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Assessing the Importance of Wetlands on Department of Defense Installations for the Persistence of Wetland-Dependent Birds in North America

Bryan S. Stevens and Courtney J. Conway

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Bryan S. Stevens
Idaho Cooperative Fish and Wildlife Research Unit
Department of Fish and Wildlife Sciences
University of Idaho

And

Courtney J. Conway
U.S. Geological Survey
Idaho Cooperative Fish and Wildlife Research Unit
Department of Fish and Wildlife Sciences
University of Idaho

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Executive Summary

Habitat modification has impacted many populations of wetland birds, and consequently these species are often considered management priorities in the United States (U.S.). Birds that require emergent marsh vegetation (marsh birds) are of particular management concern because wetlands that include marsh vegetation have declined more so than other wetland types in North America. For example, most species of secretive marsh birds inhabiting North America are species of conservation concern. Many U.S. Department of Defense (DoD) installations exist in coastal areas, near major estuaries, or adjacent to large river systems, and consequently contain wetland complexes with emergent marsh vegetation. Failing to manage habitat for secretive marsh birds therefore has the potential to curtail the military's mission and reduce readiness via regulatory requirements. Yet, many wetlands are not actually occupied by these species, and thus determining which installations harbor optimal habitat for secretive marsh birds and which do not will benefit both the military and conservation efforts.

We used field sampling data collected from 1999-2012 to develop habitat models that predict the distribution of 11 species of secretive marsh birds across 593 DoD installations within the continental U.S., and used these models to rank all 593 installations and identify the most important installations for these species. The 11 species we examined were American bittern (*Botaurus lentiginosus*), least bittern (*Ixobrychus exilis*), pied-billed grebe (*Podilymbus podiceps*), American coot (*Fulica americana*), common gallinule (*Gallinula galeata*), purple gallinule (*Porphyrio martinicus*), clapper rail (*Rallus crepitans*), king rail (*Rallus elegans*), Ridgway's rail (*Rallus longirostris*), sora (*Porzana carolina*), and Virginia rail (*Rallus limicola*). We developed optimally predictive multi-scale habitat models for these 11 secretive marsh birds by using hierarchical occupancy models within a Bayesian statistical framework for model fitting, model selection, and inference. These species-specific models account for imperfect detection during field sampling and predict secretive marsh bird occupancy probabilities as a function of wetland and land cover habitat variables measured over a range of local spatial scales, as well as watershed-level disturbance variables that were also measured at multiple extents. Optimally predictive habitat models were selected to predict occupancy as a function of scale-optimized habitat variables. Lastly, we used the best multi-scale habitat model for each species to predict occupancy probabilities at all 593 DoD installations, and these predictions were used to rank all DoD installations in the U.S. based on the amount of optimal habitat contained within their boundaries.

Our models demonstrate that marsh bird species responded to habitat attributes over a variety of spatial scales and those responses were species-specific. However, some patterns did emerge across species. For instance, natural wetland habitat features often increased the probability of occupancy, whereas features representing anthropogenic modification of wetlands usually decreased the probability of occupancy. Moreover, watershed-level disturbance variables were common in top models, and usually decreased the probability of species occupancy. Three species (American bittern, purple gallinule, and Ridgway's rail) showed evidence of range contraction during the 14 years of the study (i.e., declining occupancy probability over time) whereas 3 species (American coot, common gallinule, and least bittern) showed increases in occupancy probability over those same 14 years.

Our results suggest an aggregation of important marsh bird habitat on DoD sites along the east coast of the U.S. (especially in the southeast). This implies that broad-scale efforts to conserve secretive marsh birds may be most effective if focused on installations in a relatively small number of states (e.g., GA, FL, LA, NC, NJ, and TX) with additional efforts focused strategically on individual installations in other regions. Our results also suggest that optimal habitat for most secretive marsh birds occurred on only a small number of DoD installations.

This work represents a vital step towards identifying, predicting, and ultimately conserving the most valuable wetlands for secretive marsh birds on DoD lands, and therefore a step towards proactive management of these species on lands administered by DoD. In addition to facilitating conservation of important habitat for marsh birds, this work provides baseline estimates of the amount of high-quality habitat for these 11 species that currently exists on DoD lands, which can be used in development of integrated natural resource management plans, as well as to measure effects of habitat management and conservation at DoD sites in the future. Moreover, the results contribute to the DoD mission by providing information regarding which DoD training activities on specific installations will and will not likely require regulatory hurdles and thereby help ensure that secretive marsh bird conservation efforts will be less likely to curtail training or reduce military readiness. Thus, model predictions will help minimize conflicts between military needs and the needs of secretive marsh birds.

Introduction

Wetlands are among the most imperiled ecosystems in North America, and habitat modification has impacted populations of many wetland birds. Over half of the original wetlands in the lower 48 U.S. states have been destroyed since the 1700s (Dahl 1990, 2006, 2011), and consequently many wetland-dependent bird species have suffered population declines (Eddleman et al. 1988, Conway and Sulzman 2007, Quesnelle et al. 2013). Wetland birds that require emergent marsh vegetation (marsh birds) are of particular management concern because vegetated freshwater wetlands have declined more so than other wetland types in North America (Dahl 2006, 2011). Consequently, many marsh birds are conservation and management priorities at state, regional, and national levels in the United States (U.S. Fish and Wildlife Service 2005; 2008). Indeed, >50% of birds of conservation concern in the U.S. are associated with wetlands or aquatic ecosystems (Erwin et al. 2000, U.S. Fish and Wildlife Service 2008).

Most species of secretive marsh birds in North America are species of conservation concern. For example, black rails (*Laterallus jamaicensis*), yellow rails (*Coturnicops noveboracensis*), limpkins (*Aramus guarauna*), and American bitterns (*Botaurus lentiginosus*) are Birds of National Conservation Concern (U. S. Fish and Wildlife Service 2008), and yellow rails, black rails, clapper rails (*Rallus crepitans*), and king rails (*Rallus elegans*) are “Focal” species identified for priority management action (U.S. Fish and Wildlife Service 2005). Many secretive marsh birds are also listed as priority species by Partners-in-Flight, including black rails, yellow rails, king rails, clapper rails, Ridgway’s rails (*Rallus longirostris*), American bitterns, least bitterns (*Ixobrychus exilis*), and limpkins. Moreover, many U.S. states consider these species threatened or of special concern for similar reasons, and numerous secretive marsh bird species are federally threatened or endangered in Mexico, Canada, or the U.S. (COSEWIC 2002, Diario

Oficial de la Federacion 2002). Thus, identification and wise management of wetlands that provide important habitat for these species is vital to ensuring their long-term persistence.

The Department of Defense Legacy program provides a pathway for identifying important habitats for marsh birds that occur specifically on military lands. This program emphasizes integrated natural resource management that includes regional ecosystem management, military readiness, range sustainment, and cooperative and international conservation. Although the U.S. Department of Defense (DoD) only manages approximately 1.3% of the land in the United States (29 million acres), many installations are in coastal areas, near major estuaries, or adjacent to large river systems, and thus contain wetland complexes that include marshland. Hence, the DoD may manage a disproportionate amount of the remaining high-quality habitat for secretive marsh birds in the U.S., and failure to properly manage habitat for these species has the potential to curtail the military's mission and reduce military readiness via regulatory burdens that could unnecessarily limit activities at individual installations. However, many wetlands are not actually occupied by secretive marsh birds of management concern, thus determining which installations are likely to harbor priority species will ensure management efforts are focused on the most important marsh bird habitat on military lands.

Despite the need to identify important wetlands for conserving populations of secretive marsh birds, scientists and land managers know surprisingly little about the specific habitat requirements for these birds. This information gap means that land managers are ill-equipped to properly identify, protect, and manage the most important wetlands for this group, and better information on the location of important habitats is thus needed. For example, it is necessary to understand what habitats are most important for each species and whether each installation is likely to have priority species breeding on their installation to effectively include secretive marsh birds in the Integrated Natural Resource Management Plans (INRMPs) at the installation level. Here we take a holistic, multi-species approach to the identification of important wetlands on DoD lands for 11 species of secretive marsh birds, with the complementary goal of identifying installations that are least likely to have suitable habitat for each species. We took advantage of broad-scale data on marsh bird occurrence collected by >200 federal, state, and non-governmental agencies from across North America to refine our understanding of important habitats for priority species, develop predictive models of habitat quality, and rank the importance of 593 DoD installations for each of the 11 marsh bird species. Specifically, our objectives for this project were to:

(1) Develop a habitat suitability model for each of 11 priority species of marsh birds throughout the continental U.S.

(2) Use data from a subset of sampling sites to both validate and improve the predictive ability of our models.

(3) Use the models to rank DoD installations in the continental U.S. based on their relative value to each of the 11 focal species of secretive marsh birds. We based the rankings on the estimated amount and quality of suitable habitat on each DoD installation and the threats to marsh bird habitat on adjacent non-DoD lands.

(4) Produce a map portraying high-ranking DoD installations in terms of habitat suitability for each species of marsh bird.

Study Area

The study area included marshlands throughout the continental U.S. that were contained within the geographic range of 11 priority marsh bird species: American bittern, least bittern, American coot (*Fulica americana*), clapper rail, king rail, Ridgway's rail, Virginia rail (*Rallus limicola*), sora (*Porzana carolina*), pied-billed grebe (*Podilymbus podiceps*), common gallinule (*Gallinula galeata*), and purple gallinule (*Porphyrio martinicus*). We used published ranges from the Gap Analysis Program (GAP) to identify the geographic range extent for each of the 11 species (Gergely and McKerrow 2013), and included sampling sites in our analyses for each species if they fell within the range identified by the GAP range for that species. We also visually inspected all survey sites where a species was detected outside of its published range in ArcGIS (ArcMap 10.4.1, ESRI, Redlands, CA), and included points outside a species' range in the analysis for a given species if they were near the published range boundary or fell within gaps of the published range. Decisions regarding whether to include sites where a species was detected outside of its published range were therefore subjective, but the number of these points relative to sample sizes used to build habitat models for each species was small (< 1% of data points). Thus, inferences about habitat associations were primarily determined by observations at field sampling sites within the published GAP range for each species.

Methods

Data collection. Detection-non-detection data from marsh bird surveys were collected between 1999–2012 at 8,457 sites throughout the U.S. Field surveys were completed during the marsh birds' breeding season (1 March-15 July) following the standardized North American marsh bird monitoring protocol (Conway 2011). Most surveys included both a passive and a call-broadcast segment because broadcasting marsh bird calls increases detection probabilities by eliciting vocal responses from birds occupying the area that otherwise are likely to go undetected (Conway and Nadeau 2010, Conway and Gibbs 2005, Conway and Gibbs 2011). Surveys were conducted at groups of geographically clustered sampling points that were visited repeatedly over a breeding season and many points were sampled for >1 breeding season (i.e., sampled for numerous years). Not all species were sampled beginning in 1999 due to the large extent and variety of organizations involved in data collection; for 5 of the 11 species, we used data collected over a shorter temporal extent (see Results). The initial study plan was to conduct field surveys at a subset of DoD installations after an initial set of predictive models were developed so that a second round of predictive habitat models could be generated based on those field validation efforts, but that aspect of the overall project was dropped from the initial study plan because the final 3 follow-on years were not selected for Legacy funding (the initial project indicated 4 follow-on years). Hence, we validated the models by holding out a random subset of the available sample data from 1999-2012 such that 60% of the data were used for building models and 40% were used for testing models. Nonetheless, some of the field surveys from 1999-2012 that we used in our analyses were located on DoD lands (see Results).

For each sampling visit at a given survey point within each year, detection (i.e., presence) was recorded for each species if that species was detected by observers during the survey, whereas non-detection (i.e., pseudo-absence) was recorded for a species if that species was not detected during the survey. Data were similarly collected on replicate visits at a given site during the same breeding season, which allowed estimation of the relationships between habitat covariates and probability of species occupancy while also explicitly accounting for failed detections (i.e., species present during breeding season but not detected during a given survey) that commonly occur with most biological field surveys (Kéry 2002, MacKenzie et al. 2002, MacKenzie et al. 2006). Because marsh bird vocalization and detection probabilities are influenced by a number of factors, both within and beyond the control of field investigators (Nadeau et al. 2008, Conway and Gibbs 2011), we also used survey-level attributes that were recorded during field sampling as covariates in detection models. These detection covariates included: 1) time of day at the start of each survey, 2) Julian date, 3) duration of the call-broadcast survey, and 4) a binary variable indicating whether or not the call for that species was included in the call-broadcast segment of the survey. We included these 4 detection covariates because they are variables that have been reported as factors influencing detection in previous marsh bird studies (Conway et al. 1993, Conway et al. 2004, Conway and Gibbs 2011).

We obtained spatial data over broad extents to build predictive distribution models for marsh birds as a function of habitat attributes. We used geospatial data from the National Wetland Inventory (NWI; downloaded November 2014) to characterize wetland attributes near marsh bird sampling sites. The NWI dataset consists of wetland polygons that represent contiguous areas with similar wetland characteristics, where polygon attributes are classified using a hierarchy based on hydrology, geomorphology, substrate, and the dominant form of vegetation (Cowardin et al. 1979). Following the approach described by Glisson et al. (2017), we used the following categories of the NWI classification system to characterize wetland habitats surrounding sampling sites: wetland system, wetland subsystem, wetland class, water regime modifier, and special modifier. Within each delineated wetland polygon, a code is used to describe attributes of the wetland relative to these categories (e.g., code for lacustrine and limnetic describes one possible combination of wetland system and subsystem categories), where the resulting wetland polygon is characterized by a string of codes describing the area relative to each NWI category (i.e., a code for system, subsystem, class, water regime, and special modifiers, respectively). For our analysis, we only considered habitat variables representing combinations of wetland system and wetland subsystem (wetland system-subsystem, hereafter), individual wetland classes, individual water regimes, and individual special modifiers as habitat variables to explain the distribution of marsh birds within their geographic ranges (Glisson et al. 2015, 2017). We combined the wetland classes for rock bottom, unconsolidated bottom, aquatic bed, and streambed (hereafter referred to as water) because we believed that these categories provided similar habitat for marsh birds (Glisson et al. 2017). For similar reasons, we also combined rocky shore and unconsolidated shore categories (hereafter referred to as shore). We used a total of 21 NWI wetland variables as potential habitat covariates when generating candidate models to predict the occupancy of marsh birds in our analyses (Appendix A).

We also obtained broad-scale spatial data to describe human-induced changes to the natural land cover surrounding sampling sites. We used a set of individual and composite land cover types obtained and derived from the National GAP Land Cover Dataset, Version 2 (raster data with 30-

m pixel resolution; downloaded November 2014) to assess the ability of different types of land cover alteration to predict the occupancy of marsh birds within their respective ranges. We considered 5 GAP land cover variables that were intended to describe human development (developed-open space, low-intensity development, medium-intensity development, high-intensity development, and all development land cover types combined), as well as additional variables related to modification by agriculture (cultivated-cropland cover, pasture-hay cover, and cultivated-cropland and pasture-hay combined [hereafter referred to as agriculture cover]), and introduction of non-native vegetation (non-native cover). Thus, we used 9 GAP land cover variables as covariates hypothesized to affect the distribution of marsh birds in our analyses (Appendix A). Moreover, we rasterized NWI vector data so that we could use compatible spatial units to represent NWI and GAP data, as described by Glisson et al. (2017).

Observed relationships between an animal's use of a site and the attributes of that site are usually sensitive to observational scales at which habitat attribute data are collected (Wiens 1989, Hobbs 2003, Wheatley and Johnson 2009, McGarigal et al. 2016). Thus, we examined relationships between habitat variables and species occupancy at multiple spatial extents surrounding each sampling site. We measured all habitat attributes at 3 spatial extents surrounding sampling sites (100-m, 224-m, and 500-m radii buffers). These scales correspond to the distance at which birds were commonly detected during surveys (often < 225 m), and cover a range of extents at which marsh birds commonly respond to habitat characteristics (Glisson et al. 2015, Glisson et al. 2017). We used circular moving-window analyses with radii of 100 m, 224 m, and 500 m to characterize habitat attributes at each extent around each sampling site, assigning raster cells to cover values for each wetland and land cover variable at each spatial extent. For each moving window analysis, each raster pixel was assigned a value for each covariate representing the proportion of raster cells within the window surrounding the pixel that were attributed to a given habitat variable. To align covariate measurements with sampling sites, each sampling site was assigned to its intersecting 30-m raster cell. Thus, habitat attributes of each sampling location were described at a grain of 30 m, and assigned proportional coverage values for each covariate at 3 spatial extents. The covariates were not weighted (i.e., they were all effectively weighted the same).

In addition to local habitat attributes associated with NWI and GAP data, we also characterized land cover, disturbance, and hydrologic modification of entire watersheds surrounding our field sampling sites. To examine the possible effects of mining activities on water quality (and hence on marsh bird occupancy), we obtained spatial data describing the location of all known current and former mines (metallic and non-metallic) and mineral processing plants within the U.S. from the Mineral Resources Data System (MRDS; http://mrdata.usgs.gov/mrds/) of the U.S. Geological Survey (USGS). To examine the possible effects of chemical contamination over broad scales on the occupancy of marsh birds, we used the Commission for Environmental Cooperation's spatial database documenting locations for all pollutant release and transfer reporting facilities (www.cec.org/takingstock) located within the U.S. To examine the possible effects of hydrologic modification on occupancy of secretive marsh birds, we also measured variables derived from the National Anthropogenic Barrier Dataset (NABD; Ostroff et al. 2013) and the National Hydrography Dataset Plus Version 2 (NHDPlusV2; McKay et al. 2012; http://www.horizon-systems.com/nhdplus/NHDPlusV2_home.php). Variables characterizing hydrologic modification described attributes related to the storage capacity of water by upstream dams, as well as the magnitude of restriction and interruption of natural flow regimes by upstream dams and water flow control structures for each raster pixel in a given area (Table A5). Lastly, we measured anthropogenic land cover disturbance associated with human development and agriculture within a watershed by using the composite GAP variables for development and agriculture described above.

We measured these land cover, disturbance, and hydrologic modification variables within watersheds at two spatially nested levels: catchments and networks. The NHDPlusV2 data set contains > 2.6 million water catchments within the U.S., where each catchment contained the direct drainage area for a single surface water reach (i.e., a continuous piece of surface water with similar hydrologic conditions), and catchment sizes varied considerably (range = < 1 - 7,984.0 Km^2, mean = 64.6 Km^2). Catchments receive water from upstream sources (i.e., rivers and streams flowing in from upstream catchments), and thus wetlands within a catchment may be influenced by conditions (nutrient loads, pollution, hydrologic alteration, etc.) at broader scales upstream within a watershed. To account for even broader disturbances and incorporate upstream dynamics, we treated catchments as nested within a broader network of their upstream watersheds (hereafter network). To define the wetland network spatially, we first identified all NWI wetland polygons receiving water directly from upstream sources (i.e., wetlands upstream of where a given wetland was located) by selecting the wetlands that directly intersected with the National Hydrography Dataset (NHD) flow line, and then iteratively selecting adjacent (i.e., touching) wetland polygons until no additional wetlands were available, or until a marine or riverine wetland was reached (treated as a barrier to flow among adjacent wetlands). We then rasterized all within-network wetland polygons to a spatial resolution of 30-m pixels, and defined the entire network associated with each catchment as all pixels located in upstream catchments (i.e., not including the current catchment) that were also within a 500-m buffer of these rasterized wetlands. As such, network sizes varied even more so than catchments (range = <1 – 572,655.0 Km^2, mean = 39,383.8 Km^2). Land cover, disturbance, and hydrologic modification variables characterized within watersheds were thus measured at the catchment and network levels, where catchments were nested within a network, and networks incorporated upstream dynamics for a given catchment. These covariate data were linked to secretive marsh bird sampling sites to model occupancy patterns based on the spatial location of the sites within catchments and networks. Some sampling sites were not located directly in a mapped catchment or network (n = 257 sites for catchments and n = 1,018 sites for networks). As such, these sampling sites had missing values for the watershed-disturbance variables, which effectively resulted in the covariates providing no information about occupancy status for secretive marsh birds at those sites (see *Statistical analyses*).

Statistical analysis.-We used a statistically hierarchical formulation (Royle and Dorazio 2006, 2008) of the standard multi-season occupancy model (Mackenzie et al. 2006) to predict the probability of marsh bird occupancy as a function of wetland, land cover, and hydrologic variables. This model treats the true marsh bird occupancy at a location (i.e., present or absent) as closed and unchanging within a single breeding season, but assumes the occupancy status can change among breeding seasons at a location (i.e., occupancy status is a random variable each year and is therefore open across years). In addition to modeling the relationship between species occurrence and habitat, occupancy models enable explicit modeling of the factors influencing a species detection probability during field surveys (MacKenzie et al. 2002, 2006). Ignoring failed detection (i.e., animal present but observer fails to detect it) during presence-absence surveys results in biased estimates of species-habitat relationships (Gu and Swihart 2004, MacKenzie et al. 2006, Lahoz-Monfort et al. 2014), wherein detection and occupancy probabilities are mathematically confounded and resulting models therefore predict where a species both occurs and is likely to be detected during field sampling (Kéry 2011, Elith and Franklin 2013, Guillera-Arroita et al. 2014, Guillera-Arroita et al. 2015). Thus our modeling approach allows us to build habitat models that predict the true spatial distribution (sensu Kéry 2011) of marsh birds on DoD lands as a function of habitat and disturbance variables without making the restrictive assumptions that occupancy status does not change over time and marsh bird detection probability does not change among surveys conducted at different locations and times; assumptions which are unlikely to be true (Conway and Gibbs 2011).

We used a Bayesian statistical paradigm for model fitting and inference. We fit all hypothesized occupancy and detection models by using computationally-intensive Markov chain Monte Carlo (MCMC) methods implemented in JAGS (Plummer 2003) called from within R (version 3.3.3; The R Foundation for Statistical Computing 2017) using the R2jags package (Su and Yajima 2015). To fit models, we used 3 MCMC chains with a burn-in period of 200,000 samples followed by 25,000 retained samples per chain, for a total of 75,000 samples used to describe the posterior distribution of all parameters and derived quantities. If a model failed to achieve convergence to its posterior distribution after 200,000 samples (i.e., multivariate Gelman-Rubin statistic >1.1; Gelman and Rubin 1992) we assumed that we had insufficient data to reliably estimate parameters and we did not use that model for inferential or predictive purposes.

We used Bayesian model selection procedures to optimize the covariate structure of occupancy models for predictive purposes. We randomly split the sampling sites into training and testing data sets for each species prior to analysis, where training data sets were used to fit models and estimate posterior distributions of model parameters (via MCMC as described above), and testing data sets were held out to test the predictive abilities of each model. Thus, for a given marsh bird survey route, each sampling site could have been allocated to either the training or testing data, and survey route membership had no bearing on the randomized split (ensuring spatial representation of both data sets). Specifically, we used 60% and 40% of all sampling sites for the training and testing data sets, respectively, where the entire time series of data at a site was included in the data set to which a given sampling site was randomly assigned (Table 1). We used the logarithmic scoring rule (hereafter log scoring rule; Gelman et al. 2014, Hooten and Hobbs 2015) for ranking and selecting models, where log scores for a given model were calculated from the marginal posterior predictive density of the entire testing data set (by using equations modified from Appendix S1 of Broms et al. [2016]). This is equivalent to selecting the model based on its ability to maximize the joint probability of observing the testing data set and, thus, selecting the model structure that maximizes the ability to predict data held out from model fitting and model selection processes.

Prior to including wetland, land cover, and hydrologic variables in models to describe occupancy probabilities, we selected a detection process model for each of the 11 marsh bird species based on its ability to maximize predictive capabilities in the absence of occupancy covariates (i.e., from an intercept-only occupancy model). We fit models that included detection process covariates described above in two stages. First, we compared models with a linear fixed effect to models with a quadratic effect (i.e., dome or u-shaped relationship) for sampling time and Julian date covariates of detection probability. We then used the best sampling time and Julian date model structures (i.e., linear or quadratic) from the first stage and combined them with other detection covariates to create a final detection model set consisting of 20 models for each species (Appendix B). We used the log-scoring rule to identify the best detection model (while assuming constant occupancy probability). The optimal detection model was then used for all further model fitting and to examine which habitat covariates affected occupancy probabilities for each of the 11 species.

We identified optimal habitat models for predicting occupancy probability for each marsh bird species. However, animals respond to habitat conditions over a variety of spatial scales, and different species typically demonstrate individualistic scale-specific patterns of habitat use (Wiens 1989, Levin 1992, Major et al. 2009, McGarigal et al. 2016). Evaluating the effects of habitat covariates over a range of spatial scales is therefore important for predicting species distributions, and selecting the optimal scales is an important but frequently overlooked component of multi-scale habitat analyses (McGarigal et al. 2016). Thus, we first conducted univariate scale optimizations to identify the optimal spatial scale for predicting marsh bird occupancy for each wetland and land cover variable for each species. For each of the 11 marsh bird species, we optimized the scale of each occupancy model covariate by fitting univariate occupancy models for all variables at 3 spatial scales, and selecting the optimally predictive scale for each variable as the scale with the best log score. After identifying the best spatial scale for each individual covariate, we identified the best scale-optimized habitat covariate within each of four groups of local-scale habitat variables representing wetland types and land cover disturbance (wetland system-subsystem, wetland class, water regime and special modifiers, and GAP land cover variables; Appendix A). This resulted in 4 scale-optimized habitat covariates that were used to create a multi-scale model set to describe occupancy probabilities for each of the 11 marsh bird species as a function of local-scale habitat variables surrounding each sampling site. Specifically, the habitat model set consisted of all additive combinations of each scale-optimized covariate, for a total of 15 candidate multi-scale habitat models for each species, and the best habitat model was selected from this set as the model that resulted in the optimal log-score as described above. Once an optimal model with local-scale habitat variables was identified, a final model set was created for each of the 11 species that included the best watershed-level disturbance variables and hypothesized trends in occupancy status over time, in addition to the best local-scale habitat variables for each species (Appendix C). We then used log scores to identify the overall optimally-predictive model for each of the 11 secretive marsh bird species. In summary, we used a multi-stage Bayesian model selection procedure to identify which covariates were included in the final set of habitat models for each species, and we selected the best model from that set of models as the one with the best predictive ability, where predictive ability was assessed directly from independent data that we had held out for testing purposes. Lastly, to generate final parameter estimates used in predictive modeling (see *Spatial modeling and ranking of DoD installations* below) and evaluate goodness-of-fit, we re-fit top models to the entire detection-non-detection data set for each of 11 species (i.e., combining training and testing data; Hooten and Hobbs 2015) and generated Bayesian *P*-values based on the sum of absolute residuals (pgs. 246-249 in Kéry 2010).

Spatial modeling and ranking of DoD installations.-For each of 11 marsh bird species, we combined the top statistical model with geospatial data for habitat covariates to develop spatial models that predicted species distributions on DoD lands. Specifically, we developed raster regression models in ArcGIS that used 30-m pixel raster data for each habitat covariate in the top model as inputs to predict occupancy probability for each species at a 30-m resolution on all DoD lands within the continental U.S. We created raster data sets at all 3 buffer scales for each NWI and GAP covariate, and for network-scale and catchment-scale extents for each watershed-level disturbance covariate, at the extent of the continental U.S. using the same analyses described above. Values for each variable at each pixel were assigned according to the value of that variable occurring within the buffer windows (local-scale NWI and GAP data), or within the catchment or network (watershed-level disturbance variables) associated with each pixel. This allowed us to pair scale-optimized covariates from regression analyses with identically summarized data on all DoD lands, regardless of the optimal predictive scales, ensuring identical measurement scales for data used to fit models and data used to extrapolate model predictions through space. We created all raster regression models by using the raster calculator tool in the spatial analyst extension of ArcMap (ESRI, Redlands, CA).

We ranked the value of each DoD installation for each of 11 marsh bird species according to the amount of high-quality habitat contained within the installation boundaries. First, we calculated the value associated with the top 30% of the range of predicted occupancy probabilities for each species (i.e., maximum pixel value - 0.3*(maximum pixel value - minimum pixel values for predicted probabilities occurring on DoD lands)). This allowed identification of the predicted occupancy probability associated with the largest occupancy probabilities for each species, which was used to define the locations with the best habitat for each of the 11 species across all DoD installations. Specifically, we calculated the area of habitat with predicted occupancy probabilities within the top 30% of the range of model predictions for each of 11 species at each location, and ranked DoD installations for each species based on the amount of optimal habitat. We also produced a map for each species to visually display the highest ranking installations for each species across their breeding ranges within the continental U.S. To evaluate sensitivity of DoD site rankings for each species to the threshold value used to define optimal habitat, we replicated the above calculations and ranking of DoD installations at higher (top 20% of range) and lower (top 40% of range) threshold values. Lastly, two species (least bitterns and soras) had left-skewed distributions of predicted occupancy probabilities among pixels locates at DoD sites. Thus, to avoid characterizing poor or marginal habitat as optimal for these species we ranked DoD sites as describe above, but using 3%, 5%, and 7% of the range of predicted values to define optimal habitats (instead of 20%, 30%, and 40%).

Results

We developed predictive occupancy models for 11 species of marsh birds based on field surveys replicated across the geographic range for each species. The number of sampling sites used for model development and predictive evaluation ranged from 1,625 sites for purple gallinule to 8,457 sites for pied-billed grebe, and the temporal extent of field surveys ranged from 10-14 years (Table 1). Hence, training data sets included 975-5074 sites and testing data sets included 650-3385 sites that were used to evaluate the predictive abilities of each fitted model (Table 1).

Less than 4% of the sampling sites for each species were located on DoD installations (Table 1) and, hence, the models are robust and are suitable for predictive purposes on all lands in the U.S. (i.e., DoD and non-DoD lands).

Four variables (Julian date, sampling time, call-broadcast length, and whether the focal species' calls were included in the broadcast) affected detection probability of most marsh bird species, but the specific detection models selected varied among the 11 marsh bird species (Table 2). Julian date and sampling time affected detection probability of 100% and 91% of the 11 species, respectively, whereas broadcast length and focal species' calls each affected detection probability for 64% and of the 11 species. However, the relationships between detection probability and both Julian date and sampling time were heterogeneous among species and often nonlinear (Table 2). The best detection model for 27% of species included quadratic effects for both date and time, indicating peaks in detection probability both within and among days during the breeding season. In contrast, the best detection model for 27% of species included linear effects for both date and time, indicating monotonic changes in detection probability both within and among days during the breeding season. Models for the remaining 45% of species suggested one linear and one quadratic effect (for date and time of day): 2 linear and 2 quadratic models for Julian date, and 2 linear and 3 quadratic models for sampling time. However, linear and quadratic effects for both Julian date and sampling time were competitive for most species (95% Credible Intervals overlapped), and in this case the linear models were used for detection model selection for simplicity. In addition, 64% of species detection models included interactions between Julian date and sampling time. Thus, the joint, non-linear effects of covariates on detection probability during field surveys is not straight-forward for marsh birds and effectively describing and controlling for these time-varying effects requires substantial data, and the relationships vary among marsh bird species.

The spatial distribution of marsh birds in North America was affected by wetland and land cover characteristics and watershed disturbances at numerous spatial scales, and the effects varied among species (Table 3). For all 11 species, the probability of occupancy within their breeding range was affected by habitat covariates at >1 spatial scale. Occupancy of American bittern, American coot, pied-billed grebe, and Virginia rail was most affected by habitat at the broadest spatial extent around sampling sites (500 m), whereas occupancy of least bittern and purple gallinule was most affected by local-scale habitat variables measured at fine extents surrounding sampling sites (100 m). However, most species responded to habitat covariates at all 3 spatial scales, with no discernable pattern favoring broad or fine spatial extents (Table 3), and watershed-level disturbance variables were included in the optimally-predictive model for 82% of the 11 species. Moreover, top models adequately fit the observed data ($|P| > 0.05$) for 10 of the 11 species (all species except sora).

The factors that affected occupancy varied among the 11 species, but some commonalities emerged and those commonalities reflect habitat affinities that make intuitive sense. For instance, palustrine wetland conditions, when included in top models, always had positive effects on species occupancy (Table 3). In contrast, human development, agriculture, artificial flooding, and watershed-level hydrologic modifications usually had negative effects or no discernable effects (i.e., 95% credible interval overlapped zero) when present in occupancy models for individual species (Tables 3-14). Lastly, a temporal trend in occupancy probability over the 14-

year study duration was evident for 55% of the 11 species (Table 3). For species with temporal trends in occupancy probability, American bitterns, purple gallinules, and Ridgway's rails showed decreasing occupancy probability, whereas American coots, common gallinules, and least bitterns showed increasing occupancy probability over time (Tables 3-5, 7, 9, 11, 12).

Ranking DoD installations based on quality marsh bird habitat demonstrated clear geographic clustering. Our models predicted that the best marsh bird habitat was most often found on DoD installations in the eastern (and especially southeastern) U.S. for 6 species (American coot, clapper rail, common gallinule, king rail, least bittern, and purple gallinule), whereas the best habitat for 2 species was found mostly in the western U.S. (Ridgway's rail and Virginia rail), and 3 species (American bittern, pied-billed grebe, and sora) had optimal habitats spread among DoD installations across the continental U.S. (Table 15; Figs. 1-10; Appendix D). American coot, clapper rail, common gallinule, and least bittern all had their best habitat located primarily in a combination of GA, FL, and NC (Appendix D). King rails had the best habitat at installations in NC, MN, and NJ, and purple gallinule had optimal habitat located in LA, MS, TX, and FL, respectively (Appendix D). In contrast, all of the top 5 sites for Virginia rails were located in CA and NV (Appendix D). Nearly all (>99%) of the optimal habitat for Ridgway's rail was located on one site located in AZ (Appendix D). Optimal habitats for American bitterns and pied-billed grebes were widely distributed across DoD installations located in GA, IN, MN, NC, NJ, NV, TX, VA (Table 15; Appendix D). Lastly, the ranking of DoD installations for each species was relatively insensitive to the threshold used to define optimal habitat; while the order of the top 10 sites did change in some instances, most sites included in the top 10 DoD installations for each species remained unchanged with low and high thresholds (Tables 16-26).

In addition to being geographically clustered at broad scales, optimal habitat for individual species were often highly aggregated at only a few DoD installations. The majority of optimal habitat (> 50%) for 8 of 11 species was located on 5 or fewer DoD installations (Table 15; Appendix D). Even for species where optimal habitat conditions were disbursed over a larger number of DoD installations (clapper rail, least bittern, and sora), the majority of optimal habitat was located within the top 10 DoD installations (Appendix D).

Discussion and Conclusions

This work represents the first effort to identify and predict quality of wetland habitats for secretive marsh birds at the continental scale. As such, our results will help direct habitat conservation efforts for a suite of birds that are commonly considered as conservation priorities in North America (Eddleman et al. 1988, Tacha and Braun 1994, Conway and Eddleman 2000, Conway and Timmermans 2005). Many of the 11 species of marsh birds covered in this report are identified as species of national conservation concern (e.g., least bittern, American bittern; U.S. Fish and Wildlife Service 2008), or identified as national focal species for recovery (e.g., king rail; U.S. Fish and Wildlife Service 2005). Concern over population declines for secretive marsh birds as a group has been prominent for at least 3 decades (Eddleman et al. 1988). As a consequence, many of these species have long been the focus of national conservation and management efforts (Eddleman et al. 1988), and the information presented herein is a step towards proactive management of these species on lands administered by DoD. Our efforts here to develop predictive models of marsh bird distributions were based on large, and spatially and temporally replicated, field sampling data sets with covariate data collected across numerous spatial scales. The large sample sizes and broad range of conditions sampled in this project makes inferences about habitat associations more generalizable, and also makes our analyses the most thorough continent-wide depictions of habitat associations ever conducted for secretive marsh birds. Moreover, our analyses also identify specific DoD lands that are likely to be important for each of 11 marsh bird species. Importantly, our analyses completed this spatial prioritization while also accounting for the many nuances of marsh bird detection that arise during field sampling; nuances that can bias distribution model parameter estimates (Gu and Swihart 2004, MacKenzie et al. 2006, Kéry 2011, Elith and Franklin 2013, Guillera-Arroita et al. 2014, Lahoz-Monfort et al. 2014, Guillera-Arroita et al. 2015).

Our analyses demonstrated that marsh bird detection probability during field surveys varied among species and across surveys, and this variation needs to be accounted for when building predictive habitat models with marsh bird data (as we did here). Conway and Gibbs (2011) suggested complicated spatial-temporal patterns of detectability were likely to be the norm for marsh birds, but that specific patterns associated with detection probability were poorly understood for many species. Our results support this conclusion and showed complicated temporal patterns of detectability during the breeding season arising from changes in detection with sampling dates and times, often with nonlinear patterns resulting from interactions between time and date. Importantly, this implies individual surveys are more likely to detect some species than others, and infrequent site visits during the breeding season could cause some species to be consistently overlooked even though they remain present at a site. This variation in detectability should be taken into account when building predictive habitat models, but many commonly used methods for modeling species distributions fail to separate present but not detected data points from truly absent data points (Elith and Franklin 2013, Guillera-Arroita et al. 2015). When this occurs, predictions of optimal habitat are likely to be biased (Gu and Swihart 2004, MacKenzie et al. 2006, Elith and Franklin 2013, Lahoz-Monfort et al. 2014) and subsequent ranking of important areas for conservation may be compromised (Guillera-Arroita et al. 2015). Modeling methods that explicitly incorporate imperfect detection into analyses, such as the occupancy models used here, are therefore necessary for accurate prediction and ranking of optimal sites for secretive marsh birds over broad scales.

Our distribution models for secretive marsh birds showed that species responded individualistically to habitat and anthropogenic disturbance attributes over numerous spatial scales. Species-specific and scale-specific responses of marsh birds to their environment is not surprising, and is consistent with both theoretical predictions and empirical studies for a variety of species (e.g., Levin et al. 1992, Mayor et al. 2009, McGarigal et al. 2016). Interestingly, marsh birds that responded primarily to the amount of habitat at broad scales (500 m) were all species that are themselves broadly distributed (American bittern, American coot, pied-billed grebe, and Virginia rail; Table 3). However, that pattern was not universally true (e.g., least bittern; Table 3) and, most species responded to habitat at multiple spatial scales, which implies the need to evaluate marsh bird-habitat relationships over a range of spatial scales if optimal prediction is desirable (or if conclusions regarding the relative importance of habitat variables is a goal). In addition, hierarchical occupancy models fit the observed data adequately for all species except sora. However, approximately 27% of field surveys used to build habitat models for soras were conducted before the month of May, and therefore may have detected birds during the transient phase of migration, and not strictly within breeding habitats.

Although marsh birds often demonstrated species-specific responses to specific habitat characteristics, some patterns did emerge across species. The strength of relationships and specific variables included in optimally predictive occupancy models varied, yet natural wetland habitat features (e.g., palustrine, scrub-shrub, lacustrine-littoral) often had positive effects when included in habitat models. In contrast, habitats representing anthropogenic modification of wetlands and surrounding areas (e.g., agriculture, human development, artificial flooding) usually had negative effects on secretive marsh bird occupancy. There were exceptions to these generalities; for example, excavated wetlands were sometimes positively associated with occupancy. Modification of wetlands can directly or indirectly affect a large suite of factors associated with wetland structure and function, including hydro-period, plant community composition and structure, and macroinvertebrate abundance, among others (Brinson and Inés Malvárez 2002, Zelder and Kercher 2005). Whether excavated wetlands are positively or negatively associated with occupancy may reflect hydrology of the area, what was present prior to excavation (a marsh or an upland), and how long ago the site was excavated, among other factors. Indeed, human modification of wetlands can sometimes create habitat conditions that didn't previously exist. Interestingly, our analyses also suggest that broad scale (watershed-level) disturbance and hydrologic modification may be an important but as-of-yet overlooked factor affecting the spatial distribution of secretive marsh birds. Watershed-scale variables were included in the top model for most of the 11 species, and usually had negative impacts to secretive marsh bird occupancy. To our knowledge, this study is the first effort to evaluate and incorporate these variables into distribution models for secretive marsh birds, which suggests that past habitat suitability models for these species are missing important relationships between species occurrence and human modification of entire watersheds that are manifested over broad spatial scales. Such relationships are not surprising because the water quality and wetland conditions at a local site are undoubtedly influenced by the activities upstream in the watershed and such broad-scale effects are likely more important for waterbirds than for terrestrial birds.

In addition to habitat variables, temporal trends in occupancy probability over the study duration were observed for over half of the 11 species that we examined. Previous authors have suggested that secretive marsh birds are likely declining in many regions (e.g., Eddleman et al. 1988, Conway and Sulzman 2007, Bolenbaugh et al. 2012, Hinojosa-Huerta et al. 2013), and population declines are often associated with range contractions. However, we failed to document evidence of any change in range size (i.e., changing occupancy probability) over time for 5 of 11 of the species, and we only found declining occupancy probability over time for 3 species (American bitterns and common gallinules). In contrast, our results suggested increased range size (occupancy probability) for 3 of the 11 species, including species whose populations are commonly perceived to be at risk or declining (e.g., least bitterns; Darrah and Krementz 2010, Valente et al. 2011). Although we did not model changes in abundance or density within the breeding ranges, our data suggest that range contraction was important for some (but not all) species.

Our models enabled prediction of the spatial distribution of optimal habitat conditions for secretive marsh birds across DoD installations, which provides information needed to improve both conservation and military readiness at DoD installations. At broad scales, our analysis suggests clear spatial aggregation of important marsh bird habitat on DoD installations in the southeastern U.S. This implies broad-scale efforts to conserve these species on DoD lands should include installations in areas such as GA, FL, NC, TX, LA, and NJ, with additional efforts focused strategically on important installations in other regions (e.g., western sites for least bitterns and Virginia rails). Importantly, our results also suggest that the most optimal habitat for a given species occurred on only a small number of sites. This implies that if individual species already are, or soon become, a conservation priority on DoD lands then the DoD installations that already harbor optimal habitat for that species should be a cornerstone of conservation efforts.

In addition to facilitating strategic conservation at broad scales, this work provides DoD with baseline predictions for the location of high-quality habitat for secretive marsh birds that currently exists on their lands. This amounts to a nationwide baseline of secretive marsh bird habitat that can be used for measuring effects of habitat management and conservation at DoD sites over time, and also to estimate the likely effect of future management decisions on individual marsh bird species. This information should therefore support the DoD Partners-in-Flight and species-at-risk programs, and help the DoD take a multi-species approach to protecting habitat for the suite of birds over all installations.

Lastly, this project should help the DoD fulfill its mission and increase military readiness and flexibility by identifying installations that are most valuable to marsh birds of national conservation concern (Appendix D). Consequently, this work also helps identify DoD installations that are *not* likely to harbor optimal habitat for priority species (Tables D1-D11), and thus will help minimize conflicts between military needs and the needs of secretive marsh bird species. Moreover, our habitat models and the resultant list (Table 11) and maps (Figs. 1-10) of installations with the best quality habitat can aide in development of INRMPs that explicitly incorporate marsh birds. Thus, these products (Table 15, Figs. 1-10) will help to fill existing information gaps that have prevented DoD from including these species in their existing management plans. Similarly, this information can help with strategic and scenario planning for military training exercises on DoD sites, which should facilitate military readiness and flexibility. These products will therefore help DoD more effectively plan and ensure their mission is not compromised, while also ensuring that management responsibilities for secretive marsh birds are met.

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Table 1. Sample sizes representing the number of spatial sampling sites used to fit and evaluate hierarchical multi-scale occupancy models for predicting marsh bird distributions within their geographic ranges in the continental U.S. Total number of sampling sites (Total) were randomly split into training data sets (Training) used to estimate model parameters and testing data sets (Testing) used to evaluate model predictive abilities at approximate ratios of 0.6 and 0.4, respectively. Initial Year represents the first year detection-non-detection data were collected via field sampling at any sites, and species codes are: American bittern (AMBI), American coot (AMCO), clapper rail (CLRA), common gallinule (COGA), king rail (KIRA), least bittern (LEBI), pied-billed grebe (PBGR), purple gallinule (PUGA), sora (SORA), Ridgway's rail (RWRA), and Virginia rail (VIRA). DoD indicates the percentage of all sampling sites that fell within DoD installation boundaries for each species.

		Sample sizes			
Species	Year	Training	Testing	Total	DoD
AMBI	1999	3044	2030	5074	1.56
AMCO	1999	4291	2860	7151	2.63
CLRA	2000	1079	719	1798	0
COGA	1999	3668	2446	6114	3.07
KIRA	1999	2187	1458	3645	0.63
LEBI	1999	4572	3048	7620	2.77
PBGR	1999	5074	3383	8457	2.49
PUGA	2003	975	650	1625	0
RWRA	2002	1498	999	2497	0.07
SORA	1999	4111	2740	6851	3.04
VIRA	1999	4102	2735	6837	3.06

Table 2. Top model describing detection probability for each of 11 marsh bird species (Species) during field surveys. Detection model covariates are time of day at the start of sampling (Time), Julian date on day of sampling (Date), an interaction between sampling time and Julian date (Time*Date), length of the broadcast segment of call-broadcast surveys (Broadcast), and a binary variable indicating whether or not the specific target species' call was included in the call-broadcast survey (Call). Functional form indicates whether Linear or Quadratic terms were favored for sampling time (T) and Julian date (D) covariates during analyses, and thus indicate the forms of these covariates used in detection models for each species. Inclusion of covariates in the top detection model is indicated by the letter x, whereas exclusion is indicated by a dash symbol (-). Interaction terms for models with quadratic Time or Date terms included interactions for all of the terms used to represent each variable. Species codes are: American bittern (AMBI), American coot (AMCO), clapper rail (CLRA), common gallinule (COGA), king rail (KIRA), least bittern (LEBI), pied-billed grebe (PBGR), purple gallinule (PUGA), Ridgway's Rail (RWRA), sora (SORA), and Virginia rail (VIRA).

						Functional form	
Species	Time	Date	Time*Date	Broadcast	Call	Linear	Quadratic
AMBI	x	x	x	x	x	-	T & D
AMCO	x	x	x	x	x	T	D
CLRA	-	x	-	x	x	T & D	-
COGA	x	x	-	-	-	D	T
KIRA	x	x	-	x	x	T & D	-
LEBI	x	x	x	x	x	D	T
PBGR	x	x	-	-	x	-	T & D
PUGA	x	x	x	-	-	T	D
RWRA	x	x	x	x	-	D	T
SORA	x	x	x	x	x	T & D	-
VIRA	x	x	x	-	-	-	T & D

Table 3. Optimal multi-scale habitat models used to predict occupancy probability for each of 11 species of marsh bird (Species) as a function of NWI wetland and GAP land cover variables. Occupancy model covariates are: artificial flooding (art.flood), diked-impounded (di), excavated (exc), lacustrine-littoral (lac.litt), palustrine (palus), permanently flooded (per.flood), riverine lower-perennial (riv.lp), riverine upper-perennial (riv.up), saturated (sat), scrub-shrub (sc.shrub), seasonal flooding (seas.flood), semi-permanently flooded (semi.flood), shoreline (shore), agriculture (ag), cultivated croplands (cult.crop), developed (dev), high-intensity development (dev.hi), low intensity development (dev.li), developed open-space (dev.os), watershed flow interruption (flowint), maximum water storage capacity in watershed (maxstor), normal water flow restriction (nflowrest), relative storage fluctuation (r.storfluc), and temporal trend across the 14-year study duration (trend). Direction of effects are indicated by sign (±), and spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables. Goodness-of-fit for each model to marsh bird field sampling data for each species is indicated by the Bayesian P-value scores (Bayes-P), where scores close to 0 or 1 indicate lack of fit. All covariate descriptions are provided in Appendix A.

Species	Top Model	Bayes-P
American Bittern	- riv.lp(500) - shore(500) + seas.flood(500) + dev.os(100) + r.storfluc(c) - trend	0.85
American Coot	+ palus(500) - sc.shrub(500) + semi.flood(224) - dev(500) - dev(n) + trend	0.37
Clapper Rail	+ exc(100) - dev.li(500)	0.50
Common Gallinule	+ palus(100) - art.flood(224) + cult.crop(500) – ag(n) + trend	0.64
King Rail	+ sc.shrub(224) + per.flood(500) - dev.os(224) – ag(n)	0.44
Least Bittern	+ palus(224) - exc(100) - ag(100) - maxstor(c) + trend	0.82
Pied-Billed Grebe	- riv.lp(224) + sc.shrub(500) - art.flood(500) + dev.hi(500) – ag(c)	0.47
Purple Gallinule	- sat(100) + dev(c) - trend	0.32
Ridgway’s Rail	+ riv.up(100) + sc.shrub(224) – r.storfluc(n) - trend	0.42
Sora	- sc.shrub(500) + di(100) – nflowrest(c)	0.02
Virginia Rail	+ l.litt(500) + exc(500) - dev.hi(100) – flowint(n)	0.47

Table 4. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for American bittern.

Parameter	β	CI	OR
Intercept	0.076	-0.086 – 0.242	-
Riverine lower-perennial	-0.072	-0.129 – -0.015	0.931
Shore	-0.176	-0.240 – -0.115	0.839
Seasonally flooded	0.096	0.050 – 0.144	1.101
Developed open-space	0.047	-0.007 – 0.100	1.048
Relative storage fluctuation	0.156	0.100 – 0.217	1.169
Temporal trend	-0.061	-0.078 – -0.044	0.941

Table 5. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for American coot.

Parameter	β	CI	OR
Intercept	-1.315	-1.423 – -1.207	-
Palustrine	0.092	0.044 – 0.140	1.096
Scrub-shrub	-0.106	-0.146 – -0.067	0.899
Semipermanently flooded	0.147	0.107 – 0.187	1.158
Developed	-0.038	-0.089 – 0.010	0.963
Developed[a]	-0.166	-0.247 – -0.088	0.847
Temporal trend	0.015	0.003 – 0.026	1.015

[a] Watershed level.

Table 6. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for clapper rail.

Parameter	β	CI	OR
Intercept	0.610	0.492 – 0.756	-
Excavated	1.010	0.594 – 1.668	2.746
Developed low-intensity	-0.191	-0.300 – -0.084	0.826

Table 7. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for common gallinule.

Parameter	β	CI	OR
Intercept	-1.200	-1.317 – -1.085	-
Palustrine	0.306	0.262 – 0.349	1.358
Artificially flooded	-0.211	-0.266 – -0.158	0.810
Cultivated cropland	0.073	0.022 – 0.124	1.076
Agriculture[a]	-0.181	-0.237 – -0.125	0.834
Temporal trend	0.125	0.113 – 0.138	1.133

[a] Watershed level.

Table 8. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for king rail.

Parameter	β	CI	OR
Intercept	-1.737	-1.853 – -1.621	-
Scrub-shrub	0.131	0.049 – 0.212	1.140
Permanently flooded	0.145	0.056 – 0.233	1.156
Developed open-space	-0.200	-0.321 – -0.086	0.819
Agriculture[a]	-0.143	-0.259 – -0.027	0.867

[a] Watershed level.

Table 9. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for least bittern.

Parameter	β	CI	OR
Intercept	-0.044	-0.159 – 0.073	-
Palustrine	0.121	0.074 – 0.169	1.129
Excavated	-0.108	-0.145 – -0.071	0.898
Agriculture	-0.231	-0.283 – -0.179	0.794
Maximum storage capacity	-0.014	-0.030 – 0.003	0.986
Temporal trend	0.038	0.026 – 0.051	1.039

Table 10. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for pied-billed grebe.

Parameter	β	CI	OR
Intercept	-0.247	-0.281 – -0.212	-
Riverine lower perennial	-0.135	-0.175 – -0.096	0.874
Scrub-shrub	0.126	0.096 – 0.156	1.134
Artificially flooded	-0.006	-0.034 – -0.022	0.994
Developed high intensity	0.002	-0.028 – 0.032	1.002
Agriculture[a]	-0.020	-0.058 – 0.018	0.980

[a] Watershed level.

Table 11. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for purple gallinule.

Parameter	β	CI	OR
Intercept	0.538	0.004 – 1.111	-
Saturated	-0.158	-0.362 – 0.013	0.854
Developed[a]	0.361	0.190 – 0.537	1.435
Temporal trend	-0.389	-0.480 – -0.303	0.678

[a] Watershed level.

Table 12. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for Ridgway's rail.

Parameter	β	CI	OR
Intercept	0.673	0.523 – 0.846	-
Riverine upper-perennial	0.537	0.263 – 1.407	1.711
Scrub shrub	0.066	0.014 – 0.119	1.068
Relative storage fluctuation	-0.450	-0.737 – -0.227	0.638
Temporal trend	-0.032	-0.048 – -0.016	0.969

Table 13. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for sora.

Parameter	β	CI	OR
Intercept	-0.154	-0.201 – -0.108	-
Scrub-shrub	-0.011	-0.047 – 0.026	0.989
Diked	0.091	0.053 – 0.130	1.095
Normal flow restriction	-0.028	-0.058 – 0.000	0.972

Table 14. Hierarchical occupancy model coefficient estimates (β), 95% credible intervals (CI), and odds ratios (OR) for Virginia rail.

Parameter	β	CI	OR
Intercept	-0.129	-0.165 – -0.092	-
Lacustrine littoral	0.105	0.065 – 0.146	1.111
Excavated	0.053	0.015 – 0.095	1.054
Developed high intensity	-0.037	-0.068 – -0.007	0.964
Flow interruption	-0.303	-0.391 – -0.219	0.739

Table 15. Relative ranking of best DoD installations with the largest amount of optimal habitat for each marsh bird species. The proportion of the total optimal habitat located at each installation for a given species is indicated parenthetically. Species codes are: American bittern (AMBI), American coot (AMCO), clapper rail (CLRA), common gallinule (COGA), king rail (KIRA), least bittern (LEBI), pied-billed grebe (PBGR), purple gallinule (PUGA), sora (SORA), and Virginia rail (VIRA). Ranking of DoD sites for Ridgway's Rail (RWRA) is not shown here because the overwhelming majority (> 99%) of optimal habitat was located on only one site (Yuma Proving Ground).

	Species									
Rank	AMBI	AMCO	CLRA	COGA	KIRA	LEBI	PBGR	PUGA	SORA	VIRA
1	Fort Hood (0.478)	Fort Stewart (0.385)	MCB Camp Lejeune (0.131)	Fort Stewart (0.194)	MCB Camp Lejeune West Site (0.409)	Dare County Range (0.195)	Nellis Air Force Range (0.420)	Barksdale AFB (0.246)	Camp Dodge Johnston TS (0.203)	Edwards AFB (0.377)
2	Fort Stewart (0.116)	Avon Park AF Range (0.376)	Tyndall AFB (0.085)	Eglin AFB (0.139)	Dare County Range (0.375)	Fort Stewart (0.157)	MCB Camp Lejeune West Site (0.166)	Keesler AFB (0.172)	Arnold AS (0.103)	Nellis Air Force Range (0.341)
3	NSA Crane (0.108)	Eglin AFB (0.057)	Fort Stewart (0.062)	Dare County Range (0.136)	Camp Ripley (0.071)	Elgin AFB (0.141)	Dare County Range (0.139)	NAS Corpus Christi (0.167)	Redstone Arsenal (0.101)	Twentynine Palms Main Base (0.059)
4	Camp Bullis (0.106)	Camp Joseph T Robinson (0.037)	Point Of Marsh Target (0.060)	Avon Park AF Range (0.116)	Fort Dix (0.035)	Avon Parf AF Range (0.105)	Camp Ripley (0.062)	Eglin AFB (0.108)	NAS JRB New Orleans (0.053)	NAWS China Lake (0.059)
5	Fort Bliss (0.098)	Moody AFB (0.032)	NAVSUBASE Kings Bay (0.056)	MCB Camp Lejeune West Site (0.077)	MCB Camp Lejeune (0.022)	MCB Camp Legune West Site (0.083)	Yuma Proving Ground (0.058)	MacDill AFB (0.071)	Fort Benning (0.044)	NTC and Fort Irwin (0.054)
6	Fort A P Hill (0.047)	W.H. Ford Regional Training Ctr (0.023)	NAS Key West (0.050)	MCB Camp Lejeune (0.030)	Picatinny Arsenal (0.012)	MCT-H Camp Grayling (0.029)	Fort Dix (0.036)	ALF Waldron (0.043)	Military Ocean Terminal Concord (0.038)	Sierra Army Depot (0.029)
7	Camp Maxey (0.031)	Camp Grafton (0.010)	JNTEXPBASE Little Creek FS VA (0.040)	Fort Dix (0.026)	Fort Benning (0.011)	Fort Dix (0.026)	MCB Camp Lejeune (0.022)	Patrick AFB (0.031)	Fort Stewart (0.031)	NAS Fallon Target B-20 (0.028)
8	Fort Hunter Liggett (0.004)	Fort Bliss (0.008)	NS Mayport (0.040)	MTA Camp Shelby (0.026)	MacDill AFB (0.011)	MCB Camp Lejune (0.019)	MTC-H Camp Grayling (0.012)	NAS Jacksonville (0.028)	NSA Crane (0.028)	NAS Fallon Target B-17 (0.022)
9	Joe Foss Field (0.003)	Arnold AS (0.008)	Eglin AFB (0.039)	Fort Benning GA (0.025)	Eglin AFB (0.008)	Redstone Arsenal (0.018)	Moody AFB (0.012)	Ellington Field (0.026)	Fort Benning GA (0.024)	NAS Fallon Target B-16 (0.006)
10	Camp Dodge Johnston TS (0.002)	Aberdeen Proving Ground (0.007)	MacDill AFB (0.037)	Fort Polk (0.025)	Redstone Arsenal (0.008)	Fort Benning GA (0.016)	Fort Lewis (0.007)	Hurlburt Field (0.024)	Camp Gruber (0.023)	

NAWS China Lake Randsburg Wash Area (0.005)

Table 16. Sensitivity of top DoD installation rankings for American bitterns to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Fort Hood	Fort Bliss	Fort Hood
2	Fort Stewart	Fort Hood	Fort Stewart
3	NSA Crane	Fort Stewart	NSA Crane
4	Camp Bullis	NSA Crane	Camp Bullis
5	Fort Bliss	Camp Bullis	Fort Bliss
6	Fort A P Hill	Fort A P Hill	Camp Maxey
7	Camp Maxey	Camp Maxey	Camp Dodge Johnston TS
8	Fort Hunter Liggett	Joe Foss Field	Randolph AFB
9	Joe Foss Field	Fort Hunter Liggett	Fort Leonard Wood
10	Camp Dodge Johnston TS	Fort George G Meade	Beale AFB

Table 17. Sensitivity of top DoD installation rankings for American coots to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Fort Stewart	Fort Stewart	Avon Park AF Range
2	Avon Park AF Range	Avon Park AF Range	Fort Stewart
3	Eglin AFB	Dare County Range	Camp Joseph T Robinson
4	Camp Joseph T Robinson	Eglin AFB	Eglin AFB
5	Moody AFB	Utah Test and Training Range South	Moody AFB
6	W.H. Ford Regional Training Ctr	Moody AFB	W.H. Ford Regional Training Ctr
7	Camp Grafton	Camp Joseph T Robinson	Fort Bliss
8	Fort Bliss	W.H. Ford Regional Training Ctr	Arnold AS
9	Arnold AS	MCB Camp Lejeune West Site	MCB Camp Lejeune
10	Aberdeen Proving Ground	Camp Grafton	Camp Grafton

Table 18. Sensitivity of top DoD installation rankings for clapper rails to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	MCB Camp Lejeune	Eglin AFB	MCB Camp Lejeune
2	Tyndall AFB	Fort Stewart	Tyndall AFB
3	Fort Stewart	MCB Camp Lejeune West Site	NAVSUBASE Kings Bay
4	Point Of Marsh Target	Fort A P Hill	Point Of Marsh Target
5	NAVSUBASE Kings Bay	Dare County Range	Fort Stewart
6	NAS Key West	MCB Camp Lejeune	NAS Key West
7	JNTEXPBASE Little Creek FS VA	Tyndall AFB	JNTEXPBASE Little Creek FS VA
8	NS Mayport	Point Of Marsh Target	NS Mayport
9	Eglin AFB	NWS Charleston	Cape Canaveral AFS
10	MacDill AFB	NAVSUBASE Kings Bay	MacDill AFB

Table 19. Sensitivity of top DoD installation rankings for common gallinules to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Fort Stewart	Fort Stewart	Dare County Range
2	Eglin AFB	Eglin AFB	Fort Stewart
3	Dare County Range	Avon Park AF Range	Eglin AFB
4	Avon Park AF Range	Dare County Range	Avon Park AF Range
5	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site
6	MCB Camp Lejeune	MTA Camp Shelby	Fort Dix
7	Fort Dix	MCB Camp Lejeune	MCB Camp Lejeune
8	MTA Camp Shelby	Fort Polk	Fort Benning GA
9	Fort Benning GA	Fort Benning GA	Fort Polk
10	Fort Polk	Fort Dix	MTA Camp Shelby

Table 20. Sensitivity of top DoD installation rankings for king rails to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site
2	Dare County Range	Dare County Range	Dare County Range
3	Camp Ripley	Camp Ripley	Camp Ripley
4	Fort Dix	Fort Dix	Fort Dix
5	MCB Camp Lejeune	MCB Camp Lejeune	MCB Camp Lejeune
6	Picatinny Arsenal	Fort Benning	Picatinny Arsenal
7	Fort Benning	Camp Dodge Johnston TS	MacDill AFB
8	MacDill AFB	Picatinny Arsenal	Redstone Arsenal
9	Eglin AFB	Eglin AFB	Eglin AFB
10	Redstone Arsenal	Redstone Arsenal	NAS Key West

Table 21. Sensitivity of top DoD installation rankings for least bitterns to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 3% (High), 5% (Original), and 7% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Dare County Range	Dare County Range	Fort Stewart
2	Fort Stewart	Eglin AFB	Dare County Range
3	Eglin AFB	Fort Stewart	Eglin AFB
4	Avon Park AF Range	Avon Park AF Range	Avon Park AF Range
5	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site
6	MTC-H Camp Grayling	MTC-H Camp Grayling	MTC-H Camp Grayling
7	Fort Dix	Fort Dix	Fort Dix
8	MCB Camp Lejeune	Redstone Arsenal	MCB Camp Lejeune
9	Redstone Arsenal	MCB Camp Lejeune	Redstone Arsenal
10	Fort Benning GA	Dare County Range	Fort Benning GA

Table 22. Sensitivity of top DoD installation rankings for pied-billed grebes to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Nellis Air Force Range	Nellis Air Force Range	Nellis Air Force Range
2	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site	MCB Camp Lejeune West Site
3	Dare County Range	Dare County Range	Dare County Range
4	Camp Ripley	Camp Ripley	Yuma Proving Ground
5	Yuma Proving Ground	MCB Camp Lejeune	Camp Ripley
6	Fort Dix	Fort Drum	Moody AFB
7	MCB Camp Lejeune	Fort Dix	MCB Camp Lejeune
8	MTC-H Camp Grayling	MTC-H Camp Grayling	Fort Dix
9	Moody AFB	Eglin AFB	MTC-H Camp Grayling
10	Fort Lewis	Fort Bragg	MacDill AFB

Table 23. Sensitivity of top DoD installation rankings for purple gallinules to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Barksdale AFB	MacDill AFB	Barksdale AFB
2	Keesler AFB	Barksdale AFB	Keesler AFB
3	NAS Corpus Christi	Eglin AFB	NAS Corpus Christi
4	Eglin AFB	NAS Corpus Christi	MacDill AFB
5	MacDill AFB	Keesler AFB	Patrick AFB
6	ALF Waldron	NWS Charleston	NOLF Holley
7	Patrick AFB	Charleston AFB	Corry Station
8	NAS Jacksonville	NAS Pensacola	Gulfport-Biloxi Regional Airport (ANG)
9	Ellington Field	Fort Polk	NWS Charleston
10	Hurlburt Field	Hurlburt Field	NG Gulfport AVCRAD

Table 24. Sensitivity of top DoD installation rankings for Ridgway's rail to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Yuma Proving Ground	Yuma Proving Ground	Yuma Proving Ground
2	Military Ocean Terminal Concord	-	NB Coronado Imperial Beach
3	-	-	Military Ocean Terminal Concord

Table 25. Sensitivity of top DoD installation rankings for soras to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 3% (High), 5% (Original), and 7% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Camp Dodge Johnston TS	Camp Dodge Johnston TS	Camp Dodge Johnston TS
2	Arnold AS	Redstone Arsenal	Arnold AS
3	Redstone Arsenal	Arnold AS	Redstone Arsenal
4	NAS JRB New Orleans	NAS JRB New Orleans	NAS JRB New Orleans
5	Fort Benning	Fort Benning	Fort Benning
6	Military Ocean Terminal Concord	Military Ocean Terminal Concord	Military Ocean Terminal Concord
7	Fort Stewart	Fort Benning GA	Fort Stewart
8	NSA Crane	Fort Stewart	NSA Crane
9	Fort Benning GA	NSA Crane	Camp Joseph T Robinson
10	Camp Gruber	Camp Gruber	Camp Gruber

Table 26. Sensitivity of top DoD installation rankings for Virginia rails to the threshold occupancy probability used to define optimal habitat. Thresholds used to define optimal habitat included the top 20% (High), 30% (Original), and 40% (Low) of the range of predicted occupancy probabilities.

Rank	Original	Low	High
1	Edwards AFB	Edwards AFB	Edwards AFB
2	Nellis Air Force Range	Nellis Air Force Range	Nellis Air Force Range
3	Twentynine Palms Main Base	NAWS China Lake	Twentynine Palms Main Base
4	NAWS China Lake	Twentynine Palms Main Base	NAWS China Lake
5	NTC and Fort Irwin	NTC and Fort Irwin	NTC and Fort Irwin
6	Sierra Army Depot	Sierra Army Depot	Sierra Army Depot
7	NAS Fallon Target B-20	NAS Fallon Target B-20	NAS Fallon Target B-20
8	NAS Fallon Target B-17	NAS Fallon Target B-17	NAS Fallon Target B-17
9	NAS Fallon Target B-16	MCB Camp Lejeune	White Sands Missile Range
10	NAWS China Lake Randsburg Wash Area	Camp Dodge Johnston TS	Minot AFB

Figure 1. Locations of high ranking (top 10) DoD installations containing quality habitat for American bitterns.

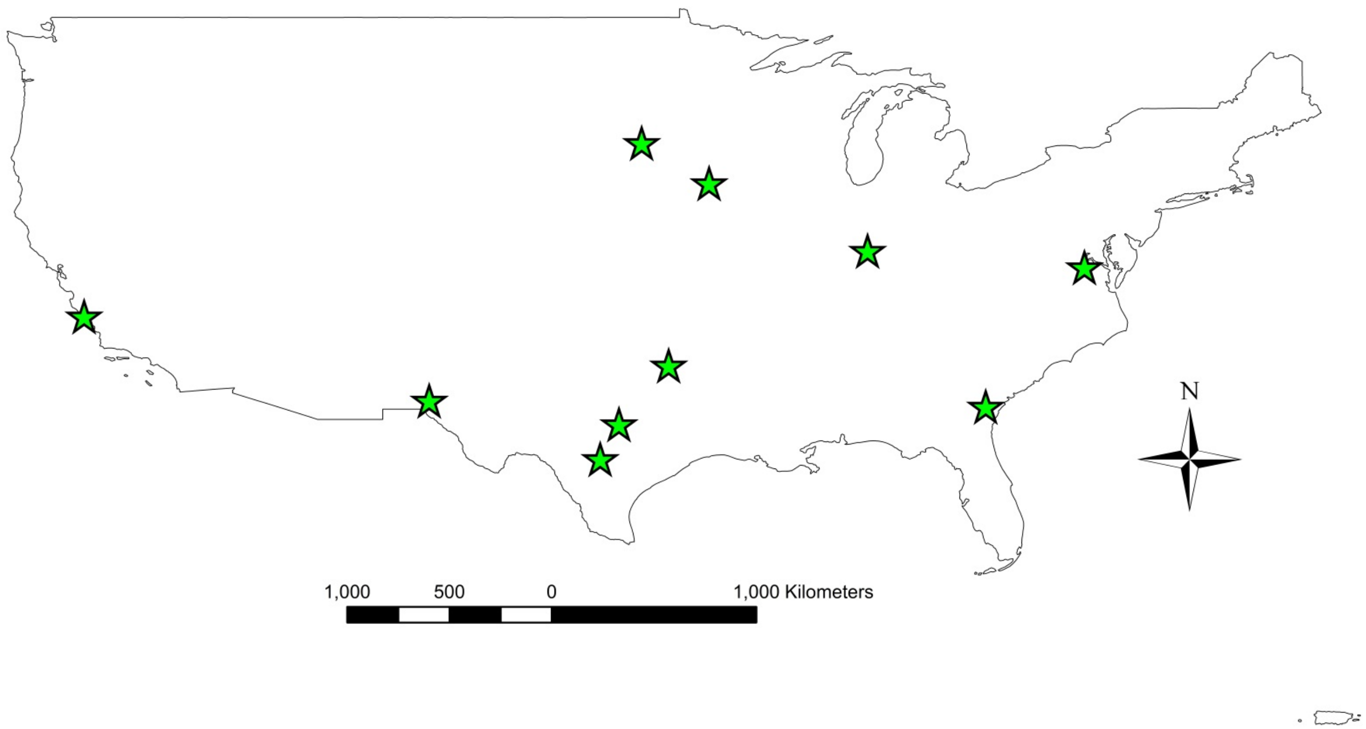

Figure 2. Locations of high ranking (top 10) DoD installations containing quality habitat for American coots.

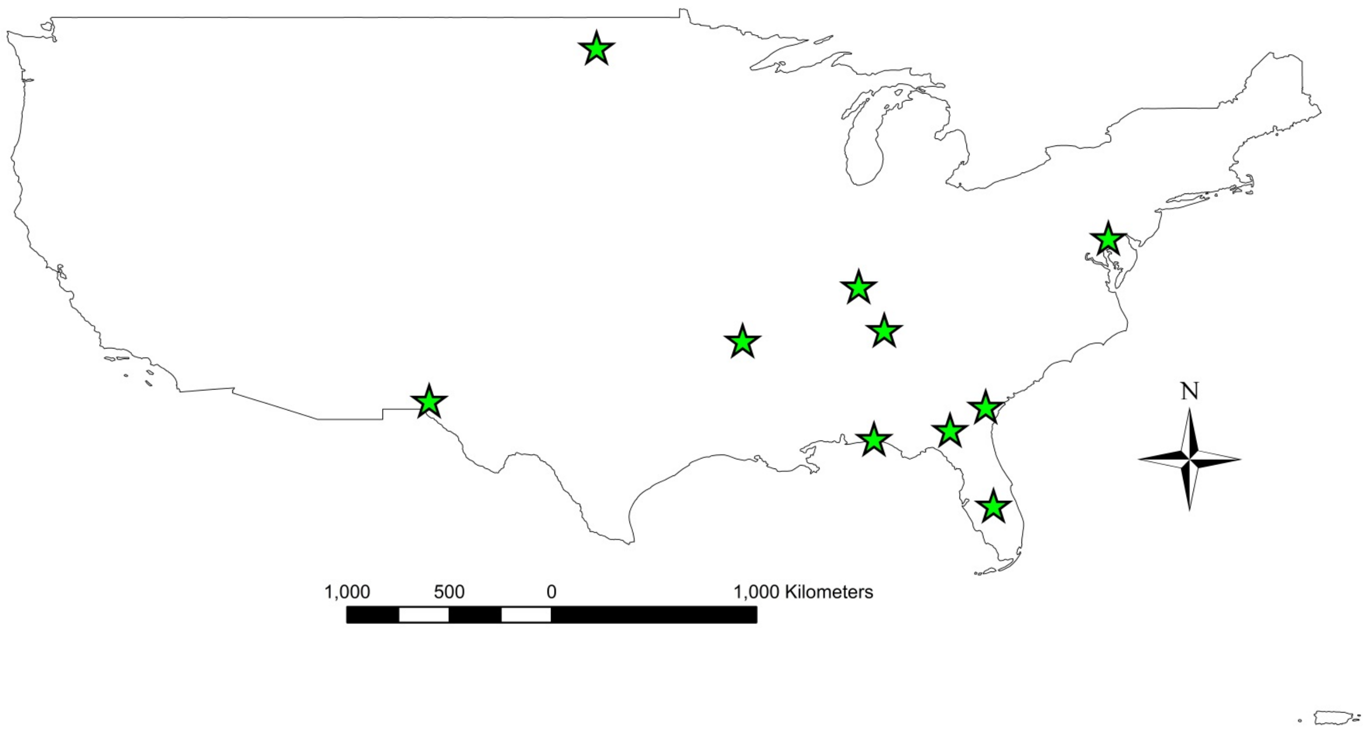

Figure 3. Locations of high ranking (top 10) DoD installations containing quality habitat for clapper rails.

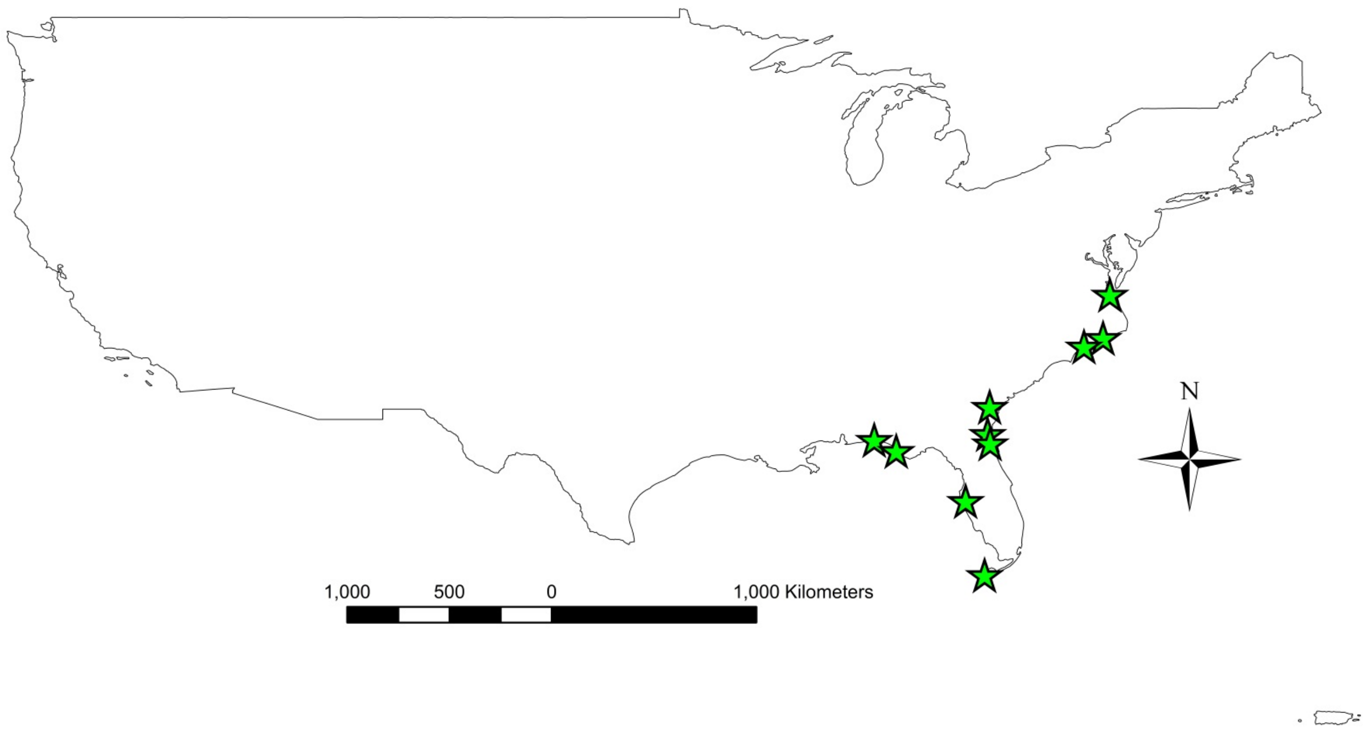

Figure 4. Locations of high ranking (top 10) DoD installations containing quality habitat for common gallinules.

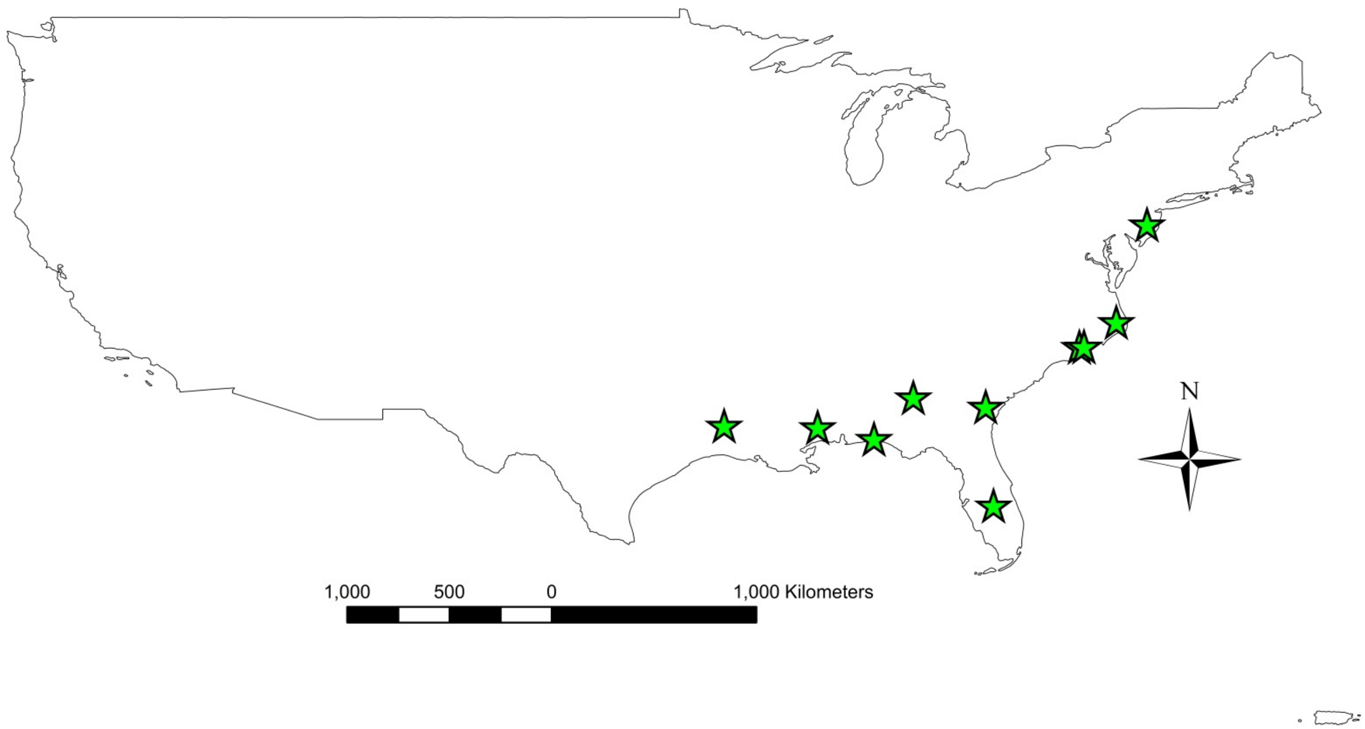

Figure 5. Locations of high ranking (top 10) DoD installations containing quality habitat for king rails.

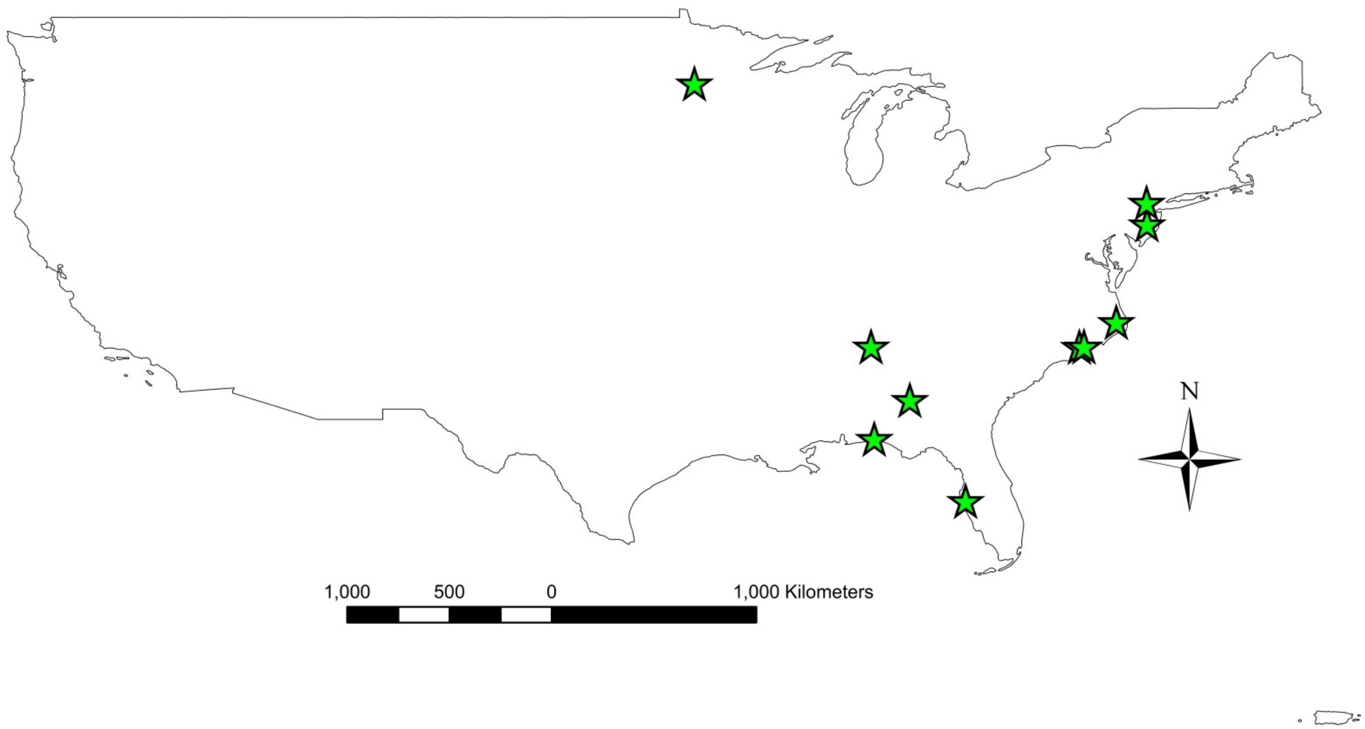

Figure 6. Locations of high ranking (top 10) DoD installations containing quality habitat for least bitterns.

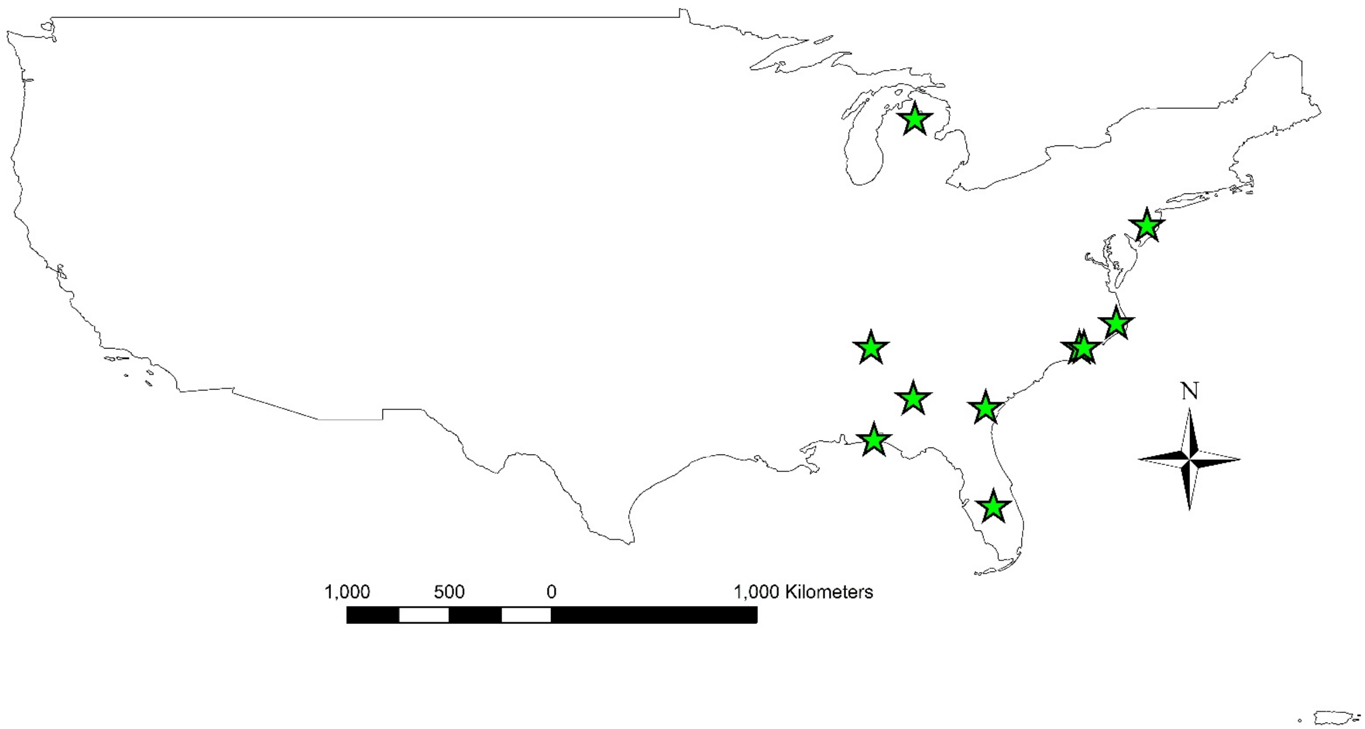

Figure 7. Locations of high ranking (top 10) DoD installations containing quality habitat for pied-billed grebes.

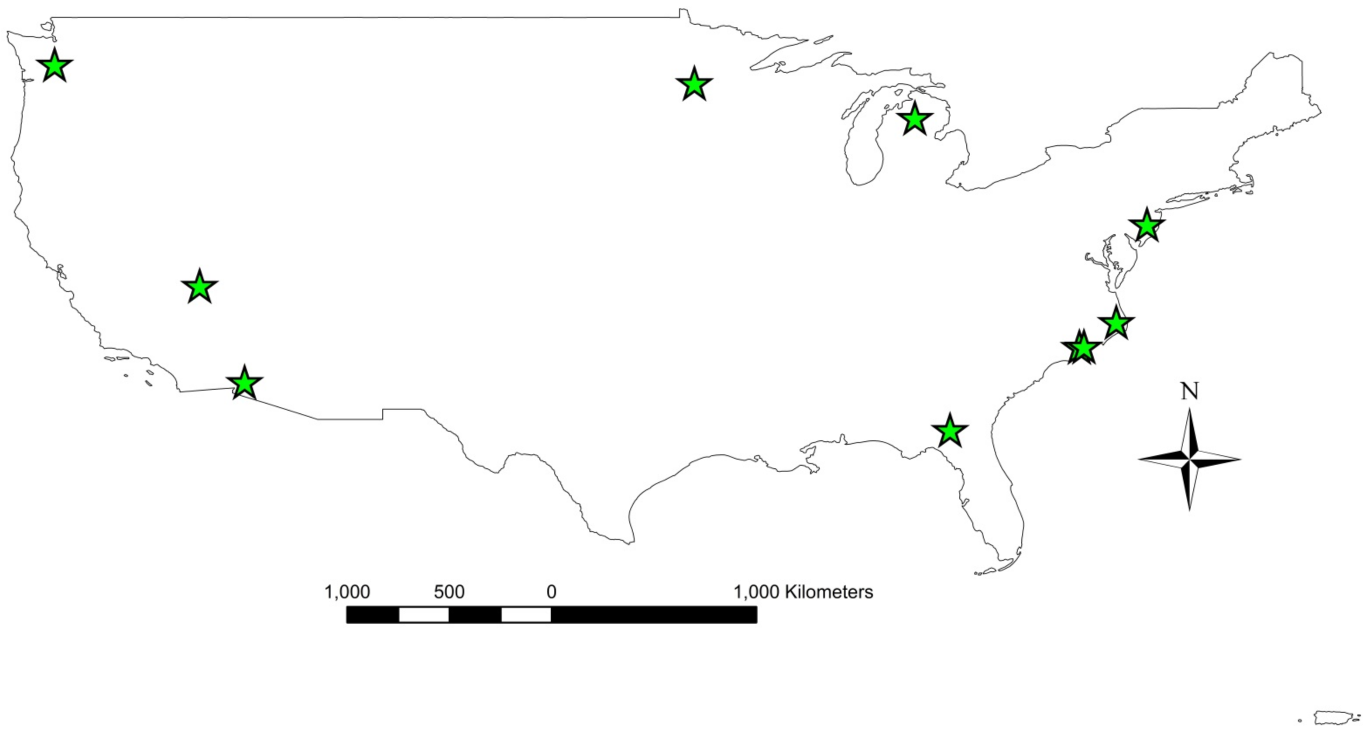

Figure 8. Locations of high ranking (top 10) DoD installations containing quality habitat for purple gallinules.

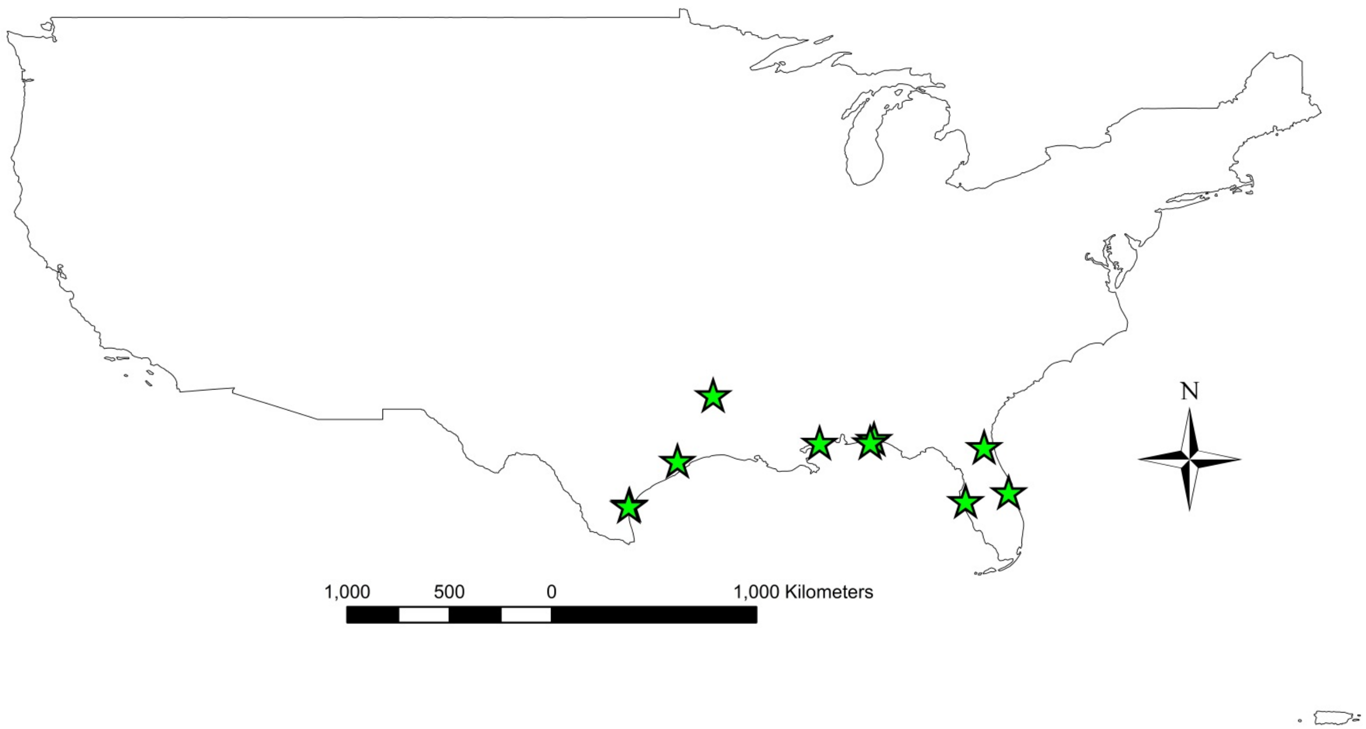

Figure 9. Locations of high ranking (top 10) DoD installations containing quality habitat for soras.

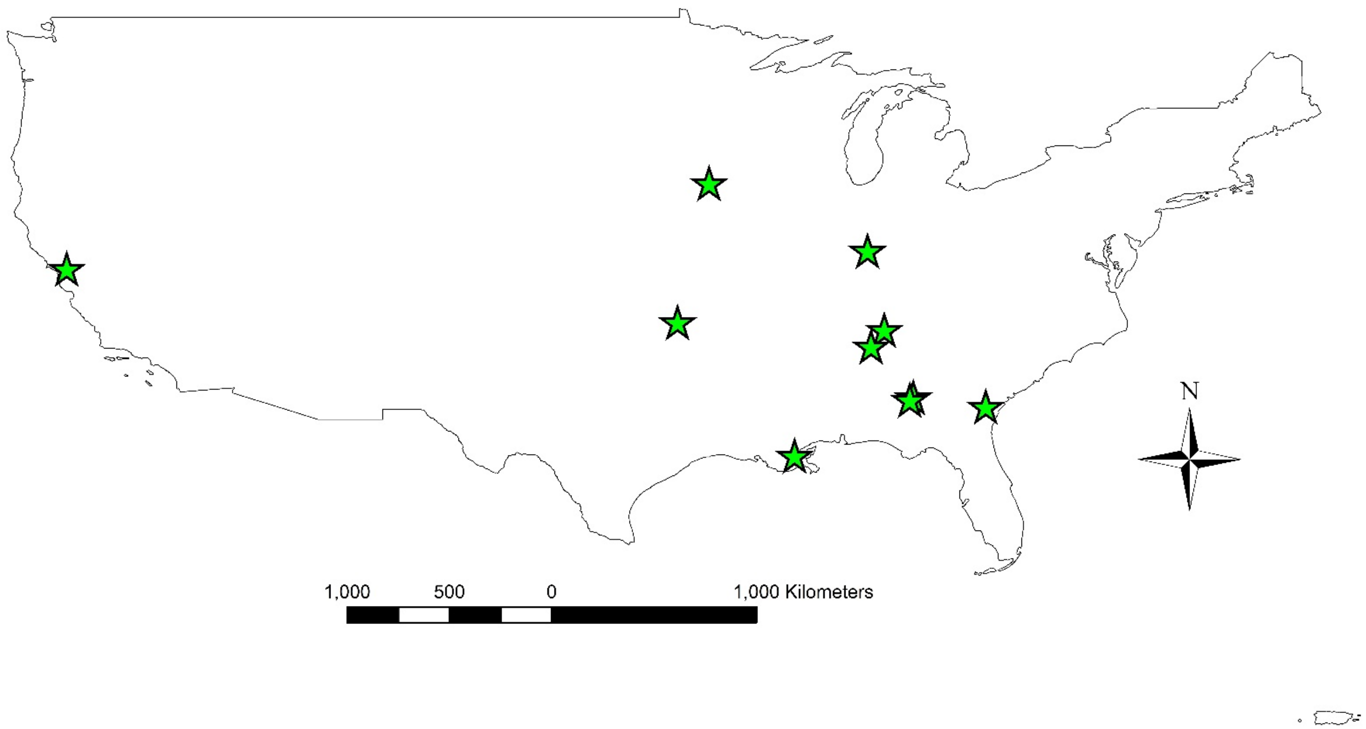

Figure 10. Locations of high ranking (top 10) DoD installations containing quality habitat for Virginia rail.

Appendix A: Descriptions of NWI and GAP covariates used for hierarchical multi-scale occupancy analyses for marsh birds.

Table A1. NWI wetland system-subsystem variables. Phrases in italics identify characteristics that separate subsystems of a given system.

Variable	NWI code	Description
Lacustrine Limnetic	L1	*Deepwater habitats* that are situated in a topographic depression or dammed river channel, lacking trees, shrubs, or persistent emergent vegetation with > 30% cover, and with a total area >8 ha
Lacustrine Littoral	L2	*Wetland habitats* extending from the shoreward boundary of the Lacustrine system to a depth of 2 m that are situated in a topographic depression or dammed river channel, lacking trees, shrubs, or persistent emergent vegetation with > 30% cover, and with a total area >8 ha
Palustrine	P	All non-tidal wetlands dominated by trees, shrubs, and persistent emergent vegetation, and similar tidal wetlands where salinity is $<0.5\ {}^{0}/_{00}$
Riverine Lower-Perennial	R2	Wetlands and deepwater habitats contained within a channel where *some water flows year round, the gradient is low, water velocity is slow, and there is no tidal influence*.
Riverine Upper-Perennial	R3	Wetlands and deepwater habitats contained within a channel, where *some water flows throughout the year, the gradient is high, water velocity is fast, and there is no tidal influence*
Riverine Intermittent	R4	Wetlands and deepwater habitats contained within a channel that *contains flowing water for only part of the year*

Table A2. NWI wetland class variables. Phrases in italics identify characteristics that distinguish a given wetland class from similar wetland classes.

Variable	NWI code	Description

Emergent	EM	Wetlands characterized by perennial, erect, rooted, *herbaceous hydrophytic vegetation* (excluding mosses and lichens), where the vegetation is present for most the growing season
Forested	FO	Wetlands dominated by *woody vegetation* (broad- and needle-leaved deciduous, broad- and needle-leaved evergreen) *greater than 6 m tall*
Scrub-shrub	SS	Wetlands dominated by *woody vegetation* (broad- and needle-leaved deciduous, broad- and needle-leaved evergreen) *less than 6 m tall*
Shore	RS, US	Wetlands with less than 30% areal cover of vegetation, and characterized by bedrock, stones, boulders, or smaller unconsolidated materials which are *exposed all or most of the time*
Water	RB, UB, AB, SB	Wetlands and deepwater habitats with less than 30% areal cover of vegetation and are *submerged all or most the time*

Table A3. NWI water regime and special modifier variables.

Variable	NWI code	Description
Permanently Flooded	H	Water covers the land surface throughout the year in all years

Intermittently Exposed	G	Surface water is present throughout the year, except in years of extreme drought
Semipermanently Flooded	F	Surface water persists throughout the growing season in most years
Seasonally Flooded	C	Surface water is present for extended periods especially early in the growing season, but is absent by the end of the season in most years. After flooding, water table is variable
Saturated	B	The substrate is saturated to the surface for extended periods during the growing season, but surface water is seldom present
Temporarily Flooded	A	Surface water is present for brief periods during the growing season, but the water table usually lies well below the soil surface for most of the season
Intermittently Flooded	J	The substrate is usually exposed, but surface water is present for variable periods without detectable seasonal periodicity
Artificially Flooded	K	The amount and duration of flooding is controlled by means of pumps or siphons in combination with dikes or dams
Diked/Impounded	h	Created or modified by a barrier or dam which purposefully or unintentionally obstructs the outflow of water
Excavated	x	Wetland lies within a basin or channel excavated by man

Table A4. GAP land cover variables.

Variable	Description
Cultivated cropland	Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled

Pasture-hay	Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation
Agriculture	Composite variable representing the combination of cultivated cropland and pasture-hay.
Introduced vegetation	Areas dominated by plant species that are not native to the contiguous U.S.
Developed-open space	Areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes
Developed low-intensity	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units
Developed medium- intensity	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units
Developed high-intensity	Highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover
Developed	Composite variable representing the combination of all developed categories indicated above

Table A5. Watershed-level disturbance variables.

Variable	Description
Agriculture	Composite variable representing the combination of cultivated cropland and pasture-hay
Developed	Composite variable representing the combination of all developed categories indicated above

Normal storage	Normal storage (in acre feet) of all dams within the catchment or network
Maximum storage	Maximum storage capacity (in acre feet) of all dams within the catchment or network
Relative storage fluctuation	Standardized storage fluctuation calculated using all dams within the catchment or network. This metric was calculated as the amount of storage fluctuation in acre feet (maximum storage – normal storage) divided by the normal storage
Flow interruption	Dam storage fluctuation as a proportion of the average annual flow out of the catchment or network
Normal flow restriction	Normal storage as a proportion of the average annual flow out of the catchment or network
Maximum flow restriction	Maximum storage as a proportion of the average annual flow out of the catchment or network
Mining activity	Density (per km^2) of all former and currently active mines (metallic, non-metallic, and mineral processing) within the catchment or network
Pollutant release	Density (per km^2) of all pollutant release sites within the catchment or network

Appendix B: Detection model set compared for each species.

Table B1. Set of models describing detection probability during field surveys for each of 11 marsh bird species (Species). Detection model covariates are time of day at the start of sampling (Time), Julian date on day of sampling (Date), an interaction between sampling time and Julian date (Time*Date), length of the broadcast segment of call-broadcast surveys (Broadcast), and a binary variable indicating whether or not the specific target species' call was included in the call-broadcast segment (Call). Functional forms used to represent sampling time and Julian date covariates (either linear or quadratic) were species-specific (see Table 1) and based on results of preliminary analyses. Model 1 (.) indicates an intercept-only model with constant detection probability through space and time.

Model no.	Detection model structure
1	.
2	Time
3	Date
4	Broadcast
5	Call
6	Time + Date
7	Time + Broadcast
8	Time + Call
9	Date + Broadcast
10	Date + Call
11	Broadcast + Call
12	Time + Date + Broadcast
13	Time + Date + Call
14	Time + broadcast + Call
15	Date + Broadcast + Call
16	Time + Date + Broadcast + Call
17	Time + Date + Time*Date
18	Time + Date + Time*Date + Broadcast
19	Time + Date + Time*Date + Call
20	Time + Date + Time*Date + Broadcast + Call

Appendix C: Univariate scale optimization results for 11 species of secretive marsh birds.

Table C1. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of American bitterns. Occupancy model covariates are: riverine lower-perennial (riv.lp), seasonal flooding (seas.flood), shoreline (shore), developed open-space (dev.os), relative storage fluctuation (r.storfluc), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
riv.lp(500) + shore(500) + seas.flood(500) + dev.os(100) + r.storfluc(c) + trend	**10386.8**
riv.lp(500) + shore(500) + seas.flood(500) + dev.os(100) + trend	10396.4
r.storfluc(c) + trend	10398.5
riv.lp(500) + shore(500) + seas.flood(500) + dev.os(100) + r.storfluc(c)	10414.7
trend	10416.3
riv.lp(500) + shore(500) + seas.flood(500) + dev.os(100)	10427.0
r.storfluc(c)	10429.2
.	10453.6

Table C2. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of American coots. Occupancy model covariates are: palustrine (palus), scrub-shrub (sc.shrub), semi-permanently flooded (semi.flood), developed (dev), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
palus(500) + sc.shrub(500) + semi.flood(224) + dev(500) + dev(n) + trend	**17421.2**

palus(500) + sc.shrub(500) + semi.flood(224) + dev(500) + dev(n)	17424.6
palus(500) + sc.shrub(500) + semi.flood(224) + dev(500) + trend	17428.0
palus(500) + sc.shrub(500) + semi.flood(224) + dev(500)	17431.2
dev(n) + trend	17446.2
dev(n)	17449.8
trend	17456.0
.	17459.3

Table C3. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of clapper rails. Occupancy model covariates are: excavated (exc), low intensity development (dev.li), watershed flow interruption (flowint), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-Score
exc(100) + dev.li(500)	**4144.8**

exc(100) + dev.li(500) + flowint(c)	4145.0
exc(100) + dev.li(500) + trend	4146.0
exc(100) + dev.li(500) + flowint(c) + trend	4146.1
flowint(c)	4150.3
trend	4150.8
flowint(c) + trend	4150.8
.	4152.5

Table C4. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of common gallinules. Occupancy model covariates are: artificial flooding (art.flood), palustrine (palus), agriculture (ag), cultivated croplands (cult.crop), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
palus(100) + art.flood(224) + cult.crop(500) + ag(n) + trend	**23837.7**

palus(100) + art.flood(224) + cult.crop(500) + trend	23857.6
ag(n) + trend	23929.9
palus(100) + art.flood(224) + cult.crop(500) + ag(n)	23948.4
Trend	23964.8
palus(100) + art.flood(224) + cult.crop(500)	23973.2
ag(n)	24047.4
.	24091.3

Table C5. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of king rails. Occupancy model covariates are: permanently flooded (per.flood), scrub-shrub (sc.shrub), agriculture (ag), developed open-space (dev.os), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model no.	Log-score
sc.shrub(224) + per.flood(500) + dev.os(224) + ag(n)	**2888.6**

sc.shrub(224) + per.flood(500) + dev.os(224) + ag(n) + trend	2890.0
sc.shrub(224) + per.flood(500) + dev.os(224)	2891.0
sc.shrub(224) + per.flood(500) + dev.os(224) + trend	2891.8
ag(n)	2904.3
ag(n) + trend	2906.5
.	2908.0
trend	2909.5

Table C6. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of least bitterns. Occupancy model covariates are: excavated (exc), palustrine (palus), agriculture (ag), maximum water storage capacity in watershed (maxstor), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
palus(224) + exc(100) + ag(100) + maxstor(c) + trend	**26947.3**

palus(224) + exc(100) + ag(100) + trend	26947.8
palus(224) + exc(100) + ag(100) + maxstor(c)	26957.4
palus(224) + exc(100) + ag(100)	26958.0
trend	27001.2
maxstor(c) + trend	27001.4
maxstor(c)	27009.0
.	27009.1

Table C7. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of pied-billed grebes. Occupancy model covariates are: artificial flooding (art.flood), riverine lower-perennial (riv.lp), scrub-shrub (sc.shrub), agriculture (ag), high-intensity development (dev.hi), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
riv.lp(224) + sc.shrub(500) + art.flood(500) + dev.hi(500) + ag(c)	**32802.5**

riv.lp(224) + sc.shrub(500) + art.flood(500) + dev.hi(500) + ag(c) + trend	32803.6
riv.lp(224) + sc.shrub(500) + art.flood(500) + dev.hi(500)	32803.7
riv.lp(224) + sc.shrub(500) + art.flood(500) + dev.hi(500) + trend	32805.1
ag(c)	32829.4
ag(c) + trend	32830.8
.	32837.9
trend	32839.4

Table C8. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of purple gallinules. Occupancy model covariates are: saturated (sat), developed (dev), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
sat(100) + dev(c) + trend	**916.5**
sat(100) + trend	918.6

dev(c) + trend	919.8
trend	922.0
sat(100) + dev(c)	947.7
sat(100)	947.9
dev(c)	955.4
.	955.7

Table C9. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of Ridgway's rail. Occupancy model covariates are: riverine upper-perennial (riv.up), scrub-shrub (sc.shrub), relative storage fluctuation (r.storfluc), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-Score
riv.up(100) + sc.shrub(224) + r.storfluc(n) + trend	**15216.8**
riv.up(100) + sc.shrub(224) + trend	15218.8

riv.up(100) + sc.shrub(224) + r.storfluc(n)	15221.5
riv.up(100) + sc.shrub(224)	15223.6
r.storfluc(n) + trend	15278.2
r.storfluc(n)	15280.4
trend	15281.5
.	15283.7

Table C10. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of soras. Occupancy model covariates are: diked-impounded (di), scrub-shrub (sc.shrub), normal water flow restriction (nflowrest), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-Score
sc.shrub(500) + di(100) + nflowrest(c)	**20320.7**
sc.shrub(500) + di(100) + nflowrest(c) + trend	20320.8

sc.shrub(500) + di(100)	20326.6
sc.shrub(500) + di(100) + trend	20326.8
nflowrest(c)	20339.6
nflowrest(c) + trend	20339.8
.	20347.5
Trend	20347.5

Table C11. Final model set and model selection results for identifying habitat models to predict the range-wide breeding distribution of Virginia rails. Occupancy model covariates are: excavated (exc), lacustrine-littoral (lac.litt), high-intensity development (dev.hi), watershed flow interruption (flowint), temporal trend across the study duration (trend), and intercept-only (.). Spatial scales are indicated parenthetically and include 100 m, 224 m, and 500 m for local-scale habitat variables, and catchment (c) and network (n) for watershed-level disturbance variables.

Model	Log-score
l.litt(500) + exc(500) + dev.hi(100) + flowint(n)	**26428.0**
l.litt(500) + exc(500) + dev.hi(100) + flowint(n) + trend	26431.3

l.litt(500) + exc(500) + dev.hi(100)	26431.8
l.litt(500) + exc(500) + dev.hi(100) + trend	26434.3
flowint(n)	26435.2
flowint(n) + trend	26437.6
.	26442.8
trend	26444.4

Appendix D: Full site ranking results for all DoD facilities for 11 species of secretive marsh birds.

Table D1. DoD installation (Site) rankings for American bittern (AMBI). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Fort Hood	Texas	Army Active	0.479

Fort Stewart	Georgia	Army Active	0.116
NSA Crane	Indiana	Navy Active	0.108
Camp Bullis	Texas	Air Force Active	0.106
Fort Bliss	Texas	Army Active	0.098
Fort A P Hill	Virginia	Army Active	0.047
Camp Maxey	Texas	Army Guard	0.031
Fort Hunter Liggett	California	Army Reserve	0.004
Joe Foss Field	South Dakota	Air Force Guard	0.003
Camp Dodge Johnston TS	Iowa	Army Guard	0.002
Beale AFB	California	Air Force Active	0.002
Randolph AFB	Texas	Air Force Active	0.002
Fort Leonard Wood	Missouri	Army Active	0.001
Fort George G Meade	Maryland	Army Active	< 0.001
Milan AAP	Tennessee	Army Active	< 0.001

Table D2. DoD installation (Site) rankings for American coot (AMCO). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Fort Stewart	Georgia	Army Active	0.385
Avon Park AF Range	Florida	Air Force Active	0.376
Eglin AFB	Florida	Air Force Active	0.057

Camp Joseph T Robinson	Arkansas	Army Guard	0.037
Moody AFB	Georgia	Air Force Active	0.032
W.H. Ford Regional Training Ctr	Kentucky	Army Guard	0.023
Camp Grafton	North Dakota	Army Guard	0.010
Fort Bliss	Texas	Army Active	0.008
Arnold AS	Tennessee	Air Force Active	0.008
Aberdeen Proving Ground	Maryland	Army Active	0.007
Fort Hunter Liggett	California	Army Reserve	0.006
Redstone Arsenal	Alabama	Army Active	0.006
MCB Camp Lejeune	North Carolina	Marine Corps Active	0.006
Camp Minden TS	Louisiana	Army Guard	0.005
NG Arden Hills Army TS	Minnesota	Army Guard	0.005
MCB Camp Lejeune West Site	North Carolina	Marine Corps Active	0.004
Fort Benning GA	Georgia	Army Active	0.004
OLF Whitehouse	Florida	Navy Active	0.003
Harvey Point NC	North Carolina	Navy Active	0.003
Fort Carson	Colorado	Army Active	0.003
Hawthorne Army Depot	Nevada	Army Active	0.003
Utah Test and Training Range South	Utah	Air Force Active	0.001
Fort Polk	Louisiana	Army Active	0.001
MWTC Bridgeport	California	Marine Corps Active	0.001
Dare County Range	North Carolina	Air Force Active	0.001
NAS Meridian	Mississippi	Navy Active	0.001
Fort Gordon	Georgia	Army Active	< 0.001
Wallops Island	Virginia	Navy Active	< 0.001
MCAS Cherry Point Oak Grove	North Carolina	Marine Corps Active	< 0.001
Fort Benning	Alabama	Army Active	< 0.001
Yuma Proving Ground	Arizona	Army Active	< 0.001
Fort Lewis	Washington	Army Active	< 0.001
MTA Camp Shelby	Mississippi	Army Guard	< 0.001
Fort Jackson	South Carolina	Army Active	< 0.001
NAS Lemoore	California	Navy Active	< 0.001
Picatinny Arsenal	New Jersey	Army Active	< 0.001
Kennedy Space Center Communications	Florida	Air Force Active	< 0.001
MCLB Albany	Georgia	Marine Corps Active	< 0.001
Fort A P Hill	Virginia	Army Active	< 0.001

Table D3. DoD installation (Site) rankings for clapper rail (CLRA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
MCB Camp Lejeune	North Carolina	Marine Corps Active	0.131
Tyndall AFB	Florida	Air Force Active	0.085
Fort Stewart	Georgia	Army Active	0.062
Point Of Marsh Target	North Carolina	Marine Corps Active	0.060

NAVSUBASE Kings Bay	Georgia	Navy Active	0.056
NAS Key West	Florida	Navy Active	0.050
JNTEXPBASE Little Creek FS VA	Virginia	Navy Active	0.040
NS Mayport	Florida	Navy Active	0.040
Eglin AFB	Florida	Air Force Active	0.039
MacDill AFB	Florida	Air Force Active	0.037
Cape Canaveral AFS	Florida	Air Force Active	0.035
Hurlburt Field	Florida	Air Force Active	0.033
Military Ocean Tml Sunny Point	North Carolina	Army Active	0.029
Patrick AFB	Florida	Air Force Active	0.023
MCB Camp Lejeune West Site	North Carolina	Marine Corps Active	0.016
Fort Eustis	Virginia	Air Force Active	0.014
MCSF Blount Island	Florida	Marine Corps Active	0.014
Dare County Range	North Carolina	Air Force Active	0.013
Homestead ARB	Florida	Air Force Reserve	0.013
NAS Oceana	Virginia	Navy Active	0.011
MCAS Cherry Point	North Carolina	Marine Corps Active	0.011
NAS Pensacola	Florida	Navy Active	0.010
NAS Key West Dredgers Key-Sigsbee	Florida	Navy Active	0.010
Wallops Island	Virginia	Navy Active	0.009
NAS Oceana Dam Neck	Virginia	Navy Active	0.009
ALF Fentress Chesapeake	Virginia	Navy Active	0.009
MCAS Beaufort	South Carolina	Marine Corps Active	0.009
Langley AFB	Virginia	Air Force Active	0.008
Lakehurst	New Jersey	Air Force Active	0.008
Dover AFB	Deleware	Air Force Active	0.007
NAS JRB New Orleans	Louisiana	Navy Active	0.007
Fort A P Hill	Virginia	Army Active	0.007
NWS Charleston	South Carolina	Air Force Active	0.006
MCRD Beaufort Parris Island	South Carolina	Marine Corps Active	0.006
Fort Monroe	Virginia	Army Active	0.006
ALF Waldron	Texas	Navy Active	0.005
NS Norfolk	Virginia	Navy Active	0.005
NSA Norfolk NW Chesapeake	Virginia	Navy Active	0.005
NWS Earle	New Jersey	Navy Active	0.005
Fort Lee	Virginia	Army Active	0.004
NAS Key West Trumbo Point Annex	Florida	Navy Active	0.004
OLF Atlantic	North Carolina	Marine Corps Active	0.004
MTA Camp Edwards	Massachusetts	Army Guard	0.004
Harvey Point NC	North Carolina	Navy Active	0.004
NAS Key West Fleming Key Magazine	Florida	Navy Active	0.003
NAS Kingsville	Texas	Navy Active	0.003
JEBLCFS East	Virginia	Navy Active	0.003

CBC Gulfport	Mississippi	Navy Active	0.003
NAVSUBASE New London	Connecticut	Navy Active	0.002
Craney Island	Virginia	Navy Active	0.002
ALF Bogue	North Carolina	Marine Corps Active	0.002
NSY Portsmouth	Maine	Navy Active	0.002
OLF Bronson	Florida	Navy Active	0.002
NSA Panama City	Florida	Navy Active	0.002
Barin Field	Alabama	Navy Active	0.001
NG NGTC Sea Girt NJ	New Jersey	Army Guard	0.001
NAS Corpus Christi	Texas	Navy Active	0.001
ALF Cabaniss	Texas	Navy Active	0.001
NSA Norfolk	Virginia	Navy Active	0.001
Keesler AFB	Mississippi	Air Force Active	0.001
Naval Hospital Key West	Florida	Navy Active	0.001
NSA South Potomac	Virginia	Navy Active	0.001
Defense General Supply Center	Virginia	Army Active	0.001
Charleston AFB	South Carolina	Air Force Active	0.001
Malabar Transmitter Annex	Florida	Air Force Active	0.001
Corry Station	Florida	Navy Active	0.001
Ellington Field	Texas	Air Force Guard	< 0.001
NG Camp Villere	Louisiana	Army Guard	< 0.001
Saufley Field	Florida	Navy Active	< 0.001
NG Bethany Beach TS	Delaware	Army Guard	< 0.001
Savannah/Hilton Head IAP	Georgia	Air Force Guard	< 0.001
Kennedy Space Center Communications	Florida	Air Force Active	< 0.001
Waterfront Earle	New Jersey	Navy Active	< 0.001
NOLF Santa Rosa	Florida	Navy Active	< 0.001
NAS Whiting Field Milton	Florida	Navy Active	< 0.001
Fort Monmouth Main Post	New Jersey	Army Active	< 0.001
Pease ANGB	New Hampshire	Air Force Guard	< 0.001
MCAS Cherry Point Oak Grove	North Carolina	Marine Corps Active	< 0.001

Table D4. DoD installation (Site) rankings for common gallinule (COGA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

SITE_NAME	State	Branch	Scaled-area
Fort Stewart	Georgia	Army Active	0.194
Eglin AFB	Florida	Air Force Active	0.139
Dare County Range	North Carolina	Air Force Active	0.136

Avon Park AF Range	Florida	Air Force Active	0.116
MCB Camp Lejeune West Site	North Carolina	Marine Corps Active	0.077
MCB Camp Lejeune	North Carolina	Marine Corps Active	0.030
Fort Dix	New Jersey	All five (Active)	0.026
MTA Camp Shelby	Mississippi	Army Guard	0.026
Fort Benning GA	Georgia	Army Active	0.025
Fort Polk	Louisiana	Army Active	0.025
Tyndall AFB	Florida	Air Force Active	0.020
Edwards AFB	California	Air Force Active	0.010
Yuma Proving Ground	Arizona	Army Active	0.009
Fort Gordon	Georgia	Army Active	0.009
Hurlburt Field	Florida	Air Force Active	0.009
Moody AFB	Georgia	Air Force Active	0.007
Aberdeen Proving Ground	Maryland	Army Active	0.006
MCB Camp Pendleton	California	Marine Corps Active	0.006
NWS Earle	New Jersey	Navy Active	0.006
Fort Jackson	South Carolina	Army Active	0.006
NAS JRB New Orleans	Louisiana	Navy Active	0.006
MTC-H Camp Grayling	Michigan	Army Guard	0.006
NG Beauregard Training Range	Louisiana	Army Guard	0.006
MCB Quantico	Virginia	Marine Corps Active	0.006
Vandenberg AFB	California	Air Force Active	0.005
Fort Bragg	North Carolina	Army Active	0.005
Military Ocean Tml Sunny Point	North Carolina	Army Active	0.004
Red River Army Depot	Texas	Army Active	0.004
NSA Norfolk NW Chesapeake	Virginia	Navy Active	0.004
Fort Rucker	Alabama	Army Active	0.004
OLF Atlantic	North Carolina	Marine Corps Active	0.003
Ravenna Training and Log Site	Ohio	Army Guard	0.003
Fort A P Hill	Virginia	Army Active	0.003
NWS Charleston	South Carolina	Air Force Active	0.003
Fort Hunter Liggett	California	Army Reserve	0.003
Lakehurst	New Jersey	Air Force Active	0.002
NAS Oceana Dam Neck	Virginia	Navy Active	0.002
MCAS Cherry Point	North Carolina	Marine Corps Active	0.002
Camp Minden TS	Louisiana	Army Guard	0.002
Fort Benning	Alabama	Army Active	0.002
NAS Oceana	Virginia	Navy Active	0.002
Picatinny Arsenal	New Jersey	Army Active	0.002
Fort Drum	New York	Army Active	0.002
NAS Jacksonville	Florida	Navy Active	0.002
Cape Canaveral AFS	Florida	Air Force Active	0.002
ALF Fentress Chesapeake	Virginia	Navy Active	0.002

Sierra Army Depot	California	Army Active	0.002
CTC Fort Custer Trng Center	Michigan	Army Guard	0.001
Barksdale AFB	Louisiana	Air Force Active	0.001
NAVSUBASE Kings Bay	Georgia	Navy Active	0.001
Wallops Island	Virginia	Navy Active	0.001
Woolmarket (De Soto)	Mississippi	Navy Active	0.001
North Air Force Auxiliary Field	South Carolina	Air Force Active	0.001
NAS Pensacola	Florida	Navy Active	0.001
NG Esler Field	Louisiana	Army Guard	0.001
Fort Belvoir	Virginia	Army Active	0.001
McGuire	New Jersey	Air Force Active	0.001
Fort Eustis	Virginia	Air Force Active	0.001
NB Coronado Imperial Beach	California	Navy Active	0.001
NG Youngstown TS	New York	Army Guard	0.001
JEBLCFS East	Virginia	Navy Active	0.001
MCAS Beaufort	South Carolina	Marine Corps Active	0.001
Harvey Point NC	North Carolina	Navy Active	0.001
NG MTA Camp Curtis Guil	Massachusetts	Army Guard	0.001
OLF Whitehouse	Florida	Navy Active	0.001
NOLF Brewton	Alabama	Navy Active	0.001
NB Coronado Silver Strand	California	Navy Active	0.001
Fort Lee	Virginia	Army Active	0.001
NG TS Ethan Allen Range	Vermont	Army Guard	0.001
Jacksonville IAP	Florida	Air Force Guard	< 0.001
Plattsburg AFB	New York	Air Force Active	< 0.001
NAWS China Lake	California	Navy Active	< 0.001
NOLF Holley	Florida	Navy Active	< 0.001
Beale AFB	California	Air Force Active	< 0.001
McEntire Joint NGB	South Carolina	Air Force Guard	< 0.001
OLF Bronson	Florida	Navy Active	< 0.001
NAS Lemoore	California	Navy Active	< 0.001
Fort George G Meade	Maryland	Army Active	< 0.001
NAS Fallon	Nevada	Navy Active	< 0.001
Selfridge ANGB	Michigan	Air Force Guard	< 0.001
MCLB Albany	Georgia	Marine Corps Active	< 0.001
SMR Camp Beauregard	Louisiana	Army Guard	< 0.001
Saufley Field	Florida	Navy Active	< 0.001
NS Norfolk	Virginia	Navy Active	< 0.001
Mather AFB	California	Air Force Active	< 0.001
MCAS Cherry Point Oak Grove	North Carolina	Marine Corps Active	< 0.001
Longhorn AAP	Texas	Army Active	< 0.001
MTC-H Camp Roberts	California	Army Guard	< 0.001
Homestead ARB	Florida	Air Force Reserve	< 0.001

Fort Bliss	Texas	Army Active	< 0.001
Charleston AFB	South Carolina	Air Force Active	< 0.001
Cape San Blas Tracking Annex D-3	Florida	Air Force Active	< 0.001
Langley AFB	Virginia	Air Force Active	< 0.001
Eglin Afb Site 2 (Santa Rosa Island)	Florida	Air Force Active	< 0.001
NAS Corpus Christi	Texas	Navy Active	< 0.001
NSA Midsouth Memphis	Tennessee	Navy Active	< 0.001
NWS Yorktown	Virginia	Navy Active	< 0.001
Seymour Johnson AFB	North Carolina	Air Force Active	< 0.001
NOLF Evergreen	Alabama	Navy Active	< 0.001
Stones Ranch Military Reservation	Connecticut	Army Guard	< 0.001
Shaw AFB	South Carolina	Air Force Active	< 0.001
Sewage Evaporation Pon	California	Navy Active	< 0.001
Camp Mackall	North Carolina	Army Active	< 0.001
Camp Perry Joint Training Center	Ohio	Army Guard	< 0.001
NS Mayport	Florida	Navy Active	< 0.001
CBC Gulfport	Mississippi	Navy Active	< 0.001
Nellis Air Force Range	Nevada	Air Force Active	< 0.001
MacDill AFB	Florida	Air Force Active	< 0.001
NWS Seal Beach	California	Navy Active	< 0.001
NAS Key West	Florida	Navy Active	< 0.001
Fort Monmouth Main Post	New Jersey	Army Active	< 0.001
NAS Whiting Field Milton	Florida	Navy Active	< 0.001
NG Ethan Allen AFB MTA	Vermont	Army Guard	< 0.001
NWS Seal Beach Fallbrook California	California	Navy Active	< 0.001
Camp Ashland	Nebraska	Army Guard	< 0.001
Dover AFB	Delaware	Air Force Active	< 0.001
Craney Island	Virginia	Navy Active	< 0.001
Little Mountain Test Annex	Utah	Air Force Active	< 0.001
NAS Patuxent River	Maryland	Navy Active	< 0.001
JNTEXPBASE Little Creek FS VA	Virginia	Navy Active	< 0.001
ALF Bogue	North Carolina	Marine Corps Active	< 0.001
ITC Camp San Luis Obisbo	California	Army Guard	< 0.001
Andrews AFB	Maryland	Air Force Active	< 0.001
MCSF Blount Island	Florida	Marine Corps Active	< 0.001
NAVPMOSSP Magna Utah	Utah	Navy Active	< 0.001
NAS Brunswick	Maine	Navy Active	< 0.001
NOLF Choctaw	Florida	Navy Active	< 0.001
MCAS Miramar	California	Marine Corps Active	< 0.001
Fort Huachuca	Arizona	Army Active	< 0.001
NB Coronado	California	Navy Active	< 0.001
Gulfport-Biloxi Regional Airport (ANG)	Mississippi	Air Force Guard	< 0.001
White Sands Missile Range	New Mexico	Army Active	< 0.001

Arbuckle Airfield	Florida	Air Force Active	< 0.001
NAVBASE Ventura City Point Mugu	California	Navy Active	< 0.001
Dixie Target Range	Texas	Navy Active	< 0.001
Riverbank AAP	California	Army Active	< 0.001
NSA South Potomac	Virginia	Navy Active	< 0.001
ALF Orange	Texas	Navy Active	< 0.001
FLC Fuel Depot Heckscher	Florida	Navy Active	< 0.001
Fort Indiantown Gap	Pennsylvania	Army Guard	< 0.001
Blossom Point Research Facility	Maryland	Army Active	< 0.001
NSA Norfolk	Virginia	Navy Active	< 0.001
Savannah/Hilton Head IAP	Georgia	Air Force Guard	< 0.001
4th MARDIV Jacksonville Maint	Florida	Marine Corps Reserve	< 0.001
Military Ocean Terminal Concord	California	Army Active	< 0.001
NG Lawrenceville	New Jersey	Army Guard	< 0.001
Camp Swift	Texas	Army Guard	< 0.001
NOLF Summerdale	Alabama	Navy Active	< 0.001
Davis Communications Annex Site 1	California	Air Force Active	< 0.001
Malabar Transmitter Annex	Florida	Air Force Active	< 0.001
NSA Panama City	Florida	Navy Active	< 0.001
MTA Camp Edwards	Massachusetts	Army Guard	< 0.001
Laughlin AFB	Texas	Air Force Active	< 0.001
NAVSUPPDET Monterey	California	Navy Active	< 0.001
Camp Smith	New York	Army Guard	< 0.001
Kennedy Space Center Communications	Florida	Air Force Active	< 0.001
Camp Navajo	Arizona	Army Guard	< 0.001
Camp Maxey	Texas	Army Guard	< 0.001
NUWC Fishers Island	New York	Navy Active	< 0.001
Nalf Goliad	Texas	Navy Active	< 0.001
NAVSUPPDET Monterey Dixon Transmitter Fac	California	Navy Active	< 0.001
NAVSUBASE New London	Connecticut	Navy Active	< 0.001
Kirtland AFB	New Mexico	Air Force Active	< 0.001
JBSA-Medina Annex	Texas	Air Force Active	< 0.001
Newington Defense Fuel Support Point	New Hampshire	Air Force Active	< 0.001
NAS Kingsville	Texas	Navy Active	< 0.001
NB San Diego Mission Gorge	California	Navy Active	< 0.001
Waterfront Earle	New Jersey	Navy Active	< 0.001
Solomons Island	Maryland	Navy Active	< 0.001
MCRD Beaufort Parris Island	South Carolina	Marine Corps Active	< 0.001
NG New Hampshire TS	New Hampshire	Army Guard	< 0.001
Camp Bullis	Texas	Air Force Active	< 0.001
Naval Academy North Severn	Maryland	Navy Active	< 0.001

Niagara Falls	New York	Air Force Reserve	< 0.001
NS Newport	Rhode Island	Navy Active	< 0.001
NG Camp Villere	Louisiana	Army Guard	< 0.001
Defense Distribution Region West Tracy	California	Army Active	< 0.001
Cairns Basefield	Alabama	Army Active	< 0.001
NG Camp Mabry	Texas	Army Guard	< 0.001
NSA South Potomac Pumpkin Neck	Virginia	Navy Active	< 0.001
NG Auburn TS	Maine	Army Guard	< 0.001
NSA South Potomac Stump Neck Area	Maryland	Navy Active	< 0.001
Patrick AFB	Florida	Air Force Active	< 0.001
ALF Waldron	Texas	Navy Active	< 0.001
Channel Islands ANGS	California	Air Force Guard	< 0.001
Detroit Arsenal	Michigan	Army Active	< 0.001
Defense General Supply Center	Virginia	Army Active	< 0.001
Fort Sam Houston	Texas	Air Force Active	< 0.001
Atlantic City IAP	New Jersey	Air Force Guard	< 0.001
Verona Test Annex	New York	Air Force Active	< 0.001
Highbluff Stagefield	Alabama	Army Active	< 0.001
NSY Portsmouth	Maine	Navy Active	< 0.001
NAF El Centro	California	Navy Active	< 0.001
Hawthorne Army Depot	Nevada	Army Active	< 0.001
Det Concord (BRAC)	California	Navy Active	< 0.001

Table D5. DoD installation (Site) rankings for king rail (KIRA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
MCB Camp Lejeune West Site	North Carolina	Marine Corps Active	0.409
Dare County Range	North Carolina	Air Force Active	0.375
Camp Ripley	Minnesota	Army Guard	0.071
Fort Dix	New Jersey	All five (Active)	0.035

MCB Camp Lejeune	North Carolina	Marine Corps Active	0.022
Picatinny Arsenal	New Jersey	Army Active	0.012
Fort Benning	Alabama	Army Active	0.011
MacDill AFB	Florida	Air Force Active	0.011
Eglin AFB	Florida	Air Force Active	0.008
Redstone Arsenal	Alabama	Army Active	0.008
Fort Leavenworth	Kansas	Army Active	0.005
Camp Dodge Johnston TS	Iowa	Army Guard	0.005
NAS JRB New Orleans	Louisiana	Navy Active	0.004
Fort Stewart	Georgia	Army Active	0.004
OLF Atlantic	North Carolina	Marine Corps Active	0.003
Camp Atterbury	Indiana	Army Guard	0.003
Tyndall AFB	Florida	Air Force Active	0.003
NAS Key West	Florida	Navy Active	0.003
Avon Park AF Range	Florida	Air Force Active	0.002
MTA Camp Shelby	Mississippi	Army Guard	0.002
Pine Bluff Arsenal	Arkansas	Army Active	0.002
Military Ocean Tml Sunny Point	North Carolina	Army Active	0.001
Fort Benning GA	Georgia	Army Active	0.001
Fort Eustis	Virginia	Air Force Active	0.001
Selfridge ANGB	Michigan	Air Force Guard	< 0.001
Lakehurst	New Jersey	Air Force Active	< 0.001

Table D6. DoD installation (Site) rankings for least bittern (LEBI). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Dare County Range	North Carolina	Air Force Active	0.195
Fort Stewart	Georgia	Army Active	0.157
Eglin AFB	Florida	Air Force Active	0.141
Avon Park AF Range	Florida	Air Force Active	0.105
MCB Camp Lejeune West Site	North Carolina	Marine Corps Active	0.084

MTC-H Camp Grayling	Michigan	Army Guard	0.029
Fort Dix	New Jersey	All five (Active)	0.026
MCB Camp Lejeune	North Carolina	Marine Corps Active	0.019
Redstone Arsenal	Alabama	Army Active	0.018
Fort Benning GA	Georgia	Army Active	0.016
Tyndall AFB	Florida	Air Force Active	0.014
Camp Ripley	Minnesota	Army Guard	0.014
MTA Camp Shelby	Mississippi	Army Guard	0.012
Hurlburt Field	Florida	Air Force Active	0.010
Yuma Proving Ground	Arizona	Army Active	0.009
Moody AFB	Georgia	Air Force Active	0.009
Fort Polk	Louisiana	Army Active	0.009
Fort Drum	New York	Army Active	0.007
Edwards AFB	California	Air Force Active	0.007
NAS JRB New Orleans	Louisiana	Navy Active	0.007
Fort Gordon	Georgia	Army Active	0.006
Fort Leavenworth	Kansas	Army Active	0.005
NSA Norfolk NW Chesapeake	Virginia	Navy Active	0.005
NWS Earle	New Jersey	Navy Active	0.005
Camp Dodge Johnston TS	Iowa	Army Guard	0.005
Arnold AS	Tennessee	Air Force Active	0.004
OLF Atlantic	North Carolina	Marine Corps Active	0.004
Red River Army Depot	Texas	Army Active	0.004
NG Beauregard Training Range	Louisiana	Army Guard	0.003
Pine Bluff Arsenal	Arkansas	Army Active	0.003
Military Ocean Tml Sunny Point	North Carolina	Army Active	0.003
Camp Joseph T Robinson	Arkansas	Army Guard	0.003
Camp Mackall	North Carolina	Army Active	0.003
NAS Meridian	Mississippi	Navy Active	0.003
NSA Crane	Indiana	Navy Active	0.003
MCB Quantico	Virginia	Marine Corps Active	0.003
MCB Camp Pendleton	California	Marine Corps Active	0.002
ALF Fentress Chesapeake	Virginia	Navy Active	0.002
Columbus AFB	Mississippi	Air Force Active	0.002
Ravenna Training and Log Site	Ohio	Army Guard	0.002
NAS Oceana Dam Neck	Virginia	Navy Active	0.002
Lakehurst	New Jersey	Air Force Active	0.002
W.H. Ford Regional Training Ctr	Kentucky	Army Guard	0.002
Scott AFB	Illinois	Air Force Active	0.002
Fort Bragg	North Carolina	Army Active	0.002
MCAS Cherry Point	North Carolina	Marine Corps Active	0.002
North Air Force Auxiliary Field	South Carolina	Air Force Active	0.002
Fort Jackson	South Carolina	Army Active	0.001

NWS Charleston	South Carolina	Air Force Active	0.001
Milan AAP	Tennessee	Army Active	0.001
NAS Jacksonville	Florida	Navy Active	0.001
Aberdeen Proving Ground	Maryland	Army Active	0.001
Fort Campbell	Kentucky	Army Active	0.001
NG Youngstown TS	New York	Army Guard	0.001
Camp Atterbury	Indiana	Army Guard	0.001
Fort Benning	Alabama	Army Active	0.001
NG Esler Field	Louisiana	Army Guard	0.001
NB Coronado Imperial Beach	California	Navy Active	0.001
NAS Oceana	Virginia	Navy Active	0.001
JEBLCFS East	Virginia	Navy Active	0.001
McGuire	New Jersey	Air Force Active	0.001
Picatinny Arsenal	New Jersey	Army Active	0.001
Camp Minden TS	Louisiana	Army Guard	0.001
Fort Pickett, ARNG MTC	Virginia	Army Guard	0.001
NG Arden Hills Army TS	Minnesota	Army Guard	0.001
NAS Pensacola	Florida	Navy Active	0.001
Fort Rucker	Alabama	Army Active	0.001
NG VTS Milan	Tennessee	Army Guard	0.001
Harvey Point NC	North Carolina	Navy Active	0.001
Barksdale AFB	Louisiana	Air Force Active	0.001
NG MTA Camp Curtis Guil	Massachusetts	Army Guard	0.001
Woolmarket (De Soto)	Mississippi	Navy Active	<0.001
NOLF Brewton	Alabama	Navy Active	<0.001
Wallops Island	Virginia	Navy Active	<0.001
CTC Fort Custer Trng Center	Michigan	Army Guard	<0.001
Cape Canaveral AFS	Florida	Air Force Active	<0.001
Fort Belvoir	Virginia	Army Active	<0.001
SMR Camp Beauregard	Louisiana	Army Guard	<0.001
Volk ANGB	Wisconsin	Air Force Guard	<0.001
Jacksonville IAP	Florida	Air Force Guard	<0.001
OLF Whitehouse	Florida	Navy Active	<0.001
NOLF Holley	Florida	Navy Active	<0.001
NAVSUBASE Kings Bay	Georgia	Navy Active	<0.001
MCAS Cherry Point Oak Grove	North Carolina	Marine Corps Active	<0.001
Fort George G Meade	Maryland	Army Active	<0.001
Fort Lee	Virginia	Army Active	<0.001
Pelham Range Training Site-Ft McClellan	Alabama	Army Guard	<0.001
Fort A P Hill	Virginia	Army Active	<0.001
Saufley Field	Florida	Navy Active	<0.001
NG Sparta Armory	Illinois	Army Guard	<0.001
MCLB Albany	Georgia	Marine Corps Active	<0.001

OLF Bronson	Florida	Navy Active	<0.001
MCAS Beaufort	South Carolina	Marine Corps Active	<0.001
NAS Portsmouth NCTS Cutler VLF Area	Maine	Navy Active	<0.001
NAS Key West	Florida	Navy Active	<0.001
McEntire Joint NGB	South Carolina	Air Force Guard	<0.001
Fort Eustis	Virginia	Air Force Active	<0.001
NB Coronado Silver Strand	California	Navy Active	<0.001
Fort Hood	Texas	Army Active	<0.001
Mather AFB	California	Air Force Active	<0.001
NSA Midsouth Memphis	Tennessee	Navy Active	<0.001
Camp Perry Joint Training Center	Ohio	Army Guard	<0.001
CBC Gulfport	Mississippi	Navy Active	<0.001
Fort Leonard Wood	Missouri	Army Active	<0.001
West Point Mil Reservation	New York	Army Active	<0.001
Seymour Johnson AFB	North Carolina	Air Force Active	<0.001
NG Macon TS	Missouri	Army Guard	<0.001
Longhorn AAP	Texas	Army Active	<0.001
NOLF Choctaw	Florida	Navy Active	<0.001
Columbus Auxiliary Airfield	Mississippi	Air Force Active	<0.001
NG MTA Camp Clark Nevada	Missouri	Army Guard	<0.001
NAS Whiting Field Milton	Florida	Navy Active	<0.001
NAVBASE Ventura City Point Mugu	California	Navy Active	<0.001
Eglin Afb Site 2 (Santa Rosa Island)	Florida	Air Force Active	<0.001
Duluth IAP	Minnesota	Air Force Guard	<0.001
Blue Grass Army Depot	Kentucky	Army Active	<0.001
NS Norfolk	Virginia	Navy Active	<0.001
Kennedy Space Center Communications	Florida	Air Force Active	<0.001
NAS Corpus Christi	Texas	Navy Active	<0.001
Dover AFB	Delaware	Air Force Active	<0.001
Westover ARB	Massachusetts	Air Force Reserve	<0.001
Savannah/Hilton Head IAP	Georgia	Air Force Guard	<0.001
Homestead ARB	Florida	Air Force Reserve	<0.001
NOLF Evergreen	Alabama	Navy Active	<0.001
Charleston AFB	South Carolina	Air Force Active	<0.001
NG Hollis Plains TS	Maine	Army Guard	<0.001

Table D7. DoD installation (Site) rankings for pied-billed grebe (PBGR). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Nellis Air Force Range	Nevada	Air Force Active	0.420
MCB Camp Lejeune West Site	North Carolina	Marine Corps Active	0.166
Dare County Range	North Carolina	Air Force Active	0.139
Camp Ripley	Minnesota	Army Guard	0.062
Yuma Proving Ground	Arizona	Army Active	0.058
Fort Dix	New Jersey	All five (Active)	0.036
MCB Camp Lejeune	North Carolina	Marine Corps Active	0.022

MTC-H Camp Grayling	Michigan	Army Guard	0.012
Moody AFB	Georgia	Air Force Active	0.012
Fort Lewis	Washington	Army Active	0.007
MacDill AFB	Florida	Air Force Active	0.006
Eglin AFB	Florida	Air Force Active	0.006
Holloman AFB	New Mexico	Air Force Active	0.005
Redstone Arsenal	Alabama	Army Active	0.004
Fort Leavenworth	Kansas	Army Active	0.004
Fort Drum	New York	Army Active	0.004
Fort Stewart	Georgia	Army Active	0.004
NAS JRB New Orleans	Louisiana	Navy Active	0.004
Camp Atterbury	Indiana	Army Guard	0.003
Tyndall AFB	Florida	Air Force Active	0.003
Picatinny Arsenal	New Jersey	Army Active	0.003
Cape Canaveral AFS	Florida	Air Force Active	0.003
Fort Eustis	Virginia	Air Force Active	0.003
Avon Park AF Range	Florida	Air Force Active	0.002
Military Ocean Tml Sunny Point	North Carolina	Army Active	0.002
OLF Atlantic	North Carolina	Marine Corps Active	0.002
Fort Benning	Alabama	Army Active	0.002
NAS Portsmouth NCTS Cutler VLF Area	Maine	Navy Active	0.002
Lakehurst	New Jersey	Air Force Active	0.001
NAS Key West	Florida	Navy Active	0.001
MCLB Albany	Georgia	Marine Corps Active	0.001
NWS Charleston	South Carolina	Air Force Active	< 0.0001
MCAS Beaufort	South Carolina	Marine Corps Active	< 0.0001
Fort Bragg	North Carolina	Army Active	< 0.0001
Fort Benning GA	Georgia	Army Active	< 0.0001
White Sands Missile Range	New Mexico	Army Active	< 0.0001
MTA Camp Shelby	Mississippi	Army Guard	< 0.0001
McGuire	New Jersey	Air Force Active	< 0.0001

Table D8. DoD installation (Site) rankings for purple gallinule (PUGA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Barksdale AFB	Louisiana	Air Force Active	0.246
Keesler AFB	Mississippi	Air Force Active	0.172
NAS Corpus Christi	Texas	Navy Active	0.167
Eglin AFB	Florida	Air Force Active	0.108
MacDill AFB	Florida	Air Force Active	0.071
ALF Waldron	Texas	Navy Active	0.043

Patrick AFB	Florida	Air Force Active	0.031
NAS Jacksonville	Florida	Navy Active	0.028
Ellington Field	Texas	Air Force Guard	0.026
Hurlburt Field	Florida	Air Force Active	0.024
West Bank	Louisiana	Navy Active	0.024
NOLF Holley	Florida	Navy Active	0.019
Corry Station	Florida	Navy Active	0.016
Gulfport-Biloxi Regional Airport (ANG)	Mississippi	Air Force Guard	0.016
NWS Charleston	South Carolina	Air Force Active	0.007
NG Gulfport AVCRAD	Mississippi	Army Guard	0.002
FLC Fuel Depot Heckscher	Florida	Navy Active	0.002
Jonathan Dickinson Tracking Annex	Florida	Air Force Active	0.001
CBC Gulfport	Mississippi	Navy Active	< 0.001
Camp Joseph T Robinson	Arkansas	Army Guard	< 0.001
Little Rock AFB	Arkansas	Air Force Active	< 0.001

Table D9. DoD installation (Site) rankings for Ridgway’s rail (RWRA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Yuma Proving Ground	Arizona	Army Active	0.995
Military Ocean Terminal Concord	California	Army Active	0.005

Table D10. DoD installation (Site) rankings for sora (SORA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Camp Dodge Johnston TS	Iowa	Army Guard	0.203
Arnold AS	Tennessee	Air Force Active	0.103
Redstone Arsenal	Alabama	Army Active	0.101
NAS JRB New Orleans	Louisiana	Navy Active	0.053
Fort Benning	Alabama	Army Active	0.044
Military Ocean Terminal Concord	California	Army Active	0.038
Fort Stewart	Georgia	Army Active	0.031

NSA Crane	Indiana	Navy Active	0.028
Fort Benning GA	Georgia	Army Active	0.024
Camp Gruber	Oklahoma	Army Guard	0.023
Camp Joseph T Robinson	Arkansas	Army Guard	0.022
McAlester AAP	Oklahoma	Army Active	0.021
Fort Rucker	Alabama	Army Active	0.020
Pine Bluff Arsenal	Arkansas	Army Active	0.019
MCB Quantico	Virginia	Marine Crops Active	0.018
Fort Sill	Oklahoma	Army Active	0.017
Fort Bragg	North Carolina	Army Active	0.015
Picatinny Arsenal	New Jersey	Army Active	0.015
Fort Pickett, ARNG MTC	Virginia	Army Guard	0.013
NWS Charleston	South Carolina	Air Force Active	0.011
Yuma Proving Ground	Arizona	Army Active	0.010
Edwards AFB	California	Air Force Active	0.009
West Point Mil Reservation	New York	Army Active	0.008
Fort Jackson	South Carolina	Army Active	0.008
Fort Gordon	Georgia	Army Active	0.007
MCB Camp Pendleton	California	Marine Crops Active	0.007
Military Ocean Tml Sunny Point	North Carolina	Army Active	0.006
W.H. Ford Regional Training Ctr	Kentucky	Army Guard	0.006
Fort Bliss	Texas	Army Active	0.006
Red River Army Depot	Texas	Army Active	0.005
NAS Meridian	Mississippi	Navy Active	0.005
Fort Dix	New Jersey	All five (Active)	0.005
NG VTS Smyrna	Tennessee	Army Guard	0.005
Fort Hood	Texas	Army Active	0.004
Fort Knox	Kentucky	Army Active	0.004
MTCH Camp Guernsey	Wyoming	Army Guard	0.004
Maxwell AFB	Alabama	Air Force Active	0.004
Aberdeen Proving Ground	Maryland	Army Active	0.004
NG Muscatatuck Urban Training Center	Indiana	Army Guard	0.004
Fort Drum	New York	Army Active	0.004
Cheatham Annex	Virginia	Navy Active	0.003
Eglin AFB	Florida	Air Force Active	0.003
Fort Carson	Colorado	Army Active	0.003
Fort A P Hill	Virginia	Army Active	0.003
Blue Grass Army Depot	Kentucky	Army Active	0.003
Wallops Island	Virginia	Navy Active	0.003
Fort Hunter Liggett	California	Army Reserve	0.003
Camp Mackall	North Carolina	Army Active	0.002
Fort Campbell	Kentucky	Army Active	0.002
NAVBASE Ventura City Point Mugu	California	Navy Active	0.002

Fort Indiantown Gap	Pennsylvania	Army Guard	0.002
Iowa AAP	Iowa	Army Active	0.002
NAS Lemoore	California	Navy Active	0.002
Fort Leonard Wood	Missouri	Army Active	0.002
JNTEXPBASE Little Creek FS VA	Virginia	Navy Active	0.002
Mather AFB	California	Air Force Active	0.001
Camp Bullis	Texas	Air Force Active	0.001
NWS Seal Beach	California	Navy Active	0.001
Moody AFB	Georgia	Air Force Active	0.001
Fort Polk	Louisiana	Army Active	0.001
Lakehurst	New Jersey	Air Force Active	0.001
New Boston AS	New Hampshire	Air Force Active	0.001
Camp Atterbury	Indiana	Army Guard	0.001
Little Mountain Test Annex	Utah	Air Force Active	0.001
Yakima Training Center	Washington	Army Active	0.001
Norco	California	Navy Active	0.001
Tobyhanna Army Depot	Pennsylvania	Army Active	0.001
MTA Camp Shelby	Mississippi	Army Guard	0.001
Camp Maxey	Texas	Army Guard	0.001
MTA Camp Butner	North Carolina	Army Guard	0.001
Fort Eustis	Virginia	Air Force Active	0.001
Peterson AFB	Colorado	Air Force Active	0.001
Little Rock AFB	Arkansas	Air Force Active	0.001
Vandenberg AFB	California	Air Force Active	0.001
SMR Camp Beauregard	Louisiana	Army Guard	0.001
CTA Camp McCain	Mississippi	Army Guard	0.001
NAS Portsmouth Redington Township	Maine	Navy Active	0.001
Fort Riley	Kansas	Army Active	<0.001
Pelham Range Training Site - Fort McClellan	Alabama	Army Guard	<0.001
Kansas AAP	Kansas	Army Active	<0.001
Anniston Army Depot	Alabama	Army Active	<0.001
NAS Pensacola	Florida	Navy Active	<0.001
NAS Patuxent River	Maryland	Navy Active	<0.001
Lake City AAP	Missouri	Army Active	<0.001
NAS Portsmouth NCTS Cutler VLF Area	Maine	Navy Active	<0.001
NG MTA Camp Clark Nevada	Missouri	Army Guard	<0.001
NG MTA Clarks Hill Reservation	South Carolina	Army Guard	<0.001
Nalf Goliad	Texas	Navy Active	<0.001
ITC Camp San Luis Obisbo	California	Army Guard	<0.001
Camp Smith	New York	Army Guard	<0.001
Fort Huachuca	Arizona	Army Active	<0.001
MCLB Albany	Georgia	Marine Crops Active	<0.001
NAVSUPPDET Monterey	California	Navy Active	<0.001

Scott AFB	Illinois	Air Force Active	<0.001
Fort Gillem	Georgia	Army Active	<0.001
NWS Yorktown	Virginia	Navy Active	<0.001
NWS Earle	New Jersey	Navy Active	<0.001
Plattsburg AFB	New York	Air Force Active	<0.001
McConnell AFB	Kansas	Air Force Active	<0.001
MTC-H Camp Grayling	Michigan	Army Guard	<0.001
Shaw AFB	South Carolina	Air Force Active	<0.001
Laughlin AFB	Texas	Air Force Active	<0.001
Rock Island Arsenal	Illinois	Army Active	<0.001
Camp Navajo	Arizona	Army Guard	<0.001
NB Coronado Silver Strand	California	Navy Active	<0.001
NOLF Evergreen	Alabama	Navy Active	<0.001
Dobbins ARB	Georgia	Air Force Reserve	<0.001
Fort George G Meade	Maryland	Army Active	<0.001
MCB Camp Lejeune	North Carolina	Marine Crops Active	<0.001
NG MTA Camp Fretterd	Maryland	Army Guard	<0.001
Canyon Lake Recreation Annex	Texas	Air Force Active	<0.001
CTC Fort Custer Trng Center	Michigan	Army Guard	<0.001
Hawthorne Army Depot	Nevada	Army Active	<0.001
MCRD Beaufort Parris Island	South Carolina	Marine Crops Active	<0.001
NWS Seal Beach Fallbrook California	California	Navy Active	<0.001
Fort Belvoir	Virginia	Army Active	<0.001
McEntire Joint NGB	South Carolina	Air Force Guard	<0.001
NWS Charleston Short Stay	South Carolina	Air Force Active	<0.001
Thunderbird Youth Academy	Oklahoma	Army Guard	<0.001
Camp Minden TS	Louisiana	Army Guard	<0.001
MCAS Miramar	California	Marine Crops Active	<0.001
Naval Academy North Severn	Maryland	Navy Active	<0.001
NG Beauregard Training Range	Louisiana	Army Guard	<0.001
Orchard Range TS Boise	Idaho	Army Guard	<0.001
US Army Soldier Systems Center Natick	Massachusetts	Army Active	<0.001
NG Camp Mabry	Texas	Army Guard	<0.001
Whiteman AFB	Missouri	Air Force Active	<0.001
Ellsworth AFB Site 1	South Dakota	Air Force Active	<0.001
Bonito Lake System Annex	New Mexico	Air Force Active	<0.001
Letterkenny Army Depot	Pennsylvania	Army Active	<0.001
Minot AFB	North Dakota	Air Force Active	<0.001
Randolph AFB	Texas	Air Force Active	<0.001

Table D11. DoD installation (Site) rankings for Virginia rail (VIRA). Only sites with non-zero amounts of optimal habitat are presented, and scaled-area represents the fraction of total optimal habitat for this species that occurred at a given site. Branch represents the military branch associated with each DoD installation.

Site	State	Branch	Scaled-area
Edwards AFB	California	Air Force Active	0.377
Nellis Air Force Range	Nevada	Air Force Active	0.341
Twentynine Palms Main Base	California	Marine Corps Active	0.059
NAWS China Lake	California	Navy Active	0.059
NTC and Fort Irwin	California	Army Active	0.054
Sierra Army Depot	California	Army Active	0.029
NAS Fallon Target B-20	Nevada	Navy Active	0.028

NAS Fallon Target B-17	Nevada	Navy Active	0.022
NAS Fallon Target B-16	Nevada	Navy Active	0.006
NAWS China LakeRandsburg Wash Area	California	Navy Active	0.005
White Sands Missile Range	New Mexico	Army Active	0.004
Minot AFB	North Dakota	Air Force Active	0.003
Sewage Evaporation Pon	California	Navy Active	0.002
Fort Hunter Liggett	California	Army Reserve	0.002
JNTEXPBASE Little Creek FS VA	Virginia	Navy Active	0.002
NS Mayport	Florida	Navy Active	0.001
UTTR - North	Utah	Air Force Active	0.001
Camp Grafton	North Dakota	Army Guard	0.001
Cape Canaveral AFS	Florida	Air Force Active	0.001
Offutt AFB	Nebraska	Air Force Active	0.001
Dover AFB	Deleware	Air Force Active	< 0.001
NAVSUBASE Kings Bay	Georgia	Navy Active	< 0.001
Camp Perry Joint Training Center	Ohio	Army Guard	< 0.001
Tyndall AFB	Florida	Air Force Active	< 0.001
MCSF Blount Island	Florida	Marine Corps Active	< 0.001
Fort Lewis	Washington	Army Active	< 0.001
Camp Dodge Johnston TS	Iowa	Army Guard	< 0.001
Fort Carson	Colorado	Army Active	< 0.001
NAVBASE Ventura City Point Mugu	California	Navy Active	< 0.001
Craney Island	Virginia	Navy Active	< 0.001
MCB Camp Pendleton	North Carolina	Marine Corps Active	< 0.001
Long Beach Fuel Complex	California	Navy Active	< 0.001
ALF Waldron	Texas	Navy Active	< 0.001