# Testing prediction accuracy and climate change estimation with spatially explicit models for grassland birds

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# Introduction

Grasslands are one of the world’s most endangered ecosystems, with declines of 82.6-99.9% of tallgrass prairie, 30-99.9% of mixed-grass prairie, and 20-85.8% of short-grass prairie in the plains states and provinces of North America (Samson & Knopf 1994). Drivers of decline include land use conversion via agriculture and changes in fire and grazing regimes (Samson, Knopf & Ostlie 2004), but specifics vary by region (Askins *et al.* 2007). The already tenuous status of grassland birds is further threatened by conversion to new crops resulting in permanent land use changes (Wright & Wimberly 2013), generational changes in land use (Higgins, Naugle & Forman 2002), changes in conservation programs for grassland habitats (Klute, Robel & Kemp 1997), and alterations to vegetation (Alward 1999) and ecosystem structure (Brown, Valone & Curtin 1997) from climate change (McCarty 2001). Grassland bird species are declining faster than other groups of birds as well (Knopf 1994; Askins *et al.* 2007) and thus continued to be imperiled by these new threats to their habitat.

To help understand environmental and land use factors that drive declines, species distribution modeling (SDM) is a tool that uses environmental and geographic variables to predict what areas are suitable for a species and to better understand what factors constrain species’ ranges (Elith & Leathwick 2009). SDM can also be used to predict potential impacts of climate and land use change(Beaumont *et al.* 2007; Lipsey *et al.* 2015). Newer regression and machine learning techniques incorporated into SDM continue to increase prediction accuracy (Phillips, Dudík & Schapire 2004; Elith *et al.* 2006; Cutler *et al.* 2007; Elith, Leathwick & Hastie 2008; Lorena *et al.* 2011). Such range-wide distribution predictions have been made for grassland birds but some species with smaller ranges were not accurately modeled (O’Connor et al. 1999), perhaps because different drivers of distribution vary by region (Bakker, Naugle & Higgins 2002; Askins *et al.* 2007). To increase accuracy in the face of variation in regional drivers, a new method called Spatiotemporal Exploratory Modeling (STEM) uses smaller, overlapping subsets of data to generate regional predictions that are combined into an average (Fink *et al.* 2010). This averaging of overlapping smaller models allows the local models to correctly model patterns that may not occur in all parts of the study area, resulting in an overall map with more accurate predictions.

The original STEM was used on continent-scale survey data and can be used with any base model (Fink et al. 2010, Fink et al. 2013). Additional uses of this approach also cover continent- to hemisphere-wide scales (Fink, Damoulas & Dave 2013). We tested the spatially explicit modeling approach in a smaller region to see if it is suitable (as their largest subset is the size of many US states), and worth the extra computational power, at a state scale relative to a simple species distribution model without spatiotemporal variation in base models. A suitable test state should have regional variation in habitat and climate. In the southern Great Plains, the U.S. state of Oklahoma has over a third of its land area as grasslands and over 15% as croplands, containing grassland birds characteristic of habitats ranging from southeastern pine savannahs to tallgrass, mixed-grass, and shortgrass prairies (Askins *et al.* 2007; Diamond & Elliott 2015). Additionally, climate change is forecast to impact the Great Plains strongly (National Assessment Synthesis Team (U.S.) 2001; Loarie *et al.* 2009) and the climate of temperate grasslands are predicted to change rapidly relative to other biomes (Loarie *et al.* 2009). Oklahoma’s grassland habitats, agricultural importance, and forecast impact by climate change makes it an ideal region to test relative efficacy of different methods for modeling current and forecast species distributions.

The objectives of our study were threefold. First, we estimated the distribution, abundance, and density of Oklahoma grassland birds to understand current distribution statewide with standard species distribution modeling and survey methods. Next, these statewide current distribution predictions allowed us to compare the statewide species distribution model for each species with ensemble spatiotemporally explicit models to see whether this approach is suitable in terms of increased accuracy relative to increased computational power required for spatially explicit species distribution modeling. Finally, we ask how estimates of distributional changes from climate change may be altered by use of different spatial scale support sets. Our results will allow managers to make decisions on whether increased accuracy in modeling is worth the additional computational effort required by newer modeling techniques

# Methods

## Study area

Oklahoma contains diverse vegetation and climate, making it a suitable region to examine effects of spatially explicit models. There are ca. 165 vegetation types (based on soil and vegetation composition) in 15 land cover types (Diamond & Elliott 2015), with over a third of the vegetation in grasslands. Historically, grasslands were tallgrass (3 million ha), mixed grass (2.5 million ha), and shortgrass (1.3 million ha) (Samson & Knopf 1994). Rainfall and temperature vary across the state (Oklahoma Climatological Survey), with annual precipitation of about 17” of rain in the western portion to 56” in the eastern part of the state; mean annual temperature ranges from approximately 62°F in the southeast to about 56°F in the northwestern part of the state. Summer temperatures over 90°F can occur from 60-115 days out of the year varying statewide. Agriculture accounts for over $2.8 billion in the state’s gross domestic product in the study years (US Department of Commerce 2016) and includes crops such as winter wheat, hay, corn for grain, soybeans, and cotton, as well as cattle and hog ranching (*Oklahoma Agricultural Statistics 2016* 2016), ranking in the top 5 of US acreage for wheat for grain, winter wheat for grain, and forage land for hay (USDA/NASS 2016).

## Response data

We focused on 10 species of grassland birds found during our general surveys, plus Brown-headed Cowbirds (an obligate brood parasite with presence often depending on land use factors) (Benson, Chiavacci & Ward 2013), for a total of 11 species. Many of these species are declining at the state or North American level and none are increasing in population (Table 2). We collected data 1-4 times each at 339 8-min roadside point counts (0.13 hr and 0 km long) and at 87 cross-country transects 0.3-3.1 hrs and 0.3-4.3 km long (mean±SD: 1.2±0.6 hrs and 1.8±0.8 km). Each survey was conducted stationary (point counts) or walking at an even pace (transects). The observer noted species, number of individuals, and distance and angle to each sighting. Perpendicular distance from the transect line was calculated using distance and angle for transects. We had 14 observers total (6 in 2013 and 8 in 2014).

For species distribution models, we supplemented our survey data with citizen science data from the eBird Reference Dataset (Munson *et al.* 2014). We used complete data from 2011-2014 and excluded casual counts. In the case of multiple checklists for a given sampling event, we used the primary checklist. Our maximum survey transect effort was 4.3 km length and 3.1 hrs time, so we restricted use of eBird samples to ≤4.3km and ≤3.1 hours to have comparable effort in all checklists. When combining our survey data with eBird data for use in species distribution models, we used the point count center or the transect midpoint as the count location to have comparable precision to eBird coordinates (Fink *et al.* 2010). We also only used survey sightings within 500 m of the point or transect for the species distribution models. For training data, we used data from 2013 and 2014. Because some observers entered sightings from before and during our surveys into eBird, we eliminated 14 counts from 2013 and 2014 that were within two hours of the actual survey start time and within 15 km of the survey start location. For model evaluation data, we used datasets from 2011 and 2012. These filters resulted in a training dataset of 5423 complete checklists (158 transect sampling events, 614 point count sampling events, and 4651 eBird sampling events) and a temporally independent evaluation dataset of 2541 complete checklists (2541 eBird sampling events).

## Predictors

We used climatic variables, conservation easement status (O’Connor *et al.* 1999), and land cover variables to predict bird distribution (Table 1). We also used effort (length of observation in distance and time). Mean effort (distance and time) rasters were created for prediction, such that all predictions are created assuming effort that does not vary geographically and amounts of effort that are typical for both surveys and citizen science efforts in 2013 and 2014 (mean time: 0.73 hr; mean distance: 0.75 km). Neighborhood predictors were calculated by the values in rectangular areas around each point, at the scale of 5 x 5 pixels (150 x 150 m) and 15 x 15 pixels (450 x 450 m) (Fink et al. 2010). We looked at proportion of each land cover class and proportion of summed open space land covers (grasslands, hay/pasture, cropland, herbaceous wetlands, and barren land) since grassland bird occupancy can be influenced by the total non-structural cover (McDonald 2017). Neighborhoods were created in QGIS 2.16 with the GRASS r.neighbors processing tool (Quantum GIS Development Team 2016).

We chose only one climate model as the purpose of our climatic predictions is to give a range of estimates based on STEM scaling. We used the HadGEM2-ES (The HadGEM2 Development Team: G. M. Martin *et al.* 2011) downscaled Bioclim rasters for an intermediate climate model (4.5).

## Current distribution

### Density estimations

To estimate species density and abundance, we used our survey data in the form of point counts and line transects. We estimated density and abundance estimates in the R package Distance (Miller 2016). All datasets were truncated by 10% for distance outliers. We fitted the models with half-normal and hazard-rate models, with no adjustments as we included covariates. For each type of model (except uniform, which does not allow covariates) we tested covariates for observer, time of day, month, and year. We selected the best models with ΔAIC <2 (Burnham & Anderson 2008) for each species and survey type and give goodness of fit tests, density, and abundance estimates for the models.

### Statewide species distribution model

All models were created using random forest classification trees (Breiman 2001) in the R package randomForest (Liaw & Wiener 2002). Random forest gives results competitive to those from other machine learning techniques such as boosted regression trees and bagged decision trees (used in Fink et al. 2010 for the non-spatially-explicit comparison model). Minimal tuning parameters are required (Caruana & Niculescu-Mizil 2006; Cutler *et al.* 2007; Guo *et al.* 2010). They are suitable for species distribution models (Prasad, Iverson & Liaw 2006; Lorena *et al.* 2011) and can use small sample sizes for presence records (Mi *et al.* 2017). The random forest algorithm bootstraps a subset of the data using only a set proportion of the predictor variables. It then calculates the error rate on training data using the “out of bag” sample (the portion of data not used in the bootstrap for each tree) (Hastie, Tibshirani & Friedman 2001). The trees are then averaged for a final model. The use of only some variables in each bootstrapped tree allows estimation of variable importance. A random forest model was created for the statewide scale for each species using all training data, with a prediction raster created using the predict function in the R package raster (Hijmans 2016). All random forests (including those in later models) were generated with 500 trees (checking that out-of-bag accuracy stabilized within 500 trees). We used the default number of variables per bootstrap tree (default ‘mtry’=the square root of the number of predictor variables) for all trees because this is known to result in accurate predictions (Cutler et al. 2007).

To determine which predictors were important in current species distributions, for each species we ranked variables using the statewide model. We used the mean decrease in accuracy given by randomForest R package to rank variable importance. Mean decrease in accuracy (unscaled) with no sampling replaced is the least biased variable importance selection method available in randomForest (Strobl *et al.* 2007) We created partial dependence plots of the top variables for each statewide model to show how each variable increases or decreases probability of presence (Hastie, Tibshirani & Friedman 2001; Cutler *et al.* 2007). Variable importance can be measured more accurately in other packages at the expense of computational power (Strobl *et al.* 2007), so we tested variable importance again in the party package (Strobl *et al.* 2007, 2008). Due to the substantial increase in raster prediction time, we were unable to create predict rasters with cforest() in party, but this allowed us to compare variable importance in an unbiased manner with the multiple measurements scales of our rasters.

## Spatially explicit model accuracy and computational time

To model current species distributions based on our predictors, we created four models for each species at varying spatial scales: the previous statewide model and three spatially explicit ensemble models. The statewide model allowed use to compare the performance of the more computationally intense STEMs. The remaining models are three STEMs at varying support set scales, with some modifications from Fink et al. (2010). These locally dynamic models should provide more accurate maps than the statewide model for predicting species distribution both currently and in the future. Because they consist of numerous models (each which could generate its own set of variable importance rankings), they are too complex to use for variable importance ranking without a focal subregion. It is typical that models with increasing local accuracy are harder to interpret (because more accurate methods are often not very transparent) and generalize (because they typically fit the training dataset very well without regards to its ability to extrapolate) (James *et al.* 2013). With the diverse habitats and climatic variables found across Oklahoma, the models created by an ensemble of regional support sets should provide better predictions than the statewide model because the regional support sets will allow regional differences in important variables for prediction. Using both the statewide and spatially-explicit models give us complementary information on factors affecting species distribution in Oklahoma in addition to testing the usefulness of STEMs at this scale.

We adapted the STEM approach for our study in several ways. First, the scale of our support sets reflects the state extent (i.e. our small, medium, and large scales are relatively smaller than those needed for a continent-wide scale). As our survey goals are to determine breeding distribution only, we used a broader temporal window (April-July in all years) for our model (unlike Fink et al. 2010, who used single date windows). Secondly, for all base models, we used random forest classification trees (Breiman 2001) as described above. Finally, our geographic sampling of the training and evaluation datasets, described in more detail in the next paragraph, reflects the differing nature of our base models. Fink et al. (2010) sample 63% of each support set to imitate bootstrapping sampling, but because each support set is being bootstrapped by the random forest algorithm, we can use the full support set for each region.

For the spatially explicit models, we created stratified random points in the study area (with the spsample function from the R package sp (Pebesma & Bivand 2005; Bivand, Pebesma & Gomez-Rubio 2013) and created a square of size small (100 points with 120 x 120 km), medium (37 points with 200 x 200 km), or large (12 points with 450 x 450 km) around these points, which resulted in no significant difference in pixel coverage (F2,147=0.63, p=0.53) before removing support sets with too few checklists. Each support set included all checklists from the training dataset located within its boundaries. The support set was discarded if it contained fewer than 25 checklists or did not contain both presences and absences. We used the same random forest settings and created a prediction raster for each support set as for the statewide model. All support set rasters for a given scale (small, medium, or large) were stacked using the raster mosaic() function to get the mean value of each pixel, creating the spatially explicit ensemble (Hastie, Tibshirani & Friedman 2001; Fink *et al.* 2010; Oppel *et al.* 2012) made of many regional random forest predictions. This process was repeated at the three support set spatial scales, resulting in three spatially explicit, stacked ensembles per species for current distribution.

The statewide model was trained with the full training set (5423 checklists, as described previously). We tested the current distribution models with eBird data from 2011 and 2012 (2541 checklists, as described previously), sampled repeatedly for spatial uniformity (see below). Using data from different years results in a more accurate evaluation of whether the model generalizes well beyond its training timeframe (Araújo & Guisan 2006; Cutler *et al.* 2007). To evaluate model performance and choose between the four models for each species, we tested the models on the temporally independent evaluation dataset. To ensure spatially uniform testing (Fink *et al.* 2010), we created a statewide grid of 10 x 10 km cells. We randomly sampled no more than 10 observations from each grid cell in the evaluation dataset. We repeated the spatial sampling procedure randomly 50 times to get a distribution of performance for each model (Fink et al. 2010). We tested four models in this way for each species and noted the scale (small, medium, large, statewide) with best performance measures for each species. Performance measures were root mean square error (RMSE) and area under the receiver operating curve (AUC). RMSE is calculated from the model residuals, taking the squared value of observed minus expected values, then taking the square root to return to original units; thus a larger value indicates the model deviates farther from expected values (Kuhn & Johnson 2013). AUC is a summary of model performance measuring how often the model misclassifies individual test observations; AUC ranges from 0 to 1, with 1 being perfect and 0.5 being a model that performs no better than random chance (Hanley & McNeil 1982; James *et al.* 2013). Finally, to compare times to create trees and models, we used the R package ‘microbenchmark’ to measure the time to run for each of the four models of the 11 species, resulting in 11 samples in each of the four model scales to compare computing efficiency. The time included all randomForest trees and the raster prediction. We did not include the mosaic time for the ensembles.

## Variation in future distribution predictions with use of STEM

We used the future models to test how much variation in range predictions is caused by the use of statewide versus spatiotemporally explicit models. We estimated percent loss of range area from the comparable-scale (statewide, small, medium, large) current distribution.

# Results

## Current distribution

Table ? shows the estimated densities and abundances for each species. Figure ? shows current statewide distributions of species.

## Spatially explicit model accuracy and computational time

Small, medium, large, and statewide maps (Figure ?) of current predicted distribution for each species result in greater/less/equal measures of accuracy (Figure ) for each species. Computational times versus AUC and RMSE are shown in Figure ?.

## Variation in future distribution predictions with use of STEM

Table (or figure?) shows differences in estimated range loss by scale.

# Discussion

Spatially explicit models are useful/not useful. While large-scale solutions to conserve grasslands are needed (Samson, Knopf & Ostlie 2004), local and regional conservation and management efforts can also have critical impacts (Brennan, Kuvlesky & Morrison 2005).

Spatially explicit models add/don’t add a lot of variation to future climate range loss predictions. Our data show that in addition to be careful in one’s choice of climate models, the scale of prediction matters/doesn’t matter much. We should be careful extrapolating climate change to extinction (Schwartz et al. 2006). We also must be careful in prediction to climates where analogs do not exist (Boiffin, Badeau & Bréda 2017). Finally, climate change models may be overall accurate but poorly forecast a given region without additional interpretation by local experts (Risbey *et al.* 2002). For the climate change models, we must take care to note that climate models are generated at much coarser scales than our response dataset (Harris *et al.* 2014) and that we have chosen only (one? Two?) scenarios out of numerous models. Bounding box approach of “what areas are suitable in multiple scenarios (Harris *et al.* 2014).

We recommend … something.

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# Tables

Table 1. Predictors used in models.

|  |  |  |
| --- | --- | --- |
| Predictor variable name | Definition | Source |
| effort\_length | Length of survey (km) | Survey data |
| effort\_time | Duration of survey (hr) | Survey data |
| conservation\_easements\_presenceabsence | Presence (1) or absence (0) of a conservation easement | (USDA/NRCS - National Geospatial Center of Excellence 2010) |
| conservation\_easements\_CalcArea | Area of the conservation easement in which a given pixel exists (acres) |
| nlcd\_ok\_utm14\_okmask | NLCD2011 Landcover Classes | (USDA/NRCS - National Geospatial Center of Excellence 2011)  Neighborhoods modified from NLCD landcover classes. |
|  | NLCD 2.25 ha (5x5 cells) and 20.25 ha (15 x 15 cells) neighborhoods: proportion of neighborhood with the named land cover classes (values range from 0 to 1). Definitions described the land cover type and list the category numbers included in each neighborhood. |
| undevopenspace\_5cell\_okmask  undevopenspace\_15cell\_okmask | Undeveloped open space (11, 31, 71, 81, 82, 95) |
| openwater11\_5cell\_okmask  openwater11\_15cell\_okmask | Open water (11) |
| dev\_openspace21\_5cell\_okmask  dev\_openspace21\_15cell\_okmask | Developed open space (21) |
| dev\_low22\_5cell\_okmask | Low intensity development (22) |
| dev\_med23\_5cell\_okmask | Medium intensity development (23) |
| dev\_high24\_5cell\_okmask | High intensity development (24) |
| barren31\_5cell\_okmask  barren31\_15cell\_okmask | Barren (31) |
| forest41to43\_5cell\_okmask | Forest (41, 42, 43) |
| scrub52\_5cell\_okmask | Scrub and shrubland (52) |
| grasslands71\_5cell\_okmask | Grasslands (71) |
| pasturehay81\_5cell\_okmask | Pasture and hay (81) |
| croplands82\_5cell\_okmask | Croplands (82) |
| woodywetlands90\_5cell\_okmask | Woody wetlands (90) |
| herbwetlands95\_5cell\_okmask | Herbaceous wetlands (95) |
| census\_utm\_30m | Human population density in number per km2 | (U.S. Department of Commerce/U.S. Census Bureau 2010) |
| bio1\_12\_OK | BIO1 = Annual Mean Temperature | Bioclim variables from Worldclim (Hijmans *et al.* 2005) |
| bio\_12\_OK | BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp)) |
| bio3\_12\_OK | BIO3 = Isothermality (BIO2/BIO7) (\* 100) |
| bio4\_12\_OK | BIO4 = Temperature Seasonality (standard deviation \*100) |
| bio5\_12\_OK | BIO5 = Max Temperature of Warmest Month |
| bio6\_12\_OK | BIO6 = Min Temperature of Coldest Month |
| bio7\_12\_OK | BIO7 = Temperature Annual Range (BIO5-BIO6) |
| bio8\_12\_OK | BIO8 = Mean Temperature of Wettest Quarter |
| bio9\_12\_OK | BIO9 = Mean Temperature of Driest Quarter |
| bio10\_12\_OK | BIO10 = Mean Temperature of Warmest Quarter |
| bio11\_12\_OK | BIO11 = Mean Temperature of Coldest Quarter |
| bio12\_12\_OK | BIO12 = Annual Precipitation |
| bio13\_12\_OK | BIO13 = Precipitation of Wettest Month |
| bio14\_12\_OK | BIO14 = Precipitation of Driest Month |
| bio15\_12\_OK | BIO15 = Precipitation Seasonality (Coefficient of Variation) |
| bio16\_12\_OK | BIO16 = Precipitation of Wettest Quarter |
| bio17\_12\_OK | BIO17 = Precipitation of Driest Quarter |
| bio18\_12\_OK | BIO18 = Precipitation of Warmest Quarter |
| bio19\_12\_OK | BIO19 = Precipitation of Coldest Quarter |

Table 2. Study species with their Breeding Bird Survey trends for Oklahoma and North America (Sauer et al. 2017). Values are reported as trends with 95% credible intervals (lower, upper). Significant declines are marked with **boldface**. Sample size is reported as number of routes. Species with a decline at any region or timeframe are in italics.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Species | Breeding bird survey trend in Oklahoma 1966-2015 | 2005-2015 | n | BBS trend North America 1966-2015 | 2005-2015 | n |
| *Northern Bobwhite* | **-1.57**  **(-2.24, -0.89)\*** | **-3.03**  **(-5.50, -0.57)\*** | 60 | **-3.48**  **(-3.77, -3.24)** | **-2.79**  **(-3.51, -2.07)** | 1983 |
| Upland Sandpiper | 0.20  (-2.71, 2.51) | 3.21  (-6.07, 14.80) | 32 | 0.40  (-0.14, 0.87) | 1.50  (0.33, 2.77) | 994 |
| *Horned Lark* | 0.61  (-1.47, 2.78) | 1.64  (-2.20, 7.89) | 53 | **-2.46**  **(-2.84, -2.12)** | **-2.08**  **(-2.66, -1.48)** | 2598 |
| Cassin’s Sparrow | 0.01  (-4.03, 4.13) | 2.29  (-6.71, 13.46) | 25 | -0.75  (-2.30, 0.33) | -1.72  (-4.27, 1.20) | 333 |
| *Field Sparrow* | **-2.94**  **(-3.59, -2.29)\*** | **-6.63**  **(-9.05, -4.26)\*** | 53 | **-2.33**  **(-2.60, -2.17)** | **-2.18**  **(-2.71, -1.67)** | 2192 |
| *Lark Sparrow* | **-1.20**  **(-1.97, -0.39)** | -0.88  (-2.44, 0.88) | 60 | **-0.78**  **(-1.19, -0.39)** | 0.07  (-0.62, 0.77) | 1628 |
| *Grasshopper Sparrow* | 0.20  (-1.22, 1.61) | 0.87  (-2.30, 4.73) | 56 | **-2.52**  **(-3.69, -2.04)** | -0.77  (-1.98, 0.45) | 2161 |
| Dickcissel | 0.65  (-0.22, 1.55) | 1.18  (-1.60, 4.30) | 60 | -0.36  (-0.86, 0.05) | 0.74  (-0.27, 1.72) | 1269 |
| *Eastern Meadowlark* | **-2.09**  **(-2.63, -1.53)** | **-2.64**  **(-4.18, -1.03)** | 55 | **-3.28**  **(-3.60, -3.03)** | **-3.05**  **(-3.56, -2.29)** | 2526 |
| *Western Meadowlark* | -1.24  (-2.47, 0.04) | -1.84  (-4.28, 0.96) | 38 | **-1.29**  **(-1.54, -1.11)** | **-1.21**  **(-1.61, -0.83)** | 2085 |
| *Brown-headed Cowbird* | **-1.34**  **(-1.87, -0.77)** | -1.40  (-2.89, 0.22) | 60 | **-0.66**  **(-0.81, -0.51)** | -0.07  (-0.51, 0.41) | 4409 |

# Figures