*Joint breeding and migratory season species distribution models better facilitate habitat conservation for a short distance migratory bird*

Target: Journal of Applied Ecology

**Introduction**

Species distribution models are frequently used to convert data about species occurrence and habitat associations into tools to assist conservation decision-making (Miller 2010). However, species distribution models are known to have issues with spatial transferability, where species distribution models may not be reflective of animal distributions in other parts of their range (spatial transferability; Randin et al. 2006), or for predicting species distributions into the future (temporal transferability; Dobrowski et al. 2011). We posit that an additional subcategory of temporal transferability exists, called cross-seasonal transferability, for species which have differing habitat use between seasons or life stages. Wildlife science has a long history of bias towards studying animals during the breeding season, which neglects the value of non-breeding habitat for survival and carry-over effects into the breeding season (Marra paper tk). By building species distribution models which focus solely on the breeding season, and neglect habitat which may be important in the non-breeding season and in early life stages, we underestimate critical facets of these animal’s habitats and have the potential to overestimate the range of potential habitat for some species.

Migratory birds are potentially vulnerable to issues of cross-seasonal transferability, as they use different geographic areas throughout their annual cycle that can be coarsely divided into breeding, wintering, and migratory seasons (Marra et al. 2015). Resource requirements frequently differ among these three seasons, which frequently results in birds using fundamentally different types of habitat in each season (Allen et al. 2020, Stanley et al. 2021). Despite differences in habitat, there are circumstances in which breeding, wintering, and migratory habitat may occur in the same region, especially for short-distance migrants (ex. American woodcock, Figure 1). This would necessitate creating separate distribution models for each overlaping season, and approaches to incorporate multiple models into the management decision process.

Spatial decision support systems (SDSS) may provide a useful mechanism to combine distribution models from multiple seasons of the full annual cycle during the decision-making process. SDSS utilize user-friendly, interactive toolsets to guide users through making a set of spatial prioritization decisions. SDSS frequently come as extensions of existing geographic information systems such as ArcMap (McConnell & Burger 2011), but the learning curve and costs associated with professional geographic information systems can often be an impediment to reaching the intended user base (Harper 2006). The widespread adoption of interactive online mapping tools, such as the leaflet javascript library and ArcGIS Online, has greatly expanded custom built SDSS that are accessible via a web browser and can be easily used by decision makers with little additional training (Sugumaran & Sugumaran 2007).

SDSS provide an interface which allows users to interact with multiple spatial data layers, such as species distribution models. In circumstances where species distribution models have low cross-seasonal transferability, SDSS can also be used to compensate by incorporating multiple season-specific species distribution models into the decision-making process. An SDSS approach might allow for species distribution models from different seasons to be combined into a single predictive layer using user-specified weights. For example, a user might want to primarily conserve breeding habitat for a species and conserve migratory habitat as a secondary objective. Using an SDSS, the user could weight a breeding season species distribution model to 70% and a migratory season species distribution model to 30% and output a single predictive habitat layer that prioritized management areas according to the user’s seasonal management objectives.

Here we demonstrate a SDSS framework for users to spatially prioritize land conservation while accommodating the cross-seasonal transferability necessary to capture multiple seasons of a migratory bird’s full annual cycle. Our case study is focused on American woodcock (*Scolopax minor*;hereinafter woodcock) in the state of Pennsylvania, USA. Woodcock are short distance migrants with extensive overlap among migratory, breeding, and wintering ranges (Fig. 1), and fundamentally different habitat requirements among seasons (Myatt and Krementz 2007, Allen et al. 2020). Pennsylvania provides breeding habitat for an estimated 2.3% of the global woodcock population (52,400 birds), but it potentially provides migratory stopover habitat for a much larger proportion of woodcock that breed throughout the northeastern United States and eastern Canada (30.5%, 684,500 birds; Kelley et al. 2008). Therefore, managing for woodcock habitat in both the breeding and migratory stages have been identified as priorities by the Pennsylvania Game Commission, and our goal was to develop a SSDS tool to aid managers considering trade-offs between those priorities. We used a multi-season habitat modeling framework to predict the distribution of migratory and breeding habitats, which we combine in a SSDS for habitat prioritization. By identifying areas that might meet joint objectives to conserve habitat during multiple seasons, users could improve full annual cycle conservation and more efficiently allocate management resources.



Figure 1. Seasonal ranges and hypothetical migration routes of American woodcock. Seasonal ranges were delineated by eBird’s Status and Trends project (Fink et al. 2022) using citizen science data. Migration routes illustrate potential connections between eastern (dashed line), central (solid line), and western (dotted line) population segments. Migration routes were originally proposed by Glasgow (1958) and were later reproduced by Moore et al. (2019). Inset illustrates multiple migration routes intersecting with the breeding range in the state of Pennsylvania.

**Methods**

*Breeding season species distribution model*

We modelled distribution of woodcock habitat during the breeding season (March–May) using survey data collected as part of the federally-coordinated American Woodcock Singing Ground Survey (Seamans and Rau 2020) and through additional state-level monitoring conducted by the Pennsylvania Game Commission. Surveys consisted of 5.76 km routes with 10 evenly spaced points, where observers listened for woodcock calls during their crepuscular breeding display. Presence was determined at each point based on whether male displays were recorded during 2-minute intervals shortly after dusk. Singing Ground Survey routes were randomly distributed (Clark 1970), while Pennsylvania surveys were located purposefully near state gamelands or in areas where managers believe woodcock occupancy was likely. We used survey data collected from 2016–2020, and distilled records to presence or likely absence based on detection of at least one male during the 5-year period.

We selected explanatory variables with presumed relevance to woodcock habitat associations, with suites of variables including land use/land cover, forest successional class, topography, region, and soil moisture (Table A1). We additionally calculated landscape metrics from the landscapemetrics package (Hesselbarth et al. 2019) in program R (R Core Team 2022), which represented landscape composition and configuration. To generate composition metrics, we resampled the National Land Cover Dataset to a 90m resolution, and then calculated the percent of each cover type within a 500m, 1km, 5km, and 10km radius for each pixel. For configuration metrics, we used the National Land Cover Dataset to create a binary forest/non-forest layer which we resampled to a 90m resolution, and then calculated the appropriate configuration metric within a 500m, 1km, 5km, and 10km radius of each pixel

Table A1. Explanatory variables used in the modeling of woodcock distributions in Pennsylvania, USA. Suites indicate conceptual grouping of variables into classes relevant to woodcock occupancy.

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| --- | --- | --- |
| **Suite** | **Covariate** | **Source** |
| Land use/land cover | Land use/land cover | National Land Cover Dataset (Jin et al. 2019) |
| Forest successional class | Forest successional class | LANDFIRE (USGS and USDA 2020) |
| Topography | Elevation | USGS 2000 |
| Slope | Derived from elevation |
| Region | EPA level 3 ecoregions | Omernik and Griffith 2014 |
| Soil moisture | Soil drainage | Web soil survey (NRCS 2021) |
| Topographic wetness index | Derived from elevation using Fink (2013) |
| Landscape composition  (0.5, 1, 5, and 10km scales) | % Forest | Derived from National Land Cover Dataset using landscapemetrics (Hesselbarth et al. 2019) |
| % Agricultural |
| % Developed |
| Landscape configuration  (0.5, 1, 5, and 10km scales) | Aggregation index | Derived from National Land Cover Dataset using landscapemetrics (Hesselbarth et al. 2019) |
| Cohesion |
| Edge density |

We evaluated several modeling techniques fit to a smaller subset of woodcock occurrence data using MaxEnt (Phillips et al. 2006), random forest classification (Breiman 2001), classification and regression trees (Brieman et al. 1984), and neural networks (Hopfield 1982). All models were fit using the R package SDMtune (Vignali et al. 2020). We compared model outputs using area-under-the-curve (AUC), a common metric of predictive accuracy for classification models. After finding that the random forest classifier had the highest AUC, we used random forest techniques for all subsequent models.

For the breeding season model, we used a random forest classifier designed for clustered data (Wang and Chen 2016), using survey route id as a clustering variable to compensate for spatial autocorrelation among points on the same survey route. We also included survey type (state vs federal) as an explanatory variable to account for the non-random distribution of state survey routes. We assessed the accuracy of our random forest models using a k-fold cross validation approach with 10 folds, using 90% of the data in each fold as a training dataset and the remaining 10% as a testing dataset. We averaged AUCs for each of the 10 folds to produce a mean AUC and created a predictive layers that averaged each of the 10-fold layers together for each model. To avoid overwhelming the model with highly correlated variables, we selected a final model for each analysis using a three-step backwards variable-selection approach (Genuer et al. 2019), where each step produced a more parsimonious model. The first step eliminated variables which had a variable importance value below a threshold value determined based on the guidelines provided in Genuer et al. (2015), removing variables that were irrelevant to the model. The second step retained only the variables in the analysis which led to the smallest out-of-bag error rates when training the model, effectively eliminating variables which had some relevance but were not critical for prediction. The third step used an incremental process to adding variables to a model, only including a variable if doing so would lead to an appreciable increase in the model’s out-of-bag error. This effectively removed redundant variables from consideration (Genuer et al. 2015). As past studies have found that the removal of unimportant

While this process was designed to allow for clearer interpretation of variable importance in random forest modeling, we found that the exclusion of unimportant variables substantially increased the predictive accuracy of our breeding season model. Therefore, we

eliminated variables with little importance to prediction, the second step removed variables with some relevance but not critical for prediction, and the third step eliminated variables that were redundant. We calculated AUC metrics to determine which step produced the most predictive model and used that model to create a final predictive .

*Migratory season species distribution model*

We identified woodcock migratory stopover sites throughout Pennsylvania using GPS-tracking data from the Eastern Woodcock Migration Research Cooperative, a collaboration of 42 federal, state, provincial, non-profit, and university partners throughout the United States and Canada (www.woodcockmigration.org). Woodcock were captured at 34 sites in Quebec, Ontario, Nova Scotia, Maine, Vermont, New York, Rhode Island, Pennsylvania, Maryland, West Virginia, Virginia, North Carolina, South Carolina, Georgia, Alabama, and Florida using mist nets during morning and evening flights (Sheldon 1960), and on night roosts using spotlights and dip nets (Rieffenberger and Kletzly 1966, McAuley et al. 1993). We attached 4g, 5g, and 6.3g PinPoint GPS Argos transmitters (Lotek Wireless Inc., Newmarket, Ontario, CA) to captured woodcock. Transmitters recorded locations at 12–60m accuracy and were programmed to record locations every 1–3 days at 0900 or 1500 Eastern Time, outside of the woodcock’s nocturnal migration period. Transmitters, bands, and attachment materials never exceeded 4% of a bird’s body weight, and all capture and handling were conducted with methods approved by the University of Maine Institutional Animal Care and Use Committee (Protocol # A2020-07-01).

We filtered woodcock location data to select migratory locations, which we delineated based on the first and last movements made by each bird that were > 16.1 km. Because woodcock migrate at night, we considered all diurnal locations between migratory initiation and termination to be stopovers. Consecutive locations from the same individual within 3 km of each other were considered the same stopover, so we selected one location randomly, and removed the remainder from the analysis to reduce pseudoreplication and spatial autocorrelation of closely clustered locations.

We combined woodcock stopover locations with 10,000 locations randomly distributed throughout Pennsylvania, which we considered pseudoabsence locations. We used similar methods as the breeding season model to build the migratory model. As survey route groupings were not necessary for the migratory model, we replaced the mixed random forest model structure used in the breeding season model with a traditional random forest classification model, written using the randomForest package in R (Liaw & Wiener 2002). We used the same backwards variable selection approach as we used in the breeding season model to select the explanatory variables, and generated AUC values and a final predictive layer using the methods described above.

*Analysis of covariate relationships*

Our intent was to predict woodcock habitat distribution, and not to establish woodcock-habitat associations per se. However, …tk. To determine the relationships between each covariates and the predictive layers, we sampled covariate values and predicted migratory and breeding season suitability at 10,000 randomly distributed points throughout Pennsylvania. We then used hex plots to visually identify trends between covariates and predictive layers. We used the same 10,000 points to create a figure illustrating the differences in distribution of breeding and migratory habitat by ecoregion, to identify ecoregions which would be best suited for breeding or migratory habitat management.

*Decision support tool*

To facilitate user choice in the importance of migratory and breeding season habitat to local management, we created a decision making tool in the Shiny ecosystem (Chang et al. 2021) that allows users to assign weights to each seasonal layer in 10% increments (ex. 20% migratory and 80% breeding season), and combine them into a single multi-season layer (Fig. 2). The weighting was conducted on a pixel-by-pixel basis

where *pw* indicates the value of the weighted pixel value, *wm* the weight of importance for migratory habitat, *wb* the breeding season weight, *pm* the migratory pixel value, and *pb* the breeding season pixel value. *pw* therefor provides a simple weighted average based on user-defined weightings for each season.

Because our application targeted users in the Pennsylvania Game Commission, the application also shows the comparative suitability of Pennsylvania state game lands for each weighted layer. We used four metrics for comparing the habitat suitability of game lands: average pixel value, total habitat, % high quality, and % medium quality. Each of these metrics had relative strengths and weaknesses. Average pixel value, or the mean of all pixels within a state gameland, tended to favor small gamelands that were predominantly composed of woodcock habitat. Total habitat was average pixel value multiplied by the acreage of the gameland, which favored larger gamelands that might not be entirely composed of woodcock habitat but might contain a large amount of woodcock habitat in aggregate by virtue of their size. Percent high quality habitat was the percentage of cells within a gameland greater than the 33rd percentile of all pixels in the state, and percent medium quality was the percentage of cells falling between the 66th and 33rd percentile. These two percentile-based metrics allowed for …tk.

Both the average pixel value and total habitat metrics display some bias based on gameland size, with average pixel value favoring small gamelands and total habitat favoring large gamelands. We intend for these metrics to be useful in different management situations. For example, if a user is curious about which gamelands would have the total highest impact if they were managed for woodcock, they would use landscape suitability index. However, if the user was interested in where a small amount of habitat management might have the largest returns for woodcock management, they would choose average pixel value instead. We recommended that users use average pixel value and landscape suitability index in coordination with the last two metrics, percent high quality and percent medium quality, when estimating the proportion of each gameland suitable for woodcock management. By multiplying the percent of the gameland that is high or medium quality by gameland acreage (also supplied by the tool), the user can extract the total number of acres on each gameland that could be managed for woodcock effectively.

The decision support tool also included several features to facilitate effective use of the application. The tool redirects all users to a landing page on opening the application, which displays information on how the tool was created and its intended use. It also warns users that the spatial scale of the application is not suitable for micro-scale habitat management, as both the breeding and migratory season distribution models were built using landscape metrics that were calculated at multi-kilometer scales. We included a detailed manual on how to use the application, and a recording of a workshop for Pennsylvania Game Commission employees, to ensure that the uses of this decision support tool fit the assumptions that were made when making the component species distribution models. This layer is publicly accessible at www.woodcock.shinyapps.io/W-PAST.

A picture containing application

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Figure 2. Conceptual diagram of the decisions users can make in the Woodcock Priority Area Siting Tool (W-PAST). Users can choose the weighting of migratory and breeding season habitat based on management priorities. The resulting weights are used to generate the statewide predictive layer and gameland prioritization metrics, which allow the user to compare the suitability of gamelands for woodcock management.

**Results**

We deployed transmitters on 463 woodcock from fall 2017 to spring 2021, with 82 individuals recording a total of 113 GPS locations at migratory stopovers in Pennsylvania. Breeding season survey data were available for 770 locations along 77 American Woodcock Singing Ground Survey routes and 800 locations along 80 Pennsylvania Game Commission survey routes. The most predictive (AUC = 0.83) breeding season model was the most constrained model, for which all unpredictive and autocorrelated variables were removed. This model was heavily informed by landscape variables at 5 and 10 km scales (Table 1). No variables at the finest landscape scale (0.5km), or in the suite of moisture variables, were included in the most informative model. Tk Graphs of habitat suitability for each covariate showed strong, non-linear relationships with several of the most informative variables (Fig. 3). Suitability was highest for landscapes with 0–25% developed land area, 0–50% agricultural land area, and aggregation index values of 80–100, all at the 10km scale. At the 5km scale, the breeding season model also showed high suitability in landscapes with 30–100% forest cover (Fig. 3).

The most predictive (AUC=0.78) migratory model was the full model, including all landscape, land cover, geographic, and moisture covariates (Table 1). Likely due to the wide array of covariates influencing the model, individual covariate graphs do not show clear visual patterns between migratory habitat suitability and any one covariate. However, the migratory model illustrated greater tolerance of migrant woodcock for developed and dis-aggregated landscapes at a 10km scale than the breeding season model (Fig. 3). The two models were also distinguished by the scale at which covariates influenced habitat suitability. While the most informative breeding season model was not influenced by any landscape covariates at the 500m scale, and only 1 landscape covariate at the 1km scale, the most informative migratory model included all available small-scale landscape covariates. This caused the migratory model to provide predictions at a finer spatial scale than the breeding season species distribution map (Fig. 4).

Breeding season habitat was not evenly distributed among ecoregions (Fig. 5), with mean habitat suitability values ranging from 22.9 – 86.0%. Migratory habitat was more evenly distributed, with mean habitat suitability values ranging from 46.5 – 87.5%. Most of the difference between the distribution of migratory and breeding season habitat was in the Northern Piedmont, Middle Atlantic Coastal Plain, and Central Appalachians ecoregions, which had mean breeding season habitat suitability values of < 30% and mean migratory season habitat suitability values of >60%.

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| --- | --- | --- |
| Suite | Migratory | Breeding |
| Landscape (500m) | Aggregation Index, Cohesion, Edge Density, % Forest, % Agricultural, % Developed |  |
| Landscape (1km) | Aggregation Index, Cohesion, Edge Density, % Forest, % Agricultural, % Developed | % Agricultural |
| Landscape (5km) | Aggregation Index, Cohesion, Edge Density, % Forest, % Agricultural, % Developed | Cohesion, % Forest, % Agricultural, % Developed |
| Landscape (10km) | Aggregation Index, Cohesion, Edge Density, % Forest, % Agricultural, % Developed | Aggregation Index, Cohesion, % Agricultural, % Developed |
| Land Cover | Forest, Successional Class |  |
| Geography | Elevation, Slope, Ecoregions | Elevation, Ecoregions |
| Moisture | Drainage, Topographic Wetness Index |  |

Table 1. Variables selected via backwards variable selection in VSURF for the migratory and breeding season models. The migratory model employs the full set of variables, while the breeding season model uses a subset of variables inclined towards coarse resolution landscape variables.

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Figure 3. Comparison of relationships between landscape variables and habitat suitability for migratory and breeding season models. During the breeding season, woodcock habitat suitability is highest in highly aggregated landscapes with ~75% forest and ~25% agricultural cover. During the migratory season, however, woodcock become far more tolerant of landscapes that are unsuitable during the breeding season, including landscapes with higher proportions of developed cover.



Figure 4. Breeding and migratory layers suggest that woodcock select habitat at different scales in different seasons. This also shows that certain areas which are not productive for breeding season habitat management, such as southeastern Pennsylvania, may be productive for migratory habitat management.



Figure 5. Migratory and breeding season habitat suitability for woodcock by EPA level 3 ecoregion in Pennsylvania (Omernik and Griffith 2014). Three ecoregions, Northern Piedmont, Middle Atlantic Coastal Plain, and Eastern Great Lakes Lowlands, had mean breeding season habitat suitability values of < 30% and mean migratory season habitat suitability values of >60%.

**Discussion**

Our goal was to demonstrate integration of multiple spatial distribution models into a single decision support tool. For our case study, we show that American woodcock occur in distinctly different habitat during the breeding and migratory stages in Pennsylvania. A planning approach using only breeding habitat would have overlooked stopover habitat for woodcock in southeastern Pennsylvania, where there is little breeding habitat but considerable migratory traffic. By including information about both seasons, with the ability to customize seasonal weights, users can decide the extent to which they prioritize each habitat for management, and determine which sites are best suited for management based on that prioritization.

We found that woodcock select habitat at radically different scales between seasons, demonstrating that migratory bird management across multiple seasons is also likely to need to be multi-scalar. The two models produced predictive layers with very different spatial resolutions, largely due to the role of different covariate relationships during each of the two seasons. During the breeding season, woodcock habitat suitability is dependent primarily on variables at 5 and 10 km scales, while during the migratory period habitat suitability was additionally dependent on covariates at 500m and 1 km scales. This pattern supports past observations that migratory birds select habitat at a finer scale during the migratory season (Stanley et al. 2021). Due to these differences in the scale at which migratory birds select for habitat, managers may need to adjust the scale of their management to match the scale of the season of interest. For example, woodcock management for breeding season habitat in Pennsylvania might focus on conserving broad swaths of habitat on large public lands, such as Pennsylvania state gamelands. As the predictive layer is fairly uniform across even large state gamelands, performing habitat management at that scale would likely be effective. However, the migratory model had a much finer spatial resolution, and was much more prone to having small pockets of habitat in areas not traditionally targeted by wildlife management agencies, such as urban areas. Habitat management targeting migratory habitat would likely want to match this spatial scale, focusing on the preservation of greenspaces that might be too small to be managed for breeding season habitat. By acknowledging that the spatial scale of selection changes between seasons, we can tailor our migratory bird management to the appropriate scale to ensure that our conservation efforts are the most successful.

Multi-season distribution modeling may also highlight areas that are not traditionally managed for wildlife habitat. Woodcock were more tolerant of developed land cover during the migratory season than the breeding season, and the migratory season model predicted use of highly developed areas such as suburban Philadelphia and Pittsburg. This corresponds with findings of Buler and Dawson (2014), who found that migratory birds heavily used urban greenspaces during stopover, presumably due to attraction to high levels of artificial light at night (McLaren et al. 2018) and lack of other stopover options. One implication is that, in addition to management for woodcock at smaller spatial scales, we may need to consider management of urban greenspaces for migratory birds. One opportunity for urban habitat conservation might be through partnerships with public and private landowners, such as urban parks and utilities, to conserve migratory habitat in urban greenspaces. Another opportunity for urban habitat conservation might be the Urban National Wildlife Refuge program, which has dual roles in preserving wildlife habitat and expanding access to natural areas for historically excluded communities. Pennsylvania is host to one Urban National Wildlife Refuge, John Heinz National Wildlife Refuge at Tinicum, located in the Philadelphia suburbs. The refuge is modeled as having high migratory habitat suitability for woodcock, demonstrating how urban wildlife refuges may provide crucial migratory stopover habitat in heavily urbanized areas.

The regional differences between the breeding and migratory models underscore the importance of multi-season distribution models in delineating regional priorities for migratory bird management. For the woodcock model, we found low breeding season suitability of the Northern Piedmont, Middle Atlantic Coastal Plain, and the Eastern Great Lakes Lowlands ecoregions, despite high migratory suitability. This is one example of a circumstance in which a user-weighted prioritization of seasonal habitat might be particularly effective. Managers in regions in which woodcock breeding habitat is scarce might instead decide to prioritize migratory habitat management, for example, allowing managers to play to their regions’ strengths. On the other hand, a manager of an area that provides breeding habitat in a region where breeding habitat is scarce might decide that their most effective move would be to prioritize breeding habitat as much as possible. The common thread here is that there might be several effective management strategies based on the information provided in seasonal distribution models. By providing these models as a part of a decision support tool, where the user can actively choose the relative weight of each model, we empower the user to consider multiple possible management decisions and customize the information provided to inform their management strategy.

We believe that this decision support tool framework, encompassing multiple seasonal distribution models, is particularly well suited to migratory bird management due to its flexibility in application of multiple data sources. One of the benefits of this type of analysis is that the breeding and migratory seasons can easily use separate data streams, which is particularly useful for species that are studied using separate techniques and surveys during each season. While there are several surveys for examining bird distribution during the breeding and wintering seasons, including the Breeding Bird Survey and Project Feederwatch (Robbins et al. 1986, Bonter and Greig 2021), examining bird habitat use during the migratory period continues to be a challenge. Individually-marked birds with GPS transmitters are the gold standard for this type of analysis, as stopover locations can be separated from breeding and wintering locations for each tagged bird. However, GPS transmitters are still too large to attach to many migratory passerines, and the low number of stopovers attained per individual (mean = 1.4, sd = 0.6 in this study) combined with the considerable price of these transmitters may make attaining a large sample size a financial difficulty for most study species. The use of citizen science data collected during migration, such as the eBird data collection platform (Sullivan et al. 2009), may provide a more generalizable way to collect migratory stopover location data, but certain assumptions may have to be made to distinguish true migratory locations from early breeding/wintering season arrivals. Decisions on seasonal management priorities should also be informed by other data sources, such as full annual cycle survival models to determine whether breeding or migratory habitat has a greater role in limiting survival, and migratory corridor models to identify high densities of migrants (Cohen et al. 2022). With this added context, decision support tools incorporating multi-season habitat suitability models provide valuable support for the management of many migratory bird species.

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