

Tools for Analyzing the Built Environment: Spatial Temporal Aggregated Predictors

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Ann Arbor R User's Group

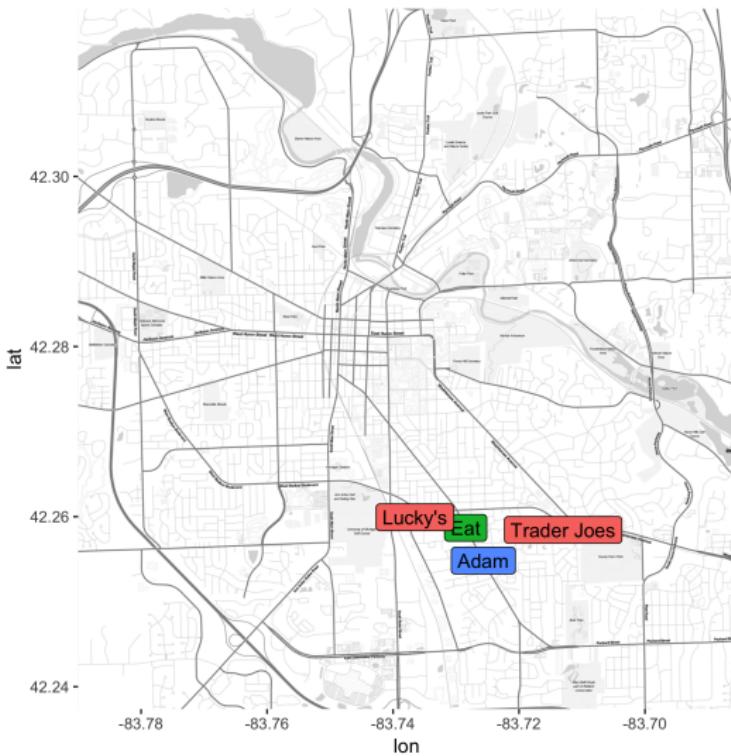
April 11, 2019

Once upon a time...

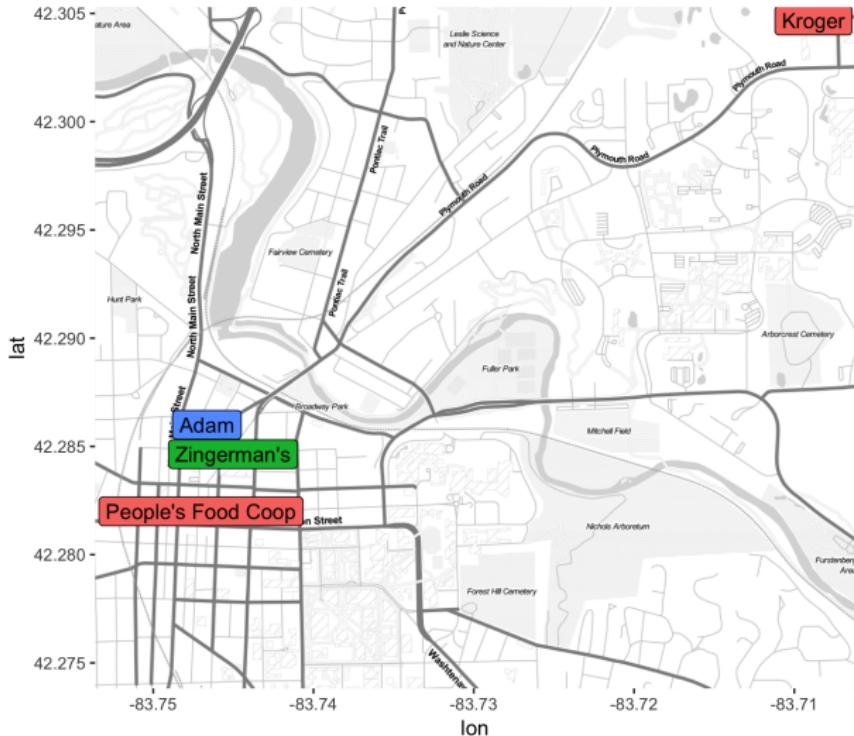


A young biostatistics
graduate student moved to
Ann Arbor, MI

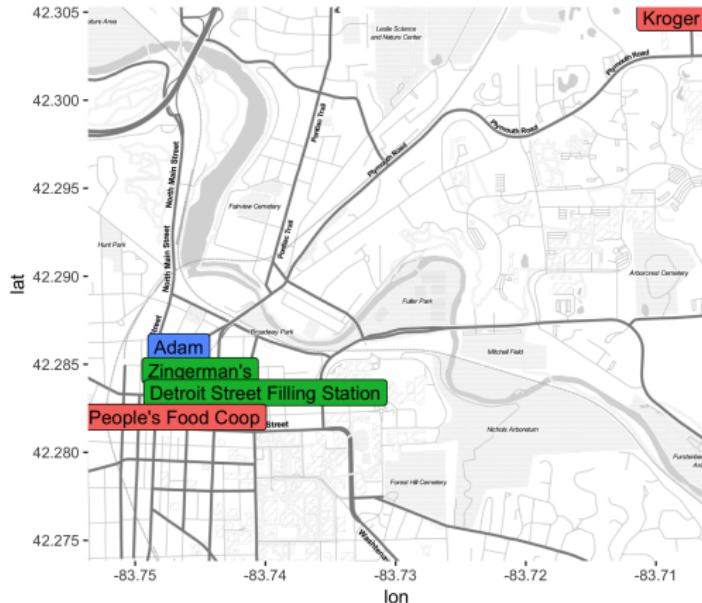
He lived in the south-east corner of AA



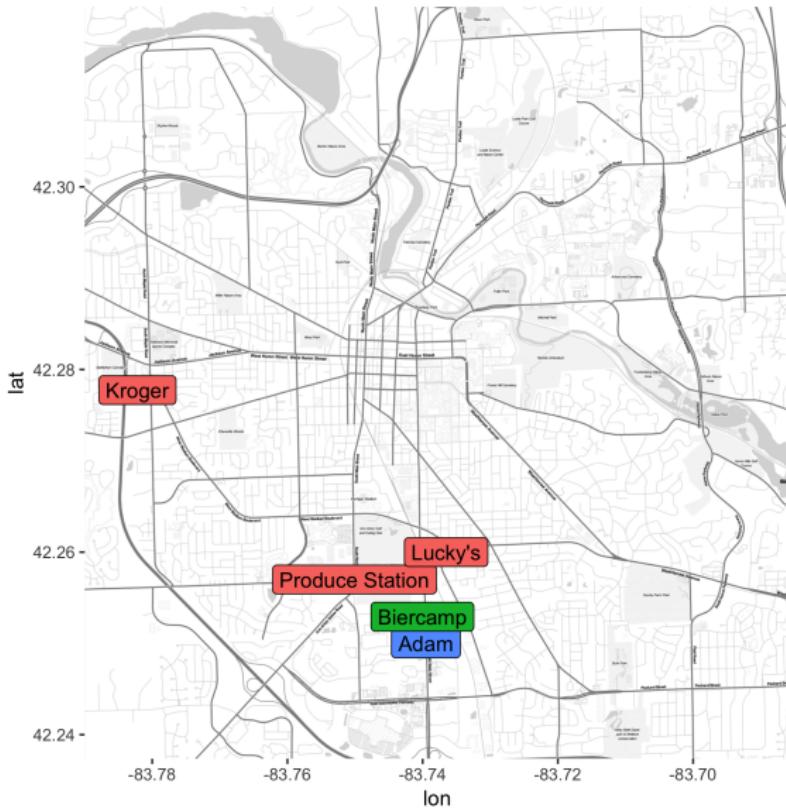
And then he moved...



he stayed there a while...

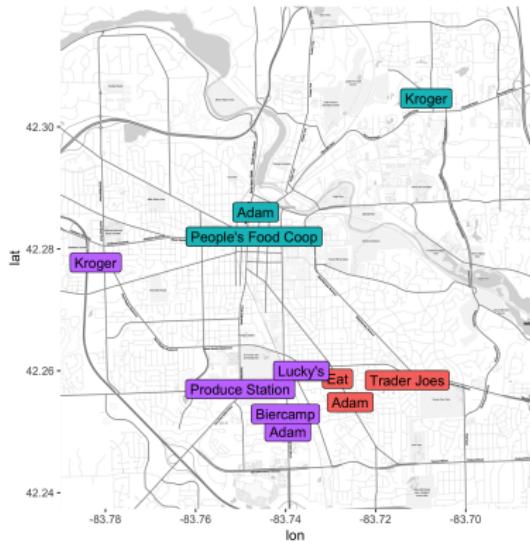


but then he eventually moved again...



Scientific questions:

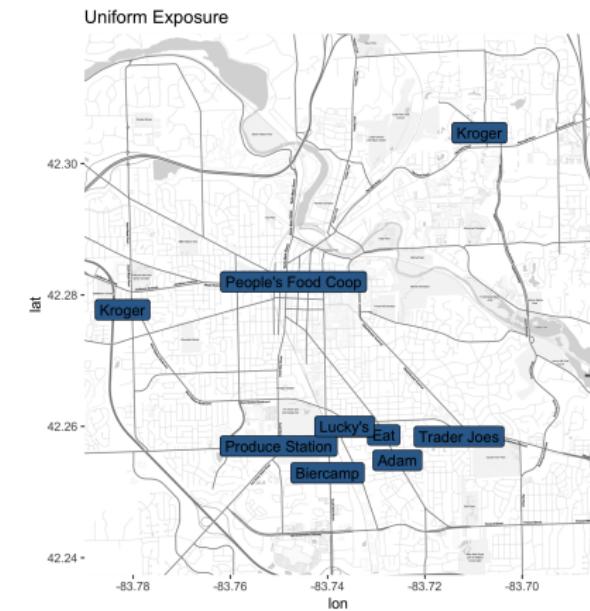
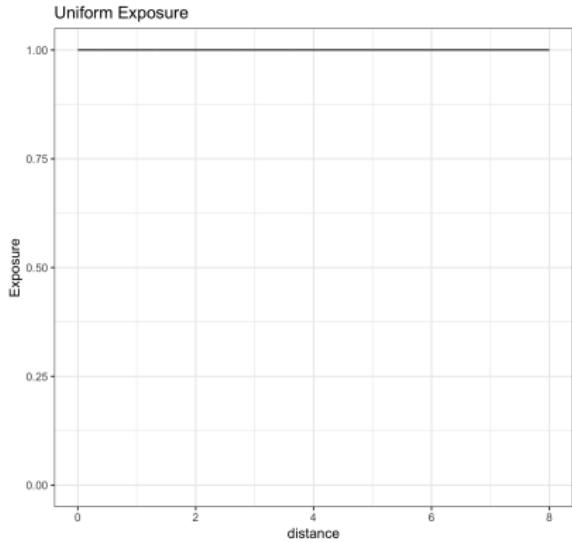
- ▶ Do these differing food environments effect Adam's health at all?
- ▶ If so,
 - ▶ What role does distance play in this effect?
 - ▶ How about time?



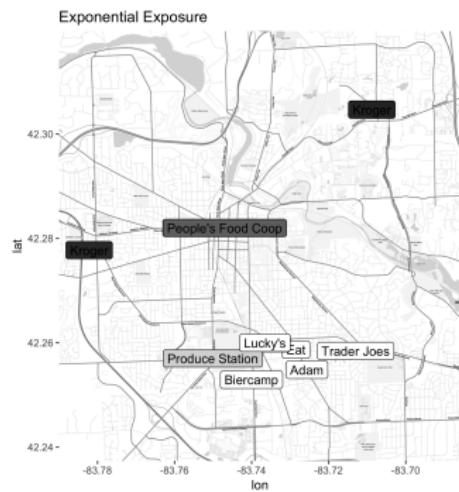
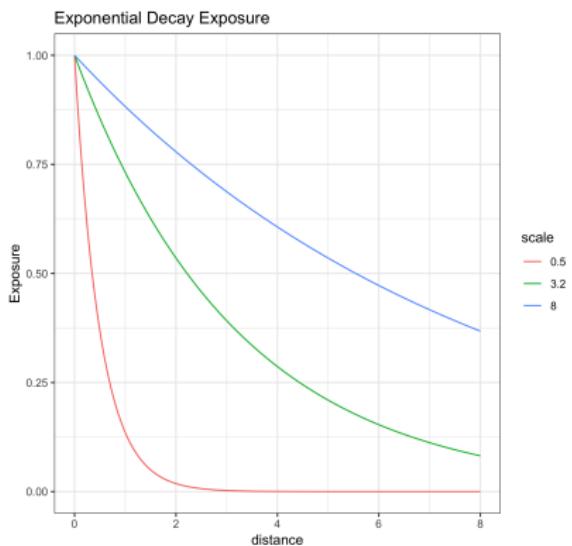
How would distance mediate the effect of a single store?

- ▶ What would the null look like?
- ▶ What might a more likely scenario look like?

The Null



Alternative



The Model: Built Environment Point Pattern Exposure

Spatial Aggregated Covariate

$$X_i := \sum_{d \in \mathcal{D}} \mathcal{K}_s\left(\frac{d}{\theta^s}\right)$$

- ▶ d : a *known* distance between subject i and a built environment feature
- ▶ \mathcal{D} : set of distances between subject i and all built environment features of a certain class.
- ▶ θ : *unknown* scale describing the distance - exposure relationship
- ▶ \mathcal{K}_s : “known” spatial weighting function - e.g. e^{-x}

Explicitly

Business	Class	Distance (mi)
Eat	Restaurant	0.20
Trader Joes	Grocery Store	0.88
Lucky's	Grocery Store	0.75

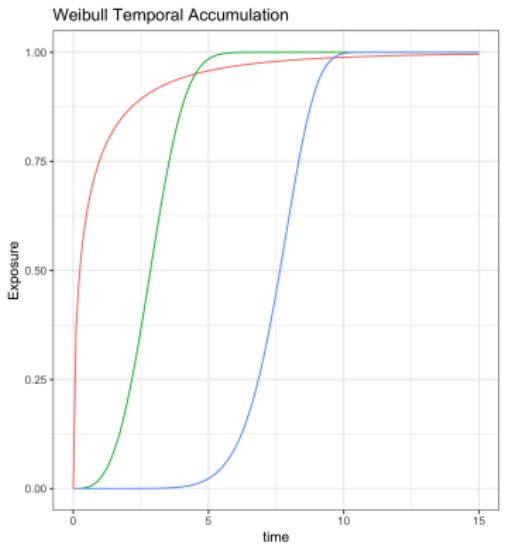
$$X_{Adam,R} = e^{-\frac{.2}{\theta_R^s}} = .81 \quad (\text{theta} = 1)$$

$$X_{Adam,G} = e^{-\frac{.88}{\theta_G^s}} + e^{-\frac{.75}{\theta_G^s}} = 1.33 \quad (\text{theta} = 2)$$

$$E[BM|_{Adam, Year1}] = \alpha + \text{male}\delta_{male} + \text{Age}\delta_{Age} + \dots + X_{Adam,G}\beta_G + X_{Adam,R}\beta_R$$

What about time?

- Would it be that much harder to look at the temporal relationship?



Temporal Aggregated Covariate

$$X_i := \sum_{t \in \mathcal{T}} \mathcal{K}_t\left(\frac{t}{\theta^t}\right)$$

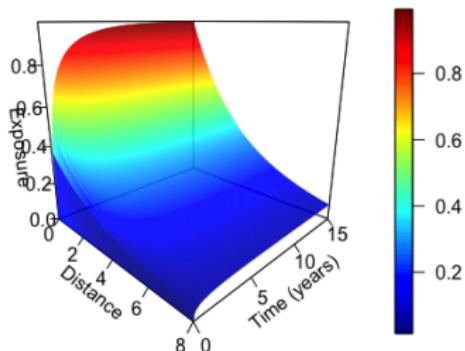
- ▶ t : The *known* time subject i has been exposed to a built environment feature at the time of measurement
- ▶ \mathcal{T} : set of times between subject i and all built environment features of a certain class.
- ▶ θ : *unknown* scale describing the time - exposure relationship
- ▶ \mathcal{K}_t : “known” temporal weighting function - e.g. $1 - e^{-x}$

Put them together and what have you got?

Spatial-Temporal Aggregated Covariate

$$X_i = \sum_{(d,t) \in S} \mathcal{K}_s\left(\frac{d}{\theta^s}\right) \mathcal{K}_t\left(\frac{t}{\theta^t}\right)$$

Exposure Across Space and Time



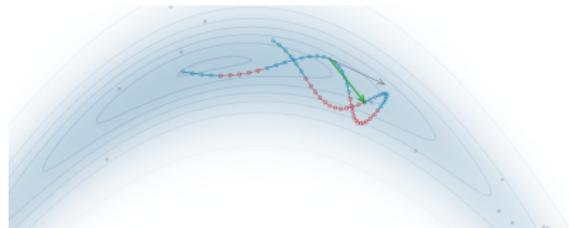
Some technical details

Final Model: Spatial Temporal Aggregated Predictors

$$g(E[Y_{i,j}]) = \mathbf{Z}_{i,j}^T \boldsymbol{\delta} + X_{i,j,k}(\theta_k^s, \theta_k^t) \beta_k + X_{i,j,l}(\theta_l^s) \beta_l + X_{i,j,p}(\theta_p^t) \beta_p + \mathbf{W}_{i,j}^T \mathbf{b}_i$$

- ▶ size of $\mathcal{S}, \mathcal{D}, \mathcal{T}$
- ▶ Space-Time Assumption: $\mathcal{K}_s\left(\frac{d}{\theta^s}\right)\mathcal{K}_t\left(\frac{t}{\theta^t}\right)$
- ▶ No features? $X_{i,j} = 0 + \sum_{(d,t) \in \mathcal{S}_j} \mathcal{K}_s\left(\frac{d}{\theta^s}\right)\mathcal{K}_t\left(\frac{t}{\theta^t}\right)$
- ▶ Some other assumptions
 - ▶ direct vs. indirect exposure
 - ▶ point process vs. continuous spaces

Estimation



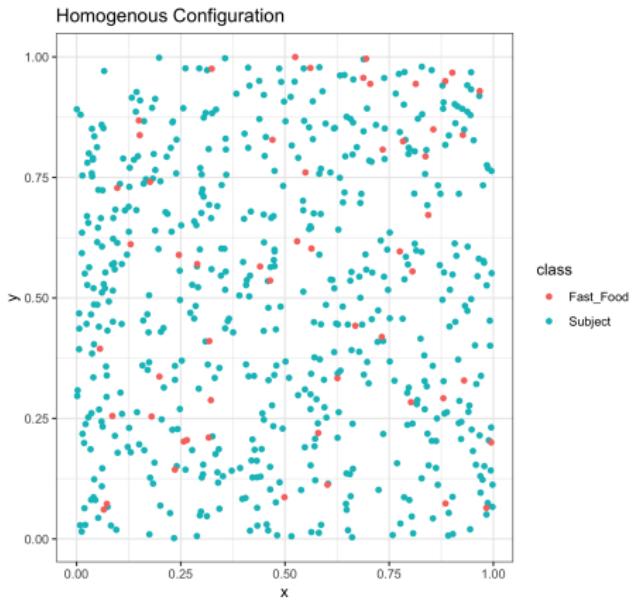
- ▶ Motivation
 - ▶ STKAP - MH/Gibbs
- ▶ Technical Details
 - ▶ HMC-NUTS

Applications

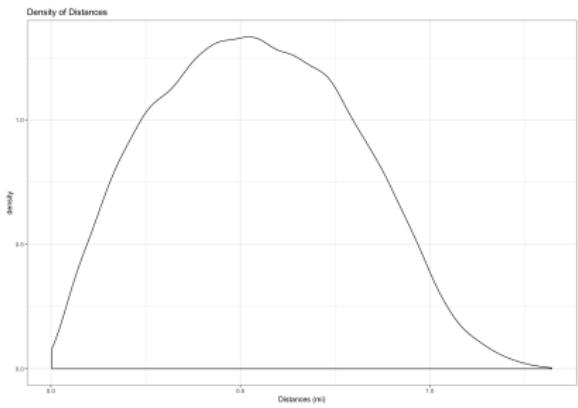
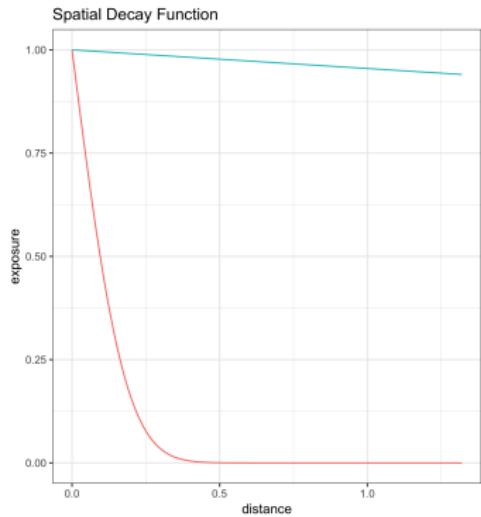
- ▶ Simulation - inclusion distance
- ▶ Real data
- ▶ rstatp

Simulation: Set-Up

$$E[\text{"BMI"}] = \alpha + \text{sex}\delta + FF(\theta_s)\beta$$



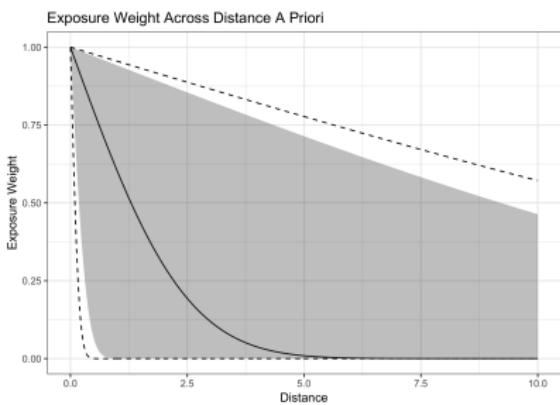
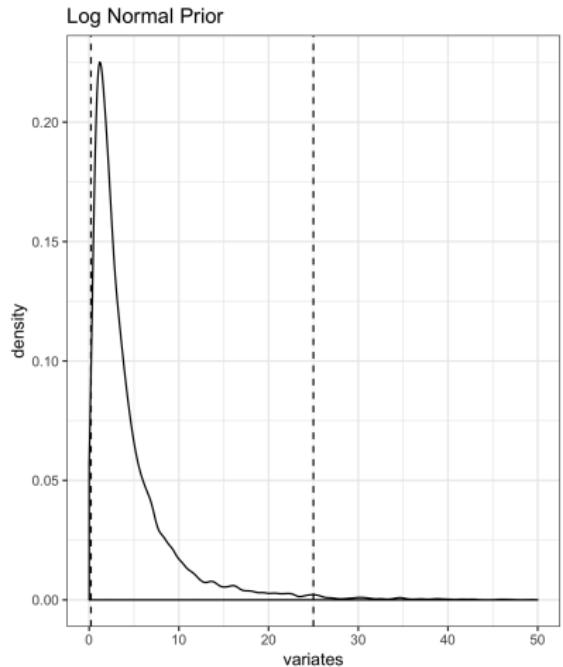
Simulation: Descriptives



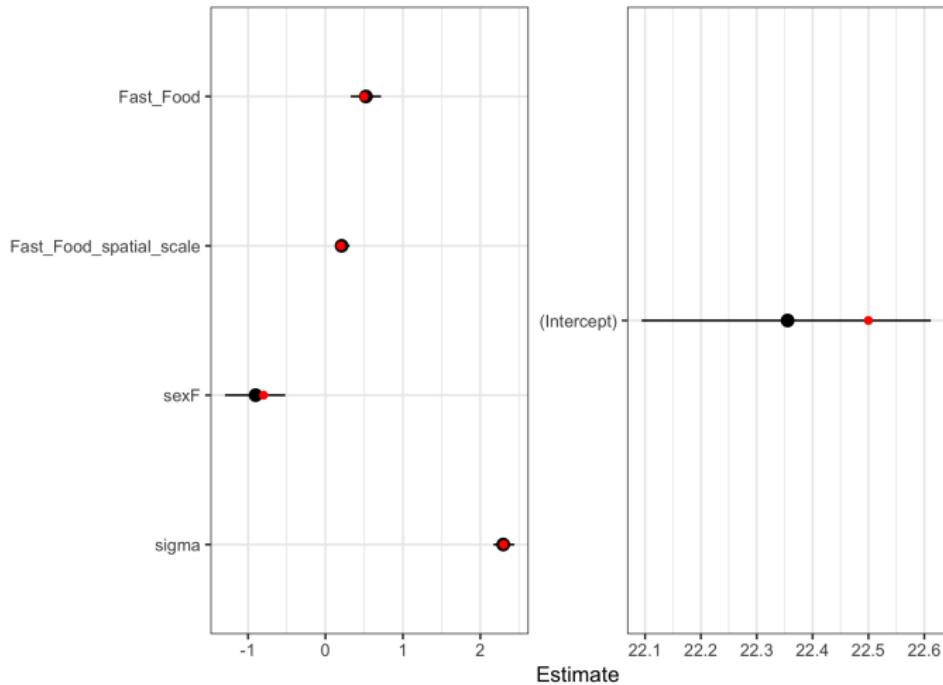
Model Fitting

```
fit <- stap_glm(BMI ~ sex + sap(Fast_Food),  
                  subject_data = subject_data,  
                  distance_data = distance_data,  
                  family = gaussian(link = "identity"),  
                  id_key = "subj_id",  
                  prior = normal(location = 0, scale = 5),  
                  prior_intercept = normal(26,5),  
                  prior_stap = normal(0, 3),  
                  prior_theta = log_normal(1, 1),  
                  prior_aux = cauchy(location = 0, scale = 5),  
                  max_distance = max(dists), chains = 4,  
                  iter = 2E3, cores = 4, warmup = 1E3)
```

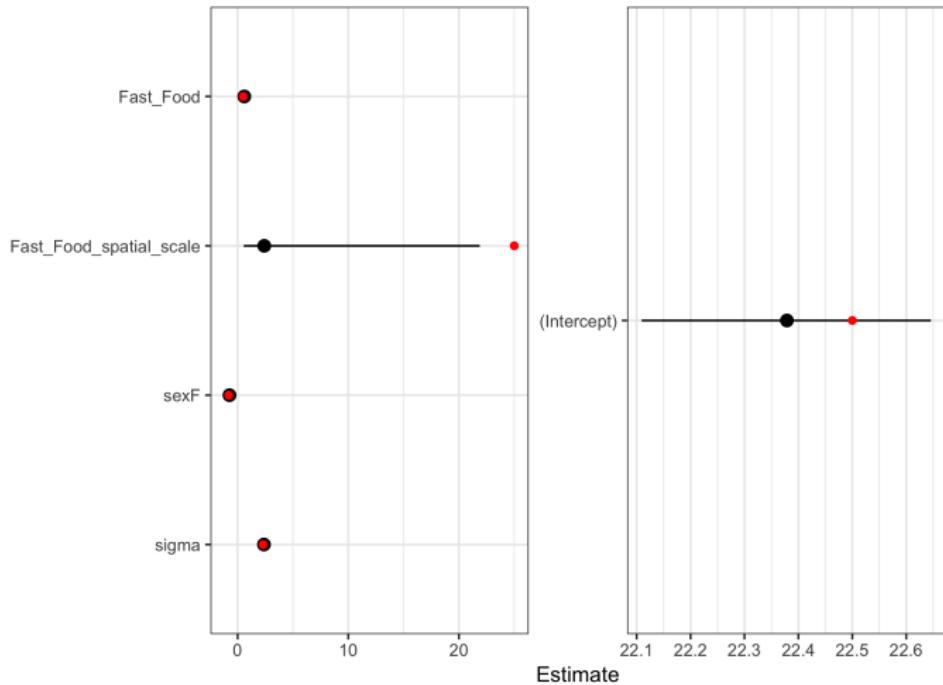
Model fitting, priors



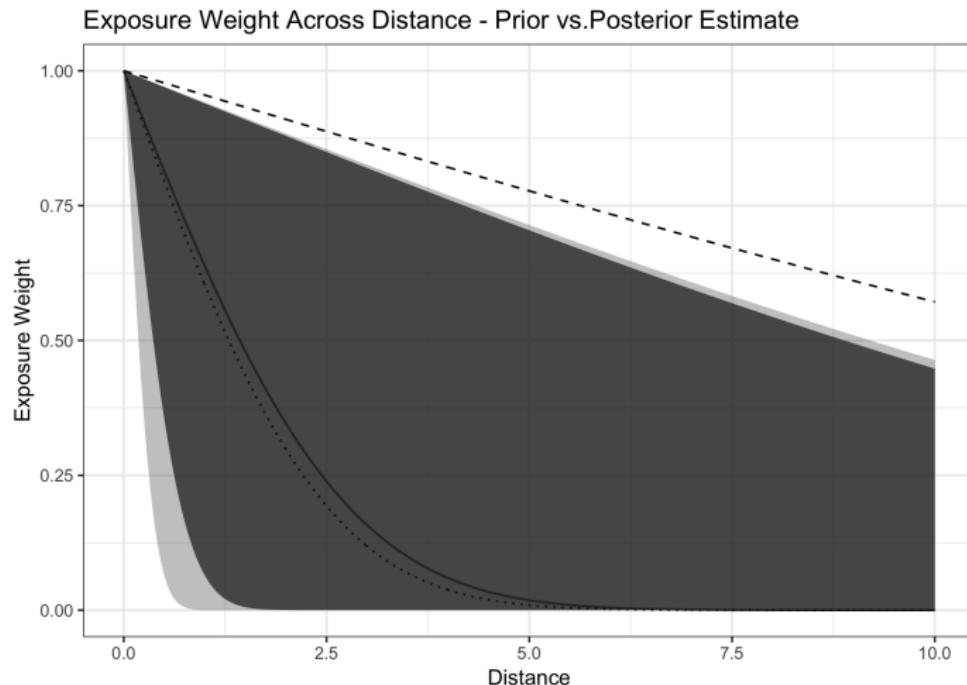
Results - "sharp decay"



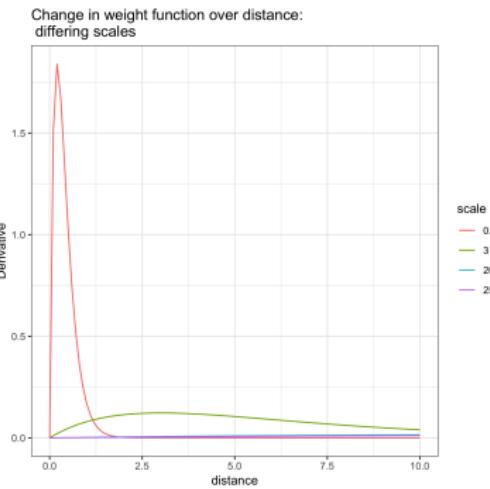
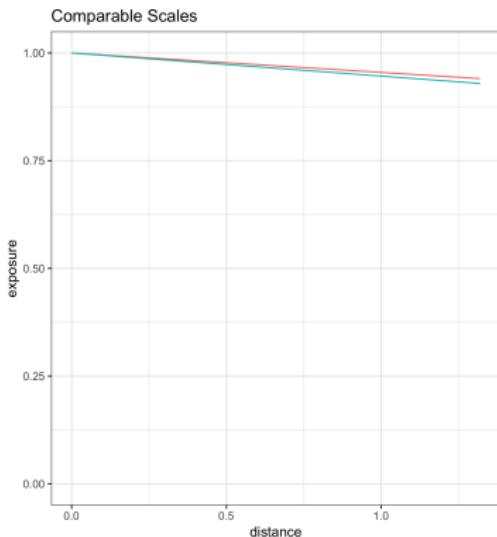
Results - “slow decay”



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Estimating the Main Effect - Explanation

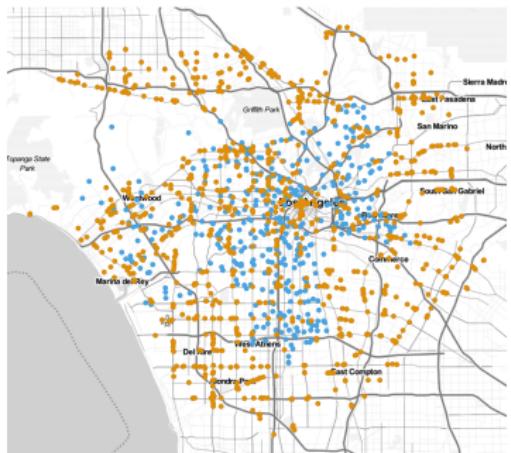


Real Data: Description

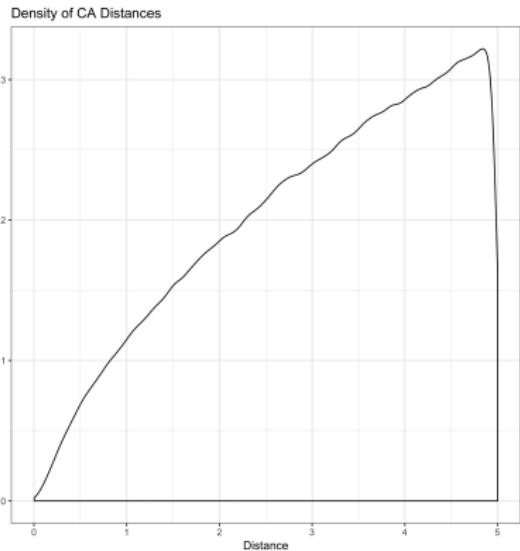
- ▶ CA Dept. of Ed. Fitnessgram project
- ▶ Academic Year 2010
- ▶ Built Environment Data: NETS database

Strata	Urban
Total Schools	2386
Mean # of Obese Students	33.1
Mean # of Total Students	86.6

Real Data: Descriptives

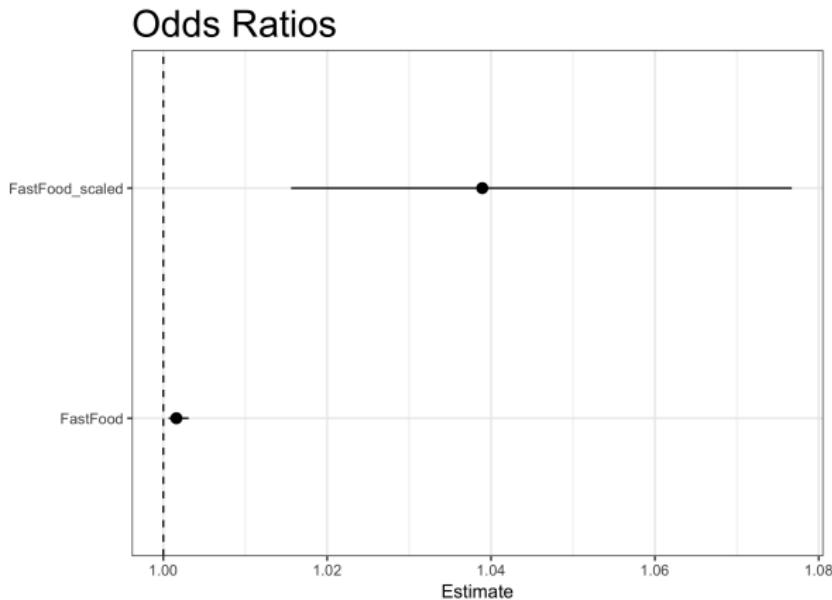


class
FFC
School

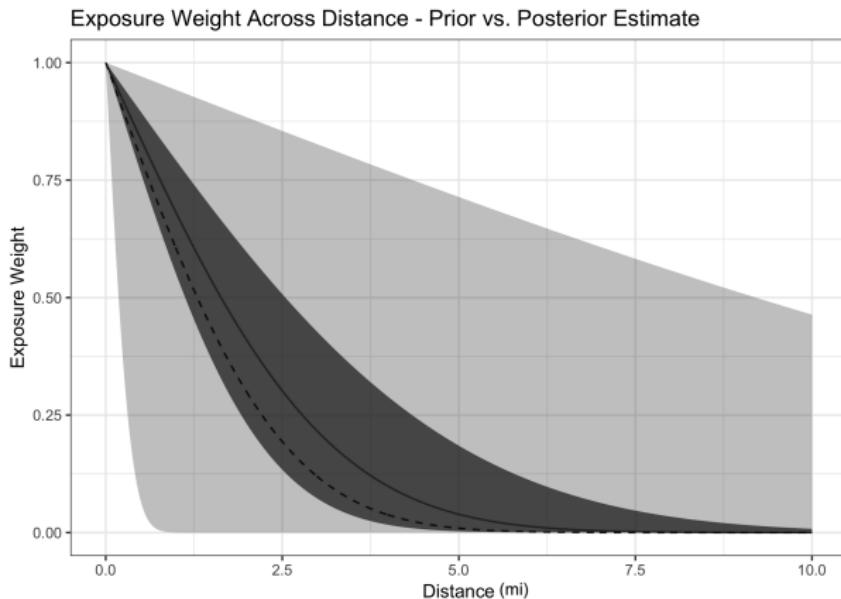


Real Data: Model and Estimates

$$\text{logit}(\mu_i) = \alpha + \mathbf{Z}_i^T \delta + X_{i,FF}^T(\theta_s) \beta$$



Real Data: Spatial Scales



Distance at which Exposure Effect is Negligible (mi)

	2.5%	50%	97.5%
Urban	4.27	6.28	9.62

Future Directions

- ▶ Causal Inference - Difference in Differences
- ▶ Faster sampling - custom C++
- ▶ Non-monotonic Spatial scales

References

- ▶ <https://biostatistics4socialimpact.github.io/rstap/>
- ▶ Neal, Radford M. "MCMC using Hamiltonian dynamics." *Handbook of Markov Chain Monte Carlo* 2.11 (2011): 2.
- ▶ Betancourt, Michael. "A conceptual introduction to Hamiltonian Monte Carlo." arXiv preprint arXiv:1701.02434 (2017).
- ▶ Heaton, Matthew J., and Alan E. Gelfand. "Spatial regression using kernel averaged predictors." *Journal of agricultural, biological, and environmental statistics* 16.2 (2011): 233-252

Questions?