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Spatio-temporal Trend Analysis of Spring Arrival Data for Migratory Birds

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There is increasing interest in spatio-temporal analysis of environmental and ecological responses to changes in the climate due to the recent concerns about climate change. In this work, we propose a spatio-temporal modeling framework for analyzing environmental and ecological data while accounting for spatial and temporal structure, as well as climate effects. As an example, we consider data on bird migration in the United States and analyze the spring arrival dates of Purple Martins between historical data (1905–1940) from the North American Bird Phenology Program and recent data (2001–2010) from the Purple Martin Conservation Association. The proposed approach allows researchers to compare mean arrival dates while accounting for spatial and temporal variability. Our results for Purple Martins showed statistically significant earlier spring arrivals in parts of United States over the recent years. The proposed approach provides a useful tool for statistical analysis of spatio-temporal data related to studies of climate change.

Keywords Bird migration; Climate change; Hierarchical Bayesian models; Markov chain Monte Carlo; Spatio-temporal analysis.

Mathematics Subject Classification 62; 92.

1. Introduction

The study of environmental and ecological response to climate change in recent years has provided ample evidence of the ecological impacts of recent climate change (e.g., Walther et al., 2002). In particular, bird migration is known to be sensitive to changes in the climate and thus, there is increased interest in analyzing potential changes in the migration patterns of migratory birds that may provide insight on environmental and ecological response to climate change.

The history of bird migration studies dates back to Aristotle who compiled notes on more than 140 species of birds and formalized ornithology as a science (Alerstam, 1990; Berthold, 2001). Historically, ecologists and ornithologists have studied patterns of bird

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migration to learn about individual or groups of bird species, as well as to understand the ecological impact of long- and short-term migration processes on local and global ecosystems. Recently, statistical analysis of bird migration and phenological changes has become increasingly popular in the context of more general problems such as climate change (e.g., Cox, 2010; Møller et al., 2004; Sherry, 2011) and epidemiology of infectious diseases that are linked to bird migration such as avian influenza outbreaks (e.g., Bourouiba et al., 2010; Feare, 2007; Liu et al., 2005). Often, these analyses require spatial or spatio-temporal modeling due to the nature of migration data, which includes spatio-temporal variability. There are several recent examples of such efforts in ornithology (e.g., Hüppop and Winkel, 2006; Tøttrup et al., 2006) and epidemiology literature (e.g., LaDeau et al., 2008, 2010; Munster et al., 2007; Onozuka and Hagihara, 2008; Si et al., 2009).

In this article, we focus on the analysis of migratory bird data in order to detect shifts in spatio-temporal patterns of spring arrival dates in the United States (specifically, east of the Rocky Mountains). Notwithstanding the spatial and spatio-temporal nature of the spring arrival process, the literature on analysis of spring arrival dates using spatial and spatio-temporal models is sparse (e.g., Both and te Marvelde, 2007; Gordo, 2007, use spatial models; Hurlbert and Liang, 2012; Fink et al., 2010, use spatio-temporal models). In this article, our goal is to develop a straightforward spatio-temporal approach for analyzing spring arrival data. The proposed framework allows us to include weather, climate, and other types of predictor variables in the model. The main focus is on developing a general framework as an exploratory data analysis tool for inferential purposes. However, the flexibility of the proposed framework allows for using this approach for predictive purposes too. As a case study for spatio-temporal analysis of spring arrival dates, we assess changes in arrival dates of Purple Martins between a historical and recent time period. Section 2 discusses the data and introduces the methodology. Results are given in Section 3, followed by discussion and conclusions in Section 4.

2. Materials and Methods

2.1 *Spring Arrival Data*

The Purple Martin (*Progne subis*) is the largest member of the swallow family in North America and is of special interest to birders, in large part, because of the close proximity of its nesting sites to human settlements. Purple Martins spend the nonbreeding season in Brazil and migrate to North America to nest, where naturalists have documented their arrivals for more than a century. Adult Purple Martins commonly return to the same nesting sites where they were successful in previous years and are easily detected by their unique morphology and vocalization (Brown, 1997).

The North American Bird Phenology Program (NABPP) coordinated the efforts of over 3,000 volunteer naturalists to collect data on bird migration and breeding and wintering distributions from 1881 to 1970. In response to recent climate change concerns, the NABPP was revitalized in 2008 (Zelt et al., 2012) and is currently digitizing and transcribing the nearly 6 million first arrival records reported for the more than 200 bird species tracked by volunteers between 1881 and 1970. To date, more than a million handwritten records have been scanned and transcribed, including all first arrival records for the Purple Martin in the eastern United States (24°N–49°N, 67°–94°W; Courter, 2012). Once completed and validated, the full complement of records will be freely accessible to biologists, managers, and the general public. Since 2012, Georgetown University has established a partnership program with the NABPP in order to accelerate the data digitization/validation process,

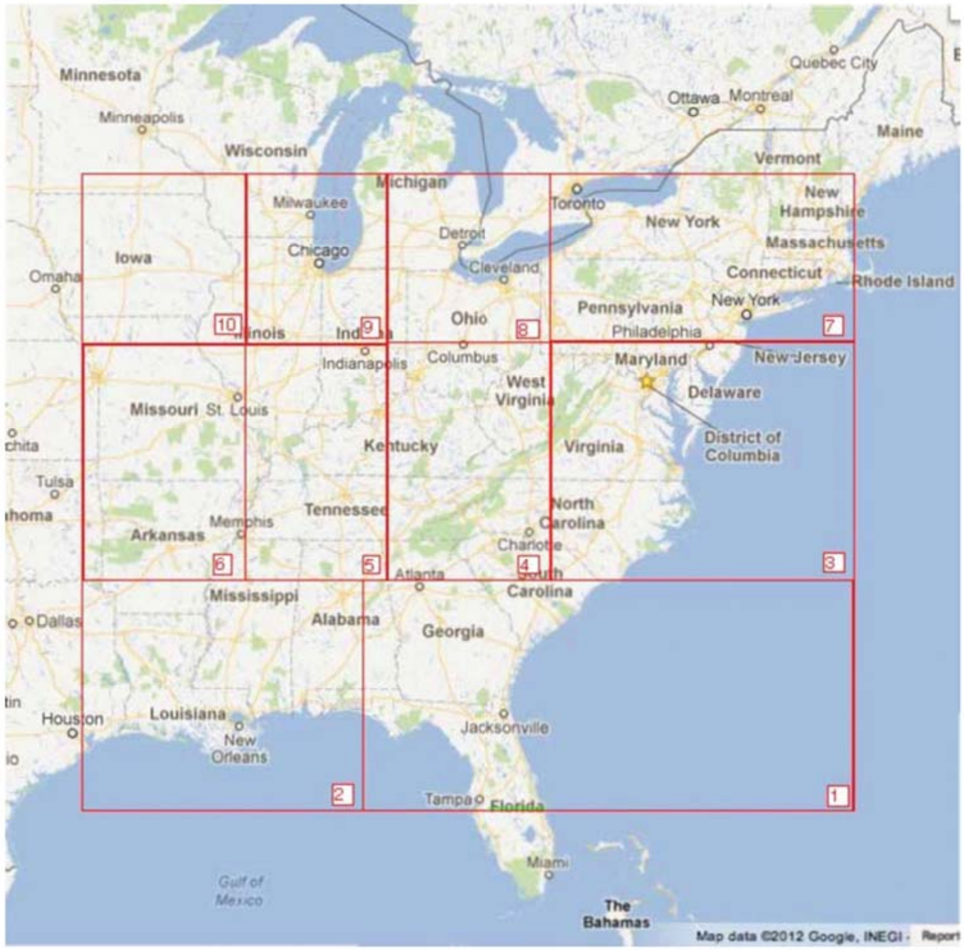

Figure 1. Map of the study area with numbered grid cells.

as well as implement data visualization and statistical analysis tools to effectively extract useful information from these data. The current attempt is an effort in developing a statistical analysis tool along these goals.

To assess migratory changes over time, Purple Martin first arrival dates from the NABPP were compared with recent first arrival dates collected by a contemporary network of volunteer naturalists from the Purple Martin Conservation Association (PMCA; www.purplemartin.org). Typical contributors to both programs were considered competent naturalists (Courter, Johnson, Stuyck, et al., 2013), data collection protocols were generally similar (see http://www.pwrc.usgs.gov/bpp/ and purplemartin.org), and data from both programs were collected and compared at the same spatial extent (Fig. 1). The only notable difference was mode of reporting; most recent arrival records were reported online, whereas most historical records were submitted by mail. Due to low sampling efforts during the early decades as well as the last decades of the existence of NABPP, we only considered Purple Martin arrival data for the period 1905–1940. We label these historical records as "old" data in our analysis. Similarly, we analyze data compiled by the PMCA for the period 2001–2010, a period of consistently high volunteer participation, and we refer to these data as "new." Unfortunately, there are no comprehensive and reliable sources (or no straightforward methods) to provide data with acceptable spatial coverage and sampling effort for our analysis for the period between the 1960s and the late 1990s, therefore these years are omitted from our analysis.

Here, we convert arrival dates to day-of-year, which is based on the number of days in a calendar year starting January 1st for each year. For example, an arrival date of February 1st corresponds to "day 32" (of course, one has to account for leap years accordingly). We consider a spatial grid with 10 irregular sized cells (Fig. 1). The spatial grid and cell sizes were decided based on a data criterion that required each grid cell and year combination to include at least five data points to ensure that reasonable variability in arrival data for each grid cell was achieved. By combining first arrival dates by grid cell (Fig. 1) and requiring 5 observations per year, our study actually compares mean first arrival dates over space and time and abates a common criticism (Dickinson et al., 2010; Gordo and Sanz, 2006) that individual first arrival observations are affected by differences in observer effort (Courter, Johnson, Hubbard, et al., 2013).

Since we are interested in understanding the relationship between migration patterns and climate, we include climate effects as predictor variables in the model. As an example, we consider data on Winter North Atlantic Oscillation (Winter NAO or WNAO; http://climatedataguide.ucar.edu/). The Winter NAO index we use is based on the difference of normalized sea level pressure (SLP) between several stations averaged over monthly data for the winter season (December–March). Positive values of the WNAO index are typically associated with stronger-than-average wind over the middle latitudes and more intense weather systems over the North Atlantic. Spring arrival of migratory birds is known to depend on the NAO (e.g., see Hüppop and Hüppop, 2003; Vähätalo et al., 2004). Similarly, other climate indices and weather variables can be easily included in the model.

2.2 *Hierarchical Spatio-temporal Modeling*

We use a hierarchical modeling approach to account for spatial and temporal variability in the data. Hierarchical modeling has become increasingly popular in environmental studies due to their flexibility for complex data (Clark, 2005; Wikle, 2003). In a hierarchical model, a complex problem is decomposed into a series of simpler sub-problems linked by rules of conditional probability (Arab et al., 2008; Berliner, 1996). This flexible modeling approach allows the analyst to simultaneously account for data sampling variability, parameter uncertainty, and potential dependence structures such as spatial and temporal structures.

Let $\mathbf{Y}_t = (Y_{1,t}, \ldots, Y_{n,t})'$ denote the vector of mean arrival days for the grid cells ($n = 1, \ldots, 10$) over the total number of years in the study ($t = 1, \ldots, 46$; 36 years in the old data for 1905–1940, and 10 years in the new data for 2001–2010), where $Y_{i,t}$ represent the mean arrival days for the ith grid cell in the tth year. Using a hierarchical modeling framework (Berliner, 1996), which relies on three stages of data, process, and parameter models, we define the following *Data Model*

$$\mathbf{Y}_\mathrm{t} \sim N(\mathbf{m}_\mathrm{t}, \sigma^2\mathbf{I}), \tag{1}$$

where $\mathbf{m}_\mathrm{t}$ denotes the mean arrival process and σ^2 denotes measurement error. Here, the observed arrival days in (1) are assumed to be conditionally independent (conditioned on a process model that accounts for spatial and temporal dependence).

The *Process Model* is defined following a time series threshold modeling approach (Geweke and Terui, 1993; Tong, 1983):

$$\mathbf{m}_t = b_0 + \boldsymbol{\mu}_0 + \begin{cases} b_{0,1} + \boldsymbol{\mu}_{1,\text{sp}} + b_{1,1}\mathbf{X}_t + \mathbf{e}_{1,\text{t}} & \text{if } 1 \le t \le 36 \text{ (years 1905–1940)} \\ b_{1,2}\mathbf{X}_\text{t} + \mathbf{e}_{2,\text{t}} & \text{if } 37 \le t \le 46 \text{ (years 2001–2010)} \end{cases}$$

where $\boldsymbol{\mu}_0 = (\mu_{0,1}, \ldots, \mu_{0,n})'$ denotes the spatially varying common mean for the old and new data, $\boldsymbol{\mu}_{1,\text{sp}} = (\mu_{1,1}, \ldots, \mu_{1,n})'$ denotes the spatially varying mean specific to the old data. Parameters b_0 and $b_{0,1}$ represent the constant means for both periods, and the old data, respectively. The predictor data on Winter NAO is given in the variable $\mathbf{X}_t$ with different coefficients for old ($b_{1,1}$) and new data ($b_{1,2}$). Also, we consider different autoregressive error processes $\mathbf{e}_{1,t}$ and $\mathbf{e}_{2,t}$, for the old and new data, respectively.

The autoregressive error processes are assumed to be different for the two periods. This assumption is critical to account for potential autocorrelation for the arrival data within each period. We define the error processes based on the following AR(1) models (e.g., Cressie and Wikle, 2011):

$$\mathbf{e}_{1,t} = \nu_1 \mathbf{e}_{1,t-1} + \eta_{1,t}, \quad \eta_{1,t} \sim N\big(0, \sigma^2_{\eta_1}\big) \tag{2}$$

$$\mathbf{e}_{2,t} = \nu_2 \mathbf{e}_{2,t-1} + \eta_{2,t}, \quad \eta_{2,t} \sim N\big(0, \sigma^2_{\eta_2}\big) \tag{3}$$

and the spatial structure for the spatially varying parameters $\boldsymbol{\mu}_{p,\text{sp}}$, for $p = 0, 1$ is based on Conditional Autoregressive (CAR) models (see, e.g., Arab et al., 2008; Banerjee et al., 2004; Cressie, 1993):

$$\mu_{p,l} | \mu_{p,m}, \tau^2_{p,l} \sim N\left(\bar{\mu}_{p,l} + \sum_{m \in N_l} c_{p,lm}(\mu_{p,m} - \bar{\mu}_{p,m}), \tau^2_{p,l}\right), \tag{4}$$

where $l, m = 1, \ldots, n$, and $c_{p,lm}$'s are weights defined such that $c_{p,lm} = 1$ for $l \neq m$, $c_{p,qq} = 0$ for $q = 1, \ldots, n$, and $c_{p,lm}\tau^2_{p,l} = c_{p,ml}\tau^2_{p,m}$.

2.3 *Model Fitting and Inference*

Inference is conducted in a Bayesian framework using Markov chain Monte Carlo (MCMC; Casella and George, 1992; Robert and Casella, 2004). The Bayesian framework requires that we define prior distributions for unknown parameters (also called the *Parameter Models* in the hierarchical framework). We define the following relatively noninformative prior distributions (i.e., distributions with small mean and relatively large variance) for the unknown parameters

$$\begin{aligned} b_0 &\sim N(\mu = 0, \sigma^2 = 100), \\ b_{0,1} &\sim N(\mu = 0, \sigma^2 = 100), \\ b_{j,k} &\sim N(\mu = 0, \sigma^2 = 100), \quad j = 1,\ k = 1, 2, \\ \sigma^2 &\sim \text{InvGamma}(\text{mean} = 1, \text{Var} = 100) \\ \nu_1 &\sim \text{Uniform}(-1, 1) \\ \nu_2 &\sim \text{Uniform}(-1, 1) \end{aligned}$$

$$\sigma^2_{\eta_1} \sim \text{Uniform}(0, 100)$$
$$\sigma^2_{\eta_2} \sim \text{Uniform}(0, 100)$$

We also define the following prior distributions for the variance components of the CAR priors (i.e., hyperparameters for the CAR priors)

$$\tau^2_p \sim \text{InvGamma (mean} = 1, \text{Var} = 100), \quad p = 0, 1, 2. \tag{5}$$

Also, for the AR(1) models in (2) and (3), we need to define initial states, $\mathbf{e}_{1,0}$ and $\mathbf{e}_{2,0}$. Thus, we assign the following prior distributions for these initial states

$$\mathbf{e}_{1,0} \sim N\left(0, \sigma^2_{\eta_1}\right) \text{ (Old data; years 1905, \ldots, 1940)}$$
$$\mathbf{e}_{2,0} \sim N\left(0, \sigma^2_{\eta_2}\right) \text{ (New data; years 2001, \ldots, 2010).}$$

Note that we have already defined prior distributions for the variance parameters (i.e., hyperparameters) $\sigma^2_{\eta_1}$ and $\sigma^2_{\eta_2}$.

The proposed hierarchical model implementation although not trivial can be conducted based on the MCMC algorithm, and in particular, Gibbs sampling (Casella and George, 1992; Gelfand and Smith, 1990). We implement the model with a slight different formulation for the threshold process model in OpenBUGS (http://www.openbugs.info/; see, e.g., Congdon, 2010). In particular, we use an indicator variable notation to represent the thresholding:

$$\mathbf{m}_t = b_0 + \boldsymbol{\mu}_0 + (b_{0,1} + \boldsymbol{\mu}_{1,\text{sp}} + b_{1,1}\mathbf{X}_t + \mathbf{e}_{1,t}) \times (1 - \mathbf{I}_t) + (b_{1,2}\mathbf{X}_t + \mathbf{e}_{2,t}) \times \mathbf{I}_t, \tag{6}$$

where $\mathbf{I}_t =$ is a vector of indicator variables and is defined as

$$\mathbf{I}_t = \begin{cases} 0 & \text{if } 1 \le t \le 36 \text{ (years 1905–1940)} \\ 1 & \text{if } 37 \le t \le 46 \text{ (years 2001–2010)} \end{cases}$$

The algorithm was implemented for 100,000 iterations. We discarded the first 10,000 iteration for "burn-in" and based our inference on the remaining 90,000 iterations. The MCMC algorithm achieved convergence rapidly within the first few thousand iterations. Convergence was assessed using visual inspection, as well as autocorrelation of the MCMC chains. Sample BUGS code is provided in Appendix A.

2.4 *Model Selection*

We consider several different models based on spatial and temporal structures in the models and conduct model selection to investigate if the proposed model in the previous section is appropriate. We use a common and easy to implement method for model selection for hierarchical Bayesian models, the deviance information criterion (DIC). DIC was introduced by Spiegelhalter et al. (2002) as a generalization of Akaike's information criterion (AIC). DIC is a penalized likelihood method based on the posterior distribution of the deviance statistic. Based on the DIC criterion, models with relatively lower DIC values indicate a better fit to the data compared with models with higher DIC values. DIC is defined as

$$\text{DIC} = 2\bar{D} - D(\bar{\boldsymbol{\theta}}),$$

Table 1
Model comparison results based on DIC and p_D values

Model	p_D	DIC
Model 1	15.4	3,253
Model 2	8.7	3,274
Model 3	6.4	3,991
Model 4	3.0	3,987
Model 5	19.4	3,292
Model 6	21.91	3,302

where $\bar{D}$ is the posterior mean of the deviance, and $D(\bar{\boldsymbol{\theta}})$ is the deviance of the vector of the posterior mean values for the model parameter vector ($\boldsymbol{\theta}$).

We consider six different models:

- Model 1: This is the model described in the previous section, which includes spatially varying means and AR(1) error terms.
- Model 2: Similar to Model 1 but without the AR(1) error terms.
- Model 3: Similar to Model 1 but without spatially varying mean parameters.
- Model 4: This is the simplest model that assumes no spatially varying means and AR(1) error terms.
- Model 5: Similar to Model 4 but a spatially varying common mean is included.
- Model 6: Similar to Model 4 but spatially varying parameters for Winter NAO are included.

In the next section, we present model selection results and discuss results for the selected preferred model.

3. Results

3.1 *Model Selection Results*

As discussed in the previous section, model selection was conducted based on DIC. DIC results are provided in wTable 1. Based on DIC values Model 1 is the most preferred model. The DIC for Model 2 is only slightly larger than the DIC for Model 1 and thus, Model 2 can be considered as good as Model 1 based on DIC. However, we decide to choose Model 1 as the "best" model as it accounts for temporal variability. Other models (Models 3–6) are not considered as good as Models 1 and 2.

Table 2
Posterior results for the model parameters

Parameter	Posterior mean	Posterior st. dev.	95% Credible interval
b_0	14.63	9.313	(−3.127, 32.53)
$b_{0,1}$	14.71	1.54	(11.8, 17.53)
$b_{1,1}$	29.28	5.25	(19.03, 39.34)
$b_{1,2}$	−9.488	9.593	(−29.02, 8.744)

Table 3
Posterior results for the overall difference in spatial means of the old and new data ($b_{0,1} + \boldsymbol{\mu}_{1,sp}$)

Grid cell	Posterior mean	95% Credible interval
1	17.94	(12.41, 23.55)
2	19.93	(14.25, 25.82)
3	17.09	(11.62, 22.69)
4	20.21	(14.74, 26.05)
5	17.88	(12.62, 23.51)
6	11.34	(5.754, 16.84)
7	14.75	(9.08, 20.37)
8	9.995	(4.124, 15.52)
9	9.517	(3.814, 14.97)
10	8.475	(2.632, 14.22)

3.2 *Model 1 Results*

Model 1 results show significant changes in arrival dates of Purple Martins in recent years. Table 2 shows the posterior inference for the regression parameters. Table 3 shows the inference for the overall difference in total means for the new and old data (combined mean effect of the constant and spatially varying means, $b_{0,1} + \boldsymbol{\mu}_{1,sp}$).

Figure 2 shows the map of posterior means of differences between the new and old. Figure 3 shows the map of posterior standard deviation of differences between the new

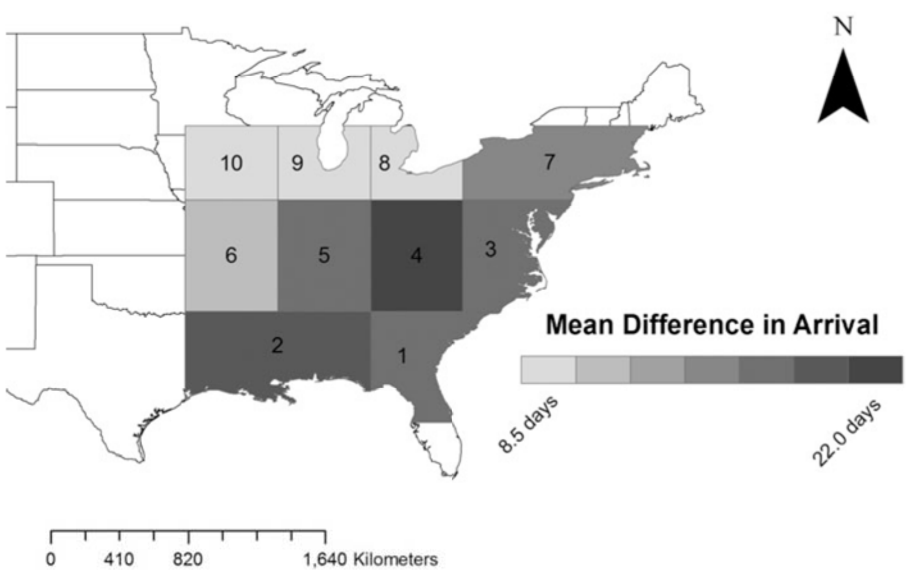

Figure 2. Posterior means of the mean difference (constant and spatially varying; $b_{0,1} + \mu_{1,sp}$) between the data for 1905–1940 and 2001–2010.

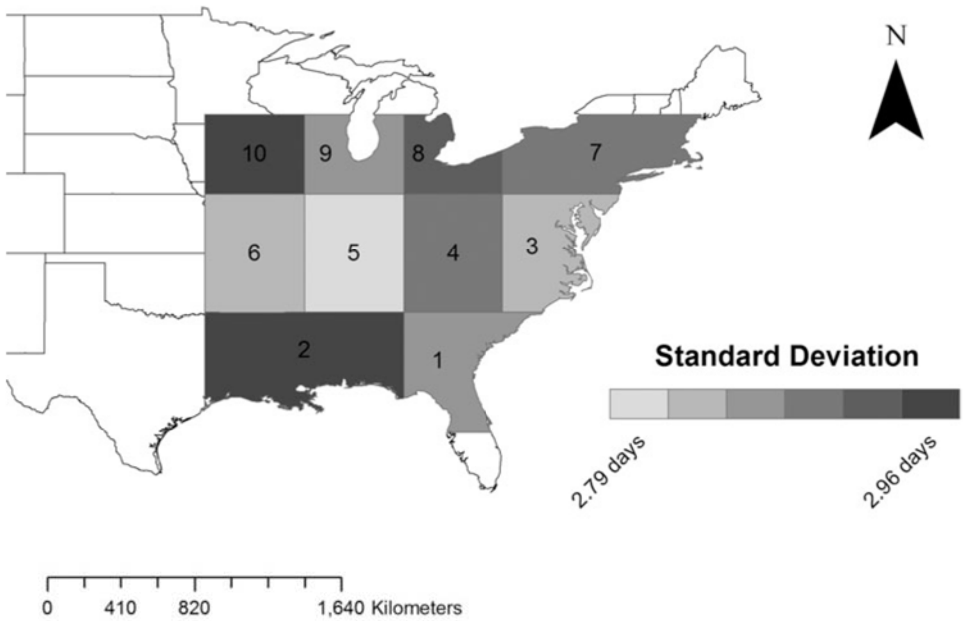

Figure 3. Posterior standard deviations of the mean difference (constant and spatially varying; $b_{0,1} + \mu_{1,\mathrm{sp}}$) between the data for 1905–1940 and 2001–2010.

and old. Also, we have detected a significantly positive association between the Winter NAO index and the mean arrival days for the old data (1905–1940). No significant effect of Winter NAO was detected for the new data (see Table 2).

4. Conclusion and Discussion

Our model results show significant shifts in the mean arrival days of Purple Martins in the study area (Table 3) with significantly earlier arrivals for the recent data compared with the old data. However, the differences in arrival dates seem to be of higher magnitude in South, East, Midwest, and part of Northeast of the United States and smaller (but still statistically significant) in the Northern United States (including Great Lakes area; grid cells 8–10; Table 3). For example, the mean difference in arrival dates for grid cell 10 is statistically significantly smaller than the mean difference in arrival dates of grid cells 2 and 4. The detected decrease in mean arrivals over the recent years may be an indication of the linkage between the recent changes in the climate and shifts in the Purple Martin migration patterns. However, other factors such as potential differences in sampling efforts between the two periods, changes in the population of Purple Martins, increase in bird houses, and changes in the forestation/deforestation patterns and access to food resources may explain the significant shifts in the migration patterns of Purple Martins between the two periods. In particular, reforestation in the Northeast during the beginning of the 20th century and increasing use of artificial martin houses may have increased martin populations during this time, and may partially explain migratory advancements noted.

As mentioned in the previous section, we detected a significant effect of Winter NAO for the old data but not for the new data. We suspect that this may be mainly due to low variability in the Winter NAO data for the recent data. Specifically, the 2000s Winter NAO values are mostly negative with low variability (e.g., the standard deviation of Winter NAO values for the old period is more than 2.5 times the standard deviation of the values for the recent period). We did not find any evidence of spatially varying effect of Winter NAO; this was explored in the model selection stage based on Model 6, which had a relatively high DIC value compared to Model1.

As mentioned in the previous section, the inherent spatial latitudinal and longitudinal structure highlights the importance of considering spatially varying mean parameters and our results show that shifts in arrival patterns of Purple Martins are not constant over space.

Potential future directions include analysis of multivariate spring arrival data for closely related bird species, and characterization of the potential association between the changes in the arrival dates and climate change. In this work, as an example, we used a climate index (Winter NAO) as a predictor variable in the model. However, for a thorough investigation of the link between changes in the climate and shifts in migration patterns, one should consider other related weather variables (e.g., temperature, precipitation) and climate indices (e.g., North Pacific (NP); Atlantic Multi-decadal Oscillation (AMO); information on El Niño and La Niña seasons).

Also, another important future direction for this type of analysis includes accounting for changes in bird populations. Although this is a difficult problem, reasonable estimates of bird populations are available through long-term bird monitoring programs that often use capture–recapture sampling to assess estimates of bird species populations. Thus, the hierarchical Bayesian framework is a natural setting for combining bird arrival data with estimates of bird populations to analyze the spatial-temporal response to climate change.

Finally, the proposed approach presents a flexible tool with straightforward implementation for comparing bird arrival data from two different time periods. Given data availability for more time periods, this modeling approach can be easily extended to include several time periods. Alternatively, one could consider a “meta-population” approach and combine data from different sources (i.e., different local and global monitoring programs) and from different time periods to create a more comprehensive analysis of bird migration over the last decades or even centuries. Again, the hierarchical Bayesian approach is ideal due to its flexibility for combining data from several resources.

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Appendix A: BUGS Code

The code for implementing the model in OpenBUGS or WinBUGS is provided below:

```
model{
for (i in 1:n){
for (j in 1:T){  # T is the total number of years in the study; T=t1+t2
x[i,j]~dnorm(mu[i,j],tau)

mu[i,j]<-b[1]+sp[i]+sp1[i]*(1-ind[j])+b[2]*(1-
ind[j])+b[3]*WNAO1[1:t1]+b[4]*WNAO2[t1+1:t2] +e[j]
# ind is an indicator variable (0 for period 1, and 1 for period 2)

# Priors for parameters
# CAR prior distribution for random effects:
sp[1:K] ~ car.normal(adj[], weights[], num[], tau)
sp1[1:K] ~ car.normal(adj[], weights[], num[], tau1)

for(k in 1:sumNumNneigh ) {weights[k] <- 1}

# AR(1) error processes
# initial state
e[1] ~ dnorm(0,tau.1)

# AR model
for (t in 2:t1){e[t] ~ dnorm(mu.e[t],taue1)
mu.e[t] <- rh1*e[t-1]}; tau.1 <- (1-rh1*rh1)*taue1
sig1 ~ dunif(0,100); taue1 <- 1/(sig1*sig1);
s2e1<-1/taue1
rh1 ~ dunif(-1,1);

# initial state
e[t1+1] ~ dnorm(0,tau.2)
for (t in t1+2:t2){e[t] ~ dnorm(mu.e[t],taue2)
mu.e[t] <- rh2*e[t-1]}; tau.2 <- (1-rh2*rh2)*taue2
sig2 ~ dunif(0,100); taue2 <- 1/(sig2*sig2)
s2e2<-1/taue2
rh2 ~ dunif(-1,1)

# priors for variances
tau~dgamma(.01,.01)
tau1~dgamma(.01,.01)

# priors for coefficients
for (i in 1:4){
b[i]~dnorm(0,.01)}

diffsp[i]<-b[2]+sp1[i]
for (i in 1:n){diffsp[i]<-sp1[i]-sp2[i]}}
```

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