Mapping Habitat and Potential Distributions of Invasive Plant Species on USFWS National Wildlife Refuges

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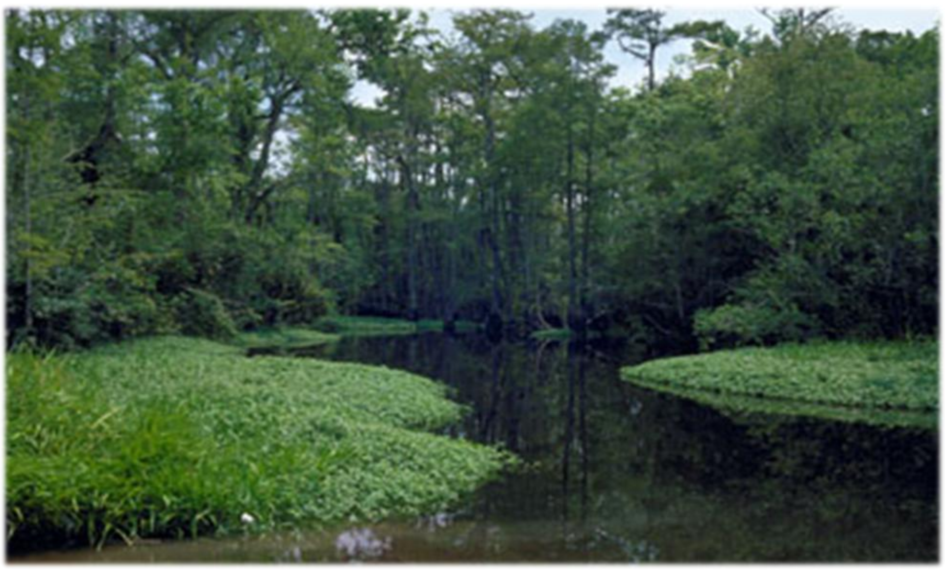

Alligator Weed (*Alternanthera philoxeroides*)

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INTRODUCTION

Many scientists recognize invasive species as the number one environmental threat of the 21st Century (Stohlgren and Schnase, 2006). Invasive species pose threats to global ecosystems, including processes, functions, and the life they sustain (Mack et al., 2000). The invasion of non-native plants, animals, and pathogens has escalated dramatically over the last few decades with the increase of trade, transportation, and other elements of globalization, often negatively affecting state, regional, national, and global ecosystems, economies, and human health. The economic costs and environmental consequences negatively affect all levels of society from indigenous cultures to world powers. The overall economic costs associated with invasive species in the United States are estimated to exceed $120 billion per year in terms of control costs, lost productivity, reduced water salvage, and reductions in rangeland quality and property values (Pimentel et al. 2000; 2005). The global economic costs of invasive species are estimated at $1.4 trillion annually, representing five percent of the global economy (Keller et al., 2007; Yemshanov et al., 2009).

Early detection and ecological forecasting of invasive species are urgently needed for rapid response and remains a high priority for resource managers. Ecological niche models (also called species distribution models and habitat suitability models) are increasingly being used to model and map invasive species distributions. Combining statistical algorithms with geographic information systems (GIS), models attempt to predict probability of occurrence of a species by using presence-only or presence-absence data in combination with environmental variables to predict the species' potential or actual distribution across a landscape (see recent reviews by Elith and Leathwick 2009; Franklin, 2009; Newbold, 2010). These models are based on Hutchinson's (1957) classical niche concept: the distributions of species are constrained by biotic interactions (e.g., competition and predation) and abiotic gradients (e.g., elevation, temperature and precipitation; Elith and Leathwick, 2009; Franklin, 2009; Sinclair et al., 2010).

Use of models for invasive species forecasting can be extremely challenging because the process attempts to statistically extrapolate the potential of species occurrences to novel environments or climates. Although widely accepted as a critical tool for invasive species management, models have been used cautiously because they typically violate the assumption that an organism is in (evolutionary) equilibrium with its environment (Vaclavik and Meentemeyer, 2009). However, that is simply the reality of invasive species science and the challenge with managing them. Different invasive species will exhibit varying degrees of equilibrium with their environment; for example, well established invaders may be in relatively greater equilibrium with their environment than early invaders. The degree of equilibrium for an invasive species is rarely as constant as for native species, and they often are better suited for conditions associated with anthropogenic and natural disturbances (e.g., fire, climate change). Additionally, intra-action within an invasive species population and interactions with its environment and other organisms (e.g., competition, predation) further add to the challenge of predicting distributions and risks.

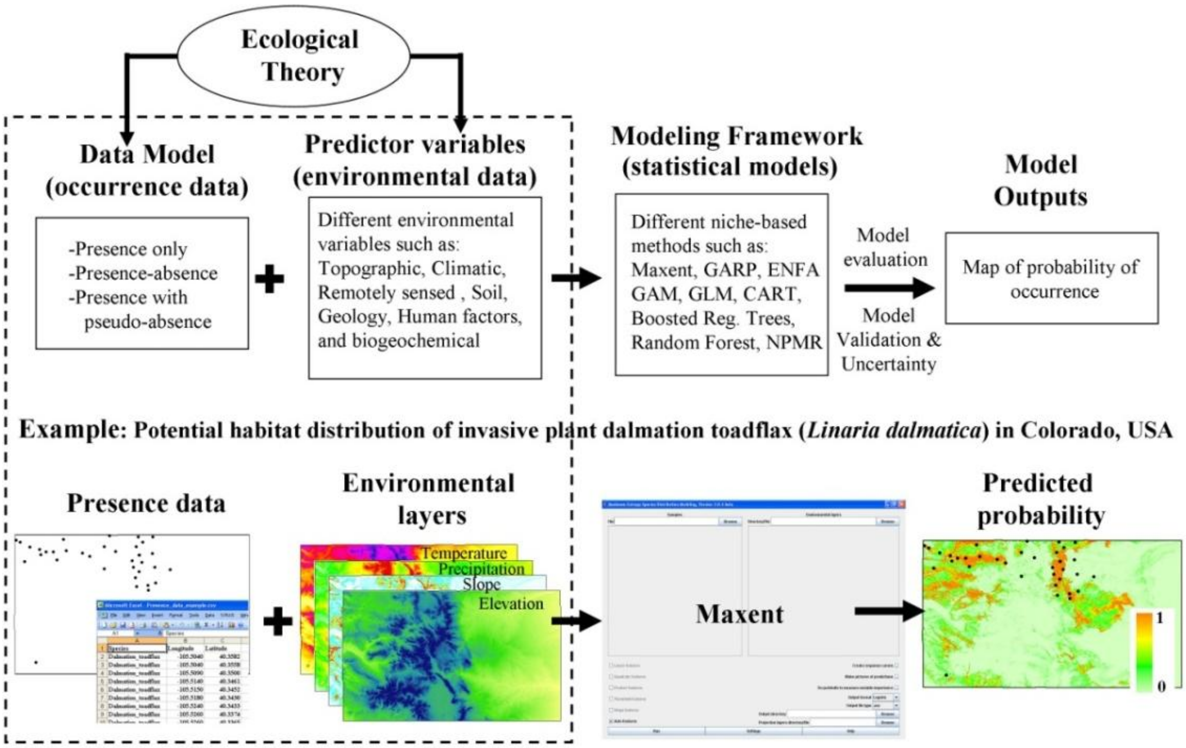

Figure 1. Diagrammatic representation of ecological niche modeling components for modeling species distributions. Bottom part of the figure shows potential habitat distribution map for invasive plant dalmation toadflax (*Linaria dalmatica*) in Colorado, USA (adapted from Franklin, 2009).

Today's ecological niche models generally rely on occurrence data collected from observations, field surveys, or aerial imagery. Occurrences may be presence-only data or presence and absence data. For most biological and species modeling efforts, presence and absence data performs best because they can be analyzed independently and against each other (e.g., Evangelista et al., 2008). For invasive species, however, there is greater uncertainty for absence data than with native species which has evolved within a particular ecosystem. In other words, we do not know if an absence point for an invasive species is a *true* absence or rather a point on the landscape that has yet to be invaded. Many studies and observations have documented a lag between the time a species is introduced and the time it displays invasive characteristics (Ellstrand and Schierenbeck, 2000; Allendorf and Lundquist, 2003). In some cases, an invasive species will exhibit several lag-times as, a population has time to adapt, its environment becomes modified, and in some cases, the occurrence of hybridization (e.g., *Tamarix* spp.). For these reasons, many invasive species ecologists prefer to use ecological niche models that rely on presence-only data and not make any assumptions on whether or not an absence point is *truly* an absence point. Presence-only models generally attempt to identify environmental similarities that are defined by the presence-points and/or compare them with the environmental background. They make no distinction between presence and absence, rather base predictions largely on verified occurrences (Figure 1).

GOALS AND OBJECTIVES

The purpose of the modeling efforts for this project is to provide useful information to selected U.S. National Wildlife Refuges (NWR) and public/private partners by building on existing datasets and new field surveys conducted under this project. Broadly summarized, the goals are to:

- Provide models/maps of the potential distribution and risk of particularly problematic invaders at two scales: (1) the extent of the participating NWR, and (2) the associated Landscape Conservation Cooperative (LCC).
- Identify the environmental conditions that facilitate invasions for participating National Wildlife Refuges and the associated LCC.
- Utilize proven spatial statistical methods for model training and evaluation.
- Provide some insight on distribution trends and response of each of the targeted species for participating NWRs and the associated LCC.

To meet these goals, we completed the following objectives, as listed in the Statement of Work:

1) Conduct a literature review of selected invasive species to determine the best predictor variables to use in geospatial analyses.
2) Assess the field data provided by USFWS and collaborate with Refuge staff to determine the appropriate model to use.
3) Test multiple models and select the best approach for the available field data and geospatial predictors.
4) Train models and Evaluate performances by multiple statistical means.
5) Provide a final report that describes in detail our methods, results (including maps and evaluations), conclusions, and references.
6) Provide all generated geospatial data and model results in ESRI ArcGIS formats.

METHODS

Study Sites and Priority Species

Four U.S. Fish and Wildlife Refuges were pre-selected for this study: Alligator River NWR in North Carolina; Quivira NWR in Kansas; Silvio O. Conte NWR in Connecticut, Massachusetts, New Hampshire and Vermont; and San Diego NWR in California. In addition to modeling at the refuge-scale, models were run at each of the associated Landscape Conservation Cooperatives. These are the South Atlantic LCC (Alligator River NWR), Great Plains LCC (Quivira NWR), North Atlantic LCC (Silvio O. Conte NWR) and California LCC (San Diego NWR).

Although field sampling activities at each NWR targeted multiple invasive species, ecological niche models were limited to two priority species for each refuge determined at the Priority Workshops. For Alligator River NWR, the selected invaders were *Phragmites* spp. and *Alternanthera philoxeroides* (a.k.a. alligator weed); for Quivira NWR, *Phragmites* spp. and *Tamarix* spp. (a.k.a. tamarisk, salt cedar); for Silvio O. Conte NWR, *Alliaria petiolata* (a.k.a. garlic mustard) and *Microstegium vimineum* (a.k.a. Japanese stiltgrass); for San Diego NWR, *Brachypodium distachyon* (a.k.a. false brome) and *Brassica tournefortii* (a.k.a. Sahara mustard). Once identified, occurrence data (i.e., presence-only) were collected at each NWR by our Utah State University collaborators. Occurrence data for the LCC landscapes were acquired from the National Institute of Invasive Species Science (NIISS; http://www.niiss.org/), EDDMapS (http://www.eddmaps.org/) and Global Biodiversity Information Facility (GBIF; http://www.gbif.org/) websites. After combining respective species data, all points that possessed a location accuracy error greater than one kilometer were removed.

Model Selection and Comparisons

We selected the Maxent model to conduct all analyses for three primary reasons. First, multiple studies have found that Maxent regularly performs better, or as well, as other ecological niche models for invasive species (Ficetola et al., 2007, Evangelista et al., 2008, Kumar et al., 2009). Secondly, Maxent is designed to handle the types of survey data collected for the study; specifically point data collected with a GPS (as opposed to plot data and percent cover) and presence-only (as opposed to presence-absence data). Third, Maxent has several built-in features that are of particular importance to refuge managers, including performance evaluations (e.g., Area Under the Curve) and percent contribution of predictor variables.

The Maxent model was designed as a general-purpose predictive model that can be applied to incomplete data sets (Phillips et al., 2004, Phillips et al., 2006). Relatively new, the Maxent model is freely distributed on the web (www.cs.princeton.edu/~schapire/maxent/). It operates on the principle of maximum entropy, making inferences from available data while avoiding unfounded constraints from the unknown (Phillips et al., 2006). Entropy is the measure of uncertainty associated with a random variable; the greater the entropy, the greater the uncertainty. Adhering to these concepts, Maxent utilizes presence-only points of occurrence, avoiding absence data and evading assumptions on the range of a given species. Predictions are most often reported as relative logistic probabilities ranging from 0:1.

The validation of model outputs from Maxent is accomplished in several ways. First, the user has the option of defining a percentage of the data for model testing that: (1) plots testing and training omissions against threshold; (2) plots predicted area against threshold; and (3) calculates the receiver operating curve (ROC). The Area Under the Curve (AUC) is calculated for each. Second, a jackknife option allows the estimation of the bias and standard error in the statistics and the test of variable importance. Finally, Maxent will generate response curves for each predictor variable. Maxent has also been found to perform well in cases of small sample sizes (as low as four; Pearson et al., 2007) and has recently been applied in remote sensing of invasive species (Evangelista et al., 2009, York et al., 2011).

To ensure that Maxent was the best model selected for this study, we tested it against three other ecological niche models that are also commonly used for predicting species occurrences at the refuge-scale only. These were Boosted Regression Trees (BRT), Multivariate Adaptive Regression Splines (MARS) and the Generalized Linear Model (GLM). Our tests were conducted for all species at the refuge scale except those associated with San Diego NWR.

Boosted regression trees are similar to other tree based models in that they attempt to minimize the loss function by generalizing many simple classifications and regression trees. They accomplish this by applying rules to the predictors that partition the data into rectangles with the most homogeneous response (Elith et al., 2008). What makes BRT's different from other tree based methods is in the resampling method it employs; boosting. Boosting is a form of re-sampling that, unlike other methods such as bagging or sub-sampling, applies a weighted probability of a response to be re-sampled based on previous classifications (Franklin, 2009).

Generalized Linear Models are regression based models that are well suited for ecological data (Guisan et al., 2002). One of the first methods used in ecological niche modeling, GLMs are still common. GLMs are well established statistical modeling frameworks that use maximum likelihood and can handle non-normal distributions in the response variable with many predictors.

Multivariate Adaptive Regression Splines are a piecewise step method capable of handling many predictors (Freidman, 1991). Relatively new to ecological niche modeling, MARS have become popular because they are computationally fast and can model complex relationships. MARS also allow for interaction between variables in predicting a species distribution (Franklin, 2009).

Boosted regression trees, GLMs, and MARS all require absence points to model a species distribution. Absence points were not specifically collected for the species targeted in this report. For invasive species, true absence points are difficult to acquire and often unreliable (Brown et al., 1996). Therefore, absence points needed to be generated for these models. To accomplish this, we explored several absence data generation techniques. In similar modeling efforts, some have used the presence locations of another species that was included in the same survey to act as the absence points for the species being modeled (Phillips et al., 2009). In other cases, it may be more beneficial to generate random absence points within the surveyed area of the overall study area. While these randomly generated points will not perfectly represent absences for the species, collectively they are able to characterize less suitable habitat for the species being modeled. We conducted models using both techniques and chose the random-point method due to significantly improved evaluation statistics.

Predictor Variables

For each NWR, we attempted to collect environmental predictor variables (in GIS raster format) from each refuge to use in our models. These datasets varied considerably in quality and quantity, so additional data sources were identified to support modeling efforts (Appendix 1). For models run at LCC scales, 32 environmental predictor variables were used for all models. These included 19 seasonal climatic indices (BioClim; Table 1), elevation, number of annual growing days and frost days, flow accumulation, distance from water, maximum and minimum annual temperature, slope (i.e., degrees), humidity, precipitation frequency, geology and solar radiation.

Table 1. List and description of BioClim seasonal climatic indices used for LCC modeling. For more detailed information, see Hijmans, 2006.

BioClim Predictor Variables	
Bio 1	Annual Mean Temperature
Bio 2	Mean Diurnal Range (mean of monthly (max temp-min temp))
Bio 3	Isothermality (mean diurnal range/temperature annual range)
Bio 4	Temperature Seasonality (standard deviation * 100)
Bio 5	Max Temperature of Warmest Month
Bio 6	Min Temperature of Coldest Month
Bio 7	Temperature Annual Range (Bio 5 - Bio 6)
Bio 8	Mean Temperature of Wettest Quarter
Bio 9	Mean Temperature of Driest Quarter
Bio 10	Mean Temperature of Warmest Quarter
Bio 11	Mean Temperature of Coldest Quarter
Bio 12	Annual Precipitation
Bio 13	Precipitation of Wettest Month
Bio 14	Precipitation of Driest Month
Bio 15	Precipitation Seasonality (Coefficient of Variation)
Bio 16	Precipitation of Wettest Quarter
Bio 17	Precipitation of Driest Quarter
Bio 18	Precipitation of Warmest Quarter
Bio 19	Precipitation of Coldest Quarter

Modeling

The study areas or model's spatial extent was defined by the boundaries of each NWR and LCC. Analyses at both the NWR and LCC scales consisted of ten replicate models. Each model used 80% of the presence points to train the model for each targeted invasive species and used the remaining 20% for model validation. Each additional model replicate used the same method; however, new training and validation points were randomly selected each time.

The ten model iterations for each species were averaged in a single output and included a predictive map (ASCII file), average AUC value, and percent variable contributions. A final model was generated for each species excluding any predictive variables that had less than a 1% contribution in the replicates. To calculate the predicted area at risk for infestation, a 10% training presence logistic threshold was applied to each model output. This threshold displayed areas at risk of infestation for each species modeled and provided a way to estimate the area of predicted risk. When necessary, the regularization parameter was increased to reduced over-fitting.

RESULTS

Model Comparisons

Overall, Maxent produced the most reasonable distribution maps across all evaluation metrics for alligator weed (Figure 2), *Phragmites* spp. (Figure 3, Appendix 2), tamarisk (Appendix 3), and japanese stiltgrass (Appendix 4). Comparisons of model training data and test data evaluation statistics support this in three of the four tests with Maxent reporting a higher AUC than the other model methods.

However, model evaluation and accuracy is not solely dependent on automated evaluation statistics produced by each development method. Distribution maps produced by all models were carefully assessed in regards to life history and on-the-ground observations of the invasive species in question. The three tests with highest AUC values reported by Maxent models are alligator weed at the Alligator River NWR, *Phragmites* spp. at the Alligator River NWR, and tamarisk at Quivira NWR with reported values of 0.98, 0.97, and 0.82, respectively. These three tests also corresponded with what we believed to be the most accurate models representing local observations of the species within its particular refuge.

Table 2. Table of comparison AUC values reported by all models tested at both the refuge scale and LCC scale for each invasive species. The chosen Maxent modeling method values include Training and Test AUC's.

		Maxent		BRT	MARS	GLM
		Training	Test			
Alligator River						
	Alligator weed	0.99	0.98	0.89	0.78	0.77
	Phragmites spp.	0.98	0.97	0.96	0.82	0.66
Quivira						
	Phragmites spp.	0.97	0.97	N/A	0.98	0.98
	Tamarisk	0.84	0.82	0.88	0.73	0.61
Silvio O. Conte						
	Garlic mustard	0.95	0.82	0.96	0.97	0.82
	Japanese stiltgrass	0.99	0.99	N/A	1	0.98
San Diego						
	False brome	0.86	0.83	N/A	N/A	N/A
	Sahara mustard	0.94	0.88	N/A	N/A	N/A

The fourth test, *Phragmites* spp. at Quivira NWR, produced a top AUC value of 0.98 using a GLM. Following were MARS and Maxent results with AUC values of 0.98 and 0.97, respectively (Table 2). Due to the lack of observations of *Phragmites* spp. within the surveyed area of the refuge (where GLM and MARS predict its presence), our confidence in the MARS and GLM predictive models were lowered significantly. The 0.01 difference between the top performing GLM model and Maxent model evaluation statistics was not noteworthy enough to sequester belief in what we believe to be the best representation of infestation risk on-the-ground. Therefore, our comparisons of BRT, MARS, Maxent and GLM model results supported our decision to use the Maxent model for all tests in this study.

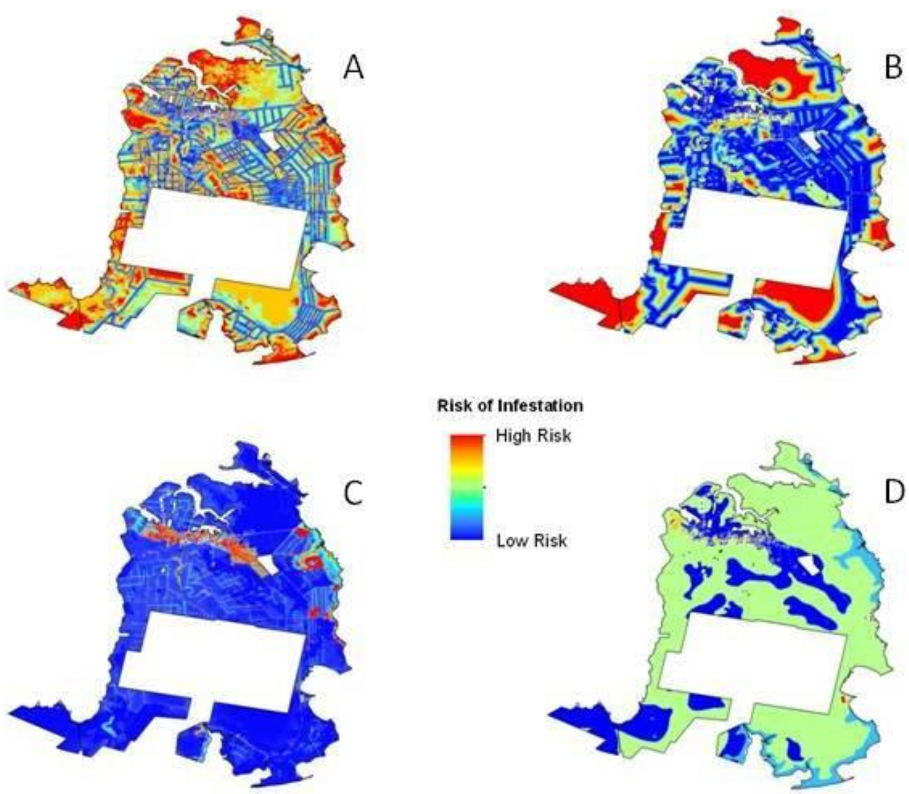

Figure 2. Model results for alligator weed at Alligator River NWR. The models tested were (A) Boosted Regression Tree, (B) Multivariate Adaptive Regression Splines, (C) Maxent and (D) General Linear Model.

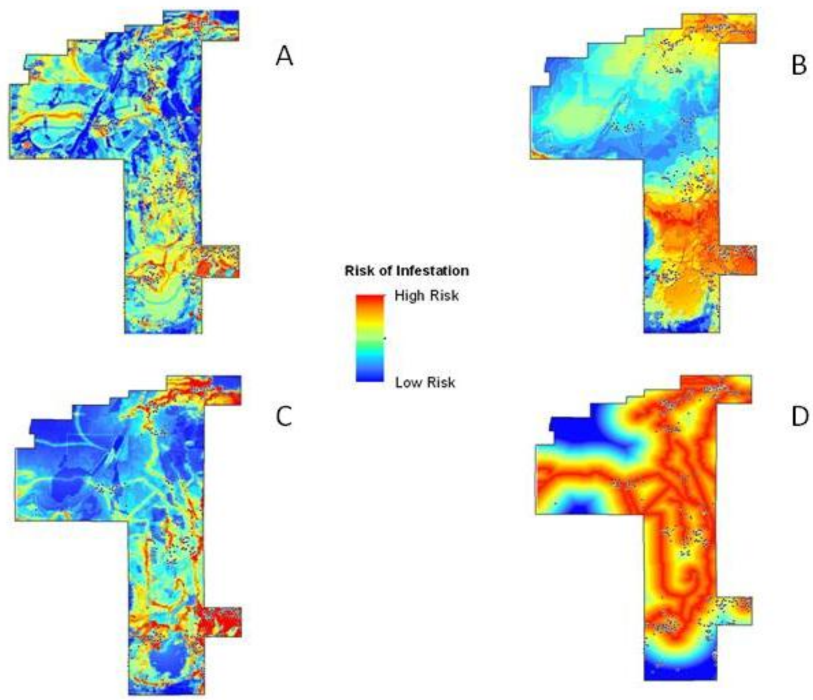

Figure 3. Model results for tamarisk at Quivira NWR. The models tested were (A) Boosted Regression Tree, (B) Multivariate Adaptive Regression Splines, (C) Maxent and (D) General Linear Model.

Final Models: Alligator River NWR and South Atlantic LCC

Within the Alligator River NWR boundaries, the Maxent model for alligator weed predicted 7,649 acres at risk of invasion or approximately 3.5 % of the total refuge acreage. The AUC evaluation was 0.98 with the distance from water having the most contribution to the final model (Table 3). The model shows existing canals and other water sources as the area most at risk (Figure 4). The model also predicted higher risk along highway 64 that runs east and west across the refuge.

Table 3. The top three environmental predictors and their percent contribution for alligator weed in Alligator River NWR.

Predictor	Percent Contribution
Distance to Water	62.6%
Land Cover Type	20.7%
Slope	8%

For the South Atlantic LCC, approximately 26,200,000 acres or 24.9% of the area is at risk of invasion by alligator weed, *provided surface water is present*. The number of frost days and humidity contributed the most to the final Maxent model prediction (Table 4), which performed with an AUC evaluation of 0.89. The higher risk areas are near the Atlantic coast and along major river drainages (Figure 4).

Table 4. The top five environmental predictors and their percent contribution for alligator weed in South Atlantic LCC.

Predictor	Percent Contribution
Number of Frost Days	20.7%
Humidity	17.9%
Precipitation of Wettest Quarter (Bio 16)	10%
Minimum Temperature of Coldest Month (Bio 6)	7%
Number of Growing Days	6.9%

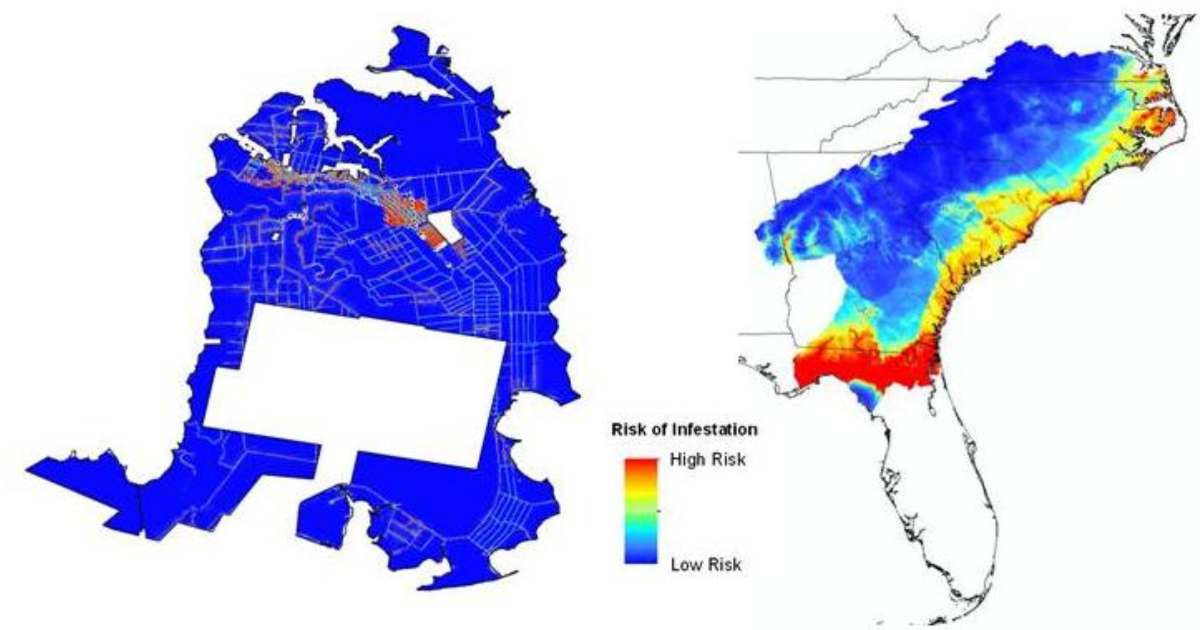

Figure 4. Predicted distribution of alligator weed in Alligator River NWR (left) and the South Atlantic LCC (right) using the Maxent model.

The Maxent results for *Phragmites* spp. at the Alligator River NWR predicted 25,697 acres at risk of infestation, or 11.75% of the refuge. Land cover type and distance to water were the top predictor variables (Table 5) with the AUC evaluation at 0.97. Similar to the alligator weed model, the predicted risk for *Phragmites* spp. was concentrated around existing canals and water sources but showed a higher risk on the north east coast from Manns harbor south along the Croatan sound (Figure 5).

Table 5. Top three environmental predictors and their percent contribution for *Phragmites* spp. in Alligator River NWR.

Predictor	Percent Contribution
Land Cover Type	35.9%
Distance to Water	32.1%
Prescribed Fire Treatment Areas	11.3%

For the South Atlantic LCC, approximately 35,500,000 acres or 33.7% of the area is at risk of *Phragmites* spp. infestation. The Maxent model had an AUC evaluation of 0.79 with mean diurnal range and solar radiation having greatest predictive contributions (Table 6). The model predicted high risk near the coastal areas and further north in the LCC (Figure 5).

Table 6. Top five environmental predictors and their percent contribution for *Phragmites* spp. in South Atlantic LCC.

Predictor	Percent Contribution
Mean Diurnal Range (Bio 2)	20%
Radiation	18.6%
Elevation	17.3%
Geology	5.5%
Mean Temperature of Wettest Quarter (Bio 8)	5.1%

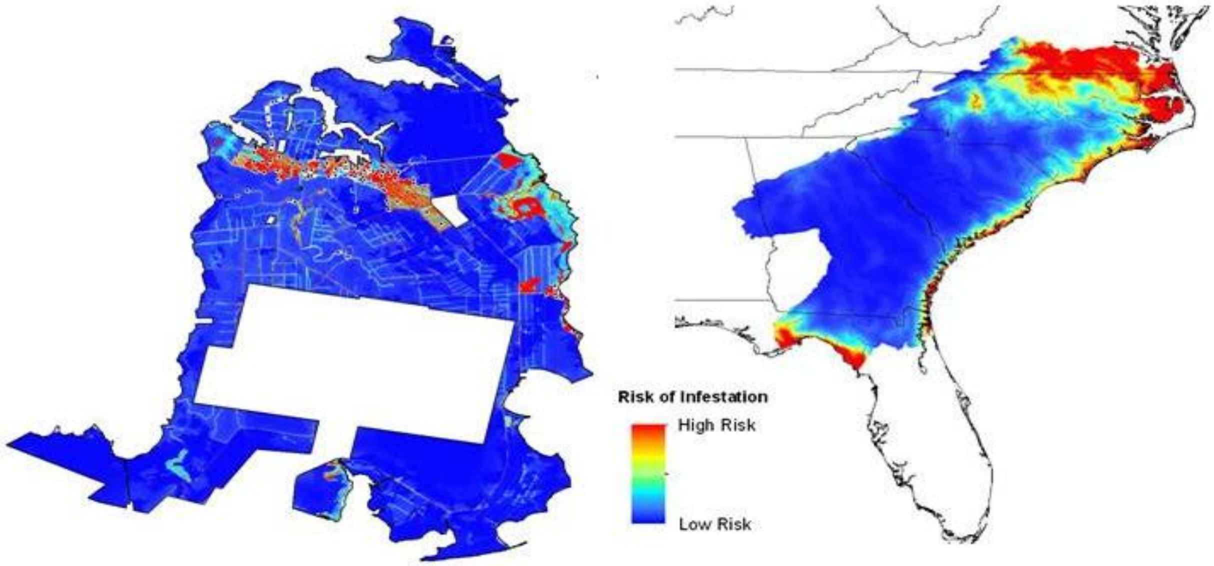

Figure 5. Predicted distribution of *Phragmites* spp. in Alligator River NWR (left) and the South Atlantic LCC (right) using the Maxent model.

Final Models: Quivira NWR and Great Plains LCC

Within the Quivira NWR, the Maxent model predicted that 28,000 acres were at risk for tamarisk invasion, or 49.5% of the refuge. The model had an AUC value of 0.82 with elevation, soils and distance to water having almost equal contributions and the greatest predictive contributions of all the predictors used to develop the model (Table 7). Higher risk areas were predicted in the north and southeast near water sources and moist soils and along streams (Figure 6).

Table 7. Top three environmental predictors and their percent contribution for tamarisk in Quivira NWR.

Predictor	Percent Contribution
Elevation	33.8%
Soil	27.7%
Distance to Water	23.3%

The Great Plains LCC, covering portions of 8 states, was predicted to have 48,700,000 acres, or 20.0% of the total area, at risk to tamarisk invasion. The model had an AUC value of 0.89 with distance to water and geology having the greatest predictive contributions (Table 8). Model predictions of tamarisk risk at the Great Plans LCC were concentrated along river corridors and higher in the west than east (Figure 6).

Table 8. Top five environmental predictors and their percent contribution for tamarisk in Great Plains LCC.

Predictor	Percent Contribution
Distance to Water	34.2%
Geology	16.7%
Radiation	11.1%
Precipitation of Wettest Quarter (Bio 16)	7.5%
Temperature Seasonality (Bio 4)	6.2%

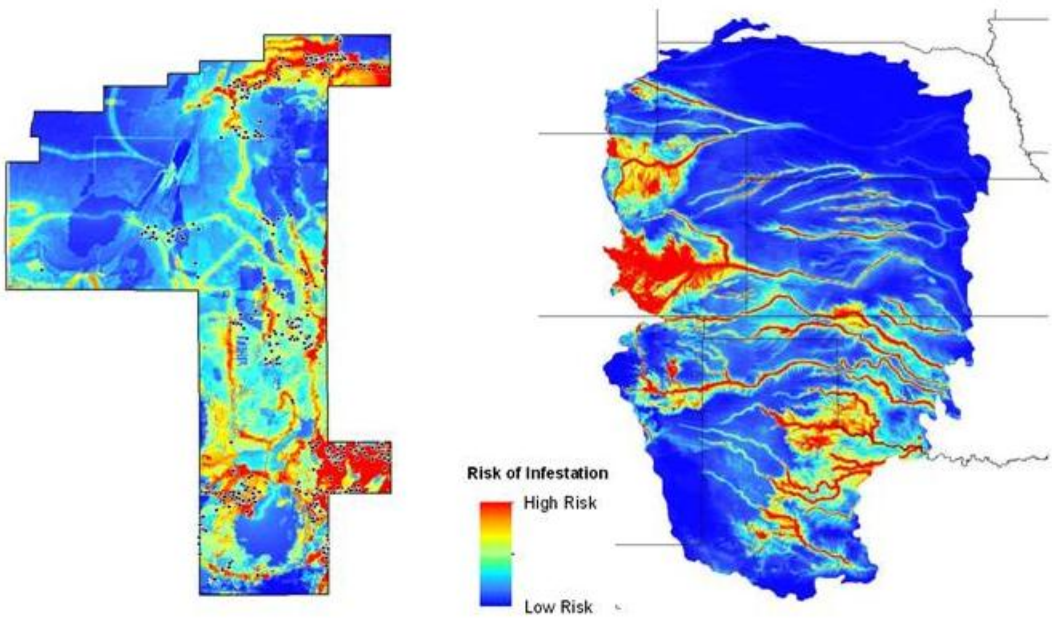

Figure 6. Predicted distribution of tamarisk in Quivira NWR (left) and the Great Plains LCC (right) using the Maxent model

For the Quivira NWR, *Phragmites* spp. predicted 3,617 acres or 12.9% of the total area at risk to invasion. The Maxent results had an AUC value of 0.97 with the elevation, soil and land cover type as the top three environmental predictor variables in the final model (Table 9). Areas of predicted higher risk of *Phragmites* spp. were primarily in and around Little Salt Marsh and nearby wetlands in the southern portion of Quivira NWR (Figure 7).

Table 9. Top three environmental predictors and their percent contribution for *Phragmites* spp. in Quivira NWR.

Predictor	Percent Contribution
Elevation	56.8%
Soil	18.6%
Land Cover Type	12.2%

For the Great Plains LCC, the model predicted that 142,200,000 acres or 58.5% of total area was at risk to *Phragmites* spp.. The model results had a lower AUC value of 0.68 with distance to water having the greatest predictive contribution (Table 10). Predicted risk for the Great Plains LCC was distributed along river cooridros and showed higher risk in the norhter portion of the LCC (Figure 7).

Table 10. The top five environmental predictors and their percent contribution for *Phragmites* spp. in Great Plains LCC.

Predictor	Percent Contribution
Distance to Water	36.2%
Frequency of Precipitation	12.2%
Temperature Annual Range (Bio 7)	9.5%
Temperature Seasonality (Bio 4)	7.2%
Mean Temperature of Wettest Quarter (Bio 8)	5.7%

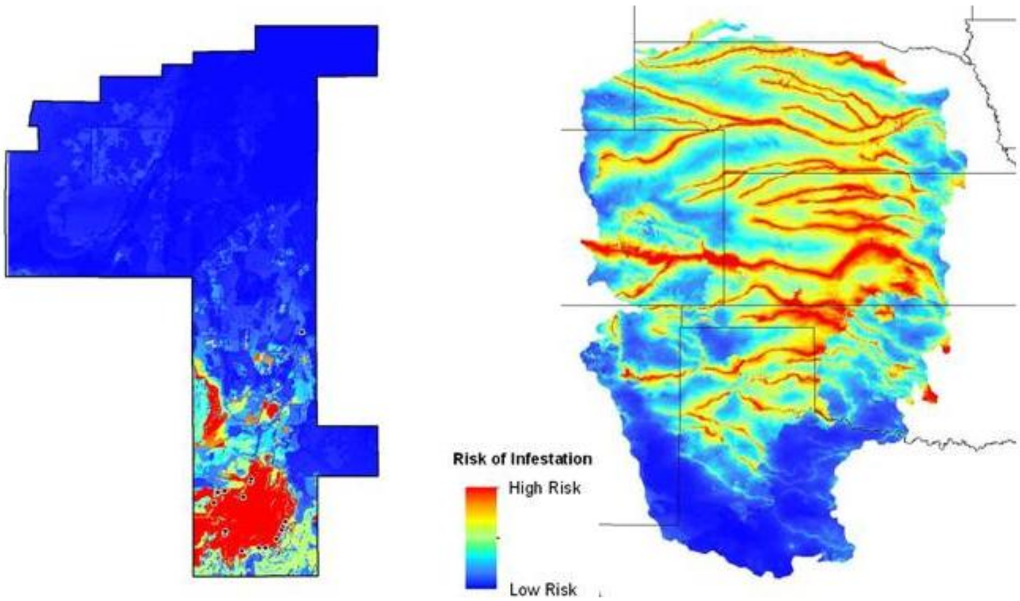

Figure 7. Predicted distribution of *Phragmites* spp. in Quivira NWR (left) and the Great Plains LCC (right) using the Maxent model.

Final Models: Silvio O. Conte NWR and North Atlantic LCC

Within the Silvio O. Conte NWR boundaries, the Maxent model for garlic mustard predicted 1,150,000 acres at risk of invasion or approximately 45.5% of the total watershed acreage. The AUC evaluation was 0.82 with the elevation having the most predictive contribution (Table 11). Higher areas of risk were concentrated along major rivers and in the southern portion of the NWR.

Table 11. The top three environmental predictors and their percent contribution for garlic mustard in Silvio O. Conte NWR.

Predictor	Percent Contribution
Elevation	49.2%
Soil	36.5%
Land Cover Type	10.3%

For the North Atlantic LCC, approximately 27,000,000 acres or 28.5% of the area is at risk of infestation by garlic mustard (Figure 8). The maximum temperature and geology contributed the most to the final Maxent model prediction (Table 12), which performed with an AUC evaluation of 0.89.

Table 12. The top five environmental predictors and their percent contribution for garlic mustard in North Atlantic LCC.

Predictor	Percent Contribution
Max Temperature of Warmest Month (Bio 5)	29.3%
Maximum Temperature	13.1%
Geology	11.9%
Min Temperature of Coldest Month (Bio 6)	7.2%
Number of Growing Days	4.8%

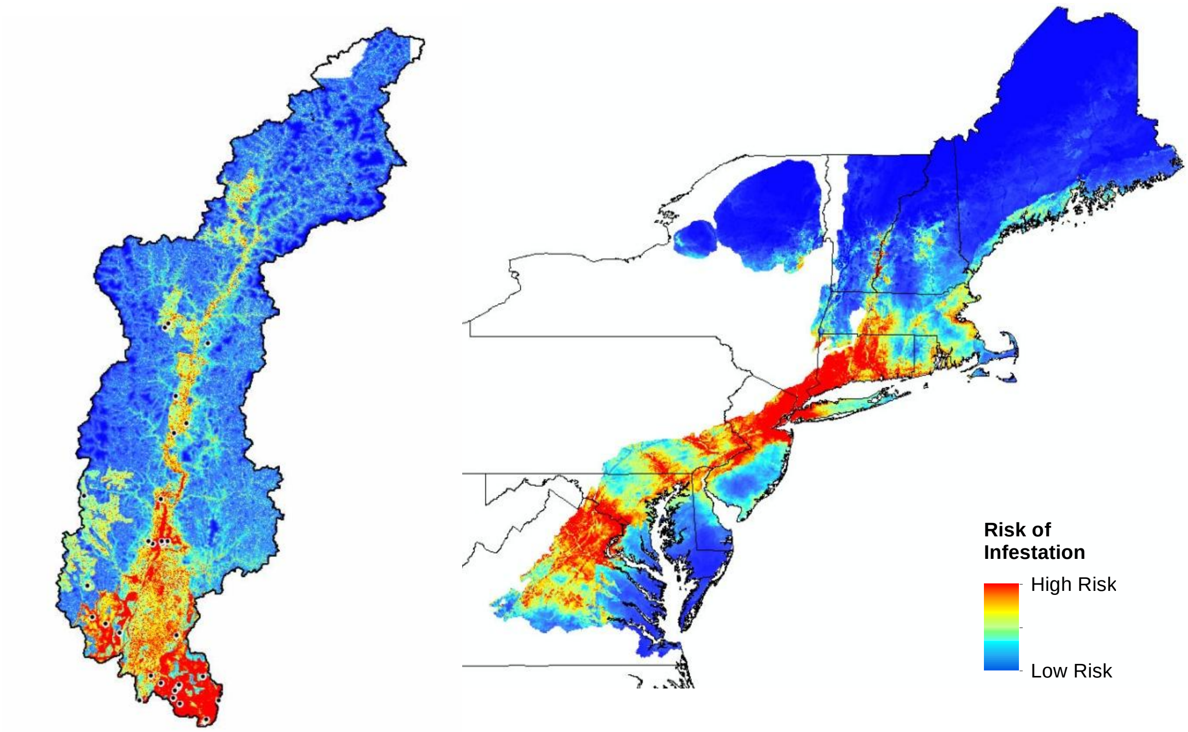

Figure 8. Predicted distribution of garlic mustard in Silvio O, Conte NWR (left) and North Atlantic LCC (right) using the Maxent model.

Within the Silvio O. Conte NWR watershed, the Maxent model predicted that 82,000 acres were at risk for Japanese stiltgrass invasion, or 22.7% of the refuge watershed. The predicted area at risk was restricted to the south central portion of the NWR (Figure 9). The model had an AUC value of 0.98 with elevation, soils, and distance to water having the greatest predictive contributions (Table 13). The area of risk was

Table 13. Top three environmental predictors and their percent contribution for Japanese stiltgrass in Silvio O. Conte NWR.

Predictor	Percent Contribution
Soil	53.8%
Elevation	38.8%
Land Cover Type	4.6%

The North Atlantic LCC, was predicted to have 24,000,000 acres, or 25.3% of the total area, at risk to Japanese stiltgrass invasion. The model reported an AUC value of 0.89 with humidity and radiation having the greatest predictive contributions (Table 14).

Table 14. Top five environmental predictors and their percent contribution for Japanese stiltgrass in the North Atlantic LCC.

Predictor	Percent Contribution
Humidity	36.8%
Radiation	18.1%
Geology	10.3%
Annual Precipitation	10.2%
Maximum Temperature	6.7%

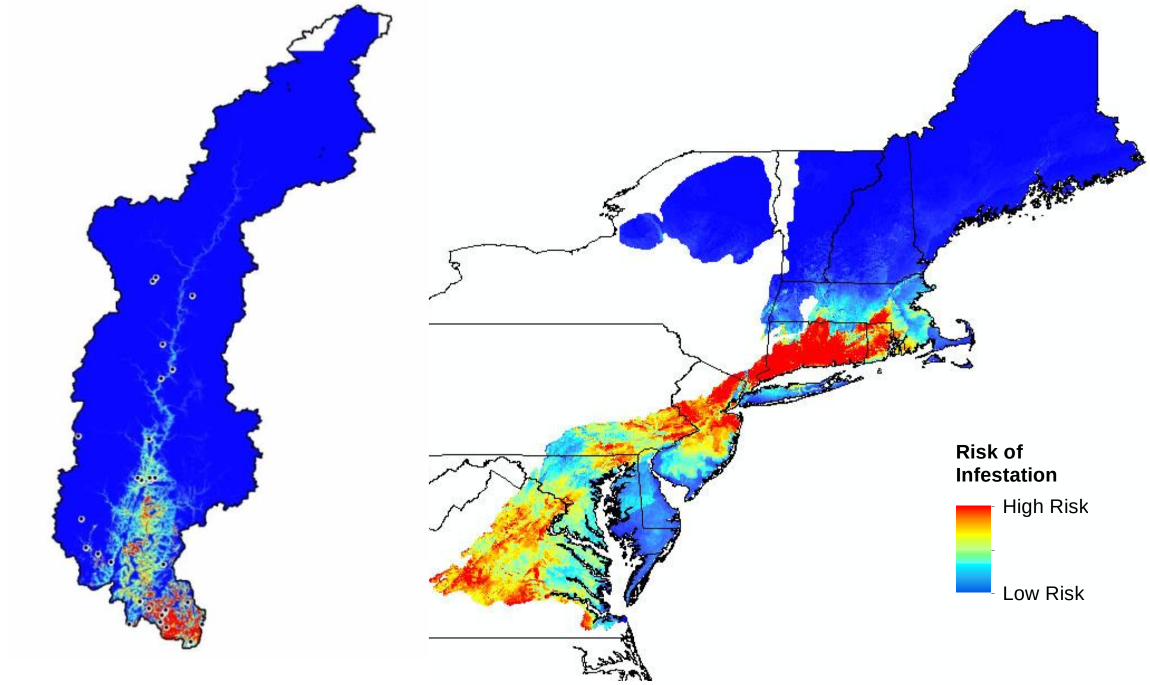

Figure 9. Predicted distribution of Japanese stiltgrass in in Silvio O, Conte NWR (left) North Atlantic LCC (right) using the Maxent model.

Final Models: San Diego NWR and California LCC

At the San Diego NWR, false brome was predicted to be a potential risk for 4,658 acres or 41.7% of the refuge. The Maxent model had an AUC value of 0.83 with soils as the top contributing predictor to false brome's distribution (Table 15). Areas of predicted higher risk of false brome were throughout the western, northern and northeastern part of the refuge (Figure 10).

Table 15. Top three environmental predictors and their percent contribution for false brome in San Diego NWR.

Predictor	Percent Contribution
Soils	37.6%
Land Cover Type	20.8%
Slope	24.3%

The model of false brome at the California LCC scale predicted 19,188,000 acres or 29.7% of the LCC area is at risk for false brome. The humidity predictor had the largest influence on the output, while the temperature seasonality had the second largest influence (Table 16). False brome is projected to be distributed from San Diego to Los Angeles, around the Bay Area, and west of the Sierra foothills within the Sacramento Valley (Figure 10).

Table 16. Top five environmental predictors and their percent contribution for false brome in the California LCC.

Predictor	Percent Contribution
Humidity	42.6%
Temperature Seasonality (bio 4)	21.2%
Distance to Water	11.4%
Precipitation of Seasonality (bio 15)	8.5%
Elevation	5.3%

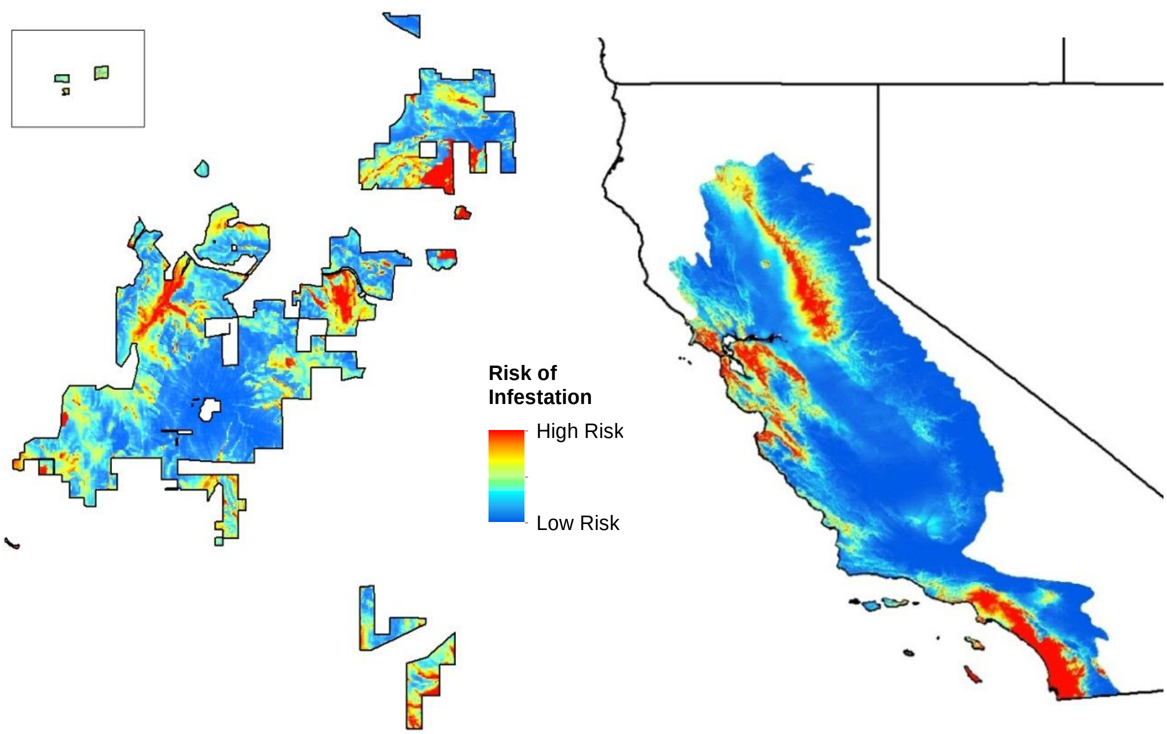

Figure 10. Predicted distribution of false brome in San Diego NWR (left) and California LCC (right) using the Maxent model.

The Sahara mustard is projected to encompass 1,722 acres of the San Diego NWR. This equals 15.4% of the refuge Extent. For the mustard, the Maxent model had an AUC value of 0.88 with elevation being the top projector for the distribution (Table 17). Maxent projected Sahara mustard to have a higher likelihood of occurrence in the northeastern part of the refuge.

Table 17. Top three environmental predictors and their percent contribution for Sahara mustard in San Diego NWR.

Predictor	Percent Contribution
Elevation	30.8%
Soil	26.2%
Land Cover Type	17.8%

The model for the Sahara mustard at the California LCC level predicted 17,129,000 acres at risk, approximately 26.5% of the California LCC. Slope had the most influence of where the Sahara mustard is projected, while the mean temperature of the wettest quarter also had the second largest influence (Table 18). Sahara mustard has a higher risk of vitality on the Southern California coastal environments (Figure 11).

Table 18. Top five environmental predictors and their percent contribution for Sahara mustard in the California LCC.

Predictor	Percent Contribution
Slope	58.0%
Mean Temperature of Wettest Quarter (bio 8)	14.2%
Mean Temperature of Coldest Quarter (bio 11)	11.9%
Number of Frost Days	5.3%
Annual Precipitation (bio 12)	2.6%

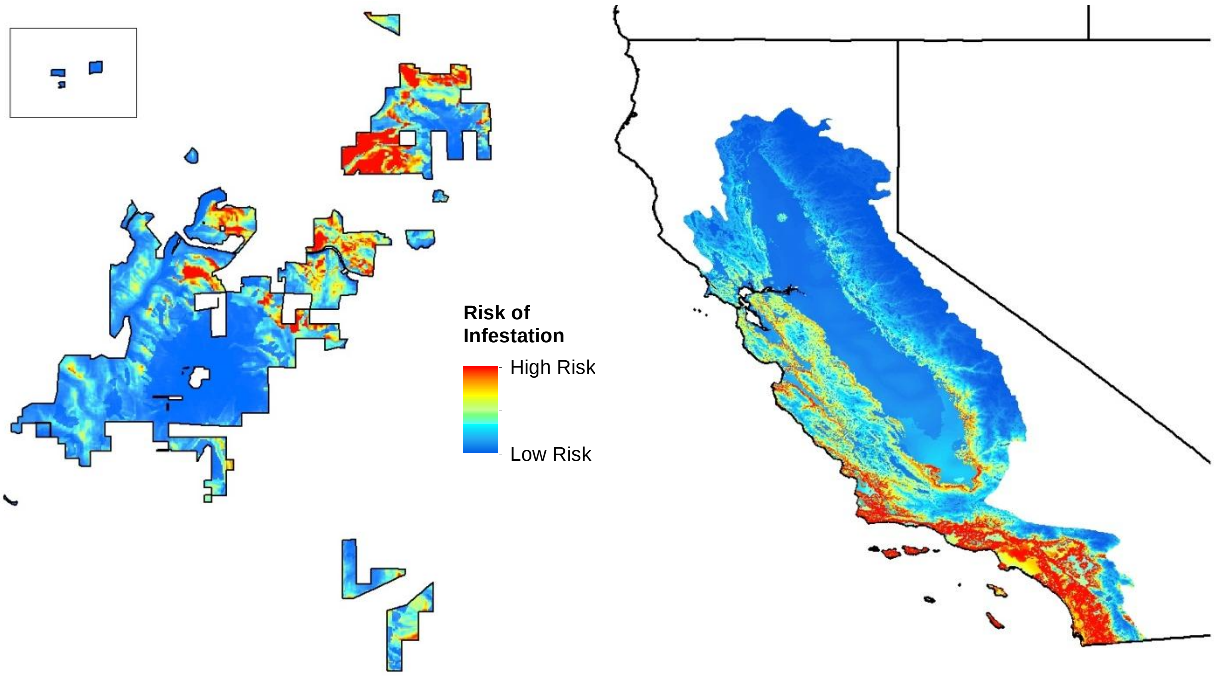

Figure 11. Predicted distribution of Sahara mustard in San Diego NWR (left) and California LCC (right) using the Maxent model.

DISCUSSION

All Maxent models for the priority invasive species at the refuge and landscape scale performed well with an AUC > 0.80. The results of these models provide maps showing potential risk of the invasive species for the selected refuges and the associated LCCs. All models used tested and proven statistical methods for model development and model evaluation. These models also identified the environmental conditions that contribute the most to each species potential distribution. In addition, the model results provide estimates of the area at risk of invasion in terms of acres and proportion of modeled area for each species at both scales (refuge and LCC). Although we tested multiple modeling techniques, only Maxent demonstrated consistent performance.

The Maxent modeling method outperformed the presence-absence methods that were tested in this report in both statistical evaluation and comparing model predictions to in the field observed distributions. Even in the cases where the AUC for Maxent was not the highest, the model predictions matched what was observed at the refuge much more accurately than the higher statistically performing methods. The relatively poor performance of the other methods is most likely due to the sampling design. Unlike Maxent, the presence-absence methods require stricter sampling designs that fit the statistical designs to perform reliably (Cawsay et al., 2002). While methods are being developed to generate suitable absence point for these presence-absence methods (e.g., trend surface analysis; Acevedo et al., 2012), Maxent continues to be the most appropriate modeling technique for this type of data (i.e., opportunistic sampling and invasive species) collected for this report (Phillips et al., 2009).

Limitations of the quantity and/or the distribution of training data reduced model performance for some species and scales (e.g., garlic mustard at Silvio O. Conte NWR and Sahara mustard at the California LCC extent). While models still performed well in these instances, additional data would likely increase the accuracy of model predictions. Furthermore, for some of the refuges, there was little to no GIS data available which also constrained fine-scale modeling (e.g., management activities, treatment). Although in these cases additional environmental predictor variables were downloaded to supplement the model, there may have been predictor variables that were not included that were importance drivers of the species distribution.

Future efforts to model potential risk of invasive species using ecological niche models should focus on collecting presence points that capture the spatial and environmental range of the species of interest across the study area (Thuiller et al., 2004). Although the Maxent model can handle a variety of collected data (e.g., observations, sample plots, historical records), we strongly recommend that a system sampling strategy be considered for future efforts. By sampling throughout each NWR and across the environmental range, predictions can be greatly improved and be more informative. If absence data are collected, the presence-absence methods for modeling potential distributions may also provide reliable predictions, but the issues of true absences for invasive species are likely to still cause concern when interpreting model results (Václavík and Meentemeyer, 2009).

CONCLUSION

Ecological niche models are commonly used to help anticipate and predict species invasions across geographic scales (Peterson et al., 2003). At the refuge level, these results provide statistically supported guidance for directing management initiatives, prioritizing early detection/rapid response, and quantifying risk. For example, model predictions are often used to prioritize search efforts to those areas with potentially higher invasion risk reducing the time and area to search, while conserving economic and management resources. Furthermore, the estimates of potential acres at risk in combination with the maps of predicted risk can provide accepted risk assessments to inform policy makers on land-management decisions (Arriaga et al., 2004), and be used to solicit funds for species specific management. As new species locations are collected, additional and higher quality predictor layers are developed, and modeling methods improve, distribution predictions can be iteratively updated to provide the most current maps of invasive species risk.

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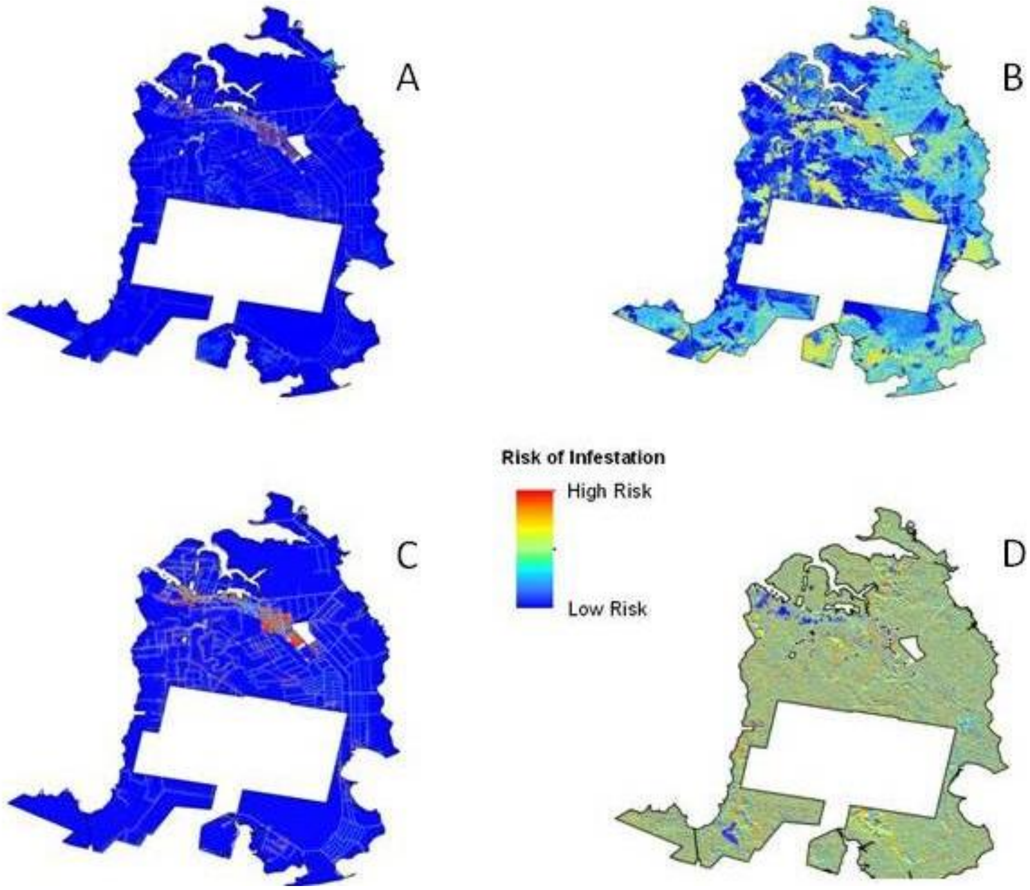
APPENDICES

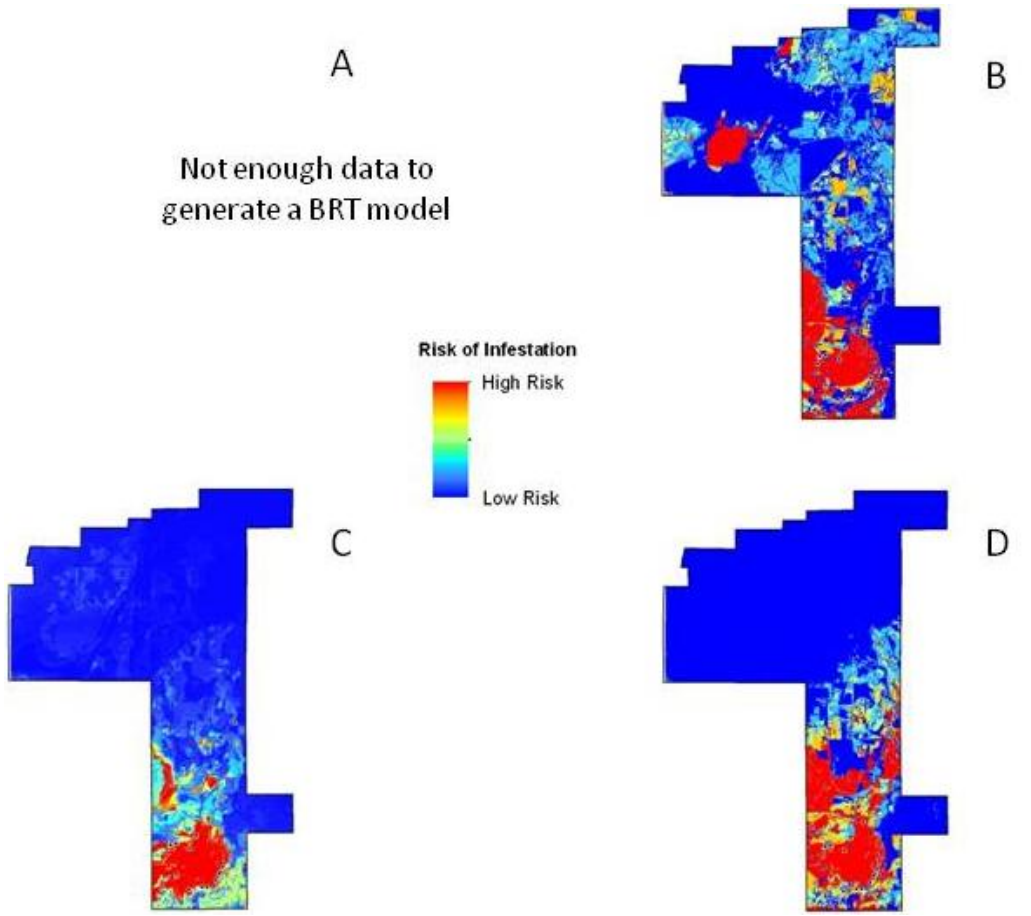
Appendix 1. Predictor variables used to generate models at each refuge. The Source of the predictor variable Land Cover Type varied from GAP (Quivira), DARE (Alligator River), and Landfire(Silvio O. Conte), Vegetation 1995 (San Diego) depending on the refuge.

Predictor	Alligator River	Quivira	Silvio O. Conte	San Diego
Aspect	x	x	x	x
Digital elevation model	x	x	x	x
Distance to water	x	x	x	x
Fire Management Areas	x			
Invasive Plant Management Areas		x		
Land Cover Type	x	x	x	x
Normalized Difference Vegetation Index (NDVI)		x		
Pretreatment areas	x			
Slope	x	x	x	x
Soils (USGS SURGO)	x	x	x	x
Vegetation Management		x		
Distance to road				x

Appendix 2. Model results for *Phragmites* spp. at Alligator River NWR. The models tested were (A) Boosted Regression Tree, (B) Multivariate Adaptive Regression Splines, (C) Maxent and (D) General Linear Model.



Appendix 3. Model results for tamarisk at Quivira NWR. The models tested were (A) Boosted Regression Tree, (B) Multivariate Adaptive Regression Splines, (C) Maxent and (D) General Linear Model.



Appendix 4. Model results for Japanese stiltgrass at Silvio O. Conte NWR. The models tested were (A) Boosted Regression Tree, (B) Multivariate Adaptive Regression Splines, (C) Maxent and (D) General Linear Model.