Methods and Results

## Methods

We designed the model to estimate the effects of annual climate patterns on abundance of Black Terns observed during BBS surveys, while accounting for medium- and long-term population trends that were not associated with these climate patterns. We used two annual climate covariates: one that represented the local moisture conditions using the Standardized Precipitation Evapotranspiration Index (SPEI (Beguería et al., n.d.)); and, a second that represented the North Atlantic Oscillation Index (NAOI, (Hurrell 1995), accessed through <https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml>) from the previous winter (January - June, on a 1-year lag, 18 - 12 months before the BBS surveys were conducted; following (Davis et al. 2023)). We fit three models: a base model that did not include climate data; a climate model that included the effects of SPEI and NAOI on the annual abundance; and a climate-plus-core model that also included the annual SPEI in the core of the species’ range as a predictor on the annual abundance outside of the core. All of the models included spatially varying effects of the climate predictors and spatially varying population trends, so that these effects could vary across the species’ range and so that information could be shared in a way that respects the geographic structure of the data (Thorson et al. 2023).

### Moisture - SPEI

We used SPEI as an indicator of the local annual moisture conditions that Black Terns would experience at the beginning of the breeding season. The SPEI is a multiscale, standardized index that characterizes moisture conditions over different time- scales prior to a given month (e.g., the previous 1-month or the previous 6 months). Negative SPEI values indicate drought or dry conditions , while positive SPEI values indicate relatively wet conditions . The SPEI data are spatially explicit (available as a spatial raster layer), and so we sumarised these data for a given year and a given spatial stratum (1-degree by 1-degree grid cell), so they would represent the moisture conditions specific to the area and time when the BBS surveys were conducted. We used a 15-month SPEI for the month of June in each year. This index captures the moisture conditions that birds experienced at the beginning of a given breeding season, based on the moisture balance from the previous 15 months (i.e., the preceding year plus the previous spring). We acknowledge that this 15-month period is somewhat arbitrary. We also compared this to an alternative where we modeled separate effects of both a 3-month SPEI (i.e., the moisture conditions from that spring) plus a 1-year lagged measure of 3-month SPEI from the previous June (i.e., the moisture conditions from the previous spring). This alternative model had lower out-of-sample predictive accuracy than the 15-month SPEI model (Table 1). We have not included detailed results from this model here, but the qualitative results were essentially the same as those for the model here.

### NAOI

We used the winter NAOI (January-May) from the previous year (NAOI from 18-12 months before each breeding season). The NAOI is an annual index that does not include a spatial component, so NAOI predictor values are the same across the species’ range in each year. However, the models allowed the effect of the annual NAOI to vary in space (details below).

#### Base model

The base model was the spatially explicit GAMYE models described in (Smith et al. 2024). In the GAMYE model, the population trajectory (pattern of annual abundance through time) is modeled as an additive combination of a non-linear smooth (i.e., the GAM component) and year-effects that model the annual fluctuations around the smooth (the YE component). In this particular version, we used a spatially explicit, hierarchical model structure to share information on the non-linear smooth component among strata. This spatial model allowed us to fit the model using a relatively fine-grained spatial stratification based on 1-degree longitude by 1-degree latitude grid ((Smith et al. 2024)). The spatially explicit aspects ensure that the medium- and long-term trends can vary among strata, but that trends in nearby strata are more similar than trends in strata further away. The model also included all of the parameters regularly included in models for the BBS data to account for variation among observers, among routes, and first-year observer start-up effects ([Edwards, Smith, and LaZerte (2023)](Smith et al. 2024)).

In the base model, we estimated the observed counts () of Black Terns on route-r, in stratum-i and year-t, by observer-j as as realizations of a negative binomial distribution, with mean and inverse dispersion parameter . The log of the mean () of the negative binomial distribution was modeled as an additive combination of stratum-level intercepts (), the year-specific location along the stratum-level non-linear smooth (), year-effects (), observer-effects (), and a first-year observer-effect (). The year-effects () in this model are random-effects that track annual fluctuations as departures from the medium- and long-term changes modeled by the smooths (). In this base model, they are estimated for each stratum-i and year-t as a random variate drawn from a normal distribution centered on 0, and with an estimated standard deviation (). All of the data manipulation, model structure, and model fitting for the base model were conducted using the r-package bbsBayes2 (Edwards, Smith, and LaZerte 2023).

#### Climate model

We built the climate model by starting with the base model and adding a sub-model to estimate the year-effects using two climate-based predictors. With these predictors, the annual fluctuations in stratum-i and year-t () were an additive combination of the effect of SPEI in that year and stratum (), the effect of the NAOI in the previous year (), and an additional random variate ().

The effects of both SPEI and NAOI were allowed to vary among strata, as spatially varying coefficients ((Thorson et al. 2023)). Each of the stratum-specific parameters for the effects of SPEI () and NAOI (), were estimated as a combination of spatially-varying effects (), estimated with a zero-sum constraint and a hyperparameter () that represents the mean effect of each covariate across all strata.

We estimated the spatially-varying component () using the same intrinsic spatial conditional autoregressive (iCAR) neighbourhood matrix used to estimate the spatially varying smooths ((Smith et al. 2024)). This iCAR modelling structure estimates the stratum-level component for each covariate as a normally distributed variate, centered on the mean of the parameters in the surrounding strata, with an estimated among-strata standard deviation or . So, the local component of the effect of SPEI on the annual relative abundance in stratum-i () is a normal variate centered on the mean of the effect in the set of the -strata that are direct neighbours of stratum-i. These spatially varying effects are estimated using a soft, sum-to-zero constraint ((Morris et al. 2019)) to ensure they are centered on the hyperparameter , representing the mean effect across all strata.

#### Climate-plus-core model

This model started with the climate model plus an effect of annual moisture in the core of the species’ range () on the annual abundance in strata outside of the core. We defined the core of the species range as strata that fall completely within the Prairie Potholes Bird Conservation Region (BCR 11, Figure 2). So, this effect of moisture in the core () only contributes to estimating the annual abundance in strata outside of the core, has a constant effect across all strata where it is relevant (i.e., it is not spatially varying), and has no effect on estimates within the core range. The term is an indicator variable that takes the value 0 for all strata inside the core of the species range and 1 for all strata outside of the core.

We calculated the values by averaging the across all core strata for that year.

### Trends

In all models, the trends represent changes in Black Tern populations that are occurring on medium- to long-term time scales and not the result of annual variations. We estimated trends using only the smooth component of the model, after removing the effects of the annual fluctuations, following (Smith et al. 2024) and (Smith and Edwards 2021). As a result, trends from the climate and climate-plus-core models represent changes in populations after removing the effects of variation in these annual factors.

### Model Fit

We compared the fit of the models to the BBS data using an approximate out-of-sample predictive accuracy metric for Bayesian models: estimated log predictive density (elpd, [Gelman, Hwang, and Vehtari (2014)](Vehtari, Gelman, and Gabry 2017)). This metric is an approximation of the ability for each model to accurately estimate data that were not used to fit the model, much like AIC (Burnham and Anderson 2002).

### Parameter estimates

For the effects of the climate predictors, we explored both the overall mean effects (hyperparameters e.g., ) as well as the spatial pattern in the spatially varying effects (e.g., ). We report the posterior means as well as the upper and lower limits of the 90% highest posterior density interval as summaries of the posterior distributions of the estimates (Gelman et al. 2013). Highest posterior density intervals are similar to standard percentile credible intervals, but are guaranteed to include the posterior mode.

# References Cited

Beguería, Santiago, Sergio M. Vicente Serrano, Fergus Reig-Gracia, and Borja Latorre Garcés. n.d. “SPEIbase v.2.9 [Dataset].”

Burnham, K. P., and D. R. Anderson. 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*. Springer New York. <https://books.google.ca/books?id=IGJ8cgAACAAJ>.

Davis, Kayla L., Sarah P. Saunders, Stephanie Beilke, Erin Rowan Ford, Jennifer Fuller, Ava Landgraf, and Elise F. Zipkin. 2023. “Breeding Season Management Is Unlikely to Improve Population Viability of a Data-Deficient Migratory Species in Decline.” *Biological Conservation* 283 (July): 110104. <https://doi.org/10.1016/j.biocon.2023.110104>.

Edwards, B. P. M., A. C. Smith, and S. LaZerte. 2023. “bbsBayes2: Hierarchical Bayesian Analysis of North American BBS Data.” <https://github.com/bbsBayes/bbsBayes2>.

Gelman, Andrew, John, B. Carlin, Hal S. Stern, David, B. Dunson, Aki Vehtari, and Donald, B. Rubin. 2013. *Bayesian Data Analysis*. 3rd ed. Chapman; Hall/CRC. <https://doi.org/10.1201/b16018>.

Gelman, Andrew, Jessica Hwang, and Aki Vehtari. 2014. “Understanding Predictive Information Criteria for Bayesian Models.” *Statistics and Computing* 24 (6): 9971016. <https://doi.org/10.1007/s11222-013-9416-2>.

Hurrell, James W. 1995. “Decadal Trends in the North Atlantic Oscillation: Regional Temperatures and Precipitation.” *Science* 269 (5224): 676–79. <https://doi.org/10.1126/science.269.5224.676>.

Morris, Mitzi, Katherine Wheeler-Martin, Dan Simpson, Stephen J. Mooney, Andrew Gelman, and Charles DiMaggio. 2019. “Bayesian Hierarchical Spatial Models: Implementing the Besag York Mollié Model in Stan.” *Spatial and Spatio-Temporal Epidemiology* 31 (November): 100301. <https://doi.org/10.1016/j.sste.2019.100301>.

Smith, Adam C, Allison D. Binley, Lindsay Daly, Brandon P M Edwards, Danielle Ethier, Barbara Frei, David Iles, Timothy D Meehan, Nicole L Michel, and Paul A Smith. 2024. “Spatially Explicit Bayesian Hierarchical Models Improve Estimates of Avian Population Status and Trends.” *Ornithological Applications* 126 (1): duad056. <https://doi.org/10.1093/ornithapp/duad056>.

Smith, Adam C, and Brandon P M Edwards. 2021. “North American Breeding Bird Survey Status and Trend Estimates to Inform a Wide Range of Conservation Needs, Using a Flexible Bayesian Hierarchical Generalized Additive Model.” *The Condor* 123 (1): duaa065. <https://doi.org/10.1093/ornithapp/duaa065>.

Thorson, James T., Cheryl L. Barnes, Sarah T. Friedman, Janelle L. Morano, and Margaret C. Siple. 2023. “Spatially Varying Coefficients Can Improve Parsimony and Descriptive Power for Species Distribution Models.” *Ecography* 2023 (5): e06510. <https://doi.org/10.1111/ecog.06510>.

Vehtari, Aki, Andrew Gelman, and Jonah Gabry. 2017. “Practical Bayesian Model Evaluation Using Leave-One-Out Cross-Validation and WAIC.” *Statistics and Computing* 27 (5): 1413–32. <https://doi.org/10.1007/s11222-016-9696-4>.