

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

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Abstract

There is increasing interest in spatio-temporal analysis of environmental and ecological response 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 historic 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 the 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.

1 Introduction

The study of environmental and ecological response to climate change in the 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, recently there is increasing interest in analyzing potential changes in the migration patterns of migratory bird 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 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., Møller et al. 2004; Cox 2010) and epidemiology of infectious diseases that are linked to bird migration such as avian influenza outbreaks (e.g., Liu et al. 2005; Feare 2007; Bourouiba et al. 2010). 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., Tøttrup et al. 2006; Hüppop and Winkel 2006) and epidemiology literature (e.g., Munster et al. 2007; Onozuka and Hagihara 2008; LaDeau et al. 2008; Si et al. 2009; LaDeau et al. 2010).

In this paper, we focus on the analysis of migratory birds 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., Gordo 2007; and Both and et Marvelde 2007, use spatial models; Fink et al. 2010, Hulbert and Liang 2012, use spatio-temporal models). In this paper, 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 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 discuss the analysis of historic and recent data on Purple Martins. Section 2 discusses the data and introduces the methodology. Results are given in Sections 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 their non-breeding season in Brazil and migrate to North America to nest. Adult Purple Martins commonly return to the same nesting sites where they were successful in previous years (see e.g., www.purplemartin.org for more information).

The North American Bird Phenology Program (NABPP) was a volunteer-based program, active between 1881-1970, that using a network of over 3,000 volunteers collected data on bird migration, breeding, wintering, and distributions. The NABPP, currently housed in the United States Geological-Patuxent Wildlife Research Center (USGS-PWRC), was revitalized in 2008 (Zelt et al. 2012). The NABPP houses millions of data index cards on more than 200 bird species collected over a 90 year span between 1881-1970. As of date, over a million handwritten records have been scanned, in an effort to digitize the data and are going through a thorough data validation process. Once validated, the records will be freely accessible online by biologists, managers, and the general public. Since 2012, Georgetown University has started a partnership program with the NABPP in order to accelerate the data digitization/validation process, 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 statistical analysis tool along these goals.

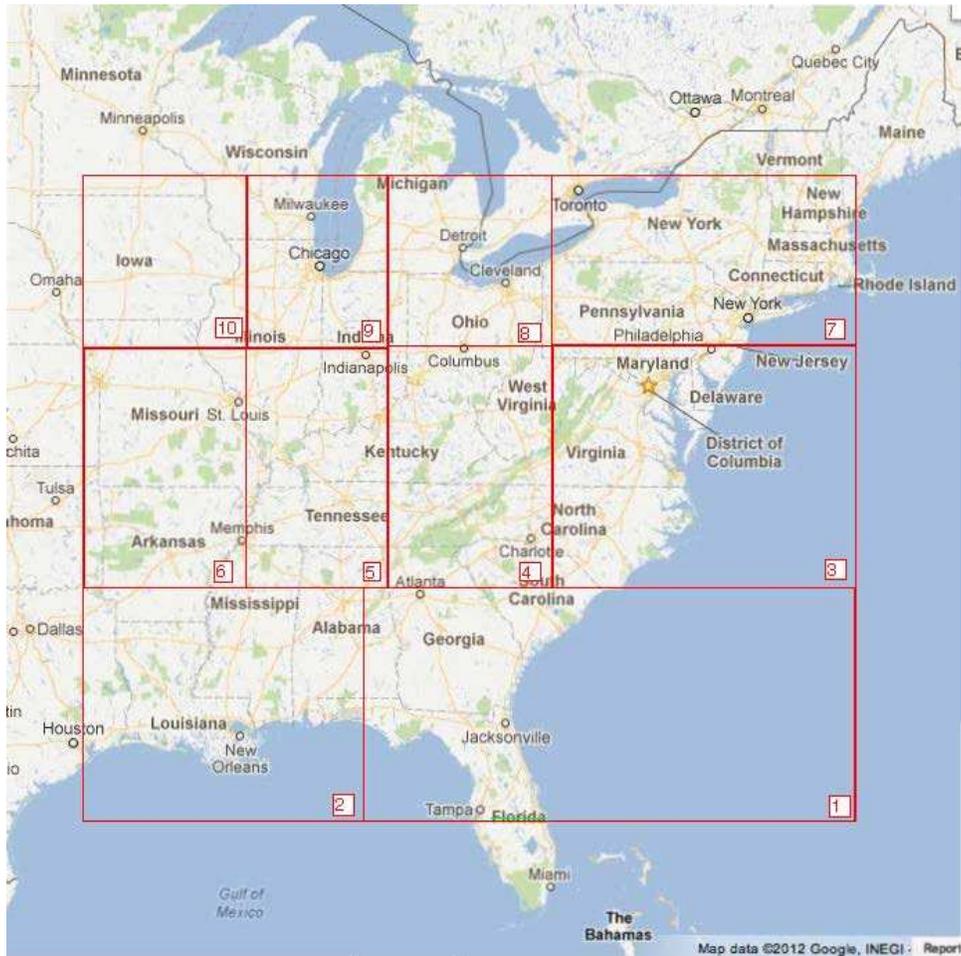


Figure 1: Map with grid cells.

Due to low sampling efforts during the early decades as well as the last decades of the existence of NABPP, we considered data for the period 1905-1940 on arrival dates of Purple Martins. We label these historic records as “old” data in our analysis. We also use data from Courter (2012) on arrival dates of Purple Martins between 2001-2010 collected by the Purple Martin Conservation Association (www.purplemartin.org). In our analysis, we label the recent data as “new” data. Unfortunately, there are no comprehensive and reliable sources (or no straightforward methods) to compile data with acceptable spatial coverage and sampling effort that is of interest in this study on arrival records of Purple Martins for the period between the 1960s and the late 1990s.

Here, we convert the arrival dates to Julian Date (or Day-of-Year) calendar, 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, translates to 32 under the Julian Date Calendar, as it is the 32nd day of the year (of course, one has to account for leap years accordingly). We consider a spatial grid with ten irregular sized cells (Figure 1). The spatial grid and cell sizes were decided based on a data criteria which requires each grid cell and for each year to include at least five data points to achieve reasonable variability in arrival data within each cell.

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/>). 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 (Wikle 2003; Clark 2005). In a hierarchical model, a complex problem is decomposed into a series of simpler sub-problems linked by rules of conditional probability (Berliner 1996, Arab et al. 2008). 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 $\mathbf{Y}_t = (Y_{1,t}, \dots, Y_{n,t})'$ denote the vector of mean arrival days for the grid cells ($n = 1, \dots, 10$) over the total number of years in the study ($t = 1, \dots, 46$; 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 i -th grid cell in the t -th 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*

$$\mathbf{Y}_t \sim \mathbf{N}(\mathbf{m}_t, \sigma^2 \mathbf{I}) \quad (1)$$

where \mathbf{m}_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 (Tong 1983;

Geweke and Terui 1993)

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

where $\boldsymbol{\mu}_0 = (\mu_{0,1}, \dots, \mu_{0,n})'$ denotes the spatially-varying common mean for the old and new data, $\boldsymbol{\mu}_1 = (\mu_{1,1}, \dots, \mu_{1,n})'$ denotes the spatially-varying mean specific to the old data, and $\boldsymbol{\mu}_2 = (\mu_{2,1}, \dots, \mu_{2,n})'$ denotes the spatially-varying mean specific to the new data. 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 ($b_{1,2}$). Parameters $b_{0,1}$ and $b_{0,2}$ represent the constant means for the old and new data, respectively. 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):

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

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

and the spatial structure for the spatially-varying parameters $\boldsymbol{\mu}_p$, for $p = 0, 1, 2$, are based on Conditional Autoregressive (CAR) models (see e.g., Cressie 1993; Banerjee et al. 2004; Arab et al. 2008)

$$\mu_{p,l} | \mu_{p,s}, \tau_{p,l}^2 \sim N(\bar{\mu}_{p,l} + \sum_{s \in N_l} c_{p,ls} (\mu_{p,s} - \bar{\mu}_{p,s}), \tau_{p,l}^2). \quad (4)$$

where $l, s = 1, \dots, n$, and $c_{p,ls}$'s are weights defined such that $c_{p,ls} = 1$ for $l \neq s$, $c_{p,qq} = 0$ for $q = 1, \dots, n$, and $c_{p,ls} \tau_{p,l}^2 = c_{p,sl} \tau_{p,s}^2$.

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 non-informative prior distributions (i.e., distributions

with small mean and relatively large variance) for the unknown parameters

$$\begin{aligned}
b_{j,k} &\sim N(\mu = 0, \sigma^2 = 100), \quad j = 0, 1, \quad k = 1, 2, \\
\sigma^2 &\sim \text{InvGamma}(\text{mean} = 1, \text{var} = 100) \\
\nu_1 &\sim \text{Uniform}(-1, 1) \\
\nu_2 &\sim \text{Uniform}(-1, 1) \\
\sigma_{\eta_1}^2 &\sim \text{Uniform}(0, 100) \\
\sigma_{\eta_2}^2 &\sim \text{Uniform}(0, 100)
\end{aligned}$$

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

$$\tau_p^2 \sim \text{InvGamma}(\text{mean} = 1, \text{var} = 100), \quad p = 0, 1, 2. \quad (5)$$

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

$$\begin{aligned}
\mathbf{e}_{1,0} &\sim N(0, \sigma_{\eta_1}^2) \quad (\text{Old data; years 1905, } \dots, \text{1940}) \\
\mathbf{e}_{2,0} &\sim N(0, \sigma_{\eta_2}^2) \quad (\text{New data; years 2001, } \dots, \text{2010})
\end{aligned}$$

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

The proposed hierarchical model implementation although not trivial, can be conducted based on the MCMC algorithm, and in particular, Gibbs sampling (Gelfand and Smith 1990; Casella and George 1992). 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:

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

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

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

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.

3 Results

Model results show significant changes in arrival dates of Purple Martins in recent years. Table 1 shows the posterior inference for the regression parameters. Table 2 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, $b_{0,k} + \mu_k$ for $k = 1, 2$).

Figure 2 shows boxplots of the posterior distributions of the common spatially-varying mean for the two periods. Figures 3 and 4 show boxplots of the posterior distributions of the spatially-varying specific to the old and new data, respectively. Figure 5 shows boxplots of the posterior distributions of the difference of the spatially-varying means for the old and new data. Critically, the spatial structure (strong latitudinal effect and mild to weak longitudinal effect) pronounced in Figures 2-4 provides strong justification for the need for spatially-varying mean parameters in the model.

4 Conclusion and Discussion

Our model results show significant shifts in the mean arrival days of Purple Martins in the South, East, Midwest, and part of Northeast of the United States (grid cells 1-7; Table 2) with significantly earlier arrivals for the recent data compared to the old data. However, no statistically significant change in mean arrival dates were detected in the Northern U.S. (including Great Lakes area; grid cells 8-10; Table 2). The detected decrease in mean arrivals over the recent years may be an indication of the linkage between the recent changes in the climate (i.e., global warming) and shifts in the Purple Martin migration patterns. However, other factors such as 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 under study. 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.

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 1). We suspect that this may be mainly due to low variability in the Winter NAO data for the recent data since 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.).

As mentioned in the previous section, the inherent spatial latitudinal and longitudinal structure verifies the importance of considering spatially-varying mean parameters. Critically, 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 which often use capture-recapture sampling to assess estimates of bird species populations. Thus, the hierarchical Bayesian framework is a natural setting for fusing 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 can consider a “meta-population” approach and combine data from different sources (i.e., different local and global monitoring programs) from different time periods to create a more

Table 1: Posterior results for the model parameters.

Parameter	Posterior Mean	Posterior St. Dev.	95% Credible Interval
$b_{0,1}$	16.36	6.73	(3.177, 29.51)
$b_{0,2}$	1.675	6.721	(-11.55, 14.83)
$b_{1,1}$	35.31	4.298	(26.7, 43.73)
$b_{1,2}$	-11.06	9.605	(-30.52, 7.325)

comprehensive analysis of bird migration over the last 130 years or so. Again, the hierarchical Bayesian approach is ideal due to its flexibility for combining data from several resources.

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Table 2: Posterior results for the overall difference in spatial means of the old ($b_1 + \boldsymbol{\mu}_{1,sp}$) and new data ($b_2 + \boldsymbol{\mu}_{2,sp}$) .

Grid Cell	Posterior Mean	95% Credible Interval
1	18.02	(9.42, 26.41)
2	21.27	(12.63, 29.69)
3	17.50	(8.89, 25.84)
4	22.75	(14.20, 31.06)
5	19.90	(11.36, 28.20)
6	10.49	(1.89, 18.88)
7	14.39	(5.74, 22.77)
8	7.61	(-0.98, 15.95)
9	7.74	(-0.87, 16.10)
10	7.22	(-1.40, 15.63)

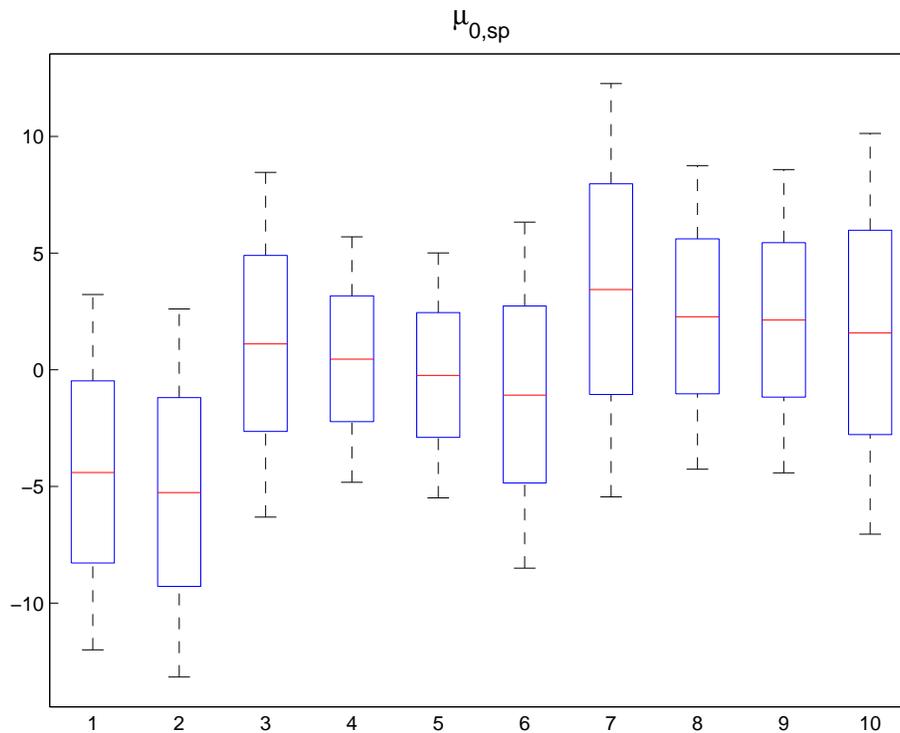


Figure 2: Common spatially-varying mean for the two periods.

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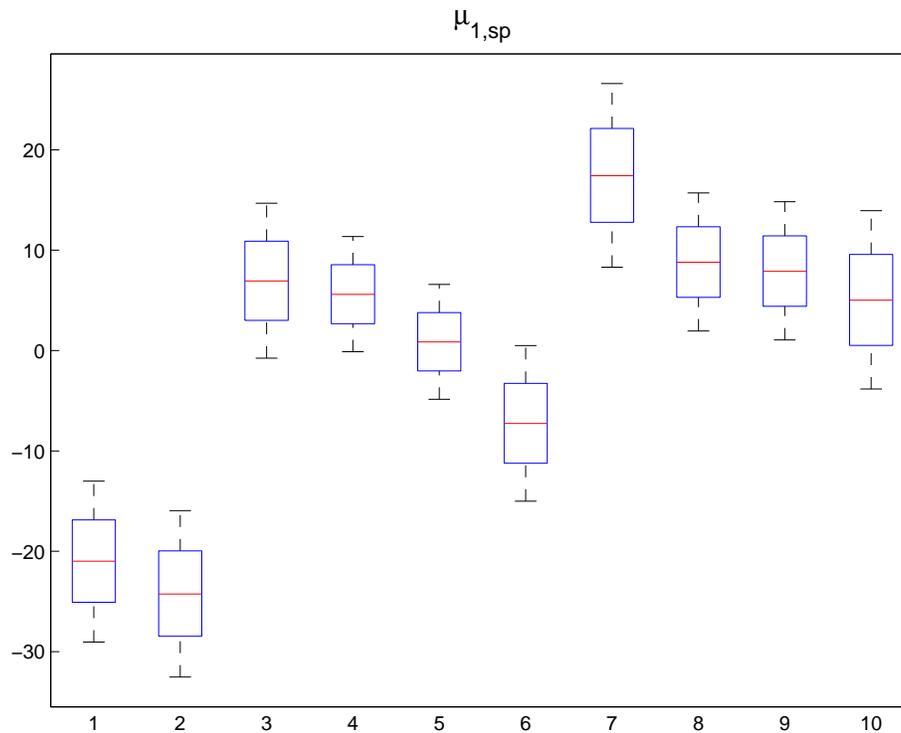


Figure 3: Spatially-varying mean for the 1905-1940 data.

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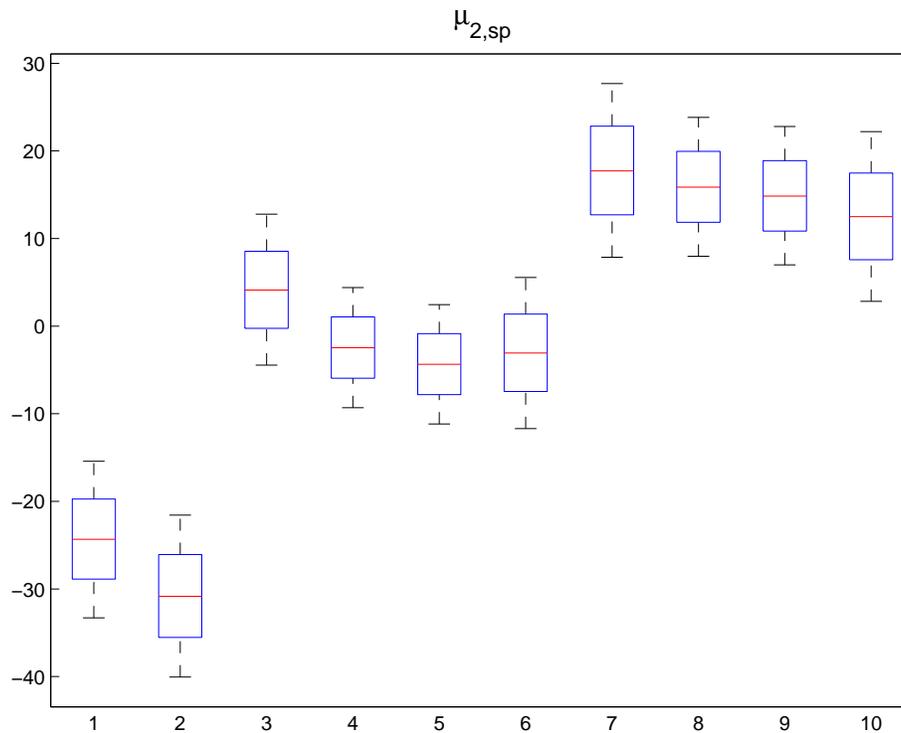


Figure 4: Spatially-varying mean for the 2001-2010 data.

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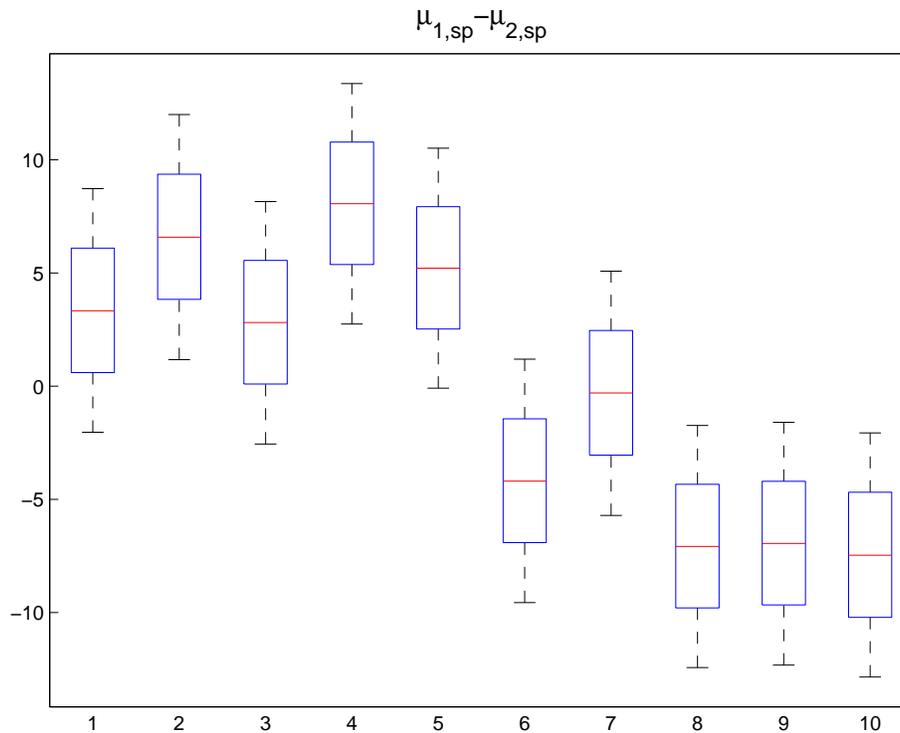


Figure 5: Difference between the spatially-varying means for 1905-1940 and 2001-2010 data.

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