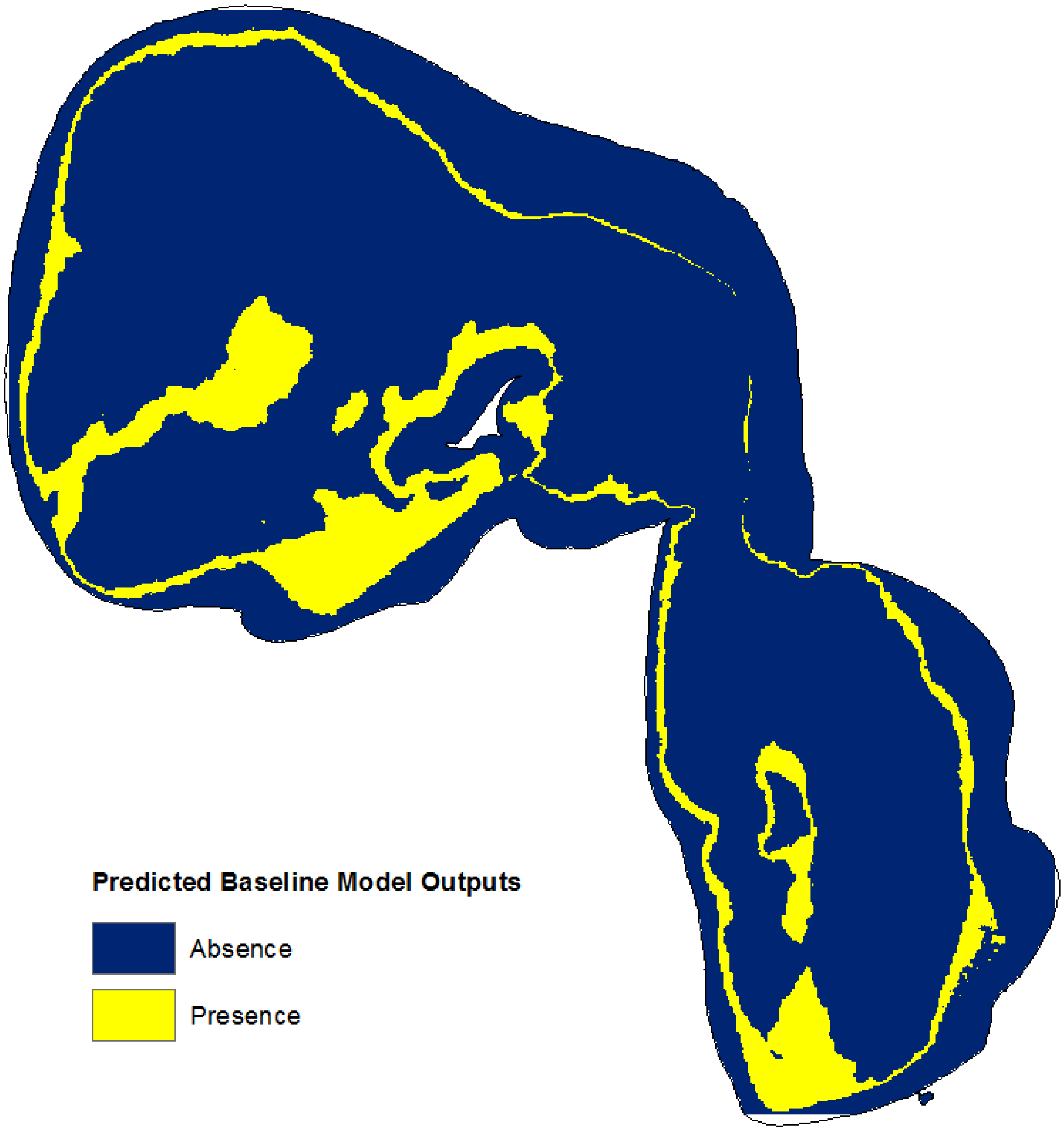

Figure 16. Predicted presence/absence map of submerged aquatic vegetation on Higgins Lake at baseline conditions (water-level at summer legal level, 351.773m AMSL).

Discussion

The results of my vegetation model indicate that for the lake-level management scenarios which are under debate by residents and stakeholders (SLL +1, SLL -9, SLL -18 and SLL -26) there would not be significant change to the distribution and areal cover of SAV on Higgins Lake. This is likely due to the morphometry of the lake; there is available area for the vegetated zone to shift up or down in conjunction with lake levels, and this is what the model suggests will occur. Relative to the baseline SAV model scenario, the model predicts declines in percent cover of vegetation of the lake (corrected for lake area at that water level) for the lower water level scenarios as well as the slightly higher water level scenario (SLL +1), with the maximum change (a loss of 0.73 percent cover, or 128.4 acres) occurring with the lowest (dam removal) lake level scenario. Under these four scenarios, the predicted areal extent of SAV ranges from 1,276 to 1,416 acres with increasing lake levels. These potential changes to aquatic vegetation are likely insufficient to measurably effect fisheries habitat on the lake (Wiley et al., 1984).

Both the mean and the median depths of SAV predicted by the model follow similar trends. The median was selected to summarize potential changes to depth to avoid influence from outliers. The predicted changes in depth of SAV change in accordance with changes in depth; raising the water level results in predicted SAV distribution moving up to more shallow water and vice-versa.

It is important to note that for the above four scenarios, there are two types of proposed lake-level elevations changes: managed and unmanaged lake-levels. The SLL -9 and SLL + 1 represent proposed water level management scenarios; that is, the dam would be managed to maintain these water levels. The other scenarios SLL-18 and SLL -26 (leaving all the dam gates open and removing the dam, respectively), represent unmanaged levels. That is, the actual lake-level under these scenarios would be determined by the hydrologic water balance, and will vary depending on short-term (seasonal) and long-term (climatic) events. Quantification of these unmanaged water levels will be evaluated by Michigan State University's hydrologic modeling of the system. I have treated them here as equilibrium elevations for the purposes of SAV modeling.

The SAV occurrence model over-predicted the percent cover of aquatic vegetation on the lake for the baseline scenario by about 2.65%, compared to the observed data. The model had an assessed accuracy of 82.5%; that is there was 82.5% agreement between the predicted value and observed value. The model was constructed so as to produce symmetrical errors (produce false positives and false negatives in equal proportion) as no advantage could be determined for a model that favored one error type. As such, the exact reasons as to why the model overestimates are difficult to assess precisely, but a basis for interpreting this is by first considering that the model outputs can be interpreted as a likelihood of occurrence of vegetation at any location, based on the covariates included in the model.

This over-prediction could be explained by several different factors; there may have been important ecological components which were limiting SAV distribution, such as herbivory or inter- or intra-species competition among aquatic plants. It is also possible that an incorporation of a variable that more directly reflects boat-wake and skiing disturbance could reduce the overestimation. Furthermore, substrate nutrients could be a limiting factor in regions of the lake. Spatially variable connections to the water table could alter patterns of nutrient availability (carbon, nitrogen, phosphorus), especially in conjunction with failing septic systems if they exist. Although I collected and analyzed surface water quality information using a YSI sonde and detected no spatial variability in phytoplankton, TDS or turbidity, nutrient concentrations were not empirically measured in this study.

The model outputs of the extreme high and extreme low water level scenarios (SLL +60 and SLL -60) were included as sensitivity tests and helped evaluate the response dynamics of the system. The SLL +60 test scenario shows a significant increase in percent cover of aquatic vegetation (a 7.92% increase equating to 1,164 additional acres above the baseline SLL scenario). This is likely also tied to the morphology of the lake; under the current lake conditions, much of the aquatic vegetation occurs at a depth that corresponds to the drop off area where the low-slope shoal meets the edge of the basins. It seems likely that the low amounts of vegetation observed on Higgins are because there is limited lake-bed area in the depth range that is most suited for aquatic vegetation. The model predicts that if the water elevation is raised drastically, much of the shelf area is now likely to experience SAV colonization as those regions are now at the suitable depth. Additionally, there is heavy human usage of the shallow shelf, which is likely negatively impacting the ability of vegetation to colonize those areas. The extreme low WSE model test predicted a loss of about 216 acres of aquatic vegetation relative to the model baseline. In areas along the drop off, it is reasonable to assume that aquatic vegetation extents would shift down the slope, so losses should not be significant in these regions. However, we can expect that in shallow and flat regions such as the sunken peninsula on the west side of the north basin and the shallow bay on the south edge of the north basin, a significant lowering of the water level would reduce the areas suitable for vegetation. The mapped model outputs reflect this (Appendix A).

Study Limitations

A limitation in this study was the lack of precise estimates of lake area under raised water level scenarios. For lower water levels, a raster mask could be applied to eliminate raster cells that would represent newly exposed shore and thus a direct estimation of lake surface area was possible. However, topographic elevation data were not collected up onto shore during the survey, and the topographic raster of the lake ended at the waters' edge. As a result, for the two raised water level scenarios (SLL +1, SLL +60), a direct calculation of lake area was not possible. Instead, a linear regression of lake area versus depth (R-squared = 0.984) was produced based on the lowered water level rasters, and used to extrapolate to higher water levels. More accurate calculations could have been made if on shore elevations (collected perpendicular to the waters' edge) were collected.

Additional limitations and/or shortcomings are associated with some of the ancillary data products used to develop the SAV model, in particular the fetch model and the sediment classification map.

The fetch analysis did not incorporate wind speed, which if included could have been used to develop a relative exposure index (after Keddy, 1982) and might have more realistically accounted for the wind-wave conditions. The relative exposure computation integrates depth, wind speed and fetch (the variables required to calculate wave height) into an index by computing the sum across wind directions of mean monthly wind for April – October from each direction multiplied by the proportion of the month that the wind was blowing from that direction, scaled from 0 to 1, and multiplied by the fetch distance for the direction.

The fetch model developed for my research was a computation of fetch weighted by the frequency of wind direction along the four cardinal axes. The meteorological record used included data from across the entire year (January – December) which is one limitation, as during months of ice cover there are no waves. During the model selection process, a fetch divided by depth covariate was tested to account for the dissipation of wave velocity (and thus bottom shear stress) with depth. This covariate however, was found to reduce the prediction accuracy of the SAV model and was removed. A simple fetch model is still a useful index of wave disturbance however, since maximum predicted wave height on lakes is proportional to the square root of the fetch (Wetzel, 2001). Furthermore, bed shear stress is a function of depth, so although a more complex wind wave model could have been generated, for the purposes of the empirical SAV model, depth would likely continue to drive model outputs. Additionally, other studies that attempt to evaluate the importance of wind conditions and fetch on wave-generated bottom shear stresses incorporated a single wind velocity in their calculations (Fagherazzi & Wiberg, 2009). So, for example, scaling the Higgins fetch model by an average windspeed across the meteorological record would not have changed its importance when incorporated into the SAV prediction model.

My sediment map was based on the relative intensity of the acoustic signal returns which serves as an index of acoustic reflectivity and therefore substrate hardness. Aquatic vegetation however, also tends to have high acoustic reflectivity which is thought to result primarily from gas within the plants (Sabo et al., 2002), and this is supported by the observation that more buoyant species (those with more gas) are more acoustically reflective (Sabol and Burczynski 1998). Because of this characteristic, locations with aquatic vegetation tended to be grouped in the hardest acoustic substrate class. Because acoustic energy is reflected off of vegetation at a high rate, this also means there is likely sampling bias for delineating the substrate where vegetation is present. This fact may explain why substrate was not a useful covariate in the empirical model. A further shortcoming was that the substrate map was ground-truthed using the MDNR Higgins Lake survey map from 1936, but obviously could have benefited from more recent on-site sampling to confirm sediment class interpretations.

Side-Scan Sonar

A tow-behind sidescan sonar unit was employed for this study as well with the intent to map both sediment and aquatic vegetation, but sidescan data were not incorporated for a few reasons. First, the output sidescan mosaics were not of high enough resolution to confidently delineate submerged aquatic vegetation beds. This was due to the fact that the unit was set to its largest range (200 m or 400 m of swath coverage). This range seemed necessary to get close to complete coverage of the lake given the time constraints of the survey. Second, there were issues associated with the drop off regions of the lake, since many of my survey tracks were parallel to these. The sidescan acoustic signal travels perpendicular to the survey vessel and can be thought of as a narrow fan extending outwards towards the waters' surface and lake bottom. When there is steep or tall topography in the lake bottom, these features result in output mosaics that are difficult to interpret because the rapid change in elevation results in a compressed and intense return signal. In this setting the 455 kHz down-scan imagery proved much more useful. However, different lake conditions (i.e. a lake with less extreme topographic features) might result in much better success with side-scan units. I also attempted to interpret side-scan data for substrate mapping using

Quester Tangent's QTC Swathview automated sediment classification software. However, this software assumes for the image classification step that the lake bottom has little to no variation in topography, and so again the steep slopes in Higgins Lake along the drop off regions compromised data interpretation.

Useful Software Packages

A number of useful software packages were employed for this study, although two of these were purchased by larger companies and are no longer available for purchase (DrDepth and UnderSee Explorer). SonarTRX (Leraand Engineering Inc.) was a very cost effective solution for use with Navitronic's file formats, and allows for easy export of downscan and sidescan imagery mosaics. I also used both Chesapeake Technology's SonarWiz 5 and Quester Tangent's QTC Swathview to process the sidescan data. These are both excellent software packages and are considered industry standards, but they are cost prohibitive.

Conclusions

My goals in this thesis research were (1) to collect and use hydroacoustic data from several different sonar systems to evaluate the bathymetry and spatial distribution of submerged aquatic vegetation on Higgins Lake; and (2) to generate a predictive SAV model that could be used to quantify how areal extents of vegetation might change in response to changes in lake-level management.

As to the first goal, hydroacoustic survey proved a very effective way to map the bathymetry and submersed aquatic vegetation on Higgins Lake. Hydroacoustic methods are less time consuming when compared to traditional lake-survey methods, and the data analysis can be automated. The image analysis scripts I developed were very effective at accurately capturing aquatic vegetation, but did require a very significant effort to run and validate and this should be considered for those attempting similar methods. Commercial packages which combine hardware and software are available (BioSonics Aquatic Habitat Echosounder, http://www.biosonicsinc.com/product-mx-habitat-echosounder.asp) which will produce bathymetric maps, classify substrate, and map submersed aquatic vegetation in real-time.

As to the second goal, the predictive model had high output accuracies and compared very well with the observed SAV found on the lake. Agreement between the baseline model output and the observed SAV provides strong confidence in my prediction of changes to SAV at different lake level management scenarios. Also, due to the fact that depth and light were the driving factors in the empirical model, it is likely that this model could be applied to other lakes with good success.

Appendix A

SAV Model Outputs

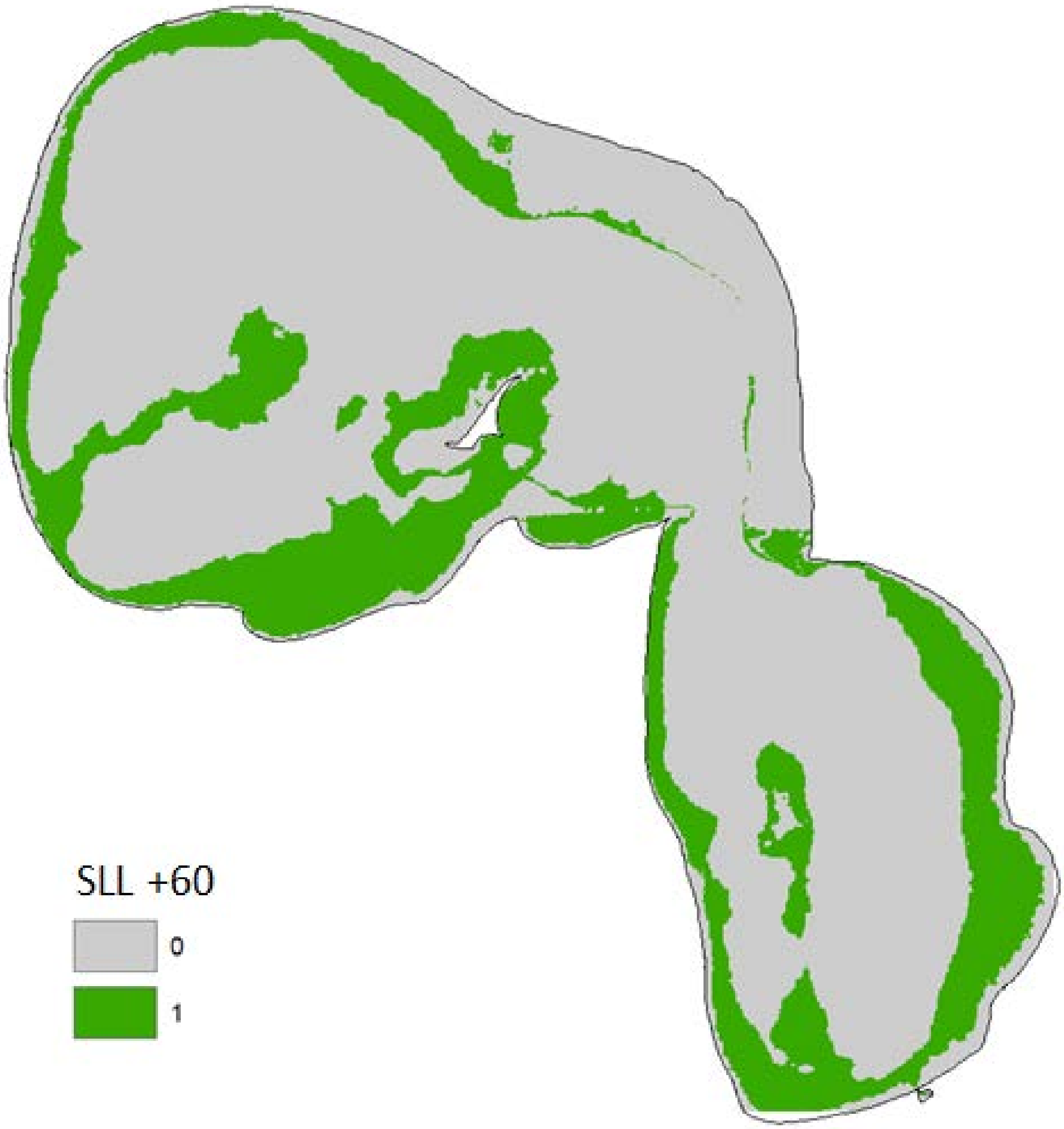

Figure 17. Model output scenario SLL +60. This scenario is a sensitivity test to determine how the dynamics of the system respond to an extreme high water level. SLL +60 stands for Summer Legal Level plus approximately 60 inches of water surface elevation.

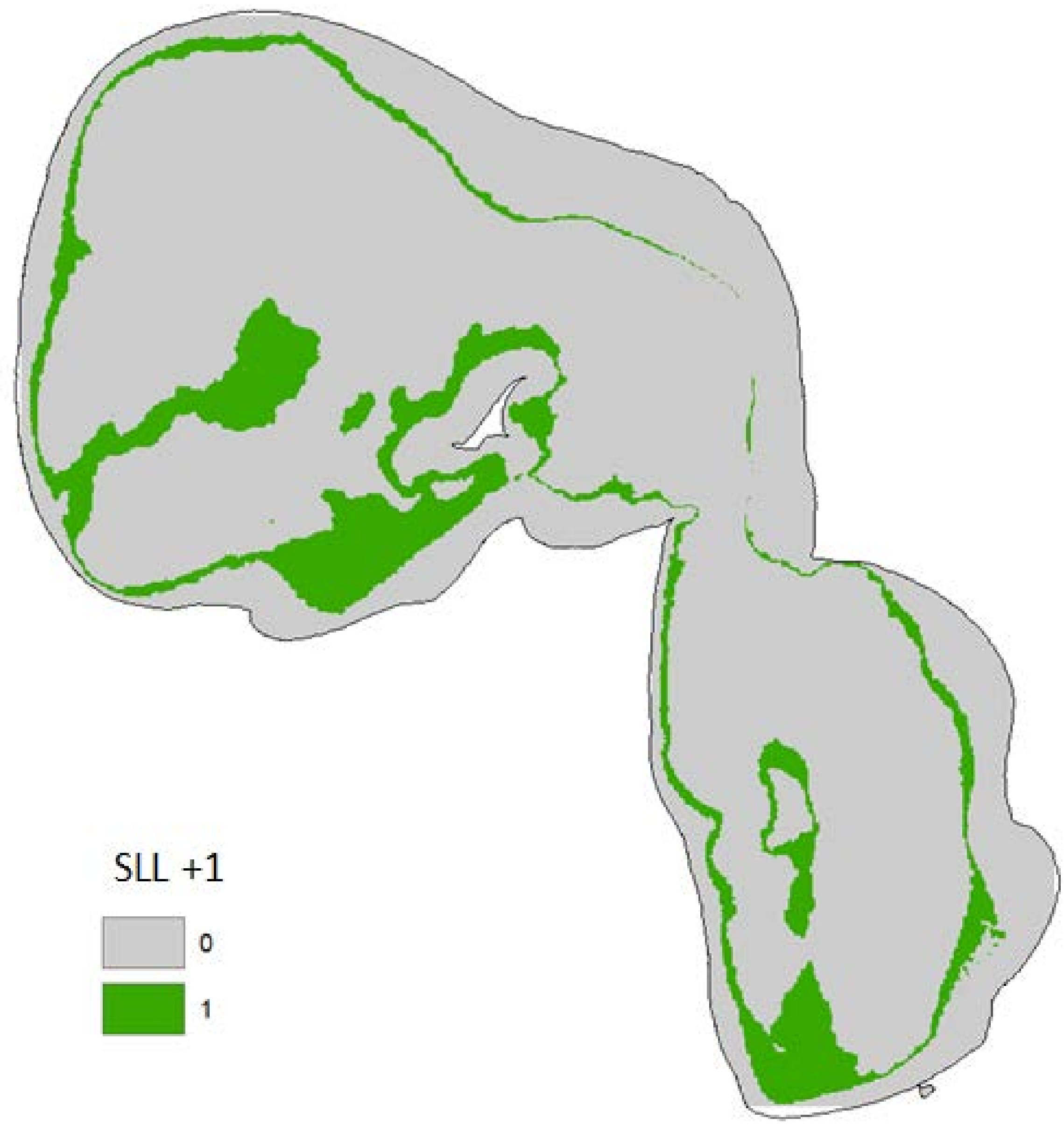

Figure 18. Model output scenario SLL +1. This scenario represents the highest water level achievable if all the dam gates and stop logs are up and in closed positions. SLL +1 stands for Summer Legal Level plus approximately 1 inch of water surface elevation.

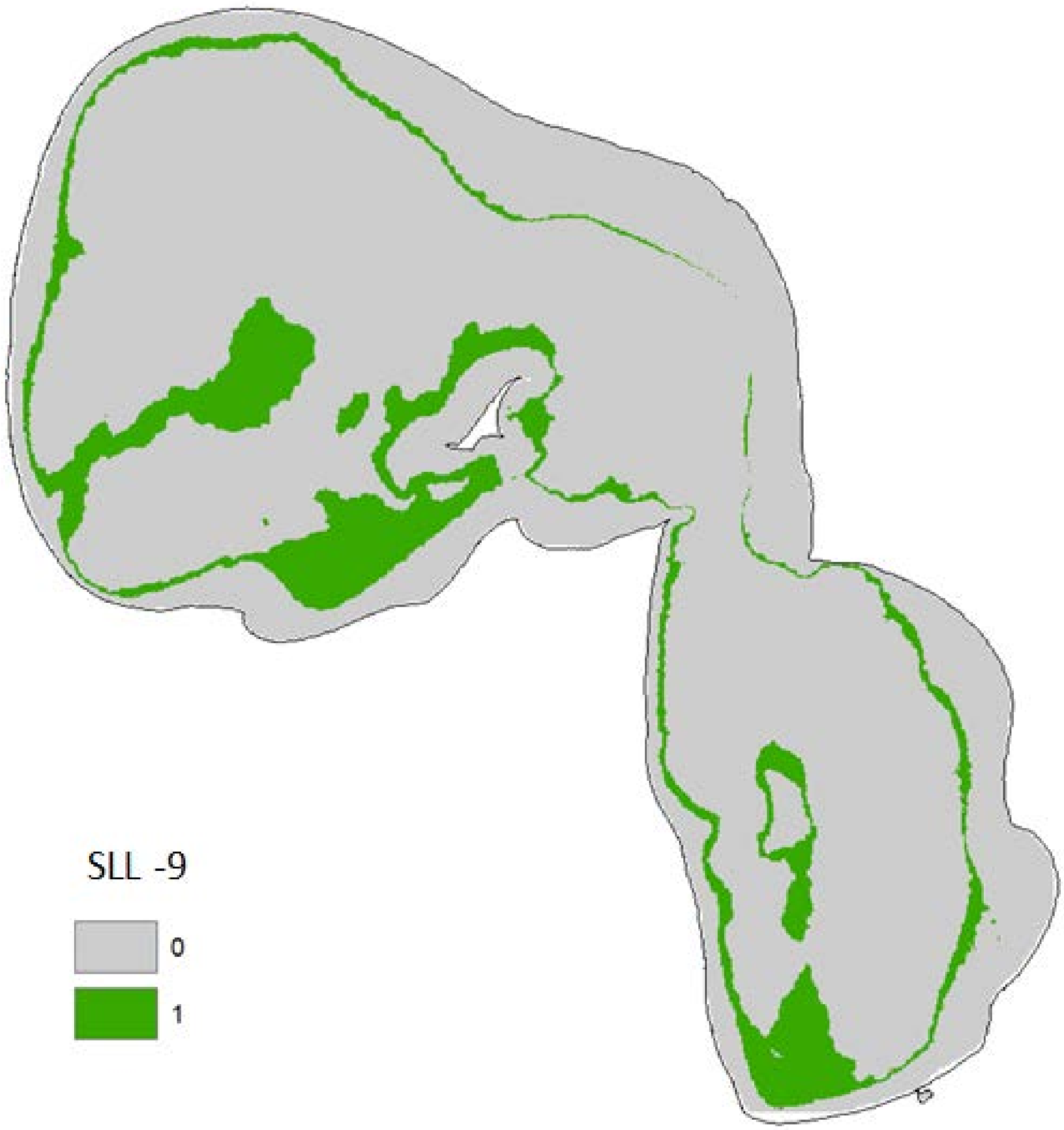

Figure 19. Model output scenario SLL -9. This scenario represents a proposed lower water level. SLL -9 stands for Summer Legal Level minus approximately 9 inches of water surface elevation.

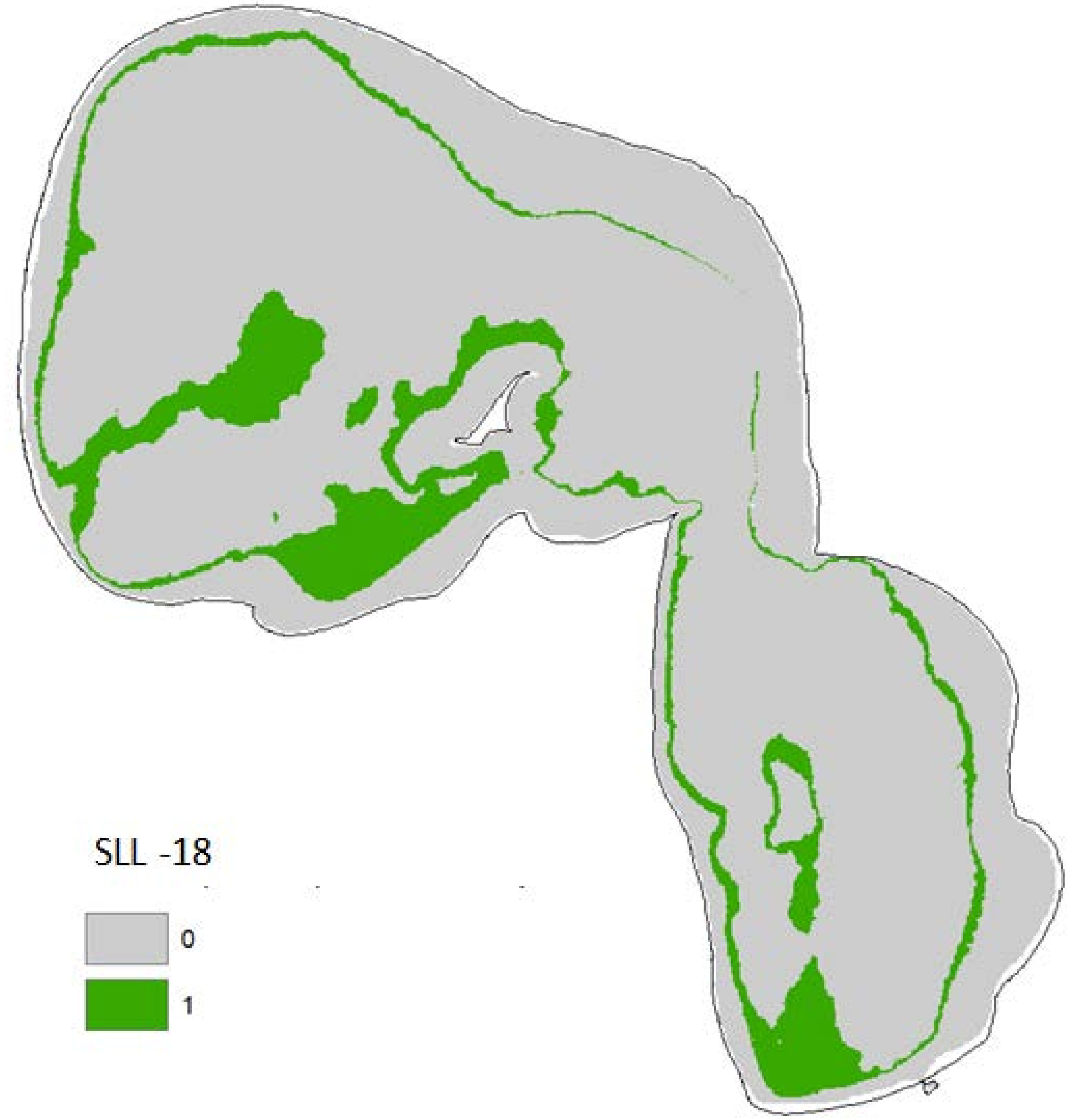

Figure 20. Model output scenario SLL -18. This scenario represents the lowest achievable water level by fully opening all gates and stop logs on the dam. This scenario assumes no modification to the dam structure. SLL -18 stands for Summer Legal Level minus approximately 18 inches of water surface elevation.

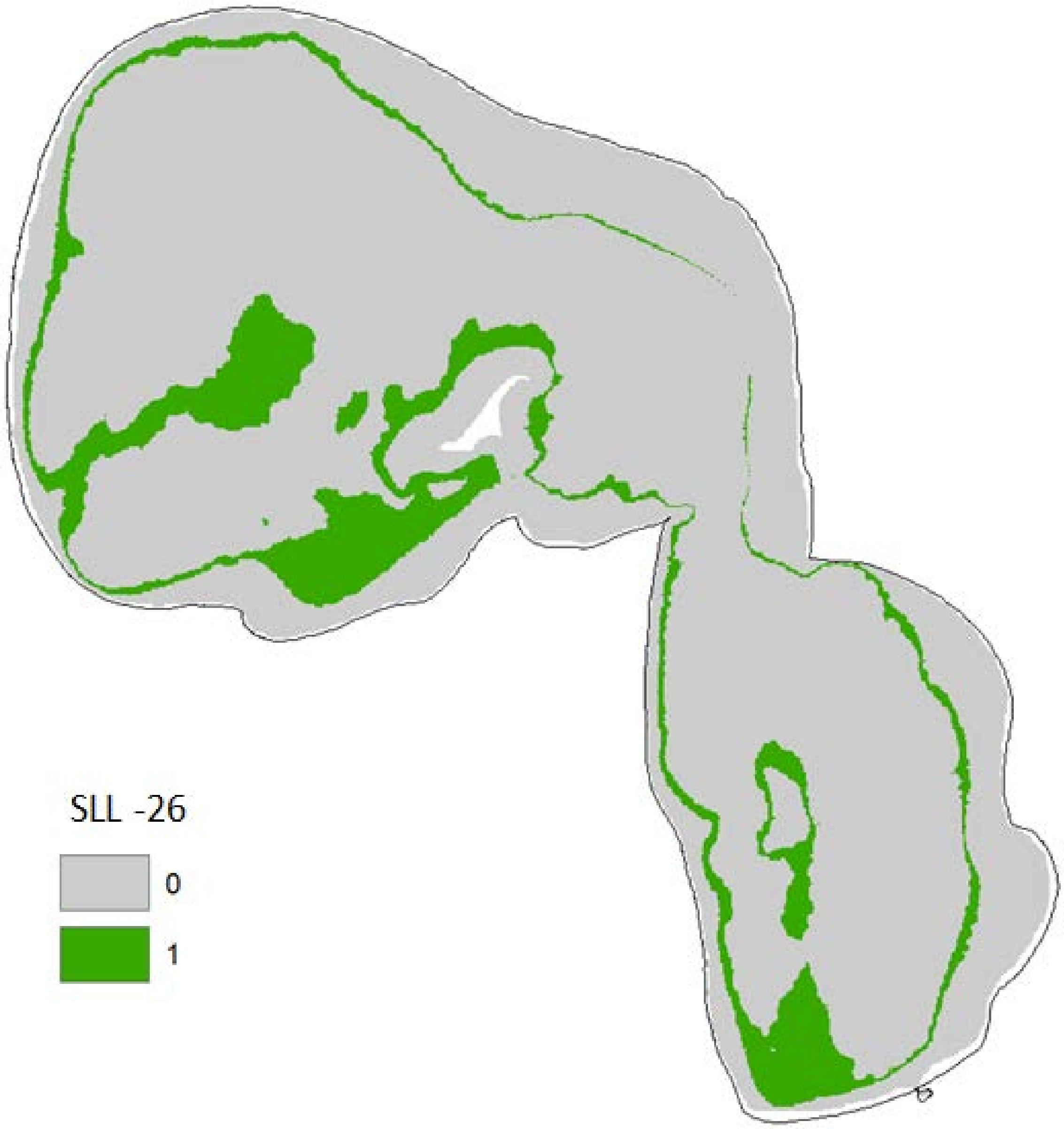

Figure 21. Model output scenario SLL -26. This scenario represents an unobstructed opening at the Cut River, which would require removal of the dam. SLL -26 stands for Summer Legal Level minus approximately 26 inches of water surface elevation.

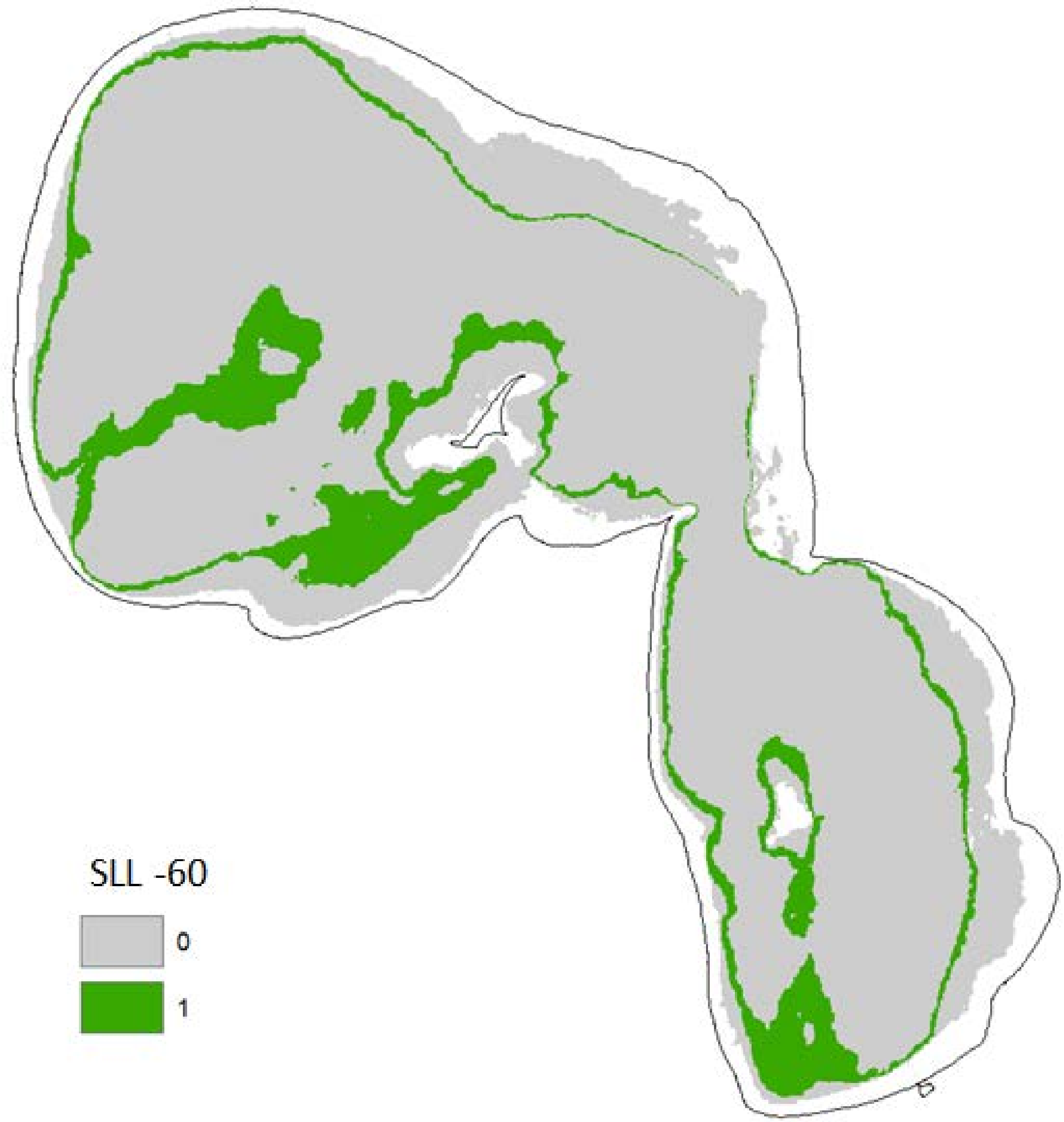

Figure 22. Model output scenario SLL -60. This scenario is a sensitivity test to determine how the dynamics of the system respond to an extreme low water level. SLL -60 stands for Summer Legal Level plus approximately 60 inches of water surface elevation.

Appendix B

MATLAB Image Analysis Scripts

```
files = dir('E:\Higgins_Lake\VegMap\SonarTRX-16AUG12LOW-20140525-
134342\Images-SpeedCorrected\*.PNG');
numfiles = numel(files);
for z = 1:numfiles
    origImage = imread(files(z).name);
    %origImage = imread('T-SpeedCorrected-007CD-16AUG12LOW.png');
    origImage = origImage(:,:,1);
    [row,col] = size(origImage);

    %replaces first fraction of columns with zeros, based on mask size, to
avoid surface noise in image analysis
    mask = round(0.10*col);
    origImage(:,1:mask) = 0;

    %median filter applied
    a = 3;
    filtI = medfilt2(origImage, 'indexed', [a a]);
    maxImage = max(filtI,[],2);
    %convert to double
    filtIdbl = im2double(filtI);
    maxIdbl = im2double(maxImage);
    %normalize every column by its maximum value so that bottom return is
255
    normIdbl = bsxfun(@rdivide, filtIdbl, maxIdbl)*255;
    normI = uint8(normIdbl);

    %Assigning variables to Correct Max Value locations to ensure bottom
continuity
    [mx, indx] = max(normI,[],2);
    mx = mx';
    indx = indx';
    mxindx = [int16(indx); uint8(mx)];
    lengthmx = length(mxindx);
    B = size(indx);
    bottomsafe = zeros(B, 'uint16');
    n = 3;

    %Use surrounding neighbor location of reported bottom to correct
    %for outliers if present. Does not correct for a long
    %string of errors.
    for i = 1
        %Columns on the edge of image are set to innner neighbor pixel
        %value to avoid filtering edge effects
        bottomsafe(i,1) = mxindx(1,3);
        bottomsafe(i, lengthmx) = mxindx(1,lengthmx-2);
        for j = 2:1:lengthmx-1
            if abs(mxindx(i,j+1) - mxindx(i,j))>=n && abs(mxindx(i,j-1) -
mxindx(i,j))>=n
```

```
                bottomsafe(i,j) = (mxindx(i,j+1) + mxindx(i,j-1))/2;
            else
                bottomsafe(i,j) = mxindx(i,j);
            end
        end
    end

    %Defines variables to begin for loop to search above max values
    vegArray = zeros(size(origImage), 'uint8');
    sznI = size(normI,1);
    b = 225; %bottom
    w = 85;  %water column

    %searches above max values for veg.
for k = sznI:-1:1
        for m = bottomsafe(1,k):-1:1;

              if normI(k,m)>=b
                  vegArray (k,m) = 255;

              elseif normI(k,m)>=w && normI(k,m)<b && normI(k,m-1)>=w &&
normI(k,m-1)<b;
                  vegArray (k,m) = 128;

              elseif normI(k,m-1)<w && normI(k,m-2)<w && normI(k,m-3)<w;
                  vegArray (k,m)=0;
                  break

              else
                  vegArray (k,m)=0;
              end

        end
end

%Extract pertinent info to form vegArray
%(Veg pres, # pixels to veg, # pixels to bottom, # pixels in veg)
ind1 = vegArray == 128; %report as 1 when value 128 present, 0 otherwise
TopVeg = [rem(sum(~cumsum(ind1'))+1,1+size(ind1,2))'];
TopVeg = flip(TopVeg);
vegYorN = nonzeros(TopVeg);

Output = zeros(lengthmx, 5);
[maxV, maxVI] = max(vegArray, [],2);
maxVI = flip(maxVI);
Output (:,1) = 1:lengthmx; %column 1 is index
Output(:,2) = maxVI; %column 2 is # pixles to bottom
Output(:,4) = TopVeg(:,1);  %column 4 is top of vegetation
Output(:,5) = (Output(:,2)-Output(:,4)); % column 5 is height of
vegetation

%column 3 is Veg Prescence (Y or N as 1 or 0)
for p = 1:1:sznI
```

```
    for q = 4
        if Output(p,q) == 0;
            Output(p,3) = 0;
            Output(p,5) = 0;
        else
            Output (p,3) = 1;
        end
    end
end

%write outputfile

%filename_out =
['C:\Users\alayman\Desktop\Higgins\Matlab\Batch_test\16AugLOW_speedCorrect
ed_sample\',files(z).name(1:end-4),'_vegOUT.csv'];
filename_out = ['E:\Higgins_Lake\VegMap\SonarTRX-16AUG12LOW-20140525-
134342\Images-SpeedCorrected\',files(z).name(1:end-4),'_vegOUT.csv'];
dlmwrite(filename_out, Output);

csvwrite(VegOut, Output);

% figure(1), imshow(vegArray)
% figure(2), imshow(origImage)
% figure(3), imshow(normI)

end

%http://www.mathworks.com/matlabcentral/newsreader/view_thread/115013

%http://www.mathworks.com/matlabcentral/newsreader/view_thread/139387
```

```
files = dir('E:\Higgins_Lake\VegMap\SonarTRX-16AUG12LOW-20140525-
134342\Images-SpeedCorrected\test\*.CSV');
numfiles = numel(files);
PyFile = dir('E:\Higgins_Lake\VegMap\SonarTRX-16AUG12LOW-20140525-
134342\*.CSV');
PyFile = csvread(PyFile.name);

 for z = 1:1%numfiles
     M = csvread(files(z).name);
     %M = csvread('T-SpeedCorrected-000CD-16AUG12LOW_vegOUT.csv');
     lenM = length(M);

     %Place start and end lat and long from Python Output at beginning and
     %ending of each image
     M(1,6) = PyFile((z*2)-1,2);
     M(1,7) = PyFile((z*2)-1,1);
     M(lenM,6) = PyFile((z*2),2);
     M(lenM,7) = PyFile(z*2,1);

     %Convert start/end lat and long to radians
     Alpha_lat_rad = M(1,6)*pi/180 ;
     Alpha_lon_rad = M(1,7)*pi/180 ;
     Omega_lat_rad = M(lenM,6)*pi/180 ;
     Omega_lon_rad = M(lenM,7)*pi/180 ;
     Alar = Alpha_lat_rad ;
     Alor = Alpha_lon_rad ;
     Olar = Omega_lat_rad ;
     Olor = Omega_lon_rad ;

     %Place start and end lat and long from Python Output at beginning and
     %ending of each image (radians)
     M(1,6) = Alar;
     M(1,7) = Alor;
     M(lenM,6) = Olar;
     M(lenM,7) = Olor;


     %Haversine formula to calc distance between start/end coordinates
     R = 6378.137; %What google folks uses as Earth's mean radius (km).
Also anything in the range between this and 6371 is acceptable
     a = sin((Olar-Alar)/2)^2 + cos(Alar) * cos(Olar) * sin((Olor-
Alor)/2)^2;
     c = 2*atan2(sqrt(a), sqrt(1-a));
     d = c*R; %distance in km between coordinates

     %Bearing Calc in radians
     bear = atan2(sin(Olor-Alor)*cos(Olar), cos(Alar)*sin(Olar)-
sin(Alar)*cos(Olar)*cos(Olor-Alor));

     %Distance per ping (actually, distance per number of rows in each
     %image) in km
```

```
     Dpp = d/lenM;

     %writes to CSV file the interpolated lat and long (radians) for each
row of
     %image; that is, given a start point, initial bearing and distance,
     %calculates each "desitnation" point (and final bearing, if deemed
     %necessary) when travelling along a shortest distance great circle
     %arch (http://www.movable-type.co.uk/scripts/latlong.html)
     for i = 2:lenM-1
         M(i,6) = asin(sin(M(i-1,6))*cos(Dpp/R)+cos(M(i-
1,6))*sin(Dpp/R)*cos(bear)); %next lat coor
         M(i,7) = M(i-1,7) + atan2(sin(bear)*sin(Dpp/R)*cos(M(i-1,6)),
cos(Dpp/R)-sin(M(i-1,6))*sin(M(i,6)));%next long coor
     end

     %converts final output to lat and long from radians
     for j = 1:lenM
         M(j,6) = M(j,6)*180/pi;
         M(j,7) = M(j,7)*180/pi;
     end

    filename_out = ['E:\Higgins_Lake\VegMap\SonarTRX-16AUG12LOW-20140525-
134342\Images-SpeedCorrected\test\',files(z).name];%(1:end-
4),'_vegOUT_fin.csv'];
    dlmwrite(filename_out, M,'precision','%.13f');  %rewrites output file
with lat and long now included, and set to 13 decimel places
end



%Py = csvread('E:\Higgins_Lake\VegMap\SonarTRX-16AUG12LOW-20140525-
134342\*.CSV');
```

Literature Cited

Angradi, Ted R., Mark S. Pearson, David W. Bolgrien, Brent J. Bellinger, Matthew A. Starry, and Carol Reschke. 2013. "Predicting Submerged Aquatic Vegetation Cover and Occurrence in a Lake Superior Estuary." *Journal of Great Lakes Research* 39 (4): 536–46.

Bretschneider, C. L. 1966. "Wave generation by wind, deep and shallow water." *Estuary and coastline hydrodynamics*, 133-196.

Chambers, Patricia A. 1987. "Nearshore Occurrence of Submersed Aquatic Macrophytes in Relation to Wave Action." *Canadian Journal of Fisheries and Aquatic Sciences* 44 (9): 1666–69.

Fielding, A. H., and J. F. Bell. 1997. "A review of methods for the assessment of prediction errors in conservation presence/absence models." *Environmental Conservation* 24:38-49.

Huron Pines Resource Conservation & Development Area Council, Inc., 2002. "Eurasian Watermilfoil in Higgins Lake: A Resource Assessment."

Hutchinson, G. E. 1975. *A treatise on limnology. Volume III. Limnological botany*. Wiley.

Jupp, B. J., and D. H. N. Spence. 1977. "Limitations of Macrophytes in a Eutrophic Lake, Loch Leven: II. Wave Action, Sediments and Waterfowl Grazing." *The Journal of Ecology* 65 (2): 431.

Keddy, Paul A. 1982. "Quantifying within-Lake Gradients of Wave Energy: Interrelationships of Wave Energy, Substrate Particle Size and Shoreline Plants in Axe Lake, Ontario." *Aquatic Botany* 14 (0): 41–58.

King, J. E. 2008. "Binary logistic regression." *Best practices in quantitative methods*, 358-384.

Koch, Evamaria W. 2001. "Beyond Light: Physical, Geological, and Geochemical Parameters as Possible Submersed Aquatic Vegetation Habitat Requirements." *Estuaries* 24 (1): 1–17.

Lee Long, W. J., Roder, C. A., McKenzie, L. J., & Hundley, A. J. 1998. "Preliminary evaluation of an acoustic technique for mapping tropical seagrass habitats." Great Barrier Reef Marine Park Authority.

Maceina, M. J., & Shireman, J. V. 1980. "The use of recording fathometer for determination of distribution and biomass of hydrilla." *Journal of Aquatic Plant Management*, *18*, 34-39.

Minnerick, R.J. 2001. Effects of Residential Development on the Water Quality of Higgins Lake, Michigan 1995-99. Dept. of the Interior, U.S. Geological Survey, Water Resources Division, Michigan District.

Moreno, A., Siljestrom, P., & Rey, J. 1998. “Benthic phanerogam species recognition in side scan sonar images: Importance of the sensor direction.” In A. Alippi, & G. B. Cannelli (Eds.), *Proceedings of the 4th European Conference on Underwater Acoustics. Italian National Research Council, Rome, Italy* (pp. 173-178).

Oliver, M. A., & Webster, R. 1990. “Kriging: a method of interpolation for geographical information systems.” *International Journal of Geographical Information System*, 4(3), 313-332.

Powles, Stephen B. 1984. “Photoinhibition of Photosynthesis Induced by Visible Light.” *Annual Review of Plant Physiology* 35 (1): 15–44.

Robusto, C. C. 1957. “The Cosine-Haversine Formula.” *The American Mathematical Monthly*, 64 (1): 38–40.

Sabol, B. M., & Burczynski, J. 1998. “Digital echo sounder system for characterizing vegetation in shallow-water environments. “In *Proceedings of the Fourth European Conference on Underwater Acoustics* (Vol. 1998, pp. 165-171). Rome, Italy.

Sabol, Bruce M., R. Eddie Melton, Robert Chamberlain, Peter Doering, and Kathy Haunert. 2002. “Evaluation of a Digital Echo Sounder System for Detection of Submersed Aquatic Vegetation.” *Estuaries* 25 (1): 133–41.

Stein, M. L. 1999. “Interpolation of spatial data: some theory for kriging.” Springer Science & Business Media.

U.S. Army Coastal Engineering Research Center. 1977. *Shore Protection Manual*. Vol.1. 3rd edn., U.S. Government Printing Office, Washington, DC, 514 pp.

Valley, Ray D., Melissa T. Drake, and Charles S. Anderson. 2005. “Evaluation of Alternative Interpolation Techniques for the Mapping of Remotely-Sensed Submersed Vegetation Abundance.” *Aquatic Botany* 81 (1): 13–25.

Wiley, M. J., R. W. Gorden, S. W. Waite, and T. Powless. 1984. “The Relationship between Aquatic Macrophytes and Sport Fish Production in Illinois Ponds: A Simple Model.” *North American Journal of Fisheries Management* 4 (1): 111–19.

Winfield, I. J., C. Onoufriou, M. J. O’Connell, M. Godlewska, R. M. Ward, A. F. Brown, and M. L. Yallop. 2007. “Assessment in Two Shallow Lakes of a Hydroacoustic System for Surveying Aquatic Macrophytes.” *Hydrobiologia* 584 (1): 111–19.