Modeling the Spatiotemporal Influence of Climate on American Avian Migration

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Abstract

North and South American Birds have adapted to climatic and ecological patterns to inform their Spring and Fall migration timings. Temperature and precipitation patterns are shifting under anthropogenic climate change, which has downstream effects on for instance plant flowering cycles, insect populations, and habitat availability. Understanding how these cues trigger migration could improve the effectiveness and timing of bird surveys, as well as informing habitat protection and creation efforts to lessen biodiversity loss due to climate change. In this work, we train an ensemble of random forest regressors on subsets of North and South American climate data to predict distributions of historical eBird occurrence probability for passerine bird species in a North American forested region using eBird citizen science surveys from 2008-2018. By running these ensembles with lagged climate data, we study spatiotemporal effects on bird migration through the resulting error and feature importance metrics. We find statistically significant decreases in error when using lagged climate features rather than the same-month climate to predict species communities in October, when many passerines have begun their southward winter migration, with longer temporal effects for precipitation than temperature. North American climate features were more important than South American features for prediction of species communities in Fall months, suggesting the

model drew upon regional climatic cues for predicting when species would migrate southward. By predicting species occurrence using 2021-2040 climate projections, we predict that projected species occurrence probabilities will increase in April and May, agreeing with existing literature suggesting earlier Spring arrival of migratory birds. These results demonstrate that machine learning models have the potential to elucidate complex relationships between climate and bird behavior that linear models may miss. A deeper understanding of such spatiotemporal effects will be required to support biodiversity protection through climate change.

Introduction

Across the globe, birds undertake Spring migrations to breeding grounds and Fall migrations to winter in warmer climates. In the Western Hemisphere specifically, many bird species migrate northward from their winter homes in the Southeastern USA, the Caribbean, Mexico, and Central America to breeding grounds in the Northern forests of Canada and the United States each Spring, then again southward in the Fall (Jahn, Levey and Smith, 2004; Faaborg *et al.*, 2010). Bird species rely on climatic and ecological conditions such as temperature, pressure, precipitation, and food availability to trigger the timings of their migrations (Sutherland, 1998; Lemoine, Schaefer and Böhning-Gaese, 2007; Visser *et al.*, 2010; Koleček, Adamík and Reif, 2020) in addition to their endogenous rhythms (Marra *et al.*, 2005; Miller-Rushing *et al.*, 2008; Åkesson and Helm, 2020). However, these climatic and ecological triggers are shifting with climate change. In North America, these are projected to be characterized by warming of northern breeding regions, increased rainfall during Spring migration, and less rainfall in southern regions during non-breeding season (La Sorte *et al.*, 2017).

The broad effects of climate change on migrations have already been demonstrated: shifts to earlier Spring first arrival dates (Butler, 2003; Marra *et al.*, 2005; Mills, 2005; Faaborg *et al.*,

2010; Koleček, Adamík and Reif, 2020), smaller and more dispersed migratory cohorts (Miller-Rushing *et al.*, 2008), and a northward shifts in breeding grounds (La Sorte and Thompson, 2007). Bird species will have to adapt behavioral patterns more quickly to these habitat and climatic changes than has been done before anthropogenic climate change began (Faaborg *et al.*, 2010). However, the sensitivities to environmental and ecological cues have been genetically shaped by natural selection to correctly time behaviors such as egg laying to the availability of food, and species often over- or under-correct their timings (Visser, Holleman and Gienapp, 2006; Visser *et al.*, 2010). Understanding the fine details of these shifts in behavior is key to conserving biodiversity through the era of climate change. For example, the optimal times and places to conduct bird surveys may shift. Additionally, understanding the climatic and ecological factors underlying changing bird migration behavior could support habitat protection and creation.

Many studies have explored relationships between migration timings and climatic features through linear-based models. For example, linking warmer Spring temperatures in the Northeastern USA to earlier arrivals (Marra *et al.*, 2005; Miller-Rushing *et al.*, 2008), or demonstrating effects of local weather on autumn migration timing and stopovers (Shipley, Kelly and Frick, 2018; Haest *et al.*, 2019). The literature demonstrates clearly that changes in bird migratory behavior are correlated with, and to some degree explained by, the changing climate. Still, many of these papers show trends from post-hoc analyses and do not directly use climatic features to predict how migratory patterns may change. With machine learning methods such as random forests, non-linear and complex trends in ecological data can be leveraged (Cutler *et al.*, 2007; Hunt *et al.*, 2022) to elucidate historical trends and make predictions of future behavior. Random forest models are high-performing, efficient to train compared to neural networks under limited data, have built-in feature importance metrics, and have been

successfully applied in ecological settings to relate climate and ecological features to biodiversity (Martín *et al.*, 2020; Hunt *et al.*, 2022).

Here, we seek to build upon the existing literature with a predictive modeling approach for species occurrence and migration patterns. Specifically, we use a random forest multi-regression to predict eBird ('eBird Basic Dataset', 2022) checklist occurrences of common migrating passerine species in a large North American forested region, using monthly averages of climate features (maximum temperature, minimum temperature, and precipitation) across North, Central, and South America as feature sets. By repeating this analysis across lags in the features, we explore which regions and times are critical for predicting species Spring arrival and Fall departure dates in North American forests. Through this approach, we make use of model error and feature importance metrics to explore which features, at which times and places, are most useful for prediction of migration. We demonstrate that random forest regressors can accurately predict passerine species occurrence, even when presented with limited training data. We also show that lagged temperature and precipitation features are as predictive, and often more predictive, of species occurrence probability than non-lagged features. Additionally, to test if this modeling approach agrees with the general literature consensus of earlier species Spring arrival times and later Fall departure times due to climate change, we test another random forest regression model on several climate models projections averaged from 2021-2040. All data and Python notebooks required to run these analyses are available at doi.org/10.5281/zenodo.7769656.

Methods

eBird Data

We used the eBird Basic Dataset from 2008-2018 (‘eBird Basic Dataset’, 2022) to derive the occurrence rate of bird species across surveys in our study area, representing a species “encounter rate” metric for the target species on a monthly scale (Johnston *et al.*, 2021). Checklists were first filtered to our study area, the Level 2 Ecoregion “Atlantic Highlands” within the Level 1 “Northern Forests” Ecoregion (Fig. 1) (‘Level I and II Ecoregions of North America’, 2010). These EPA Ecoregions seek to aggregate areas of similar plant and animal species, as well as abiotic characteristics such as water availability (Omernik and Griffith, 2014). The “Northern Forests” ecoregion is characterized by extensive boreal forests and lakes (*Ecological regions of North America: toward a common perspective*, 1997), as well as extensive coverage by eBird surveys.

Checklists were further processed according to methods recommended by Johnston shown to improve the performance of species occupancy and detection models when using eBird data, especially in models with large survey sample sizes (Johnston *et al.*, 2021). Specifically, we included only ‘complete’ checklists where observers have noted down all birds that they have observed were included, checklists with ‘traveling’ or ‘stationary’ counts (removing area counts), and excluded surveys with very high effort, specifically those lasting over three hours and traveling more than 5 km. We also removed duplicate surveys from group survey events.

We next limited the species of interest to the 50 most common passerine species, as such birds in general have a lower body mass and higher cold sensitivity, which can induce migratory behaviors (Dawson, Marsh and Yacoe, 1983). Of these species, we filtered down to 41 species (mean observations: 3,571, std: 2,044) (SI Table 1) which are either short-distance or long-distance migrants rather than resident species, based on distribution maps from Birds of the World (Billerman *et al.*, 2022) and expert opinion. To further refine our analysis to only forested regions, we filtered out all checklists with less than 50% surrounding tree cover based on 100m

resolution tree cover density data (‘Copernicus 2018 100m Forest Cover Fraction’, 2020). From 2008 until 2018, the number of annual surveys in eBird has greatly increased. To avoid bias in inferred species richness in later years which have a greater number of surveys, we randomly subsampled 1601 surveys at the annual scale, the number of surveys in 2008 after filtering for forest cover and survey type (SI Fig. 1). We then calculated the percentage of surveys on which each species appears on a monthly scale to create our target features.

Climate Data

To study historical patterns in migration and climate, we utilized WorldClim monthly historical raster data (Harris *et al.*, 2014) downscaled with WorldClim 2.1 (Fick and Hijmans, 2017) for monthly minimum temperature, maximum temperature, and precipitation at 2.5 minute spatial resolution across North and South America. The raster data were averaged into EPA Level 1 Ecoregions for North and South America (Fig. 1a) that fall within typical migration pathways for birds that spend their breeding season in the eBird study region. Features were then individually normalized by setting a mean of 0 and scaling features to unit variance. Each of the three feature sets (maximum temperature, minimum temperature, and precipitation) had a total of 15 features per month, from eight North American Ecoregions and seven South American Ecoregions. One feature set containing all three climate features was also created, with 45 features in total.

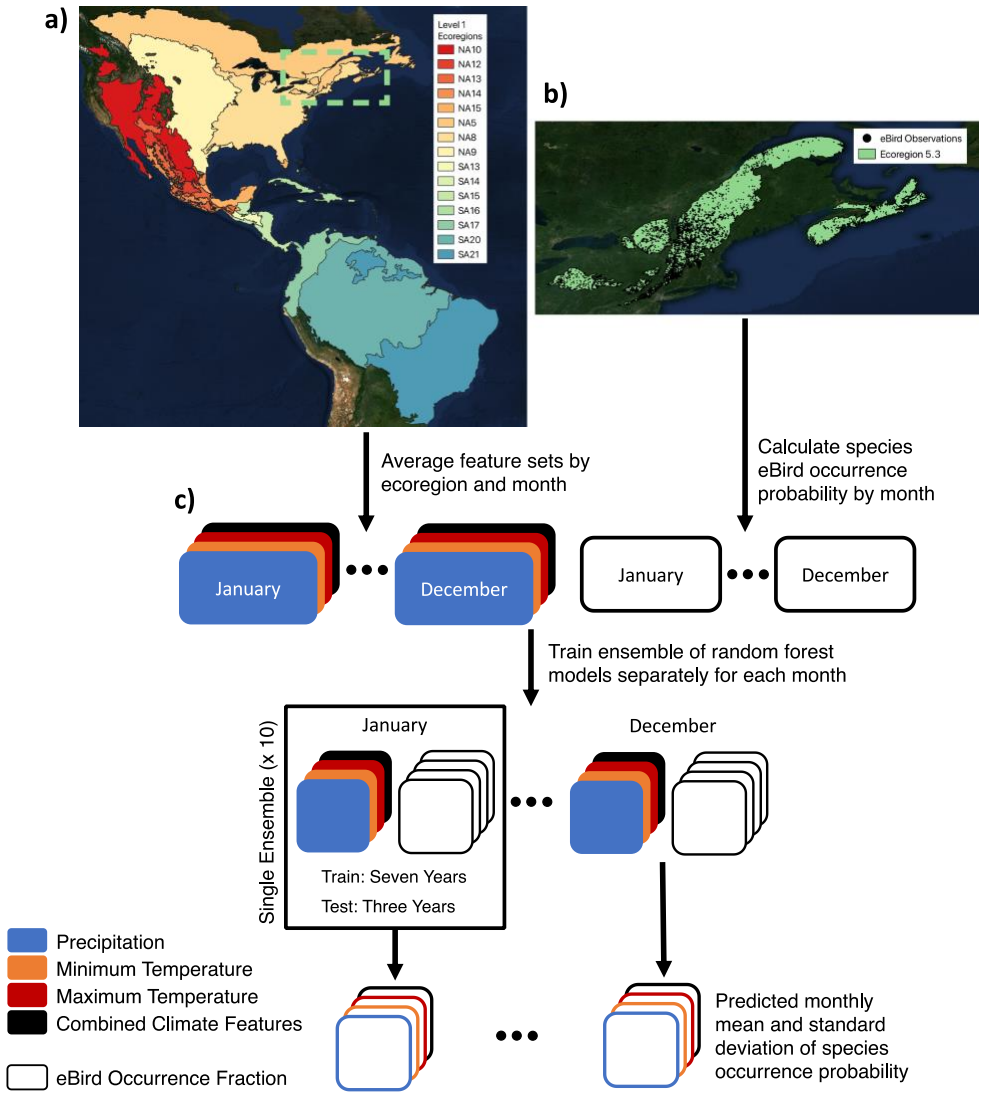

Figure 1: Map of targeted EPA Ecoregions and eBird survey locations. a) North and South American Level 1 Ecoregions for averaging of climate variables. b) The eBird study region Ecoregion 5.3, a subset of Level 1 Ecoregion 5 (NA5), outlined in light green with individual eBird survey coordinates in black. c) Data flow through random forest model ensembles. Monthly climate features are aggregated to the Level 1 Ecoregion spatial scale and monthly eBird species occurrence fractions across checklists are calculated for the Ecoregion 5.3 study region. An ensemble of ten models is trained and tested for each month and climate feature combination to predict checklist occurrence fractions, and the results of the ensemble are then averaged.

Similarly, to generate projected climate features, we utilized WorldClim monthly projected data from the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Fick and Hijmans, 2017),

aggregated and averaged to the same EPA Level 1 Ecoregions. The CMIP6 framework forms the standard for international climate assessments, such as those from the Intergovernmental Panel on Climate Change (Eyring *et al.*, 2016) and includes an ensemble of climate models from various research groups that rely on common historical training data. For each CMIP6 model, we also tested several radiative forcing pathways, dubbed the Shared Socioeconomic Pathways (SSP) (O'Neill *et al.*, 2016), which compared the effects of various greenhouse gas emissions scenarios. Due to our use of a random forest regressor, which cannot predict any new values outside of training data it has seen, our projections of species occurrence fall within the bounds of observed species occurrences on eBird checklists from 2008-2018. Still, in order to avoid projecting species occurrence rates in radically different climatic conditions, we limited our study to the 2021-2040 averaged WorldClim datasets. This consists of the mean projected monthly minimum temperature, maximum temperature, and precipitation from 2021 to 2040. We used four CMIP6 models available from WorldClim which performed best on tests comparing probability distributions of projections to historical observations and the regularity of climate fluctuations (Papalexiou *et al.*, 2020).

Analysis of Historical Avian Migration

We trained Random Forest regressors on the historical climate features to predict the eBird checklist target features (Fig. 1c). Twelve ensembles of models were trained in total, one for prediction of eBird checklist occurrences in each month of the year. This separate training of models for each month of the year and lag on the climate feature dataset enabled us to study seasonal patterns in the error rates and feature importance. Each ensemble of models consists of ten 1000-tree Random Forest models trained with varying 30:70 test-train splits across the ten years of data being studied (2009-2018). For example, the first model was trained on 2009, 2010, and 2011 data, and tested on 2012-2018 data, the second model was trained on 2010,

2011, and 2012 data, and tested on 2013-2018 and 2009 data, and so forth. Each model is trained on 7 years x 15 aggregated climate features, or 7 x 45 when using all temperature and precipitation features. This process was then repeated while lagging the climate features from one to six months. For example, the climate features from March were used to train models to predict the checklist occurrences in April, and so forth. The use of this ensemble of models trained on various subsets of the climate feature sets is to generate a distribution of predictions, errors, and feature importance to be later compared in two-sided permutation tests. These tests evaluate the likelihood that two sets of numbers are pulled from different distributions and allow us to test whether certain models are truly performing better than others, or if certain groups of features are more important.

From each group of ten models (an ensemble), we calculated the mean and variance of the test set predictions, mean absolute errors, and random forest feature importance. Feature importance was calculated from the mean decrease in node impurity within the random forest models. The features ranking highest in importance were those which best splits the distribution of target features across all nodes in the decision trees. These forest importance metrics are relative, and sum to one (‘Feature Importances with a Forest of Trees’, 2023).

Projections of Avian Migration Shifts

We trained Random Forest models on the combined feature set of 45 historical climate features (minimum temperature, maximum temperature, and precipitation) across Ecoregions to predict the target eBird data from 2009-2015. Validation was performed on 2016-2018 data (SI Fig. 6, 7). We then used this model to project on the 2021-2040 monthly average climate projections from the four CMIP6 models (EC-Earth3-Veg, INM-CM4-8, MPI-ESM1-2-HR, and GISS-E2-1-H.) and four SSP projections (SSP 1, 2, 3, and 5). As with the historical ensemble of models, a

separate model was trained to predict each month of the year. Projected species-wise shifts in monthly occurrence probability were calculated by subtracting the mean monthly eBird checklist occurrences (2009-2018) from the mean projected occurrences for each of the four CMIP6 models and four projections.

Results

We found accurate per-species predictions of eBird checklists for the 41 passerines studied (Fig. 2a) were made with monthly mean climate data (Fig. 2d) as well as with lagged climate data up to 6 months (Fig. 2f). Average monthly errors in predictions were generally low across all months and across climate features, ranging from 1.7 to 3.8 percent error in eBird checklist occurrence fraction averaged across all species (Fig. 3, SI Fig 2), with higher errors in the Spring and Summer months when species richness was also higher. We noted a trend in the mean annual error across species where the model tended to under-predict species occurrence fraction in earlier years and over-predict species occurrence fraction in later years (Fig 3a-d). This pattern in error followed a trend in the underlying eBird data; on average, each species in the study occurred on 2.6% fewer eBird checklists from 2009 to 2018 (Fig. 2c), a trend apparent for most species (Fig. 2e, 2g).

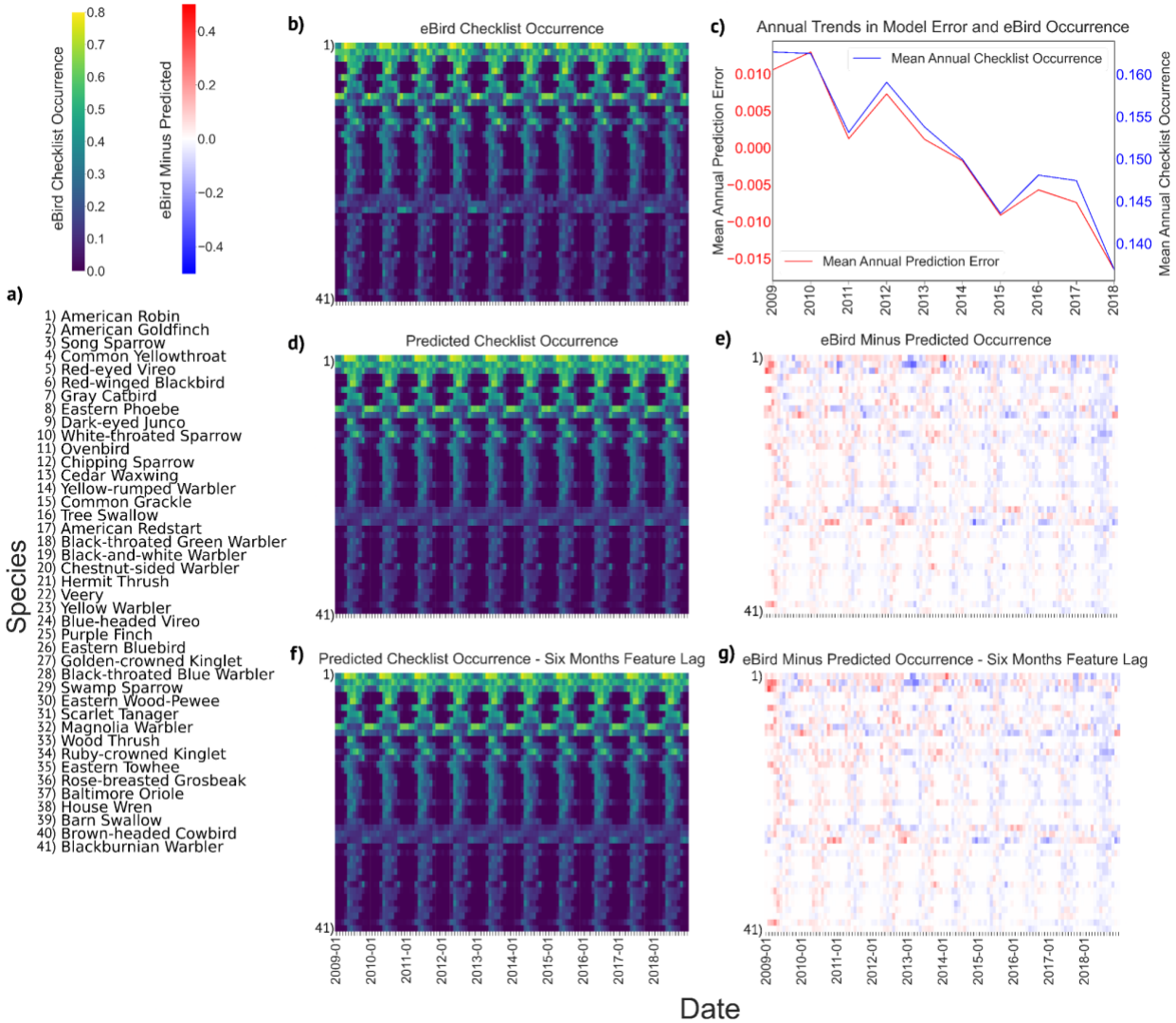

Figure 2: Aggregated climate data supports accurate predictions of eBird species checklist occurrences - a) List of 41 common migrating passerine bird species observed in forested areas of the study region, representing the y-axis of the following heatmaps. b) Actual eBird checklist occurrence fractions for all species. c) Mean annual eBird checklist occurrence across all species (blue) and the mean annual error in occurrence fraction predictions (red) across all species. d) The Random Forest-predicted eBird checklist occurrence fractions for all species utilizing all available climate variables (minimum temperature, maximum temperature, and precipitation), e) the error compared to the actual eBird data, f) the predictions using six month lagged climate variables, and g) the corresponding error compared to eBird checklists.

Figure 3 illustrates the accuracy of the random forest ensembles for prediction of species occurrence fractions, but also how the temporal trends in the underlying eBird features impacted model performance. The model increasingly tended to overpredict individual species checklist

occurrence towards later years in the analysis (Figs. 3c, 3d). Following this, the derived species richness was also increasingly over-predicted (Figs. 3a, 3b). Figure 3e and 3f focus on April and October specifically, as these months are transitory periods between breeding and winter seasons (Fig. 2b) when migratory species are arriving and departing our study area. We noted higher volatility and no apparent trend in model error for April (Fig. 3e). In October, however, the lowest error occurred when climate feature sets were lagged by one to three months (Fig. 3f). A two-sided permutation test (100,000 permutations) showed the mean absolute errors using non-lagged feature sets was significantly lower than using lagged feature sets in October (SI Table 3). No such significant differences in error were found in April.

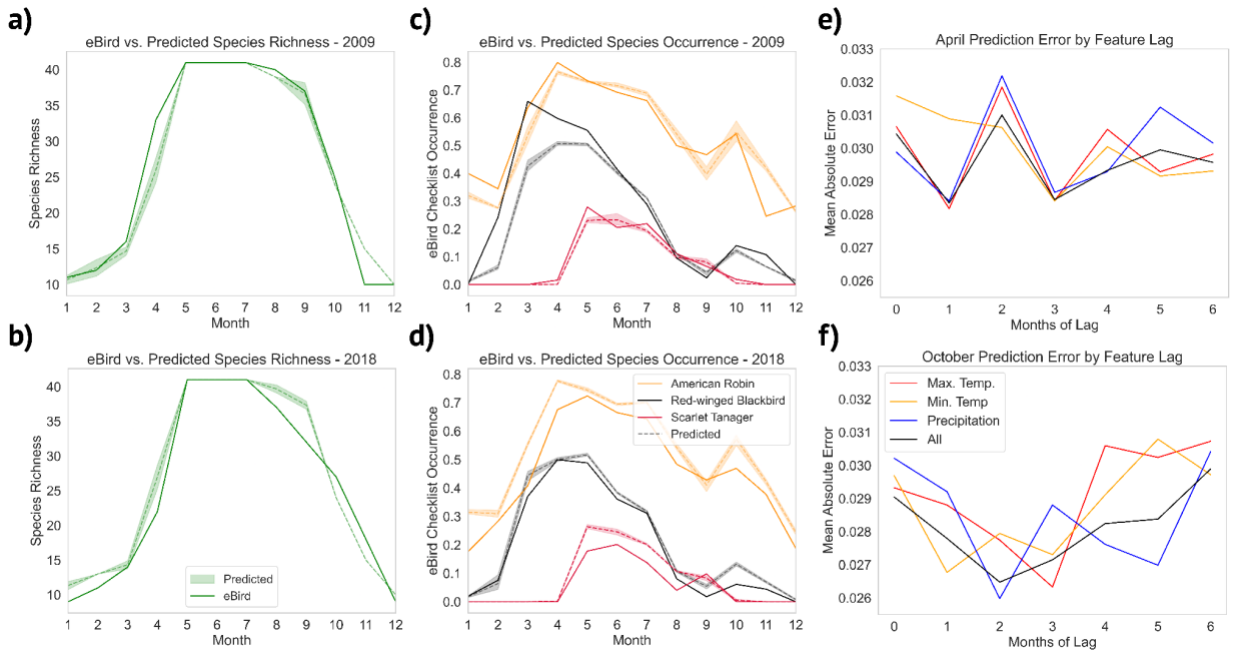

Figure 3: Model predictions across years reveal underlying shifts in eBird species occurrence and strength of lagged climate data for predictions. a) 2009 and b) 2018 eBird species richness versus mean and standard deviation of predicted species richness across the model ensemble. Species richness shown includes all species appearing on more than two percent of actual and predicted eBird checklists. c) 2009 and d) 2018 eBird ground truth versus predicted checklist occurrence fraction, showing mean and standard deviation of predictions across the model ensemble. e) Average random forest mean absolute test set errors by month of feature lag for April and f) October across all species and climate features.

In our analysis of spatiotemporal feature importance, we noted a trend in precipitation importance for prediction of Spring month (March, April, and May) species occurrence probability in the study region, where southern regions have higher importance values than northern regions (SI Fig. 3) when predicting with 0 to four months of feature lag (SI Table 3a). We found a significant difference ($p=0.0312$) between the distributions of precipitation importance for Northern American and South American ecoregions when using two month-lagged features, demonstrating the lagged effects of precipitation in these regions for predicting the passerine species arriving in northern forests in Spring and early Summer. This trend was not apparent with the maximum temperature (SI Fig. 4) and minimum temperature (SI Fig. 5) importance in spring months (SI Table 3b, 2c). However, when predicting species occurrence probability in fall months (September, October, November) when passerines are generally leaving the study region southward to winter, maximum temperature found to be more important in Northern than Southern Ecoregions across all lags (SI Table 3b), significantly for lags of one month ($p=0.0302$) and six months ($p < 0.001$). Significance was also found for minimum temperature at six months lag ($p < 0.001$) (SI Table 3c).

By training on the 2008-2018 eBird checklists with all climate features and testing on CMIP6 climate projections (making broad assumptions of no change in habitat or species abundance), we projected higher positive shifts in checklist occurrence probability for April through August (ranging from 0.36% to 0.75%), with less change projected for Fall months (ranging from 0.011 to 0.19%) (Fig. 4a). We found an increase in species occurrence probability across models projected for 25 of 41 species in April (mean: 0.80%), 15 species having a projected decrease (mean: -0.36%), and one species with no change (Fig. 4b). Results were more mixed for October, with projected occurrence probability increases for 20 of 41 species (mean: 0.67%), decreases for 19 (mean: -0.46%), and no change for two species (Fig. 4c). In contrast to the variation within eBird training data, the variance of occurrence probability for all species was

effectively zero across all four CMIP6 models and four SSP projections tested, indicating that the random forest model consistently reached the bounds of known distributions of checklist occurrences across the available climate training data.

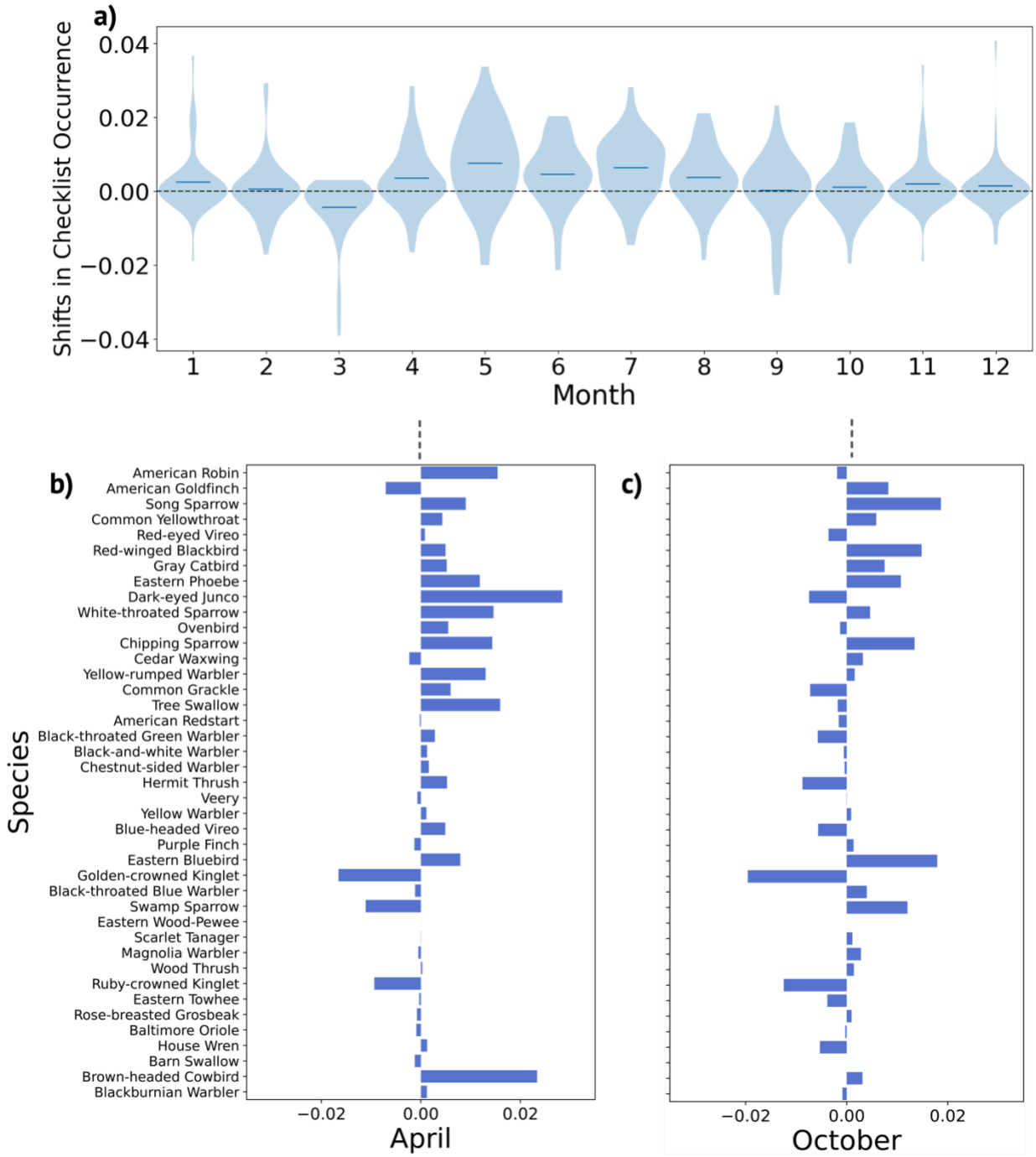

Figure 4: Projections of eBird checklist occurrences from 2021-2040 show earlier Spring occurrence probability for passerine species - a) Violin plot showing mean projected shifts of occurrence probability for 41 passerine species in 2021-2040 compared to historical eBird monthly means from 2008-2018 in Ecoregion 5.3 b) April and c) October per-species difference between mean historical eBird occurrence probability and mean 2021-2040 projected occurrence probability .

Discussion

Here, we show that aggregated North and South American Climate features support accurate predictions of eBird checklist occurrence probability for 41 passerine species (Fig. 2b) in our North American forest study region, despite the small size of the training sets. Accuracy was largely unaffected by which climate variable was chosen as a training feature (Fig. 3e, 3f, SI Fig. 2). We also find that the trend in mean annual model error closely follows that of the mean annual checklist occurrence over time across all species (Fig. 2c), suggesting that the error stems from underlying trends in decreasing biodiversity and total bird counts over the study period, at least as identified by the eBird checklists, a trend echoed by other studies (Anders and Post, 2006; Sauer and Link, 2011).

We also note the predictive power of lagged climate data for prediction of bird species occurrence probability. In October, when species are in the process of migrating southward from our study region (Fig. 3a), we show statistically significant lower error across all climate feature sets when they are lagged compared to using non-lagged features (Fig. 3b, SI Table 3). The precipitation feature set shows the most significant decreases in error, and with the longest lagged effect, at 2-, 4-, and 5-months lag (SI Table 3). In months when birds are arriving to the Northern study area from Southern wintering grounds (March, April, and May) (Fig. 2b), we find that the feature importance of precipitation in South American Ecoregions is largely higher than in the Southern Ecoregions, especially at a lag of 2 months, where the difference is significant (SI Table 3a). Conversely, maximum and minimum temperature features in North American

Ecoregions were found to be largely more important than those in Southern Ecoregions for predicting species occurrences during departure months (September, October, November), again showing statistically significant results (SI Table 3b, 2c). This shows that a machine learning model can identify spatially and temporally important features for the arrival and departure timing of bird species.

These results also concur with other work that indicates time lagged effects of climate on migration triggers, specifically for precipitation. When calculating how climate variables explain variance in Fall migration timings in Europe, Haest et al. (2019) find that while the importance of temperature was focused during or immediately before migration, the influential time windows of precipitation were more varied. They point to indirect lagged influences of precipitation, including for food availability. Changing precipitation, temperature, and other climate features have also been linked to shifts in plant flowering phenology (Sparks, Jeffree and Jeffree, 2000; Keatley *et al.*, 2002; Rawal *et al.*, 2015), which in turn affect insect populations and insectivorous species (Visser, Holleman and Gienapp, 2006; Evans *et al.*, 2019) .

Our projections of bird species in 2021-2040 are not intended to model future changes in biodiversity and abundance, but to examine how bird species would react if future climatic conditions occurred suddenly next year, for example. In this sense, we sought to uncover what historical trends in climate and bird migration tell us about future trends. Additionally, as we use a random forest model architecture, projections of future species occurrence probability fall within the bounds of the historical training data, making them inherently conservative. They do not account for land-use and development (La Sorte *et al.*, 2017), shifts in the timing of food availability from insects and flowering plants (Sparks, Jeffree and Jeffree, 2000; Keatley *et al.*, 2002; Visser, Holleman and Gienapp, 2006; Rawal *et al.*, 2015; Evans *et al.*, 2019), or shifts in inter-species competition (Freeman 2022), all of which affect bird populations and distributions.

However, within these bounds we were still able to identify potential future trends in arrival and departure times which support existing literature and empirical research, including earlier Spring arrival of species in North American forests (Fig. 4b), but more mixed trends in autumn months (Fig. 4c) (Haest 2019, Mills 2005). Several results indicate more climate sensitivity and volatility in the Spring migration than the Fall migration: higher test set error in April compared to October (Fig. 3e, 3f), and larger and wider shifts in projected future species occurrences in April and May than in Fall Months (Figs. 4a, 4b and 4c). It should be noted that test set error of the climate projection model was higher than training set (2008-2015) error and increased over time from 2016 to 2018 (SI Fig. 6, 7), to a monthly maximum mean absolute error of 5.3% for August 2018. This error results primarily from an underestimate of species occurrence probability (SI Fig. S6), likely partially due to underlying decreases in species occurrence (Fig. 2c). This suggests that further projections would result in similar increases in error partially due to further decreases in abundance.

The monthly scale data resolution and resulting small dataset size in this analysis limited our ability to utilize relevant deep learning techniques such as recurrent neural networks, which could capture temporal influences of climate on migration. However, the use of random forests decision trees had the benefit of both built-in feature importance methods, as well as constraining future predictions within the range of the training set data, while a simpler model such as a multiple linear regression would have projected outside of the historical range. Future studies could expand the temporal scale and resolution of the dataset or focus on abundance as a target variable to account for population decreases. They could also include other climate features known to affect migrations such as wind speed and direction (Haest 2019), as well as indices derived from satellite data such as Normalized Difference Vegetation and Water Indices, which correspond with food availability and drought conditions (Alessandrini *et al.*, 2022; Hunt *et al.*, 2022).

Conclusions

Here, we demonstrated a modeling approach for identifying spatiotemporal climate features triggering bird migration behavior, as well as for potential future trends in migratory behavior. We found that random forest models trained on aggregated climate features accurately predicted eBird checklist occurrence probability across all months in a northern forested region. Lagged precipitation, minimum temperature, and maximum temperature feature sets were shown to predict passerine species occurrence probability in Fall months more accurately than the actual climate in those months. The models also identified spatiotemporal importance of North American features over South American features in Fall when species begin migrating southward to wintering sites. Using 2021-2040 mean climate projections from CMIP6, we showed an increased occurrence probability in Spring and Summer months, but less effect in Fall and Winter. These findings aligned with existing literature in predicting a spreading out of migratory timings with climate change, with a trend towards earlier spring first arrivals and later autumn final departures. Future work could include creating a larger and higher temporal resolution climate dataset, which would enable the use of temporally informed machine learning models such as recurrent neural networks for studying complex and non-linear spatiotemporal effects of climate on bird behavior and abundance.

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Author Contributions

IAB led manuscript writing and methodology design and ran the analyses. VB, MP, KR, and SS advised on methodology design and research questions and made significant contributions to the manuscript. All authors reviewed and approved the manuscript.

Conflicts of Interest

The authors have no conflicts of interest to declare.

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Supplemental Information

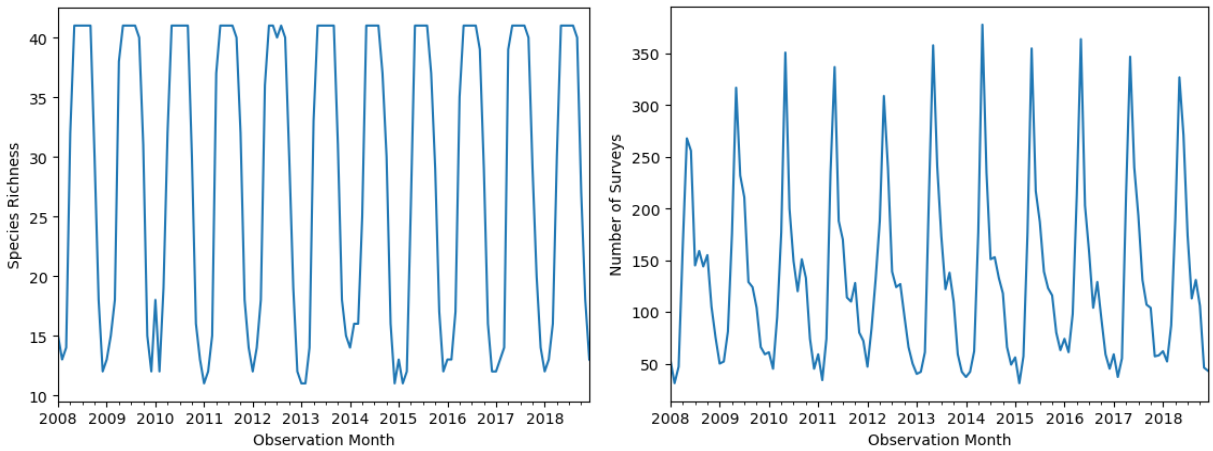

Figure S1 - Monthly species richness for migrating passerine species (left) and number of sampled eBird surveys per month (right).

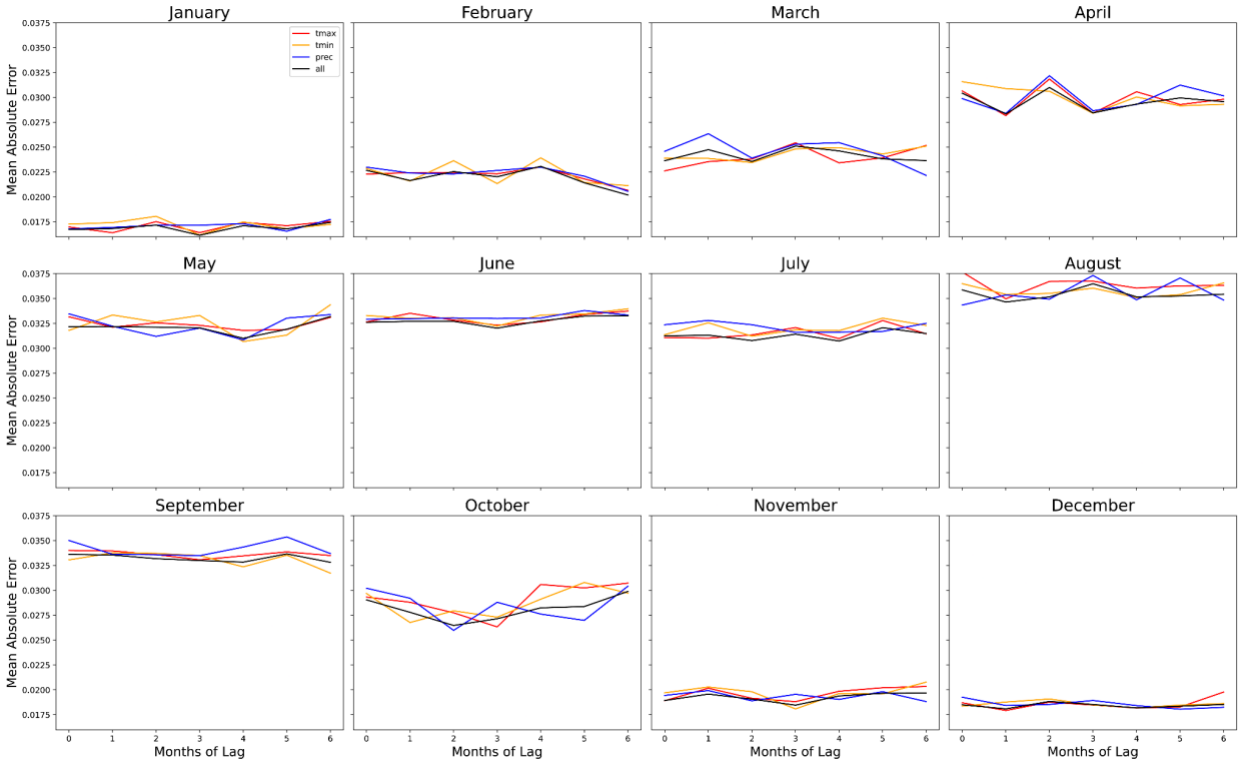

Figure S2 - Monthly mean absolute error of eBird checklist occurrence predictions by month of feature lag.

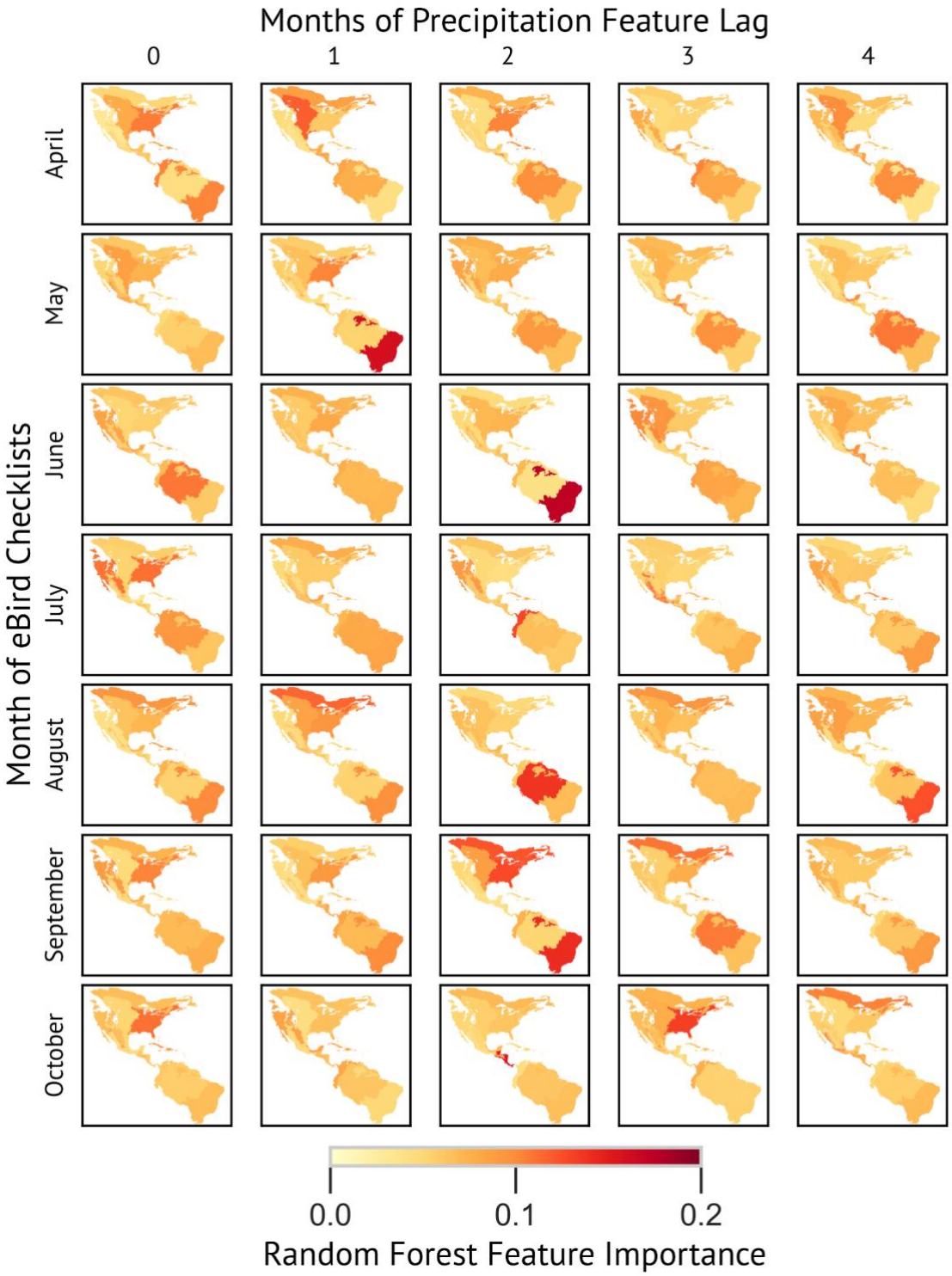

Figure S3 - Mean Random Forest precipitation importances across Level 1 Ecoregions for prediction of species checklists in Ecoregion 5.3 from April through October.

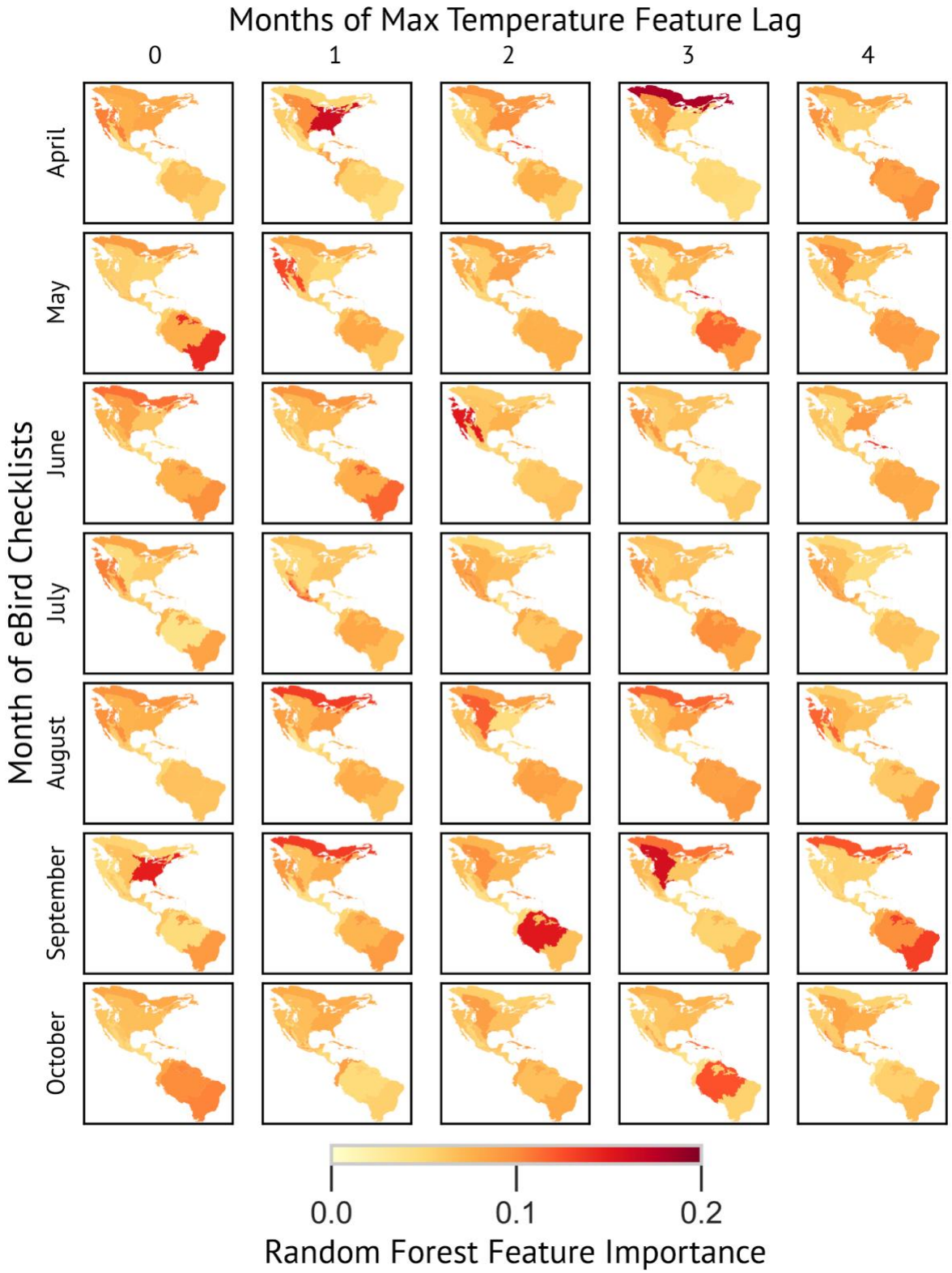

Figure S4 - Mean Random Forest maximum temperature importance across Level 1 Ecoregions for prediction of species checklists in Ecoregion 5.3 from April through October.

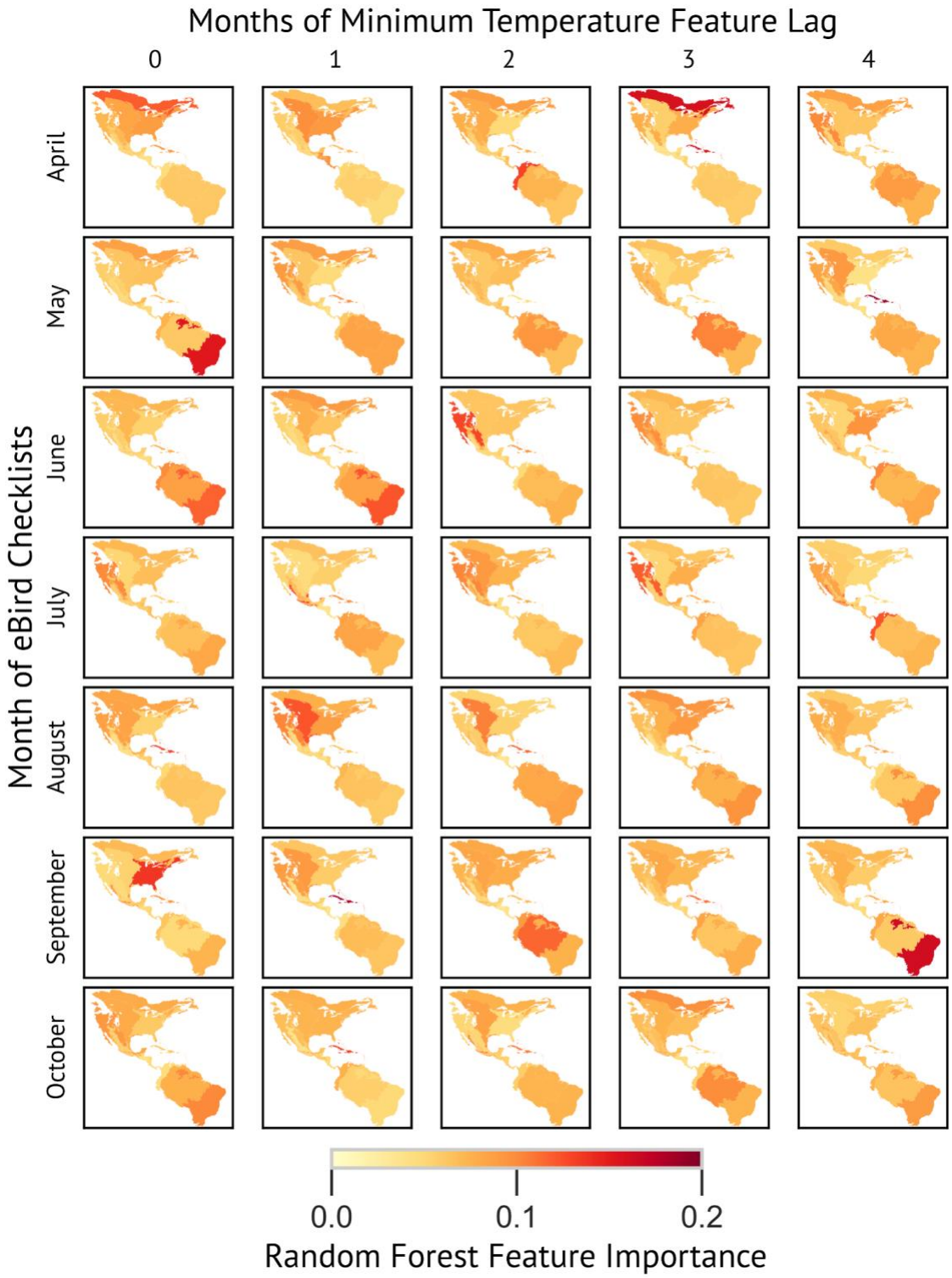

Figure S5 - Mean Random Forest minimum temperature importance across Level 1 Ecoregions for prediction of species checklists in Ecoregion 5.3 from April through October.

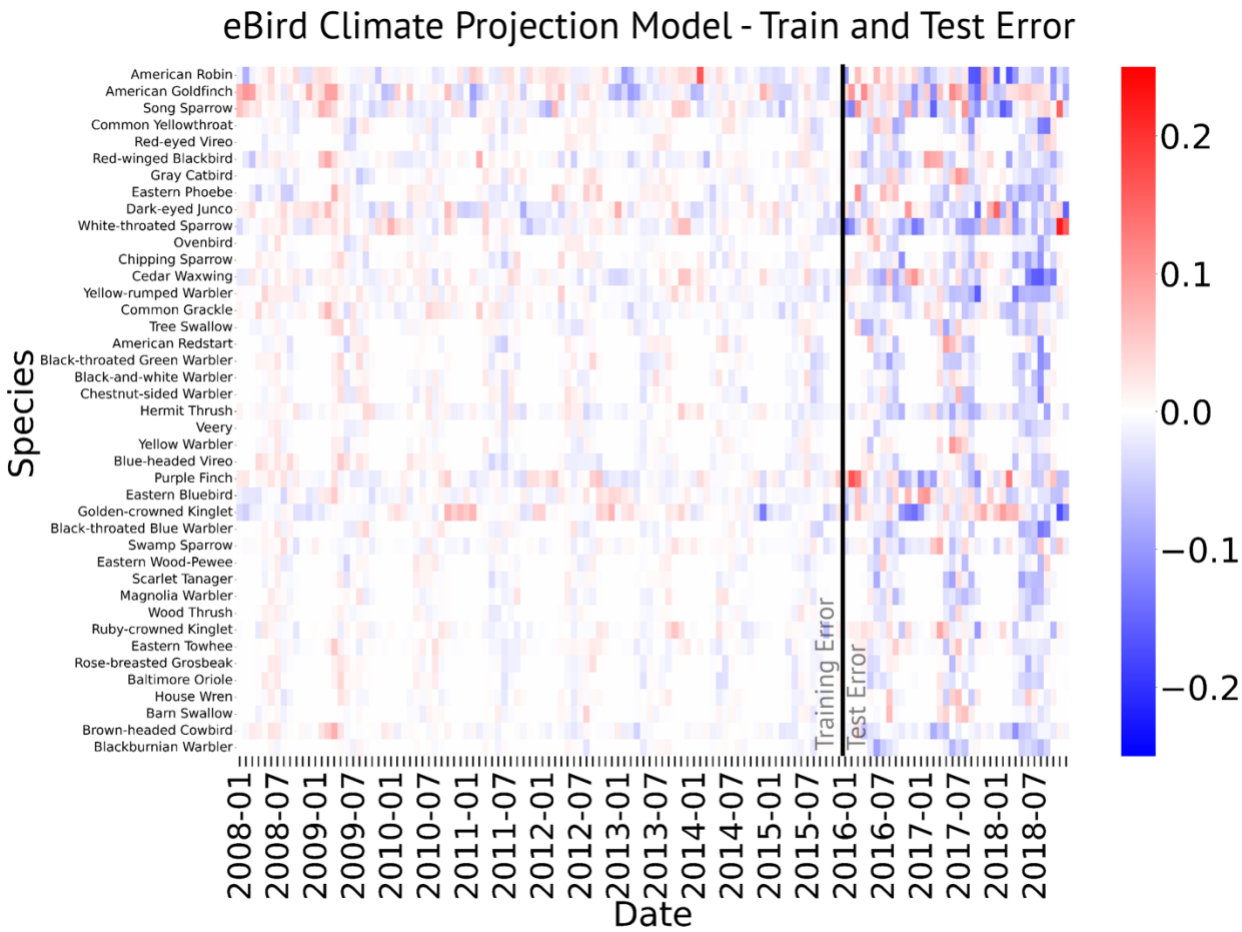

Figure S6 - Random Forest training set (2008-2015) and test set (2016-2018) error for climate projection model

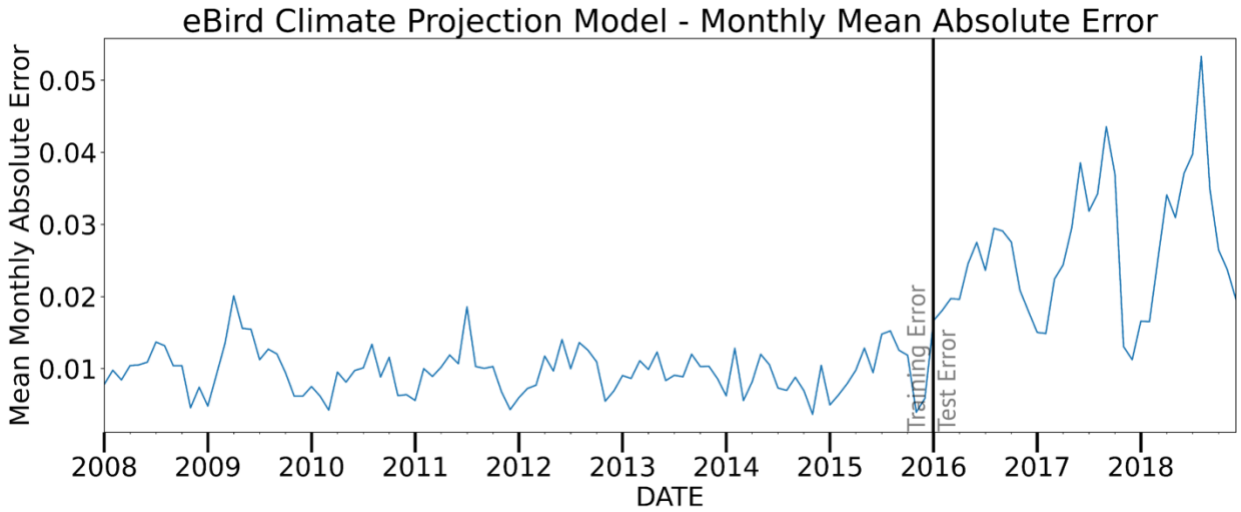

Figure S7 - Random forest training set (2008-2015) and test set (2016-2018) monthly mean absolute error across all species for climate projection model

Table S1 – Observation count per species across eBird checklists

Species	Observations
American Robin	10685
American Goldfinch	8637
Song Sparrow	8510
Common Yellowthroat	5881
Red-eyed Vireo	5585
Red-winged Blackbird	5491
Eastern Phoebe	5214
Gray Catbird	5184
Dark-eyed Junco	4914
White-throated Sparrow	4602
Chipping Sparrow	4464
Ovenbird	4409
Cedar Waxwing	4405
Yellow-rumped Warbler	4004
Common Grackle	3762
Black-throated Green Warbler	3371
Tree Swallow	3295
American Redstart	3177
Chestnut-sided Warbler	3011
Black-and-white Warbler	2954
Hermit Thrush	2933
Veery	2827
Blue-headed Vireo	2512
Yellow Warbler	2511
Eastern Bluebird	2418
Purple Finch	2303
Black-throated Blue Warbler	2229
Scarlet Tanager	2200
Eastern Wood-Pewee	2144
Golden-crowned Kinglet	2099
Swamp Sparrow	2067
Brown-headed Cowbird	1988
Baltimore Oriole	1987
Rose-breasted Grosbeak	1974
Eastern Towhee	1933
Wood Thrush	1911
Magnolia Warbler	1900
House Wren	1837
Blackburnian Warbler	1787
Barn Swallow	1764
Ruby-crowned Kinglet	1689

Table S2 - Two-sided permutation test (permutations = 100,000) p-values between model ensemble mean absolute errors at various lags of the climate feature sets

Lag	All Months, 3 Clim Vars, n = 360	All Months, Precipitation, n = 120	All Months, Tmax, n = 120	All Months, Tmin, n = 120	April, 3 Clim Vars, n = 30	April, Precipitation, n = 10	April, Tmax, n = 10	April, Tmin, n = 10	October, 3 Clim Vars, n = 30	October, Precipitation, n = 10	October, Tmax, n = 10	October, Tmin, n = 10
0	0.9970	0.9970	0.9985	0.9970	0.9956	1.0000	1.0000	0.9996	0.9986	1.0000	1.0000	0.9993
1	0.6310	0.8109	0.6525	0.8816	0.2249	0.2337	0.2337	0.7701	0.0502	0.4156	0.7043	**0.0404**
2	0.6949	0.5083	0.9782	0.9538	0.4518	0.4872	0.4872	0.5924	**0.0006**	**0.0004**	0.2199	0.2289
3	0.4064	0.7994	0.6354	0.4763	0.0772	0.3256	0.3256	0.1485	**0.0018**	0.2405	**0.0125**	0.0769
4	0.6293	0.5541	0.9975	0.7940	0.5799	0.9672	0.9672	0.5125	0.3659	**0.0240**	0.2939	0.6655
5	0.9057	0.9017	0.9251	0.8488	0.5408	0.5274	0.5274	0.3161	0.5978	**0.0107**	0.4517	0.4475
6	0.9889	0.6305	0.7089	0.8897	0.4819	0.7179	0.7179	0.3389	0.4194	0.8530	0.2349	0.9785

Table S3 - Two-sided permutation test (permutations = 100,000) p-values and test-statistics between the random forest feature importance of the North American Ecoregion climate features to the South American Ecoregion features for a) precipitation b) maximum temperature, and c) minimum temperature. Results are shown for random forest importance of

predictions in migration arrival months (March, April, and May) and for departing months (September, October, and November).

a)

Lag	March, April, May Precipitation, n = 24 (N.A.), n = 21 (S.A.)	Test Statistic, Mean(N.A Importance) - Mean(S.A Importance)	September, October, November Precipitation, n = 24 (N.A.), n = 21 (S.A.)	Test Statistic, Mean(N.A Importance) - Mean(S.A Importance)
0	0.3167	-0.005514	0.5999	0.002564
1	0.3703	-0.007045	0.0735	-0.009292
2	**0.0312**	-0.011977	0.6069	-0.004127
3	0.1527	-0.008448	0.6836	0.002445
4	0.4365	-0.004539	**0.0462**	0.011670
5	0.9166	0.000608	0.3088	-0.006789
6	0.6735	-0.003371	0.7439	0.002001

b)

Lag	March, April, May Tmax, n = 24 (N.A.), n = 21 (S.A.)	Test Statistic, Mean(N.A Importance) - Mean(S.A Importance)	September, October, November Tmax, n = 24 (N.A.), n = 21 (S.A.)	Test Statistic, Mean(N.A Importance) - Mean(S.A Importance)
0	0.575054249	0.004935	0.927490725	0.000663
1	0.765732343	-0.002370	**0.030239698**	0.013469
2	0.647553524	-0.002664	0.953430466	0.000501
3	0.374716253	0.007870	0.479615204	0.005521
4	0.421715783	-0.005201	0.911590884	0.000838
5	0.646893531	0.002638	0.956770432	0.000362
6	0.177638224	-0.006326	**0.006919931**	0.012735

c)

Lag	March, April, May Tmin, n = 24 (N.A.), n = 21 (S.A.)	Test Statistic, Mean(N.A Importance) - Mean(S.A Importance)	September, October, November Tmin, n = 24 (N.A.), n = 21 (S.A.)	Test Statistic, Mean(N.A Importance) - Mean(S.A Importance)
0	0.623613764	0.003693	0.51497485	0.004523
1	0.938790612	0.000481	0.738572614	0.003217
2	0.298117019	-0.006688	0.788412116	0.001605
3	0.590874091	0.004671	0.932610674	0.000488
4	0.635053649	-0.004124	0.922450775	-0.000650
5	0.176838232	0.010145	0.719072809	0.002362
6	0.831531685	-0.001094	**2.00E-05**	0.022503