Bayesian Computations

Method 1: Conditional Model : Fit $[y|\Omega] \times [\Omega]$

- conjugate full conditionals for β, τ^2, σ^2 and w.
- easier to program.

Method 2: Marginalized Model: Fit $[y|\beta, w, \tau^2] \times [w|\sigma^2, \phi] \times [\Omega]$

- need Metropolis or Slice Sampling for σ^2, ϕ, τ^2.
- reduced parameter space $\Rightarrow$ faster convergence
- $\sigma^2 R(\phi) + \tau^2 I$ stabler than $\sigma^2 R(\phi)$

$R^{-1}(\phi)$ is EXPENSIVE.

Spatial surface $w|y$

$$[w|y, x] = \int [w|\Omega, y, x] \times [\Omega|y, x] \, d\Omega$$

Sampling Scheme

- Obtain $\Omega^{(1)}, \cdots, \Omega^{(G)} \sim [\Omega|y, x]$
- For each $\Omega^{(g)}$, draw $w^{(g)} \sim [w|\Omega^{(g)}, y, x]$

Predictions

$$[\tilde{y}|y, x, \tilde{x}] = \int [\tilde{y}, \Omega|y, x, \tilde{x}] \, d\Omega$$

$$= \int \underbrace{[\tilde{y}|y, \Omega, x, \tilde{x}]}_{\text{MVN}} [\Omega|y, x] \, d\Omega$$

Sampling Scheme

- Obtain $\Omega^{(1)}, \cdots, \Omega^{(G)} \sim [\Omega|y, x]$
- For each $\Omega^{(g)}$, draw $\tilde{y}^{(g)} \sim [\tilde{y}|y, \Omega^{(g)}, x, \tilde{x}]$