Lecture 13

Gaussian Process Models - Part 2

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EDA and GPs

Variogram

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2\gamma(t_i, t_j) &= Var(Y(t_i) - Y(t_j)) \\
&= E([(Y(t_i) - \mu(t_i)) - (Y(t_j) - \mu(t_j))]^2)
\end{aligned}
$$

where $\gamma(t_i, t_j)$ is called the semivariogram.

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If the process has constant mean (e.g. $\mu(t_i) = \mu(t_j)$ for all *i* and *j*) then we can simplify to

$$2\gamma(t_i, t_j) = E([Y(t_i) - Y(t_j)]^2)$$

Some Properties of the theoretical Variogram / Semivariogram

- both are non-negative

$$\gamma(t_i, t_j) \geq 0$$

- both are 0 at distance 0

$$\gamma(t_i, t_i) = 0$$

- both are symmetric

$$\gamma(t_i, t_j) = \gamma(t_j, t_i)$$

- there is no dependence if

$$2\gamma(t_i, t_j) = Var(Y(t_i)) + Var(Y(t_j)) \quad \text{for all } i \neq j$$

- if the process *is not* stationary

$$2\gamma(t_i, t_j) = Var\Big(Y(t_i)\Big) + Var\Big(Y(t_j)\Big) - 2\,Cov\Big(Y(t_i), Y(t_j)\Big)$$

- if the process *is* stationary

$$2\gamma(t_i, t_j) = 2Var\Big(Y(t_i)\Big) - 2\,Cov\Big(Y(t_i), Y(t_j)\Big)$$

Empirical Semivariogram

We will assume that our process of interest is stationary, in which case we will parameterize the semivariagram in terms of $h = \left|t_i - t_j\right|$.

Empirical Semivariogram:

$$\hat{\gamma}(h) = \frac{1}{2\,N(h)} \sum_{|t_i - t_j| \in (h-\epsilon, h+\epsilon)} \left(Y(t_i) - Y(t_j)\right)^2$$

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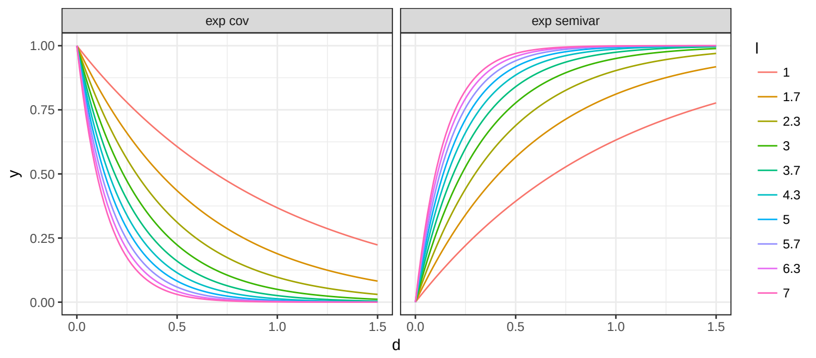
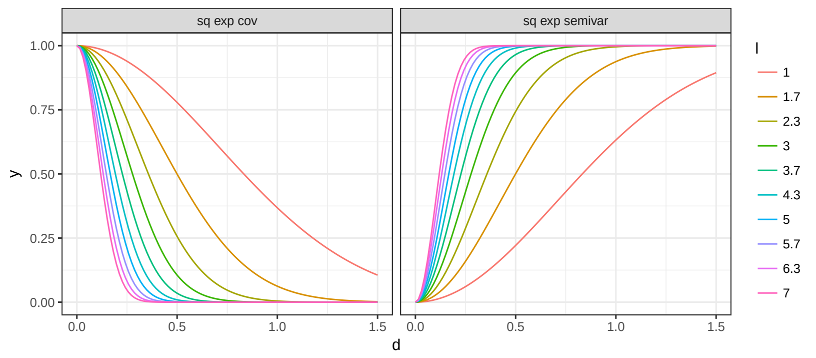
Practically, for any data set with n observations there are $\binom{n}{2} + n$ possible data pairs to examine. Each individually is not very informative, so we aggregate into bins and calculate the empirical semivariogram for each bin.

Connection to Covariance

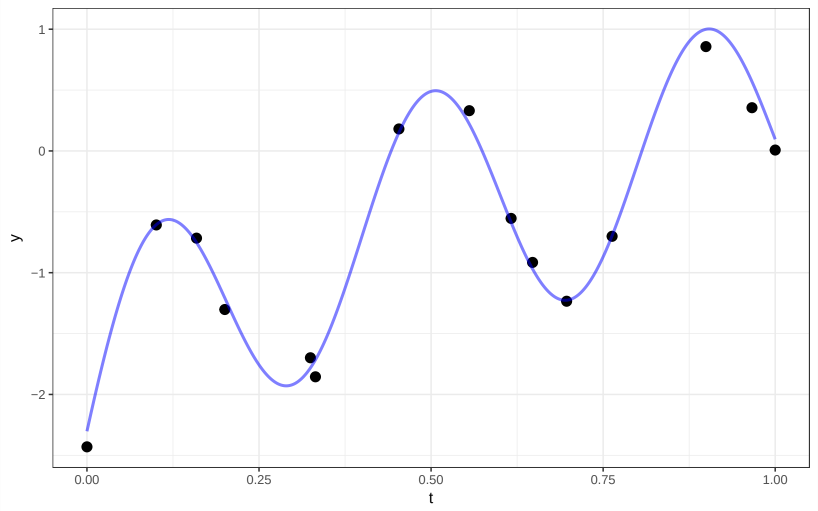
Covariance vs Semivariogram - Exponential



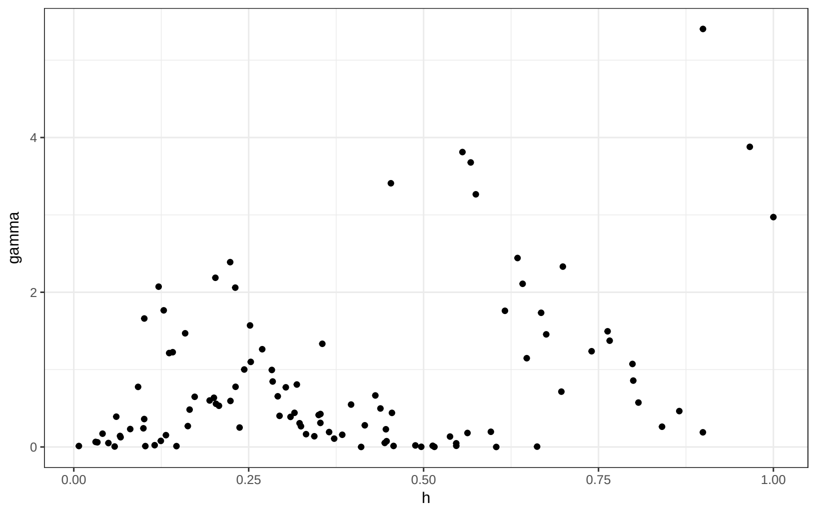
Covariance vs Semivariogram - Square Exponential



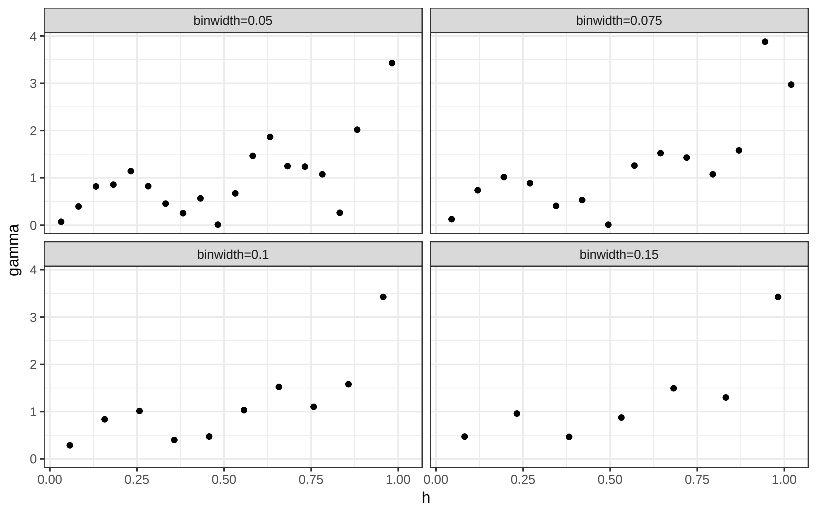
From last time



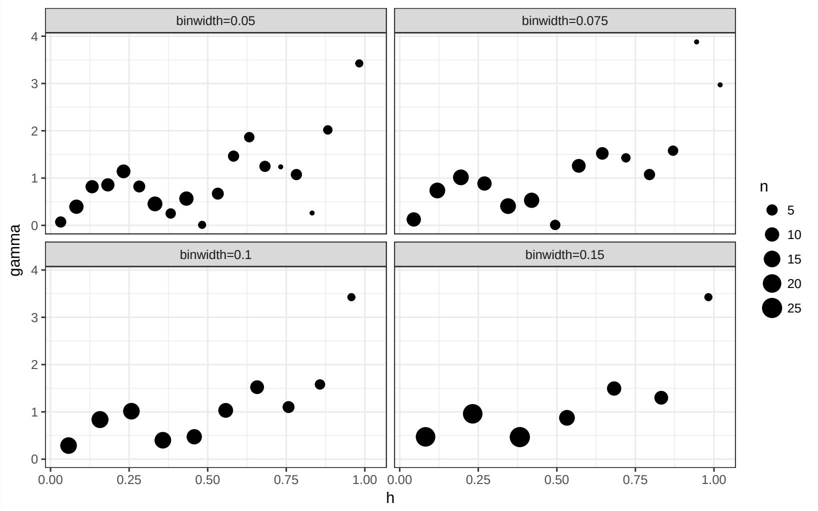
Empirical semivariogram - no bins / cloud



Empirical semivariogram (binned)



Empirical semivariogram (binned + n)



Theoretical vs empirical semivariogram

After fitting the model last time we came up with a posterior median of $\sigma^2 = 1.89$ and $l = 5.86$ for a square exponential covariance.

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\gamma(h) &= \sigma^2 - \sigma^2 \exp\left(-\,(h\,l)^2\right) \\
&= 1.89 - 1.89 \exp\left(-\,(5.86\,h)^2\right)
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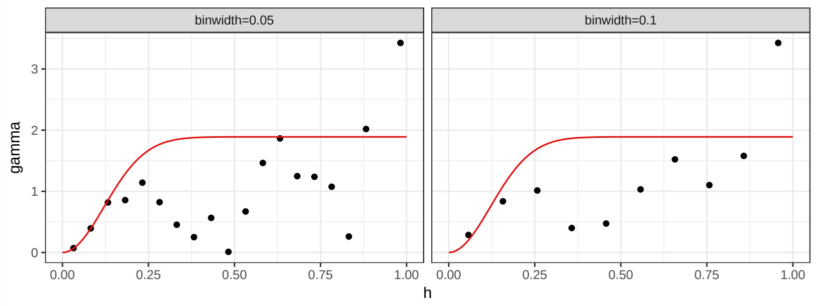
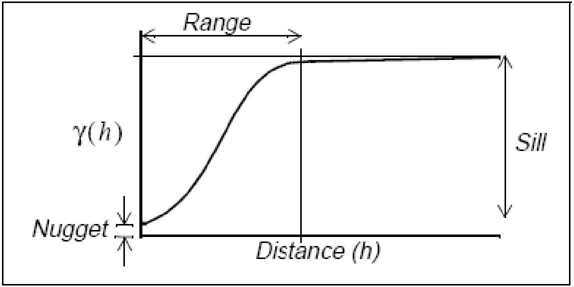


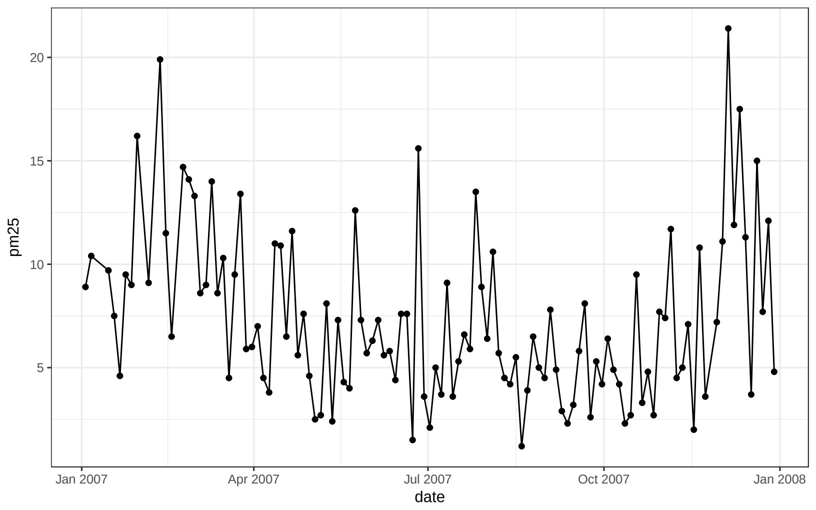
Variogram features



PM2.5 Example

FRN Data

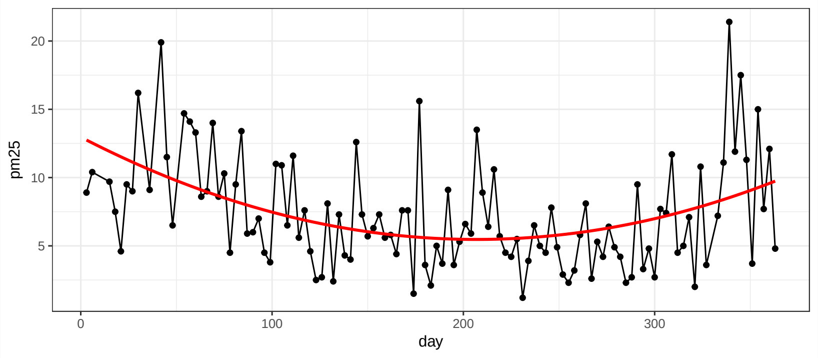
Measured PM2.5 data from an EPA monitoring station in Columbia, NJ.



FRN Data

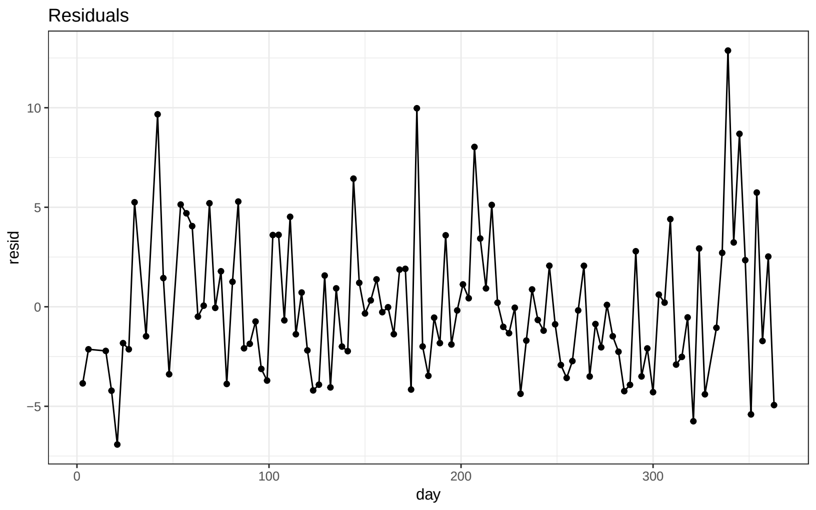
site	latitude	longitude	pm25	date	day
230031011	46.682	-68.016	8.9	2007-01-03	3
230031011	46.682	-68.016	10.4	2007-01-06	6
230031011	46.682	-68.016	9.7	2007-01-15	15
230031011	46.682	-68.016	7.5	2007-01-18	18
230031011	46.682	-68.016	4.6	2007-01-21	21
230031011	46.682	-68.016	9.5	2007-01-24	24
230031011	46.682	-68.016	9.0	2007-01-27	27
230031011	46.682	-68.016	16.2	2007-01-30	30
230031011	46.682	-68.016	9.1	2007-02-05	36
230031011	46.682	-68.016	19.9	2007-02-11	42
230031011	46.682	-68.016	11.5	2007-02-14	45
230031011	46.682	-68.016	6.5	2007-02-17	48
230031011	46.682	-68.016	14.7	2007-02-23	54
230031011	46.682	-68.016	14.1	2007-02-26	57
230031011	46.682	-68.016	13.3	2007-03-01	60
230031011	46.682	-68.016	8.6	2007-03-04	63
230031011	46.682	-68.016	9.0	2007-03-07	66
230031011	46.682	-68.016	14.0	2007-03-10	69
230031011	46.682	-68.016	8.6	2007-03-13	72
230031011	46.682	-68.016	10.3	2007-03-16	75

Mean Model

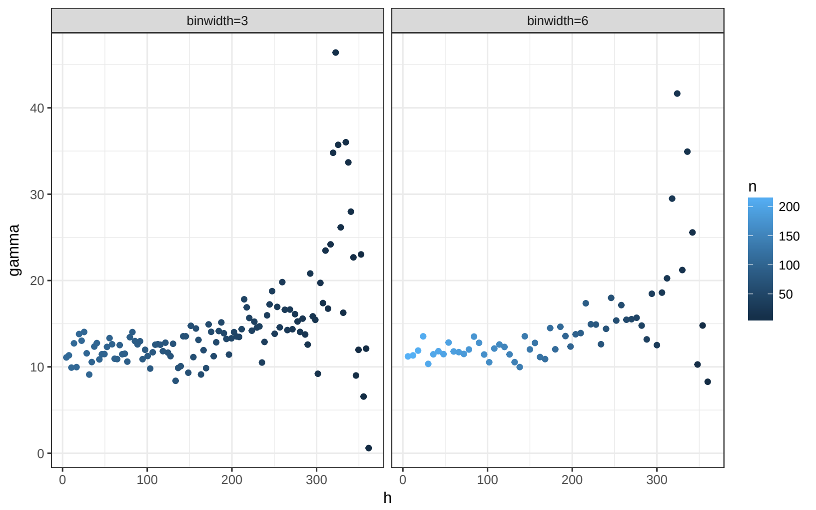



```
##
## Call:
## lm(formula = pm25 ~ day + I(day^2), data = pm25)
##
## Coefficients:
## (Intercept)          day     I(day^2)
##  12.9644351   -0.0724639    0.0001751
##
## Call:
## lm(formula = pm25 ~ day + I(day^2), data = pm25)
```

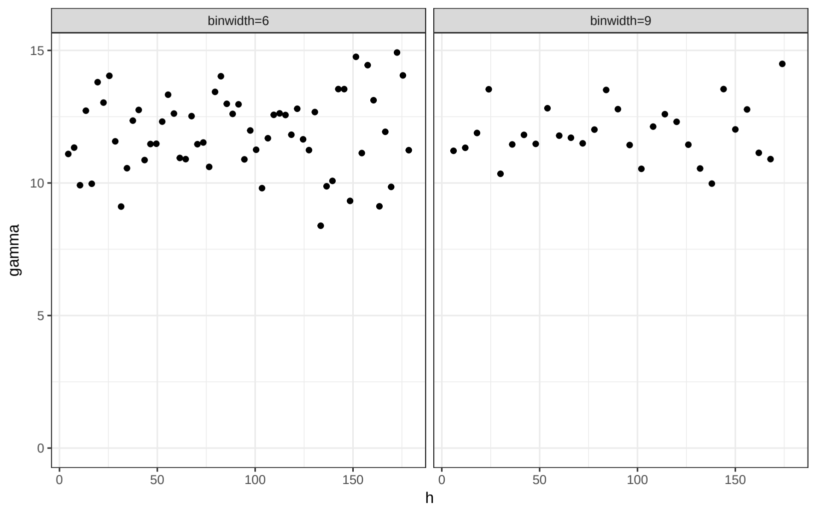
Detrended Residuals



Empirical Variogram



Empirical Variogram



Model

What does the model we are trying to fit actually look like?

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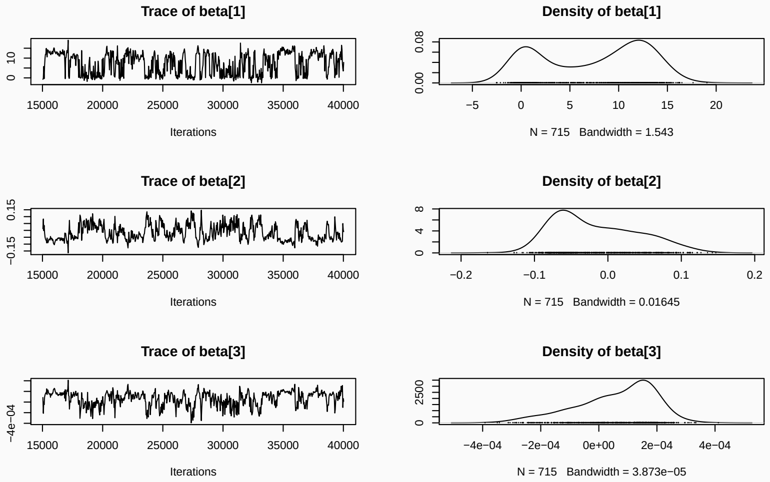
$$y(d) = \mu(d) + w(d) + w$$

where

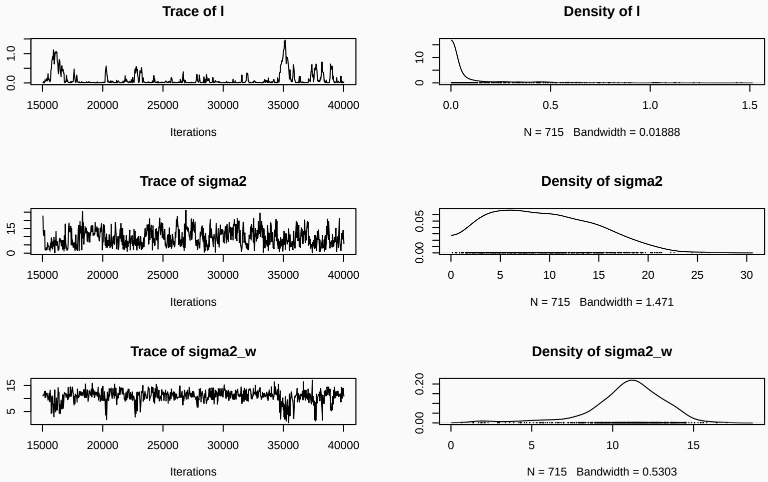
$$\begin{aligned} \mu(d) &= \beta 0 + \beta_1 \, d + \beta_2 \, d^2 \\ w(d) &\sim \mathcal{GP}(0, \Sigma) \\ w &\sim \mathcal{N}(0, \sigma_w^2) \end{aligned}$$

```
## model{
##   y ~ dmnorm(mu, inverse(Sigma))
##
##   for (i in 1:N) {
##     mu[i] <- beta[1]+ beta[2] * x[i] + beta[3] * x[i]^2
##   }
##
##   for (i in 1:(N-1)) {
##     for (j in (i+1):N) {
##       Sigma[i,j] <- sigma2 * exp(- pow(l*d[i,j],2))
##       Sigma[j,i] <- Sigma[i,j]
##     }
##   }
##
##   for (k in 1:N) {
##     Sigma[k,k] <- sigma2 + sigma2_w
##   }
##
##   for (i in 1:3) {
##     beta[i] ~ dt(0, 2.5, 1)
##   }
##   sigma2_w ~ dnorm(10, 1/25) T(0,)
##   sigma2   ~ dnorm(10, 1/25) T(0,)
##   l        ~ dt(0, 2.5, 1) T(0,)
## }
```

Posterior - Betas



Posterior - Covariance Parameters

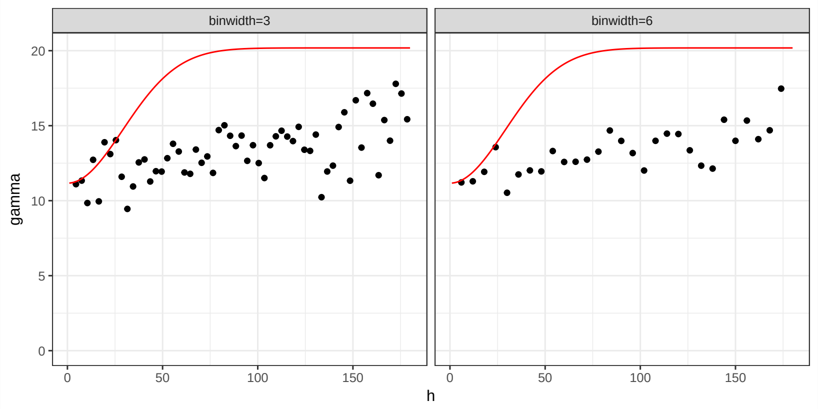


Posterior

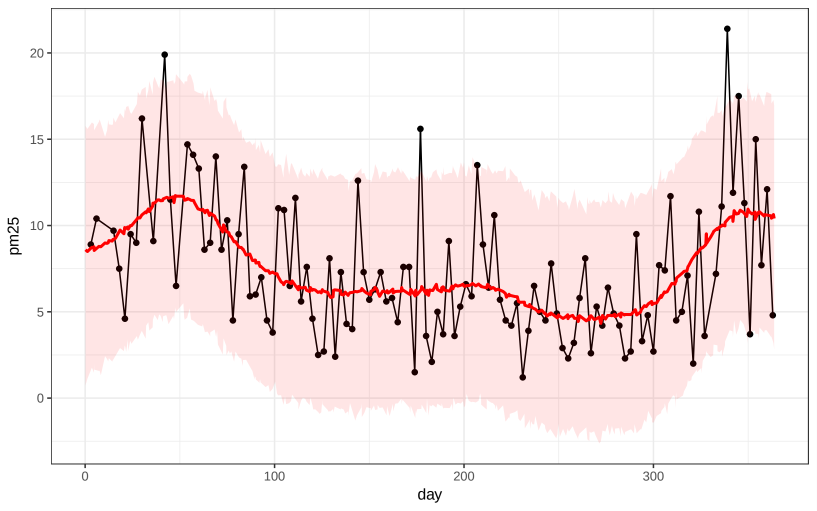
```
## # A tibble: 6 × 5
##      param     post_mean      post_med    post_lower   post_upper
## *    <chr>         <dbl>         <dbl>         <dbl>        <dbl>
## 1  beta[1]  7.283488e+00  8.667009e+00 -0.7461648059 1.503065e+01
## 2  beta[2] -1.627421e-02 -2.817415e-02 -0.0988863015 1.026401e-01
## 3  beta[3]  5.858818e-05  8.569993e-05 -0.0002481874 2.567976e-04
## 4        l  1.277712e-01  2.433287e-02  0.0060909947 8.443888e-01
## 5   sigma2  9.379213e+00  9.016621e+00  1.5643832453 1.979094e+01
## 6 sigma2_w  1.088809e+01  1.116626e+01  4.2665826402 1.448447e+01
```

Fitted Variogram

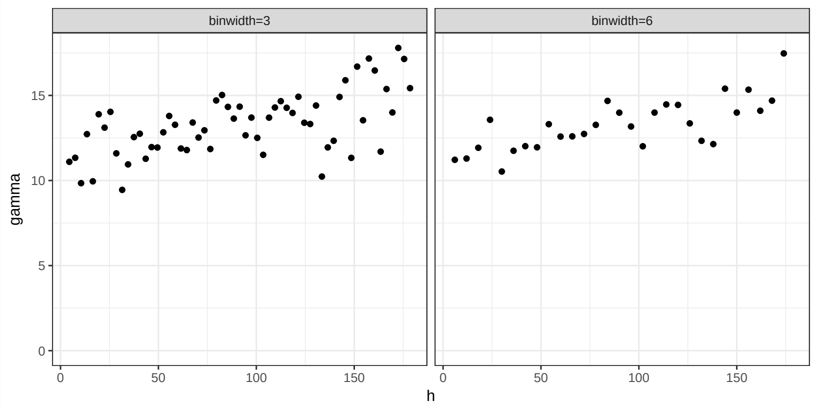
Empirical + Fitted Variogram



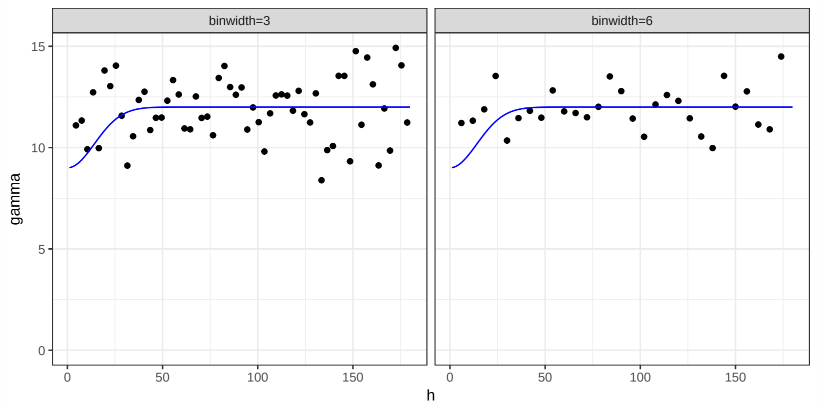
Fitted Model + Predictions



Empirical Variogram (again)



Empirical Variogram Model



Empirical Variogram Model + Predictions