Web-based Supplementary Materials for "Spatial-Temporal Modeling of the Association between Air Pollution Exposure and Preterm Birth: Identifying Critical Windows of Exposure"

by

Joshua Warren, Montserrat Fuentes, Amy Herring, and Peter Langlois

1 Web Appendix A

The final dataset that we analyze for Model 6 consists of $N = 43{,}607$ women with full covariate information. There are 3,458 (7.93%) preterm births in the data. The fitting of the model, including the MCMC analysis, is handled using the R Statistical Software package. The following section is valid for the fixed pollution exposure case.

1.1 Basic Setup

$$Y_i|\boldsymbol{\beta}, \boldsymbol{\theta} \overset{ind}{\sim} \text{Bernoulli}\left\{p_i(\boldsymbol{\beta}, \boldsymbol{\theta})\right\}; \quad i = 1, \ldots, N$$
$$\Phi^{-1}\left\{p_i(\boldsymbol{\beta}, \boldsymbol{\theta})\right\} = \mathbf{x}_i{}^T\boldsymbol{\beta} + \mathbf{z}_i{}^T\boldsymbol{\theta}\left\{\boldsymbol{B}\left(\boldsymbol{s}_i\right)\right\} = \mathbf{x}_i{}^T\boldsymbol{\beta} + \mathbf{z}_i^{*T}\boldsymbol{\theta}$$

- $\boldsymbol{B}\left(\boldsymbol{s}\right) \in \left\{\boldsymbol{s}_1^*, \ldots, \boldsymbol{s}_L^*\right\}$
- $\mathbf{x}_i = p$ dimensional column vector of included covariates for birth i
- $\mathbf{z}_i =$ J*M dimensional column vector of weekly pollution exposure information ($PM_{2.5}$ and ozone) for birth i
- $\mathbf{z}_i^* =$ J*M*L dimensional column vector of weekly pollution exposure information with zeros filled in for the non-relevant spatial locations
  - $\mathbf{z}_1^* = (\mathbf{z}_1^T, \mathbf{0}^T, \ldots, \mathbf{0}^T)^T$, if $\boldsymbol{B}\left(\boldsymbol{s}_1\right) = \boldsymbol{s}_1^*$
  - $\mathbf{z}_2^* = (\mathbf{0}^T, \mathbf{z}_2^T, \mathbf{0}^T, \ldots, \mathbf{0}^T)^T$, if $\boldsymbol{B}\left(\boldsymbol{s}_2\right) = \boldsymbol{s}_2^*$
  - etc...
- $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)^T$
- $\boldsymbol{\theta}\left\{\boldsymbol{B}\left(\boldsymbol{s}_i\right)\right\} = \left[\theta\left\{1, 1, \boldsymbol{B}\left(\boldsymbol{s}_i\right)\right\}, \ldots, \theta\left\{1, M, \boldsymbol{B}\left(\boldsymbol{s}_i\right)\right\}, \ldots, \theta\left\{J, 1, \boldsymbol{B}\left(\boldsymbol{s}_i\right)\right\}, \ldots, \theta\left\{J, M, \boldsymbol{B}\left(\boldsymbol{s}_i\right)\right\}\right]^T$
  - $\theta\left\{j, w, \boldsymbol{B}\left(\boldsymbol{s}\right)\right\} =$ pollutant j, week w, location $\boldsymbol{s}$ within region $\boldsymbol{B}\left(\boldsymbol{s}\right)$ pollution coefficient
- $\boldsymbol{\theta} = \left\{\boldsymbol{\theta}(\boldsymbol{s}_1^*)^T, \ldots, \boldsymbol{\theta}(\boldsymbol{s}_L^*)^T\right\}^T$
  - J= number of pollutants
  - M= number of weeks
  - L= number of unique spatial locations (L $\leq$ N)

1.2 Priors

- $\boldsymbol{\beta} \sim \text{MVN}(\mathbf{0}, \sigma^2_{\boldsymbol{\beta}} I_p)$
  - $\sigma^2_{\boldsymbol{\beta}}$ fixed, large
- $\boldsymbol{\theta} \sim \text{MVN}(\mathbf{0}, \phi_0 \boldsymbol{\Sigma})$, where entries of $\phi_0 \boldsymbol{\Sigma}$ are given by:

$$\text{cov}\left\{\theta(j, w, \boldsymbol{s}^*), \theta(j', w', \boldsymbol{s}^{*'})\right\} = \phi_0 \exp\left\{-\phi_1 ||\boldsymbol{s}^* - \boldsymbol{s}^{*'}|| - \phi_2 |w - w'| - \phi_3 I(j \neq j')\right\}$$

- $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_1 \otimes \boldsymbol{\Sigma}_2 \otimes \boldsymbol{\Sigma}_3$
  - $\boldsymbol{\Sigma}_1$ = L x L spatial correlation function; $\boldsymbol{\Sigma}_1(i,j) = \exp\left(-\phi_1 ||\boldsymbol{s}^*_i - \boldsymbol{s}^*_j||\right)$
  - $\boldsymbol{\Sigma}_2$ = J x J pollutant correlation function; $\boldsymbol{\Sigma}_2(i,j) = \exp\left\{-\phi_3 I(i \neq j)\right\}$
  - $\boldsymbol{\Sigma}_3$ = M x M temporal correlation function; $\boldsymbol{\Sigma}_3(i,j) = \exp\left(-\phi_2 |w_i - w_j|\right)$
- $\phi_0 \sim$ Inverse gamma(a_0, b_0)
- $\phi_k \overset{ind}{\sim}$ Uniform(a_k, b_k); $k = 1, 2, 3$

1.3 Latent Variables $W_1, W_2, \ldots, W_N$

- $W_i = \mathbf{x}_i{}^T \boldsymbol{\beta} + \mathbf{z}^{*T}_i \boldsymbol{\theta} + e_i;\ i = 1, \ldots, N$
  - $e_i \overset{iid}{\sim} \text{N}(0, 1)$
- $Y_i = \begin{cases} 0, \text{ if } W_i < 0 \\ 1, \text{ if } W_i \geq 0 \end{cases}$
  - $p_i(\boldsymbol{\beta}, \boldsymbol{\theta}) = P(Y_i = 1) = P(W_i \geq 0) = \Phi(\mathbf{x}_i{}^T \boldsymbol{\beta} + \mathbf{z}^{*T}_i \boldsymbol{\theta})$

1.4 Full Conditionals

1.4.1 W_i Parameters

$$\begin{aligned} f(W_i | rest) &\propto f(Y_i | W_i) f(W_i | \boldsymbol{\beta}, \boldsymbol{\theta}) \\ &= P(W_i \geq 0)^{Y_i} \left\{1 - P(W_i \geq 0)\right\}^{1 - Y_i} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2}(W_i - \mathbf{x}_i{}^T \boldsymbol{\beta} - \mathbf{z}^{*T}_i \boldsymbol{\theta})^2\right\} \\ &\propto \begin{cases} \exp\left\{-\frac{1}{2}(W_i - \mathbf{x}_i{}^T \boldsymbol{\beta} - \mathbf{z}^{*T}_i \boldsymbol{\theta})^2\right\} I(W_i < 0), \text{ if } Y_i = 0 \\ \exp\left\{-\frac{1}{2}(W_i - \mathbf{x}_i{}^T \boldsymbol{\beta} - \mathbf{z}^{*T}_i \boldsymbol{\theta})^2\right\} I(W_i \geq 0), \text{ if } Y_i = 1 \end{cases} \end{aligned}$$

$$W_i | rest \sim \begin{cases} N(\mathbf{x}_i{}^T \boldsymbol{\beta} + \mathbf{z}^{*T}_i \boldsymbol{\theta}, 1) I(W_i < 0), \text{ if } Y_i = 0 \\ N(\mathbf{x}_i{}^T \boldsymbol{\beta} + \mathbf{z}^{*T}_i \boldsymbol{\theta}, 1) I(W_i \geq 0), \text{ if } Y_i = 1 \end{cases}$$

$\Rightarrow W_i | rest \sim$ Truncated normal$(\mathbf{x}_i{}^T \boldsymbol{\beta} + \mathbf{z}^{*T}_i \boldsymbol{\theta}, 1)$, where the truncation is determined by Y_i

1.4.2 $\boldsymbol{\beta}$ Parameters

$$
\begin{aligned}
f(\boldsymbol{\beta}|rest) &\propto f(\mathbf{W}|\boldsymbol{\beta},\boldsymbol{\theta})f(\boldsymbol{\beta}|\sigma^2_{\boldsymbol{\beta}})\\
&\propto \left[\prod_{i=1}^{N}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{1}{2}(W_i-\mathbf{x}_i{}^T\boldsymbol{\beta}-\mathbf{z}_i^{*T}\boldsymbol{\theta})^2\right\}\right]\frac{1}{(2\pi)^{\frac{p}{2}}|\sigma^2_{\boldsymbol{\beta}}\mathbf{I}|^{\frac{1}{2}}}\exp\left\{-\frac{1}{2}\boldsymbol{\beta}^T(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\boldsymbol{\beta}\right\}\\
&\propto \exp\left\{-\frac{1}{2}(\mathbf{W}-X\boldsymbol{\beta}-Z^*\boldsymbol{\theta})^T(\mathbf{W}-X\boldsymbol{\beta}-Z^*\boldsymbol{\theta})-\frac{1}{2}\boldsymbol{\beta}^T(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\boldsymbol{\beta}\right\}\\
&= \exp\left\{-\frac{1}{2}(\mathbf{W}^T-\boldsymbol{\beta}^TX^T-\boldsymbol{\theta}^TZ^{*T})(\mathbf{W}-X\boldsymbol{\beta}-Z^*\boldsymbol{\theta})-\frac{1}{2}\boldsymbol{\beta}^T(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\boldsymbol{\beta}\right\}\\
&\propto \exp\left[-\frac{1}{2}\left\{-\mathbf{W}^TX\boldsymbol{\beta}-\boldsymbol{\beta}^TX^T\mathbf{W}+\boldsymbol{\beta}^TX^TX\boldsymbol{\beta}+\boldsymbol{\beta}^TX^TZ^*\boldsymbol{\theta}+\boldsymbol{\theta}^TZ^{*T}X\boldsymbol{\beta}+\right.\right.\\
&\left.\left.\boldsymbol{\beta}^T(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\boldsymbol{\beta}\right\}\right]\\
&= \exp\left(-\frac{1}{2}\left[\boldsymbol{\beta}^T\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}\boldsymbol{\beta}-\boldsymbol{\beta}^T\left(X^T\mathbf{W}-X^TZ^*\boldsymbol{\theta}\right)-\left(\mathbf{W}^TX-\boldsymbol{\theta}^TZ^{*T}X\right)\boldsymbol{\beta}\right]\right)
\end{aligned}
$$

Let $\boldsymbol{\mu}=X^T\mathbf{W}-X^TZ^*\boldsymbol{\theta}$

$$
\begin{aligned}
\Rightarrow &= \exp\left(-\frac{1}{2}\left[\boldsymbol{\beta}^T\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}\boldsymbol{\beta}-\boldsymbol{\beta}^T\boldsymbol{\mu}-\boldsymbol{\mu}^T\boldsymbol{\beta}\right]\right)\\
&\propto \exp\left(-\frac{1}{2}\left[\boldsymbol{\beta}^T\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}-\boldsymbol{\mu}^T\right]\left[\boldsymbol{\beta}-\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\boldsymbol{\mu}\right]\right)\\
&= \exp\left(-\frac{1}{2}\left[\boldsymbol{\beta}^T-\boldsymbol{\mu}^T\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\right]\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}\left[\boldsymbol{\beta}-\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\boldsymbol{\mu}\right]\right)\\
&= \exp\left(-\frac{1}{2}\left[\boldsymbol{\beta}-\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\boldsymbol{\mu}\right]^T\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}\left[\boldsymbol{\beta}-\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\boldsymbol{\mu}\right]\right)\\
&\Rightarrow \boldsymbol{\beta}|rest\sim \mathrm{MVN}\left[\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\boldsymbol{\mu},\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\right]
\end{aligned}
$$

$$
\Rightarrow \boldsymbol{\beta}|rest\sim \mathrm{MVN}\left[\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}X^T\left(\mathbf{W}-Z^*\boldsymbol{\theta}\right),\left\{X^TX+(\sigma^2_{\boldsymbol{\beta}}\mathbf{I})^{-1}\right\}^{-1}\right]
$$

1.4.3 $\boldsymbol{\theta}$ Parameters

$$
\begin{aligned}
f(\boldsymbol{\theta}|rest) &\propto f(\mathbf{W}|\boldsymbol{\beta},\boldsymbol{\theta})f(\boldsymbol{\theta}|\phi_0,\phi_1,\phi_2,\phi_3)\\
&= \left[\prod_{i=1}^{N}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{1}{2}(W_i-\mathbf{x}_i{}^T\boldsymbol{\beta}-\mathbf{z}_i^{*T}\boldsymbol{\theta})^2\right\}\right]\frac{1}{(2\pi)^{\frac{J*M*L}{2}}|\phi_0\boldsymbol{\Sigma}|^{\frac{1}{2}}}\exp\left\{-\frac{1}{2}\boldsymbol{\theta}^T(\phi_0\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\}\\
&\propto \exp\left\{-\frac{1}{2}(\mathbf{W}-X\boldsymbol{\beta}-Z^*\boldsymbol{\theta})^T(\mathbf{W}-X\boldsymbol{\beta}-Z^*\boldsymbol{\theta})\right\}\exp\left\{-\frac{1}{2}\boldsymbol{\theta}^T(\phi_0\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\}\\
&\propto \exp\left[-\frac{1}{2}\left\{-\mathbf{W}^TZ^*\boldsymbol{\theta}+\boldsymbol{\beta}^TX^TZ^*\boldsymbol{\theta}-\boldsymbol{\theta}^TZ^{*T}\mathbf{W}+\boldsymbol{\theta}^TZ^{*T}X\boldsymbol{\beta}+\boldsymbol{\theta}^TZ^{*T}Z^*\boldsymbol{\theta}+\right.\right.\\
&\left.\left.\boldsymbol{\theta}^T(\phi_0\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\}\right]\\
&= \exp\left(-\frac{1}{2}\left[\boldsymbol{\theta}^T\left\{Z^{*T}Z^*+(\phi_0\boldsymbol{\Sigma})^{-1}\right\}\boldsymbol{\theta}-\boldsymbol{\theta}^T(Z^{*T}\mathbf{W}-Z^{*T}X\boldsymbol{\beta})-(\mathbf{W}^TZ^*-\boldsymbol{\beta}^TX^TZ^*)\boldsymbol{\theta}\right]\right)
\end{aligned}
$$

$$\Rightarrow \boldsymbol{\theta}|rest \sim \text{MVN}\left[\left\{Z^{*T}Z^{*} + (\phi_0\boldsymbol{\Sigma})^{-1}\right\}^{-1} Z^{*T}(\mathbf{W} - X\boldsymbol{\beta}), \left\{Z^{*T}Z^{*} + (\phi_0\boldsymbol{\Sigma})^{-1}\right\}^{-1}\right]$$

1.4.4 ϕ_0 Parameter

$$\begin{aligned}
f(\phi_0|rest) &\propto f(\boldsymbol{\theta}|\phi_0, \phi_1, \phi_2, \phi_3) f(\phi_0) \\
&= \frac{1}{(2\pi)^{\frac{J*M*L}{2}} |\phi_0\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}\boldsymbol{\theta}^T(\phi_0\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\} \frac{b_0}{\Gamma(a_0)} \phi_0^{-(a_0+1)} \exp\left\{-\left(\frac{b_0}{\phi_0}\right)\right\} \\
&\propto \frac{1}{\phi_0^{\frac{J*M*L}{2}}} \exp\left\{-\frac{1}{2\phi_0}\boldsymbol{\theta}^T(\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\} \frac{1}{\phi_0^{a_0+1}} \exp\left\{-\left(\frac{b_0}{\phi_0}\right)\right\} \\
&= \frac{1}{\phi_0}^{\frac{J*M*L}{2}+a_0+1} \exp\left\{-\frac{1}{\phi_0}\left(\frac{\boldsymbol{\theta}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\theta}}{2} + b_0\right)\right\}
\end{aligned}$$

$$\Rightarrow \phi_0|rest \sim \text{Inverse gamma}\left(\frac{J*M*L}{2} + a_0, \frac{\boldsymbol{\theta}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\theta}}{2} + b_0\right)$$

1.4.5 ϕ_1, ϕ_2, and ϕ_3 Parameters

$$\begin{aligned}
f(\phi_1, \phi_2, \phi_3|rest) &\propto f(\boldsymbol{\theta}|\phi_0, \phi_1, \phi_2, \phi_3) f(\phi_1, \phi_2, \phi_3) \\
&= f(\boldsymbol{\theta}|\phi_0, \phi_1, \phi_2, \phi_3) f(\phi_1) f(\phi_2) f(\phi_3) \\
&= \frac{1}{(2\pi)^{\frac{J*M*L}{2}} |\phi_0\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}\boldsymbol{\theta}^T(\phi_0\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\} \prod_{k=1}^{3} \frac{1}{b_k - a_k}
\end{aligned}$$

I use the Metropolis-Hastings sampling technique to sample from the full conditional since no conjugate form is available. I transform ϕ_1, ϕ_2, and ϕ_3 to each have support on $\mathbb{R}$ so that I can work with Gaussian proposal densities.

$$\begin{aligned}
&\psi_k = \ln\left(\frac{\phi_k - a_k}{b_k - \phi_k}\right) \in \mathbb{R};\ k = 1, \ldots, 3 \\
&F_{\psi_k}(\psi) = P(\psi_k \le \psi) = P\left\{\ln\left(\frac{\phi_k - a_k}{b_k - \phi_k}\right) \le \psi\right\} = F_{\phi_k}\left\{\frac{b_k \exp(\psi) + a_k}{1 + \exp(\psi)}\right\} \\
&\Rightarrow f_{\psi_k}(\psi) = f_{\phi_k}\left\{\frac{b_k \exp(\psi) + a_k}{1 + \exp(\psi)}\right\}\left[\frac{b_k \exp(\psi)\{1 + \exp(\psi)\} - \{b_k \exp(\psi) + a_k\}\exp(\psi)}{\{1 + \exp(\psi)\}^2}\right] \\
&= \frac{1}{b_k - a_k}\left[\frac{\exp(\psi)(b_k - a_k)}{\{1 + \exp(\psi)\}^2}\right] = \frac{\exp(\psi)}{\{1 + \exp(\psi)\}^2} \\
&\Rightarrow f(\psi_1, \psi_2, \psi_3|rest) \propto \frac{1}{(2\pi)^{\frac{J*M*L}{2}} |\phi_0\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}\boldsymbol{\theta}^T(\phi_0\boldsymbol{\Sigma})^{-1}\boldsymbol{\theta}\right\} \prod_{k=1}^{3} \frac{\exp(\psi_k)}{\{1 + \exp(\psi_k)\}^2}
\end{aligned}$$

1.5 Extra

- $(\boldsymbol{\Sigma})^{-1} = (\boldsymbol{\Sigma}_1 \otimes \boldsymbol{\Sigma}_2 \otimes \boldsymbol{\Sigma}_3)^{-1} = \boldsymbol{\Sigma}_1^{-1} \otimes \boldsymbol{\Sigma}_2^{-1} \otimes \boldsymbol{\Sigma}_3^{-1}$
- $|\boldsymbol{\Sigma}| = |\boldsymbol{\Sigma}_1 \otimes \boldsymbol{\Sigma}_2 \otimes \boldsymbol{\Sigma}_3| = |\boldsymbol{\Sigma}_1|^{J*M}|\boldsymbol{\Sigma}_2|^{L*M}|\boldsymbol{\Sigma}_3|^{J*L}$

2 Web Appendix B

The following code is useful for analyzing a single region of interest where the pollution exposure is treated as a fixed input.

```
#####################################################################
#Needed Packages
#####################################################################
library(msm)    #Sampling from the truncated normal distribution
library(mnormt) #Sampling from the multivariate normal distribution
####################################################
#Stage 3 Health Model:
#phi1:  Uniform prior distribution
#phi2:  Uniform prior distribution
#Non spatial; meant for a single region of interest
#Needed:  Y vector of binary responses
#         x design matrix of covariates of interest
#         z pollution exposure matrix
#         N value of sample size
#         M value for number of weeks being analyzed
####################################################
#Random seed
set.seed(087632)

#Number of samples from the posterior to take
samples<-10000

#Initializing the parameter vectors and matrices
beta<-matrix(0,nrow=samples,ncol=ncol(x))
theta<-matrix(0,nrow=samples,ncol=ncol(z))
phi0<-rep(0,times=samples)
phi1_trans<-rep(0,times=samples)
phi2_trans<-rep(0,times=samples)
neg_two_loglike<-rep(0,times=samples)

#Prior information
a_phi1<-0.00001               #Lower bound for the phi1 uniform prior
b_phi1<-5                     #Upper bound for the phi1 uniform prior
a_phi2<-0.01                  #Lower bound for the phi2 uniform prior
b_phi2<-5                     #Upper bound for the phi2 uniform prior
sigma2_beta<-1000000000       #Prior variance for beta parameters

#Initial values
phi0[1]<-0.45
phi1_trans[1]<-log((0.1-a_phi1)/(b_phi1-0.1))  #On phi1_trans scale
phi2_trans[1]<-log((2-a_phi2)/(b_phi2-2))      #On phi2_trans scale
```

```
#Correlation creation function
corr_fun<-function(phi1_trans_val,phi2_trans_val){
#phi1 scale
phi1_val<-(b_phi1*exp(phi1_trans_val) + a_phi1)/(exp(phi1_trans_val) + 1)
#phi2 scale
phi2_val<-(b_phi2*exp(phi2_trans_val) + a_phi2)/(exp(phi2_trans_val) + 1)
#Defines the temporal part of the correlation matrix
times <- 1:M
rho <- exp(-phi1_val)
H <- abs(outer(times, times, "-"))
K <- rho^H
p <- nrow(K)
#Final matrix which describes the temporal correlation
K[cbind(1:p, 1:p)] <- K[cbind(1:p, 1:p)]
#Defines the cross pollutant correlation matrix
J<-matrix(c(1,exp(-phi2_val),exp(-phi2_val),1),nrow=2,ncol=2)
#Full correlation matrix
corr<-kronecker(J,K)
#Inverse of the correlation matrix
corr_inv<-kronecker(chol2inv(chol(J)),(chol2inv(chol(K))))
#Log of the determinant of the correlation matrix
logdeter<-nrow(J)*log(det(K)) + nrow(K)*log(det(J))
return(list(corr_inv=corr_inv,logdeter=logdeter))
}

#Log of the full conditional distribution of the
#phi1_trans and phi2_trans parameters
phis_trans_log_full_cond_fun<-function(phi1_trans_val,phi2_trans_val){
val<- -(1/2)*corr_info[[2]]
      - (1/(2*phi0[i]))*t(theta[i,])%*%corr_info[[1]]%*%theta[i,]
      + phi1_trans_val + phi2_trans_val - 2*log(1+exp(phi1_trans_val))
      - 2*log(1+exp(phi2_trans_val))
return(val)
}

#Needed in the sampling loop, but only need to be calculated once
xtx<-t(x)%*%x
xtz<-t(x)%*%z
ztz<-t(z)%*%z
ztx<-t(z)%*%x
var1<-chol2inv(chol(xtx + diag((1/sigma2_beta),nrow=nrow(xtx),ncol=ncol(xtx))))

#Keeping up with the Metropolis algorithm acceptance rates
acctot<-0
```

```
#Metropolis algorithm variances for phi1_trans and phi2_trans
mhvar_phi1<-.17
mhvar_phi2<-.71

#Initial setting for the correlation information
corr_info<-corr_fun(phi1_trans[1],phi2_trans[1])

#Main sampling loop
for(i in 2:samples){

   #Sampling W_i's from the full conditional truncated normal distribution
   #where the truncation is determined by Yi's
   w<-(((1-Y)*rtnorm(n=N,mean=x%*%beta[(i-1),]+z%*%theta[(i-1),],
      sd=1, lower=-Inf, upper=0))
      + ((Y)*rtnorm(n=N,mean=x%*%beta[(i-1),]+z%*%theta[(i-1),],
      sd=1, lower=0, upper=Inf)))

   #Sampling beta from the full conditional multivariate normal distribution
   beta[i,]<-rmnorm(n=1,mean=((var1)%*%(t(x)%*%w-(xtz%*%theta[(i-1),]))),(var1))

   #Sampling theta from the full conditional multivariate normal distribution
   var2<-chol2inv(chol((ztz)+((1/phi0[i-1])*corr_info[[1]])))
   theta[i,]<-rmnorm(n=1,mean=((var2)%*%(t(z)%*%w-(ztx%*%beta[i,]))),(var2))

   #Sampling phi0 from the full conditional inverse gamma distribution
   #This is for an invgamma(3,1) prior
   phi0[i]<-rgamma(n=1,shape=(((2*M)/2)+3),
            rate=(((t(theta[i,])%*%(corr_info[[1]])%*%theta[i,])/2)+1))
   phi0[i]<-1/phi0[i]
   ########################################################################
   #Metropolis algorithm sampling for phi1_trans and phi2_trans
   #Keeping up with current correlation information
   corr_info_old<-corr_info
   #Updating the phi1_trans and phi2_trans parameters
   phi1_trans[i]<-phi1_trans[i-1]+rnorm(n=1,mean=0,sd=sqrt(mhvar_phi1))
   phi2_trans[i]<-phi2_trans[i-1]+rnorm(n=1,mean=0,sd=sqrt(mhvar_phi2))
   #Function call for previous values
   second<-phis_trans_log_full_cond_fun(phi1_trans[i-1],phi2_trans[i-1])
   #New correlation information based on proposed phi_trans values
   corr_info<-corr_fun(phi1_trans[i],phi2_trans[i])
   #Function call for proposed values
   first<-phis_trans_log_full_cond_fun(phi1_trans[i],phi2_trans[i])
   #Determining if we should accept the proposed values
   Ratio<-exp(first-second)
```

```
if(Ratio>=1){
  acc<-1
  }
if(Ratio<1){
  if(Ratio<runif(n=1,min=0,max=1)){
    phi1_trans[i]<-phi1_trans[i-1]
    phi2_trans[i]<-phi2_trans[i-1]
    corr_info<-corr_info_old
    acc<-0
    }
  else{
    acc<-1
    }
  }
#New acceptance total
acctot<-acctot+acc
##########################################################################
#Model diagnostics analysis
probs<-pnorm((x%*%beta[i,] + z%*%theta[i,]),mean=0,sd=1,lower.tail=TRUE)
neg_two_loglike[i]<- -2*sum(log((probs^Y)*((1-probs)^(1-Y))))

#################################################################
#Prints the acceptance rate for the Metropolis algorithm sampling
print(acctot/i)
#Prints other useful information
print(c(i/samples,"2 Uniform Priors, No Space"))
}
```

3 Web Table 1

Table 1: *Posterior summaries for the covariance parameters from Model 1A. The average MC error for the means is 0.02.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Inverse gamma$(3,1)$	0.45	0.25	0.10	0.21	0.59
ϕ_2	Uniform$(0.00001,5)$	0.10	0.0001	0.00002	0.00008	0.00030
ϕ_3	Uniform$(0.01,5)$	2.00	2.95	0.80	3.00	4.83
$p_D = 42.4$	DIC= 17246.3					

4 Web Table 2

Table 2: *Posterior summaries for the covariance parameters from Model 1B. The average MC error for the means is 0.03.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Inverse gamma$(3,1)$	0.45	0.25	0.09	0.21	0.62
ϕ_2	Gamma$(1,1)$	0.10	0.00011	0.00002	0.00008	0.00039
ϕ_3	Gamma$(1,2)$	2.00	2.98	0.52	2.41	8.82
$p_D = 43.0$	DIC= 17247.8					

5 Web Table 3

Table 3: *Posterior summaries for the covariance parameters from Model 1C. The average MC error for the means is 0.03.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Inverse gamma$(3,1)$	0.45	0.25	0.10	0.21	0.63
ϕ_2	Uniform$(0.00001,5)$	0.10	0.00011	0.00002	0.00008	0.00035
ϕ_3	Gamma$(1,2)$	2.00	3.01	0.42	2.43	8.79
$p_D = 42.9$	DIC= 17247.1					

6 Web Table 4

Table 4: *Posterior summaries for the covariance parameters from Model 1D. The average MC error for the means is 0.04.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Uniform$(0.01, 10)$	0.45	0.07	0.01	0.02	0.62
ϕ_2	Uniform$(0.00001, 5)$	0.10	0.00113	0.00003	0.00083	0.00401
ϕ_3	Gamma$(1, 2)$	2.00	3.05	0.55	2.52	8.68
$p_D = 43.2$	DIC= 17247.1					

7 Web Table 5

Table 5: *Posterior summaries for the covariance parameters from Model 4. The average MC error for the means is 0.07.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Inverse gamma$(3, 1)$	0.45	0.21	0.09	0.19	0.47
ϕ_2	Uniform$(0.00001, 5)$	0.10	0.00003	0.00001	0.00002	0.00009
ϕ_3	Uniform$(0.01, 5)$	2.00	1.52	0.02	0.88	4.77

8 Web Table 6

Table 6: *Posterior summaries for the covariance parameters from Model 5. The average MC error for the means is 0.07.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Inverse gamma$(3, 1)$	0.45	0.07	0.04	0.06	0.10
ϕ_2	Uniform$(0.00001, 5)$	0.0001	0.00014	0.00005	0.00013	0.00030
ϕ_3	Uniform$(0.01, 5)$	2.00	2.23	0.01	2.32	4.83

9 Web Table 7

Table 7: *Posterior summaries for the covariance parameters from Model 6. The average MC error for the means is 0.04.*

				Percentiles		
Parameter	**Prior**	**Starting Value**	**Mean**	**0.025**	**0.50**	**0.975**
ϕ_0	Inverse gamma$(3, 1)$	0.45	0.12	0.07	0.12	0.21
ϕ_1	Uniform$(0.00001, 0.03)$	0.0001	0.000014	0.000010	0.000014	0.000021
ϕ_2	Uniform$(0.00001, 5)$	0.0001	0.00037	0.00013	0.00032	0.00084
ϕ_3	Uniform$(0.01, 5)$	2.00	2.86	0.59	2.90	4.90

10 Web Table 8

Table 8: *Posterior summaries (means and 95% credible intervals) for the spatial processes used for each weather variable in Stage 1. The trend of each variable's spatial/temporal surface is modeled using latitude, longitude, month (categorical), and date (linear) predictors. Higher order interactions are also included.*

Variable	**Spatial Covar.**	$\boldsymbol{\sigma_w^2}$	$\boldsymbol{\phi}$	**Nugget**
Avg. Temp.	Spherical	0.747 (0.716, 0.777)	0.00048 (0.00046, 0.00051)	45.167 (43.102, 47.182)
Avg. Dewp.	Spherical	0.984 (0.950, 1.019)	0.00049 (0.00046, 0.00051)	60.732 (58.051, 64.027)
Avg. Wdsp. (Square Root Scale)	Exponential	0.043 (0.041, 0.044)	0.00250 (0.00240, 0.00262)	0.268 (0.259, 0.277)
Avg. Cloud Cover (Probit Scale)	Exponential	2.033 (1.904, 2.173)	0.00189 (0.00170, 0.00209)	NA NA

Spherical: $\sigma_w^2 \left\{1 - 1.5\phi \left\| \boldsymbol{s} - \boldsymbol{s}' \right\| + 0.5 \left(\phi \left\| \boldsymbol{s} - \boldsymbol{s}' \right\|\right)^3\right\} I \left(\left\| \boldsymbol{s} - \boldsymbol{s}' \right\| < \frac{1}{\phi}\right)$

11 Web Table 9

Table 9: *Stage 2 ozone (square root scale) model results.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept	–1.14507	0.22552	–1.58726	–1.14571	–0.69999
Latitude	0.01555	0.00642	0.00307	0.01548	0.02809
Longitude	–0.02106	0.00398	–0.02905	–0.02105	–0.01324
Lat.*Lat.	–0.00025	0.00005	–0.00035	–0.00025	–0.00016
Long.*Long.	–0.00012	0.00002	–0.00016	–0.00012	–0.00007
Lat.*Long.	–0.00003	0.00006	–0.00014	–0.00003	0.00008
Month					
February vs. January	0.01822	0.00235	0.01369	0.01822	0.02277
March vs. January	0.02054	0.00232	0.01602	0.02056	0.02517
April vs. January	0.02206	0.00250	0.01719	0.02205	0.02686
May vs. January	0.01528	0.00262	0.01003	0.01528	0.02034
June vs. January	0.00374	0.00279	–0.00174	0.00374	0.00916
July vs. January	–0.00222	0.00284	–0.00781	–0.00218	0.00336
August vs. January	0.00927	0.00286	0.00377	0.00930	0.01490
September vs. January	0.01924	0.00273	0.01395	0.01924	0.02460
October vs. January	0.00068	0.00251	–0.00420	0.00067	0.00566
November vs. January	–0.00364	0.00232	–0.00819	–0.00364	0.00089
December vs. January	0.00009	0.00229	–0.00442	0.00010	0.00458
Avg. Temp.	0.00159	0.00005	0.00149	0.00159	0.00170
Avg. Dewp.	–0.00088	0.00004	–0.00096	–0.00088	–0.00078
Avg. Wdsp.	–0.00359	0.00055	–0.00472	–0.00354	–0.00263
Avg. Cloud Cover	–0.00651	0.00038	–0.00729	–0.00647	–0.00580
σ_w^2	0.00011	0.00000	0.00011	0.00011	0.00011
ϕ	0.00275	0.00007	0.00263	0.00275	0.00289
Nugget	0.00077	0.00002	0.00073	0.00077	0.00080

12 Web Table 10

Table 10: *Stage 2 $PM_{2.5}$ (cubed root scale) model results.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept	25.9136	3.6334	18.7009	25.9556	33.0324
Latitude	–0.0784	0.0747	–0.2219	–0.0784	0.0712
Longitude	0.4549	0.0640	0.3262	0.4556	0.5813
Lat.*Lat.	0.0022	0.0007	0.0009	0.0022	0.0034
Long.*Long.	0.0023	0.0003	0.0016	0.0023	0.0029
Lat.*Long.	0.0003	0.0007	–0.0011	0.0003	0.0016
Month					
February vs. January	–0.0515	0.0271	–0.1032	–0.0515	0.0022
March vs. January	–0.0915	0.0271	–0.1443	–0.0917	–0.0378
April vs. January	–0.1139	0.0301	–0.1730	–0.1138	–0.0548
May vs. January	–0.0954	0.0329	–0.1614	–0.0952	–0.0312
June vs. January	–0.3712	0.0350	–0.4396	–0.3716	–0.3011
July vs. January	–0.3501	0.0360	–0.4213	–0.3493	–0.2800
August vs. January	–0.3363	0.0361	–0.4061	–0.3362	–0.2650
September vs. January	–0.2523	0.0338	–0.3187	–0.2519	–0.1853
October vs. January	–0.3447	0.0313	–0.4058	–0.3443	–0.2837
November vs. January	–0.2191	0.0277	–0.2733	–0.2192	–0.1648
December vs. January	–0.0932	0.0272	–0.1459	–0.0935	–0.0398
Avg. Temp.	0.0125	0.0008	0.0109	0.0125	0.0142
Avg. Dewp.	0.0011	0.0008	–0.0004	0.0011	0.0026
Avg. Wdsp.	–0.1914	0.0086	–0.2065	–0.1920	–0.1736
Avg. Cloud Cover	0.0152	0.0038	0.0097	0.0143	0.0230
σ_w^2	0.01118	0.00052	0.01018	0.01119	0.01217
ϕ_1	0.00002	0.00001	0.00001	0.00002	0.00003
ϕ_2	0.02880	0.00244	0.02452	0.02871	0.03370
p_1	1.89607	0.06048	1.80993	1.88417	2.01437
p_2	0.53332	0.01534	0.50355	0.53285	0.56239
Nugget	0.10891	0.00232	0.10468	0.10886	0.11373

13 Web Table 11

Table 11: *Included covariate results for Model 2. The (**) items have 95% credible intervals which do not include zero.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept**	–1.406	0.280	–1.967	–1.402	–0.871
Maternal Race					
Black vs. White**	0.155	0.068	0.023	0.153	0.287
Hispanic vs. White	–0.042	0.039	–0.119	–0.042	0.034
Other vs. White	0.089	0.072	–0.051	0.089	0.230
Paternal Race					
Black vs. White	0.008	0.067	–0.123	0.008	0.139
Hispanic vs. White	–0.003	0.040	–0.084	–0.003	0.075
Other vs. White **	–0.190	0.077	–0.346	–0.190	–0.042
Maternal Age Group					
$20-24$ vs. $10-19$**	–0.070	0.031	–0.130	–0.069	–0.010
$25-29$ vs. $10-19$	–0.020	0.036	–0.090	–0.021	0.051
$30-34$ vs. $10-19$	0.046	0.039	–0.032	0.046	0.123
$35-39$ vs. $10-19$**	0.128	0.051	0.027	0.129	0.228
≥ 40 vs. $10-19$**	0.313	0.089	0.138	0.313	0.489
Paternal Age $\geq$ 50 vs. $<$ 50	–0.037	0.127	–0.292	–0.035	0.206
Maternal Education					
Basis Spline 1	–0.414	0.348	–1.079	–0.423	0.276
Basis Spline 2	0.173	0.176	–0.164	0.172	0.531
Basis Spline 3	0.010	0.204	–0.377	0.007	0.417
Paternal Education					
Basis Spline 1	0.170	0.304	–0.407	0.165	0.783
Basis Spline 2	–0.003	0.147	–0.279	–0.008	0.289
Basis Spline 3	–0.053	0.172	–0.381	–0.058	0.296
Female vs. Male Baby**	–0.069	0.021	–0.111	–0.069	–0.029

14 Web Table 12

Table 12: *Included covariate results for Model 3. The (**) items have 95% credible intervals which do not include zero.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept**	–1.497	0.286	–2.067	–1.494	–0.946
Maternal Race					
Black vs. White**	0.147	0.068	0.014	0.147	0.280
Hispanic vs. White	–0.046	0.038	–0.120	–0.046	0.030
Other vs. White	0.084	0.070	–0.054	0.083	0.220
Paternal Race					
Black vs. White	0.011	0.067	–0.119	0.011	0.147
Hispanic vs. White	–0.005	0.039	–0.081	–0.005	0.070
Other vs. White **	–0.190	0.074	–0.333	–0.190	–0.045
Maternal Age Group					
$20-24$ vs. $10-19$**	–0.067	0.032	–0.129	–0.068	–0.003
$25-29$ vs. $10-19$	–0.020	0.036	–0.089	–0.020	0.050
$30-34$ vs. $10-19$	0.044	0.039	–0.033	0.045	0.121
$35-39$ vs. $10-19$**	0.132	0.051	0.030	0.132	0.229
≥ 40 vs. $10-19$**	0.310	0.091	0.132	0.310	0.490
Paternal Age $\geq$ 50 vs. $<$ 50	–0.049	0.129	–0.311	–0.047	0.198
Maternal Education					
Basis Spline 1	–0.399	0.360	–1.089	–0.407	0.327
Basis Spline 2	0.187	0.177	–0.158	0.181	0.549
Basis Spline 3	0.021	0.210	–0.387	0.015	0.450
Paternal Education					
Basis Spline 1	0.137	0.308	–0.447	0.134	0.756
Basis Spline 2	–0.016	0.150	–0.302	–0.018	0.281
Basis Spline 3	–0.069	0.178	–0.413	–0.073	0.284
Female vs. Male Baby**	–0.070	0.021	–0.112	–0.070	–0.030

15 Web Table 13

Table 13: *Included covariate results for Model 4. The (**) items have 95% credible intervals which do not include zero.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept**	–1.614	0.281	–2.158	–1.616	–1.062
Maternal Race					
Black vs. White**	0.171	0.067	0.041	0.170	0.306
Hispanic vs. White	–0.036	0.038	–0.111	–0.037	0.038
Other vs. White	0.101	0.071	–0.041	0.101	0.239
Paternal Race					
Black vs. White	0.003	0.066	–0.134	0.003	0.130
Hispanic vs. White	0.003	0.039	–0.075	0.003	0.080
Other vs. White **	–0.192	0.076	–0.339	–0.191	–0.041
Maternal Age Group					
$20-24$ vs. $10-19$**	–0.069	0.031	–0.129	–0.069	–0.007
$25-29$ vs. $10-19$	–0.025	0.036	–0.095	–0.025	0.043
$30-34$ vs. $10-19$	0.049	0.040	–0.028	0.049	0.128
$35-39$ vs. $10-19$**	0.133	0.051	0.032	0.133	0.234
≥ 40 vs. $10-19$**	0.318	0.088	0.145	0.318	0.490
Paternal Age $\geq$ 50 vs. $<$ 50	–0.049	0.128	–0.307	–0.046	0.193
Maternal Education					
Basis Spline 1	–0.380	0.349	–1.070	–0.381	0.306
Basis Spline 2	0.178	0.174	–0.160	0.178	0.526
Basis Spline 3	0.030	0.204	–0.362	0.029	0.433
Paternal Education					
Basis Spline 1	0.174	0.301	–0.415	0.170	0.779
Basis Spline 2	–0.012	0.150	–0.304	–0.014	0.285
Basis Spline 3	–0.059	0.172	–0.385	–0.063	0.285
Female vs. Male Baby**	–0.068	0.020	–0.107	–0.068	–0.028

16 Web Table 14

Table 14: *Included covariate results for Model 5. The (**) items have 95% credible intervals which do not include zero.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept**	–1.431	0.259	–1.943	–1.427	–0.927
Maternal Race					
Black vs. White**	0.193	0.057	0.082	0.194	0.305
Hispanic vs. White	–0.033	0.032	–0.095	–0.033	0.029
Other vs. White	0.051	0.060	–0.068	0.050	0.171
Paternal Race					
Black vs. White	–0.012	0.056	–0.121	–0.012	0.097
Hispanic vs. White	–0.010	0.033	–0.074	–0.010	0.054
Other vs. White	–0.122	0.064	–0.245	–0.123	0.003
Maternal Age Group					
$20-24$ vs. $10-19$**	–0.083	0.028	–0.140	–0.083	–0.029
$25-29$ vs. $10-19$	–0.015	0.031	–0.077	–0.015	0.047
$30-34$ vs. $10-19$	0.047	0.034	–0.021	0.047	0.114
$35-39$ vs. $10-19$**	0.139	0.044	0.053	0.139	0.225
≥ 40 vs. $10-19$**	0.270	0.077	0.118	0.270	0.417
Paternal Age $\geq$ 50 vs. $<$ 50	–0.065	0.110	–0.279	–0.063	0.144
Maternal Education					
Basis Spline 1	–0.436	0.323	–1.055	–0.437	0.181
Basis Spline 2	0.185	0.169	–0.139	0.184	0.518
Basis Spline 3	–0.005	0.192	–0.377	–0.006	0.371
Paternal Education					
Basis Spline 1	0.211	0.277	–0.320	0.211	0.756
Basis Spline 2	0.070	0.134	–0.189	0.069	0.326
Basis Spline 3	–0.010	0.159	–0.316	–0.010	0.306
Female vs. Male Baby**	–0.068	0.018	–0.104	–0.068	–0.033

17 Web Table 15

Table 15: *Included covariate results for Model 6. The (**) items have 95% credible intervals which do not include zero.*

			Percentiles		
Covariate	**Mean**	**SD**	**0.025**	**0.50**	**0.975**
Intercept**	–1.460	0.254	–1.957	–1.458	–0.979
Maternal Race					
Black vs. White**	0.193	0.056	0.084	0.192	0.307
Hispanic vs. White	–0.030	0.032	–0.091	–0.030	0.033
Other vs. White	0.053	0.059	–0.064	0.053	0.168
Paternal Race					
Black vs. White	–0.013	0.055	–0.121	–0.013	0.096
Hispanic vs. White	–0.015	0.032	–0.077	–0.014	0.048
Other vs. White **	–0.124	0.060	–0.243	–0.125	–0.007
Maternal Age Group					
$20-24$ vs. $10-19$**	–0.082	0.029	–0.138	–0.083	–0.027
$25-29$ vs. $10-19$	–0.016	0.032	–0.078	–0.016	0.047
$30-34$ vs. $10-19$	0.047	0.035	–0.022	0.047	0.117
$35-39$ vs. $10-19$**	0.141	0.043	0.057	0.140	0.224
≥ 40 vs. $10-19$**	0.267	0.079	0.113	0.267	0.421
Paternal Age $\geq$ 50 vs. $<$ 50	–0.076	0.110	–0.294	–0.075	0.134
Maternal Education					
Basis Spline 1	–0.428	0.329	–1.046	–0.437	0.236
Basis Spline 2	0.183	0.165	–0.139	0.182	0.515
Basis Spline 3	–0.006	0.195	–0.369	–0.009	0.380
Paternal Education					
Basis Spline 1	0.200	0.289	–0.355	0.194	0.771
Basis Spline 2	0.072	0.137	–0.186	0.070	0.345
Basis Spline 3	–0.013	0.165	–0.329	–0.016	0.314
Female vs. Male Baby**	–0.066	0.018	–0.103	–0.066	–0.031

18 Web Figure 1

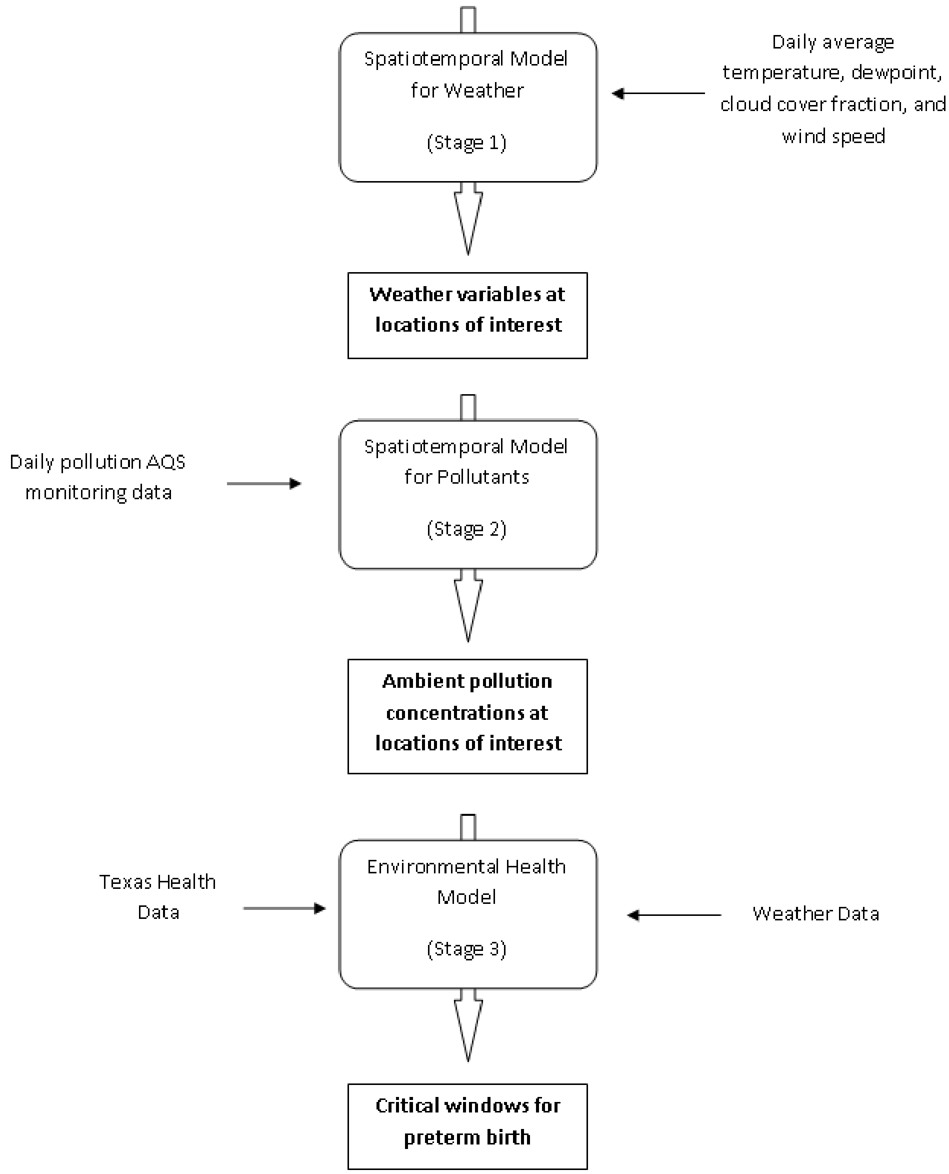
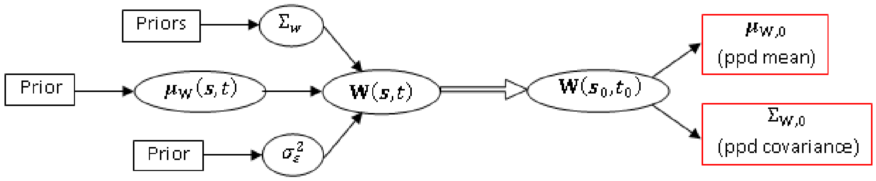
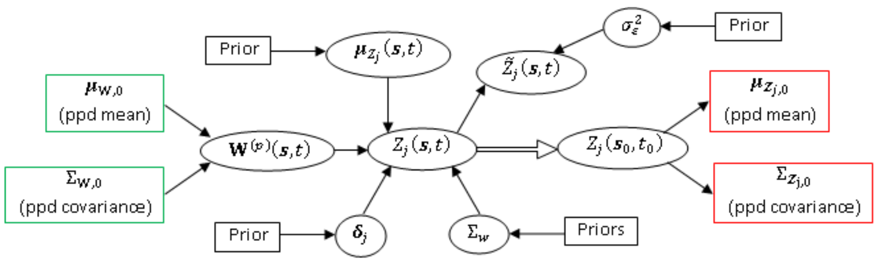


Figure 1: Large scale diagram describing the general setup of the modeling framework.

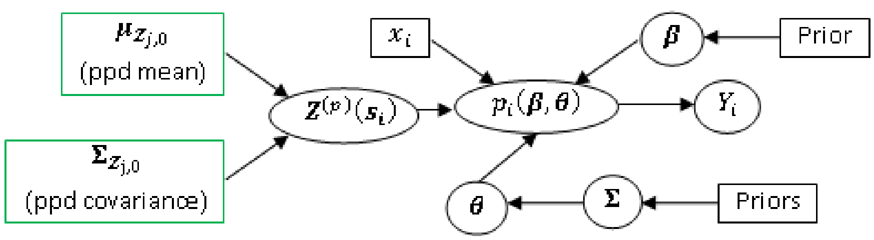
19 Web Figure 2



(a) Stage 1: Climatic.



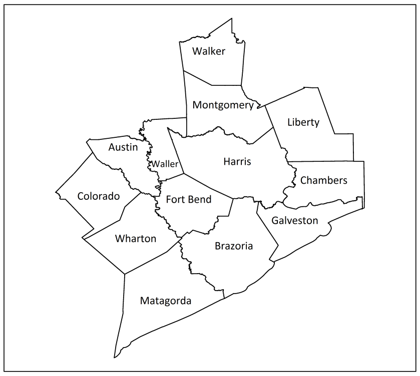
(b) Stage 2: Pollution.



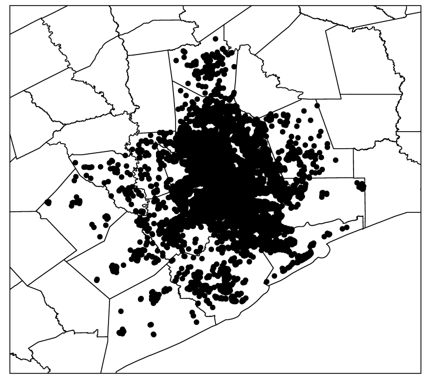
(c) Stage 3: Health.

Figure 2: Square boxes represent fixed quantities and circular boxes represent data or unknown parameters. The two-dimensional arrows indicate the ppd being obtained. Red boxes represent the end of the specified stage and the summary of the ppd. The green boxes represent the carrying over of the ppd from the previous stage into a prior distribution for the current stage.

20 Web Figure 3



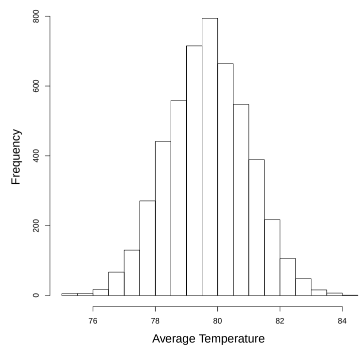
(a) Health Region Six.



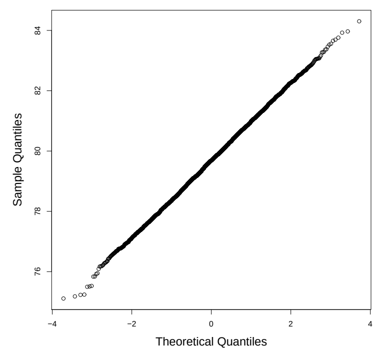
(b) Residence at Delivery.

Figure 3: Texas Department of State Health Services health service region six map (left) and plot of the residence at delivery (right) for all women included in analysis, 2002-2004.

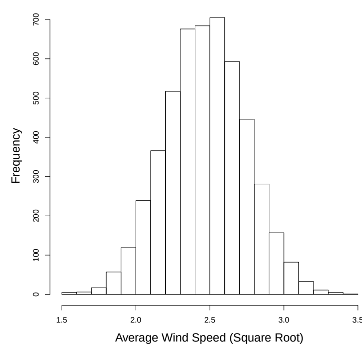
21 Web Figure 4



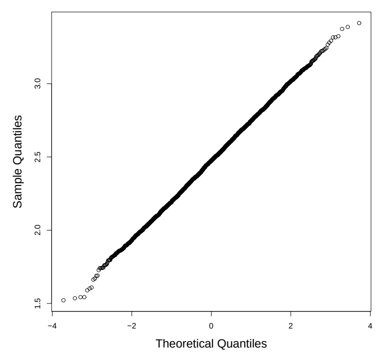
(a) PPD Histogram.



(b) Normal Q-Q Plot.



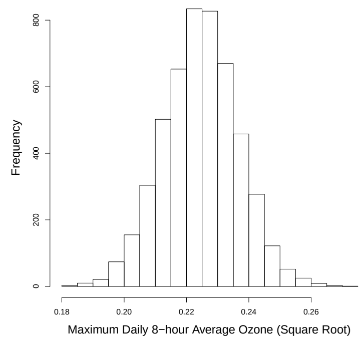
(c) PPD Histogram.



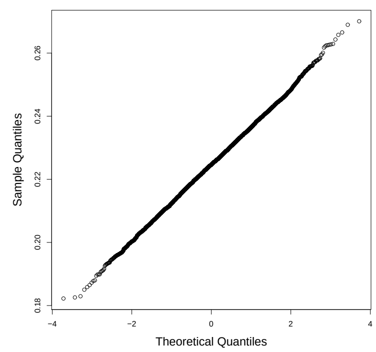
(d) Normal Q-Q Plot.

Figure 4: Histograms and normal quantile-quantile plots of ppd samples from a randomly selected location/date in the analysis domain for the daily average temperature (top row) and daily average windspeed (square root scale) (bottom row) climatic variables.

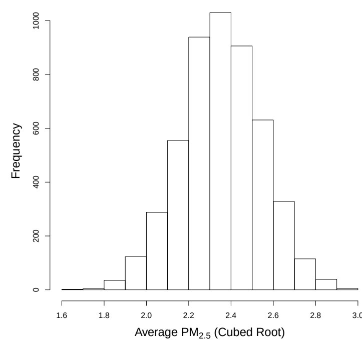
22 Web Figure 5



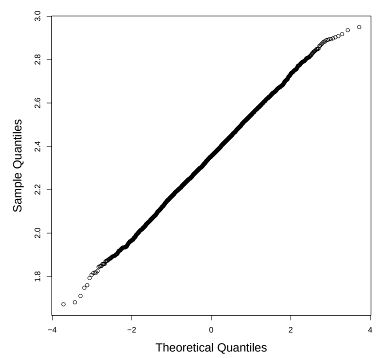
(a) PPD Histogram.



(b) Normal Q-Q Plot.



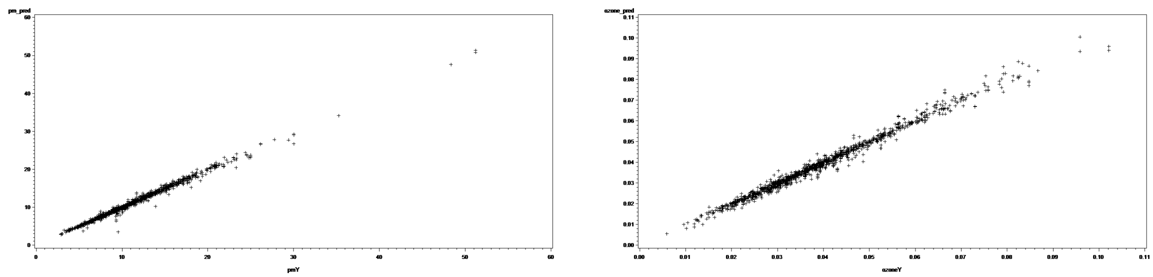
(c) PPD Histogram.



(d) QQPlot.

Figure 5: Histograms and normal quantile-quantile plots of ppd samples from a randomly selected location/date in the analysis domain for the maximum daily 8-hour average ozone (square root scale) (top row) and daily average $PM_{2.5}$ (cubed root scale) (bottom row) pollution variables.

23 Web Figure 6

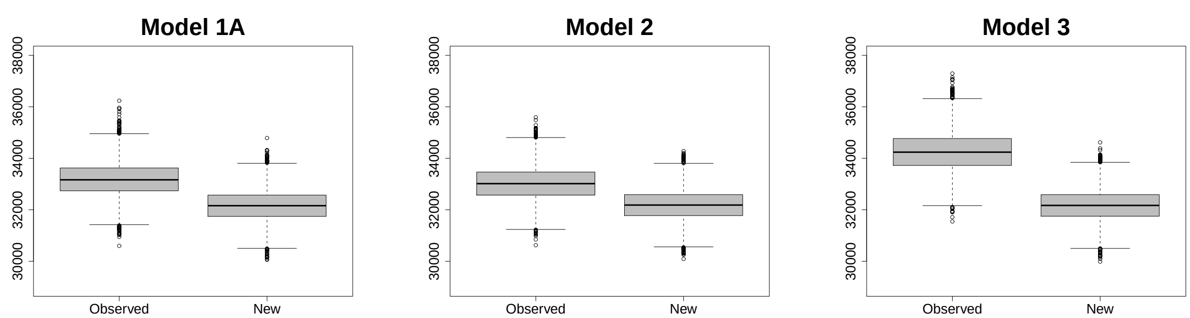


(a) Ozone.

(b) $PM_{2.5}$.

Figure 6: Plot of $\widetilde{Z}(\boldsymbol{s}, t)$ vs. $\widetilde{Z}\{A(\boldsymbol{s}), t\}$ for a randomly selected grid cell in Harris County, Texas.

24 Web Figure 7



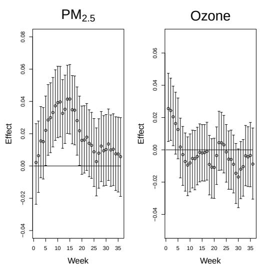
(a) Newly Introduced Model.

(b) Trimester Average Model.

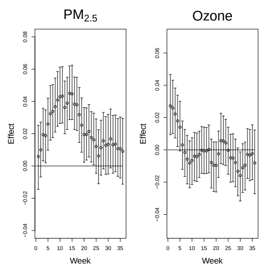
(c) Multiple Probit Model.

Figure 7: Boxplots of the total Pearson discrepancy measure sample from the observed data distribution (left) and the posterior predictive distribution (right) for Models 1A, 2, and 3.

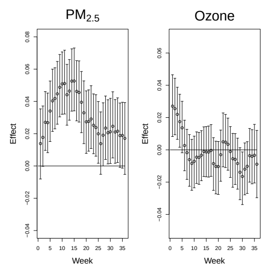
25 Web Figure 8



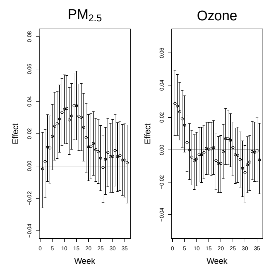
(a) Site 1.



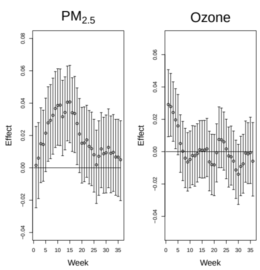
(b) Site 2.



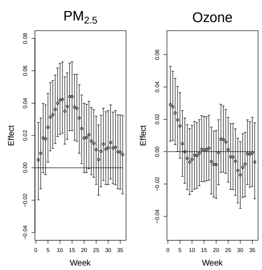
(c) Site 3.



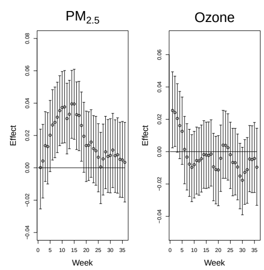
(d) Site 4.



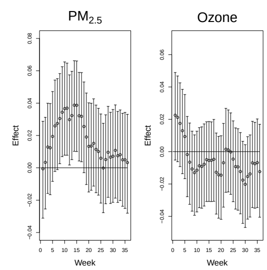
(e) Site 5.



(f) Site 6.



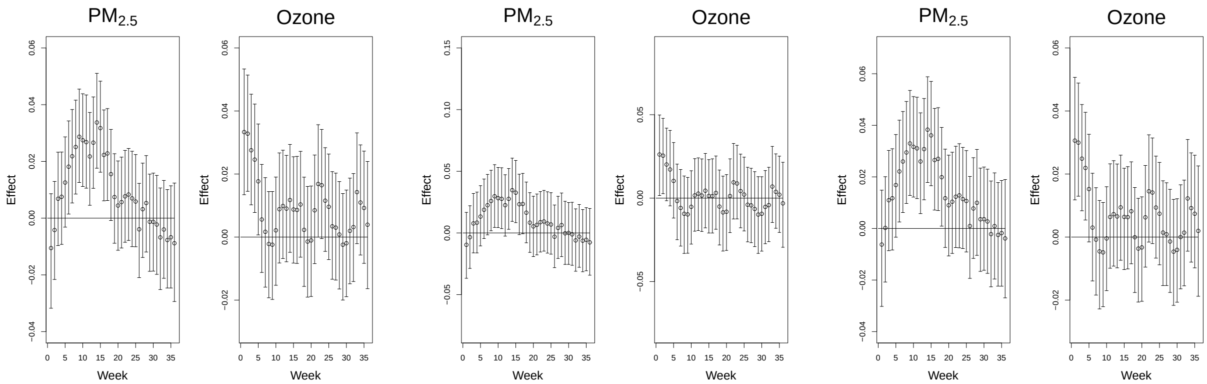
(g) Site 7.



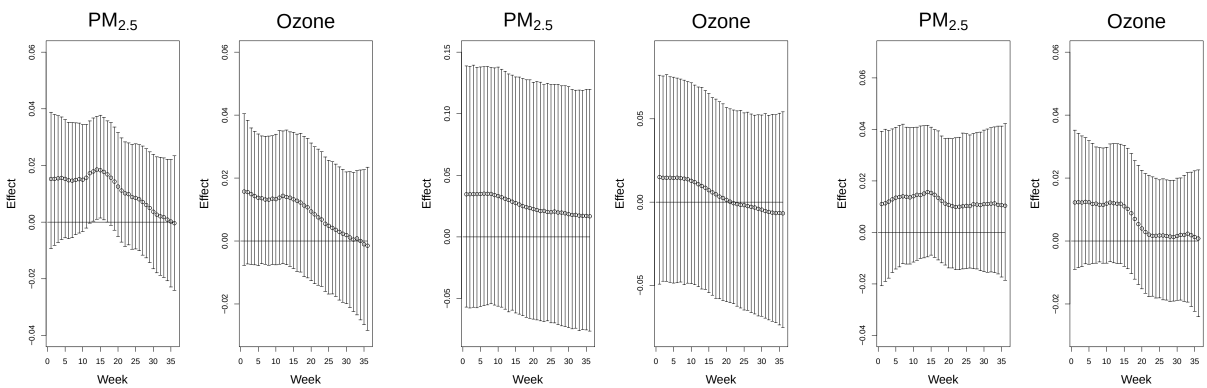
(h) Site 8.

Figure 8: Susceptible windows of exposure for the eight sites created within Harris County, shown on same scale. The eight locations were determined by placing a grid over Harris County and matching women with the closest grid point. The sample sizes for each location are as follows: Site 1: 1,716, Site 2: 15,204, Site 3: 7,889, Site 4: 3,543, Site 5: 2,068, Site 6: 806, Site 7: 804, Site 8: 140. All results based on using the modeled and predicted AQS data from 2002-2004. Posterior medians and 95% credible intervals are displayed.

26 Web Figure 9



(a) Brazoria: Spatial. (b) Waller: Spatial. (c) Montgomery: Spatial.



(d) Brazoria: Non-Spatial. (e) Waller: Non-Spatial. (f) Montgomery: Non-Spatial.

Figure 9: Susceptible windows of exposure for three selected counties (Brazoria, Waller, Montgomery) based on results from Model 6 (top row) and Model 5 (bottom row). Posterior medians and 95% credible intervals are displayed.