5-2014

Distribution and Drivers of a Widespread, Invasive Wetland Grass, *Phragmites australis*, in Great Salt Lake Wetlands

Arin Lexine Long
Utah State University

DISTRIBUTION AND DRIVERS OF A WIDESPREAD, INVASIVE WETLAND GRASS,

PHRAGMITES AUSTRALIS, IN GREAT SALT LAKE WETLANDS

by

Arin Lexine Long

A thesis submitted for the fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Ecology

Approved:

Dr. Karin Kettenring Major Advisor	Richard Toth Major Advisor
Dr. Christopher M.U. Neale Committee Member	Dr. Charles P. Hawkins Committee Member

Dr. Mark R. McLellan
Vice President for Research and
Dean of the School of Graduate Studies

UTAH STATE UNIVERSITY
Logan, Utah

2014

ABSTRACT

Distribution and Drivers of a Widespread, Invasive Wetland Grass, *Phragmites australis*, in Great Salt Lake Wetlands

by

Arin Lexine Long, Master of Science

Utah State University, 2014

Major Professor: Dr. Karin Kettenring
Department: Watershed Sciences

The introduced grass *Phragmites australis* (hereafter *Phragmites*) is one of the most widespread invasive plants in North American wetlands. *Phragmites* has been extensively studied in some regions of North America, such as the Chesapeake Bay and the Great Lakes, but little research has evaluated the extent and drivers of *Phragmites* invasion in the Intermountain West, particularly around the hemispherically important Great Salt Lake (GSL) wetlands. We used high resolution multispectral imagery to map the current distribution of *Phragmites* around GSL. We then used random forest models to determine factors associated with *Phragmites* presence in GSL and compared these factors with what is known about *Phragmites* invasion in other regions. We used these results to identify areas around GSL that might be vulnerable to future invasion. Using these methods, we estimated that *Phragmites* occupies over 93 km^2 around GSL. *Phragmites* was more likely to be found in wetland areas close to point sources of pollution, with lower elevations with prolonged inundation, and with moderate salinities.

Results from our study will assist wetlands managers in prioritizing areas for *Phragmites* monitoring and control by closely monitoring areas of prime *Phragmites* habitat.

(51 pages)

PUBLIC ABSTRACT

Distribution and Drivers of a Widespread, Invasive Wetland Grass, *Phragmites australis*, in Great Salt Lake Wetlands

by

Arin Lexine Long

Non-native invasive plant species can often have negative effects on native ecosystems, such as altered nutrient cycling, decreased habitat for wildlife, and outcompeting native plants. Around the Great Salt Lake (GSL), Utah, the invasive wetland grass *Phragmites australis* has become abundant in wetlands around the lake. *Phragmites* is replacing many native wetland plants provide important waterfowl habitat around the GSL. For successful management of *Phragmites* in GSL wetlands, it is important to know the current distribution of *Phragmites*, as well as areas that might be vulnerable to future invasion by *Phragmites*. To do this, we used multispectral aerial imagery to map the current distribution of *Phragmites*. We then created a model that statistically related the *Phragmites* distribution data to a suite of environmental predictor variables such as salinity, proximity to nutrient sources, or proximity to roads. Results from our model suggest that *Phragmites* is more likely to be found in wetland areas close to point sources of pollution, with lower elevations with prolonged inundation, and with moderate salinities. We used these results to identify areas around GSL that might be vulnerable to future invasion. Results from our study will assist wetlands managers in

prioritizing areas for *Phragmites* monitoring and control by closely monitoring areas of prime *Phragmites* habitat.

ACKNOWLEDGMENTS

I would like to thank my advisor, Karin Kettenring, and committee members Richard Toth, Christopher Neale, and Charles Hawkins for their guidance and encouragement throughout this project. Additionally, members of the Kettenring Wetland Ecology Lab provided valuable and constructive feedback during many stages of this project. Ashish Mashish provided assistance with aerial imagery processing. Joe Wheaton let me use his labs high powered computer for running several large analysis tasks. Many Great Salt Lake wetland managers and stakeholders provided essential feedback and field support during multiple stages of this project. Howard Browers, Laura Vernon, and Rich Hansen and other members of the South Shore Cooperative Weed Management Area were especially helpful. Thank you to the Watershed Sciences Department and Ecology Center for providing inspiring and supportive learning communities. Brian Bailey and Enid Kelley in the Watershed Sciences office were always extremely helpful and patient whenever I needed help. Funding for this project was supported by the Environmental Protection Agency; Kennecott Utah Copper Charitable Foundation; U.S. Fish and Wildlife Service; Utah Division of Forestry, Fire & State Lands; Utah Division of Water Quality; Utah Division of Wildlife Resources; Utah Wetlands Foundation; and the Utah Agricultural Experiment Station. Additionally, the USU office of Research and Graduate Studies, the Ecology Center, and the Lawrence W Muszynski Memorial Scholarship provided funding for conference travel.

My friends, family, and husband, Nate, were sources of endless support and encouragement throughout my graduate experience, for which I am extremely grateful.

Arin Lexine Long

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Invasive plants can negatively affect wetland ecosystems by outcompeting native vegetation, decreasing wildlife habitat, reducing water quality, and altering nutrient cycles (Zedler and Kercher 2005). Wetland systems are especially vulnerable to plant invasions as they act as landscape sinks where plant propagules and pollutants, including nutrients from upstream can accumulate (Zedler and Kercher 2004). Because of the increased vulnerability of wetlands to invasion there is a need for innovative tools for invasive species monitoring and management. Successful management of invasive wetland vegetation requires a comprehensive approach, including mapping the current distribution of invasive species, understanding the drivers of invasion, determining risk of invasion at currently unoccupied sites, and prioritizing control and management efforts (Jakubowski et al. 2010).

Detailed distribution data across large extents are important for successful invasive species management (Bradly and Marvin 2011). However, developing detailed distribution maps across large areas (such as watersheds) can be expensive, time consuming, and impractical (Andrew and Ustin 2009, Adam et al. 2009, Bradley and Marvin 2011), particularly in wetlands, which can be hard to access due to flooded conditions. Advances in remote sensing technology have led to increased availability of high resolution data (1m or less), making it possible to create detailed distribution maps of vegetation at the species level (Adam et al. 2009). In fact, remotely sensed environmental and species presence data have been shown to perform as well as field data when used in ecological modeling applications (Davis et al. 2007). Such data can be useful for (1) managing current invasions (i.e., where to target control efforts), (2) assisting with early detection and rapid response efforts (EDRR) by identifying small, isolated stands of invasive vegetation (Bradley and Marvin 2011), (3) monitoring changes in the distribution of invasive wetland vegetation over time, and (4) can be used as presence and absence inputs for predictive species distribution models (Santos et al. 2009).

Identifying environmental factors that may increase the likelihood of invasion, and predicting areas vulnerable to invasion, is another important aspect of invasive species management in wetlands (Gallien et al. 2010, Jakubowski et al. 2010, Bradley and Marvin 2011). Species distribution modeling (SDM) is a correlative statistical technique that associates presence or absence of species with biotic or abiotic predictor variables (Franklin 2009). Use of SDM is becoming increasingly common in invasion ecology to explain current distributions of riparian and wetland invasive species and predict areas of future invasions (Andrew and Ustin 2009, Menuz and Kettenring 2012. This information can aid land managers in prioritizing areas for EDRR efforts, and addressing factors that can make areas more vulnerable to invasion (Franklin 2009, Dullinger et al. 2009, Stohlgren et al. 2010). SDM requires detailed, fine-resolution data sets collected over large spatial scales, making data derived from remote sensing a good option for use in developing SDMs.

Introduced *Phragmites australis* (common reed; hereafter *Phragmites*), which includes multiple haplotypes introduced from Eurasia, is one of the most problematic invasive plants in North American wetlands (Saltonstall 2002, Meyerson et al. 2012, Kettenring et al. 2012). *Phragmites* is a tall (2-4 m), clonal, perennial grass, found in freshwater and brackish wetlands and moist, disturbed habitats. It creates dense monocultures and thereby displaces beneficial native wetland vegetation and reduces the quality of the habitat and ecosystem services provided by wetlands (Silliman and Bertness 2004, Chambers et al. 2008). Significant resources are spent controlling introduced *Phragmites* on public and private lands across North America including our study area, the Intermountain West (Hazelton et al 2014, Kettenring et al 2012, Martin and Blossey 2013). It is therefore essential for *Phragmites* managers to understand both the current extent of invasion and biotic and abiotic conditions that contribute to invasion (Carlson Mazur 2014).

Phragmites invasion has been linked to human disturbance and elevated nutrients in a number of experimental studies in New England, Chesapeake Bay, and the Great Lakes region of North America (Silliman and Bertness 2004, King et al. 2007, Chambers et al. 2008, Tulbure and Johnston 2010, Bourgeau-Chavez et al. 2012). However, little research has evaluated drivers of *Phragmites* invasion outside of these regions where *Phragmites* is also prolific but its invasion is less well understood. Understanding the ecological patterns of *Phragmites* invasion across different regions in North America is important for a more comprehensive understanding of its invasion ecology under different conditions (Kettenring et al. 2012).

Here we apply high-resolution remote sensing technology and SDM to understand the distribution of *Phragmites* in wetlands of the Great Salt Lake (GSL), the largest saline lake in North America (Figure 1). The 1,600 km^2 of wetlands around GSL constitute the majority of wetlands in the state of Utah, provide critical habitat to migratory birds on the Pacific and Central flyways (Paul and Manning 2002, Evans and Martinson 2008), and are a significant portion of wetlands in the Intermountain West . The goals of our study were to: (1) map the current distribution of *Phragmites* around GSL, (2) determine factors associated with *Phragmites* presence in GSL and compare these factors with what is known about *Phragmites* invasion in other regions, and (3) identify areas around GSL that might be vulnerable to future invasion.

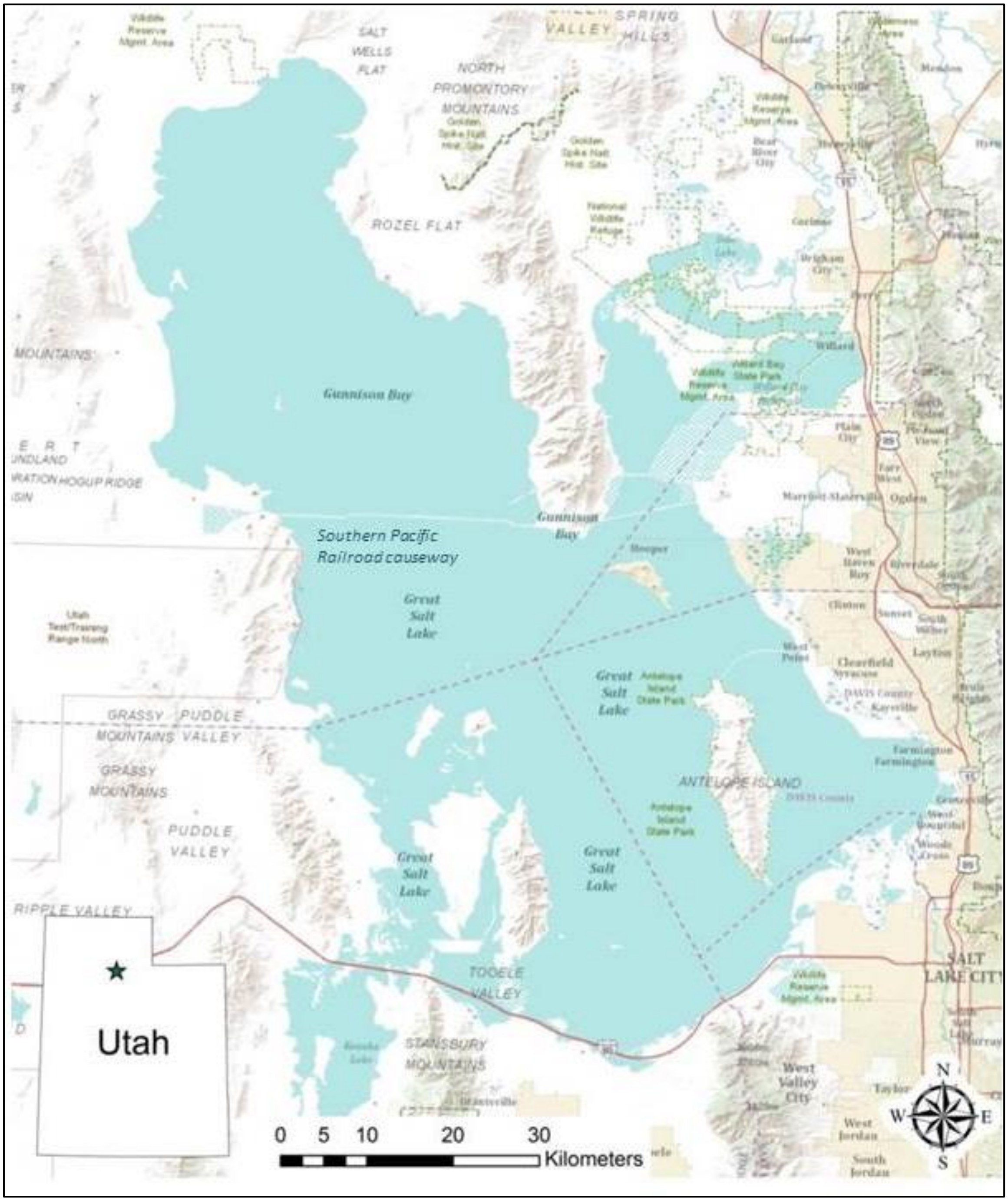


Figure 1. Map of the Great Salt Lake, UT, study region

CHAPTER 2

METHODS

We used Utah State University's (USU) airborne multispectral digital imagery system to acquire one-meter resolution imagery in all major wetland areas around GSL, a total of 1874.5 km^2. Interference bands to capture green (0.545–0.555 μm), red (0.665–0.675 μm), and near infrared (NIR) (0.790–0.810 μm) wavelengths. Image acquisition flights were flown during May and June 2011 under clear sky conditions. At the time of the flights in May and June, some but not all vegetation had emerged. This time of year can be an ideal time to distinguish *Phragmites* using remote sensing since species are at different growth stages and therefore spectral differentiation between vegetation types is possible (Maheu-Giroux and Blois 2005, Neale et al. 2007). One-meter LiDAR (Light Detection and Ranging) imagery for fine scale digital elevation models (DEM) for the same wetland areas was collected in September 2011.

We identified and took GPS points of plant species at known locations to use as training points for image classification. We visited major wetland complexes captured by the imagery in fall 2011 and spring 2012 to acquire sample points (n=1,236 ground training points). We sampled at randomly selected locations at 12 different wetland sites. We sampled at a minimum of 10 locations for each vegetation type at each site. We sampled in areas that were larger than the minimum mapping unit of the aerial imagery (1m), were dense monocultures of the vegetation type, and were well distributed across the field site.

We orthorectified, mosaicked, and calibrated the images using ERDAS Imagine 2010 before performing supervised classification of the imagery. Supervised classification is performed by using training pixels for each vegetation class based on known vegetation determined from field collected data. The computer then assigns the remaining pixels to the class that most closely matches the training pixels (Figure 2). We analyzed the training pixel signatures for spectral overlap with the Transformed Divergence method. If the training pixel signatures were too spectrally similar to each other we kept only one of the two training pixels (see methods in Neale et al. 2007). We classified vegetation into nine groups of major vegetation (Table 1). Where necessary, we manually recoded a small portion of pixels based on field data that were misclassified.

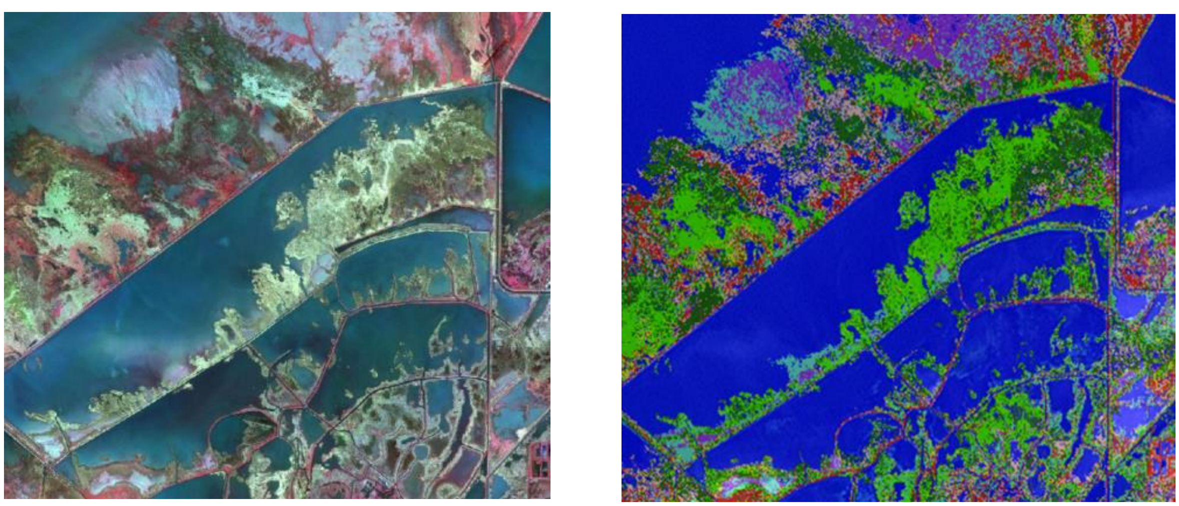


Figure 2. Example of the 1-m multispectral aerial imagery (left) and resulting classified raster (right) from Farmington Bay Wildlife Management Area produced as part of our vegetation classification efforts in Great Salt Lake wetlands. Multispectral imagery on the left consists of red, green, and NIR bands.

Following classification, we conducted an accuracy assessment to validate the imagery using about half of the field data points. We calculated user's accuracy, producer's accuracy, overall accuracy, errors of commission, and errors of omission. User's accuracy is calculated by dividing the number of correctly classified pixels in a class by the total number of pixels in that class, and is used as a measure of the reliability of a classification accuracy (Jones and Vaughn 2010). Errors of commission are calculated by subtracting 1 – the user's accuracy. Producer's accuracy is calculated by dividing the number of ground truthing data points that were correctly classified by the total number of ground truthing field points. Errors of omission are calculated by subtracting 1 minus the producer's accuracy (Jones and Vaughn 2010). After the raster data were classified, we calculated area of each vegetation class, percent of total area occupied by each class, and area of *Phragmites* in each of seven of the major managed wetland areas around GSL.

Table 1. Great Salt Lake wetland vegetation area derived from vegetation classification of remote sensing imagery.

Class Name	**Area (km^2)**	**Percent**
Open water	635.22	33.9 %
Phragmites australis (common reed)	93.29	5.0 %
Playa wetlands	382.22	20.4 %
Salicornia spp. (pickleweed) wetlands	50.72	2.7 %
Distichlis spicata (saltgrass)	77.11	4.1 %
Typha spp. (cattail species)	114.72	6.1 %
Schoenoplectus acutus (hardstem bulrush)	30.63	1.6 %
Other emergent wetland vegetation	126.30	6.7 %
Upland	363.91	19.4 %

Model predictor variables

We selected candidate model predictor variables that we expected to be important to *Phragmites* establishment and spread. We assessed correlations between the variables with Pearson correlations, and eliminated any variables that were highly correlated using 0.6 as a threshold. We assembled spatially explicit predictor variables in ArcMap 10.1. We chose predictor variables that would describe environmental characteristics (such as nutrient levels, hydrology, and salinity) and disturbance characteristics (such as land use, wetland impoundment, and road density) that may influence *Phragmites* distribution in GSL. Salinity in GSL wetlands varies with location, and is driven largely by inputs from freshwater streams and lake level (Hoven and Miller 2009, Sumner et al. 2010). GSL wetlands are often impounded to give managers increased control of water levels so they can maximize water levels for waterfowl and shorebird habitat, resulting in highly modified hydrology (Downward et al. 2013) . Additionally, GSL wetlands receive nutrient inputs from treated wastewater effluent discharges and other point sources of pollution (Carling et al. 2013).

We used LiDAR data points to create a 1m Digital Elevation Model (DEM), from which we derived site elevation, slope, and aspect. We extracted data on soil texture, soil drainage class, and soil hydrologic group from the Soil Survey Geographic Database (SSURGO) database (NRCS 2010). We used land cover data from the USGS National Land Cover Database (NLCD) to determine percent of agricultural land and percent of developed land (urban and surburban) within a 500m buffer surrounding the *Phragmites* patch. We selected the 500 m buffer distance based on literature review and wetland manger expert opinion (DeLuca et al. 2004, King et al. 2007).

We used distance to point sources of pollution as a measure of likely relative differences in nutrient inputs. Locations of major point sources of pollution were extracted from the National Pollutant Discharge Elimination System (NPDES) dataset from the EPA Enforcement and Compliance History (ECHO) database (EPA 2013). NPDES permits regulate point sources where pollutants are discharged into US waterways, and generally include pesticide discharges, combined sewer overflows, sanitary sewer overflows, treated wastewater effluent, stormwater discharges, and discharges from concentrated animal feeding operations (EPA 2013). Permitted discharges into GSL include discharges from municipal wastewater treatment facilities, stormwater, mineral extraction facilities, and other industrial facilities (Utah Department of Natural Resources 2011). We used distance from the nearest freshwater input, derived from the Utah Major Rivers and Streams layers from the Utah AGRC website, as a measure of relative salinity. Salinity differences in the GSL are heavily influenced by freshwater inflow coming from the Bear, Weber, and Jordan River drainages, as well as minor side streams (Arnow and Stephens 1990), making distance from freshwater input a reasonable measure of GSL salinity differences. We used the Near function to calculate distances in ArcGIS. Distance to the nearest road, from the Utah AGRC, was used as an index of disturbance. We used 2012 aerial imagery collected by that State of Utah (Utah AGRC) to manually digitize gravel roads and dikes that were missing from the most recent road dataset.

Model development and evaluation

We used Random Forests (RF) to model species distributions. RF is a nonparametric modeling technique that aggregates many different classification and regression tree models that are produced from bootstrapped resampling (Breiman 2001). RF models use a non-parametric classification tree algorithm to sequentially split data into groups that have similar values based on the response variable (Cutler et al. 2007). RF models have been increasingly popular in ecological research because they can handle a large number of predictor variables with complex interactions, are highly accurate, and are relatively easy to interpret (Cutler et al. 2007). We developed our RF models using the *randomForest* package in R 3.0.1 (Liaw and Wiener 2002, R Core Team 2013). We used the final classified imagery to generate presence (n=1000) and absence (n=1000; i.e., areas where *Phragmites* did not occur which were stratified between the remaining non-*Phragmites* vegetation classes) points for *Phragmites* species distribution modeling. To minimize spatial autocorrelation we set a minimum distance of 30m between sample points. We created our initial model with all predictor variables, and chose variables for the final model that maximized model performance, reduced redundancy, and were ecologically interpretable. To determine the optimal set of predictor variables we followed guidelines from Genuer et al. 2010 and Hill et al. 2013, and removed variables with small importance, and then used a stepwise variable selection procedure. We developed the final model by iteratively adding in predictor variables until the addition of predictors no longer improved model performance. Once we selected the optimal set of predictor variables, we ran the model for all raster cells across the entire study area. Our final model included 10 of the original 15 candidate predictor variables (Table 2). We also used the final model to predict the probability (0 to 1) that each raster cell was suitable habitat for *Phragmites*. We used a threshold of 0.65 as determined by the true skill statistic (TSS) to represent *Phragmites* presence. The TSS is calculated by summing the sensitivity and specificity, and then subtracting one, and has been shown to be a reliable presence threshold statistic for use in SDM (Allouche et al. 2006). The resulting raster layer allowed us to calculate suitable *Phragmites* habitat that is currently unoccupied by *Phragmites*.

To test the accuracy of our model we used “out of bag” predictions. We calculated percent correctly classified (PCC), sensitivity, specificity, and area under the curve (AUC). Percent correctly classified is the overall measure of correctly classified pixels in the raster. Sensitivity is a measure of the actual presences that are correctly predicted, and specificity is the proportion of actual absences that are correctly predicted. AUC is true positives (sensitivity) plotted over the false positives (specificity), and evaluates how well a model is discriminating between presence sites and absence sites. The AUC can range from 0 to 1, and is a measure of model accuracy, with 1 being perfect discrimination between presence and absence sites, and 0.5 being no better than random (Fielding and Bell 1997).

We used variable importance plots to evaluate the contribution of each predictor variable to the performance of the model. RF assesses relationships between predictor variables and response variables with variable importance. Variable importance is a comparison of classification accuracy with the variable of interest compared to the

Table 2. Candidate random forest model predictor variables used to create *Phragmites* habitat suitability model. Parenthesis after categorical specifies the number of categories for that variable.

Description	**Range or potential values**	**Units**
Wetland impoundment status	Yes / no	Categorical (2)
Level 8 watershed		Categorical (6)
Percent of landcover that is agricultural within 500 m buffer	0 – 99	%
Percent of landcover that is urban and suburban within 500 m buffer	0 – 82	%
Dominant landcover within 500 m buffer		Categorical (8)
Elevation based on 1m DEM from LiDAR	1280-1725	m
Distance to nearest water control structure	12-6140	m
Distance to nearest road	0 - 6,450	m
Aspect based on 1m DEM from LiDAR	0 - 360	Degrees
Distance from point source pollution	5 – 21,939	m
Distance from freshwater inflow into GSL (as a measure of differences in salinity)	1-27,600	m
Distance to open water	0 – 2,267	m
Soil Drainage Class		Categorical (5)
Soil Hydrologic Group		Categorical (5)
GSL "arm" – north or south	North / South	Categorical (2)

classification accuracy if that variable is randomly permuted (Cutler et al. 2007). Higher variable importance values mean the variable is more important in determining classification accuracy in the model. We used partial dependence plots to examine the relationship between each variable and *Phragmites* presence. Partial dependence plots graphically display the relationship between the probability of presence or absence and the predictor variable (Cutler et al 2007). We used bivariate partial dependence plots to check for interactions between predictor variables. These data are not shown because none of the plots showed strong interactions.

CHAPTER 3

RESULTS

Remote sensing results

From our classification of the high resolution multispectral imagery, we determined *Phragmites* occupies over 93 km^2 (10% of the wetland area) in GSL wetlands (Table 1; Figure 3). Although *Phragmites* is widespread along the eastern shore of GSL, it is particularly prolific in many of the state wildlife management areas and private lands around the east-central portion of GSL (Table 3).

The overall accuracy for the remote sensing classification was 81.1 % (Table 4). Of the classes, open water had the highest user's accuracy, followed by playa wetlands.

Table 3. Square kilometers of *Phragmites* in major Great Salt Lake managed wetland areas, and percent of land occupied by *Phragmites* for each managed land area.

Wetland Area	***Landowner***	***Phragmites* area (km^2)**	**Percent of land occupied by *Phragmites***
Great Salt Lake Shorelands Preserve	The Nature Conservancy	2.69	14.9%
Inland Sea Shorebird Reserve	Kennecott Utah Copper	0.73	4.5%
Harold Crane Wildlife Management Area	State of UT	3.89	9.3%
Farmington Bay Wildlife Management Area	State of UT	6.49	7.3%
Howard Slough Wildlife Management Area	State of UT	1.42	14.8%
Ogden Bay Wildlife Management Area	State of UT	9.74	14.5%
Bear River Migratory Bird Refuge	US Fish & Wildlife Service	18.23	4.4%

Table 4. Classification accuracy measures for remote sensing data. User's accuracy is a measure of the probability a pixel truly being what it is classified as. Producer's accuracy is a measure of the probability of a certain point being correctly classified.

Class Name	**User's accuracy**	**Producer's accuracy**
Open water	95.0%	71.7%
Phragmites australis (common reed)	82.5%	80.1%
Playa wetlands	92.5%	76.3%
Salicornia spp. (pickleweed) wetlands	70.0%	86.2%
Distichlis spicata (saltgrass)	75.0%	92.3%
Schoenoplectus acutus (hardstem bulrush)	71.3%	85.1%
Typha spp. (cattail species)	76.3%	83.6%
Other emergent wetland vegetation	78.8%	86.4%
Upland	88.8%	78.1%
Overall accuracy	**81.1%**	**82.20%**

Phragmites had a user's accuracy of 82.5% and a producer's accuracy of 80.1% (Table 4). *Phragmites* was most commonly confused with the playa wetlands class and less frequently with the *Typha* spp. class and the *Schoenoplectus acutus* class.

Species distribution model results

We used the partial dependence plots to create a variable relationship table that showed the direction of each variable on determining *Phragmites* presence. Predictors with high variable importance values for predicting *Phragmites* presence were distance to open water, elevation, distance to point source of pollution, and distance to freshwater input (Figure 4; Table 5). Distance to open water was by far the most important predictor. The other three variables were less important but still contributed strongly to predicting *Phragmites* occurrence. The model predicted *Phragmites* with an AUC of 0.86, a PCC of 81.3%, specificity of 77.8%, and a sensitivity of 86.43%.

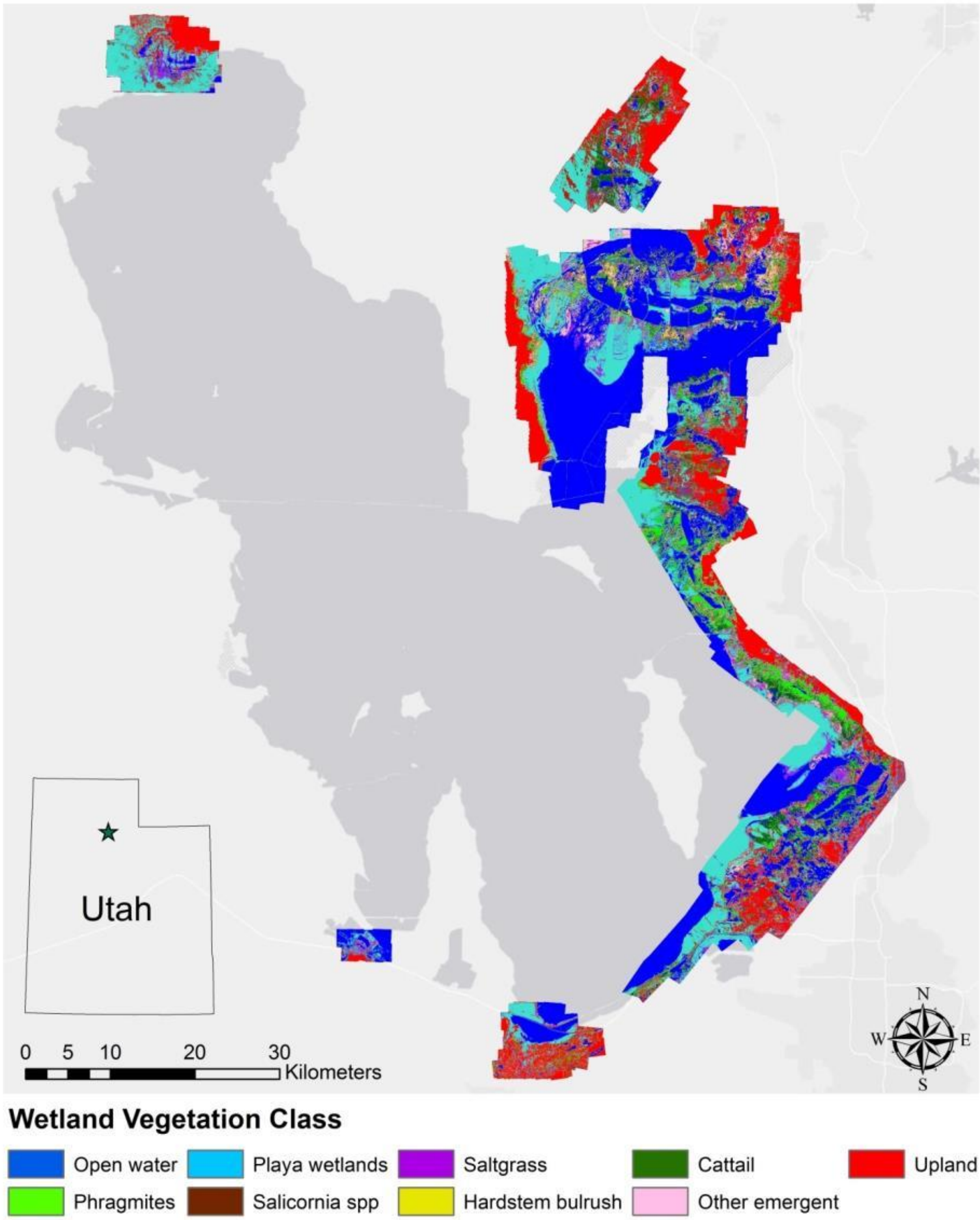


Figure 3. Wetland vegetation distribution around Great Salt Lake wetlands based on classified 1-m multispectral imagery.

We determined that there were 9.55 km^2 of habitat that were identified as suitable for *Phragmites* but not yet invaded (Figure 5). Unoccupied but suitable areas were predominately centered on two regions: (1) around the central portion of GSL, relatively close to where the Salt Lake and Davis County sewer inflows are located and (2) south of Willard Bay, which is near another wastewater treatment plant (Figure 6, 7). Several of the larger wetland complexes, such as the federal Bear River Migratory Bird Refuge (Figure 8), did not contain much suitable but currently unoccupied *Phragmites* habitat.

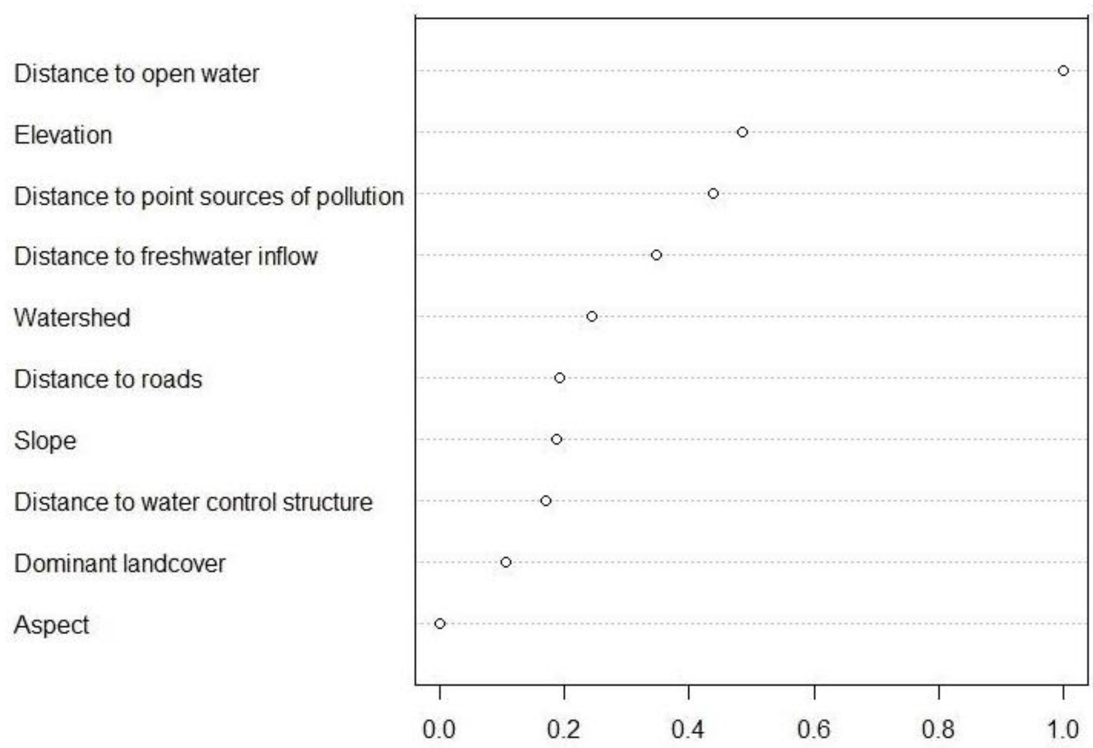
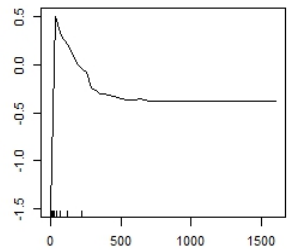
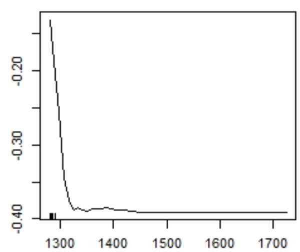
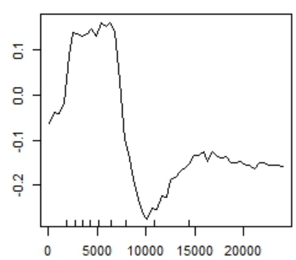
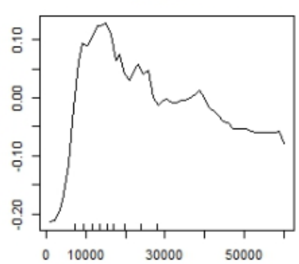
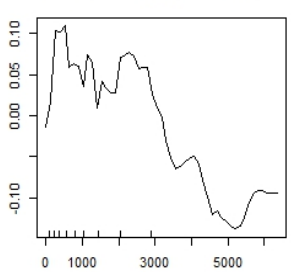
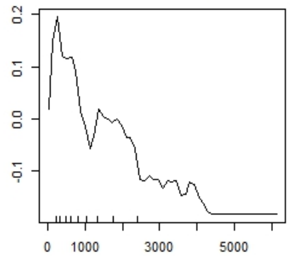
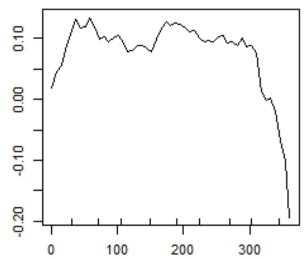
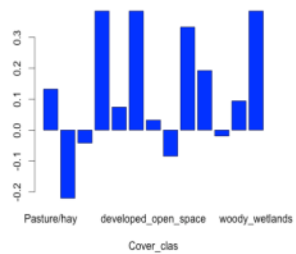
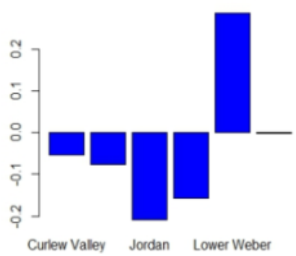
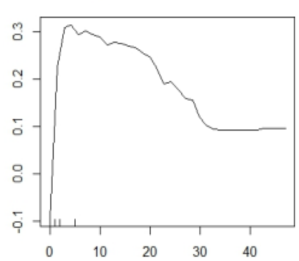


Figure 4. Variable importance plot for variables selected for final model. Variable importance plots show a comparison of classification accuracy with the variable of interest compared to the classification accuracy if that variable is randomly permuted (Cutler et al. 2007). Higher variable importance values mean the variable is more important in determining classification accuracy in the model.

Table 5. Predictor variable relationships with direction of effect and associated mechanisms for final *Phragmites* habitat suitability model. Direction of effect is illustrated by partial dependence plots, which show the marginal effect of a predictor variable on the response variable probability. Variables are listed in order of importance.

Predictor Variable	**Direction of effect**	**Interpretation**
Distance to open water (m)		*Phragmites* is a facultative wetland plant and grows best in moist soil conditions (USDA Plants), so areas closer to open water are better habitat.
Elevation (m)		Lower elevation wetland areas hold water for longer, and therefore are more hospitable for *Phragmites*. Hoffman et al 2008 also found elevation to be an important predictor for *Phragmites* distribution.
Distance to point sources of pollution (m)		Distance from point source discharges such as stormwater and treated wastewater. Point sources contribute additional nutrients to wetlands. Elevated nitrogen often correlates with *Phragmites* presence and abundance (King et al 2007).
Distance to freshwater inflow (m)		Measure of relative salinity around GSL wetlands. Areas closer to freshwater inflows are less saline. *Phragmites* is more likely to be found closer to freshwater inflows in less saline water. These findings are consistent with Vasquez et al. 2005, 2006, Medeiros et al. 2013.
Distance to nearest road (m)		Measure of disturbance. Roads have been correlated with invasive species presence and abundance in other studies (e.g., Menuz et al 2013), but this variable was not a strong predictor in our model.

Distance to water control structure (m)		Measure of hydrologic alteration, as water control structure indicates areas that have modified hydrology due to levees and diking.
Aspect		Low on the list of variable importance, and no clear relationship.
Dominant Land Cover Type within buffer		Developed and agricultural land have been associated with *Phragmites* in other studies (King et al 2007, Chambers et al 2008). Low on the list of variable importance.
Level 8 watershed		Lower Weber watershed most associated with *Phragmites* presence. The Lower Weber watershed contains large areas of rangeland.
Slope		Very low on the list of variable importance. Areas with less slope may hold water for longer, creating more hospitable wetland conditions for *Phragmites* although this relationship does not appear to be strong in our study sites.

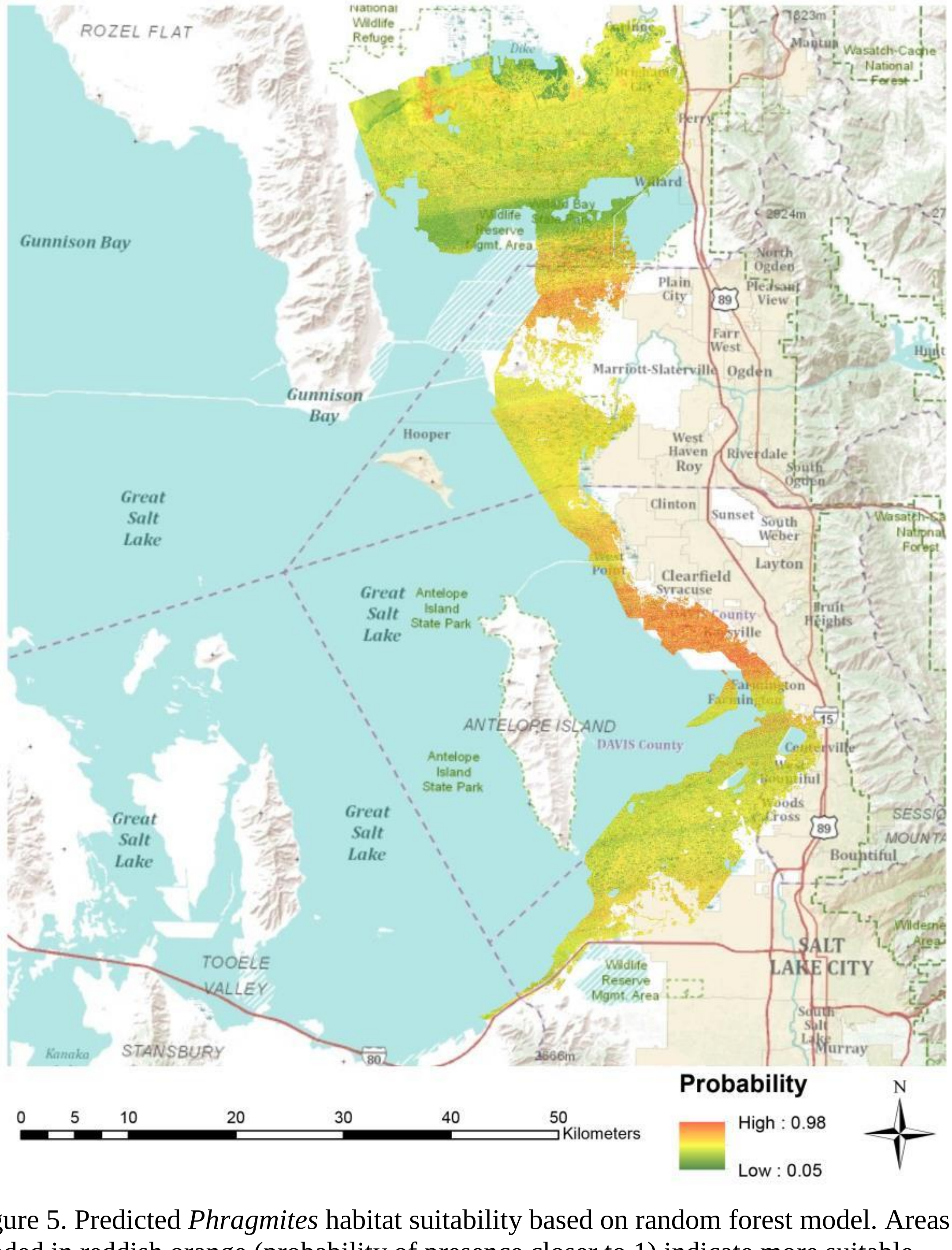


Figure 5. Predicted *Phragmites* habitat suitability based on random forest model. Areas shaded in reddish orange (probability of presence closer to 1) indicate more suitable habitat for *Phragmites*; areas shaded with greener colors (probability or presence closer to 0) are less suitable habitat for *Phragmites*.

We determined that there were 9.55 km^2 of habitat that were identified as suitable for *Phragmites* but not yet invaded (Figure 5). Unoccupied but suitable areas were predominately centered on two regions: (1) around the central portion of GSL, relatively close to where the Salt Lake and Davis County sewer inflows are located and (2) south of Willard Bay, which is near another wastewater treatment plant (Figure 6, 7). Several of the larger wetland complexes, such as the federal Bear River Migratory Bird Refuge (Figure 8), did not contain much suitable but currently unoccupied *Phragmites* habitat.

CHAPTER 4

DISCUSSION

Improved management of widespread invasions in wetlands requires an approach that integrates: (1) distribution mapping to describe the scale of the problem; (2) efforts to understand the drivers of the invasion, which can focus future management; and (3) predictions on where the species may spread to guide early detection and rapid response of new invasions. We applied this framework to the widespread invasion of *Phragmites* in wetlands along the largest saline lake in North America, the Great Salt Lake. We demonstrate that high resolution remote sensing proved to be an effective tool for mapping wetland vegetation. *Phragmites* occupies large areas (more than 93.1 km^2) and impacts virtually all of the wetland areas around GSL. By using SDM to identify environmental factors that correspond with *Phragmites* distribution we are able to highlight areas vulnerable to future invasion. This framework can be applied to other regions in North America, particularly in the Intermountain West, where this species has been largely unstudied and management needs are great.

The factors that were associated with *Phragmites* distribution around GSL do, in some cases, mirror results from *Phragmites* studies in other regions of North America. For example, hydrology and salinity are often closely linked with *Phragmites* distribution, which was reflected in our results as well. However, key differences between our findings and those of other regions exist. For example, *Phragmites* presence has often been correlated with land use such as in highly developed or agricultural watersheds (Silliman and Bertness 2004, King et al. 2007, Chambers et al. 2008).

However, we found distance from point sources of pollution to be a stronger predictor of *Phragmites* presence than surrounding land use. These differences underscore the need for regional wetland invader research to understand continental-scale invasions (Kettenring et al. 2012).

Hydrology

The two most important factors for explaining *Phragmites* presence were related to hydrology; distance to open water was by far the most important. *Phragmites* was more likely to be found closer to open water, which is not surprising as *Phragmites* is a facultative wetland plant (USDA 2014), and its ideal habitat is anywhere with moist soil conditions. Elevation was also an important hydrologic variable that correlated with *Phragmites* presence. *Phragmites* was more likely to be found in lower elevations around GSL. Elevation is often associated with or used as a proxy for hydrology in wetland studies because it correlates with differences in water levels and flooding frequency (Welch et al. 2006, Hoffman et al 2008, Andrew and Ustin 2009). Due to the arid environment of Utah, GSL wetlands dry up substantially during the summer months (Carling et al. 2013), such that lower elevations are the only remaining hospitable habitat for wetland vegetation, and therefore provide more favorable moisture conditions for *Phragmites*.

Salinity

Salinity levels vary greatly in wetlands around GSL (1-28%) largely due to anthropogenic physical barriers that prevent water flow such as the Southern Pacific

Railroad and Antelope Island causeways, and inputs from freshwater rivers and streams feeding GSL wetlands (Bear, Weber, and Jordan Rivers) that result in lower salinities near inflows (Gwynn 1980, Belovsky et al. 2011) (Figure 1). We found there was a greater likelihood of *Phragmites* presence in areas closer to freshwater inputs, meaning areas that are less saline. These findings are consistent with other studies that have shown that while *Phragmites* can tolerate a range of salinity conditions, it is often found to have higher biomass and survival at low to medium salinity levels (0-5%) (Chambers et al. 2003, Vasquez et al. 2005, 2006, Medeiros et al. 2013). When salinity is too high (>20%), *Phragmites* can have decreased germination, survival, and growth, and is not as competitive when compared with true halophytic plants (Chambers et al. 2003, Brisson et al. 2010).

We used distance to freshwater inputs as a proxy for differences in salinity around the lake, as this was the best available measure of salinity given the scale and resolution of our project. Current GSL salinity models show how river inflows and evaporation change the salinity levels in each arm of the lake (north vs. south), but these models do not show changes in relative salinity on a finer scale (Mohammed and Tarboton 2012, White et al. 2014). More precise salinity measurements on a lake-wide scale could improve the model and further clarify the effects of salinity on *Phragmites* in brackish wetlands.

Nutrient levels

Phragmites invasion has often been correlated with elevated nutrient levels in other regions of North America (Silliman and Bertness 2004, King et al. 2007, Chambers et al. 2008, Brisson et al. 2010). *Phragmites* is a high-nutrient specialist and has increased abundance, reproduction, growth, and biomass production with elevated nutrient levels than native *Phragmites* or other native wetland plants (Saltonstall and Stevenson 2007, King et al. 2007, Chambers et al. 2008, Mozdzer and Zieman 2010, Kettenring et al. 2011). For example, King et al 2007 found that in watersheds with higher anthropogenic development, nitrogen levels were higher in the water and *Phragmites* was more abundant and had elevated foliar nitrogen levels than in less-developed watersheds. They also concluded that direct sources of nutrients such as point source discharges had a greater influence on *Phragmites* abundance than areas with non-point sources of pollution such as agricultural lands (King et al. 2007). Similarly, we found that *Phragmites* was more common closer to point sources of pollution around GSL. Previous research found that *Phragmites* cover in Farmington Bay of GSL was positively correlated with several water quality metrics, including total phosphorous, pH, and dissolved oxygen (Madon 2005) . GSL wetlands receive nutrient inputs from a number of point sources, such as treated wastewater effluent from sewage treatment plants, discharge of water from industrial uses, and stormwater discharge points (Utah Division of Water Quality 2012). Treated wastewater effluent often still contains high levels of nitrogen and phosphorous (Utah Department of Natural Resources 2011). Stormwater runoff and treated wastewater effluent is projected to increase with growing development and urbanization in GSL watershed (projected 2% between 2005 and 2020; Sumner et al. 2010, Carling et al. 2013). Based on the results of our study, we expect these changes to further benefit *Phragmites* invasion in GSL wetlands.

While distance to point sources of pollution was found to be important to explaining *Phragmites* distribution, agricultural land or percent of developed land within a 500 m buffer were less important for predicting *Phragmites* presence around GSL. Consistent with our results, previous water quality monitoring in Farmington Bay of the GSL found wetlands with higher nutrient content often dominated by *Phragmites* (CH2M Hill 2005). However, our findings contrast with previous work on the Atlantic coast that shows that the amount of agricultural land and suburban and urban development within a buffer were associated with higher *Phragmites* presence and abundance (Silliman and Bertness 2004, King et al. 2007, Chambers et al. 2008). In our work, percent of agriculture within a buffer was minimally important for *Phragmites* presence, and percent of development within a buffer was not important at all. However, levels of development and land cover do not vary as much around GSL compared with other *Phragmites* research done at larger spatial scales. Additionally, much of the heavily developed or agricultural areas are further upstream in GSL watershed than our buffer distance, therefore allowing capture and integration of nutrients across multiple land use types before discharging into GSL wetlands as point sources. In GSL wetlands point sources of pollution discharge may carry a greater amount of nutrients than is captured by the amount of agricultural or developed land within a buffer, which could explain why we saw differences in nutrient variable importance in our study and differing results from previous *Phragmites* research. Given the scale and resolution of our study, distance to point sources where nutrient loads are discharging into the GSL was the best available relative nutrient input measure. Relatively little research has been done on GSL nutrient dynamics (Belovsky et al. 2011), and additional research on influence of nutrient inputs and *Phragmites* presence around the GSL would be beneficial (Downard et al. 2013).

Disturbance and propagule dispersal pathways

Proximity to or density of roads are often used as a measure of disturbance and propagule sources in SDM because roads can serve as introduction pathways or corridors for invasive species (e.g., Menuz and Kettenring 2012). However, we did not find roads to be a strong predictor of *Phragmites* presence even though proximity to roads has been an important predictor of *Phragmites* distribution in other studies (Brisson et al. 2010). Roads were one of the factors that facilitated the spread of *Phragmites* along the St. Lawrence River in Quebec (LeBlanc et al. 2010). In GSL, many wetland areas are accessible by roads or gravel dikes, and in general, there is little variation in distance to roads around the lake, which could be why road proximity had lower importance values than initially expected.

Disturbances such as shoreline alteration and dredging and diking of wetlands have been suggested as factors that could potentially facilitate spread and growth of *Phragmites* by opening up additional habitat (Chambers et al. 1999, 2003 Hudon et al. 2005, Welch et al. 2006) and have been associated with the presence of other invasive species such as reed canary grass, *Phalaris arundinacea* (Kercher and Zedler 2004). Many GSL wetlands are impounded, and we expected that areas with these hydrologic modifications might be more likely to have *Phragmites* as the dikes could have served as invasion pathways. However, impoundment status and distance to water control structure (our measures of hydrologic disturbance) were very low on the list of important variables for *Phragmites* presence. Many of these hydrologic modifications have been in place for decades, and their role as invasion pathways may be less important currently than other environmental conditions such as moisture and salinity.

While our model provided useful information on factors associated with *Phragmites*, it is important to note that SDMs are a purely correlative technique. Distributions of invasive species are also influenced by factors such as propagule pressure and residence time (Wilson and Richardson 2007, Broennimann and Guisan 2008), which we were not able to account for in our model. We used the best predictor variables that were available to us, and we believe they described the environmental conditions around GSL fairly well. For variables such as salinity and distance to point sources of pollution, we used the best available data for the scale of study, but finer scale environmental monitoring data could provide a more detailed and nuanced picture of factors driving *Phragmites* invasion. Environmental and disturbance data of this quality at the large scale of our study are rarely available, so there is a tradeoff between spatial extent of the study and resolution of data sets of predictor variables.

CHAPTER 5

CONCLUSIONS

To effectively manage invasive species in wetlands it is important to map, monitor, and understand factors driving invasion, particularly at the landscape scale. While, a number of other studies have used remote sensing to map invasive *Phragmites* distribution (Maheu-Giroux and Blois 2005, Pengra et al. 2007, Ghioca-Robrecht et al. 2008, Laba et al. 2008, Torbick et al. 2010, Bourgeau-Chavez et al. 2012), previous mapping was often done at lower resolutions (such as with Landsat imagery). Our high resolution imagery allowed us to map *Phragmites* and other wetland vegetation to the species level, and capture smaller stands of *Phragmites* that may be newer invasions and require immediate management attention. Making such data available to relevant stakeholders is essential to improving management. In our case, we created an interactive online website that displays the classified imagery and allows managers to further evaluate *Phragmites* on their management areas (http://maps.gis.usu.edu/gslw/index.html).

By using SDM to identify factors that correlate with *Phragmites* presence, we were able to pinpoint some of the potential root causes that may be facilitating *Phragmites* expansion, and identify areas that may be vulnerable to *Phragmites* invasion. When managing *Phragmites*, it will be necessary to also address factors that promote *Phragmites* expansion such as elevated nutrient levels. In particular, around GSL wetlands, this might mean reducing the amount of pollution that is being discharged into GSL from point sources by more widespread use of best management practices for stormwater and wastewater effluent (Utah Division of Water Quality 2012). Areas that are not currently occupied by *Phragmites*, but were identified as suitable habitat will be important areas to monitor for *Phragmites* expansion and subsequent EDRR efforts. More specifically, areas with elevated nutrient levels, lower elevations with prolonged inundation, and moderate salinities are prime habitat for *Phragmites* and should be monitored closely for expansion.

SDM can be useful to management of invasive species, and could be incorporated more commonly into invasive species management planning by wetland scientists and managers. While SDMs have become more popular in ecology in recent years, often the results from models are not used to make management decisions (Addison et al. 2013). There is a clear need to take the general recommendations provided by SDM results and translate these recommendations into more specific management actions for how to best prevent new invasions and prioritize management of invasive species (Papeş et al. 2011). Results from our model can be used to prioritize areas for *Phragmites* control, restoration, and monitoring across our study region. Additionally, our integrated remote sensing and SDM approaches, combined with the interactive website, provide an example for others to emulate for management of wetland invaders in other regions.

REFERENCES

Adam E, Mutanga O, Rugege D (2009) Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. Wetlands Ecol and Manage 18:281–296

Addison PFE, Rumpff L, Bau SS, Carey JM, Chee YE, Jarrad FC, McBride MF, Burgman M (2013) Practical solutions for making models indispensable in conservation decision-making. Divers Distrib 19:490–502

Allouche O, Tsoar A, Kadmon R (2006) Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J Appl Ecol 43:1223-1232.

Andrew ME, Ustin SL (2009) Habitat suitability modelling of an invasive plant with advanced remote sensing data. Divers Distrib 15:627–640

Arnow T, Stephens DW (1990) Hydrologic characteristics of the Great Salt Lake, Utah, 1847-1986. United States Geological Survey Water Supply Paper 2332

Belovsky GE, Stephens D, Perschon C, Birdsey P, Paul D, Naftz D, Baskin R, Larson C, Mellison C, Luft J, Mosley R, Mahon H, Van Leeuwen J, Allen DV (2011) The Great Salt Lake Ecosystem (Utah, USA): long term data and a structural equation approach. Ecosphere 2: 1-40

Bourgeau-Chavez LL, Kowalski KP, Carlson Mazur ML, Scarbrough KA, Powell RB, Brooks CN, Huberty B, Jenkins LK, Banda EC, Galbraith DM, Laubach ZM, Riordan K. 2012. Mapping invasive *Phragmites australis* in the coastal Great Lakes with ALOS PALSAR satellite imagery for decision support. J Gt Lakes Res 39:65-77

Bradley BA., Marvin DC (2011) Using expert knowledge to satisfy data needs: mapping invasive plant distributions in the western United States. West N Am Naturalist 71:302–315

Breiman L (2001) Statistical Modeling : The Two Cultures. Stat Sci 16:199–231

Brisson J, De Blois S, Lavoie C (2010) Roadside as invasion pathway for common reed (*Phragmites australis*). Invas Plant Sci and Manage 3:506–514

Broennimann, O, Guisan A (2008) Predicting current and future biological invasions: both native and invaded ranges matter. Biology Lett 4:585–9

Carling, GT, Richards DC, Hoven H, Miller T, Fernandez DP, Rudd A, Pazmino E, Johnson WP (2013) Relationships of surface water, pore water, and sediment chemistry in wetlands adjacent to Great Salt Lake, Utah, and potential impacts on plant community health. Sci Total Environ 443:798–811

Carlson Mazur ML, Kowalski K, Galbraith D (2014) Assessment of suitable habitat for *Phragmites australis* (common reed) in the Great Lakes coastal zone. Aquat Invasions 9:1-19

CH2M HILL (2005) Statistical analysis of 2004 data on wetland plants and invertebrates in Farmington Bay, Great Salt Lake, Utah. Final Technical Memorandum.

Chambers RM, Meyerson LA, Saltonstall K (1999) Expansion of *Phragmites australis* into tidal wetlands of North America. Aquat Bot 64:261–273

Chambers RM, Havens KJK, Killeen S, Berman M (2008) Common reed *Phragmites australis* occurrence and adjacent land use along estuarine shoreline in Chesapeake Bay. Wetlands 28:1097–1103

Chambers RM, Osgood D, Bart D, Montalto F (2003) *Phragmites australis* invasion and expansion in tidal wetlands: interactions among salinity, sulfide, and hydrology. Estuaries 26:398–406

Cutler DR, Edwards TC, Beard KH, Cutler A, Hess KT, Gibson J, Lawler JJ (2007) Random forests for classification in ecology. Ecology 88:2783–2792

Davis FW, Seo C, Zielinski WJ (2007) Regional variation in home-range-scale habitat models for fisher (*Martes pennanti*) in California. Ecol Appl 17:2195–213

DeLuca WV, Studds CE, Rockwood LL, Marra PP (2004) Influence of land use on the integrity of marsh bird communities of Chesapeake Bay, USA. Wetlands 24:837–847

Downard R, Sims KA, Long AL, Kettenring KM (2013) Assessment of wetland vegetation in the Willard Spur, Great Salt Lake, UT: a literature review. Final report to the Utah Division of Water Quality

Dullinger S, Kleinbauer I, Peterseil J, Smolik M, Essl F (2009) Niche based distribution modelling of an invasive alien plant: effects of population status, propagule pressure and invasion history. Biol Invasions 11:2401–2414

Environmental Protection Agency (EPA) (2013) Integrated Compliance Information System - National Pollutant Discharge Elimination System (ICIS-NPDES) database for Utah. < http://www.epaecho.gov/echo/compliance_report_water_icp.html> Accessed January 25, 2013

Evans KE, Martinson W (2008) Utah's featured birds and viewing sites: a conservation platform for IBAs and BHCAs. Sun Lith, Salt Lake City, USA

Fielding AH, Bell JF (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. Environ Conserv, 24: 38-49

Franklin J (2009) Mapping species distributions: spatial inference and prediction. Cambridge University Press, Cambridge, UK

Gallien L, Münkemüller T, Albert CH, Boulangeat I, Thuiller W (2010) Predicting potential distributions of invasive species: where to go from here? Divers Distrib 16:331–342

Genuer R, Poggi JM, Tuleau-Malot C (2010) Variable selection using random forests. Pattern Recog 31:2225–2236

Ghioca-Robrecht D, Johnston C, Tulbure M (2008) Assessing the use of multiseason Quickbird imagery for mapping invasive species in a Lake Erie coastal marsh. Wetlands 28:1028–1039

Gwynn JW (1980) Great salt lake: A scientific, historical, and economic overview. Utah Geological Survey

Hazelton ELG, Mozdzer TJ, Burdick DM, Kettenring KM, Whigham DF (2014) Phragmites *australis* management in the Unites States: 40 years of methods and outcomes. AoB Plants 6:1-19.

Hill R, Hawkins CP, Carlisle DM (2013) Predicting thermal reference conditions for USA streams and rivers. Fresh Sci 32:39–55

Hoffman JD, Narumalani S, Mishra DR, Merani P, Wilson RG (2008) Predicting potential occurrence and spread of invasive plant species along the North Platte River, Nebraska. Invas Plant Sci and Manage 1:359–367

Hoven H, Miller T(2009) Developing vegetation metrics for the assessment of beneficial uses of impounded wetlands surrounding Great Salt Lake, Utah, USA. Nat Resour Env Iss, 15: 63-72

Hudon C, Gagnon P, Jean M (2005) Hydrological factors controlling the spread of common reed (*Phragmites australis*) in the St. Lawrence River (Québec , Canada). Ecoscience 12:347–357

Jakubowski A, Casler M, Jackson R (2010) Landscape context predicts reed canarygrass invasion: implications for management. Wetlands 30:685–692

Jones HG, Vaughn RA (2010) Remote sensing of vegetation: principles, techniques, and applications. Oxford University Press, Oxford, UK

Kercher SM, Zedler JB (2004) Multiple disturbances accelerate invasion of reed canary grass (*Phalaris arundinacea* L.) in a mesocosm study. Oecologia 138:455–64

Kettenring KM, de Blois S, Hauber DP (2012) Moving from a regional to a continental perspective of *Phragmites australis* invasion in North America. AoB plants 2012

Kettenring KM, McCormick MK, Baron HM, Whigham DF (2011) Mechanisms of *Phragmites australis* invasion: feedbacks among genetic diversity, nutrients, and sexual reproduction. J Appl Ecol 48:1305–1313

King RS, Deluca WV, Whigham DF, Marra PP (2007) Threshold effects of coastal urbanization on *Phragmites australis* (common reed) abundance and foliar nitrogen in Chesapeake Bay. Estuaries Coasts 30:469–481

Laba M, Downs R, Smith S, Welsh S, Neider C, White S, Richmond M, Philpot W, Baveye P (2008) Mapping invasive wetland plants in the Hudson River National Estuarine Research Reserve using quickbird satellite imagery. Remote Sens Environ 112:286–300

LeBlanc MC, de Blois S, Lavoie C (2010) The invasion of a large lake by the Eurasian genotype of common reed: the influence of roads and residential construction. Jo of Gt Lakes Res 36:554–560

Liaw A, Wiener M (2002) Classification and regression by randomForest. R news 2:18–22

Madon S (2005) Statistical Analyses of 2004 Data on Wetland Plants and Invertebrates in Farmington Bay, Great Salt Lake, Utah. CH2MHill, Salt Lake City, UT

Maheu-Giroux M, Blois S (2005) Mapping the invasive species *Phragmites australis* in linear wetland corridors. Aquat Bot 83:310–320

Martin L, Blossey B (2013) The runaway weed: Costs and failures of *Phragmites* australis management in the USA. Estuaries Coasts 36:626–632

Medeiros DL, White DS, Howes BL (2013) Replacement of *Phragmites australis* by *Spartina alterniflora*: the role of competition and salinity. Wetlands 33:421–430

Menuz DR, Kettenring KM (2012) The importance of roads, nutrients, and climate for invasive plant establishment in riparian areas in the northwestern United States. Biol Invasions 15:1601–1612

Meyerson LA, Lambertini C, McCormick MK, Whigham DF (2012) Hybridization of common reed in North America? The answer is blowing in the wind. AoB plants pls022.

Mohammed IN, Tarboton DG (2012) An examination of the sensitivity of the Great Salt Lake to changes in inputs. Water Resourc Res 48: W11511

Mozdzer TJ, Zieman JC (2010) Ecophysiological differences between genetic lineages facilitate the invasion of non-native *Phragmites australis* in North American Atlantic coast wetlands. J Ecol 98:451–458

Neale CMU, Wenger D, Jayanthi H, Farag F (2007) Mapping and monitoring wetlands using airborne multispectral imagery. In Proceedings of the IAHS Symposium on Remote Sensing for Environmental Monitoring and Change Detection, Perugia, Italy pp. 100-109. IAHS Press, Oxfordshire, UK

NRCS (2010) Soil Survey Geographic (SSURGO) Database. USDA Natural Resources Conservation Service, Washington, DC

Papeş, M., M. Sällström, T. R. Asplund, and M. J. Vander Zanden (2011) Invasive species research to meet the needs of resource management and planning. Conserv Biol 25:867–72

Paul DS, Manning AE (2002) Great Salt Lake waterbird survey five-year report (1997–2001). Great Salt Lake Ecosystem Project, Utah Division of Wildlife Resources, Salt Lake City, UT

Pengra B, Johnston C, Loveland T (2007) Mapping an invasive plant, *Phragmites australis*, in coastal wetlands using the EO-1 Hyperion hyperspectral sensor. Remote Sens Environ 108:74–81

R Core Team (2013) R: A language and environment for statistical computing. Vienna, Austria

Saltonstall K (2002) Cryptic invasion by a non-native genotype of the common reed, *Phragmites australis*, into North America. PNAS 99:2445–2449

Saltonstall K, Stevenson JC (2007) The effect of nutrients on seedling growth of native and introduced *Phragmites australis*. Aquat Bota 86:331–336

Santos M, Khanna S, Hestir EL, Andrew ME, Rajapakse SS, Greenberg JA,. Anderson LWJ, Ustin SL (2009) Use of hyperspectral remote sensing to evaluate efficacy of aquatic plant management. Invas Plant Sci and Manage 2:216–229

Silliman B, Bertness M (2004) Shoreline development drives invasion of *Phragmites australis* and the loss of plant diversity on New England salt marshes. Conserv Biol 18:1424–1434

Stohlgren TJ, Ma P, Kumar S, Rocca M, Morisette JT, Jarnevich CS, Benson N (2010) Ensemble habitat mapping of invasive plant species. Risk Anal 30:224–35

Sumner R, Schubauer-Berigan J, Mulcahy T, Minter J, Dyson B, Godfrey C, Blue J (2010) Alternative futures analysis of Farmington Bay wetlands in the Great Salt Lake ecosystem. U.S. Environmental Protection Agency, Cincinnati, OH

Torbick N, Becker B, Hession S, Qi J, Roloff G, Stevenson R (2010) Assessing invasive plant infestation and disturbance gradients in a freshwater wetland using a GIScience approach. Wetlands Ecol Manag 18:307–319

Tulbure MG, Johnston C (2010) Environmental conditions promoting non-native *Phragmites australis* expansion in Great Lakes coastal wetlands. Wetlands 30:577–587

USDA (2014) The PLANTS database. National Plant Data Team, Greensboro, NC 27401-4901 USA

Utah AGRC (2012) Automated Geographic Reference Center, <http://agrc.its.state.ut.us/.> Accessed 15 Jan 2012

Utah Department of Natural Resources (2011) Great Salt Lake draft comprehensive management plan. Salt Lake City, UT

Utah Division of Water Quality (2012) A Great Salt Lake water quality strategy. Salt Lake City, UT

Vasquez E, Glenn EP, Guntenspergen GR, Brown JJ, Nelson SG (2006) Salt tolerance and osmotic adjustment of *Spartina alterniflora* (Poaceae) and the invasive M haplotype of *Phragmites australis* (Poaceae) along a salinity gradient. Am J Bot 93:1784–90

Vasquez E, Glenn EP, Brown JJ, Guntenspergen GR, Nelson SG (2005) Salt tolerance underlies the cryptic invasion of North American salt marshes by an introduced haplotype of the common reed *Phragmites australis* (Poaceae). Marine Ecol Progress Series 298:1–8

Welch B, Davis C, Gates R (2006) Dominant environmental factors in wetland plant communities invaded by *Phragmites australis* in East Harbor, Ohio, USA. Wetlands Ecol Manag14:511–525

White JS, Null SE, Tarboton DG (2014) Modeled changes to Great Salt Lake salinity from railroad causeway alteration. Final Report to the Utah Division of Forestry, Fire and State Lands

Wilson J, Richardson D (2007) Residence time and potential range: crucial considerations in modelling plant invasions. Divers Distrib 13:11–22

Zedler JB, Kercher S(2004) Causes and consequences of invasive plants in wetlands: opportunities, opportunists, and outcomes. Critical Rev Plant Sci 23:431–452

Zedler JB, Kercher S (2005) Wetland resources: status, trends, ecosystem services, and restorability. Annu Rev Environ Resour 30:39–74

APPENDIX

Site specific *Phragmites* habitat suitability maps

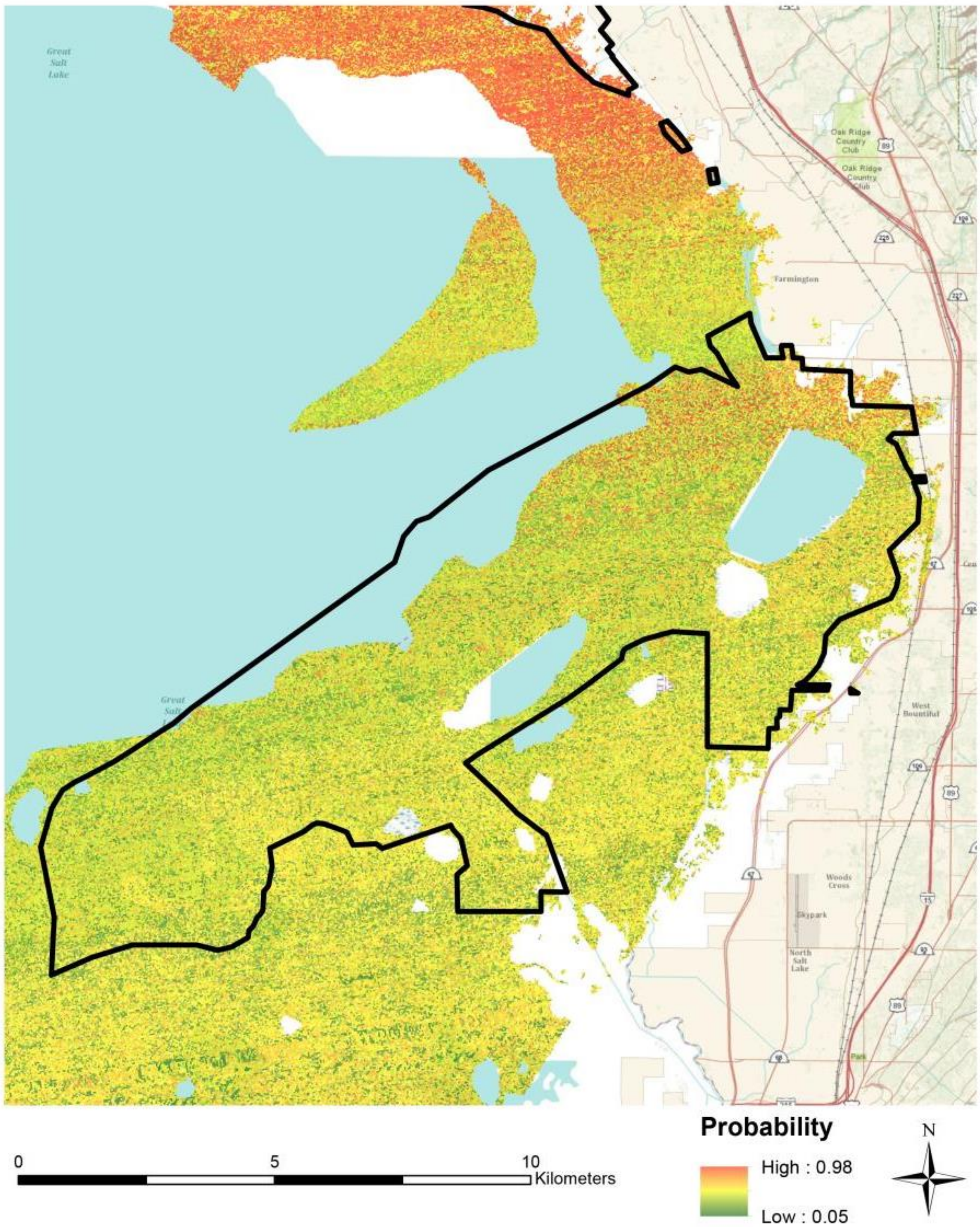


Figure 6. Predicted *Phragmites* habitat suitability for Farmington Bay Waterfowl Management Area in Farmington, UT.

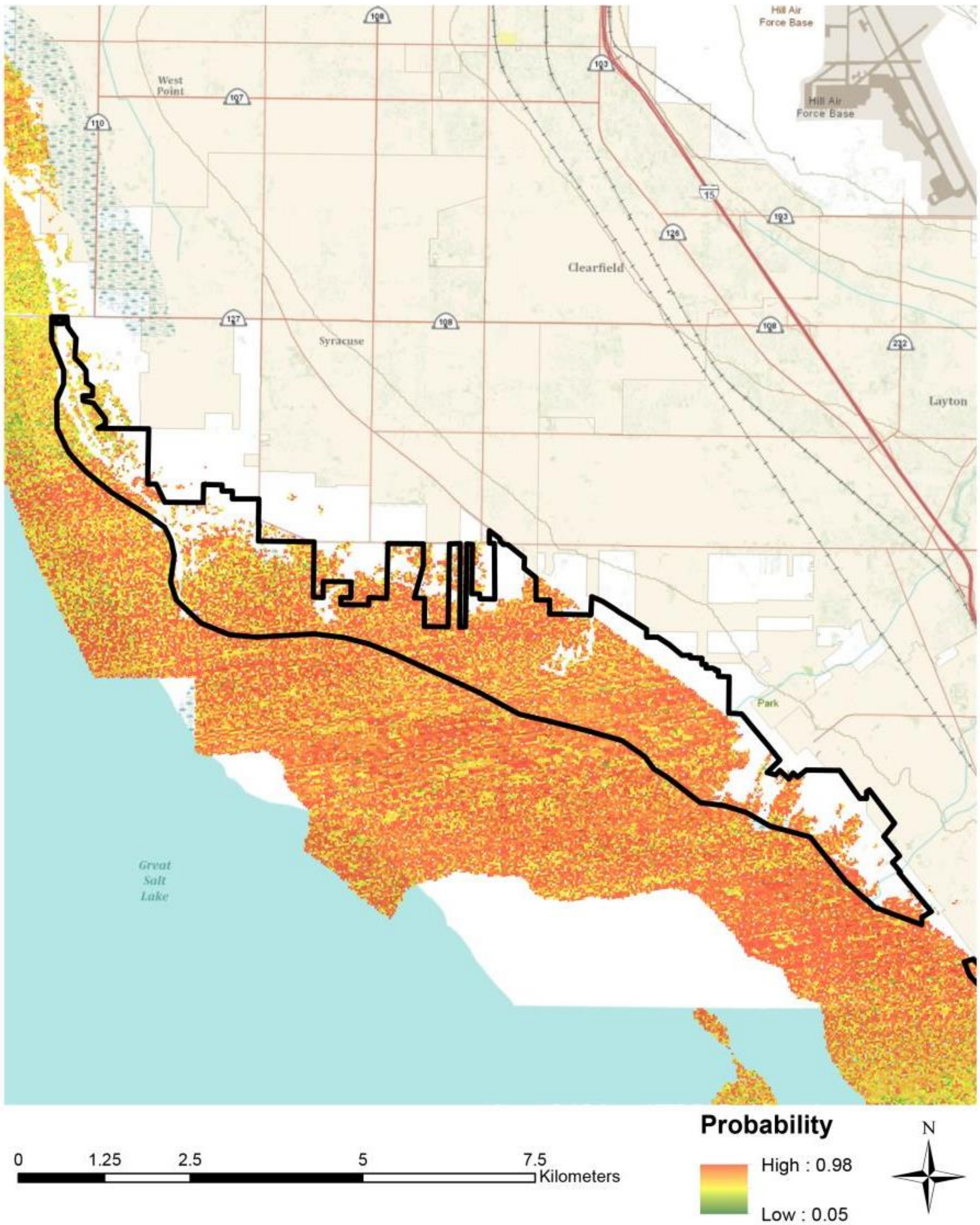


Figure 7. Predicted *Phragmites* habitat suitability for The Nature Conservancy's Great Salt Lake Shorelands Preserve.

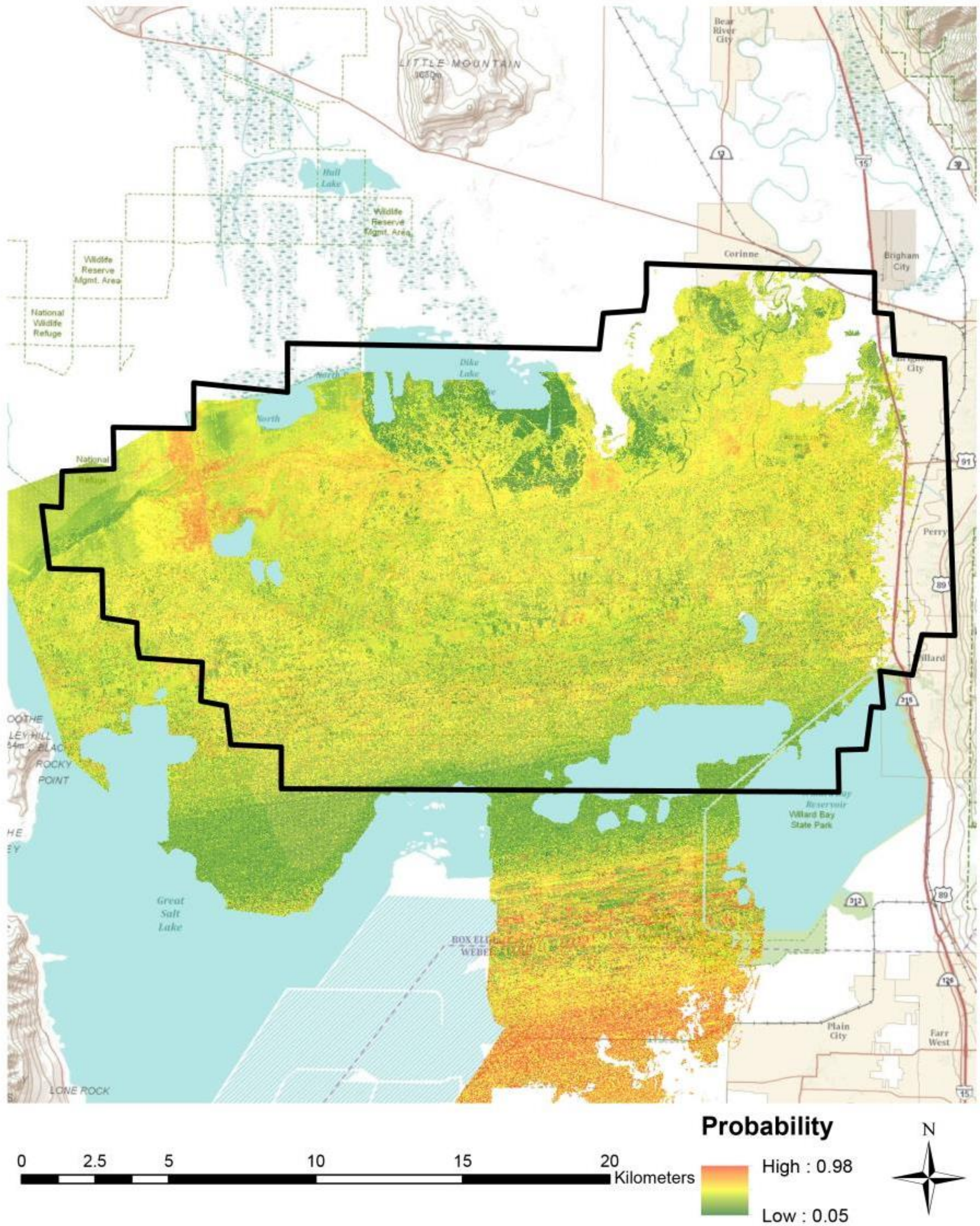


Figure 8. Predicted *Phragmites* habitat suitability for Bear River Migratory Bird Refuge, a U.S. Fish and Wildlife Service refuge located on the north end of the Great Salt Lake.