**Appendix 1. Pilot evaluation of species distribution modeling frameworks.**

We conducted a pilot evaluation of several potential modeling techniques to determine which would be best suited for species distribution modeling using these datasets. We conducted this evaluation (and all subsequent modeling) separately for breeding and migratory seasons, using the full set of covariates available at all spatial scales as predictors. All breeding season pilot models used the same set of woodcock survey data as presence and absence locations, while all migratory season pilot models used the same set of woodcock GPS points as presence locations and randomly-generated points as pseudoabsence locations.

We produced pilot models using MaxEnt (Phillips et al., 2006), random forest classification (Breiman, 2001), and boosted regression trees (Elith et al., 2008), fit using the package *SDMtune* for the statistical software R (Vignali et al., 2020, cite R tk). These models were fit using k-fold cross validation with 5 folds. For the breeding season model, we withheld 1/5th of the presence and absence data from each of 5 training folds and used the withheld data as testing folds to evaluate the model. As the migratory season dataset is effectively presence-only, we followed the presence-only k-fold technique implemented by Vignali et al. (2020), which creates random folds only for presence locations and uses the full set of pseudoabsence locations in each testing and training fold. The hyperparameters which we set for each these models are outlined in Table A1.

Table A1. Caption tk. Talk about where these defaults come from (the source packages, not just SDMTune).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Maxent** | | **Random forest** | | **Boosted regression trees** | |
| *Hyperparameter* | *Value* | *Hyperparameter* | *Value* | *Hyperparameter* | *Value* |
| Iterations | 500 | Number of trees | 2000 | Number of trees | 100 |
| Feature classes | linear, quadratic, product, hinge | Number of variables sampled at each split | 5 | Fraction of data used in tree expansion | 0.5 |
| Regularization multiplier | 1 | Minimum size of terminal nodes | 1 | Maximum depth of each tree | 1 |
|  |  |  |  | Shrinkage | 0.1 |

We compared model effectiveness using area-under-the-curve (AUC) and true skill statistic (TSS; Fielding and Bell, 1997, cite TSS paper tk). The Maxent model did not converge when applied to the breeding season data, and so AUC and TSS were not calculated for that model. When applied to the migratory dataset, the random forest model had higher AUC and TSS than Maxent or boosted regression trees (Table A2). Applied to the breeding dataset, random forest and boosted regression trees resulted in similar AUC and TSS. Based on these results, we elected to use random forest techniques for all subsequent models.

Table A2. Caption tk.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | **Maxent** | **Random forest** | **Boosted regression trees** |
| Breeding season | *AUC* | NA1 | 0.787 | 0.771 |
| *TSS* | NA1 | 0.545 | 0.548 |
| Migratory season | *AUC* | 0.617 | 0.846 | 0.628 |
| *TSS* | 0.261 | 0.586 | 0.286 |

1 The Maxent model for the breeding season did not converge after the maximum number of iterations (100,000), and therefore AUC and TSS were not calculated.

**Appendix 2. Design of W-PAST**

We created a Shiny application (Chang et al., 2022) named the Woodcock Priority Area Siting Tool (W-PAST), to facilitate local woodcock management planning. While the application was built around the breeding and migratory season layers which we derived separately, a major feature of the application was the ability to merge these layers into blended predictive layers, which would allow managers to make management decisions based on both layers simultaneously. The application allowed users to assign weights to each seasonal habitat suitability layer in 10% increments (*e.g.,* 70% breeding and 30% migratory), and then combined seasonal predictions into a single multi-season layer (Fig. A1). The weighting was conducted on a pixel-by-pixel basis as a simple weighted average 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.

In addition to blended predictive layers, W-PAST included a suite of derived prioritization metrics intended to allow the Pennsylvania Game Commission to compare habitat suitability among state-managed gamelands. We built four comparison metrics into the application that were calculated using the weighted averages of the breeding and migratory season predictive layers: average pixel value, total habitat, % high quality, and % medium quality. Average pixel value was the arithmetic mean of all pixels within a state gameland, which tended to favor small gamelands predominantly composed of woodcock habitat and was intended to demonstrate where a small amount of habitat management could increase local woodcock populations. Total habitat was average pixel value multiplied by the acreage of the gameland, which favored larger gamelands that contained relatively large amounts of woodcock habitat in aggregate by virtue of their size. Total habitat could be used to determine which gamelands would provide the most habitat in aggregate if they were managed for woodcock. Percent high quality habitat was the percentage of cells within a gameland that had values greater than the 33rd percentile of all pixel values in the state, and percent medium quality was the percentage of cells falling between the 66th and 33rd percentile. These percentile-based metrics allowed users to quantify the proportion of a gameland which might be suitable for woodcock management. By multiplying the percent high or medium quality by the gameland acreage (also provided in the tool), the user could also derive the acreage in each gameland that could be managed for woodcock effectively. Further instructions for using these metrics in management are included in a user manual, publicly available with the SDSS at <https://woodcock.shinyapps.io/W-PAST2/>.

A diagram of different layers of land

AI-generated content may be incorrect.

Figure A1. Conceptual diagram of user decision options in the Woodcock Priority Area Siting Tool (W-PAST). Users can choose the weighting of migratory and breeding season habitat at 10% increments based on management priorities. The resulting weights are used to generate a blended predictive layer and derived prioritization metrics, which allow the user to compare the suitability of gamelands for woodcock management.

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