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Modeling spatially and temporally complex range dynamics when detection is imperfect

Clark S. Rushing^{1,2}, J. Andrew Royle², David J. Ziolkowski² & Keith L. Pardieck²

Species distributions are determined by the interaction of multiple biotic and abiotic factors, which produces complex spatial and temporal patterns of occurrence. As habitats and climate change due to anthropogenic activities, there is a need to develop species distribution models that can quantify these complex range dynamics. In this paper, we develop a dynamic occupancy model that uses a spatial generalized additive model to estimate non-linear spatial variation in occupancy not accounted for by environmental covariates. The model is flexible and can accommodate data from a range of sampling designs that provide information about both occupancy and detection probability. Output from the model can be used to create distribution maps and to estimate indices of temporal range dynamics. We demonstrate the utility of this approach by modeling long-term range dynamics of 10 eastern North American birds using data from the North American Breeding Bird Survey. We anticipate this framework will be particularly useful for modeling species' distributions over large spatial scales and for quantifying range dynamics over long temporal scales.

The distribution of each species is determined by the interaction of multiple biotic and abiotic factors that vary across both space and time, including weather and climate¹, habitat availability², physiological tolerances³, and biotic interactions⁴. As a result, most species' distributions are characterized by complex spatial and temporal patterns of occurrence, which combined with the large scales over which distributions change, present challenges for both the collection and analysis of data to quantify range dynamics⁵. As habitats and climate change due to anthropogenic activities, there is an increasingly urgent need to develop species distribution models (SDMs) that can accurately and efficiently quantify complex range dynamics over large spatial and long temporal scales.

In response to this need, researchers have developed a range of SDM approaches that vary in their data requirements and analytical methods^{5,6}. Although each of these methods has strengths and weaknesses, SDMs designed to quantify range dynamics require several key features. First, SDMs must include sufficient flexibility to quantify non-linear spatial patterns in occurrence probability. Although spatial variation in occurrence can in some cases be modeled using environmental covariates, residual spatial variation (which is likely common in most applications of SDMs at large spatial scales) can bias estimates of occurrence probability^{7,8}. Second, because occurrence probability at a given point in time is not independent of occurrence probability at earlier points in time, SDMs must explicitly account for temporal auto-correlation in occurrence probability⁹. If temporal auto-correlation is not accounted for within the SDM, occurrence dynamics are likely to appear more variable than they really are, leading to spurious conclusions about temporal variation range dynamics¹⁰. Third, SDMs must uncouple true changes in occupancy from observation errors because the locations experiencing the largest changes in occupancy (e.g., range limits) are also the locations where errors arising from low detection probability are most likely^{6,11}. Although progress has been made on accounting for each of these three issues (complex spatial variation, temporal auto-correlation, and imperfect detection) in SDMs, there are few modeling frameworks that address all three simultaneously.

Dynamic (or multi-season) occupancy models, which jointly estimate temporal change in the probability of occurrence and the probability of false-negative observations⁹, provide a natural framework that potentially meets each of above criteria¹². As a result, the use of occupancy models for species distribution modeling has grown in recent years⁵. At present, most occupancy-based SDMs have been implemented using one of several likelihood-based software programs, including programs PRESENCE¹³ and MARK¹⁴ and the R

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package unmarked¹⁵. These programs allow users to fit several variations of the standard static or dynamic occupancy models⁹ using generalized linear models (GLMs) to estimate covariate effects on occupancy and detection. Although this GLM-based approach can account for covariates, imperfect detection, and temporal auto-correlation in occupancy probability, these programs are restricted in their ability to model non-linear residual spatial variation that often characterizes species' distributions. In most cases, GLM-based models assume that spatial variation can be modeled as a linear or quadratic function of latitude and longitude or environmental covariates¹⁶. For many species, however, a small number of covariates cannot reasonably model all sources of variation and therefore GLM-based occupancy models are unlikely to provide accurate estimates of spatial variation in occupancy.

One alternative to the GLM approach is to estimate non-linear spatial variation in occupancy probability using generalized additive models (GAMs). An extension of GLMs, GAMs estimate the relationship between a response variable and a smoothed non-parametric function of covariates¹⁷. Because the shape of the smoothed functions is determined by the data rather than a parametric function, GAMs can estimate complex, nonlinear spatial patterns that are not accounted for by covariates¹⁸. Like GLMs, GAMs use link functions to accommodate response variables with normal or non-normal error distributions (e.g., binomial, Poisson), making it conceptually simple to extend occupancy models to estimate non-linear effects of covariates¹⁹. Although GAMs have been used to estimate species distributions in a number of contexts^{8,20}, this approach has not been widely used in occupancy-based SDMs that account for both temporal dynamics and imperfect detection.

We propose a new model of space-time occupancy that uses a basis-function formulation and allows the basis coefficients, and thus the spatial patterns, to evolve dynamically over time. This formulation is consistent with other dimension-reduction approaches for space-time modeling²¹. The model is flexible and can accommodate data from a range of sampling designs that provide information about both occupancy and detection. Output from the model can be used to create distribution maps and to estimate intuitive indices of range shifts (range center, range limits). We demonstrate the utility of this approach by modeling long-term (1972–2015) range dynamics of 10 eastern North American birds using data from the North American Breeding Bird Survey. For this application, we also use Gibbs variable selection²² to identify species-specific relationships between climate and occupancy. We anticipate this framework will be particularly useful for modeling species' distributions over large spatial scales and for quantifying range dynamics over long temporal scales because of the improved fit to complex species distributions.

Methods

Model description. We assume that $j = 1, 2, \dots, J$ temporally or spatially replicated presence/absence surveys are conducted in $t = 1, 2, \dots, T$ primary periods at $i = 1, 2, \dots, N$ sampling locations. Further, we assume that the true (but latent) occupancy state of each site, denoted $z_{i,t}$, is closed within each primary period but can change across primary periods. During each survey, the observed occupancy state of the focal species, denoted $h_{i,j,t}$, is recorded (0 = species not observed, 1 = species observed). Our primary aim is to model temporal and spatial variation in the probability of occupancy $\psi_{i,t} = \Pr(z_{i,t} = 1)$ while accounting for imperfect detection. Below, we describe a Bayesian state-space formulation of this model that uses smoothing splines to model complex spatial and temporal auto-correlation in occupancy probability.

State model. In each primary period t , occupancy state is modeled as a Bernoulli random variable with probability $\psi_{i,t}$:

$$\begin{aligned} z_{i,t} &\sim \text{Bernoulli}(\psi_{i,t}) \\ \text{logit}(\psi_{i,t}) &= f_t(\text{lat}_i, \text{lon}_i) + \beta X_{i,t} \end{aligned} \quad (1)$$

where $f_t(\text{lat}_i, \text{lon}_i)$ is a spatial smoothing function, β is a vector of slope coefficients, and $X_{i,t}$ is a matrix containing covariate values for route i in period t . The smooth function f_t is composed of basis functions g_k and their corresponding regressions coefficients $\nu_{k,t}$:

$$f_t(\text{lat}_i, \text{lon}_i) = \sum_{k=1}^K g_k(\text{lat}_i, \text{lon}_i) \nu_{k,t}$$

Different smooth functions can be chosen based on the structure of the data^{17,18}, providing a flexible and efficient means to model complex spatial variation in occupancy probability. The basis dimension K should be large enough to approximate the smooth function (i.e., avoid over-smoothing), though the exact choice of K is not critical because the degree of smoothing is determined primarily by a smoothing penalty term λ which penalizes against over-fitting¹⁷. In a Bayesian context, this penalization can be incorporated by specifying multivariate normal priors for the ν_k coefficients, with the precision matrix proportional to λ . Larger values of λ produce more constrained priors and thus more similar (i.e., more smooth) estimates of the ν_k coefficients¹⁷.

In combination with time-varying covariates $X_{i,t}$, allowing the basis function coefficients to vary across primary periods allows occupancy probability at each site to change over time. When $t = 1$, the $\nu_{k,1}$ coefficients are estimated using the Bayesian penalization approach described above. To account for temporal auto-correlation in occupancy, the basis function coefficients in periods $t > 1$ were modeled as temporally-correlated random effects:

$$\nu_{k,t} \sim \text{Normal}(\nu_{k,t-1}, \sigma^2)$$

where σ^2 is the variance among primary periods.

Observation model. The observed status of each site during each survey ($h_{i,j,t}$) is modeled as a function of both the latent state process ($z_{i,t}$) and detection probability p_t :

$$h_{i,j,t}|z_{i,t} \sim \text{Bernoulli}(z_{i,t}p_t)$$

Covariates thought to influence the detection process (observer bias, weather, etc.) can be incorporated into this structure using a logistic link function on p_t (see below).

Distribution maps and indices of range dynamics. When latitude, longitude, and annual covariate values are available at unsampled locations within a species' range, posterior distributions of the predicted occupancy probability at those locations can be easily estimated from the posterior samples of the fitted model^{10,12}. Posterior estimates of range-wide occupancy probability can be used to visualize changes in species' distributions and to quantify indices of range dynamics¹⁰. Although many such indices are possible, we describe four that may be particularly relevant to quantifying range shifts. First, the mean occupancy probability of all map cells provides an index of changes in the proportion of area occupied¹⁰. Second, the mean breeding latitude, estimated as the sum of the cell latitudes weighted by their occupancy probabilities and divided by the total occupancy probability across all cells, can be used to quantify shifts in the center of species range¹⁰. Finally, annual indices of the northern/southern range limits can be estimated by sorting the map cells by latitude and then using a smoothing spline function to predict the latitude below/above which 99.9% of the total occupancy probability is located. Although not an absolute measure of the northern- and southern-most latitudes at which a species was found, this index provides a time series of relative change in the northern and southern range limits, which can be used to determine whether distributions have expanded or contracted over time.

Application. Data. We demonstrate the utility of this model by quantifying range dynamics of 10 eastern North American bird species: Red-bellied Woodpecker (*Melanerpes carolinus*), Fish Crow (*Corvus ossifragus*), Carolina Chickadee (*Parus carolinensis*), Carolina Wren (*Thryothorus ludovicianus*), Blue-gray Gnatcatcher (*Poliophtila caerulea*), Wood Thrush (*Hylocichla mustelina*), Golden-winged Warbler (*Vermivora chrysoptera*), Swainson's Warbler (*Limnithlypis swainsonii*), Louisiana Waterthrush (*Parus motacilla*), and Kentucky Warbler (*Geothlypis formosa*). We selected these species because they exhibit a wide range of spatial and temporal complexity in range dynamics. Data for this analysis came from the North American Breeding Bird Survey (BBS), a large-scale citizen science program consisting of over 5500 roadside survey routes of which approximately 3000 are surveyed each May or June by trained volunteers²³. The BBS was initiated in 1966, though only a small number of routes were surveyed during the early years. For this reason, we chose to use BBS data collected from 1972 to 2015²⁴. Trained observers conduct 3-minute point counts at 50 regularly spaced stops along each approximately 39.4 km-long route. See 23 for more details regarding the BBS survey protocol. Prior to analysis, we converted the raw counts to stop-level presence/absence data.

To model spatial/climate relationships across the edge of each species' occupied range, we subset all BBS routes with at least one detection of the focal species over the study period (i.e., routes occupied in at least one year). Next, we created a 2°-buffered convex hull around the occupied routes and included all routes within the buffered region.

Climate data was obtained from the University of East Anglia Climate Research Unit (CRU)²⁵. The CRU data contains global estimates of monthly surface climate variables for 0.5° grid cells²⁵. Following Clement *et al.* (2016), we converted the monthly temperature and precipitation estimates from the CRU data set into five 'bioclim' variables that have low correlation and are effective for modeling species ranges¹. Specifically, for each grid cell we calculated the mean temperature, mean diurnal temperature range, mean temperature of the wettest quarter, annual precipitation, and precipitation of the warmest quarter for the 12 months preceding each BBS survey (i.e., June-May). All estimates were obtained using the 'biovars' function in the 'dismo' package²⁶ in program R²⁷. Prior to analysis, each variable was scaled to mean = 0 and standard deviation = 1 and we extracted the annual climate values for the grid cell containing the first stop of each BBS route.

Because BBS routes are surveyed a single time each year, conventional methods for estimating detection probability from temporally replicated surveys are not possible. Instead, we adapted an occupancy model that uses the correlation between adjacent spatial replicates to estimate detection probability^{28,29}. In this model, occurrence is estimated at two scales: (1) the route-level (i.e., $z_{i,t}$), and (2) the stop-level (denoted $y_{j,i,t}|z_{i,t}$). Hereafter we follow Clement *et al.* (2016) and refer to presence at the route-level as "occupancy" and presence at the stop-level as "availability". Digital records of the raw 50-stop BBS data are only available from 1997-present. However, 10-stop summaries (sum of counts from stops 1–10, 11–20, 21–30, 31–40, and 41–50) are available for the entire BBS period²⁴. Initial testing indicated that estimates of the route-level occupancy did not differ when the model was fit using the full 50-stop data or the 10-stop summaries (i.e., 5 replicates per route). Therefore, we chose to use the 10-stop data so that inferences could be made over the entire BBS time series.

State model. Spatial and annual variation in route-level occupancy probability was modeled using a modified version of Eq. 1:

$$\text{logit}(\psi_{i,t}) = f_t(\text{lat}_i, \text{lon}_i) + \omega\beta\mathbf{X}_{i,t}$$

where ω is a vector of binary indicator variables determining whether each climate predictor is included in the model and $\mathbf{X}_{i,t}$ is a matrix containing the annual climate values in year t at route i . Estimation of ω is described below. To capture non-linear relationships between climate and occupancy, the matrix \mathbf{X} contained both the linear and quadratic terms for each of the 5 climate covariates. For the spatial smooth, we used a thin-plate

regression spline of the latitude and longitude of each BBS route. For all species, we chose $k = 60$, which initial tests indicated was large enough to approximate the smooth function for all species considered.

At the stop level, availability is modeled as a first-order Markov process with parameters:

- $\theta_{i,j,t} = \Pr(\text{availability at stop } j | \text{route } i \text{ occupied and stop } j - 1 \text{ unavailable})$
- $\theta'_{i,j,t} = \Pr(\text{availability at stop } j | \text{route } i \text{ occupied and stop } j - 1 \text{ available})$

As noted by 28, the first stop on each BBS routes has no predecessor and thus availability at stop 1 cannot be modeled using θ or θ' . Instead, we directly estimated the probability π_i that the first stop is available in year t :

$$y_{i,1,t} \sim \text{Bernoulli}(z_{i,t}\pi_i)$$

For the remaining stops, availability was modeled as:

$$y_{i,j,t} | y_{i,j-1,t} \sim \begin{cases} \text{Bernoulli}(z_{i,t}\theta), & \text{if } y_{i,j-1,t} = 0 \\ \text{Bernoulli}(z_{i,t}\theta'), & \text{if } y_{i,j-1,t} = 1 \end{cases}$$

Observation model. Numerous factors could influence detection probability in BBS surveys. Observer experience and variation among observers are both known to influence detection of many species³⁰. Weather conditions, particularly wind speed, may also influence detectability. For our analysis, we included wind speed scores recorded at the start of each BBS count using the Beaufort wind scale²³. Between 2009 and 2015, a small number of BBS routes ($n = 106$) were surveyed using a modified protocol (RPID = 501) that incorporated time and distance information³¹. Compared to the standard BBS protocol (RPID = 101), this time-distance protocol resulted in on average 10% fewer observations per survey (Sauer *et al.*)³². To account for these effects, we modeled detection conditional on stop-level availability and route-level occupancy as:

$$h_{i,j,t} \sim \text{Bernoulli}(z_{i,t}y_{i,j,t}p_{i,t})$$

$$\text{logit}(p_{i,t}) = \alpha_0 + \alpha_1 \text{WIND}_{i,t} + \alpha_2 \mathbf{I}_{i,t} + \alpha_3 \kappa_{i,t} + \eta_{i,t}$$

where α_0 is an intercept term, $\text{WIND}_{i,t}$ is the wind score, $\mathbf{I}_{i,t}$ is a binary dummy variable indicating whether year t was an observer's first year of service, $\kappa_{i,t}$ is a dummy variable indicating the survey protocol used (0 = standard BBS survey, 1 = time-distance protocol), and $\eta_{i,t}$ is a random observer effect.

Model selection. Given the large number of climate predictors in our model and the lack of *a priori* hypotheses about which predictors should influence the distribution of each species, each climate variable m was multiplied by a binary latent variable ω_m which determined whether the variable was included in the linear predictor. The posterior probability $\Pr(\omega_m = 1)$ is then a measure of the relative importance of variable m ^{22,33,34}. For the linear effect of each climate variable, we assumed mutually independent Bernoulli priors:

$$\omega_m \sim \text{Bernoulli}(0.5)$$

For the quadratic terms, we enforced marginality by setting:

$$\omega_{m^2} \sim \text{Bernoulli}(\omega_m 0.5)$$

where m^2 is the quadratic term associated with the linear term m . Thus, quadratic terms could only enter the model if the corresponding linear term is also in the model. To ensure good mixing of the ω_m parameters, we used Gibbs Variable Selection²² to create joint prior distributions for the β_m parameters conditional on ω_m :

$$\beta_m | \omega_m = \omega_m N(0, 100) + (1 - \omega_m) N(\mu_m, \sigma_m^2)$$

where $N(0, 100)$ is a non-informative normal prior when $\omega_m = 1$ and $N(\mu_m, \sigma_m^2)$ is a pseudo-prior sampled when $\omega_m = 0$. We estimated μ_m and σ_m^2 by running the correlated detection model in PRESENCE¹³ using the first 10 years of BBS data for each species and including linear and quadratic effects for all five climate predictors.

Modeling fitting and indices of range shifts. We fit the models in JAGS³⁵ called from R using the jagsUI package³⁶. As described above, we specified multivariate normal priors for the GAM smooth coefficients, Bernoulli priors for the indicator variables, and vague normal priors for the β coefficients. For all other parameters, we specified appropriate vague priors. See Data S1 for model code and specification details. We assessed goodness-of-fit using posterior predictive checks (PPC). Because conventional PPC metrics are inappropriate for binary occupancy data¹⁹, we used each posterior estimate from the fitted model to simulate the expected number of routes with each of the 32 possible detection histories in each year. We used a Freeman-Tukey statistic³⁷ to measure the discrepancy between the observed/simulated and predicted detection history frequencies and we report the Bayesian P-value from these tests.

For each species, we created annual distribution maps and range shift indices using the climate covariate values, latitude, and longitude for each 0.5° raster cell within the same buffered convex hull used to subset BBS routes. Posterior distributions of the predicted annual occupancy probability in each cell were estimated using

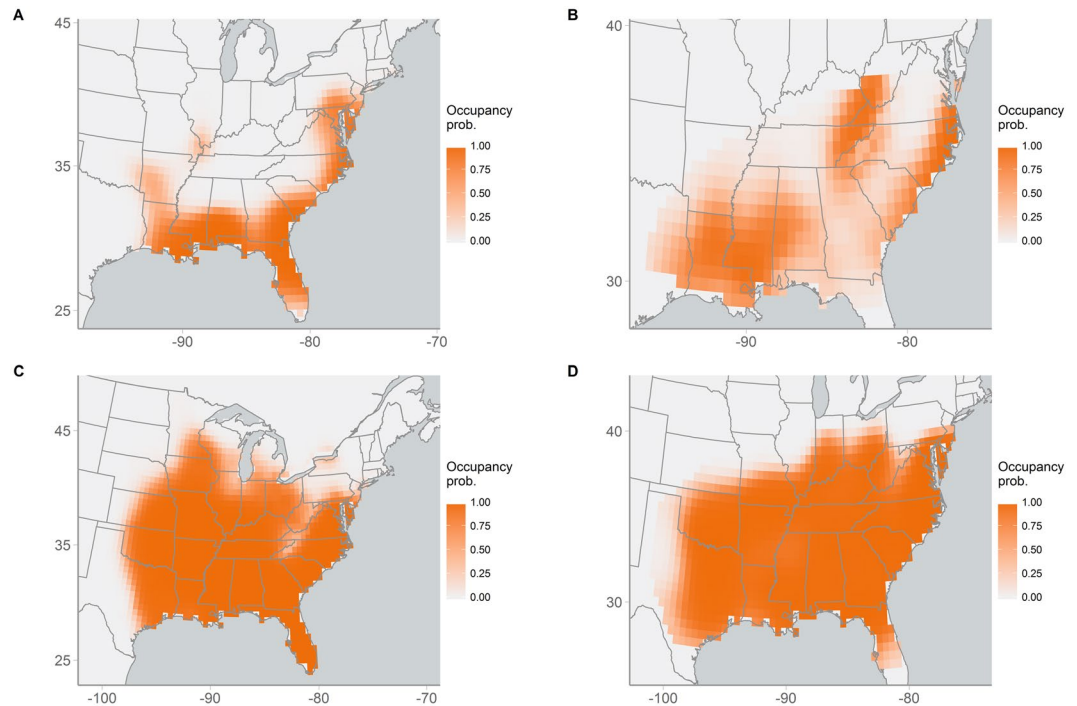


Figure 1. Distributions of (A) Fish Crow, (B) Swainson's Warbler, (C) Carolina Chickadee, and (D) Eastern Towhee. Maps show the predicted probability of occupancy in 1972 for each species.

the posterior samples for each model parameter. From these distributions we then estimated posterior distributions for the four indices described above (proportion of area occupied, mean breeding latitude, and northern/southern range limits).

Results

Posterior predictive checks did not evince lack of fit for any species (Red-bellied Woodpecker $p = 0.35$, Fish Crow $p = 0.38$, Carolina Chickadee $p = 0.63$, Carolina Wren $p = 0.42$, Blue-gray Gnatcatcher $p = 0.74$, Wood Thrush $p = 0.36$, Golden-winged Warbler $p = 0.67$, Swainson's Warbler $p = 0.44$, Louisiana Waterthrush $p = 0.72$, Kentucky Warbler $p = 0.26$), indicating that the spatial GAM was able to model both complex and relatively simple distributions. For example, species like Fish Crow and Swainson's Warbler have complex spatial distributions that do not exhibit simple linear or quadratic relationships with latitude and/or longitude. Occupancy probabilities for the Fish Crow were high along the Atlantic and Gulf coasts as well as in the southern Mississippi River valley, resulting in a U-shaped distribution with no clear range center (Fig. 1A). The distribution of Swainson's Warbler was also complex, with three distinct areas of high occupancy and low occupancy in between (Fig. 1B). In contrast, the distributions of some species, including Red-bellied Woodpecker and Carolina Chickadee, were less complex, with a large central area of high occupancy with declining occupancy along the periphery of the range (Fig. 1C,D).

The model was also able to quantify temporal changes in occupancy probability over the 43 year time period of the BBS data, revealing similarities and differences in regional dynamics in several species. For example, Louisiana Waterthrush, Kentucky Warblers, Wood Thrush, and Golden-winged Warblers all experienced large declines in occupancy probability in the eastern portions of their range, especially in the northeastern United States and Appalachia, but were relatively stable or increasing in the mid-western United States (Fig. 2). These species differed, however, in occupancy trends in the southeastern United States, with Louisiana Waterthrush and Kentucky Warblers showing modest increases in occupancy probability and Wood Thrush and Golden-winged Warblers declining in occupancy probability.

Indices of range shifts from our model indicate that some species have undergone distributional shifts over the past four decades. For example, the northern range limit of Blue-gray Gnatcatchers shifted northward by 1.2° latitude and the mean breeding latitude shifted northward by 1° (Fig. 3A,B). Interestingly, this species has shown small (0.2°) southward expansion at the southern edge of its range and as a result, the proportion of area occupied has increased over time (Fig. 3C). The indices were also able to capture transient dynamics in distributional shifts. Northern populations of Carolina Wren, for example, experienced large declines in occupancy probability in the late 1970's, resulting in a contraction of the northern range limit and mean breeding latitude by 1° latitude (Fig. 3E,F). This contraction was temporary, however, with these populations subsequently experiencing a sustained northward expansion extending 1.7° beyond their initial northern range limit (Fig. 3D).

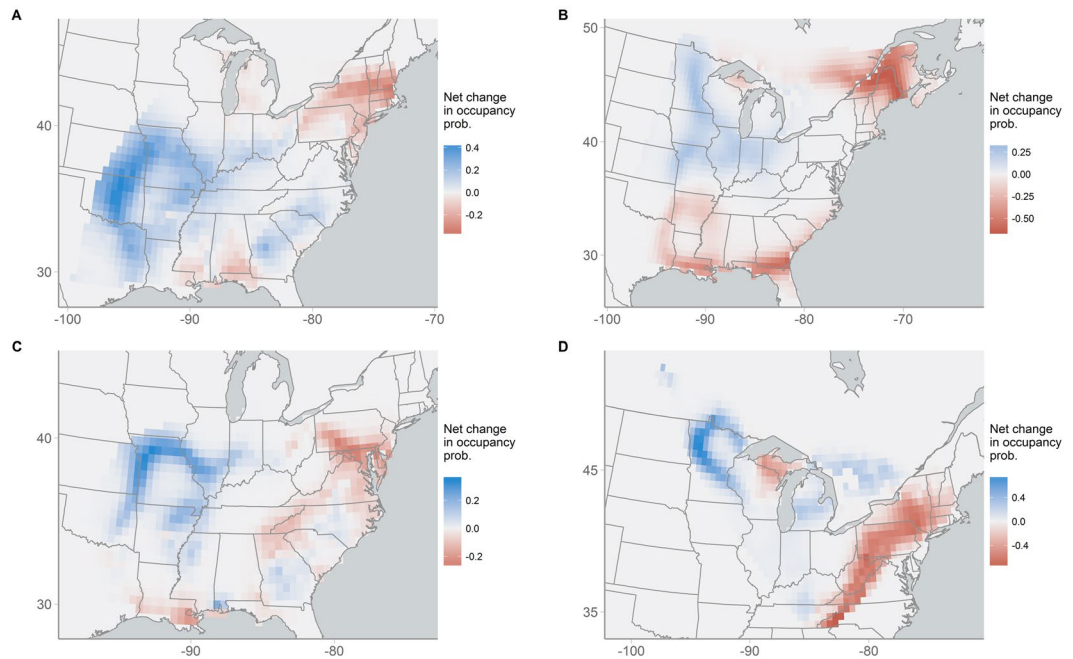


Figure 2. Net change in occupancy probability ($\psi_{2015} - \psi_{1972}$) for (A) Louisiana Waterthrush, (B) Brown Thrasher, (C) Kentucky Warbler, and (D) Golden-winged Warbler. Blue indicates areas that have increased in occupancy probability; red indicates areas that have decreased in occupancy probability.

Discussion

The distributions of most species are characterized by complex and dynamic variation in occurrence. Species distribution modeling seeks to relate this variation to environmental covariates and extrapolate these relationships to unsampled sites and times. Because habitats and species-habitat relationships change across both space and time, conventional GLM-based models rarely capture the inherent complexity of species distributions, especially when inferences are made across large spatial or long temporal scales. Here, we demonstrate a novel occupancy-based SDM that combines environmental predictors with a spatial GAM to model covariate relationships and complex, non-linear spatial variation in occupancy probability while accounting for imperfect detection.

Application of this model to 10 North American bird species demonstrates the utility and flexibility of our approach for species' distribution modeling. Unlike parametric models that use low-order polynomials to capture spatial variation in occupancy, the spatial GAM derives non-parametric occupancy patterns during estimation while avoiding overfitting through the incorporation of a smoothing penalty term. This balancing of complexity and smoothing ensures that the model allows for, but does not impose, complex spatial variation in occupancy. This formulation provides an efficient and flexible method to model large-scale spatial variation in occupancy probability, for example allowing us to model both the complex distributions of Fish Crow and Swainson's Warbler and the relatively more simple distributions of Carolina Chickadees and Red-bellied Woodpeckers using a common model structure.

Modeling the GAM coefficients as temporally-correlated random effects also allowed us to explicitly model changes in occupancy probability over time. In our analysis of BBS data, the model uncovered interesting similarities and differences in the range dynamics of several species that inhabit forest habitats in the eastern United States, including Louisiana Waterthrush, Wood Thrush, Kentucky Warblers, and Golden-winged Warblers. In the case of Wood Thrush and Golden-winged Warblers, this regional variation in occupancy dynamics is consistent with differences in demographic rates among the regions^{38,39}, suggesting that our occupancy model was able to capture spatial variation in population dynamics.

The indices of latitudinal range dynamics from our model also documented range expansions of Blue-gray Gnatcatchers and Carolina Wrens, demonstrating the utility of these metrics for quantifying range shifts over long temporal scales. The ability to document shifts at range margins while accounting for imperfect detection is particularly important given that these locations are likely to experience the largest changes in occupancy but also have the lowest detection probability. Application of this framework to a larger pool of species could indicate whether range shifts provide a consistent fingerprint of climate change. It may also be possible to quantify range shifts of entire groups of species by creating composite versions of our indices, which would be particularly useful for testing hypotheses about which traits promote or impede the ability of species to respond to habitat and climate change.

Our model differs from the conventional dynamic occupancy model in that we did not directly estimate change in occupancy as the result of extinction/colonization processes. Under the extinction/colonization formulation, occupancy probability at a given location i will converge on the stable-state occupancy distribution defined by $\bar{\psi}_i = \frac{\gamma_i}{\gamma_i + \varepsilon_i}$, where γ_i and ε_i are the colonization and extinction rates at location i ⁴⁰. Although it is possible to

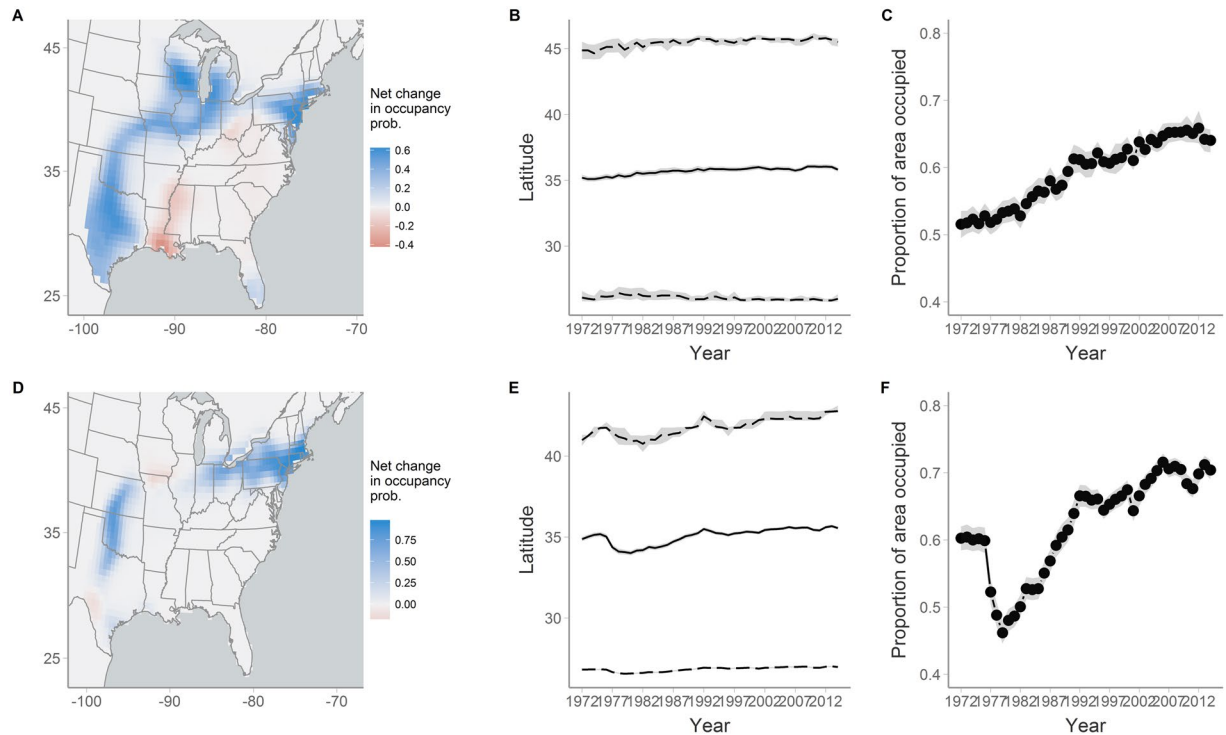


Figure 3. Net change in occupancy probability, latitudinal range indices, and proportion of area occupied for (A–C) Blue-gray Gnatcatcher and (D–F) Carolina Wren. For latitudinal range indices, solid lines indicate the mean breeding latitude and dashed lines indicate the northern and southern range limit. Gray ribbons represent the 95% credible intervals.

model non-equilibrium dynamics by including time-varying covariates, initial testing of our model using the extinction/colonization formulation resulted in extinction rates that were very low relative to colonization rates for most species. As a result, occupancy probabilities in the final year of our analysis were non-negligible (>~8–10%) at locations where the species were never detected. We suspect this may be a common issue when fitting dynamic occupancy models at large spatial and long temporal scales. Under these circumstances, our approach may be preferable when the goal is to document range shifts. In some cases, using the conventional dynamic occupancy model with spatial variation in extinction/colonization probabilities may be preferred, particularly when the focus is on mechanistic understanding of range dynamics. Additionally, GAMs generally perform poorly when predicting outside of the data used to fit the model so the conventional occupancy model may be more suitable when the goal is to predict future distributions.

The model presented in this paper builds off of recent advances in the development of occupancy-based SDMs that account for both imperfect detection and temporal auto-correlation in occupancy¹⁰. Our model extends this framework to account for complex spatial and temporal variation in occupancy probability through the use of a hierarchical Bayesian model with a spatial GAM. Accounting for complex spatial structure in SDMs is an active area of research⁴¹ and other methods exist for handling spatial structure in occupancy models, particularly through the use of conditional autoregressive (CAR) modeling^{7,8,42}. Both CAR and GAM approaches have been shown to reduce bias in SDM models⁸, though the GAM approach is generally more computationally efficient, produces more precise parameter estimates, and can be fit using most popular Bayesian software programs, including JAGS, WinBUGS⁴³, NIMBLE⁴⁴, and STAN⁴⁵. These two approaches are not mutually exclusive though and future work integrating GAM and CAR models in occupancy-based SDMs is likely to improve inferences about past and future range dynamics.

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Author Contributions

C.S.R., J.A.R. and K.L.P. conceived of the study with input from D.J.Z. C.S.R. and J.A.R. developed the methods. C.S.R. carried out all analyses and drafted the manuscript. All authors contributed to subsequent revisions.

Additional Information

Competing Interests: The authors declare no competing interests. All data and code necessary to recreate the analyses in this paper can be downloaded and run using the BBS.SDM R package, with instructions available on the author's Github page at <https://github.com/RushingLab/BBS.SDM>.

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