

Spatial Geostatistical Model

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1 Full Dimensional Model Statement - Cressie and Wikle Statistics for Spatio-Temporal Data p. 139

1.1 Data Model

$$\mathbf{y}_t = \mathbf{z}_t + \boldsymbol{\epsilon}_t$$

1.2 Process Model

$$\mathbf{z}_t = \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t + \boldsymbol{\eta}_t$$

1.3 Parameter Model

$$\begin{aligned} \boldsymbol{\beta}_t &\sim N(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}_\beta) & \boldsymbol{\Sigma}_\beta &= \sigma_\beta^2 \mathbf{I}_{n_t} \\ \boldsymbol{\eta}_t &\sim N(0, \boldsymbol{\Sigma}_{\eta_t}) & \boldsymbol{\Sigma}_{\eta_t} &= \sigma_\eta^2 \mathbf{R}(\phi) & \mathbf{R}(\phi) &= \exp(-\mathbf{D}_t/\phi) \\ \boldsymbol{\epsilon}_t &\sim N(0, \boldsymbol{\Sigma}_\epsilon) & \boldsymbol{\Sigma}_\epsilon &= \sigma_\epsilon^2 \mathbf{I}_{n_t} \\ \boldsymbol{\mu}_\beta &\sim N(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \\ \sigma_\beta^2 &\sim IG(\alpha_\beta, \beta_\beta) \\ \sigma_\eta^2 &\sim IG(\alpha_\eta, \beta_\eta) \\ \sigma_\epsilon^2 &\sim IG(\alpha_\epsilon, \beta_\epsilon) \\ \phi &\sim IG(\alpha_\phi, \beta_\phi) \end{aligned}$$

where \mathbf{I}_{n_t} is the identity matrix of size $n_t \times n_t$ where τ is the number of parameters in $\boldsymbol{\beta}_t$ and n_t is the number of samples of \mathbf{y}_t at time t and \mathbf{D}_t is the distance matrix between locations observed at time t . Define $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_\eta + \boldsymbol{\Sigma}_\epsilon$

2 Posterior

$$\prod_{t=1}^T [\boldsymbol{\beta}_t, \boldsymbol{\mu}_\beta, \sigma_\beta^2, \sigma_\eta^2, \sigma_\epsilon^2, \phi | \mathbf{y}_t] \propto \prod_{t=1}^T [\mathbf{y}_t | \boldsymbol{\beta}_t, \sigma_\eta^2, \phi, \sigma_\epsilon^2] [\boldsymbol{\beta}_t | \boldsymbol{\mu}_\beta, \sigma_\beta^2] [\boldsymbol{\mu}_\beta] [\sigma_\beta^2] [\sigma_\eta^2] [\sigma_\epsilon^2] [\phi]$$

3 Full Conditionals

3.1 Full Conditional for β_t

For $t = 1, \dots, T$,

$$\begin{aligned} [\beta_t | \cdot] &\propto [\mathbf{y}_t | \beta_t, \sigma_\eta^2, \sigma_\epsilon^2, \phi] [\beta_t | \mu_\beta, \sigma_\beta^2] \\ &\propto \exp \left\{ -\frac{1}{2} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \beta_t)^T \Sigma^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \beta_t) \right\} \exp \left\{ -\frac{1}{2} (\beta_t - \mu_\beta)^T \Sigma_\beta^{-1} (\beta_t - \mu_\beta) \right\} \\ &\propto \exp \left(-\frac{1}{2} \{ \beta_t^T (\mathbf{X}^T \mathbf{H}_t^T \Sigma^{-1} \mathbf{H}_t \mathbf{X} + \Sigma_\beta^{-1}) \beta_t - 2 \beta_t^T (\mathbf{X}^T \mathbf{H}_t^T \Sigma^{-1} \mathbf{y}_t + \Sigma_\beta^{-1} \mu_\beta) \} \right) \end{aligned}$$

which is Normal with mean $\mathbf{A}^{-1} \mathbf{b}$ and variance \mathbf{A}^{-1} where

$$\begin{aligned} \mathbf{A}^{-1} &= (\mathbf{X}^T \mathbf{H}_t^T \Sigma^{-1} \mathbf{H}_t \mathbf{X} + \Sigma_\beta^{-1})^{-1} \\ \mathbf{b} &= (\mathbf{X}^T \mathbf{H}_t^T \Sigma^{-1} \mathbf{y}_t + \Sigma_\beta^{-1} \mu_\beta) \end{aligned}$$

3.2 Full Conditional for μ_β

$$\begin{aligned} [\mu_\beta | \cdot] &\propto \prod_{t=1}^T [\beta_t | \mu_\beta, \sigma_\beta^2] [\mu_\beta] \\ &\propto \exp \left(-\frac{1}{2} \sum_{t=1}^T (\beta_t - \mu_\beta)^T \Sigma_\beta^{-1} (\beta_t - \mu_\beta) \right) \exp \left(-\frac{1}{2} (\mu_\beta - \mu_0)^T \Sigma_0^{-1} (\mu_\beta - \mu_0) \right) \\ &\propto \exp \left(-\frac{1}{2} (\mu_\beta^T (T \Sigma_\beta^{-1} + \Sigma_0^{-1}) \mu_\beta - 2 \mu_\beta^T (\sum_{t=1}^T \Sigma_\beta^{-1} \beta_t + \Sigma_0^{-1} \mu_0)) \right) \end{aligned}$$

which is multivariate normal with mean $(T \Sigma_\beta^{-1} + \Sigma_0^{-1})^{-1} (\sum_{t=1}^T \Sigma_\beta^{-1} \beta_t + \Sigma_0^{-1} \mu_0)$ and variance $(T \Sigma_\beta^{-1} + \Sigma_0^{-1})^{-1}$

3.3 Full Conditional for σ_β^2

$$\begin{aligned} [\sigma_\beta^2 | \cdot] &\propto \prod_{t=1}^T [\beta_t | \mu_\beta, \sigma_\beta^2] [\sigma_\beta^2] \\ &\propto \left(\prod_{t=1}^T |\Sigma_\beta|^{-\frac{1}{2}} \right) \exp \left(-\frac{1}{2} \sum_{t=1}^T (\beta_t - \mu_\beta)^T \Sigma_\beta^{-1} (\beta_t - \mu_\beta) \right) (\sigma_\beta^2)^{-(\alpha_\beta + 1)} \exp \left(-\frac{\beta_\beta}{\sigma_\beta^2} \right) \\ &\propto (\sigma_\beta^2)^{-(\alpha_\beta + \frac{T\tau}{2} + 1)} \exp \left(-\frac{1}{\sigma_\beta^2} \left(\frac{1}{2} \sum_{t=1}^T (\beta_t - \mu_\beta)^T (\beta_t - \mu_\beta) + \beta_\beta \right) \right) \end{aligned}$$

which is $\text{IG}(\alpha_\beta + \frac{T\tau}{2}, \frac{1}{2} \sum_{t=1}^T (\beta_t - \mu_\beta)^T (\beta_t - \mu_\beta) + \beta_\beta)$ since the determinant $|\Sigma_\beta| = (\sigma_\beta^2)^\tau$ and $\Sigma_\beta^{-1} = \frac{1}{\sigma_\beta^2} \mathbf{I}_\tau$

3.4 Full Conditional for σ_η^2

$$\begin{aligned}
[\sigma_\eta^2 | \cdot] &\propto \prod_{t=1}^T [\mathbf{y}_t | \boldsymbol{\beta}_t, \sigma_\eta^2, \phi, \sigma_\epsilon^2] [\sigma_\eta^2] \\
&\propto \left(\prod_{t=1}^T |\boldsymbol{\Sigma}|^{-\frac{1}{2}} \right) \exp \left(-\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t)^T \boldsymbol{\Sigma}^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t) \right) (\sigma_\eta^2)^{-\alpha_\eta+1} \exp \left(-\frac{\beta_\eta}{\sigma_\eta^2} \right) \\
&\propto |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp \left(-\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t)^T \boldsymbol{\Sigma}^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t) \right) (\sigma_\eta^2)^{-\alpha_\eta+1} \exp \left(-\frac{\beta_\eta}{\sigma_\eta^2} \right)
\end{aligned}$$

which can be sampled using a Metropolis-Hastings step

3.5 Full Conditional for σ_ϵ^2

$$\begin{aligned}
[\sigma_\epsilon^2 | \cdot] &\propto \prod_{t=1}^T [\mathbf{y}_t | \boldsymbol{\beta}_t, \sigma_\eta^2, \phi, \sigma_\epsilon^2] [\sigma_\epsilon^2] \\
&\propto \left(\prod_{t=1}^T |\boldsymbol{\Sigma}|^{-\frac{1}{2}} \right) \exp \left(-\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t)^T \boldsymbol{\Sigma}^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t) \right) (\sigma_\epsilon^2)^{-\alpha_\epsilon+1} \exp \left(-\frac{\beta_\epsilon}{\sigma_\epsilon^2} \right) \\
&\propto |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp \left(-\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t)^T \boldsymbol{\Sigma}^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t) \right) (\sigma_\epsilon^2)^{-\alpha_\epsilon+1} \exp \left(-\frac{\beta_\epsilon}{\sigma_\epsilon^2} \right)
\end{aligned}$$

which can be sampled using a Metropolis-Hastings step

3.6 Full Conditional for ϕ

$$\begin{aligned}
[\phi | \cdot] &\propto \prod_{t=1}^T [\mathbf{y}_t | \boldsymbol{\beta}_t, \sigma_\eta^2, \phi, \sigma_\epsilon^2] [\phi] \\
&\propto \left(\prod_{t=1}^T |\boldsymbol{\Sigma}|^{-\frac{1}{2}} \right) \exp \left(-\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t)^T \boldsymbol{\Sigma}^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t) \right) \phi^{-\alpha_\phi+1} \exp \left(-\frac{\beta_\phi}{\phi} \right) \\
&\propto |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp \left(-\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t)^T \boldsymbol{\Sigma}^{-1} (\mathbf{y}_t - \mathbf{H}_t \mathbf{X} \boldsymbol{\beta}_t) \right) \phi^{-\alpha_\phi+1} \exp \left(-\frac{\beta_\phi}{\phi} \right)
\end{aligned}$$

which can be sampled using a Metropolis-Hastings step

4 Posterior Predictive Distribution

The posterior predictive distribution for \mathbf{y}_t is sampled at each MCMC iteration k by