

# P8160 - Project 3

## Baysian modeling of hurrican trajectories

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# Motivation

Climate researchers are interested in modeling the hurricane trajectories to forecast the wind speed.

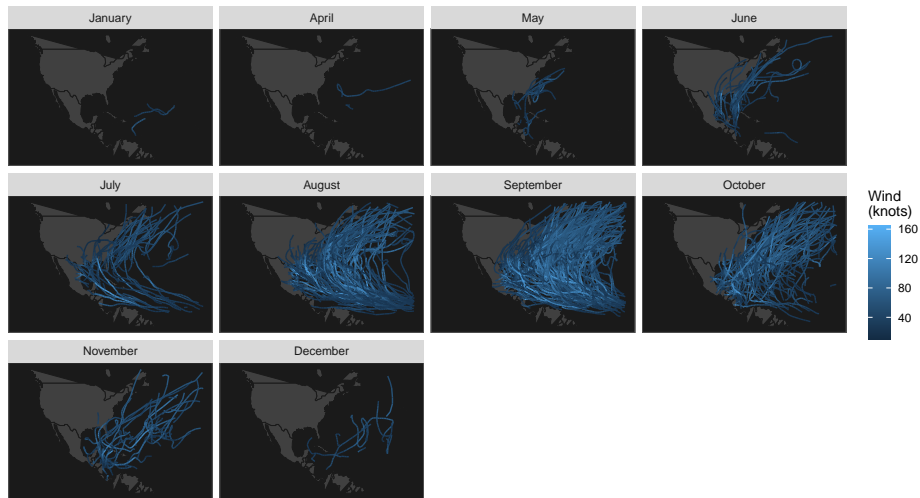
## Data

- **ID:** ID of hurricanes
- **Year:** In which the hurricane occurred
- **Month:** In which the hurricane occurred
- **Nature:** Nature of the hurricane
  - ET: Extra Tropical
  - DS: Disturbance
  - NR: Not Rated
  - SS: Sub Tropical
  - TS: Tropical Storm
- **Time:** dates and time of the record
- **Latitude** and **Longitude:** The location of a hurricane check point
- **Wind.kt:** Maximum wind speed (in Knot) at each check point

- ① Exploration into the Data
- ② Bayesian modeling of hurricane wind speed
  - Model Equation
  - Posterior Derivation
  - MCMC Algorithm
- ③ How Month, Year, and the Nature of the hurricane affect wind speed
  - Explore seasonal differences
  - Explore if wind speeds is increasing over years
- ④ Exploring wind speeds impact on death and damages
- ⑤ As well as the characteristic of a hurricane associated with damages and deaths

# Data

Atlantic named Windstorm Trajectories by Month ( 1950 – 2013 )



- We are only concerned about observations that occurred on 6 hour intervals. hour 0, 6, 12, and 18.
- In addition we will exclude all hurricane IDs that have less than 7 observations.
- We used a lag ( $t$  to  $t - 6$ ) for the latitude, longitude and wind speed.

Through this process we remove 460 observations so we are left with 21578 observations and 681 unique hurricanes.

# Bayesian Model for Hurricane Trajectories

To model the wind speed of the  $i^{th}$  hurricane at time  $t$  we will use

$$Y_i(t+6) = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t) + \epsilon_i(t)$$

Where

- $\Delta_{i,1}(t)$ ,  $\Delta_{i,2}(t)$  and  $\Delta_{i,3}(t)$  are changes in latitude longitude and wind speed respectively between  $t-6$  and  $t$
- $\epsilon_i(t) \sim N(0, \sigma^2)$  independent across  $t$
- Let  $\beta_i = (\beta_{0,i}, \beta_{1,i}, \beta_{2,i}, \beta_{3,i}, \beta_{4,i}) \sim \mathcal{N}(\mu, \Sigma)$  be multivariate normal distribution where  $\mu \in \mathbb{R}^d$  and  $\Sigma \in \mathbb{R}^{d \times d}$ .

## Prior Distributions Assumptions:

- For  $\sigma^2$  we assume  $\pi(\sigma^2) \propto \frac{1}{\sigma^2}$
- For  $\mu$  we assume  $\pi(\mu) \propto 1$
- For  $\Sigma$  we assume  $\pi(\Sigma^{-1}) \propto |\Sigma|^{-(d+1)} \exp\{-\frac{1}{2}\Sigma^{-1}\}$

**Goal:** Estimate  $\Theta = (B, \mu, \Sigma^{-1}, \sigma^2)$

# Likelihood & Prior Function

## Likelihood

$$L(Y | \theta) \propto \prod_{i=1}^m (\sigma^2)^{-\frac{n_i}{2}} \exp \left\{ -\frac{1}{2\sigma^2} (Y_i - X_i \beta_i)^T (Y_i - X_i \beta_i) \right\}$$

where  $m$  is the number of hurricane and  $n_i$  is the number of observations for  $i^{th}$  hurricane

**Prior** Let  $\theta = (B, \mu, \Sigma^{-1}, \sigma^2)$

$$\pi(\theta) \propto (\sigma^2)^{-1} |\Sigma^{-1}|^{d+1} \exp \left\{ -\frac{1}{2} \text{tr}(\Sigma^{-1}) \right\} \prod_{i=1}^m |\Sigma^{-1}|^{\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\beta_i - \mu)^T \Sigma^{-1} (\beta_i - \mu) \right\}$$

where  $d$  is the dimension of  $\mu$

# Posterior Calculation

## Posterior

$$\begin{aligned}\pi(\theta | Y) \propto (\sigma^2)^{-\left(1 + \frac{\sum_{i=1}^m n_i}{2}\right)} |\Sigma^{-1}|^{d+1+\frac{m}{2}} \exp\left\{-\frac{1}{2} \text{tr}(\Sigma^{-1})\right\} \\ \times \exp\left\{-\frac{1}{2} \sum_{i=1}^m (\beta_i - \mu)^T \Sigma^{-1} (\beta_i - \mu)\right\} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^m (Y_i - X_i \beta_i)^T (Y_i - X_i \beta_i)\right\}\end{aligned}$$

## Conditional Posterior

$$\beta_i : \pi(\beta_i | \theta_{(-\beta_i)} Y) \propto \exp\left\{-\frac{1}{2} (\beta_i - \mu)^T \Sigma^{-1} (\beta_i - \mu) - \frac{1}{2\sigma^2} (Y_i - X_i \beta_i)^T (Y_i - X_i \beta_i)\right\}$$

$$\mu : \pi(\mu | \theta_{(-\mu)}, Y) \sim N(\bar{\beta}, \Sigma/m)$$

$$\sigma^2 : \pi(\sigma^2 | \theta_{(-\sigma^2)}, Y) \propto (\sigma^2)^{-\left(1 + \frac{\sum_{i=1}^m n_i}{2}\right)} \times \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^m (Y_i - X_i \beta_i)^T (Y_i - X_i \beta_i)\right\}$$

$$\Sigma^{-1} : \pi(\Sigma^{-1} | \theta_{(-\Sigma^{-1})}, Y) \sim \text{Wishart}\left(3d + 3 + m, \left(I + \sum_{i=1}^m (\beta_i - \mu)(\beta_i - \mu)^T\right)^{-1}\right)$$



# MCMC Algorithm

We apply hybrid algorithm consisting with Metropolis-Hastings steps and Gibbs steps.

Update component wise:

- Sampling proposed  $\beta'_{ij}$ ,  $j = 0, 1 \dots 4$  for  $i^{th}$  hurricane from proposal distribution  $U(\beta_{ij}^{(t)} - a_{ij}, \beta_{ij}^{(t)} + a_{ij})$ , where  $a_{ij}$  is the search window for  $\beta_{ij}$ . Since the proposals are symmetry, the accepting or rejecting the proposed  $\beta'_{ij}$  depends on the ratio of posterior distribution.
- Then, Gibb step for  $\mu$ : Sample  $\mu^{(t+1)}$  from  $N(\bar{\beta}^{(t+1)}, \Sigma^{(t)}/m)$ , where  $\bar{\beta}^{(t+1)}$  is the average over  $\beta_i^{(t+1)}$ .
- Next, MH step to generate  $\sigma^{2'}$  from  $U(\sigma^{2(t)} - a_{\sigma^2}, \sigma^{2(t)} + a_{\sigma^2})$ .
- Finally, we sample  $\Sigma^{-1(t+1)}$  from  
Wishart  $\left( 3d + 3 + m, \left( I + \sum_{i=1}^m (\beta_i^{(t+1)} - \mu^{(t+1)}) (\beta_i^{(t+1)} - \mu^{(t+1)})^T \right)^{-1} \right)$

# Initial Starting Values

## Initial Values:

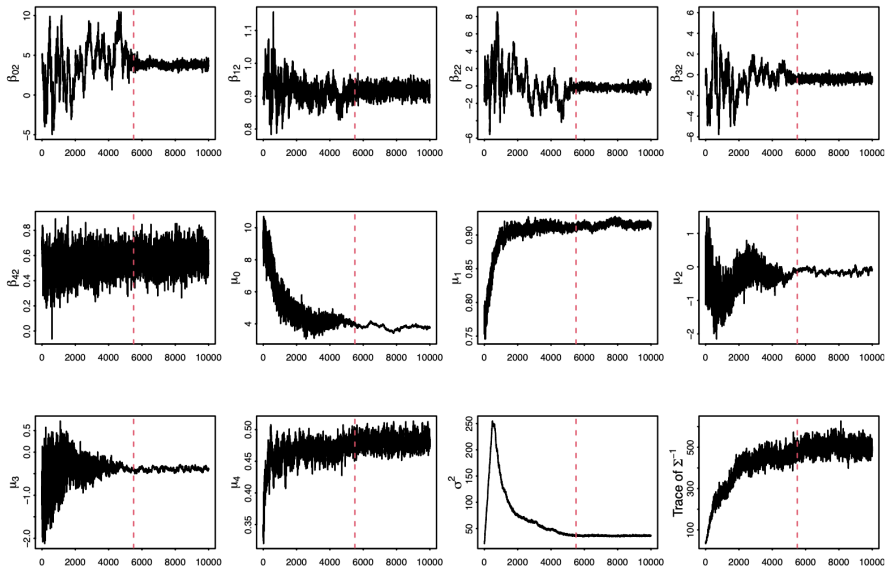
- $\beta_i$ : Fit multivariate linear regression (MLR) for  $i^{th}$  hurricane and use the coefficients as  $\beta_{i0}$
- $\mu$ : Average over all  $\beta_{i0}$  as  $\mu_0$
- $\sigma^2$ :  $\hat{\sigma}_i^2$  is the mean square residuals of the MLR model on  $i^{th}$  hurricane. Take the mean over all  $\hat{\sigma}_i^2$  as  $\sigma_0^2$
- $\Sigma^{-1}$ : Generate the covariance matrix of  $\beta_{i0}$  and take the inverse of the matrix as  $\Sigma_0^{-1}$

**Table 1:** Range of Search Window and Acceptance Rate for parameters used MH step

	Search Window	Acceptance Rate (%)
$\beta_0$	1.1	45.87 - 51.36
$\beta_1$	(0.04, 0.1)	31.67 - 63.68
$\beta_2$	(0.8, 1.0)	38.60 - 45.60
$\beta_3$	(0.5, 0.6)	33.20 - 61.32
$\beta_4$	(0.4, 0.5)	34.95 - 60.45
$\sigma^2$	2.0	44.83

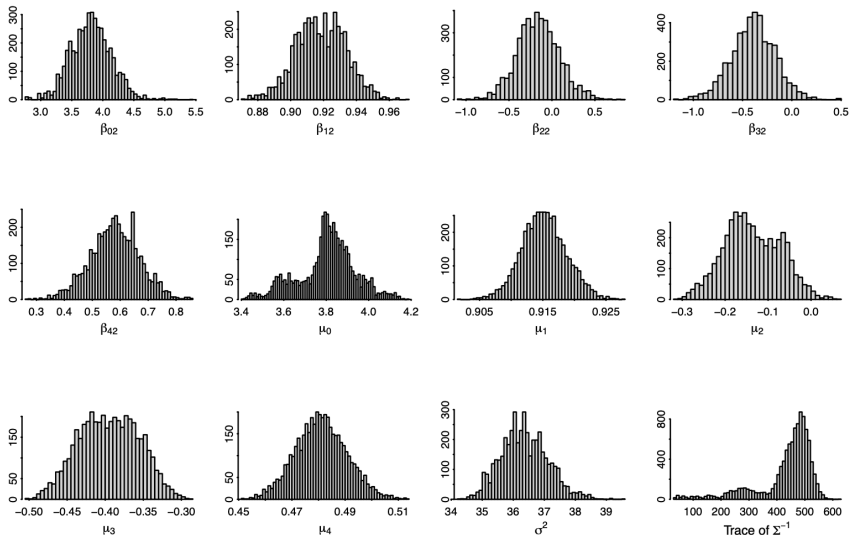
# MCMC Model Convergence

Covergence Plots of Selected Parameters



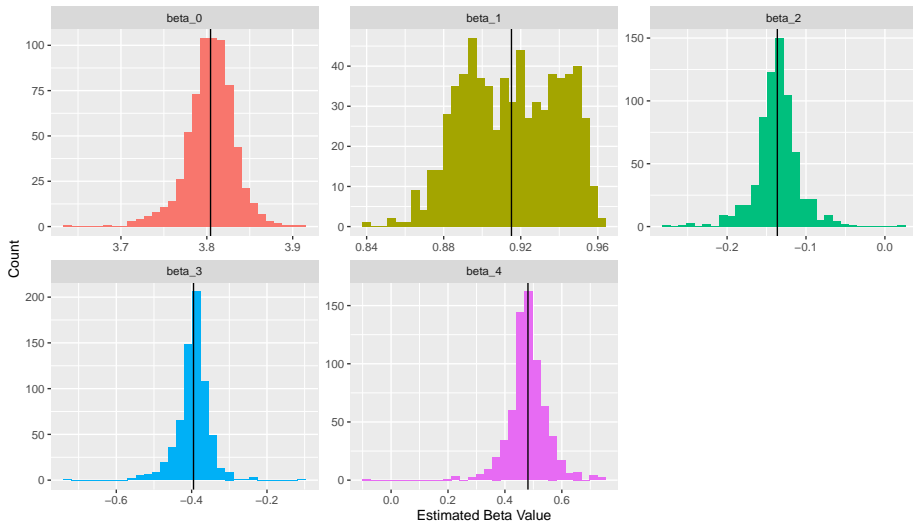
# MCMC Model Convergence

Histograms of Selected Parameters



# B Estimates

Histograms of Estimated Betas for all Hurricanes



# The $\mu$ and $\sigma^2$ Estiamtes

**Table 2:** Bayesian Estiamtes for  $\mu$  and  $\sigma^2$

	$\mu_0$	$\mu_1$	$\mu_2$	$\mu_3$	$\mu_4$	$\sigma^2$	$\sigma_{00}^2$	$\sigma_{11}^2$	$\sigma_{22}^2$	$\sigma_{33}^2$	$\sigma_{44}^2$
Estimates	3.8	0.92	-0.14	-0.39	0.48	36.36	0.063	0.003	0.047	0.042	0.018

$$\hat{\Sigma}^{-1} = \begin{bmatrix} 16.07 & 7.63 & 0.34 & -1.78 & 0.47 \\ 7.63 & 381.32 & 5.39 & 3.96 & -6.32 \\ 0.34 & 5.39 & 21.43 & 1.48 & 1.14 \\ -1.78 & 3.96 & 1.48 & 24.35 & -3.3 \\ 0.47 & -6.32 & 1.14 & -3.3 & 55.12 \end{bmatrix} \quad \hat{\rho} = \begin{bmatrix} 1 & -0.101 & -0.018 & 0.094 & -0.011 \\ -0.101 & 1 & -0.057 & -0.043 & 0.043 \\ -0.018 & -0.057 & 1 & -0.067 & -0.042 \\ 0.094 & -0.043 & -0.067 & 1 & 0.089 \\ -0.011 & 0.043 & -0.042 & 0.089 & 1 \end{bmatrix}$$

# Model Performance

The overall adjusted  $R^2$  of the estimated Bayesian model is 0.9524156.

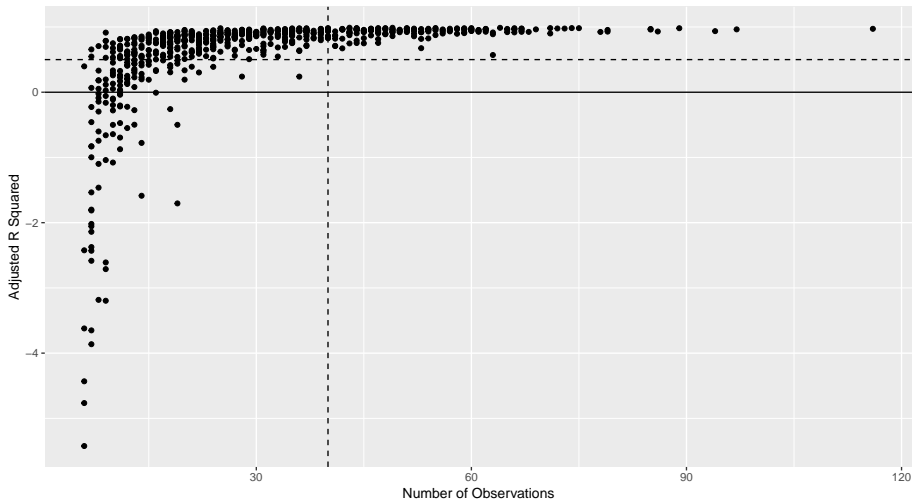
**Table 3:**  $R^2_{adj}$  for each hurricane

$R^2_{adj}$	Count of Hurricanes	Percentage(%)
0.6-1	522	76.7
0.2-0.6	79	11.6
$< 0.2$	80	11.7

# Model Performance

Adjusted R Squared Value for each Hurricane

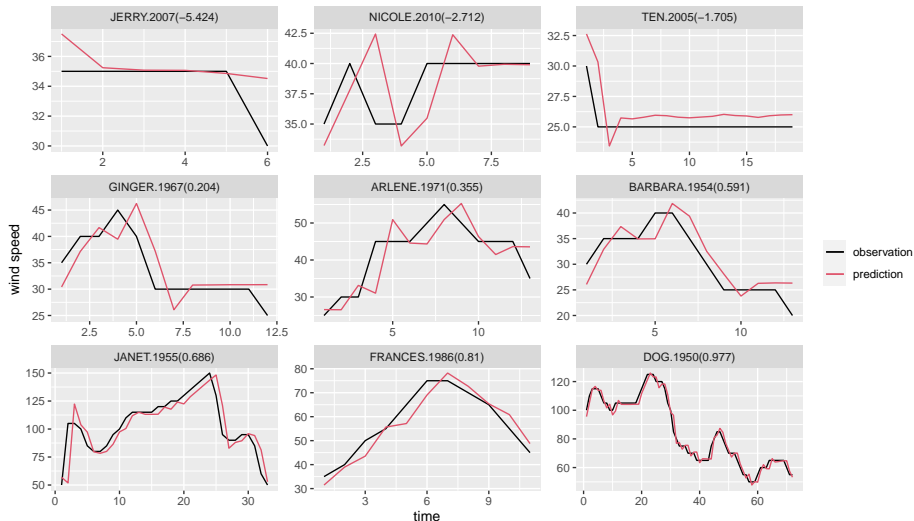
Vertical dotted line at 40, Horizontal dotted line at 0.5



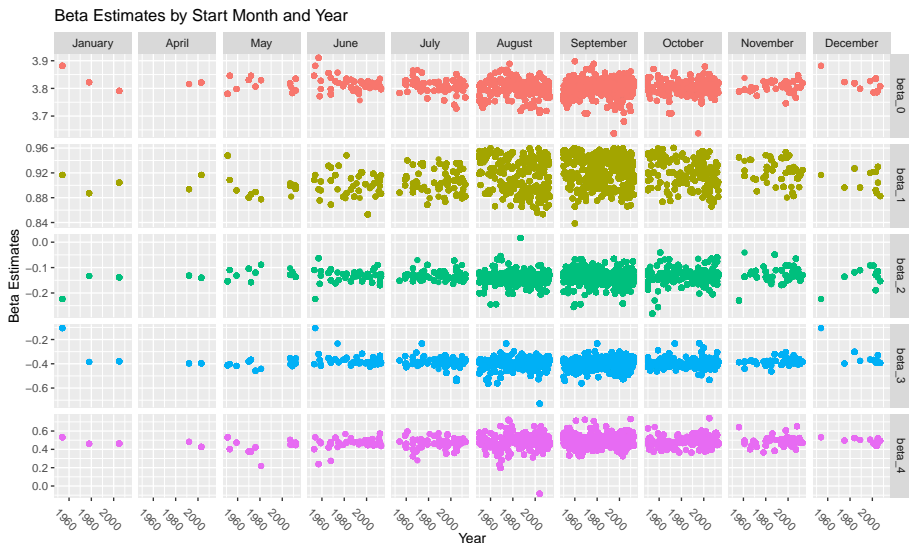


# Model Performance

Observed Wind Speed vs. Bayesian Model Estimates



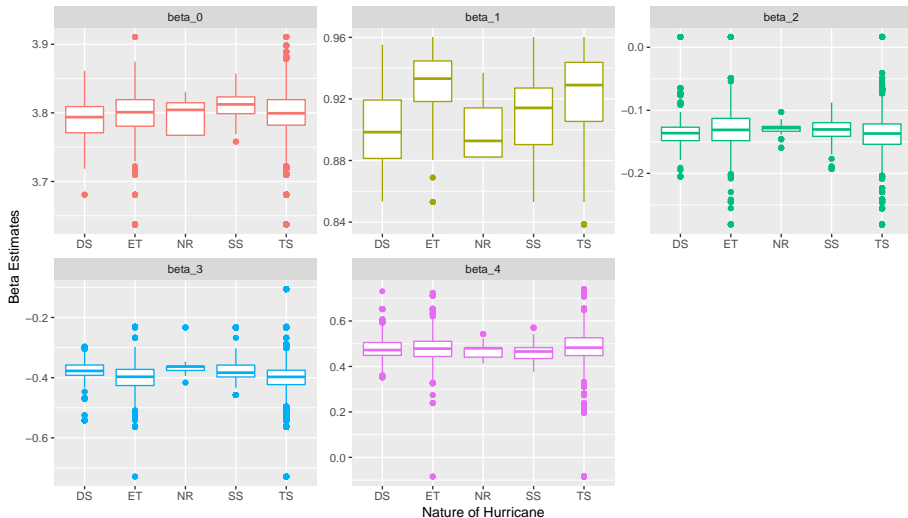
# Understanding Seasonal Differences



Typical Hurricane season is June to November

# Understanding Nature of Hurricane Differences

Beta Estimates by Nature of the Hurricane



# Modeling Seasonal, and Nature Difference

## Model:

For each  $\beta$  value we fit a different linear model.

$$Y_{ij} = \alpha_{0j} + \alpha_{1j} \times \text{Decade}_i \\ + \alpha_{(k+1)j} I(\text{Nature} = k)_i \\ + \alpha_{(l+5)j} I(\text{Month} = l)_i + \epsilon_{ij}$$

Where  $i$  is the hurricane,  $j$  is the Beta model,  $k \in (ET, NR, SS, TS)$  making DS the reference group. Let  $l \in (\text{April} - \text{December})$ .

## Results:

- Due to length each model estimate were omitted
- No Nature Indicators were significant
- No Month Indicators were significant
- For the  $\beta_1$  model the decade estimated is significant -0.003 (-0.002, -0.004)

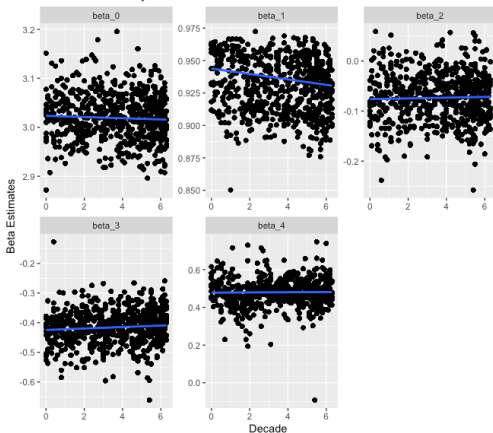
Thus Month and Nature don't have a linear association with each beta value.

# Exploring if wind speeds have increased over the years

Model:  $Y_i = \alpha_{0i} + \alpha_{1i} \times \text{Decade}$  where  $Y_i$  is each  $\beta_i$  and  $i \in (0, \dots, 4)$ .

## Linear Model Output for Each $\beta$

Beta Estimates by Decade



Characteristic	Beta	95% CI <sup>†</sup>	p-value
beta0			
decade	-0.001	-0.002, 0.000	0.2
beta1			
decade	-0.003	-0.004, -0.002	<0.001
beta2			
decade	0.000	-0.001, 0.001	0.6
beta3			
decade	0.002	0.000, 0.004	0.041
beta4			
decade	0.001	-0.002, 0.004	0.5

<sup>†</sup> CI = Confidence Interval

- $\beta_1$ : Indicates a decrease in the change of wind speed over years

# Deaths and Damages Data Exploration

# Hurricane Deaths

# Hurricane Damages



# Conclusions

- Larger Samples give better estimates
- High dim sample space, burn in takes longer than expected
  - very sensitive to starting values