# Quantifying Bird Habitat at the Salton Sea

Informing the State of California's Salton Sea Management Plan

*Photo credit: Imperial Irrigation District*

***Technical Report: Methods***

*September 30, 2016*

*By*


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## Background

The State of California is planning for future management of the Salton Sea, particularly in light of expected reductions to water inputs starting in 2018 due to existing water transfer agreements. The State is expected to produce a Salton Sea Management Plan by the end of 2016 and asked Audubon California to use habitat suitability modeling to quantify the types and extent of bird habitat needed to sustain baseline populations of birds at the Sea. This information will be used by the State to inform its Salton Sea Management Plan.

We have two objectives with this work:

1. Describe the habitat conditions sustaining bird populations at the Sea. For each type of avian habitat, we will select indicator species, consistent with the U.S. Fish & Wildlife Service (USFWS) Strategic Habitat Conservation approach, which recommends this as a “tool to help focus our biological planning efforts in a way that benefits multiple species on these landscapes” (USFWS 2016). Using the results of the modeling and based on the best available science, we will develop “recipe cards” for each type of habitat, based on the successful approach used at Owens Lake, to define ideal salinity ranges, water depths, and so on. These “recipe cards” will help ensure that limited resources (money and water) are put to the best possible use supporting high-quality habitat.
2. Understand how many acres of each type of habitat are needed to sustain bird populations at baseline (1999-2000) levels. We are treating 1999-2000 as the baseline because it is the most recent period with sea-wide bird survey data from Point Blue Conservation Science (then PRBO). While terminal lakes are dynamic ecosystems, a baseline must be selected, and this selection corresponds to the best available science. It is not likely possible to go back to bird population levels in 1999-2000; however, the State can use this baseline to consult with experts on what

extent of habitat might be feasible under future (and as yet unknown) conditions, and as a goal post for future habitat projects to ensure that adequate habitat will be created and managed as the Sea recedes.

This habitat modeling effort will provide Audubon and our partners with a roadmap, one that the State requested to inform its Salton Sea management planning process. In the end, it will be up to the State of California and other decision-makers and land managers such as USFWS to use this information to make habitat management and water allocation decisions. With this information in hand, the State can make informed decisions backed by science about where to apply increasingly limited water and how to spend conservation dollars efficiently, toward a future Salton Sea where communities and economic activities thrive alongside wildlife. Owens Lake provides a clear motivation for this type of conservation planning: large portions of the lake are being reengineered because this type of planning was not done early on and has resulted in an over-allocation of water in some areas. As USFWS notes, "because the resources needed to conserve all of our trust resources outweigh our existing capacity, we must focus our investments wisely" (USFWS 2016).



## Methods

Our habitat modeling approach consists of three steps: 1) model the suitability of habitats in the landscape for each species; 2) use the results for the indicator species for each habitat to determine the most important areas for each habitat, correcting for uncertainty in estimates; and 3) combine species results by habitat type, (tentatively) where areas with all species present represents the areas of most preferred habitat and where areas with at least 70% of species present represent preferred habitat. We followed the same approach for systematic conservation planning with density data as described in

Veloz et al. (2015), but without the use of data corrected for imperfect detection. We explain each step in detail below.

## Study area

The study area comprises the Salton Sea and the area immediately surrounding it. We used the -228 ft contour line as reference, representing the approximate water level of 1999 (Cohen 2014), and buffered it to 5 km inland to include records reported from the shoreline and reports from adjacent wetlands. We then used any data within the buffer and the sea to fit the models. Model predictions were then masked to a buffer of 1 km from the shoreline (which changes by year), and to exclude predictions to adjacent agricultural lands and other habitats. The mask preserved only adjacent wetlands, which were of interest for management purposes. Figure 1 below shows the extent of the study area.

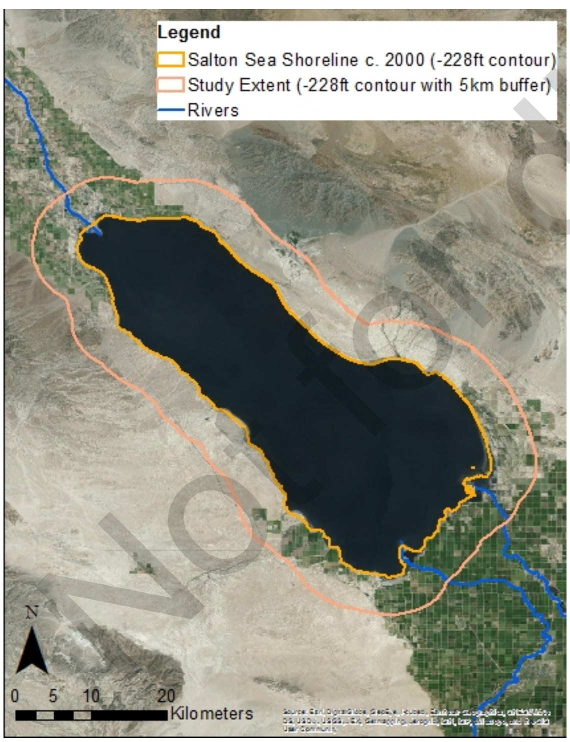



Figure 1. Extent of the study area, Salton Sea, California.

## Bird observations data

We used data from eBird and the Pacific Flyway Shorebird Survey (PFSS) to model suitability. eBird is a volunteer-science online birding checklist database that provides site-specific data on bird abundance and distribution at varying spatial and temporal scales (http://ebird.org/content/ebird/). The PFSS (Reiter 2011) is a mid-winter survey conducted by volunteer scientists following a predetermined protocol. Details on the protocol can be found here:

http://www.migratoryshorebirdproject.org/uploads/documents/AreaSearchProtocol_Coast_2012Final_rev101314.pdf

eBird data (Sullivan et al. 2009) were filtered to include only "Approved" records (i.e., records vetted by eBird's reviewers), where the observer reported all species detected (important for establishing the survey events), and only records using the following survey protocols: traveling count, stationary count, exhaustive area count, and random location counts. Similar uses of eBird data include Fink et al. (2010), and Hurlbert and Liang (2012). We included only one checklist from those survey events where a known group of observers participated in the survey and all reported separately.

Traveling counts include data from a wide range of areas covered by the reporting birdwatcher. In order to standardize the survey effort and make these counts comparable to other survey protocols in eBird and PFSS, we used a traveling distance cutoff that matches the resolution of our models: 500m. However, for three species (Common Gallinule, Gull-billed Tern, and Least Bittern) the number of detections was greatly reduced at that cutoff distance, so we extended the datasets for these three species to include traveling counts up to 2.5 km long. This undoubtedly introduced some error into the models, as the observational data were collected at a larger scale than the resolution of the models. Nevertheless, it resulted in a better model fits for these three species.

There are good reasons to use data from a mixture of survey methods to train our models. All methods we considered contribute significant amounts of data, and help reduce spatial bias in data collection. This also means that unless accounted for as a fixed effect, survey method will introduce noise and uncertainty in the predictions. Fixing the effect of survey methods would mean that our predictions would be conditional on a particular survey method (e.g., amount of suitable habitat under survey protocol “x”). This would be an important step if our goal was to estimate the magnitude of the covariate effects on habitat preference. Since we are only interested in predicting the preferred habitats, not in understanding magnitude of effects, we opted not to fix the effect of survey methods in our models. Thus, our predictions are thus unconditional on any survey method. The predictions will have some error due to unexplained variance from the use of different survey methods, but given the overall similarity of survey methods (they all have a similar ontology: survey an area of approximately the same size, for approximately the same amount of time, with the same tools), we think the error is small.



Table 1. List of indicator taxa used, the months selected for each, and the habitats they represent.

| **Species** | **Code** | **Start month** | **End month** | **Habitat** |
|---|---|---|---|---|
| Eared Grebe | EAGR | Dec | May | Deep water habitat (30 cm - 2m), with rocky substrate for invertebrates. |
| Ruddy Duck | RUDU | Oct | May | |
| American White Pelican | AWPE | Jul | Apr | |
| Double-crested Cormorant | DCCO | Jan | Dec | |
| Snowy Plover | SNPL | Jan | Dec | Playa nesting habitat for SNPL |
| American Avocet | AMAV | Jul | Apr | Mudflats, sandflats and beaches (<15 cm water depth) |
| Marbled Godwit | MAGO | Jul | Apr | |
| Dowitcher spp. | UNDO | Jul | May | |

| | | | | |
|---|---|---|---|---|
| Dunlin | DUNL | Aug | May | |
| Western Sandpiper | WESA | Jul | May | |
| Least Sandpiper | LESA | Jul | Apr | |
| Snowy Egret | SNEG | Jan | Dec | |
| Gadwall | GADW | Nov | May | Mid-depth water (15-30 cm) habitats, dabbler habitats |
| Northern Shoveler | NOSH | Jul | Apr | |
| Black Skimmer | BLSK | May | Aug | |
| Least Bittern | LEBI | Jun | Aug | |
| Virginia Rail | VIRA | Jan | Dec | Permanent wetlands with tall vegetation, rail habitats |
| Sora | SORA | Aug | Apr | |
| Common Gallinule | COGA | Jan | Dec | |
| Gull-billed Tern | GBTE | Mar | Jul | Land-sea interface habitats, generalist habitats |
| Gull spp. | GULL | Aug | May | |
| Black Tern | BLTE | Jul | Sep | |



We selected “indicator” avian species, based on expert opinion, to represent the primary habitat types at the Salton Sea (See Table 1). For each habitat type, we sought the species most commonly seen (i.e., most commonly present in the data after filtering for survey effort). The data for each species was obtained as follows. First, we generated an overall survey effort table by listing the unique locations and dates of every survey from the eBird and PFSS datasets. We then filtered this effort table for the months for which each species would be modeled (more on this below; also see Table 1), the 5 km buffer, and the wetland habitat masks. The same filter of survey months, buffer and wetlands was then applied to the observational data for the species (i.e., all records in which the species was detected). Lastly, under the knowledge that each surveyor reported all the species detected, we merged the filtered effort and observation table for each species, assigning 0 counts to those survey events where the indicator species was not detected.

As explained above, for each indicator species we filtered the data to include only records for the months determined to be the period when the species is most common in the Salton Sea. We used data collected between January 2011 and December 2015. We implicitly assume that the processes that determines habitat preference in each taxon remains unchanged in this period, so that, for example, data from 2011 are independent replicates to data from any other year in the period. After examining model fits for 54 taxa, we opted for using 22 based on the goodness of model fits and those species thought to better characterize the habitat, sorted into 6 different habitat types. For example, Eared Grebe is a common visitor of the Salton Sea, and a good representative of the deep water guild. For the playa and tall marsh habitats, the selection of species was limited to Snowy Plover and Least Bittern respectively, regardless of their frequency of detection. Only Snowy Plover truly describes the habitat, and Least Bittern is probably the least secretive of marshbirds and may be amenable to modeling without the use of imperfect detection methods. The species selected as indicators of specific habitats, the habitat definitions, and the periods of the year for which each species was filtered are listed in Table 1. For example, for Eared Grebe, we combined the records from December 2011 to May 2012, December 2012 to May 2013, December 2013 to May 2014, and December 2014 to May 2015 into a single dataset for training the habitat suitability model for the species.

The center of the lake is > 2 m deep and thus not listed as a habitat in our table. The vast majority of our observation records come from areas with water < 2.5 m deep, rendering the center as poorly sampled at best. Detweiler et al. (2002) and Riedel et al. (2002) mention that the most important areas for arthropod and fish are near-shore shallow waters, but areas of greater depths are nevertheless used. Therefore, instead of attempting to model and predict to these poorly sampled areas, we considered the center of the lake as suitable deep water habitat and unsuitable to all other habitat indicator species.

The selection of the survey periods for each species was made by modeling the counts with a generalized linear model. The model had a negative Binomial error distribution, and only month and number of survey events as covariates. We then predicted to each month while holding the number of survey events constant, to determine which months are expected to have the largest number of birds independent of survey effort. The predicted monthly abundances are shown in Figure 2. We visually compared these to the sum total of counts per month (Figure 3) and the data reported in Howell and Shuford (2008) as ways to check that our selected intervals for each species were reasonable. We used a first-pass selection of months with at least 5% of the year-round abundance. But an absolute criterion, such as a cut-off point of total or predicted counts, may result in some months excluded due to high variance and limited sampling. For example, for the American White Pelican, February may be excluded if only using the 5% cut-off from predicted abundance. Inspection of counts suggests that the species is present in that month. Ultimately, our choice was a balance among the predicted and observed counts, and the previous results in Howell and Shuford (2009). For reference, we show the total number of survey events per month in Figure 4.

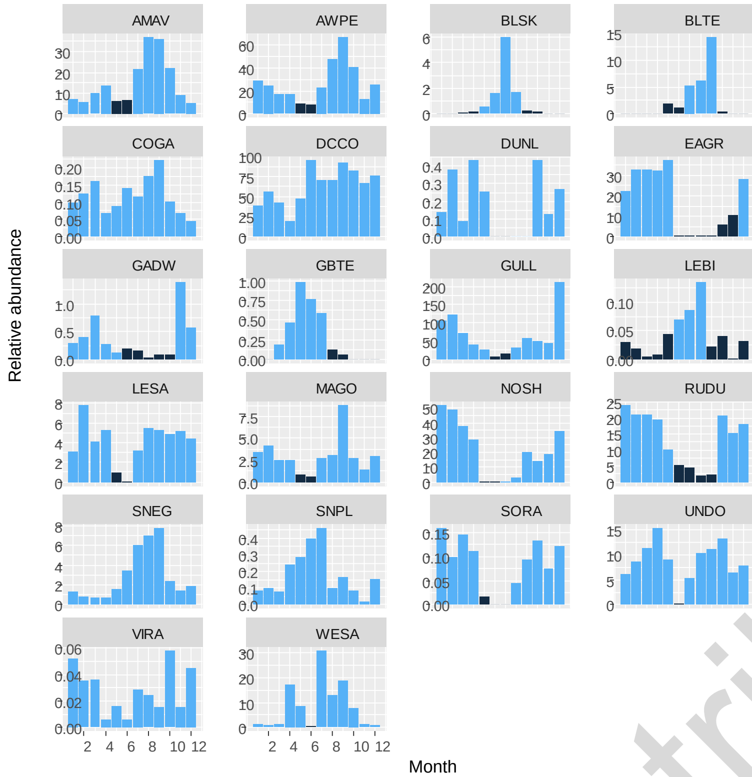



Figure 2. Predicted abundance, corrected by survey effort, by month for the 22 indicator species in the period 2013-2015. In black are the months not included in the model for each species.

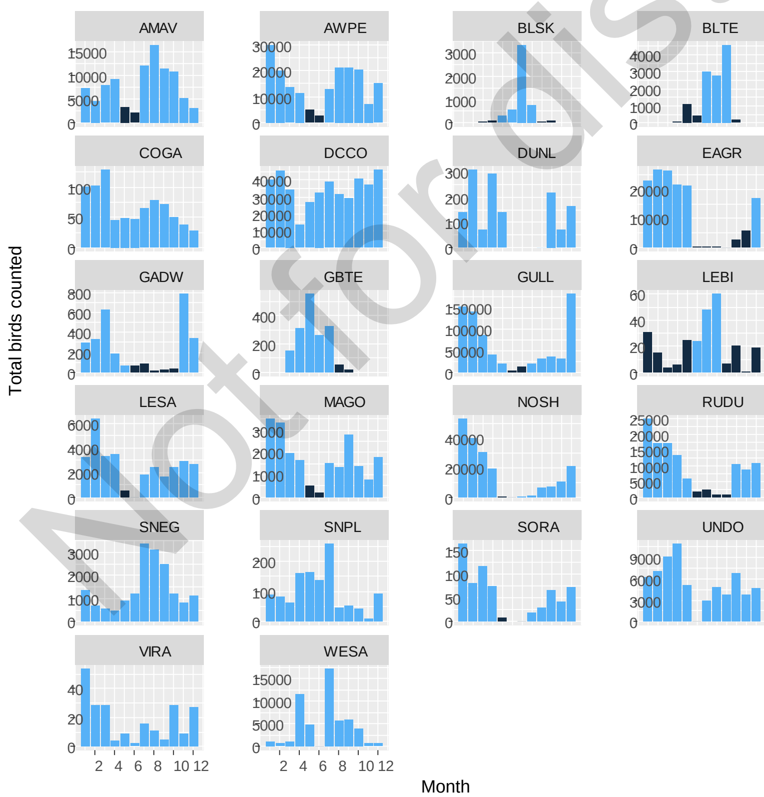
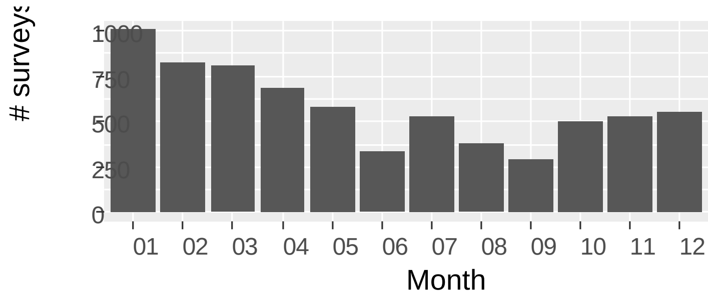



Figure 3. Sum total of counts per month for the 22 indicator species in the period 2013-2015, uncorrected for survey effort. In black are the months not included in the model for each species.

Figure 4. Survey effort (number of surveys) by month for the period 2013-2015.




## Geospatial covariate data

We sought to use covariates that are related to water level which was estimated for each pixel from the current water level and the bathymetry layer (U.S. Geological Survey [USGS], https://www2.usgs.gov/saltonsea/LiDAR.html). The water level data were obtained from the USGS (USGS, Water Gauge #10254005; http://waterdata.usgs.gov/ca/nwis/uv?site_no=10254005). Water depth was then binned to 0-15 cm, 15-30 cm, 30 cm- 2m, and > 2 m. We based these depth categories on expert opinion, and reports of depth of metazooplankton and invertebrates (Tiffany et al. 2002; Detweiler et al. 2002), which indicate that most larva and arthropods are present at depths up to 2 m. The avian fauna exploiting these depths are distinctive, where the small shorebirds would use the mudflats and shallowest waters, the waders would use the intermediate depths, and only the piscivorous and diving species would use the deeper areas. For all covariates excepting those measuring distances to features, we used two scales of effects by generating values averaged from radii of 250 m and 2,500 m from the center of each pixel.

We obtained landcover data from the 2011 National Landcover Database (NLCD) (Multi-Resolution Land Characteristics Consortium, http://www.mrlc.gov/nlcd2011.php) and the National Wetlands Inventory (NWI) (USFWS, https://www.fws.gov/wetlands/). These two land cover classification systems have different levels of resolution: one is based on aerial photography and the other on satellite data. NWI data are more precise and accurate, but not updated as frequently as the NLDC data. Here we are simply using some information from one, and some from the other, both resampled to our 500-m pixel size. We understand that there will be differential attribution error, but we think that at the scale of our models, the error will be minimal regardless of the source.

Covariates of distance to features (ShorelineDistanceMeters, RiverDistanceMeters, RiverMouthDistanceMeters) were calculated using the Euclidian Distance tool of ArcGIS 10.2 (ESRI 2013). The shoreline contour, for the calculation of distance to shoreline, was interpolated from the Digital Elevation Model (DEM) using the Contour tool of ArcGIS 10.2 (ESRI 2013). Slope was calculated using the Slope tool of ArcGIS 10.2 (ESRI 2013).

Sediment survey data for the Salton Sea was provided by USGS (Agrarian Research, https://www2.usgs.gov/saltonsea/docs/SSA/Salton%20Sediment%20Report%2020%20Oct%2003.pdf). See reference for discussion of sampling methods. From these points, we interpolated the fractions of clay, organic matter, sand, and silt reported by the survey into a raster covering the entire Sea. We used an inverse distance weighted method, specifically the IDW Interpolation tool in ArcGIS 10.2 (ESRI 2013). To minimize error and avoid egregious extrapolation, we then removed all areas of the interpolated raster that were more than 1 km from a survey point unless that area was completely surrounded by the 1 km buffer of survey points.

We resampled each layer, except for the abovementioned distance-to-feature layers, to resolutions of 500 x 500 m and 5000 x 5000 m, calculating either averages or sums as appropriate, using packages rgdal (Bivand et al. 2015) and raster (Hijmans 2015) in R version 3.2.1 (R Core Team 2015). The landscape covariates are listed with processing information and original data sources in Table 2 below. Select covariates are shown in Figure 5.

Table 2. List of covariates, their description, how processed, and data sources.

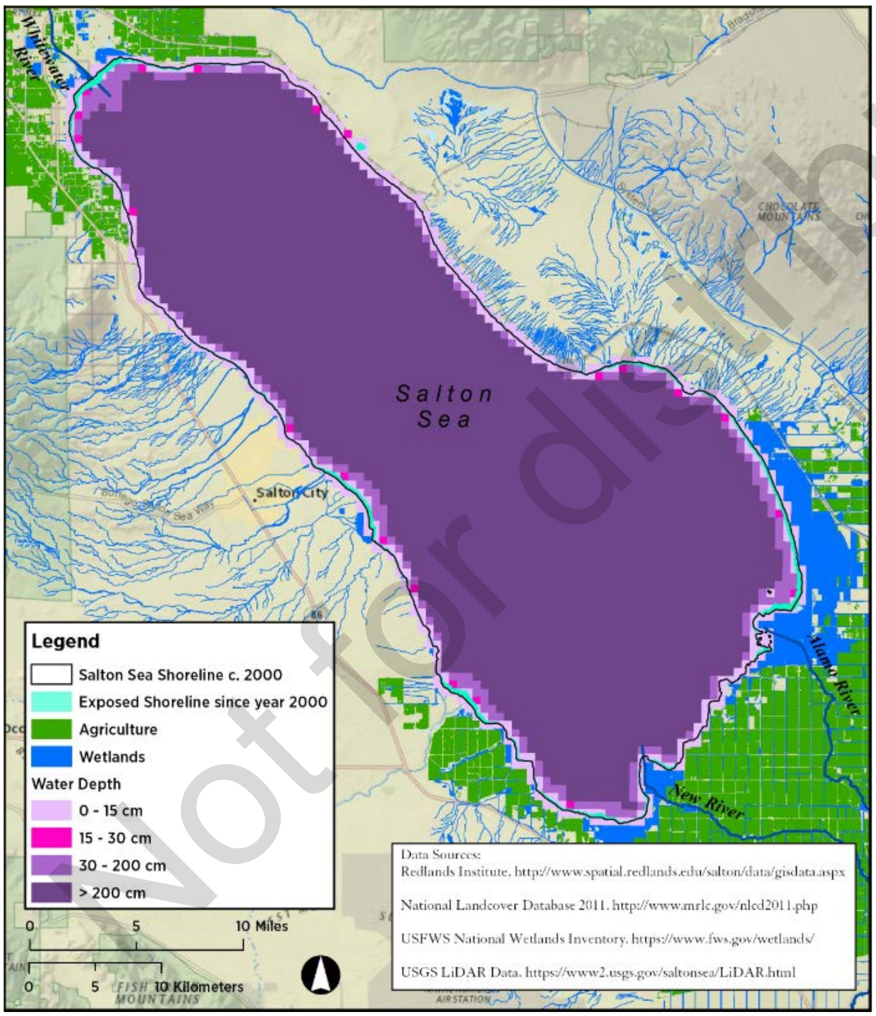
| Covariate | Description | Data processing | Data source |
|---|---|---|---|
| *WaterDepthMeters* | Average water depth in pixel | Average of DEM value, rescaled to current water level for each 500-m pixel | a, b |
| *WaterShallowsSqm_0to15cm* | Area of pixel covered by water between 0 and 15 cm deep | Reclassification of DEM value by depth, then sum the area within each 500-m pixel | a, b |
| *WaterShallowsSqm_15to30cm* | Area of pixel covered by water between 15 and 30 cm deep | Reclassification of DEM value by depth, then sum the area within each 500-m pixel | a, b |
| *WaterShallowsSqm_30to200cm* | Area of pixel covered by water between 30 and 200 cm deep | Reclassification of DEM value by depth, then sum the area within each 500-m pixel | a, b |
| *WaterShallowsSqm_200to1000cm* | Area of pixel covered by water > 200 cm deep | Reclassification of DEM value by depth, then sum the area within each 500-m pixel | a, b |
| *ExposedShoreSqm* | Area of land in pixel uncovered by water that was covered at the baseline water level of -228 ft NAVD | Reclassification of DEM value by depth, then sum the area within each 500-m pixel | a, b |
| *ShorelineDistanceMeters* | Average distance to shoreline of a pixel | Shoreline interpolated from the DEM; then calculated Euclidian distance to it, then averaged within each 500-m pixel | a, b |
| *RiverDistanceMeters* | Average distance to one of the three rivers flowing into the Salton Sea | Calculated Euclidean distance from each original 10- m pixel, and then averaged within 500-m pixel | c |
| *RiverMouthDistanceMeters* | Average distance to the point where one of the three rivers flow into the Salton Sea | Calculated Euclidean distance from each original 10- m pixel, and then averaged within 500-m pixel | c |
| *SlopeDegrees* | Average slope of the pixel | Calculated slope at each original 10-m pixel, and then averaged within each 500-m pixel | a |
| *FreshwaterEmergentSqmNWI* | Area of pixel covered by this type of wetland | Rasterized polygons at 10-m resolution, and aggregated the area within each 500-m pixel | d |
| *FreshwaterPondSqmNWI* | Area of pixel covered by this type of wetland | Rasterized polygons at 10-m resolution, and aggregated the area within each 500-m pixel | d |
| *LakeSqmNWI* | Area of pixel covered by this type of wetland | Rasterized polygons at 10-m resolution, and aggregated the area within each 500-m pixel | d |
| *RiverineSqmNWI* | Area of pixel covered by this type of wetland | Rasterized polygons at 10-m resolution, and aggregated the area within each 500-m pixel | d |
| *OtherWetlandSqmNWI* | Area of pixel covered by this type of wetland | Rasterized polygons at 10-m resolution, and aggregated the area within each 500-m pixel | d |

| | | | |
|---|---|---|---|
| *NonLakeWetlandTotalSqmNWI* | Area of pixel covered by this type of wetland | Rasterized polygons at 10-m resolution, and aggregated the area within each 500-m pixel | d |
| *OpenWaterSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *BarrenSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *HerbaceousSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *PastureSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *CultivatedSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *WetlandsWoodySqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *WetlandsHerbaceousSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *AgTotalSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *WetlandsTotalSqmNLCD2011* | Area of pixel covered by this type of landcover | Calculated by summing the area for each pixel | e |
| *ClayFraction* | Average fraction of the sediment comprised of clay | Interpolated from survey points using inverse distance weighting, removed areas farther than 1km from a survey point, and averaged. | f |
| *OrganicFraction* | Average fraction of the sediment comprised of organic material | Interpolated from survey points using inverse distance weighting, removed areas farther than 1km from a survey point, and averaged. | f |
| *SandFraction* | Average fraction of the sediment comprised of sand | Interpolated from survey points using inverse distance weighting, removed areas farther than 1km from a survey point, and averaged. | f |
| *SiltFraction* | Average fraction of the sediment comprised of silt | Interpolated from survey points using inverse distance weighting, removed areas farther than 1km from a survey point, and averaged. | f |

Data sources: a - Digital Topo-Bathymetric Model of the Salton Sea (USGS - https://www2.usgs.gov/saltonsea/LiDAR.html); b – Salton Sea Water Gauge (USGS Gauge #10254005 - http://waterdata.usgs.gov/ca/nwis/uv?site_no=10254005), c - Redlands Institute Salton Sea River Data (http://www.spatial.redlands.edu/salton/data/gisdata.aspx); d - National Wetlands Inventory (USFWS - https://www.fws.gov/wetlands/); e - National Landcover Database 2011, Multi-Resolution Land Characteristics Consortium (http://www.mrlc.gov/nlcd2011.php); f - Characterization of Shallow Sub-Surface Sediments of the Salton Sea, (Agrarian Research - https://www2.usgs.gov/saltonsea/docs/SSA/Salton%20Sediment%20Report%2020%20Oct%2003.pdf, data provided by USGS)

Salinity is a desirable covariate to use when modeling suitability. It is likely that there are different degrees of salinity within the lake, depending on proximity to freshwater sources, discharge amounts, and periods of the year. The effects of salinity are expected to be complex (Anderson et al. 2007, Barnes and Wurtsbaugh 2015). Unfortunately, there are no consistent salinity data, sampled at enough locations to help establish a geospatial layer for use in our models.

Figure 5. Select landscape covariates.






Despite the limited information available, high salinity levels are one of the most pressing issues affecting the bird fauna at the sea (Cohen 2014, Miles et al. 2009). We evaluated possible salinity effects by looking at direct measures of bird (guild) abundance versus salinity data from a 12-year series from the San Francisco Bay South Bay Salt Pond (SBSP) project conducted by USGS (De La Cruz citation to come – manuscript and report are in review). Our goal was to determine whether and how to adjust predictions of baseline (1999) habitat suitability according to differences in salinity levels from the period used to build the models (2011-2015). Since we trained our models with data from 2011-2015, predictions for the 1999 baseline may underestimate suitability, since the salinity levels in 1999 were lower than the current 2011-2015 period. We found four arguments supporting our decision to make no adjustments for salinity effects to the predictions of suitability for the baseline 1999 estimates. First, the data from SBSP suggest only a minimal change of approximately 0.25 individuals for the mean bird abundance per pond for the 5 ppt change in salinity between 1999 (45 ppt) and 2015 (50 ppt). The USGS study states that optimally most species prefer < 33 ppt but that real change happens at much higher salinities. Second, the 5 ppt difference may have an effect on suitability well within the margin of error of the USGS's and our models. Third, it is difficult to untangle ecosystem-specific responses from an absolute effect of salinity. The USGS study showed that Eared Grebe thrives at much higher salinity (109-124 ppt) than the current value (50 ppt) for the Salton Sea, as do many other shorebirds and waders, and this is due to these hypersaline environments being optimal for two arthropod genera that are prey to Eared Grebe and other waterbirds. These groups are not (yet) present in the Salton Sea. Lastly, Warnock et al. (2002) also analyzed the effect of salinity on bird abundances in the SBSP, reaching similar conclusions to those in the USGS report. .

High levels of Selenium have been repeatedly found in many areas around the Salton Sea, and in sediments in areas of the lake bottom (Anderson 2008). This contaminant should be considered when identifying the areas of suitable avian habitat. The USGS has produced maps of "Selenium hotspots", which can be juxtaposed on the projections of preferred habitat.

**Habitat suitability models**

Once the bird data were attributed with the biophysical covariates, we fit a boosted regression tree (BRT) model with binomial error distribution to detection/non-detection values (i.e., assigning a value of one if the species was detected in the survey in any number and zero otherwise). The BRT is a powerful regression-and-classification algorithm that fits small (1-5 branches) trees consecutively on the data based on the salient regression coefficients of models fit to the residuals of the cumulative set of trees, so as to increase model predictive accuracy as more trees are added to the model (Friedman 2001). It automatically handles variable interactions and determines variable relative importance. It uses standard cross-validation techniques to reduce over-fitting. The BRT method is designed to produce a model that has high predictive accuracy, not to formally test ecological significance of variables (Elith et al. 2008). Nevertheless, it provides valuable insights on the importance of covariates on the landscape use by habitat indicator species.

We used middle-of-the-road model tuning parameters: tree complexity of 3, and learning rate of 0.005, looking for fits that used a reasonable number of trees (1,000 - 4,000). Past experience has shown us that moderate tuning works well so long the number of resulting trees is reasonable. We tentatively explored fitting a Poisson error distribution to the count data for those species with <90% of the surveys being zeroes, but the model fits were largely inadequate (i.e., relatively high deviance). This is understandable, because the model is seeking a probability distribution with mean value such that there is a good probability of zero counts (as the data have many zero-detection events) along with events with high (sometimes in the tens of thousands) counts per event. Thus, we opted not to fit BRT models with Poisson error link, and only used the Bernoulli distribution link.

The challenge introduced by the zero counts is partially addressed with the binomial error distribution, but not entirely so. The preponderance of zeros indicates that the data are zero-inflated (Zuur et al.

2009). Unlike the case in Veloz et al. (2015) where the inflation was caused by imperfect detection, the datasets from the Salton Sea reflect the highly variable temporal (diel and seasonal) patterns of use by the indicator species. Two surveys occurring in the same day may result in very different counts simply because these happened at different times. Similarly, surveys occurring on the same location at different times of the year may result in very different counts.

Arguably, the preponderance of surveys with 0 detections is a reflection of suitability. For example, two areas where the species was detected may reflect different suitability if one of them is more prone produce surveys with 0 counts. So, we decided not to use zero-hurdled or zero-inflated models to preserve this information in the data. Similarly, the simple use of 1 to indicate species presence may greatly limit the information conveyed by the survey about suitability. For example, two locations where the species has been detected in surveys may differ in suitability if one has hosted no more than 5 individuals of the species, whereas counts in the other may surpass 5,000 individuals. We wanted to incorporate the information about suitability from the total counts into our binomial model. We used the log of the total count as the weight for a detection record. The records with 0 counts were all assigned the same weight of one.

Because amount of preferred habitat will be based on the combination of indicator species for the habitat, it is important that the predictive models accurately reflect the probability of detection of the species in each pixel. We assume that the probability of detection is directly related to suitability: more preferred habitats have higher probability of detection of the species. We evaluated model accuracy through three different means. First, we looked at the amount of deviance explained among competing species. Commonly, species with most data resulted in a better fit. We were able to choose species and opt for using the binomial error link by evaluating the amount of deviance explained. Second, we reviewed the list of most important covariates and their functional form with the help of expert field ornithologists. A good model would show as top covariates those expected to be the most influential in the species' selection of habitats, and the functional form of the effect should match that expectation. Third, a visual inspection of the predictions by field ornithologists familiar with how the species use the Salton Sea helped decide on the merits of including taxa as avian habitat suitability indicators.

Spatial bias in the data can be a consideration when fitting landscape models. We are confident that, by using data from various survey methods, and because the area being modeled is relatively small, spatial bias effects will be limited.

We did not conduct exhaustive determination of variable importance using common methods, such as evaluating the change in deviance when removing one variable at the time. We are not interested in identifying the complete set of important covariates. Though our covariates have some ecological relevance, their effect on avian habitat preference is often indirect. For example, the sediment layer we are using may correlate with arthropod presence, the true driver of bird presence and which we lack. So, we decided to just identify the top three variables as ranked by the summary of the model. These are likely to be among the most important, if not the top three most important, if identified using more exhaustive methods.



## Looking forward: Combining species by habitat group

We will use the same approach as used in Veloz et al. (2015). We will calculate 3 values of probability of species occurrence for each cell and each taxon: the predicted value, and the predicted value +/- 1.96*Standard Error. The standard error will be calculated as the mean of standard errors obtained from the residuals of cross-validation bootstrap. Once we have these estimates, we will hurdle them into presence/absence (1/0) values by using the prevalence of the taxon in the landscape. The prevalence will be estimated as the percentage of cells in which the species was detected. There are many proposed methods to hurdle probability of occurrence into presence/absence, and simulations have shown that prevalence is as good, if not better than, other proposed alternatives (Liu et al. 2005; Lobo et al. 2007). The result will then be, for each taxon, 3 rasters: the mean predicted presence, and the lower and upper bound estimates of presence (again, values of 0 or 1). Therefore, for each habitat we will have a stack of rasters from all indicator species we are using, for the mean presence estimates, a stack with the lower bound predicted presence, and a stack with the upper bound predicted presence. Preferred habitat suitability will tentatively be defined as: most preferred (only those cells where all species are present) and preferred (70% of the species present). We will alter these definitions upon review and consultation with experts to try to define the niche of the collective of indicator species that most closely resembles expert opinion. The area of preferred habitat for each avian habitat type will be the area of all cells of most preferred habitat summed with the area of all cells of preferred habitat.



**Looking forward: Estimating impact of sea level changes**

We will estimate how the total preferred and most preferred area for each habitat type might have changed over the past 16 years. The pattern of change is illustrative of what we may expect into the future, and would help visualize the impacts due to water level changes. Thus, we will hind-cast with our model to 2 previous time intervals to estimate total preferred area per habitat. We will recalculate all covariates related to the Salton Sea's water level for years 1999-2000 and 2011-2015. For the first period (1999-2000) we will also use a different layer of land cover (NLCD 2001) which better informed the land conditions of the period than the layer used to train the model. We will then predict to these periods and estimate total area of preferred habitat for each of the habitat types using the same methodology described above.

## Acknowledgements

This work would not be possible without private philanthropic support and the financial support of the U.S. Bureau of Reclamation. The Cornell Lab of Ornithology, USGS, USFWS, and the Redlands Institute all provided important datasets. We thank Justin Schuetz, Nicole Michel, Michael Case, and Daniel Fink for their thoughtful review of our methods, and the many other scientists and Salton Sea experts who shared their expertise. Finally, we thank Liling Lee for her mapmaking contributions.

**Literature cited**

Anderson, T. W. 2008. Avian use and Selenium risks evaluated at a constructed saline habitat complex at the Salton Sea, California. Masters Thesis, San Diego State University.

Anderson, T. W., Tiffany, M. A., and Hurlbert, S. H. 2007. Stratification, sulfide, worms, and decline of the Eared Grebe (*Podiceps nigricollis*) at the Salton Sea, California. Lake and Reservoir Management, 23: 500-517.

Barnes, B. D., and Wurtsbaugh, W. A. 2015. The effects of salinity on plankton ad benthic communities in the Great Salt Lake, Utah, USA: a microcosm experiment. Canadian Journal of fisheries and Aquatic Sciences, 72: 807-817.

Bivand, R., Keitt, T., and Rowlingson, B. 2015. rgdal: Bindings for the Geospatial Data Abstraction Library. R package version 1.1-3. http://CRAN.R-project.org/package=rgdal

Cohen, M. J. (2014). Hazard's Toll: The Costs of Inaction at the Salton Sea. Pacific Institute, Oakland California. http://pacinst.org/publication/hazards–toll

Detweiler, P., Coe, M. F., and Dexter, D. M. 2002. The benthic invertebrates of the Salton Sea: distribution and seasonal dynamics. Hydrobiologia 473: 139-160.

Elith, J., Leathwick, J.R., and Hastie T. 2008. A working guide to boosted re-gression trees. Journal of Animal Ecology 77: 802–813.

ESRI 2013. ArcGIS Desktop: Release 10.2. Redlands, CA: Environmental Systems Research Institute.

Fink, D., Hochachka, W. M., Zuckerberg, B., Winkler, D. W., Shaby, B., Munson, M. A, Riedewald, M., Sheldon, D., and Kelling, S. 2010. Spatiotemporal exploratory models for broad-scale survey data. Ecological Applications, 20: 2131-2147.

Friedman, J.H. 2001. Greedy Function Approximation: A Gradient Boosting Machine. Annals of Statistics 29: 1189-1232.

Hijmans, R. J. 2015. raster: Geographic Data Analysis and Modeling. R package version 2.5-2. http://CRAN.R-project.org/package=raster

Howell, C. A., and Shuford, W. D. 2008. Conservation Blueprint for Birds in the Imperial Valley. Report to Audubon California. PRBO Conservation Science, Petaluma, California.

Hurlbert, A. H., & Liang, Z. 2012. Spatiotemporal variation in avian migration phenology: citizen science reveals effects of climate change. PLoS One, 7(2), e31662.

Liu, C., P. M. Berry, T. P. Dawson, and R. G. Pearson. 2005. Selecting thresholds of occurrence in the prediction of species distributions. Ecography 28: 385-393.

Lobo, J. M., A. Jiménez-Valverde, and R. Real. 2008. AUC: a misleading measure of the performance of predictive distribution models. Global Ecology and Biogeography 17: 145-151.

Miles, A.K., Ricca, M.A., Meckstroth, A., and Spring, S.E. 2009. Salton Sea Ecosystem Monitoring Project: U.S. Geological Survey Open-File Report 2009-1276, 150 p.

R Core Team. 2015. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Reiter, M. E. 2011. Compilation of Existing Shorebird Monitoring Programs across California and the California Landscape Conservation Cooperative. Report to the California Landscape Conservation Cooperative. PRBO Conservation Science, Petaluma, California.

Riedel, R., Caskey, L., and Costa-Pierce, B. A. 2002. Fish biology and fisheries ecology of the Salton Sea, California. Hydrobiologia 473: 229-244.

Sullivan, B. L., Wood, C. L., Iliff, M. J., Bonney, R. E., Fink, D., & Kelling, S. 2009. eBird: A citizen-based bird observation network in the biological sciences. Biological Conservation, 142: 2282-2292.

Tiffany, M. A., Swan, B. K., Watts, J. M., and Hurlbert, S. H. 2002. Metazooplankton dynamics in the Salton Sea, California, 1997-1999. Hydrobiologia 473: 103-120.

USFWS. 2016. Strategic Habitat Conservation. https://www.fws.gov/landscape-conservation/shc.html

Veloz, S., Salas, L., Altman, B., Alexander, J., Jongsomjit, D., Elliott, N., and Ballard, G. 2015. Improving effectiveness of systematic conservation planning with density data. Conservation Biology, 29: 1217-1227.

Warnock, N., G. W. Page, T. D. Ruhlen, N. Nur, J. Y. Takekawa, and J. Hanson. 2002. Management and conservation of San Francisco Bay salt ponds: effects of pond 47 salinity, area, tide, and season on Pacific Flyway waterbirds. Waterbirds 25:79- 92.

Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., and Smith, G. M. 2009. Zero-truncated and zero-inflated models for count data. In Mixed effects models and extensions in ecology with R (pp. 261-293). Springer New York.

**Appendix A: Model Summarie**s

# Salton Sea Bird Models

*Nathan Elliott, Leonardo Salas, Katherine Krieger, Dave Shuford, Dan Cooper, and Andrea Jones*

*September 28, 2016*

## Overview

The Salton Sea provides critical habitat for birds in Southern California. In addition to supporting large breeding and wintering populations of many species, it also serves as one of the most important inland stopover points for birds migrating along the Pacific Flyway. Due to drought and diversion of water upstream, the Salton Sea has been shrinking dramatically over the past ten years (Fig. 1), a decline that will be exacerbated by the planned diversion of all Colorado River water in 2017.

To address highlight the importance of the Salton Sea for birds and enumerate the potential impacts of its shrinkage, Audubon California and Point Blue have collaborated to create habitat suitability models for 22 bird species and 6 habitat-based groupings in the Salton Sea. The following pages summarize these models.

### Study Extent

Our report focuses on the Salton Sea itself and on-shore areas within 5km of the sea (Fig. 2). This ensured that we included habitat important to the Salton Sea region that was located near the sea (e.g., wetlands, drains) and that we had adequate data to build our models.


Figure 1: The extent of our study area surrounding the Salton Sea (shown in salmon), as a 5km buffer of the sea's previously stable shoreline of -228 ft NAVD (shown in orange).

### Model Information

The following information is reported for all models:

- Type of model (see Methods)
- Distance threshold used for eBird traveling counts (see Methods)
- Number of observations included in model
- Percent and number of observations that were zeroes
- Percent of total deviance explained by the model (a measure of how well the model explains the data; higher is better)
- Number of trees
- Training data AUC score
- Cross-validated AUC score and standard error
- Table listing the relative influence of each of the included predictors. Variables are listed in descending order of influence and variables with influence of less than 5% are excluded for readability.
- Three plots showing the marginal effects of the variables with the highest model influence. Points are translucent, so darker points indicate more samples.
- A map showing the predicted distribution of the species using 1999 conditions. Darker colors indicate higher predicted counts and therefore more suitable habitat.
- A map showing the predicted habitat suitability of the Salton Sea using 2015 conditions. Darker colors indicate higher predicted counts and therefore more suitable habitat.

### Covariate Information

The first part of the variable name describes the variable. This is followed by a unit (mostly 'Sqm' for square meters), a source for wetlands/landcover data ('NWI' for the National Wetlands Inventory; 'NLCD' for the National Landcover Dataset), and the pixel size (500m or 5000m). Areas were calculated by summing across the pixel whereas other measurements (depths, etc) are means. Most of the covariates are attributed at both 500m and 5000m pixels so we can best capture the scales at which birds respond to environmental factors like land cover. A couple of variables that deserve specific clarification:

| Variable | Description |
|---|---|
| WaterShallowsSqm_XtoYcm | area of water within the pixel that is between X and Y cm deep |
| ExposedShoreSqm_ | area of land that was underwater at the previous baseline shore position of -228 ft |
| RiverDistanceMeters_ | distance to the nearest of the three main rivers (New, Whitewater, and Alamo) |
| RiverMouthDistanceMeters_ | distance to the nearest mouth of the three main rivers (where they enter the sea) |

# American Avocet

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2218

74.17 % ( 1645 of 2218 ) AMAV observations were zeroes.

**Percent of total deviance explained by model:** 34

**Total trees:** 1850

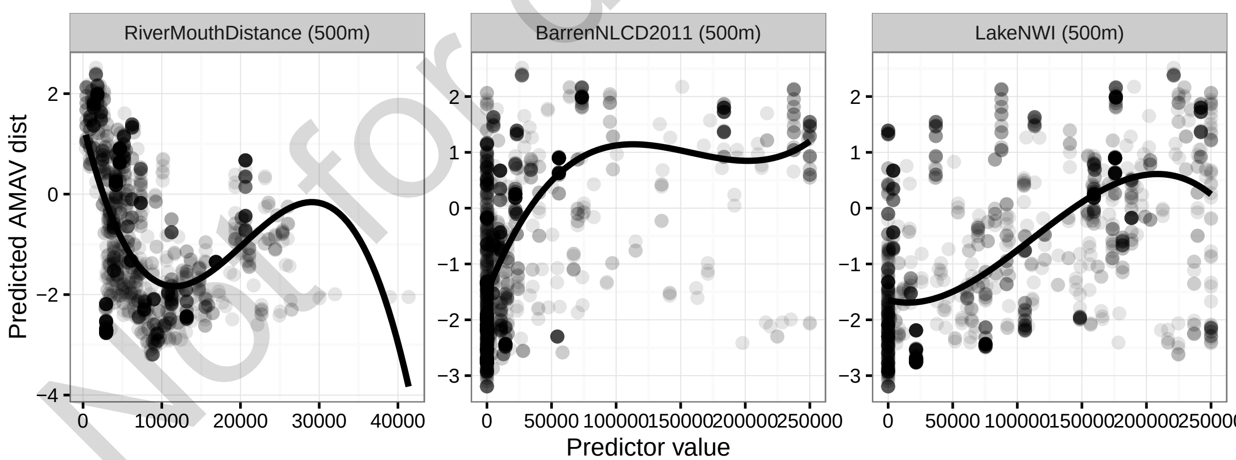
Training data AUC score = 0.812

Cross-validated AUC score = 0.761 ; standard error = 0.009

## Variable Importance

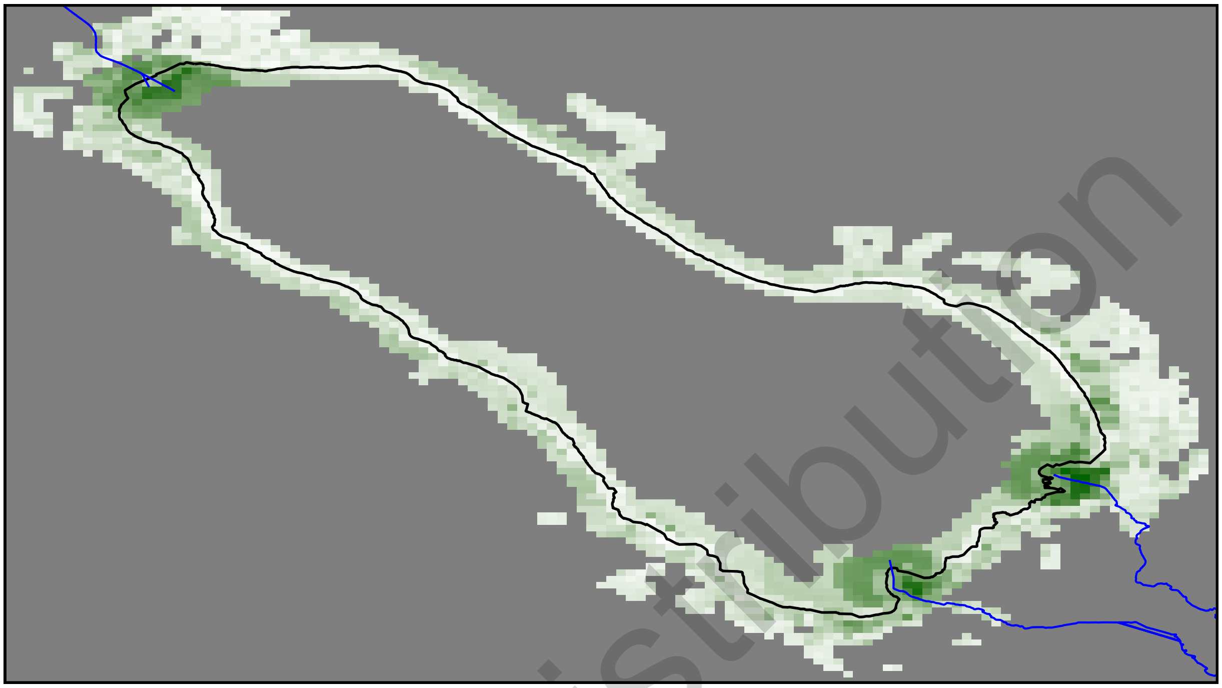
| Variable.Name | Relative.Influence |
|---|---|
| RiverMouthDistanceMeters_500m | 28.0 |
| BarrenSqmNLCD2011_500m | 10.1 |
| LakeSqmNWI_500m | 10.0 |
| SlopeDegrees_500m | 6.6 |
| ShorelineDistanceMeters_500m | 6.0 |

### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)

# American White Pelican

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2218

66.73 % ( 1480 of 2218 ) AWPE observations were zeroes.

**Percent of total deviance explained by model:** 32.7

**Total trees:** 1200

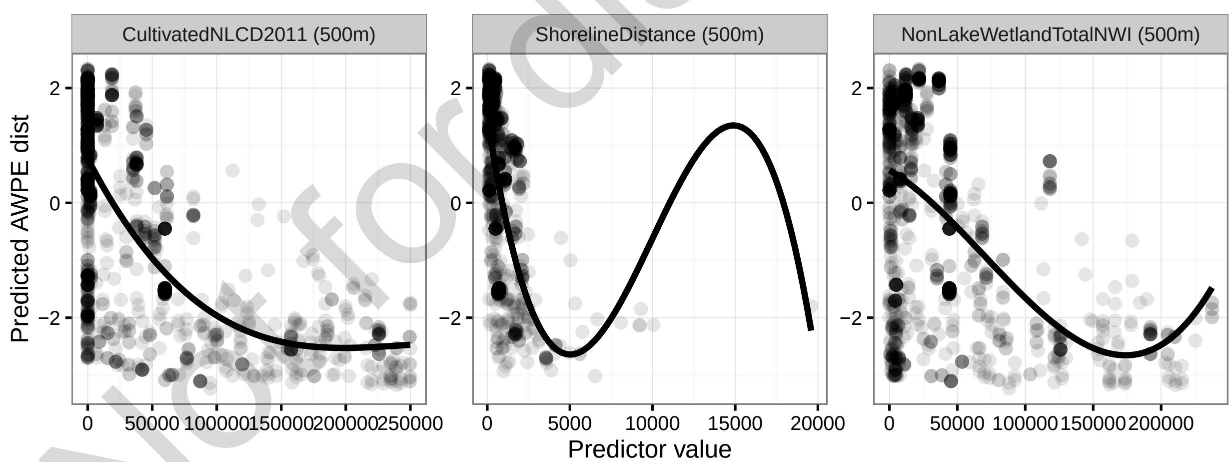
Training data AUC score = 0.832

Cross-validated AUC score = 0.799 ; standard error = 0.008

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| CultivatedSqmNLCD2011_500m | 28.9 |
| ShorelineDistanceMeters_500m | 28.2 |
| NonLakeWetlandTotalSqmNWI_500m | 4.7 |

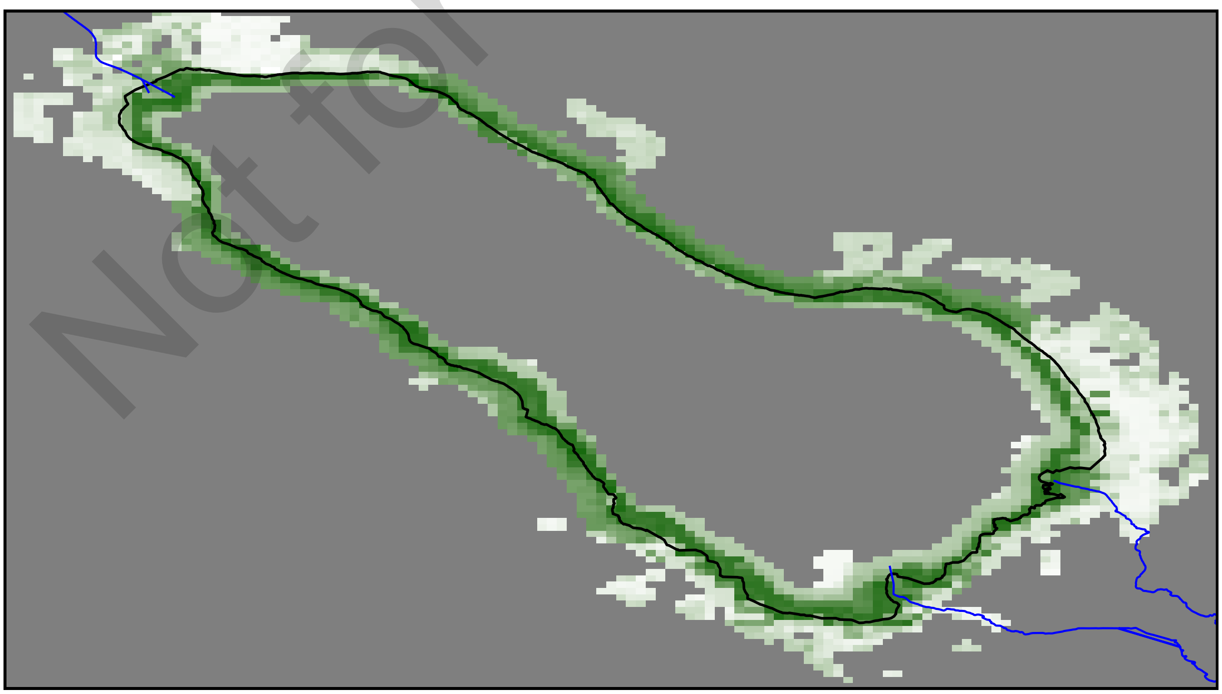
### Marginal Influence Plots



# Predicted Habitat Preference

## Predicted Habitat Preference (1999)

## Predicted Habitat Preference (2015)



# Black Skimmer

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 575

91.3 % ( 525 of 575 ) BLSK observations were zeroes.

**Percent of total deviance explained by model:** 40.7

**Total trees:** 450

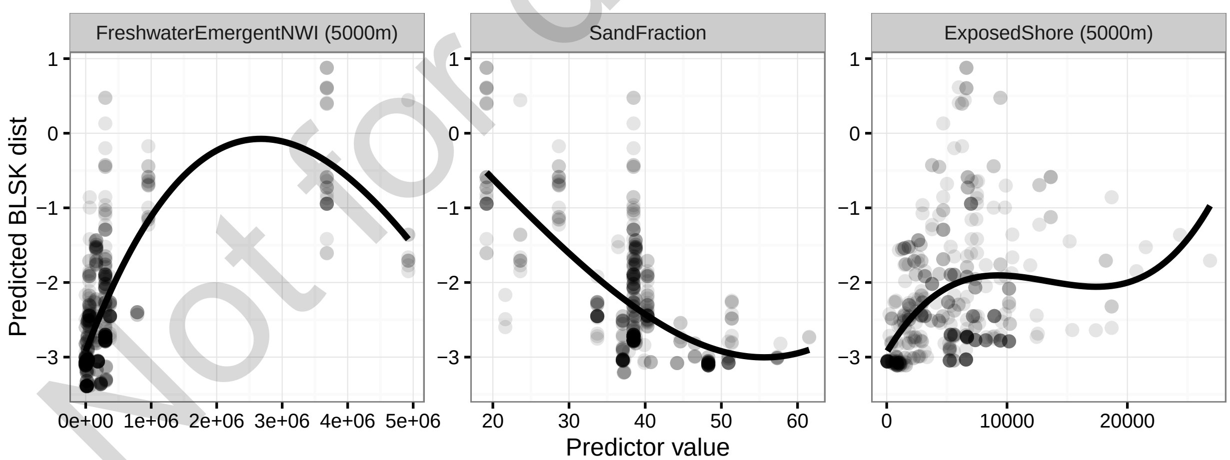
Training data AUC score = 0.856

Cross-validated AUC score = 0.738 ; standard error = 0.027

## Variable Importance

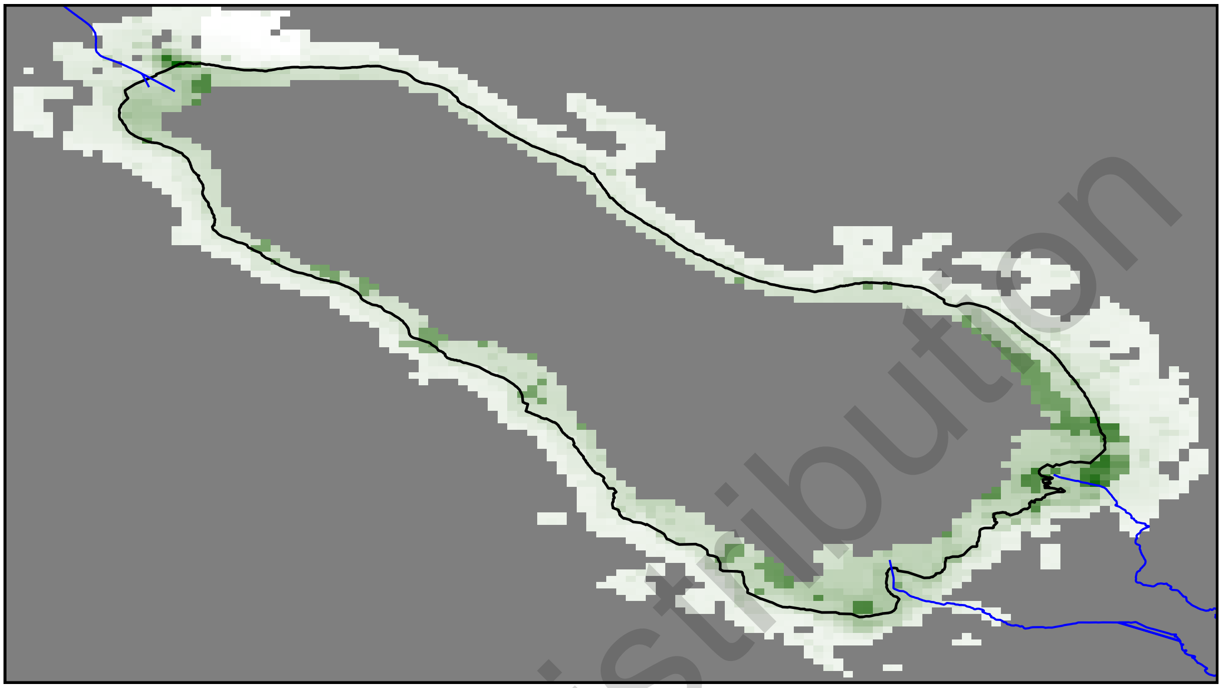
| Variable.Name | Relative.Influence |
|---|---|
| FreshwaterEmergentSqmNWI_5000m | 18.6 |
| SandFraction | 12.8 |
| ExposedShoreSqm_5000m | 6.7 |
| SlopeDegrees_500m | 6.0 |
| WaterShallowsSqm_0to15cm_5000m | 5.5 |

### Marginal Influence Plots

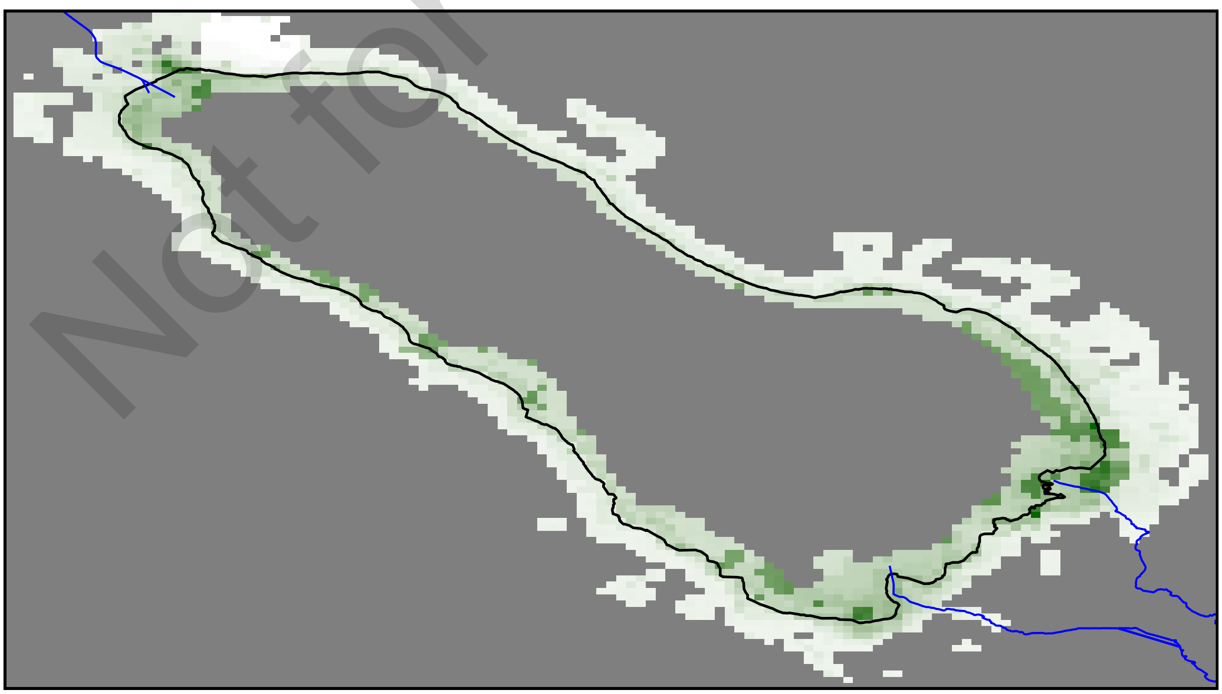


## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)



# Black Tern

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 463

78.4 % ( 363 of 463 ) BLTE observations were zeroes.

**Percent of total deviance explained by model:** 40.1

**Total trees:** 750

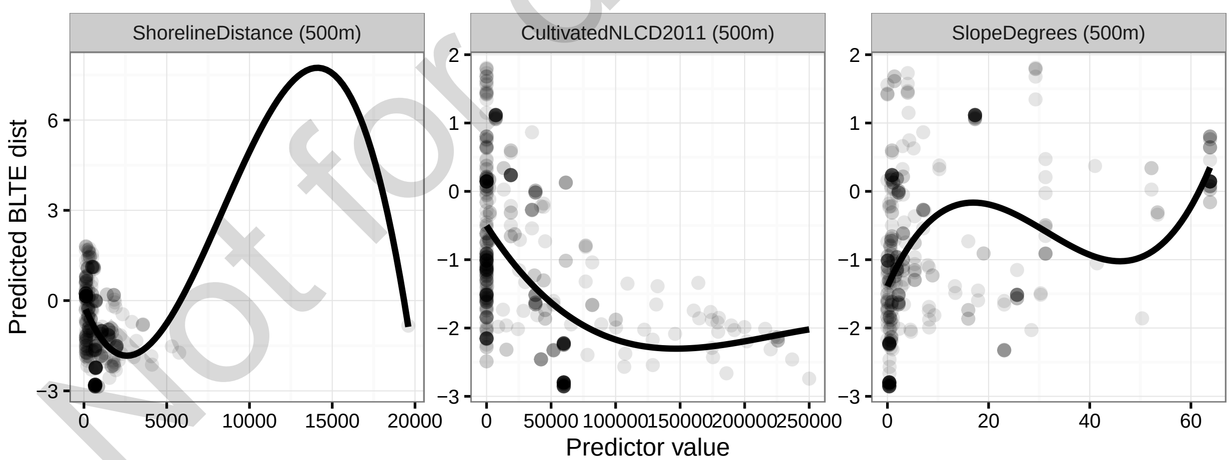
Training data AUC score = 0.87

Cross-validated AUC score = 0.749 ; standard error = 0.022

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters_500m | 14.5 |
| CultivatedSqmNLCD2011_500m | 8.0 |
| SlopeDegrees_500m | 7.1 |
| RiverMouthDistanceMeters_500m | 5.4 |
| ExposedShoreSqm_5000m | 5.2 |

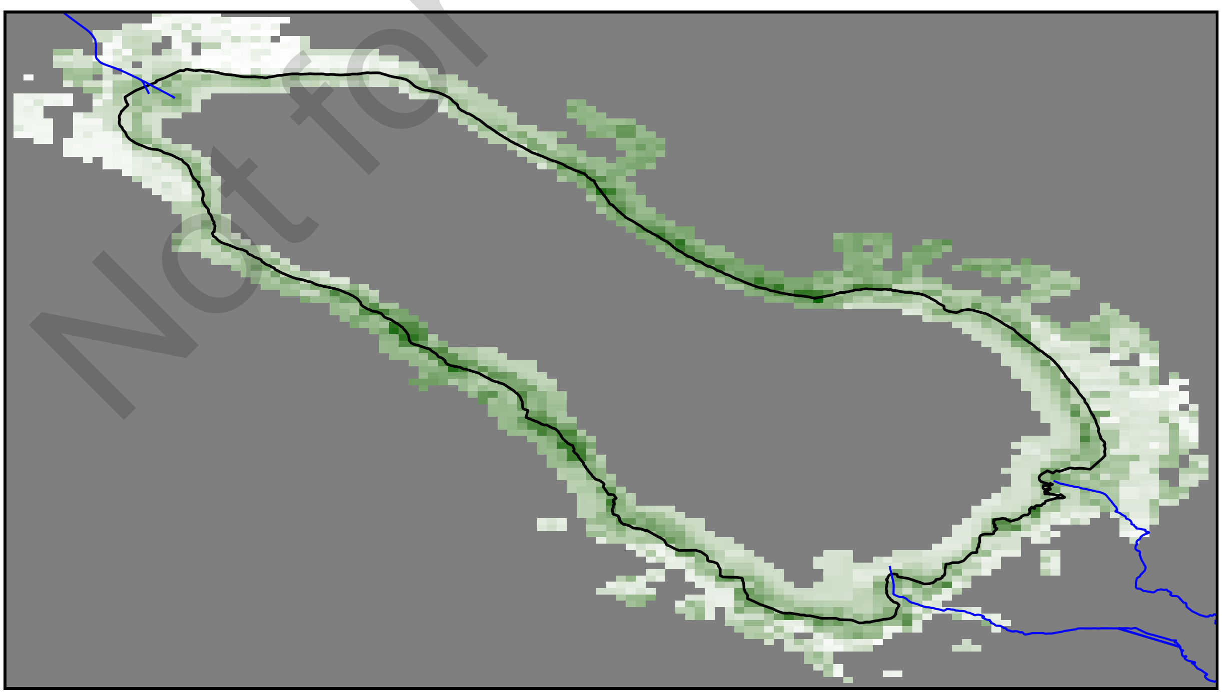
### Marginal Influence Plots



# Predicted Habitat Preference

## Predicted Habitat Preference (1999)

## Predicted Habitat Preference (2015)



# Double-crested Cormorant

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2214

70.05 % ( 1551 of 2214 ) DCCO observations were zeroes.

**Percent of total deviance explained by model:** 33.1

**Total trees:** 1600

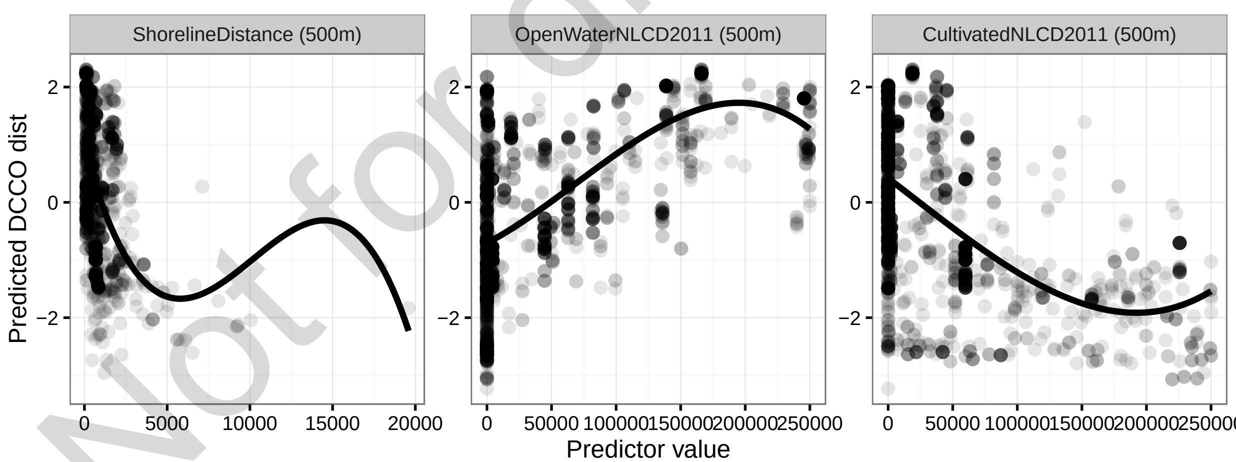
Training data AUC score = 0.825

Cross-validated AUC score = 0.779 ; standard error = 0.009

## Variable Importance

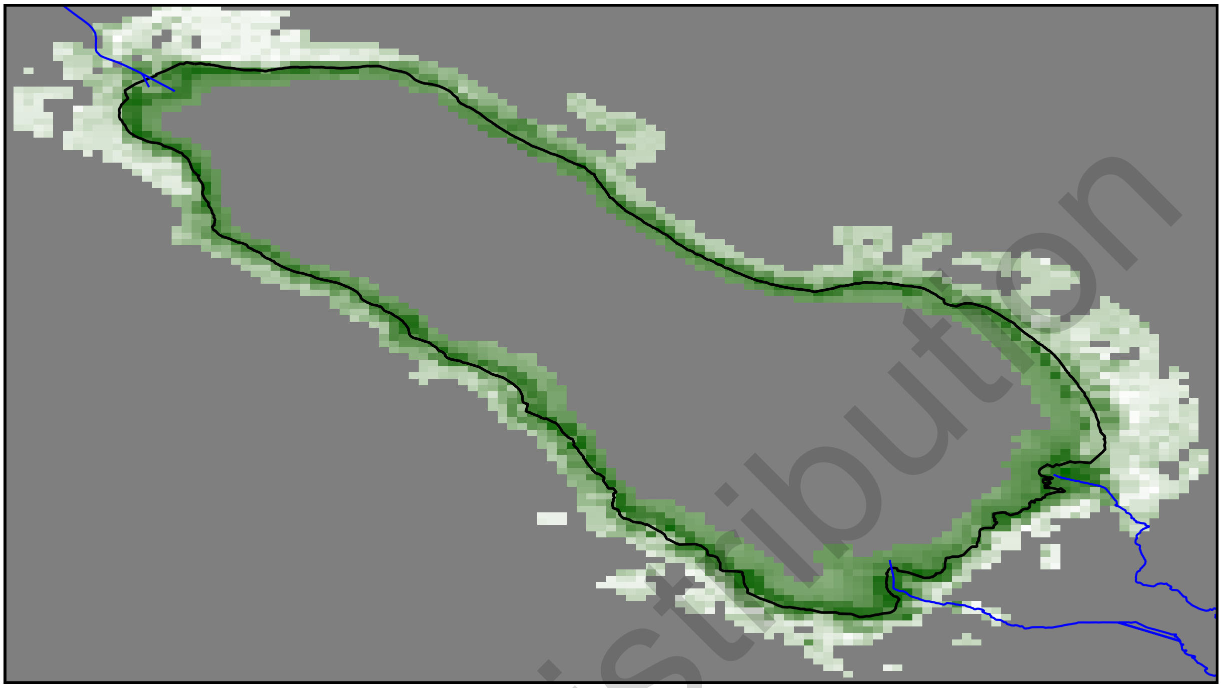
| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters_500m | 19.9 |
| OpenWaterSqmNLCD2011_500m | 13.6 |
| CultivatedSqmNLCD2011_500m | 9.0 |
| LakeSqmNWI_500m | 6.5 |

### Marginal Influence Plots

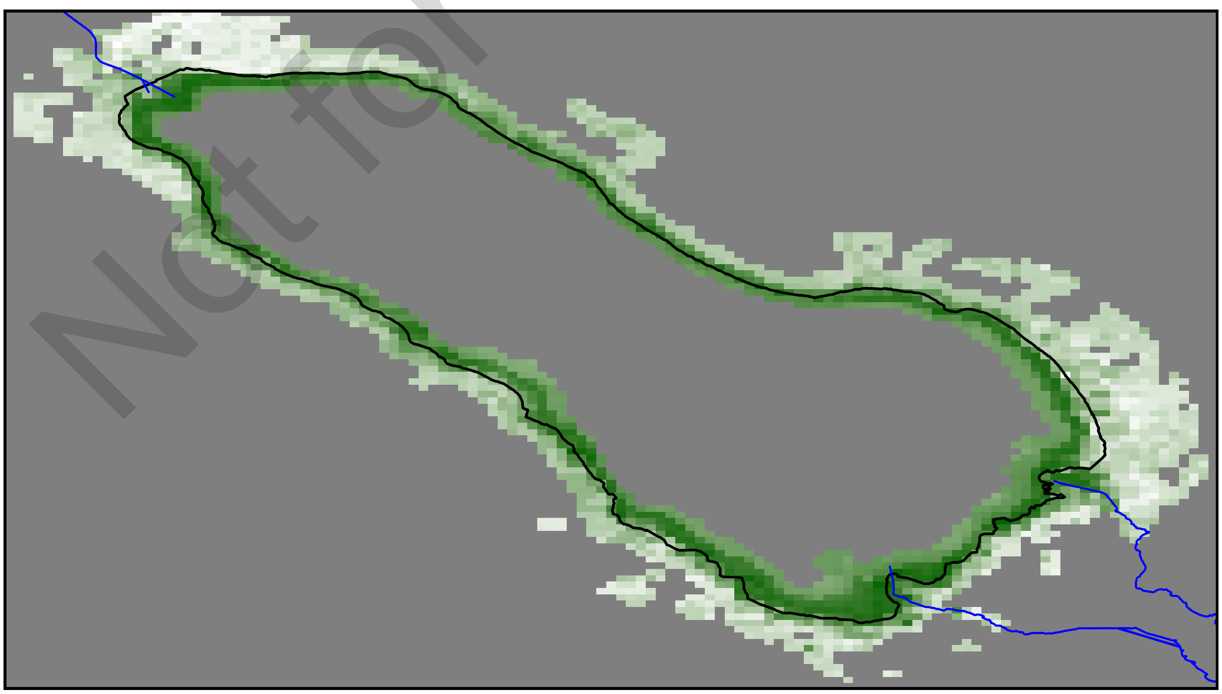


# Predicted Habitat Preference

## Predicted Habitat Preference (1999)



## Predicted Habitat Preference (2015)



# Dunlin

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2198

95.68 % ( 2103 of 2198 ) DUNL observations were zeroes.

**Percent of total deviance explained by model:** 26.3

**Total trees:** 2600

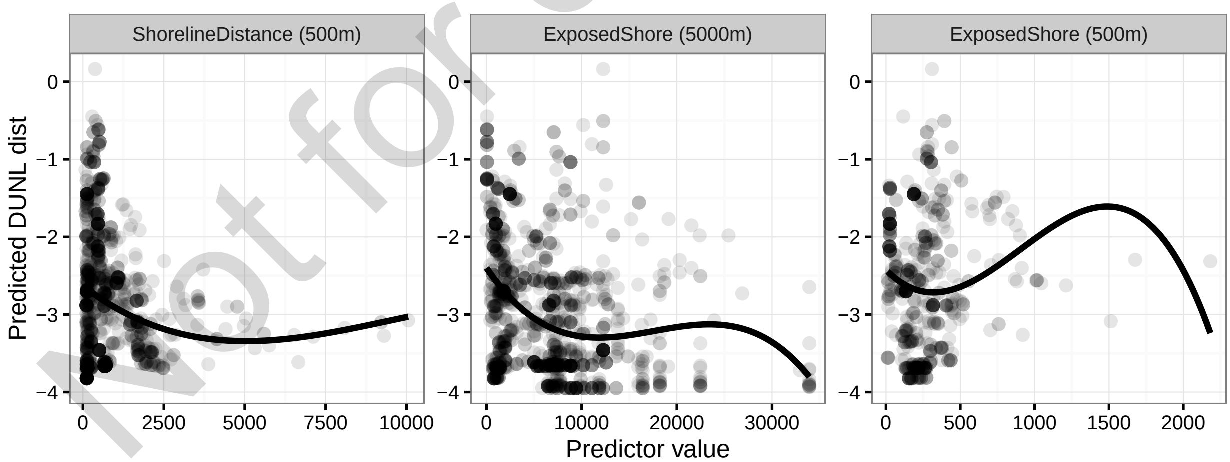
Training data AUC score = 0.847

Cross-validated AUC score = 0.771 ; standard error = 0.015

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters_500m | 21.6 |
| ExposedShoreSqm_5000m | 9.7 |
| ExposedShoreSqm_500m | 9.2 |
| SlopeDegrees_500m | 6.8 |
| WaterDepthMeters_5000m | 5.5 |
| SiltFraction | 5.2 |

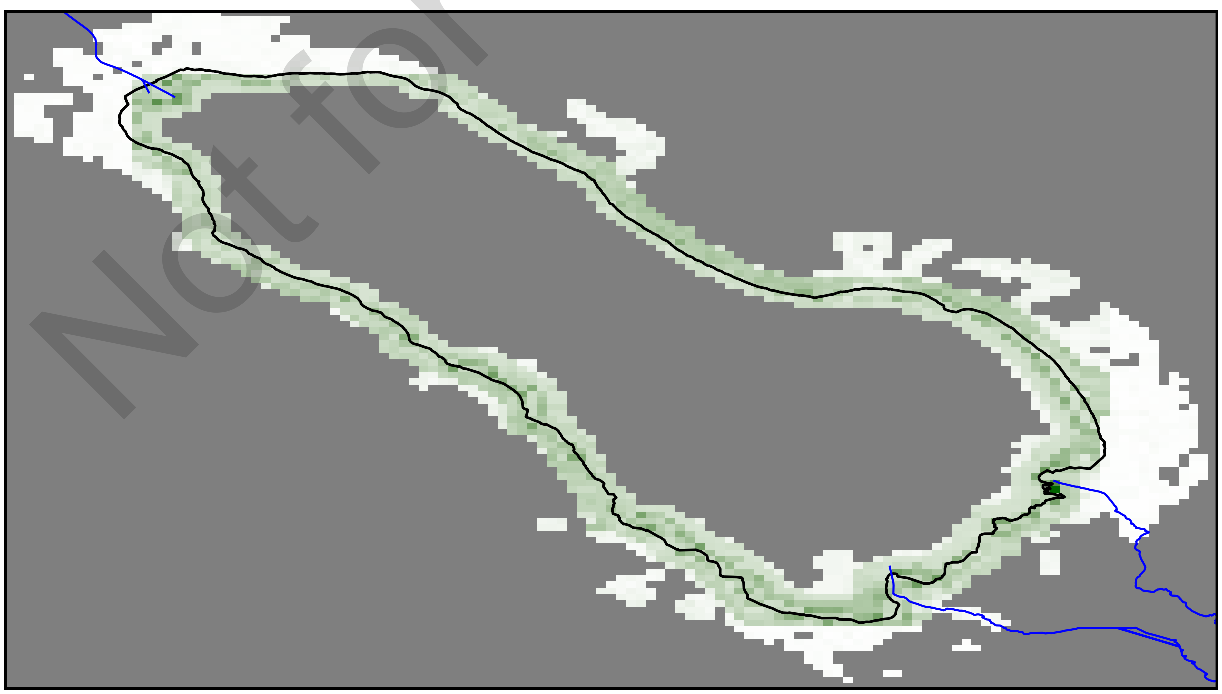
### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)

### Predicted Habitat Preference (2015)



## Eared Grebe

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 1537

71.63 % ( 1101 of 1537 ) EAGR observations were zeroes.

**Percent of total deviance explained by model:** 36.5

**Total trees:** 1050

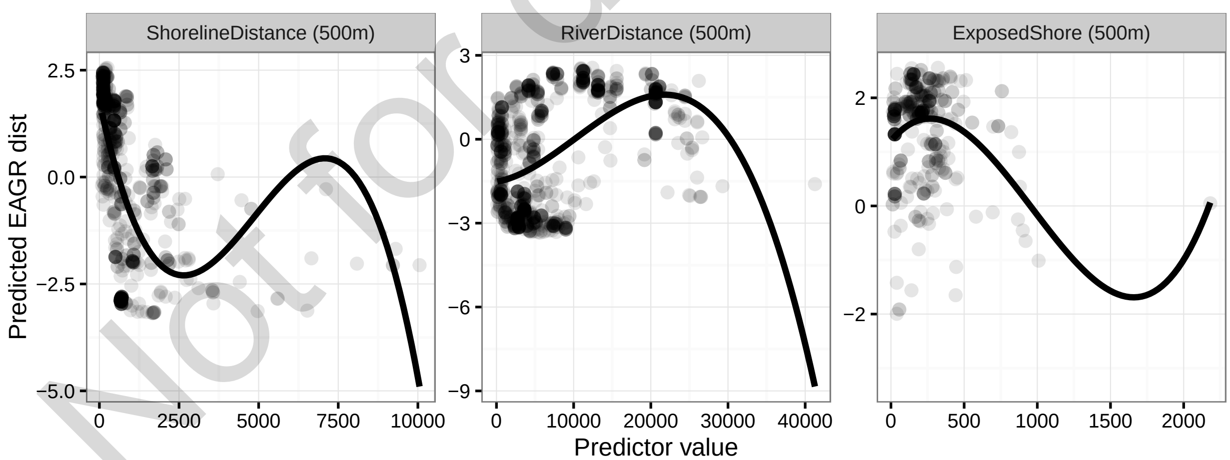
Training data AUC score = 0.831

Cross-validated AUC score = 0.798 ; standard error = 0.01

### Variable Importance

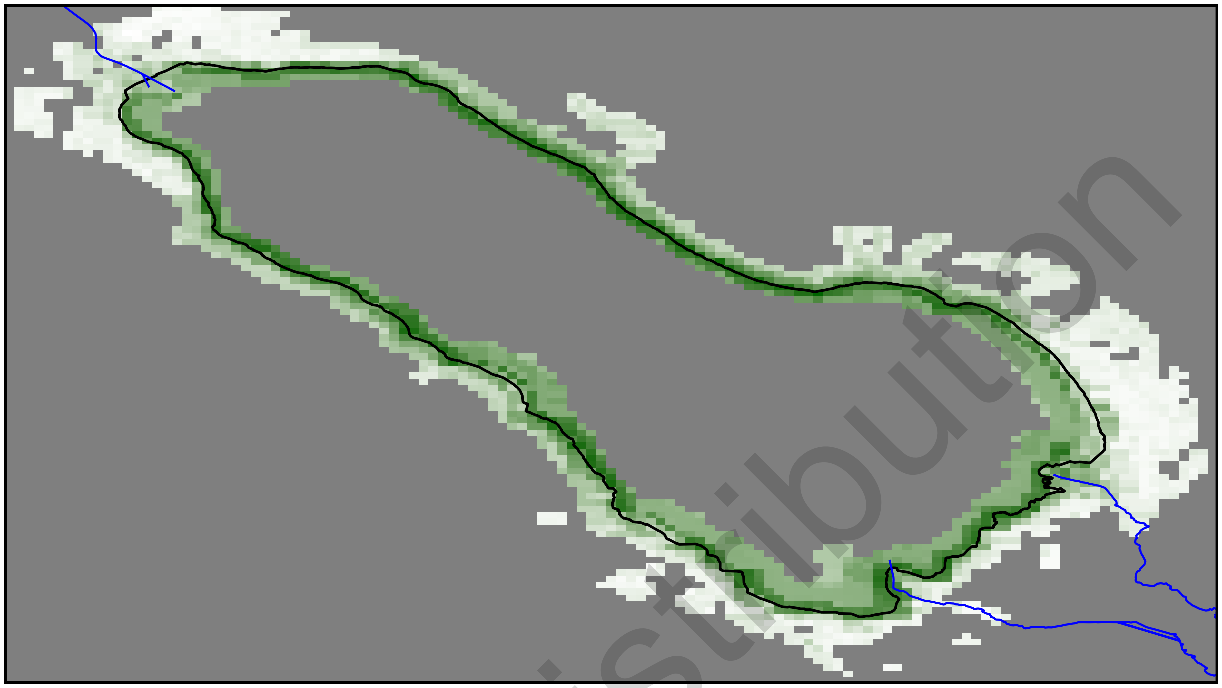
| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters__500m | 29.1 |
| RiverDistanceMeters__500m | 7.1 |
| ExposedShoreSqm__500m | 6.8 |
| FreshwaterEmergentSqmNWI__5000m | 6.1 |
| PastureSqmNLCD2011__5000m | 5.4 |

#### Marginal Influence Plots

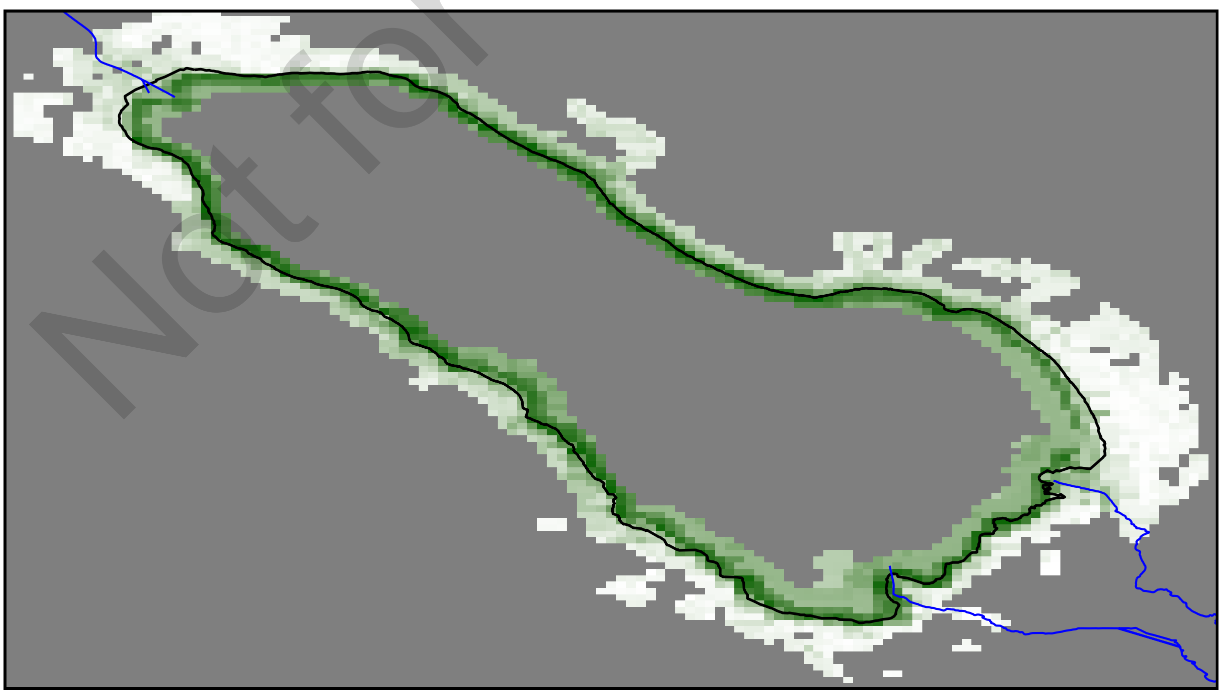


# Predicted Habitat Preference

## Predicted Habitat Preference (1999)



## Predicted Habitat Preference (2015)



# Gadwall

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 1738

95.57 % ( 1661 of 1738 ) GADW observations were zeroes.

**Percent of total deviance explained by model:** 34.5

**Total trees:** 750

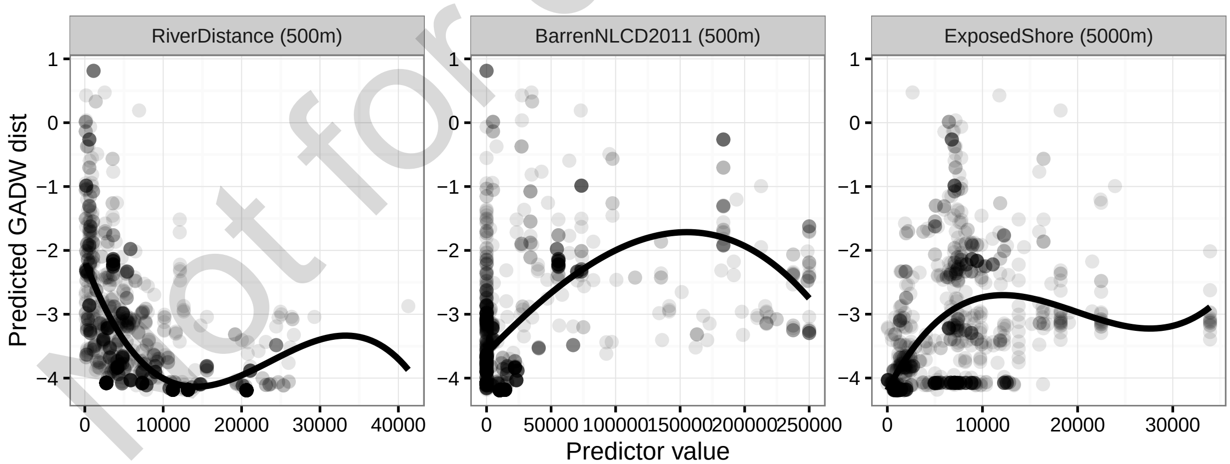
Training data AUC score = 0.869

Cross-validated AUC score = 0.764 ; standard error = 0.02

## Variable Importance

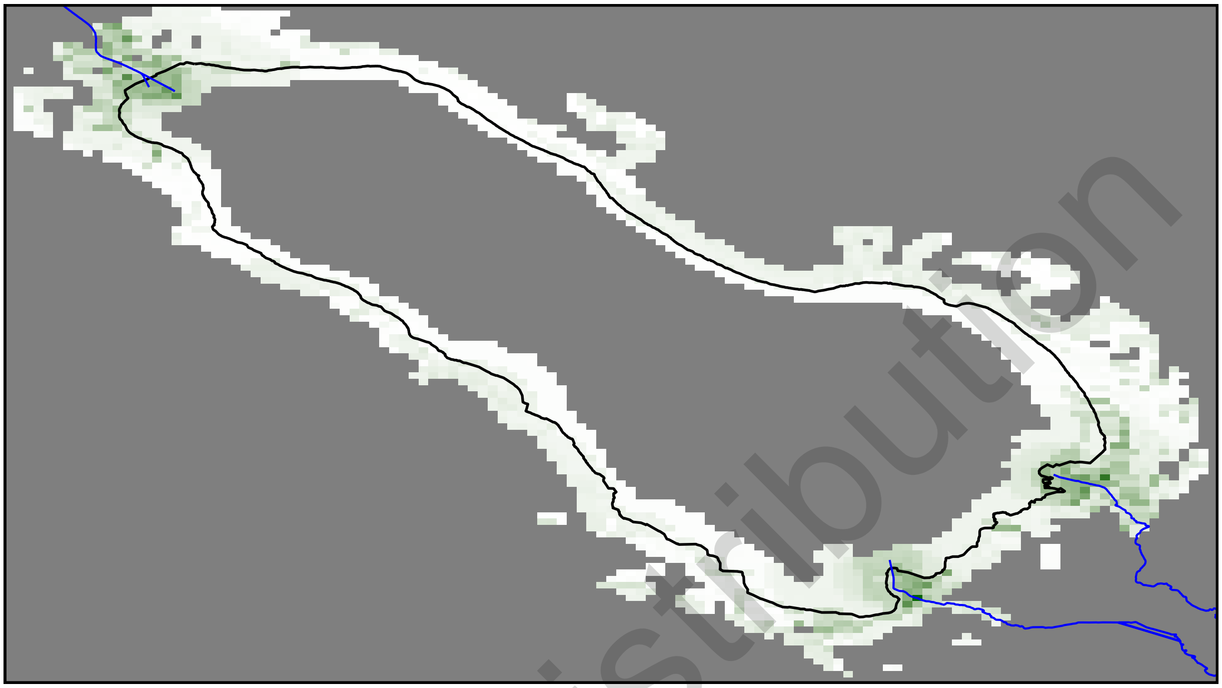
| Variable.Name | Relative.Influence |
|---|---|
| RiverDistanceMeters_500m | 12.7 |
| BarrenSqmNLCD2011_500m | 10.4 |
| ExposedShoreSqm_5000m | 8.2 |
| ShorelineDistanceMeters_500m | 7.7 |
| RiverMouthDistanceMeters_500m | 7.3 |
| LakeSqmNWI_500m | 6.3 |

### Marginal Influence Plots

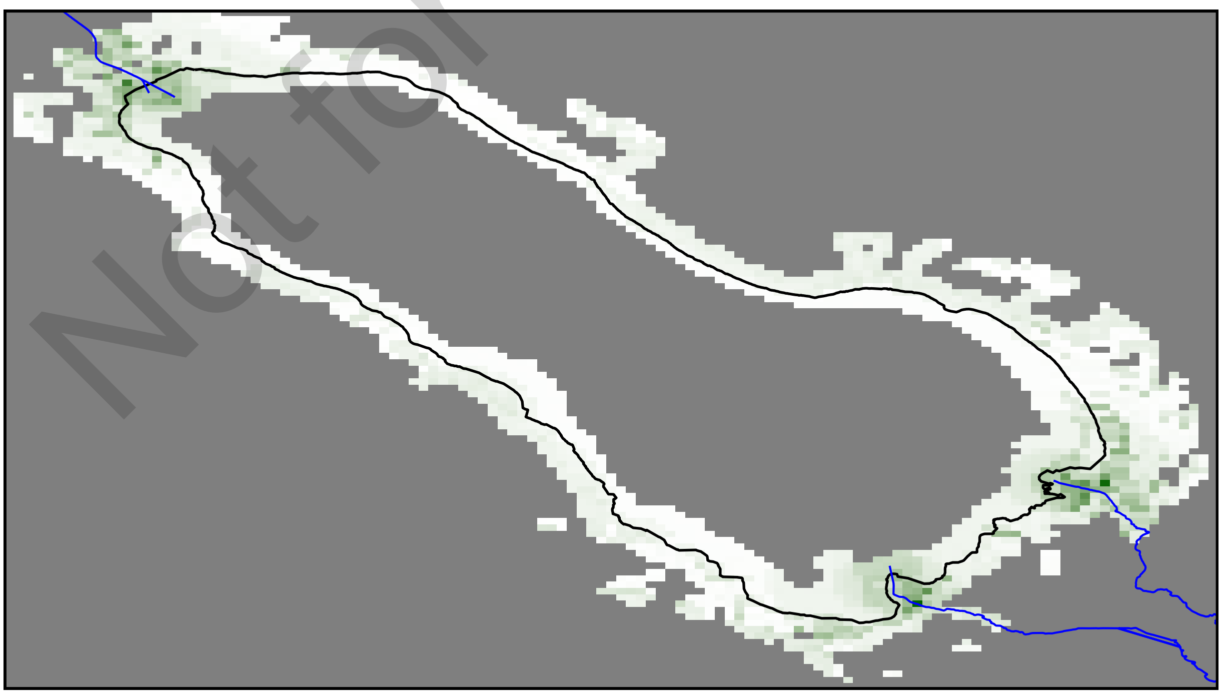


## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)



# Gull spp.

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2198

57.42 % ( 1262 of 2198 ) GULL observations were zeroes.

**Percent of total deviance explained by model:** 30.2

**Total trees:** 1200

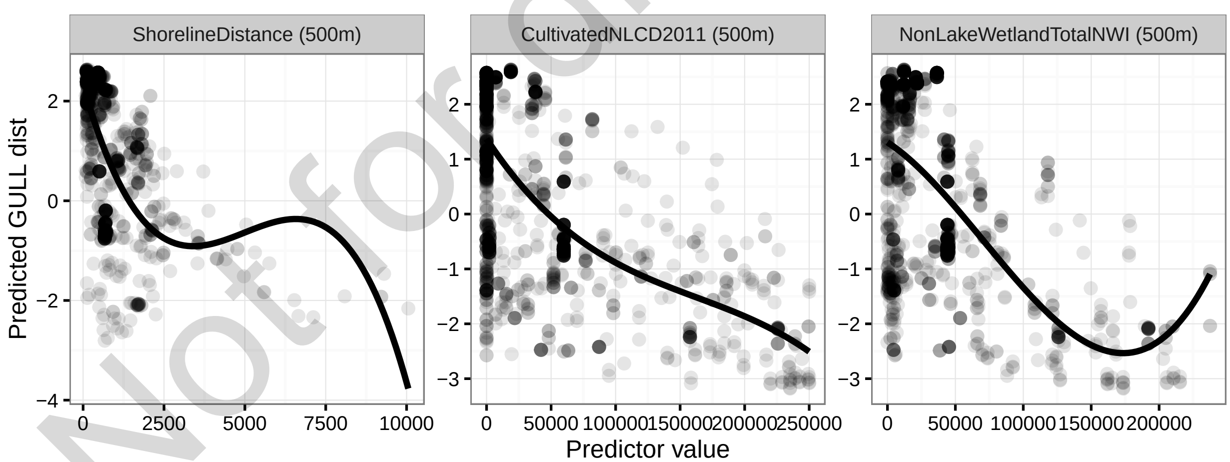
Training data AUC score = 0.814

Cross-validated AUC score = 0.785 ; standard error = 0.006

## Variable Importance

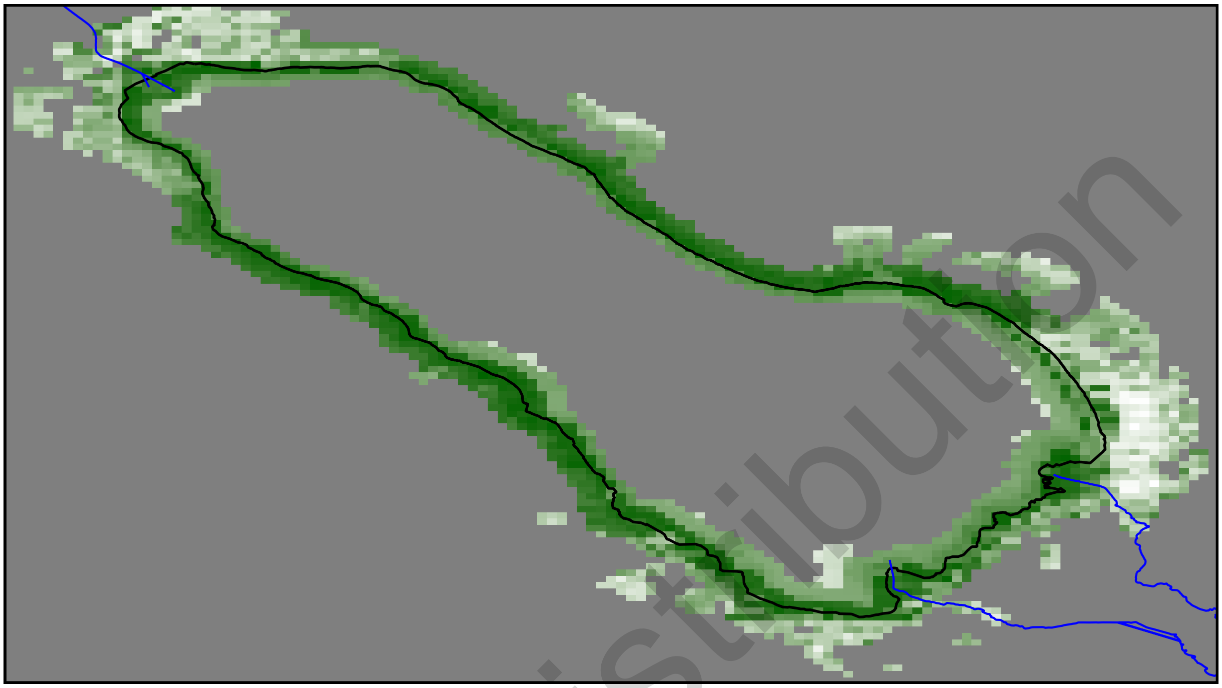
| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters__500m | 25.7 |
| CultivatedSqmNLCD2011__500m | 18.6 |
| NonLakeWetlandTotalSqmNWI__500m | 12.4 |
| NonLakeWetlandTotalSqmNWI__5000m | 5.6 |

### Marginal Influence Plots

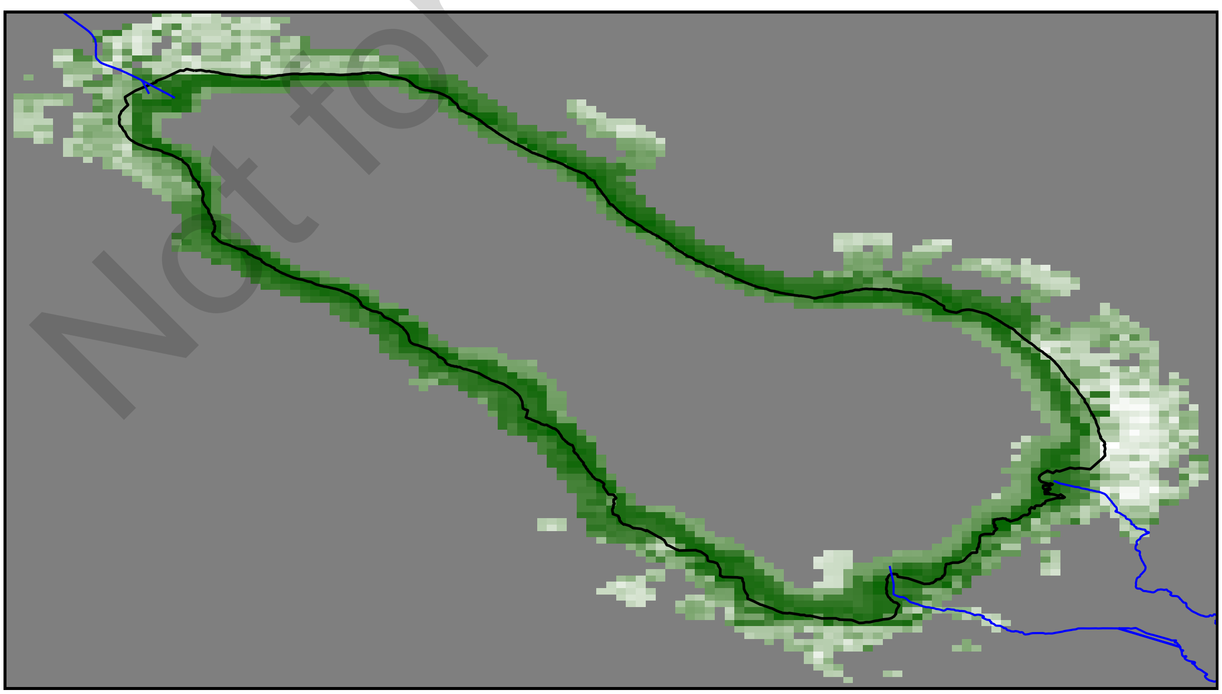


# Predicted Habitat Preference

## Predicted Habitat Preference (1999)



## Predicted Habitat Preference (2015)



# Least Sandpiper

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2218

77.55 % ( 1720 of 2218 ) LESA observations were zeroes.

**Percent of total deviance explained by model:** 24.5

**Total trees:** 1350

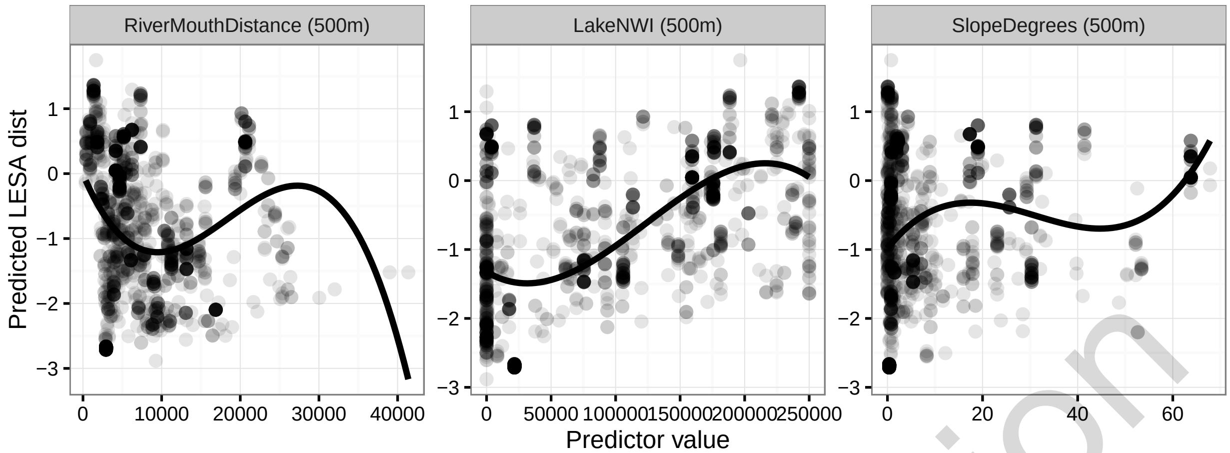
Training data AUC score = 0.795

Cross-validated AUC score = 0.722 ; standard error = 0.014

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| RiverMouthDistanceMeters_500m | 13.0 |
| LakeSqmNWI_500m | 8.2 |
| SlopeDegrees_500m | 7.3 |
| BarrenSqmNLCD2011_500m | 7.2 |
| RiverDistanceMeters_500m | 7.2 |
| ExposedShoreSqm_5000m | 7.0 |
| ShorelineDistanceMeters_500m | 6.4 |
| WetlandsHerbaceousSqmNLCD2011_5000m | 5.9 |

### Marginal Influence Plots

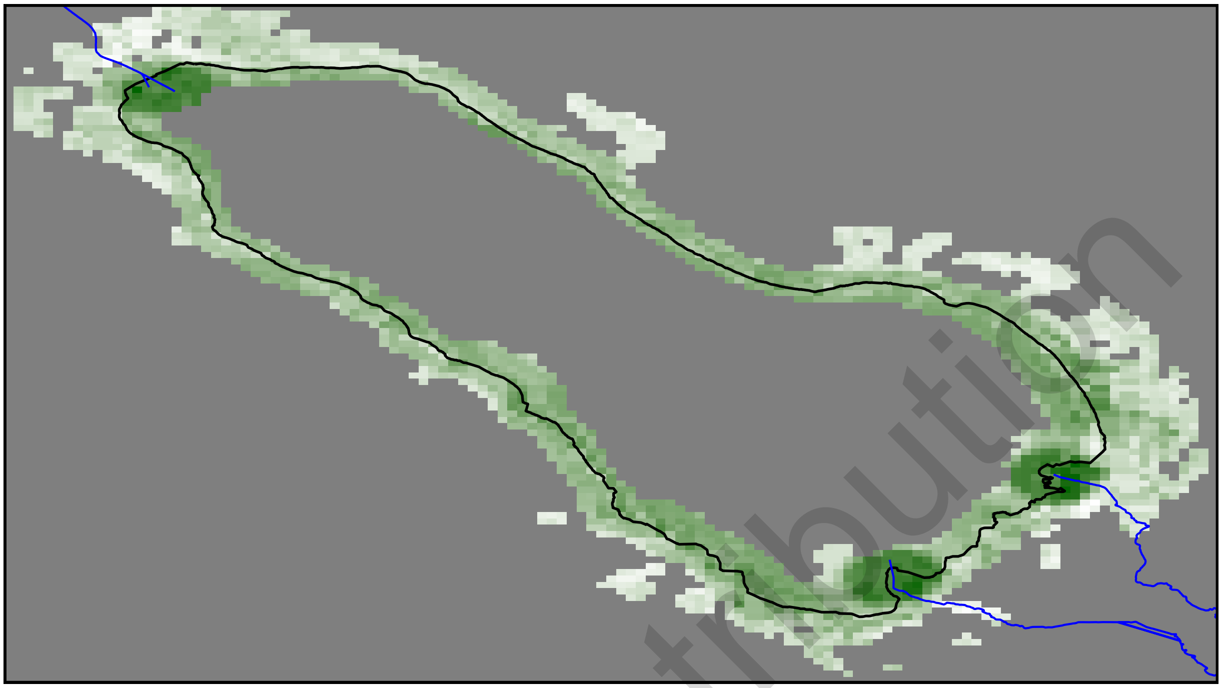





## Predicted Habitat Preference

### Predicted Habitat Preference (1999)

### Predicted Habitat Preference (2015)



# Marbled Godwit

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2218

85.48 % ( 1896 of 2218 ) MAGO observations were zeroes.

**Percent of total deviance explained by model:** 38.3

**Total trees:** 1200

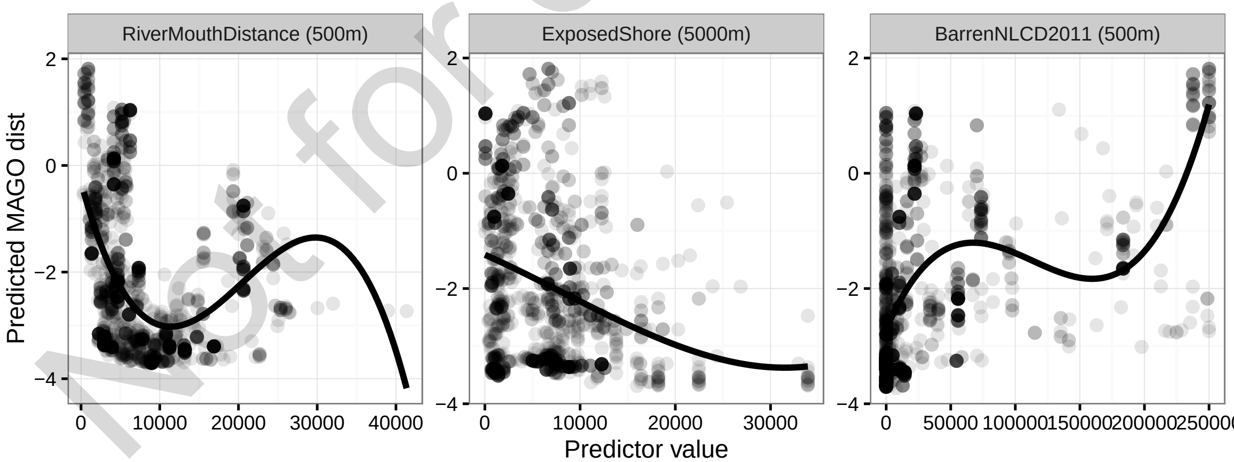
Training data AUC score = 0.86

Cross-validated AUC score = 0.824 ; standard error = 0.012

## Variable Importance

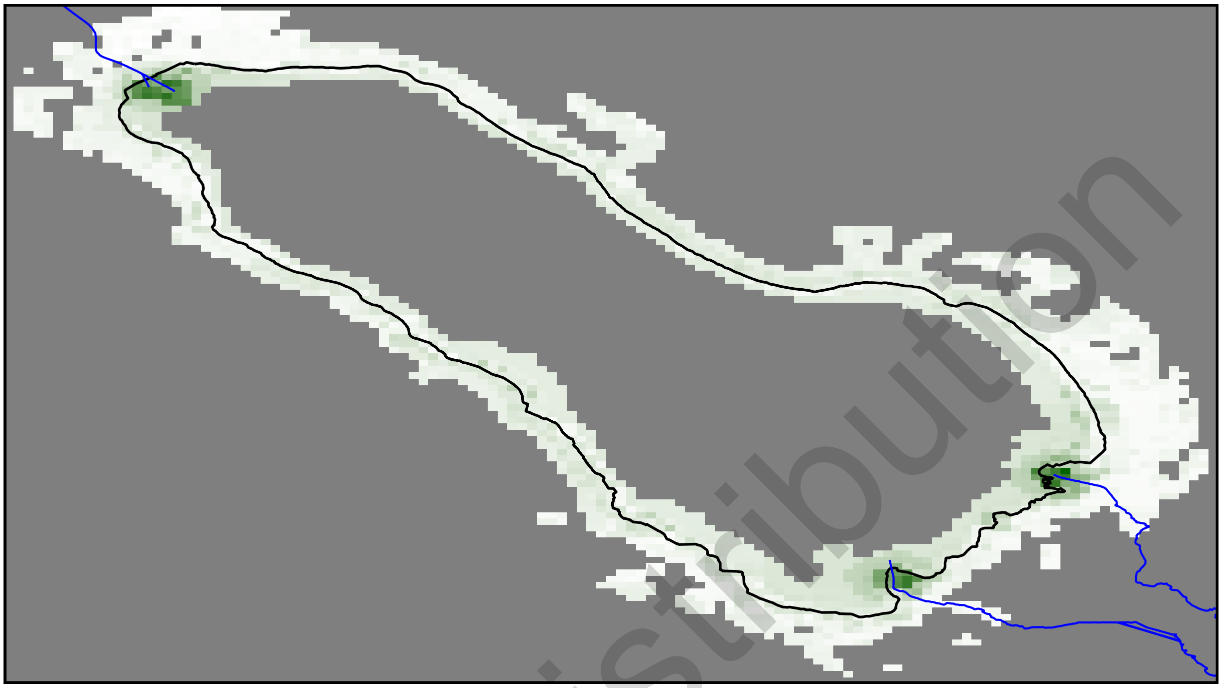
| Variable.Name | Relative.Influence |
|---|---|
| RiverMouthDistanceMeters_500m | 22.3 |
| ExposedShoreSqm_5000m | 11.8 |
| BarrenSqmNLCD2011_500m | 11.5 |
| WaterShallowsSqm_200to1000cm_5000m | 7.8 |
| WaterDepthMeters_5000m | 6.9 |
| ShorelineDistanceMeters_500m | 5.7 |

### Marginal Influence Plots

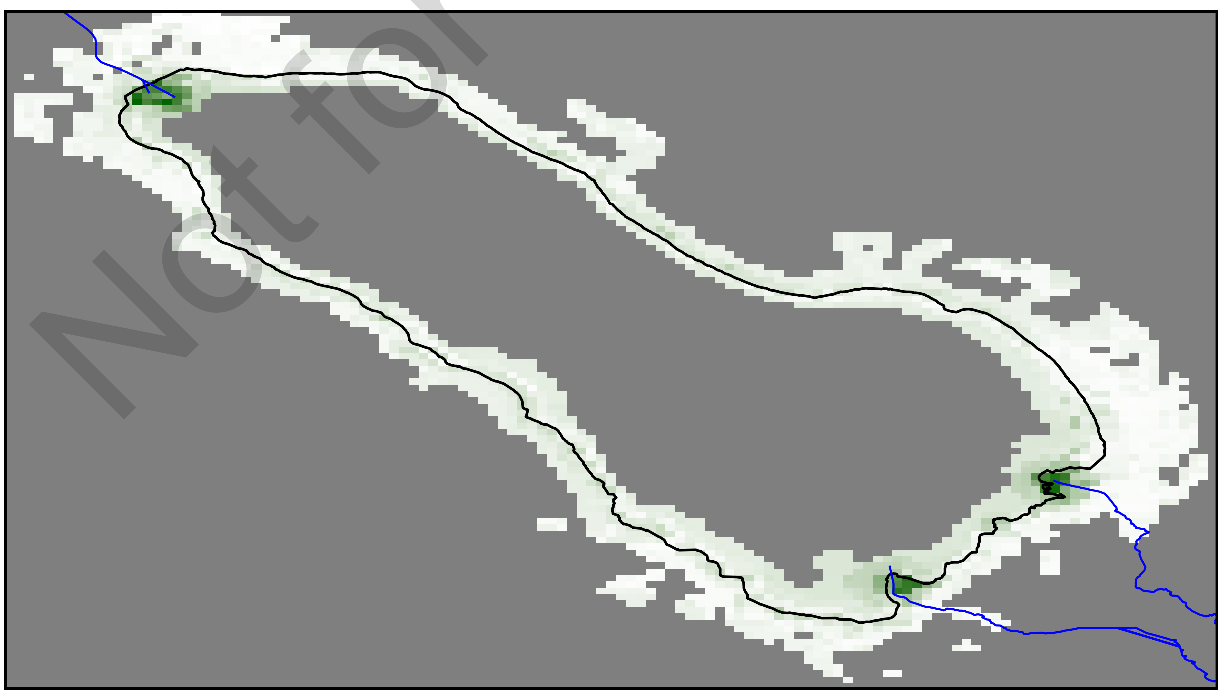


## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)



# Northern Shoveller

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2218

78.85 % ( 1749 of 2218 ) NOSH observations were zeroes.

**Percent of total deviance explained by model:** 27.8

**Total trees:** 1650

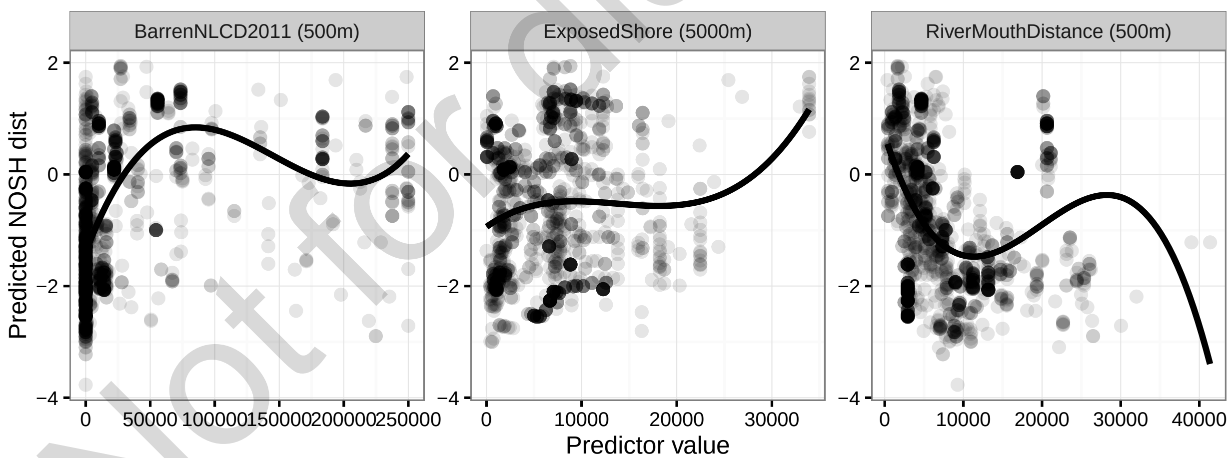
Training data AUC score = 0.813

Cross-validated AUC score = 0.752 ; standard error = 0.006

## Variable Importance

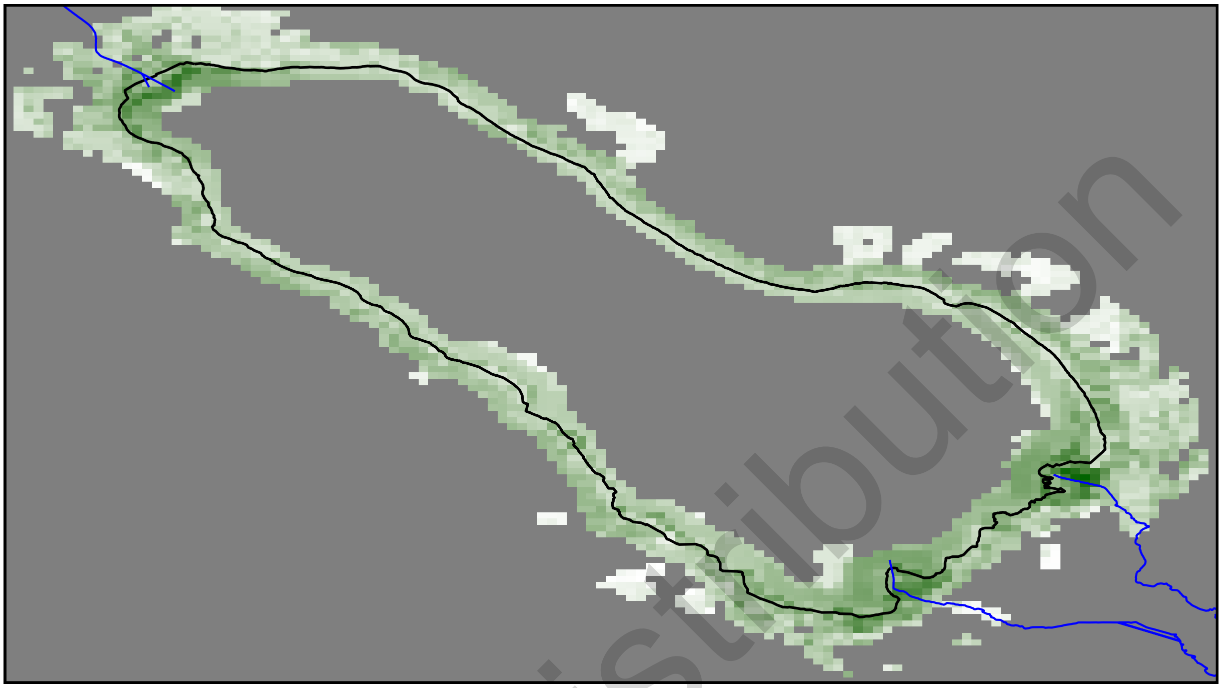
| Variable.Name | Relative.Influence |
| --- | --- |
| BarrenSqmNLCD2011_500m | 20.3 |
| ExposedShoreSqm_5000m | 6.7 |
| RiverMouthDistanceMeters_500m | 6.1 |

### Marginal Influence Plots

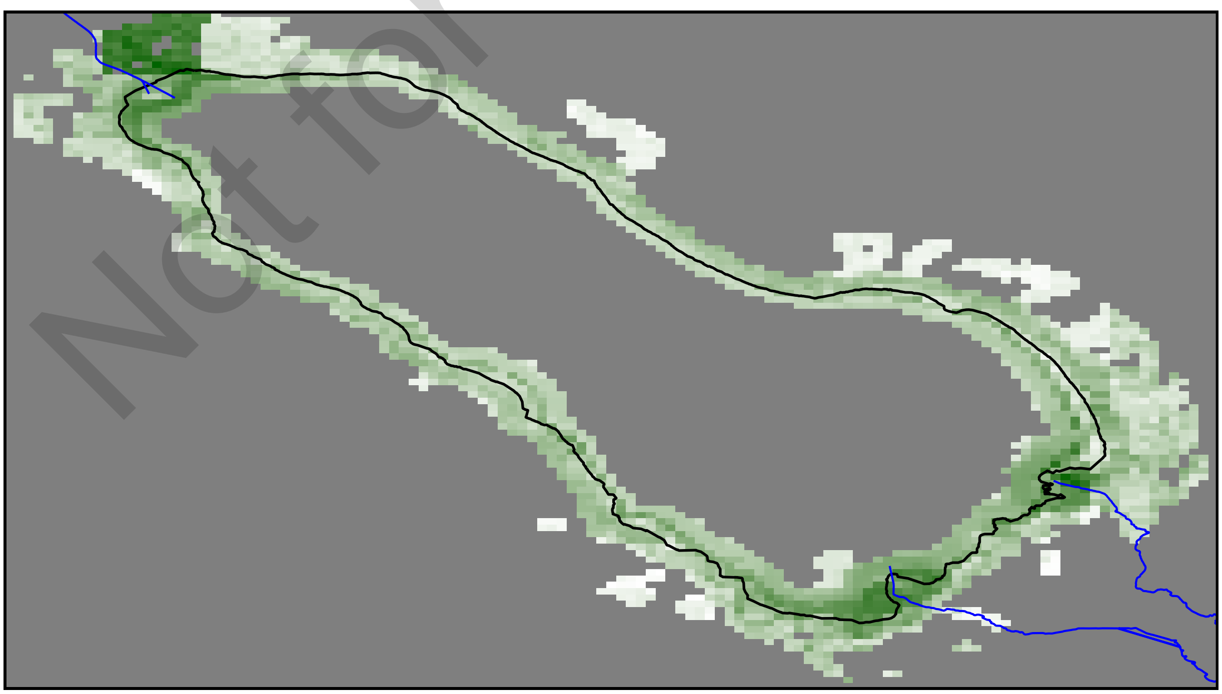


# Predicted Habitat Preference

## Predicted Habitat Preference (1999)



## Predicted Habitat Preference (2015)



# Ruddy Duck

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 1923

80.66 % ( 1551 of 1923 ) RUDU observations were zeroes.

**Percent of total deviance explained by model:** 26.7

**Total trees:** 1250

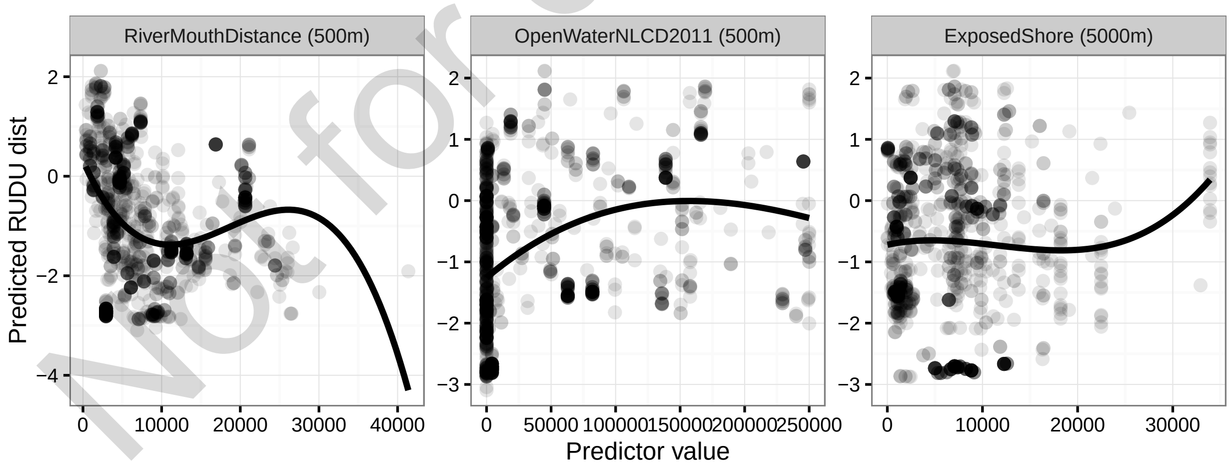
Training data AUC score = 0.802

Cross-validated AUC score = 0.731 ; standard error = 0.011

## Variable Importance

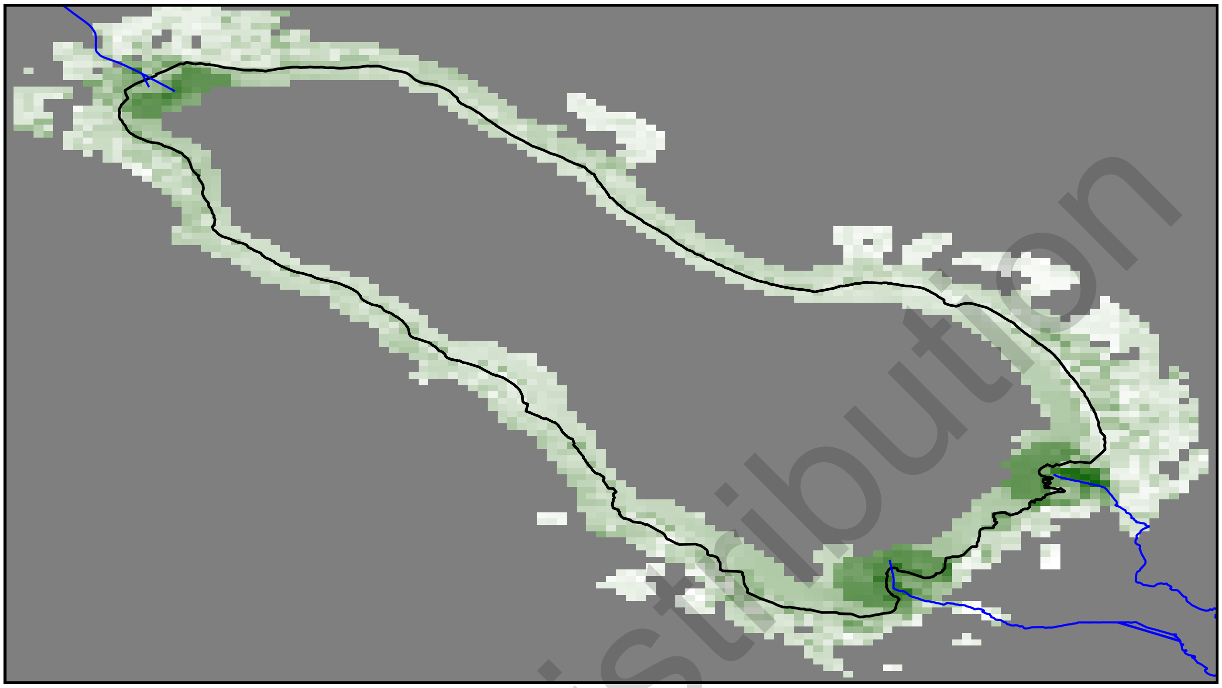
| Variable.Name | Relative.Influence |
|---|---|
| RiverMouthDistanceMeters_500m | 15.8 |
| OpenWaterSqmNLCD2011_500m | 10.7 |
| ExposedShoreSqm_5000m | 9.4 |
| SlopeDegrees_500m | 9.4 |
| LakeSqmNWI_500m | 6.3 |
| RiverDistanceMeters_500m | 6.2 |

### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)

# Snowy Egret

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2214

72.22 % ( 1599 of 2214 ) SNEG observations were zeroes.

**Percent of total deviance explained by model:** 27.1

**Total trees:** 1400

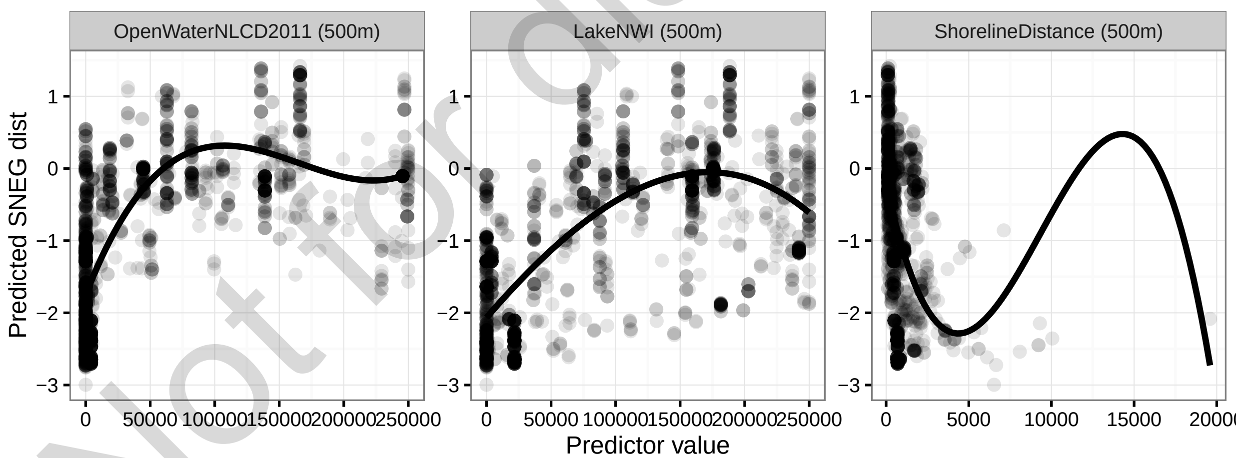
Training data AUC score = 0.79

Cross-validated AUC score = 0.732 ; standard error = 0.006

## Variable Importance

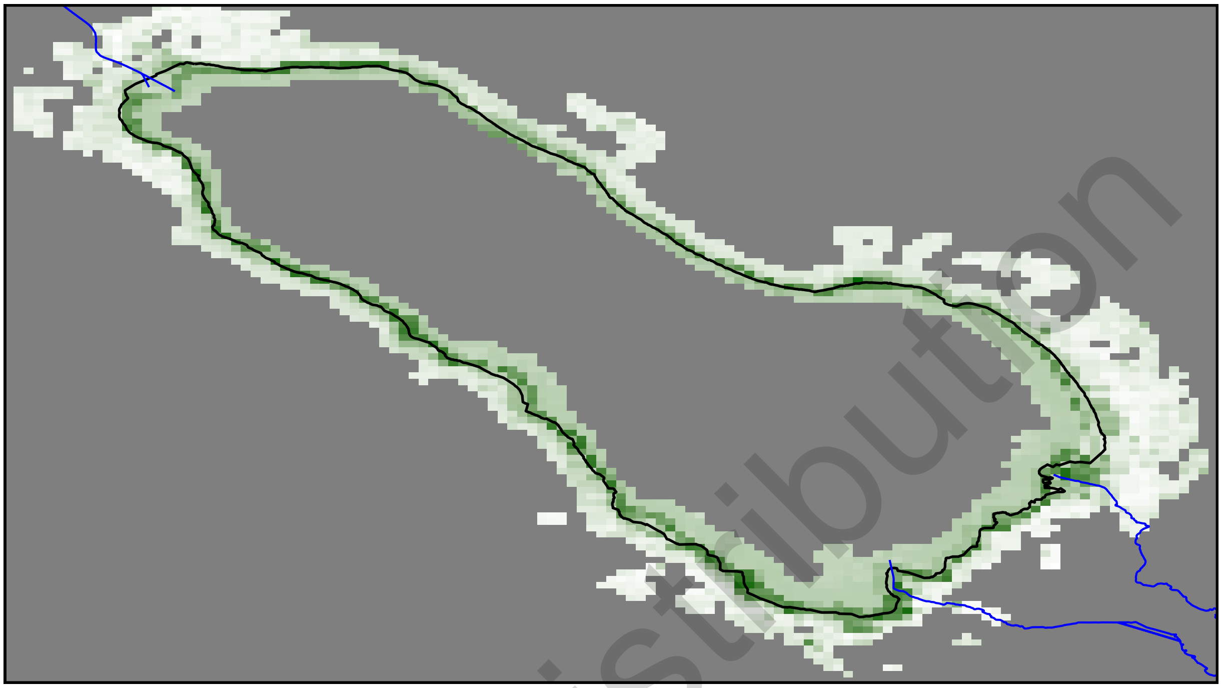
| Variable.Name | Relative.Influence |
|---|---|
| OpenWaterSqmNLCD2011_500m | 32.0 |
| LakeSqmNWI_500m | 6.7 |
| ShorelineDistanceMeters_500m | 5.2 |

### Marginal Influence Plots

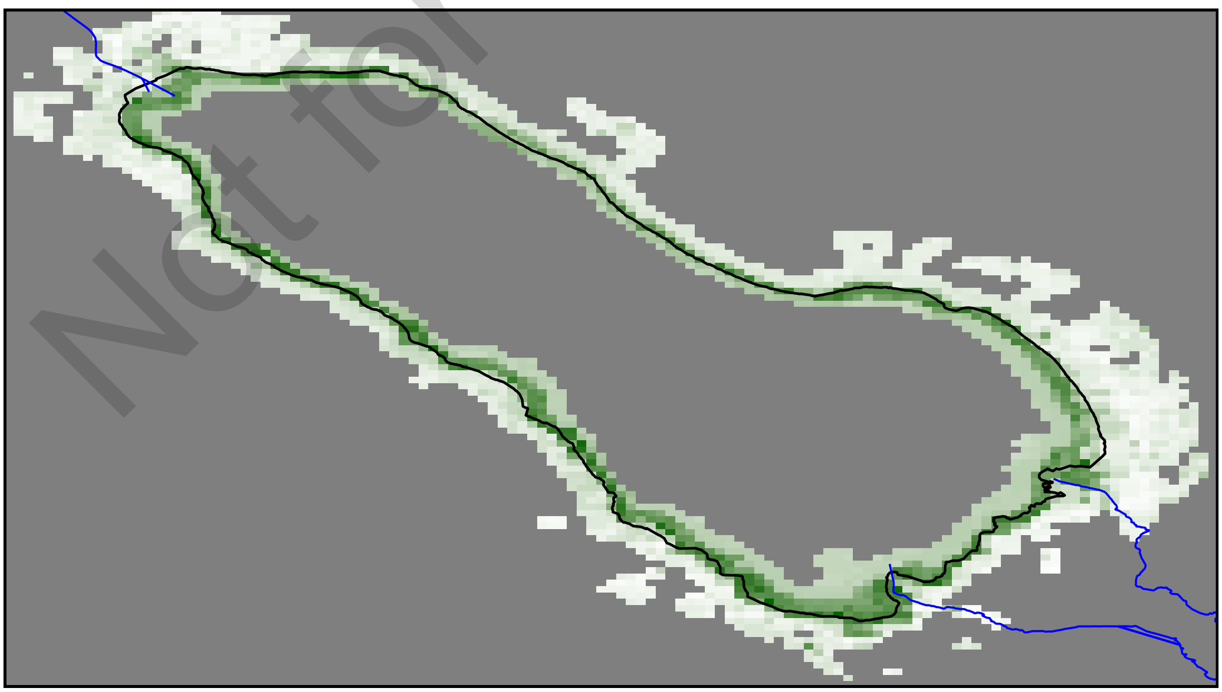


## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)



# Snowy Plover

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2214

92.73 % ( 2053 of 2214 ) SNPL observations were zeroes.

**Percent of total deviance explained by model:** 46.5

**Total trees:** 1100

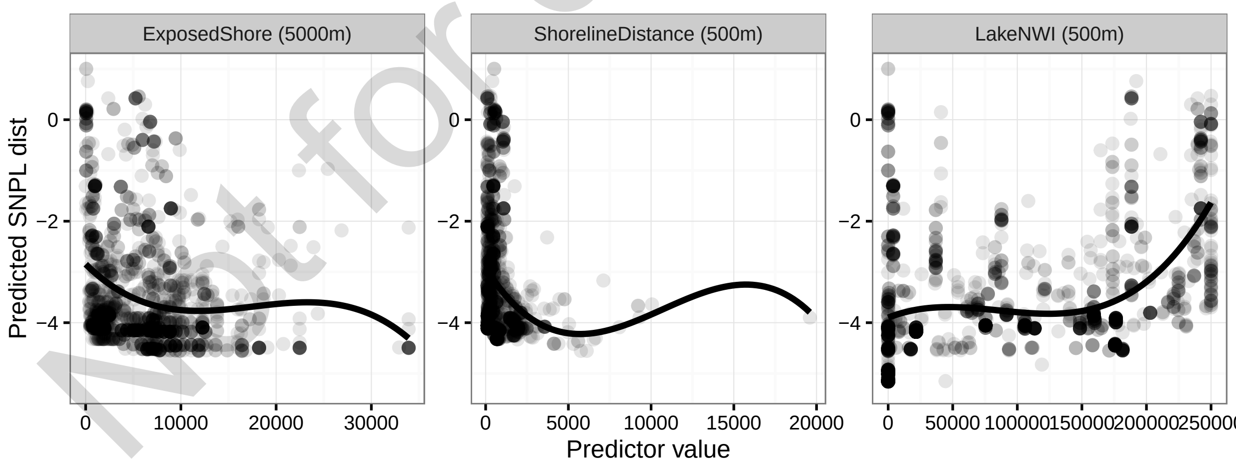
Training data AUC score = 0.89

Cross-validated AUC score = 0.851 ; standard error = 0.015

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| ExposedShoreSqm__5000m | 23.7 |
| ShorelineDistanceMeters__500m | 13.6 |
| LakeSqmNWI__500m | 8.4 |
| WaterShallowsSqm__0to15cm__500m | 7.1 |
| WaterShallowsSqm__15to30cm__5000m | 6.9 |
| ExposedShoreSqm__500m | 6.0 |

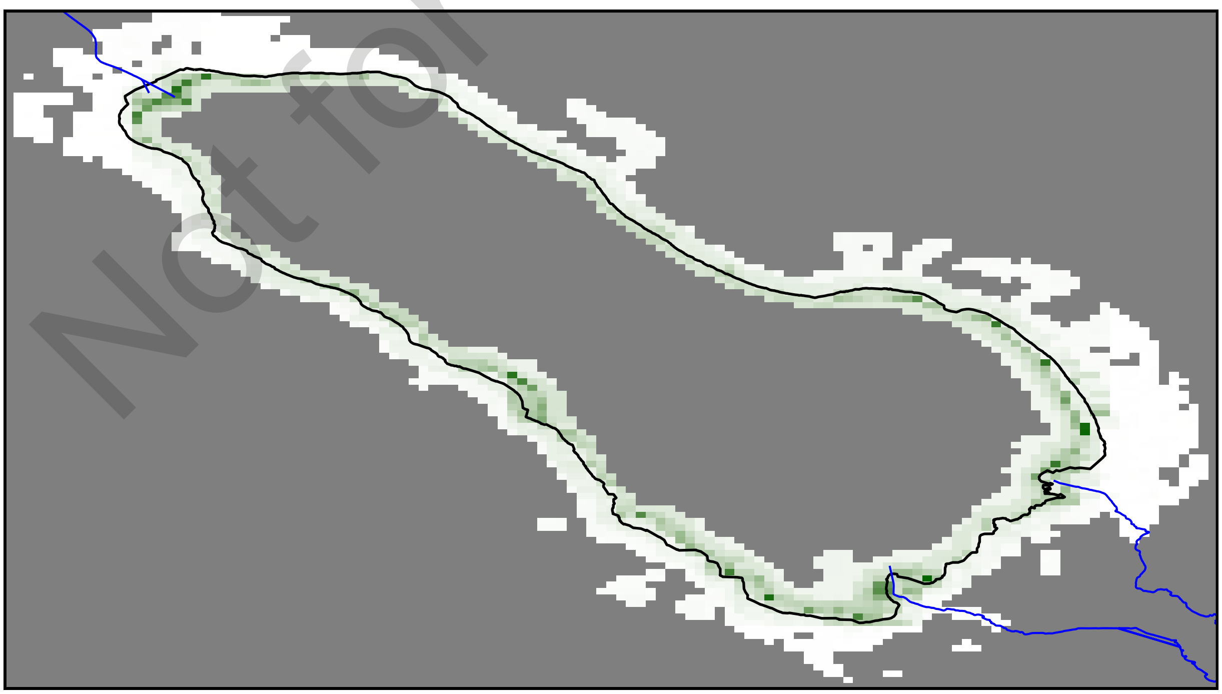
### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)

### Predicted Habitat Preference (2015)



# Sora

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2030

94.04 % ( 1909 of 2030 ) SORA observations were zeroes.

**Percent of total deviance explained by model:** 29.5

**Total trees:** 600

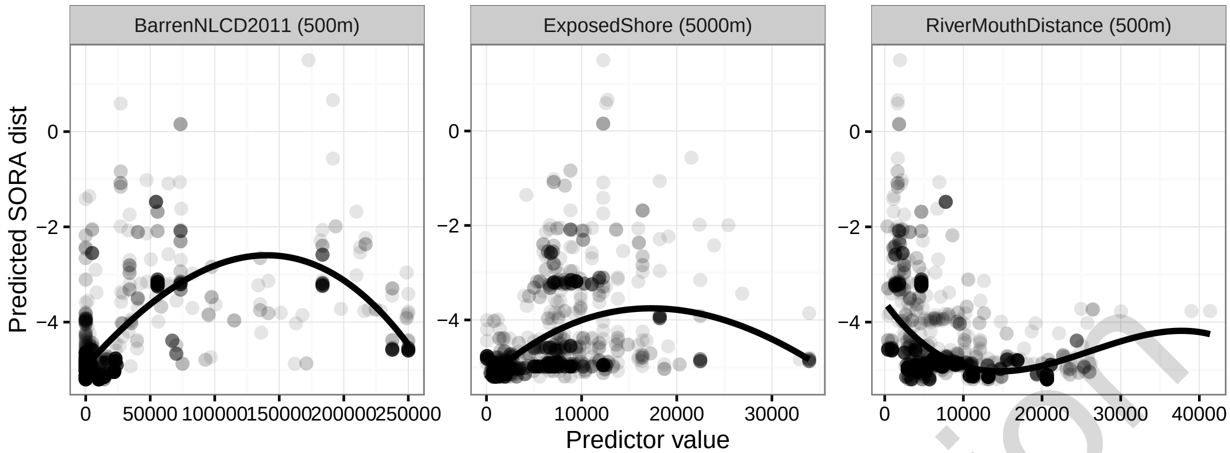
Training data AUC score = 0.772

Cross-validated AUC score = 0.744 ; standard error = 0.024

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| BarrenSqmNLCD2011_500m | 12.5 |
| ExposedShoreSqm_5000m | 11.7 |
| RiverMouthDistanceMeters_500m | 11.6 |
| ShorelineDistanceMeters_500m | 10.6 |
| WaterShallowsSqm_15to30cm_5000m | 9.3 |
| ExposedShoreSqm_500m | 7.7 |
| OpenWaterSqmNLCD2011_500m | 7.2 |
| SlopeDegrees_500m | 6.4 |

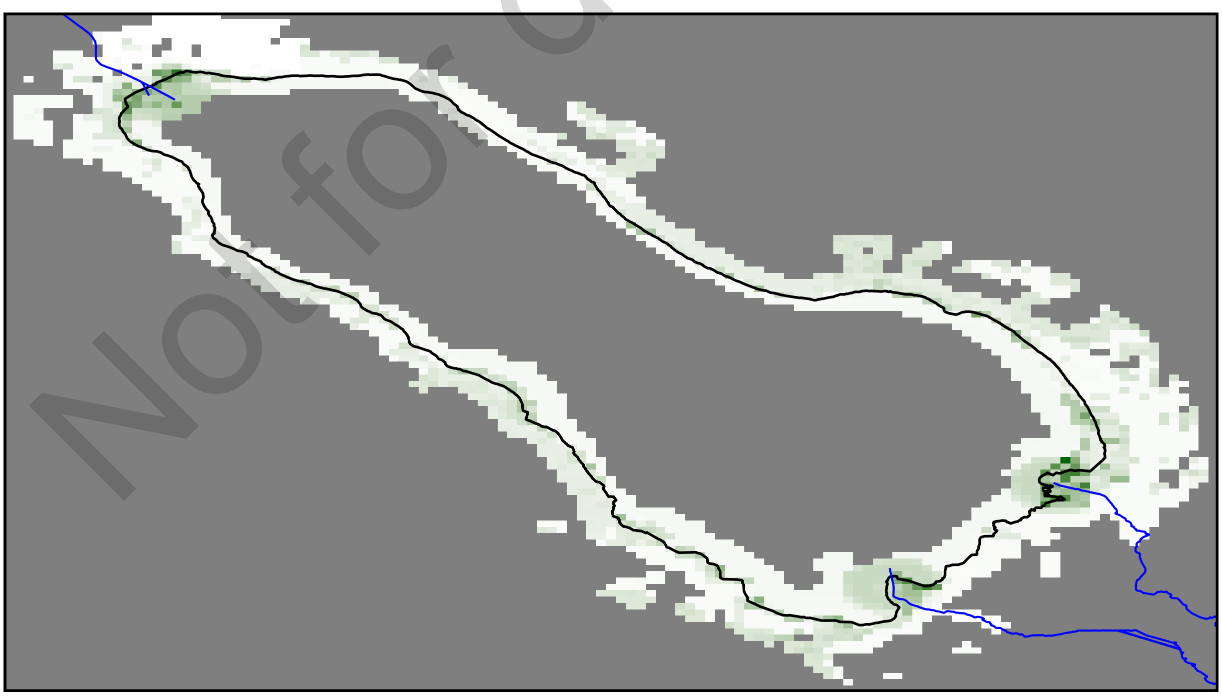
### Marginal Influence Plots



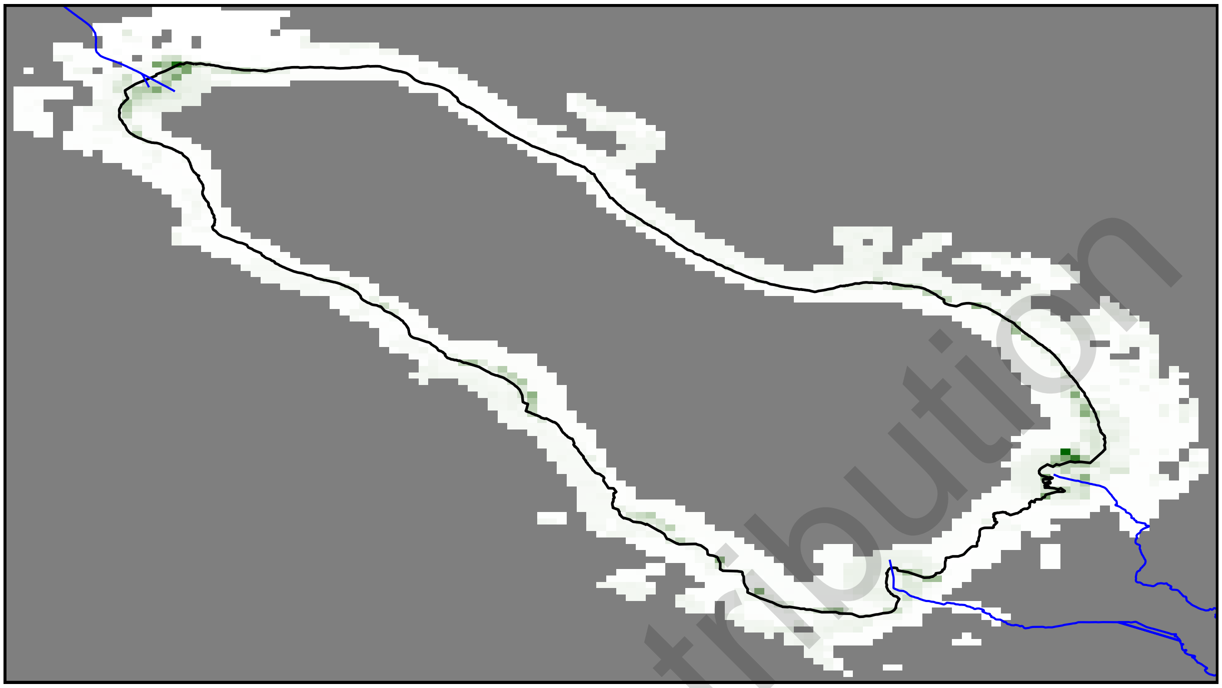



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



**Predicted Habitat Preference (2015)**



# Dowitcher spp.

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2386

79.8 % ( 1904 of 2386 ) UNDO observations were zeroes.

**Percent of total deviance explained by model:** 34.4

**Total trees:** 2050

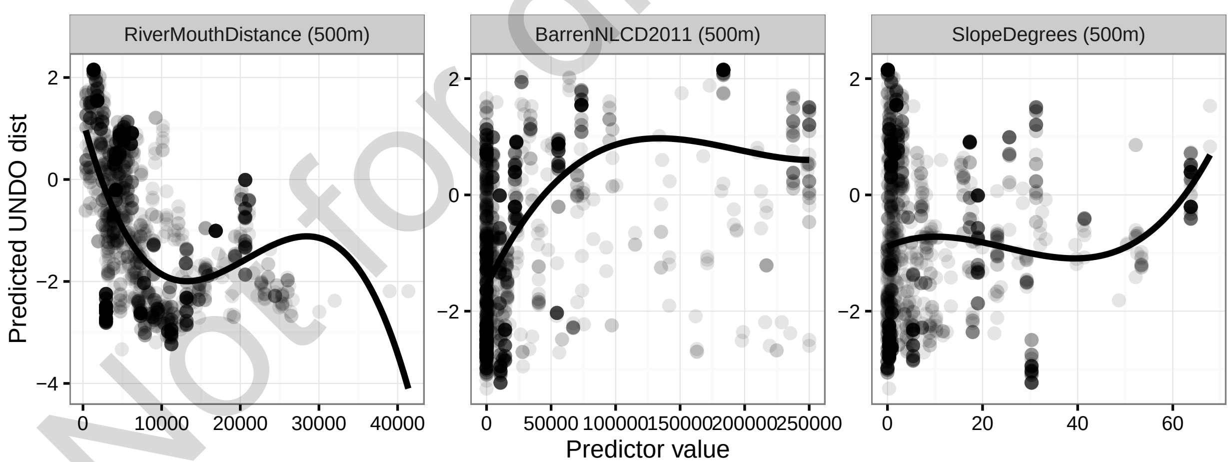
Training data AUC score = 0.836

Cross-validated AUC score = 0.781 ; standard error = 0.013

## Variable Importance

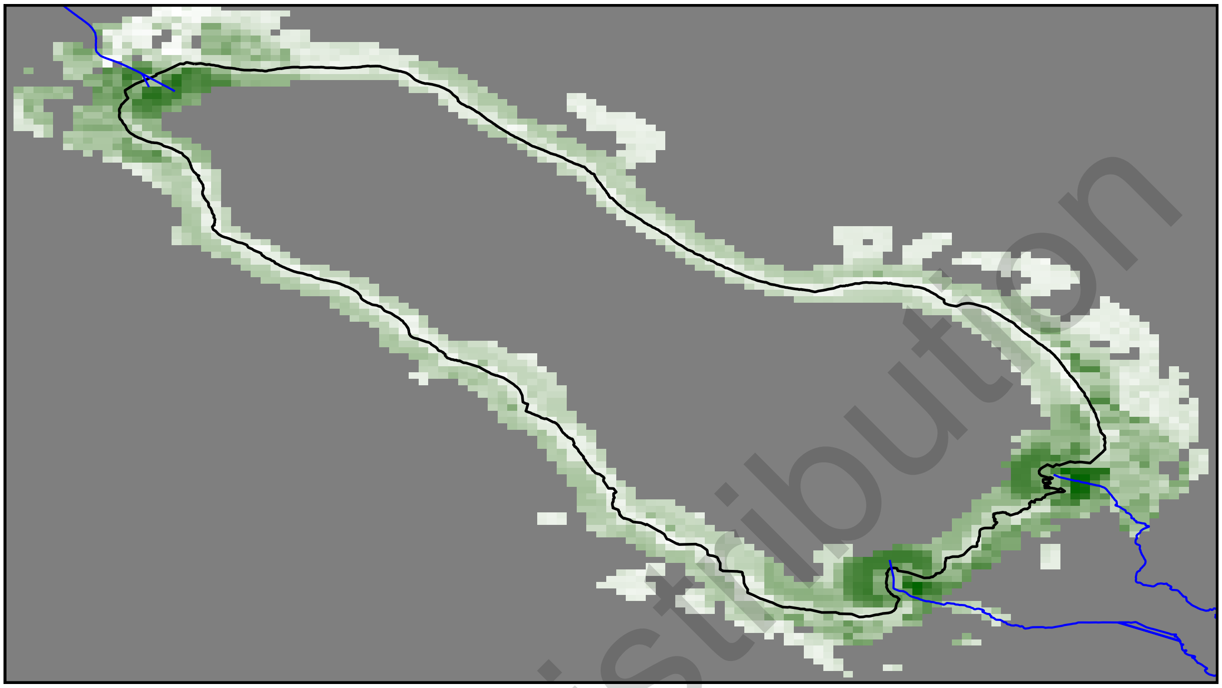
| Variable.Name | Relative.Influence |
|---|---|
| RiverMouthDistanceMeters_500m | 30.0 |
| BarrenSqmNLCD2011_500m | 8.1 |
| SlopeDegrees_500m | 7.5 |
| ShorelineDistanceMeters_500m | 5.2 |

### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)





### Predicted Habitat Preference (2015)

# Western Sandpiper

**Model Type:** Weighted by Count

**Distance Threshold:** 0.5 km

**Total Observations:** 2386

86.3 % ( 2059 of 2386 ) WESA observations were zeroes.

**Percent of total deviance explained by model:** 38.2

**Total trees:** 1750

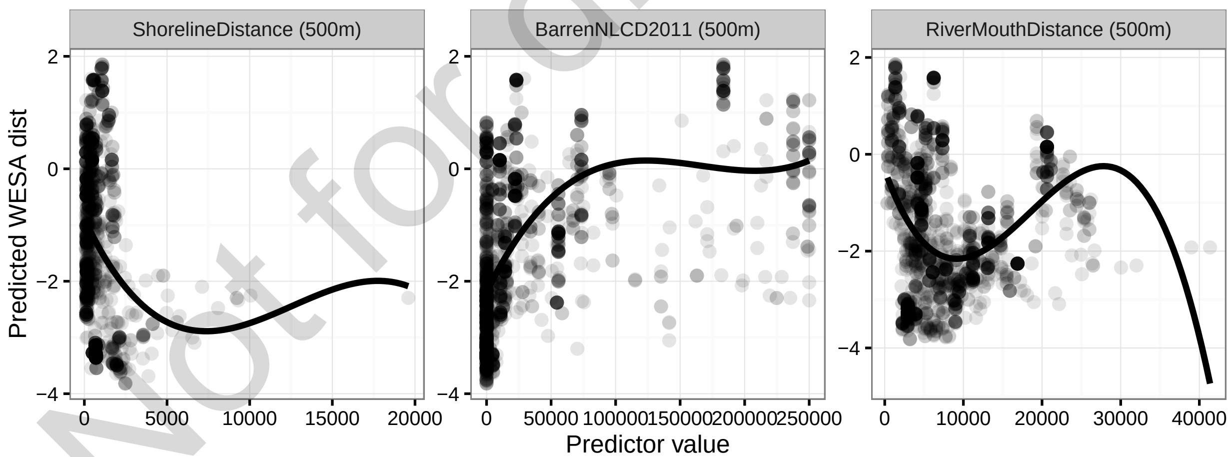
Training data AUC score = 0.837

Cross-validated AUC score = 0.778 ; standard error = 0.009

## Variable Importance

| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters_500m | 15.8 |
| BarrenSqmNLCD2011_500m | 15.0 |
| RiverMouthDistanceMeters_500m | 12.3 |
| ExposedShoreSqm_5000m | 7.4 |

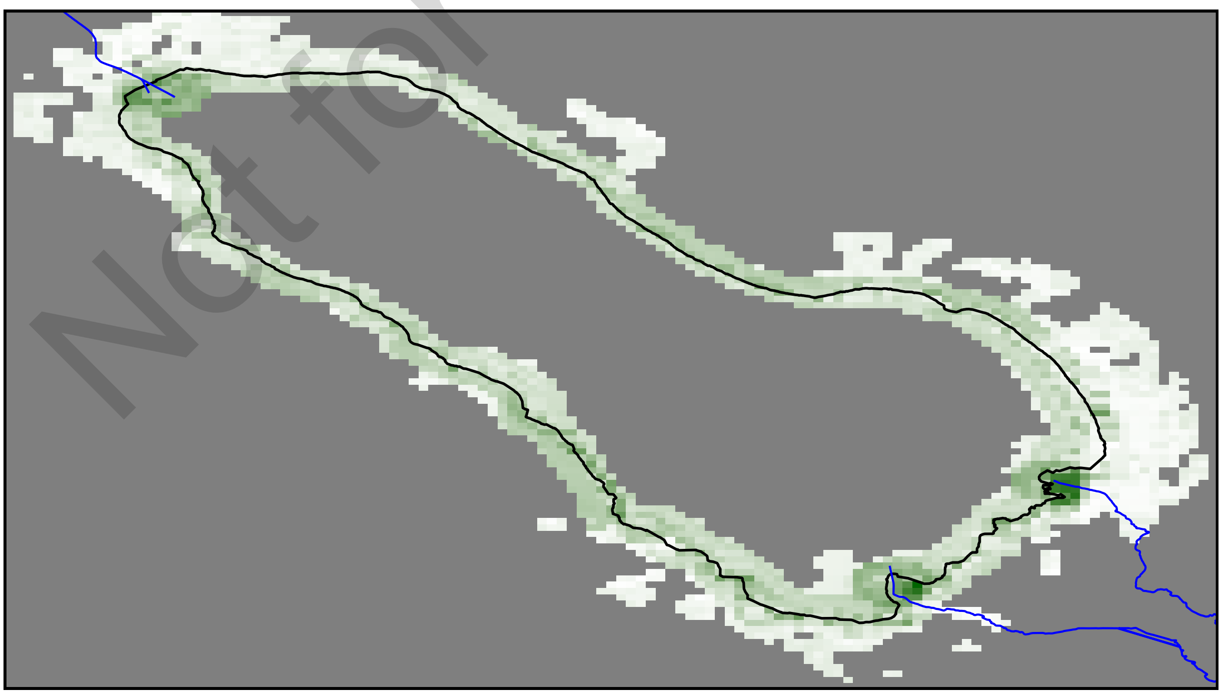
### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)

### Predicted Habitat Preference (2015)



## Common Gallinule

**Model Type:** Weighted by Count

**Distance Threshold:** 2.5 km

**Total Observations:** 3391

95.55 % ( 3240 of 3391 ) COGA observations were zeroes.

**Percent of total deviance explained by model:** 39.3

**Total trees:** 850

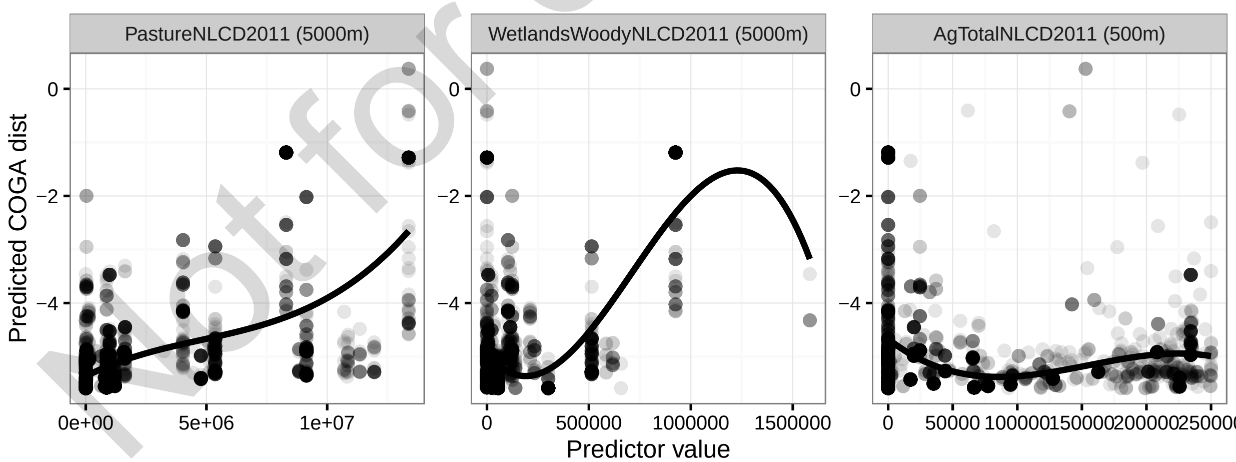
Training data AUC score = 0.816

Cross-validated AUC score = 0.776 ; standard error = 0.022

### Variable Importance

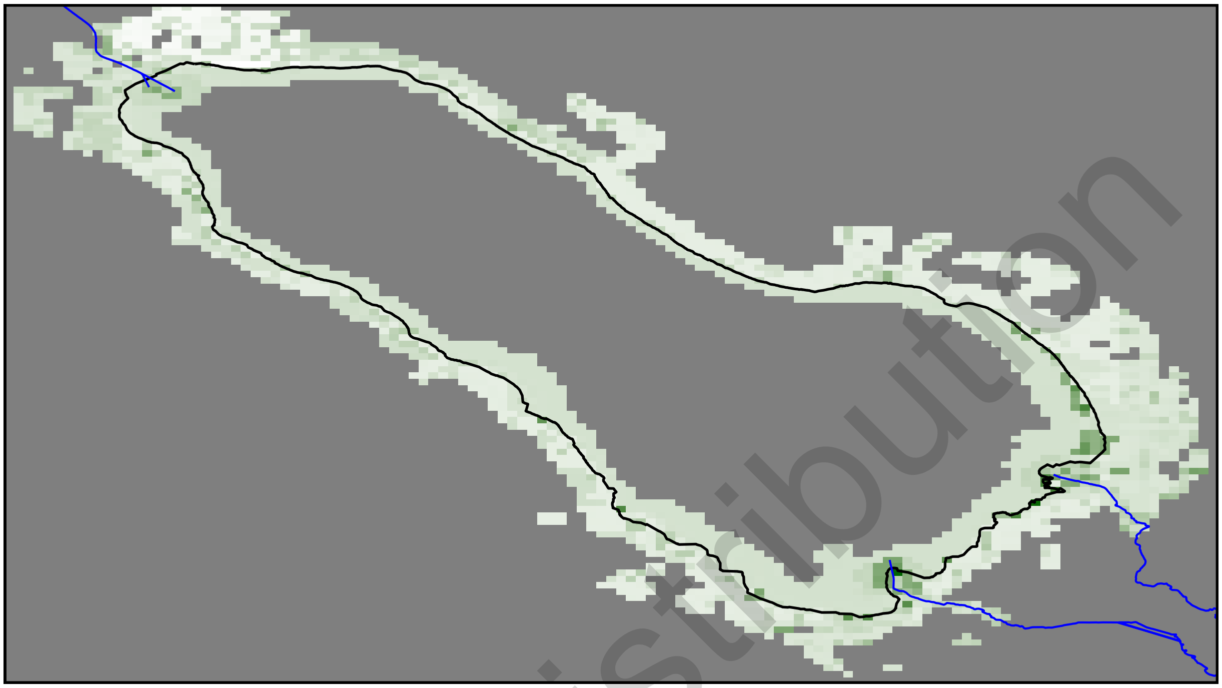
| Variable.Name | Relative.Influence |
|---|---|
| PastureSqmNLCD2011_5000m | 25.2 |
| WetlandsWoodySqmNLCD2011_5000m | 23.0 |
| AgTotalSqmNLCD2011_500m | 8.2 |
| OpenWaterSqmNLCD2011_500m | 7.1 |
| NonLakeWetlandTotalSqmNWI_500m | 6.8 |
| PastureSqmNLCD2011_500m | 5.1 |

#### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)

# Gull-billed Tern

**Model Type:** Weighted by Count

**Distance Threshold:** 2.5 km

**Total Observations:** 1299

86.37 % ( 1122 of 1299 ) GBTE observations were zeroes.

**Percent of total deviance explained by model:** 36.6

**Total trees:** 1150

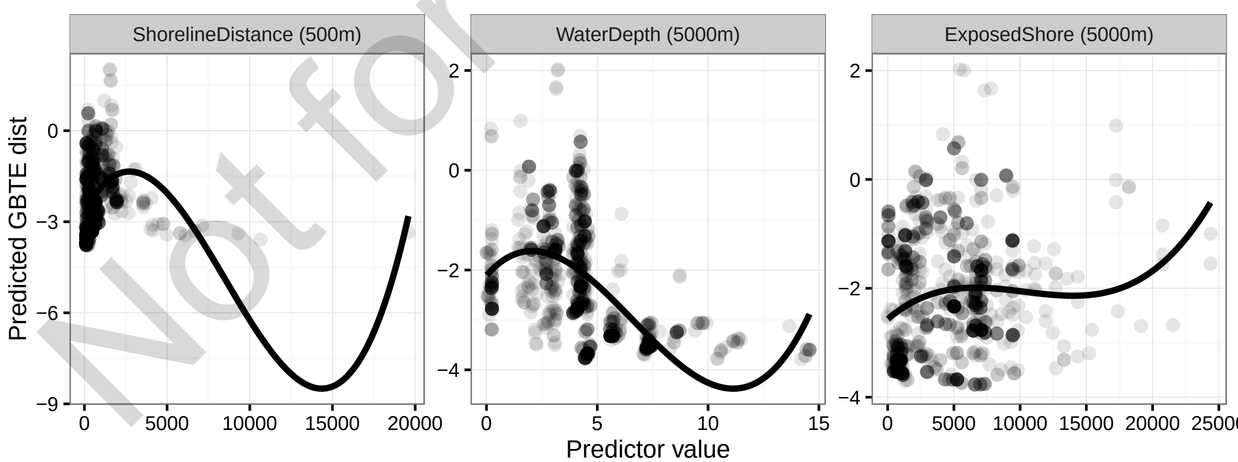
Training data AUC score = 0.825

Cross-validated AUC score = 0.748 ; standard error = 0.016

## Variable Importance

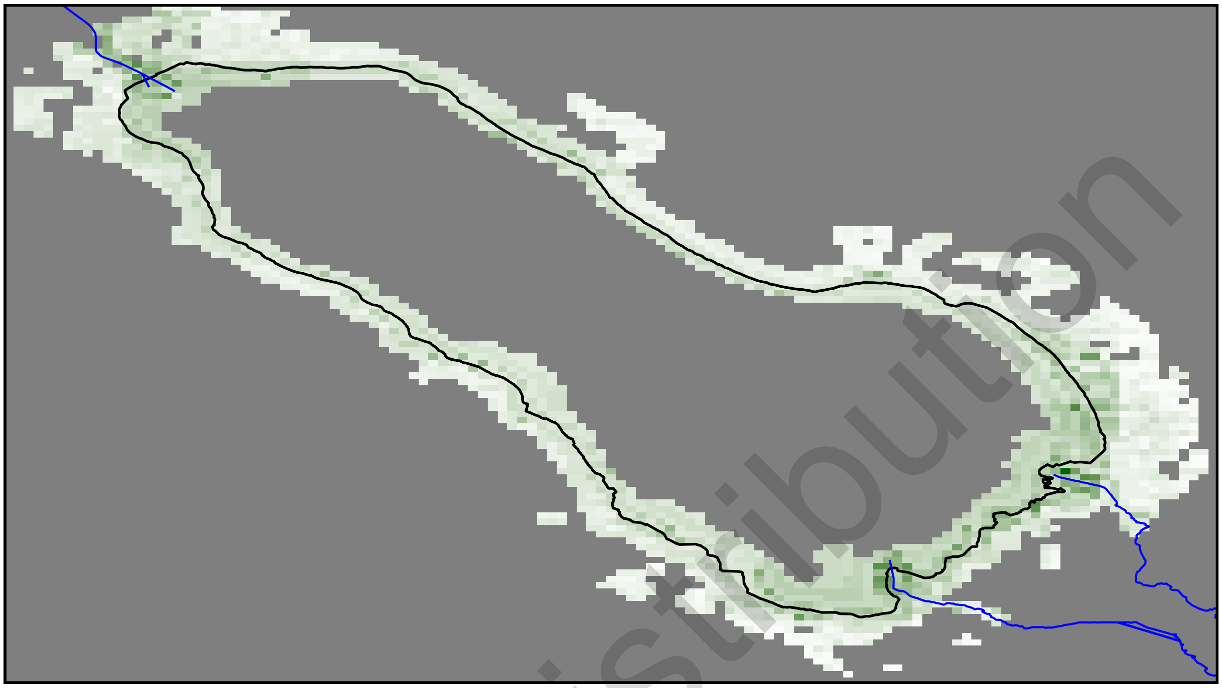
| Variable.Name | Relative.Influence |
|---|---|
| ShorelineDistanceMeters_500m | 12.5 |
| WaterDepthMeters_5000m | 9.3 |
| ExposedShoreSqm_5000m | 8.1 |
| LakeSqmNWI_500m | 5.9 |
| AgTotalSqmNLCD2011_500m | 5.5 |
| SlopeDegrees_500m | 5.5 |
| WaterShallowsSqm_200to1000cm_5000m | 5.1 |

### Marginal Influence Plots



# Predicted Habitat Preference

## Predicted Habitat Preference (1999)



## Predicted Habitat Preference (2015)

# Least Bittern

**Model Type:** Weighted by Count

**Distance Threshold:** 2.5 km

**Total Observations:** 714

95.66 % ( 683 of 714 ) LEBI observations were zeroes.

**Percent of total deviance explained by model:** 67.5

**Total trees:** 500

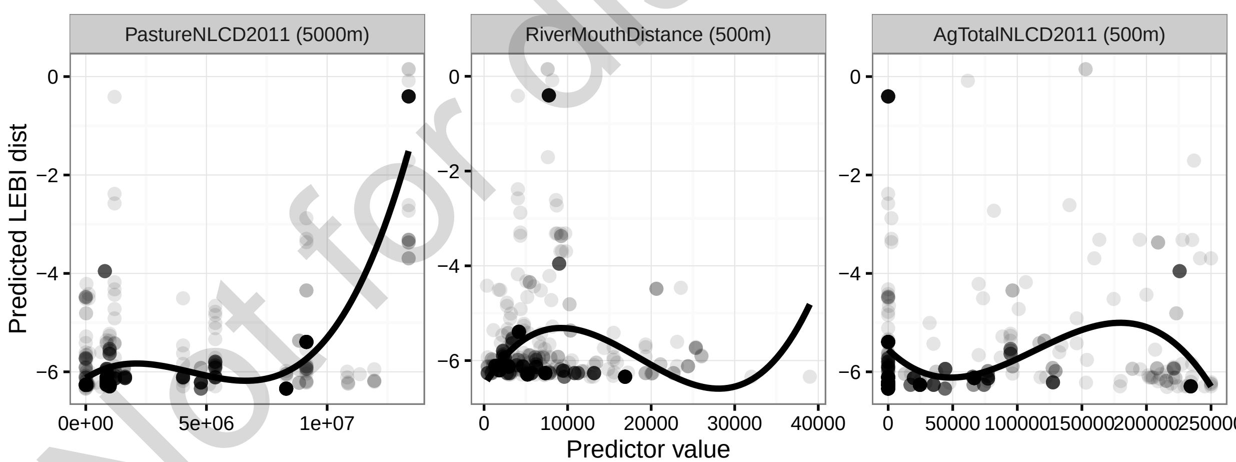
Training data AUC score = 0.798

Cross-validated AUC score = 0.766 ; standard error = 0.083

## Variable Importance

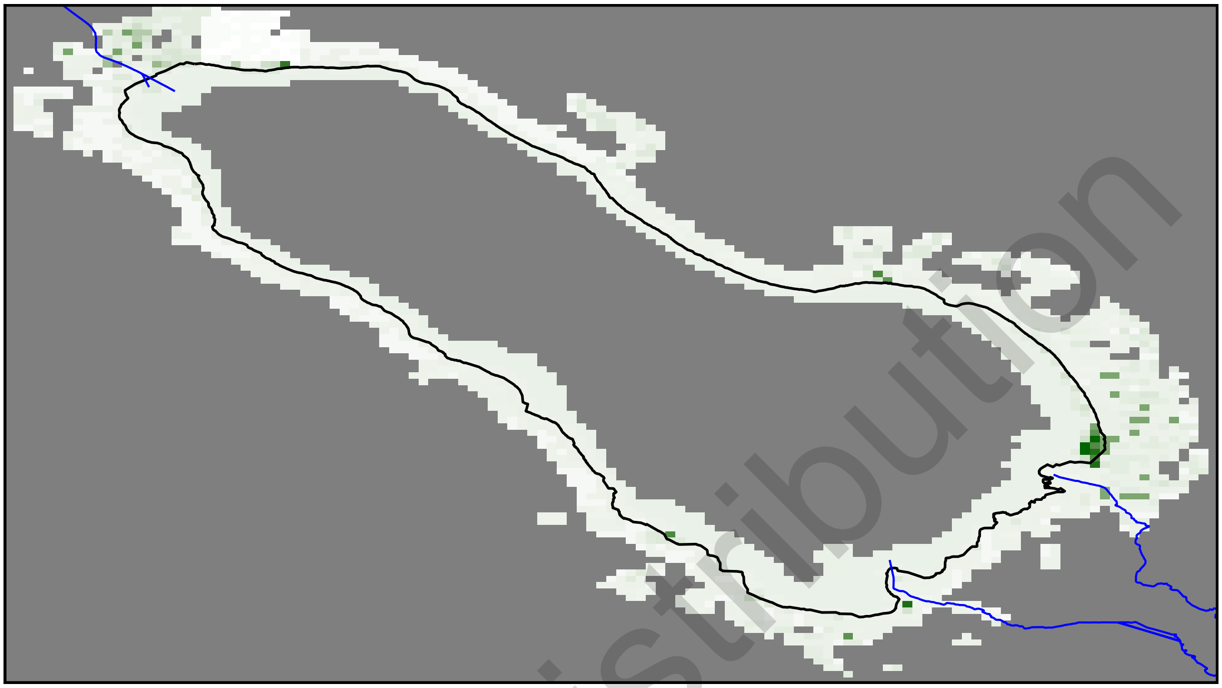
| Variable.Name | Relative.Influence |
|---|---|
| PastureSqmNLCD2011_5000m | 61.3 |
| RiverMouthDistanceMeters_500m | 14.7 |
| AgTotalSqmNLCD2011_500m | 8.3 |

### Marginal Influence Plots

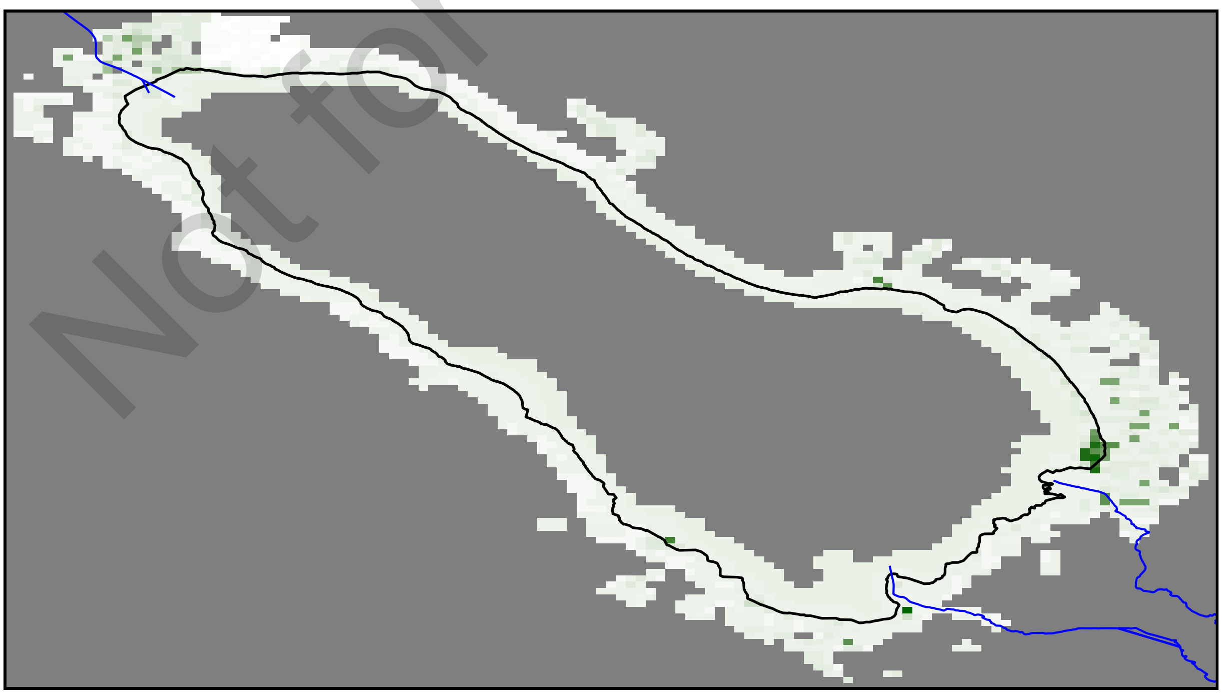


## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)



# Virginia Rail

**Model Type:** Unweighted

**Distance Threshold:** 0.5 km

**Total Observations:** 2214

98.28 % ( 2176 of 2214 ) VIRA observations were zeroes.

**Percent of total deviance explained by model:** 48.5

**Total trees:** 1050

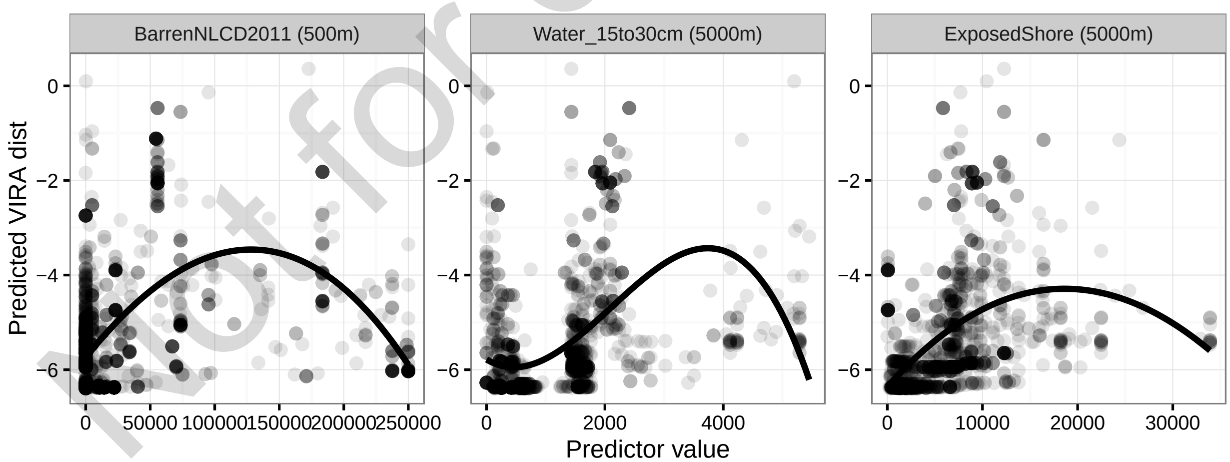
Training data AUC score = 0.978

Cross-validated AUC score = 0.887 ; standard error = 0.027

## Variable Importance

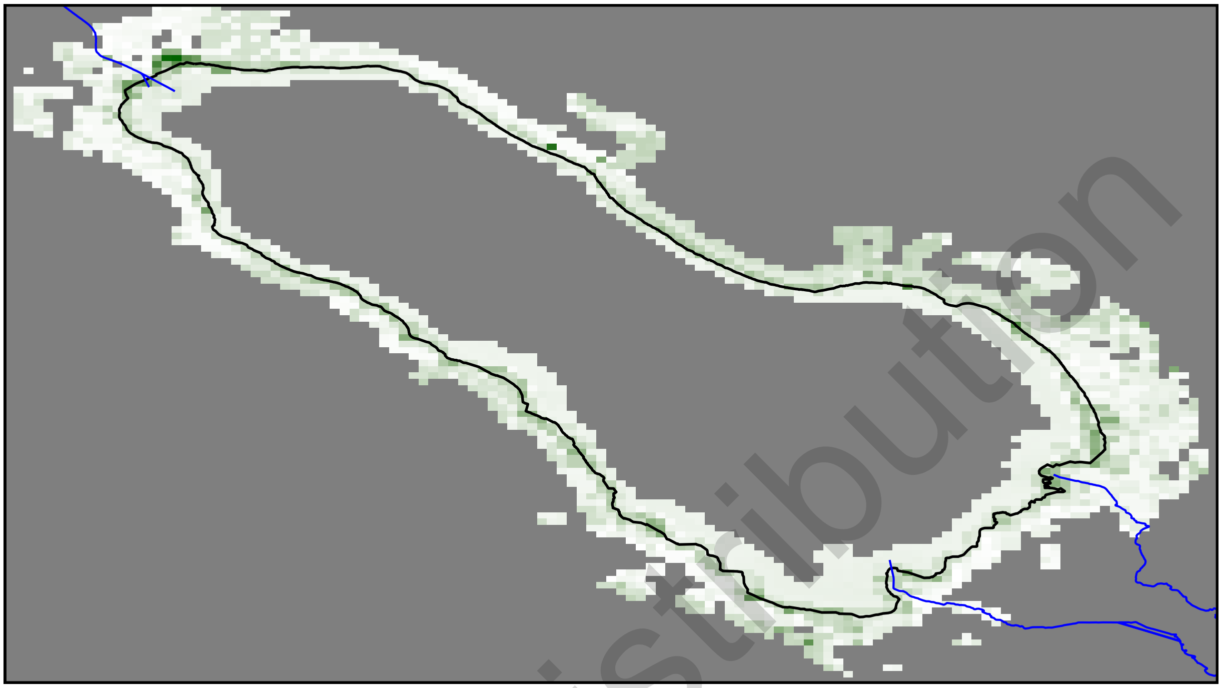
| Variable.Name | Relative.Influence |
|---|---|
| BarrenSqmNLCD2011__500m | 16.0 |
| WaterShallowsSqm__15to30cm__5000m | 13.9 |
| ExposedShoreSqm__5000m | 8.2 |
| WetlandsHerbaceousSqmNLCD2011__500m | 8.0 |
| WaterShallowsSqm__30to200cm__5000m | 6.7 |
| ShorelineDistanceMeters__500m | 6.2 |

### Marginal Influence Plots



## Predicted Habitat Preference

### Predicted Habitat Preference (1999)



### Predicted Habitat Preference (2015)