



Supplement of

Reconstruction of spatio-temporal temperature from sparse historical records using robust probabilistic principal component regression

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S Supplementary Material

S.1 Marginal distribution

Conditional on the unobserved latent principal components, we can write the robust Student's- t pPCR likelihood as

$$\begin{aligned}
5 \quad & [y_{it} | \mathbf{Z}_i, \boldsymbol{\beta}_t, v_{it}^2] [\mathbf{X}_i | \mathbf{Z}_i, \sigma] [\mathbf{Z}_i] \\
& \propto \exp \left\{ -\frac{(y_{it} - \mathbf{Z}_i \boldsymbol{\beta}_t)^2}{2v_{it}^2} - \frac{(\mathbf{X}_i - \hat{\mathbf{K}} \mathbf{Z}_i)' (\mathbf{X}_i - \hat{\mathbf{K}} \mathbf{Z}_i)}{2\sigma^2} - \frac{\mathbf{Z}_i' \mathbf{Z}_i}{2} \right\} \\
& \propto \exp \left\{ -\frac{1}{2} \mathbf{Z}_i' \left(\frac{\boldsymbol{\beta}_t \boldsymbol{\beta}_t'}{v_{it}^2} + \frac{\hat{\mathbf{K}}' \hat{\mathbf{K}}}{\sigma^2} + \mathbf{I} \right) \mathbf{Z}_i + \mathbf{Z}_i' \left(\frac{\boldsymbol{\beta}_t y_{it}}{v_{it}^2} + \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right) \right\} \\
& \quad \times \exp \left\{ -\frac{y_{it}^2}{2v_{it}^2} - \frac{\mathbf{X}_i' \mathbf{X}_i}{2\sigma^2} \right\} \\
& \propto \exp \left\{ -\frac{1}{2} (\mathbf{Z}_i - \boldsymbol{\mu}_{Z_{it}})' \boldsymbol{\Sigma}_{Z_{it}}^{-1} (\mathbf{Z}_i - \boldsymbol{\mu}_{Z_{it}}) - \frac{y_{it}^2}{2v_{it}^2} - \frac{\mathbf{X}_i' \mathbf{X}_i}{2\sigma^2} + \frac{\boldsymbol{\mu}'_{Z_{it}} \boldsymbol{\Sigma}_{Z_{it}}^{-1} \boldsymbol{\mu}_{Z_{it}}}{2} \right\}
\end{aligned}$$

10 where $\boldsymbol{\Sigma}_{Z_{it}} = \left(\frac{\boldsymbol{\beta}_t \boldsymbol{\beta}_t'}{v_{it}^2} + \frac{\hat{\mathbf{K}}' \hat{\mathbf{K}}}{\sigma^2} + \mathbf{I} \right)^{-1}$ and $\boldsymbol{\mu}_{Z_{it}} = \boldsymbol{\Sigma}_{Z_{it}} \left(\frac{\boldsymbol{\beta}_t y_{it}}{v_{it}^2} + \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right)$. Integrating the above equation with respect to \mathbf{Z}_i we get

$$\begin{aligned}
[y_{it} | \boldsymbol{\beta}_t, v_{it}^2, \sigma] & \propto \exp \left\{ -\frac{y_{it}^2}{2v_{it}^2} + \frac{\boldsymbol{\mu}'_{Z_{it}} \boldsymbol{\Sigma}_{Z_{it}}^{-1} \boldsymbol{\mu}_{Z_{it}}}{2} \right\} \\
& \propto \exp \left\{ -\frac{y_{it}^2}{2v_{it}^2} + \frac{(\boldsymbol{\Sigma}_{Z_{it}} \left(\frac{y_{it} \boldsymbol{\beta}_t}{v_{it}^2} + \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right))' \boldsymbol{\Sigma}_{Z_{it}}^{-1} (\boldsymbol{\Sigma}_{Z_{it}} \left(\frac{y_{it} \boldsymbol{\beta}_t}{v_{it}^2} + \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right))}{2} \right\} \\
& \propto \exp \left\{ -\frac{1}{2} y_{it}^2 \left(\frac{1}{v_{it}^2} - \frac{\boldsymbol{\beta}_t' \boldsymbol{\Sigma}_{Z_{it}} \boldsymbol{\beta}_t}{(v_{it}^2)^2} \right) + y_{it} \left(\frac{\boldsymbol{\beta}_t' \boldsymbol{\Sigma}_{Z_{it}} \hat{\mathbf{K}}' \mathbf{X}_i}{v_{it}^2 \sigma^2} \right) \right\}
\end{aligned}$$

15 which is $N(\mu_{y_{it}}, \sigma_{y_{it}}^2)$ with

$$\begin{aligned}
\sigma_{y_{it}}^2 &= \left(\frac{1}{v_{it}^2} - \frac{\boldsymbol{\beta}_t' \boldsymbol{\Sigma}_{Z_{it}} \boldsymbol{\beta}_t}{(v_{it}^2)^2} \right)^{-1} \\
\mu_{y_{it}} &= \left(\frac{1}{v_{it}^2} - \frac{\boldsymbol{\beta}_t' \boldsymbol{\Sigma}_{Z_{it}} \boldsymbol{\beta}_t}{(v_{it}^2)^2} \right)^{-1} \frac{\boldsymbol{\beta}_t' \boldsymbol{\Sigma}_{Z_{it}} \hat{\mathbf{K}}' \mathbf{X}_i}{v_{it}^2 \sigma^2}
\end{aligned}$$

To further simplify this equation, we use the Morrison-Woodbury matrix inversion formula

$$(\mathbf{A} + \mathbf{UDV})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{U}(\mathbf{D}^{-1} + \mathbf{VA}^{-1}\mathbf{U})^{-1}\mathbf{VA}^{-1}.$$

20 Then, defining $\mathbf{A} = v_{it}^2 \mathbf{I}$, $\mathbf{U} = \boldsymbol{\beta}'_t$, $\mathbf{V} = \boldsymbol{\beta}_t$, and $\mathbf{D} = \left(\frac{\hat{\mathbf{K}}'\hat{\mathbf{K}}}{\sigma^2} + \mathbf{I}\right)^{-1}$,

$$\begin{aligned}\sigma_{y_{it}}^2 &= \left(\frac{\mathbf{I}}{v_{it}^2} - \frac{\boldsymbol{\beta}'_t \boldsymbol{\Sigma}_{Z_{it}} \boldsymbol{\beta}_t}{(v_{it}^2)^2} \right)^{-1} \\ &= \left(\frac{\mathbf{I}}{v_{it}^2} - \frac{\boldsymbol{\beta}'_t}{v_{it}^2} \left(\frac{\boldsymbol{\beta}_t \boldsymbol{\beta}'_t}{v_{it}^2} + \frac{\hat{\mathbf{K}}'\hat{\mathbf{K}}}{\sigma^2} + \mathbf{I} \right)^{-1} \frac{\boldsymbol{\beta}_t}{v_{it}^2} \right)^{-1} \\ &= v_{it}^2 + \boldsymbol{\beta}'_t \left(\frac{\hat{\mathbf{K}}'\hat{\mathbf{K}}}{\sigma^2} + \mathbf{I} \right)^{-1} \boldsymbol{\beta}_t \\ &= v_{it}^2 + \boldsymbol{\beta}'_t \mathbf{M}_p^{-1} \boldsymbol{\beta}_t\end{aligned}$$

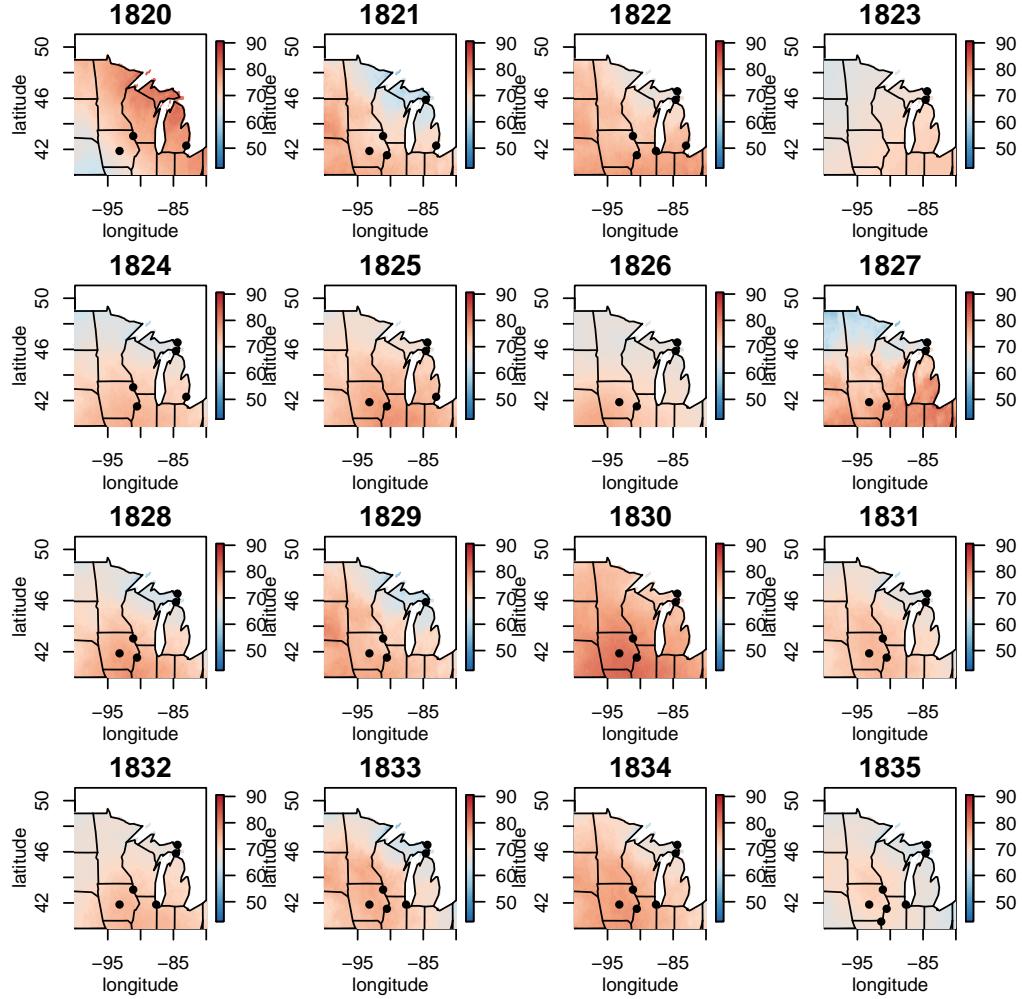
25 with $\mathbf{M}_p = \frac{\hat{\mathbf{K}}'\hat{\mathbf{K}}}{\sigma^2} + \mathbf{I}$.

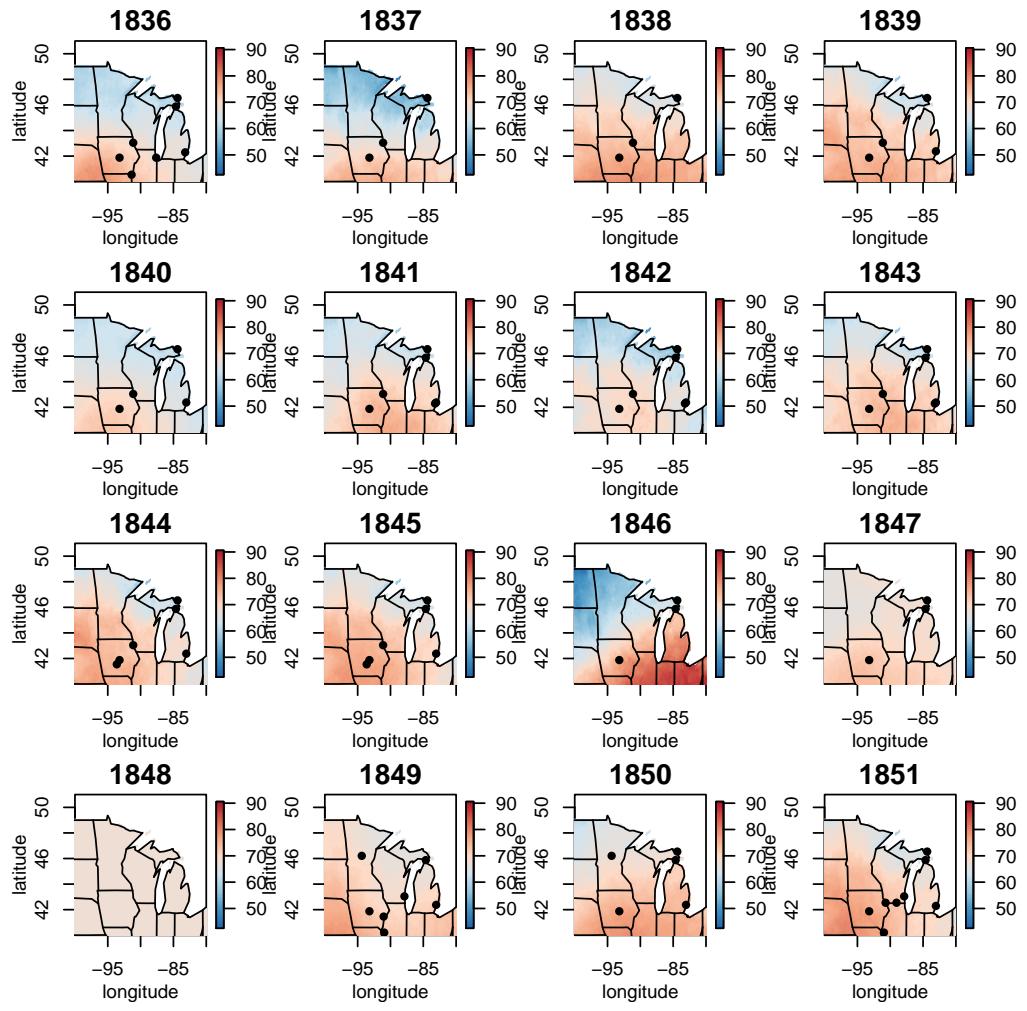
Then, letting $\mathbf{B}_t = \mathbf{M}_p^{-1/2} \boldsymbol{\beta}_t$ the conditional mean $\mu_{y_{it}}$ is

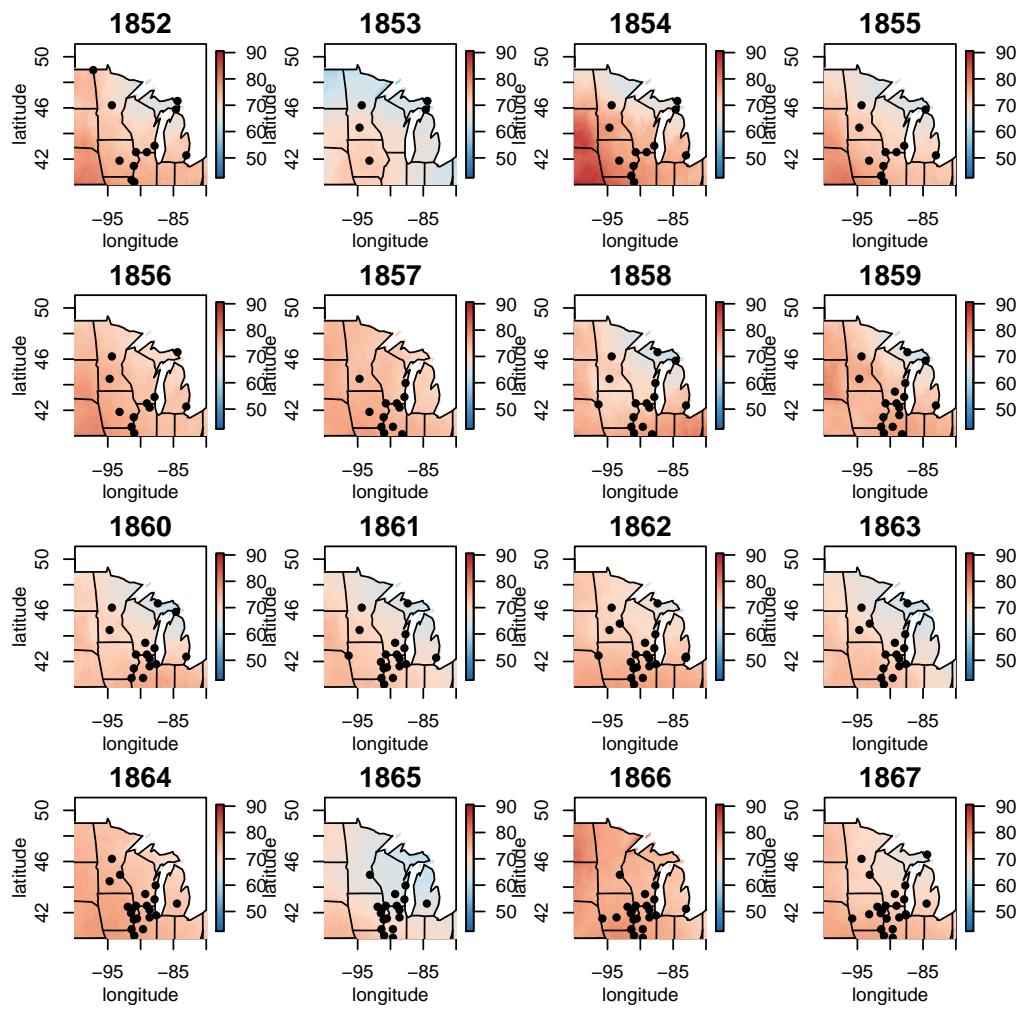
$$\begin{aligned}\mu_{y_{it}} &= \left(\frac{1}{v_{it}^2} - \frac{\boldsymbol{\beta}'_t \boldsymbol{\Sigma}_{Z_{it}} \boldsymbol{\beta}_t}{(v_{it}^2)^2} \right)^{-1} \left(\frac{\boldsymbol{\beta}'_t \boldsymbol{\Sigma}_{Z_{it}} \hat{\mathbf{K}}' \mathbf{X}_i}{v_{it}^2 \sigma^2} \right) \\ &= (v_{it}^2 + \boldsymbol{\beta}'_t \mathbf{M}_p^{-1} \boldsymbol{\beta}_t) \left(\frac{\boldsymbol{\beta}'_t}{v_{it}^2} \left(\frac{\boldsymbol{\beta}_t \boldsymbol{\beta}'_t}{v_{it}^2} + \frac{\hat{\mathbf{K}}'\hat{\mathbf{K}}}{\sigma^2} + \mathbf{I} \right)^{-1} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right) \\ &= (v_{it}^2 + \mathbf{B}'_t \mathbf{B}_t) \left(\frac{\boldsymbol{\beta}'_t}{v_{it}^2} \left(\frac{\boldsymbol{\beta}_t \boldsymbol{\beta}'_t}{v_{it}^2} + \mathbf{M}_p \right)^{-1} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right) \\ &= (v_{it}^2 + \mathbf{B}'_t \mathbf{B}_t) \left(\frac{\boldsymbol{\beta}'_t}{v_{it}^2} \left(\mathbf{M}_p^{\frac{1}{2}} \left(\frac{\mathbf{M}_p^{-\frac{1}{2}} \boldsymbol{\beta}_t \boldsymbol{\beta}'_t \mathbf{M}_p^{-\frac{1}{2}}}{v_{it}^2} + \mathbf{I} \right) \mathbf{M}_p^{\frac{1}{2}} \right)^{-1} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \right) \\ &= (v_{it}^2 + \mathbf{B}'_t \mathbf{B}_t) \frac{\mathbf{B}'_t}{v_{it}^2} \left(\frac{\mathbf{B}_t \mathbf{B}'_t}{v_{it}^2} + \mathbf{I} \right)^{-1} \mathbf{M}_p^{-\frac{1}{2}} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \\ &= \left(\mathbf{B}'_t + \frac{\mathbf{B}'_t \mathbf{B}_t \mathbf{B}'_t}{v_{it}^2} \right) \left(\frac{\mathbf{B}_t \mathbf{B}'_t}{v_{it}^2} + \mathbf{I} \right)^{-1} \mathbf{M}_p^{-\frac{1}{2}} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \\ &= \mathbf{B}'_t \left(\mathbf{I} + \frac{\mathbf{B}_t \mathbf{B}'_t}{v_{it}^2} \right) \left(\frac{\mathbf{B}_t \mathbf{B}'_t}{v_{it}^2} + \mathbf{I} \right)^{-1} \mathbf{M}_p^{-\frac{1}{2}} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \\ &= \mathbf{B}'_t \mathbf{M}_p^{-\frac{1}{2}} \frac{\hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2} \\ 35 &= \frac{\boldsymbol{\beta}'_t \mathbf{M}_p^{-1} \hat{\mathbf{K}}' \mathbf{X}_i}{\sigma^2}\end{aligned}$$

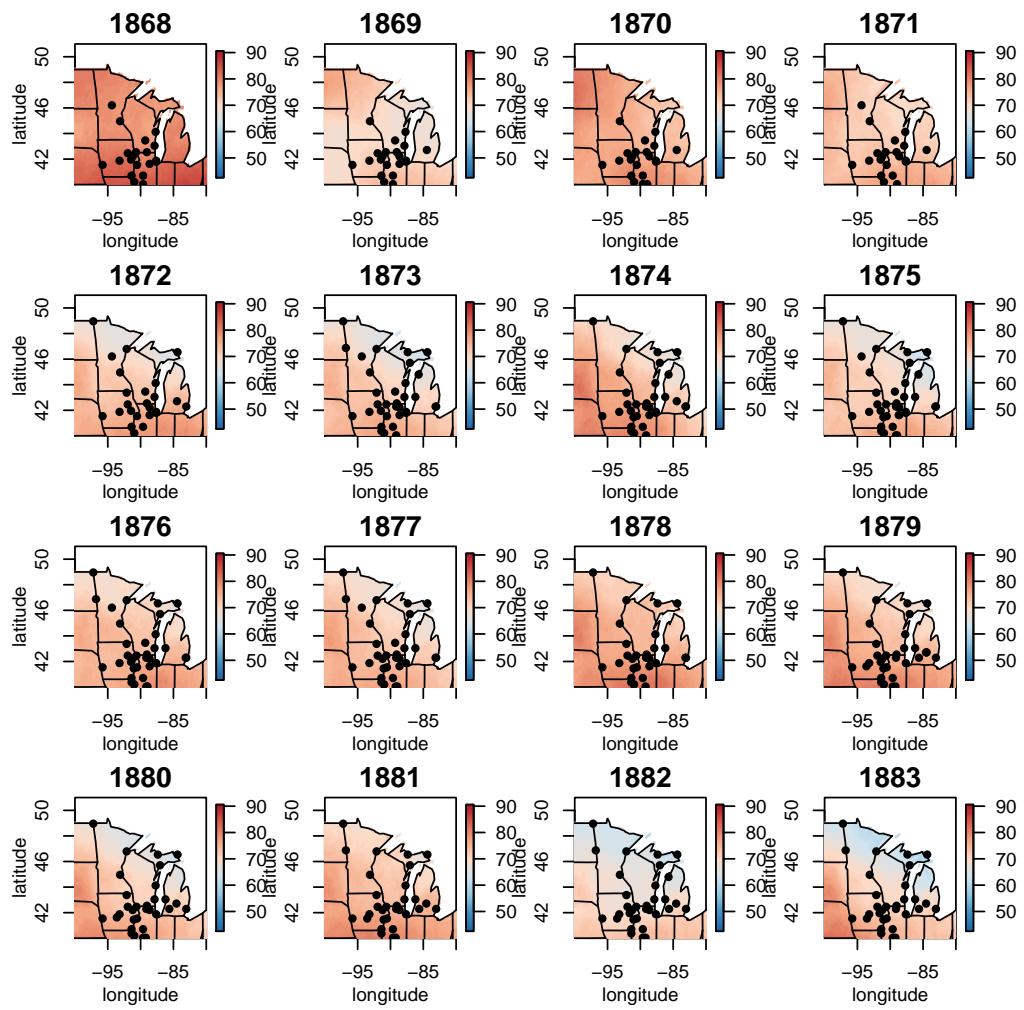
$$y_{it} | \beta_t, v_{it}^2, \sigma \sim N \left(\frac{\mathbf{X}'_i \hat{\mathbf{K}} \mathbf{M}_p^{-1} \beta_t}{\sigma^2}, v_{it}^2 + \beta_t' \mathbf{M}_p^{-1} \beta_t \right).$$

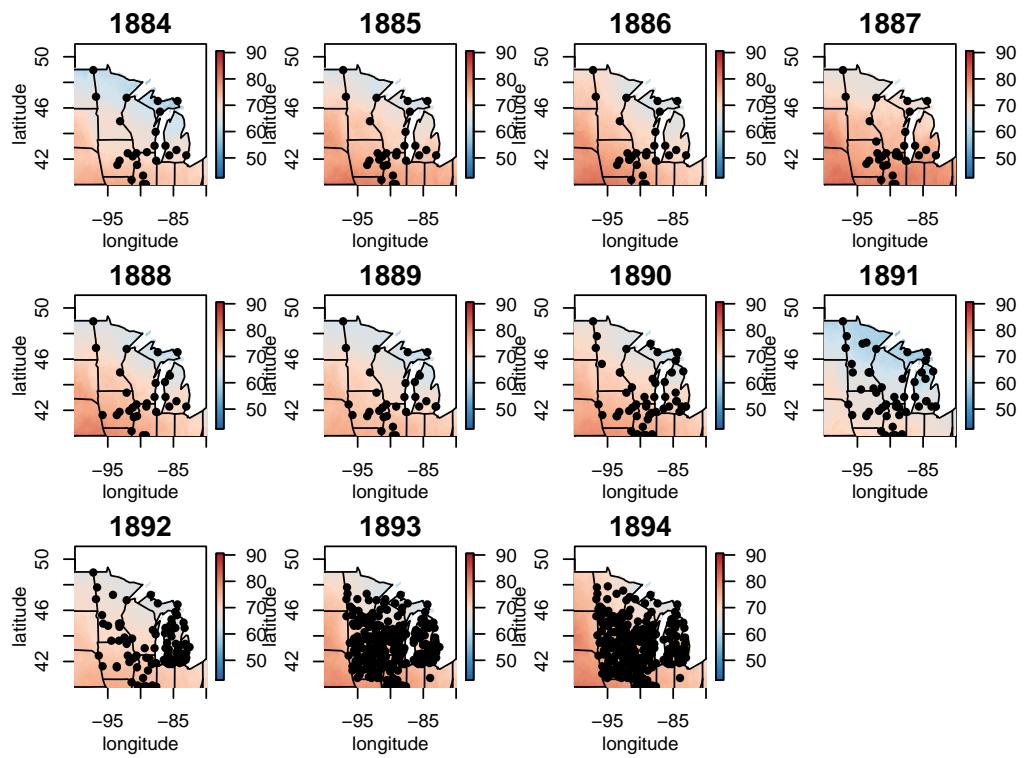
S.2 Robust PCR Model Posterior Mean July Temperature



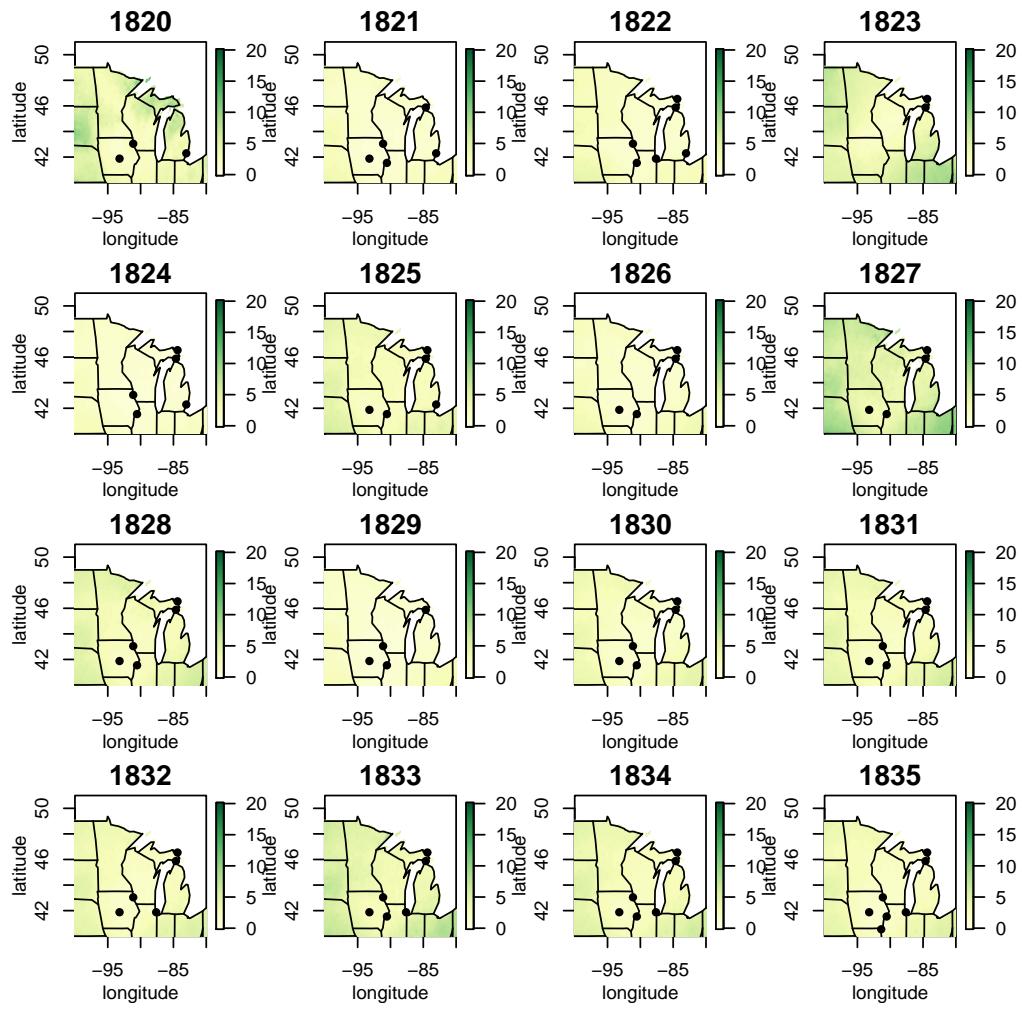


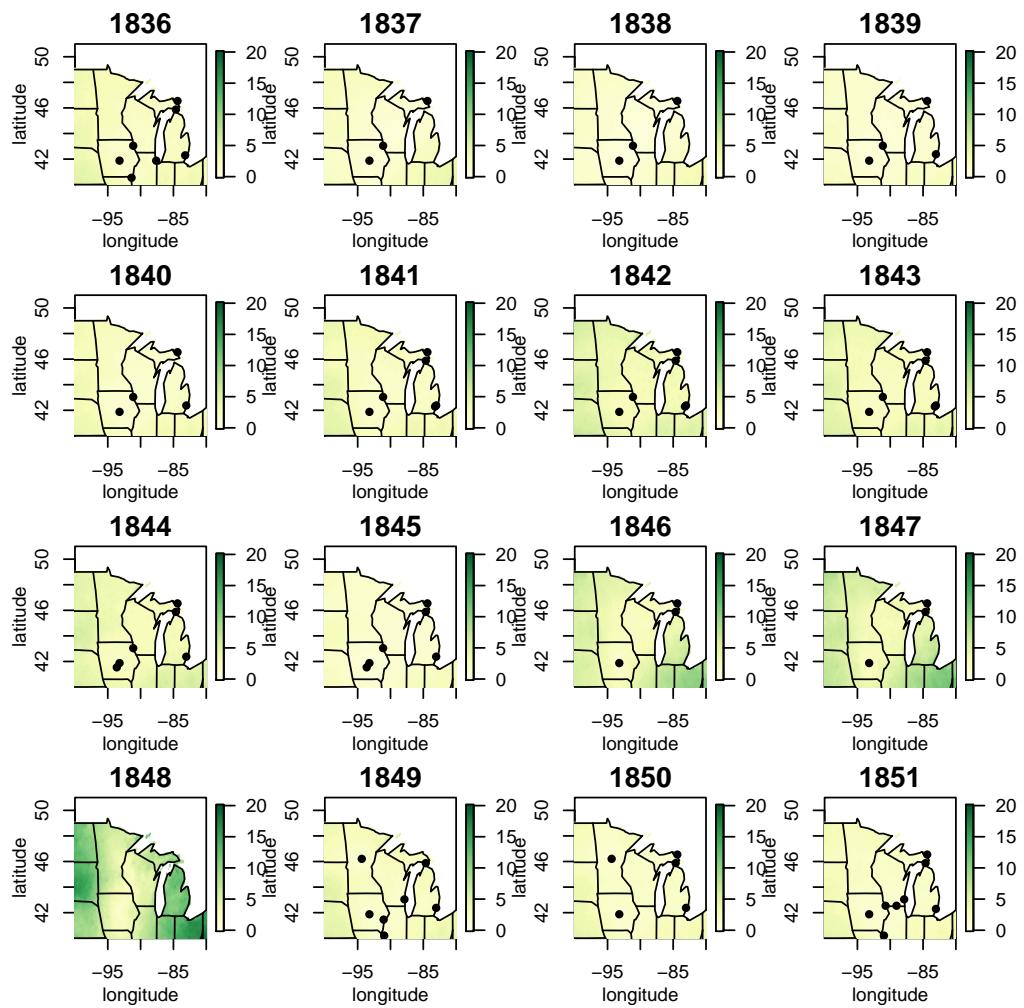


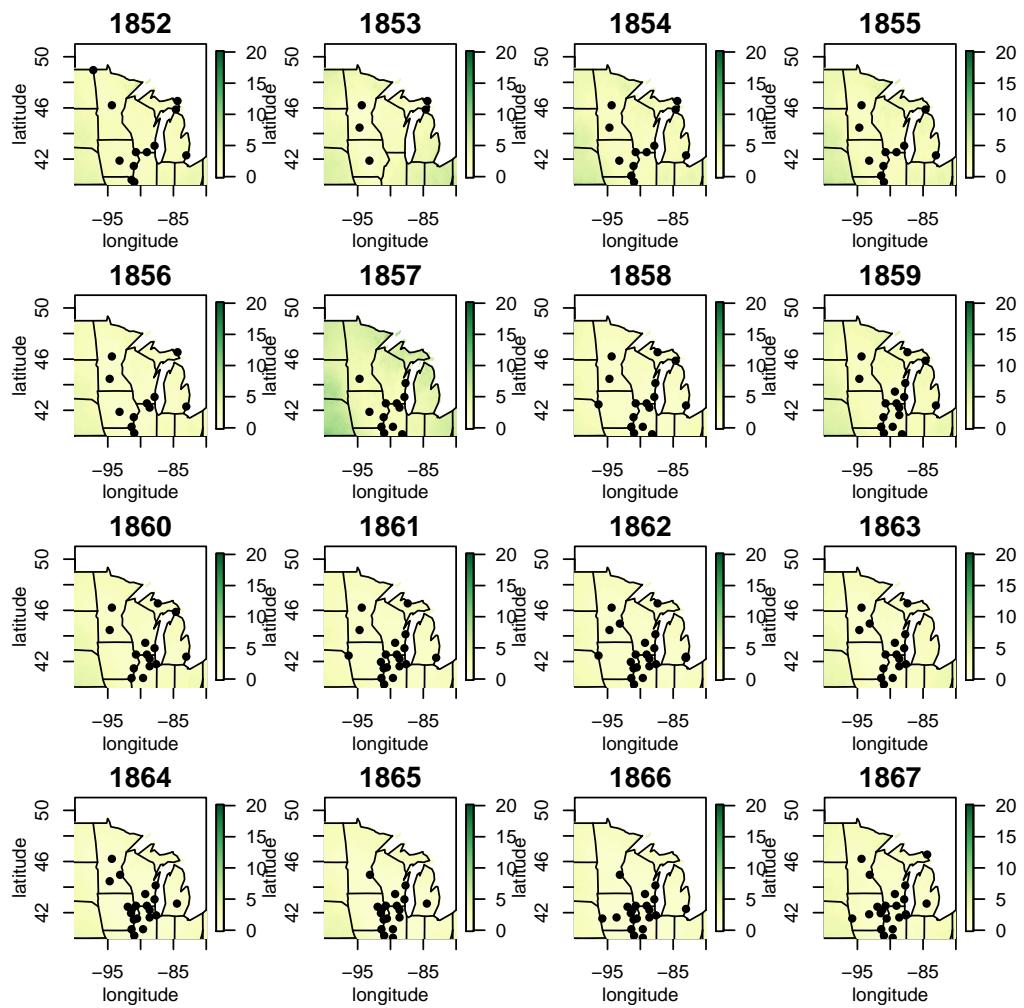


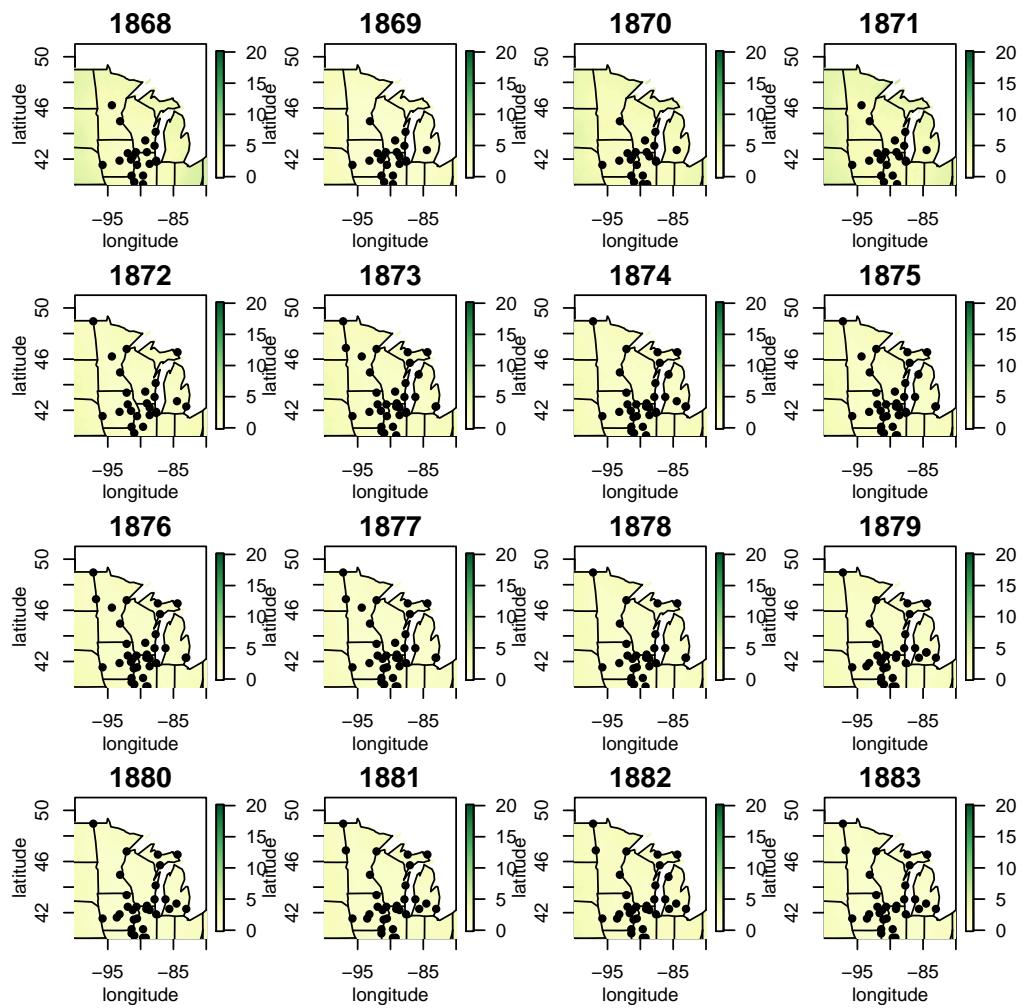


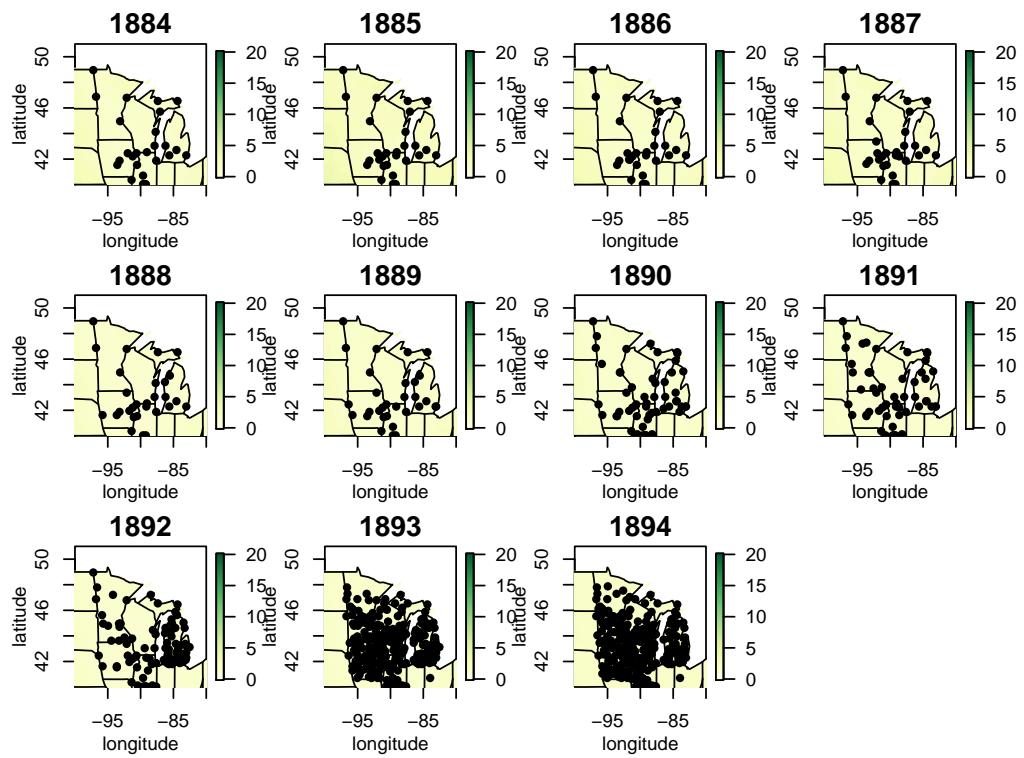
S.3 Robust PCR Model July Temperature Posterior Standard Deviations



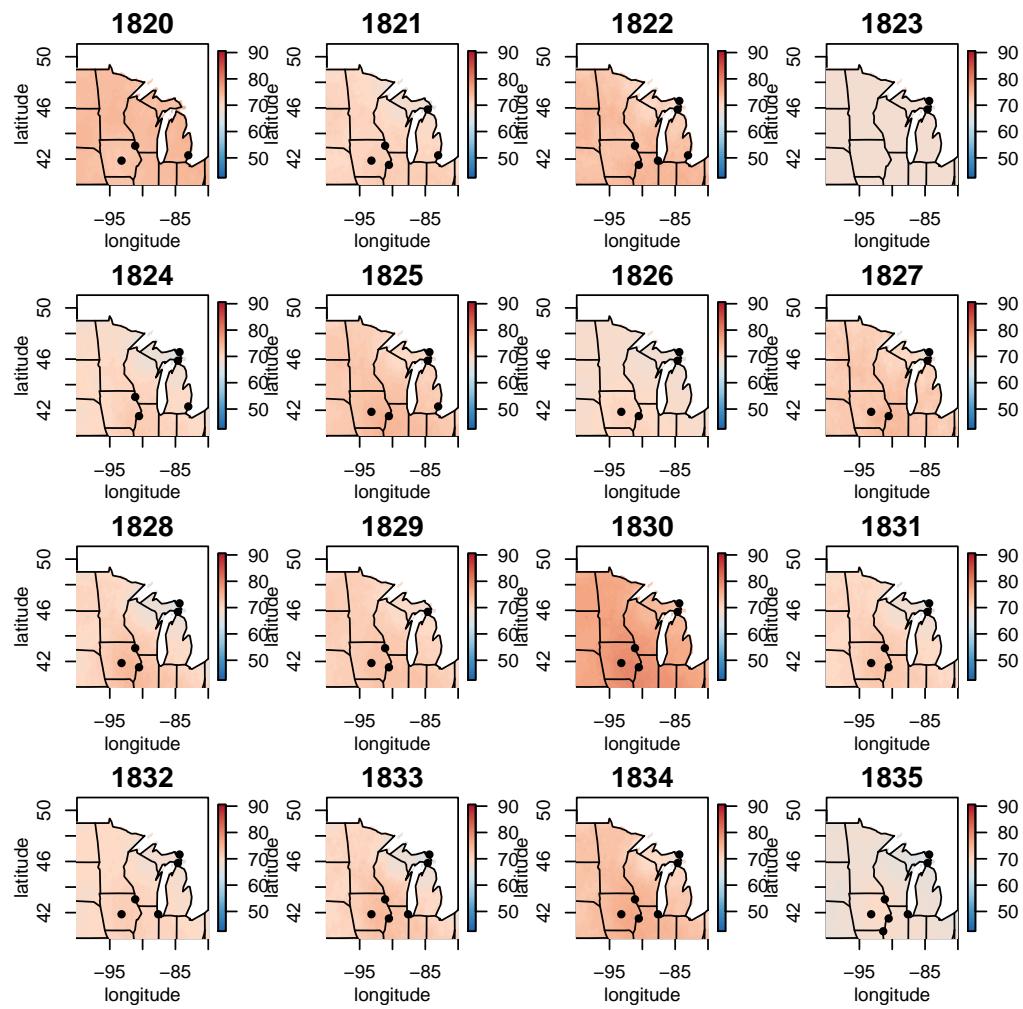


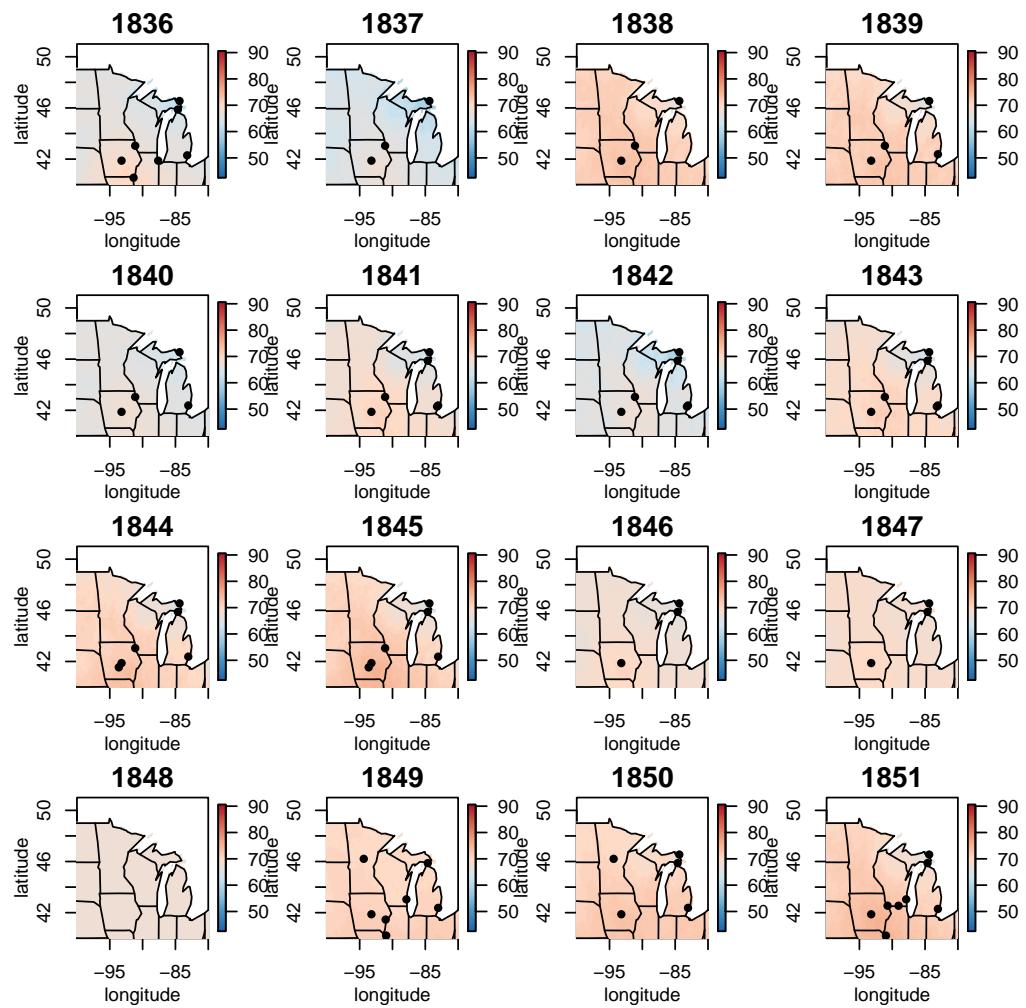


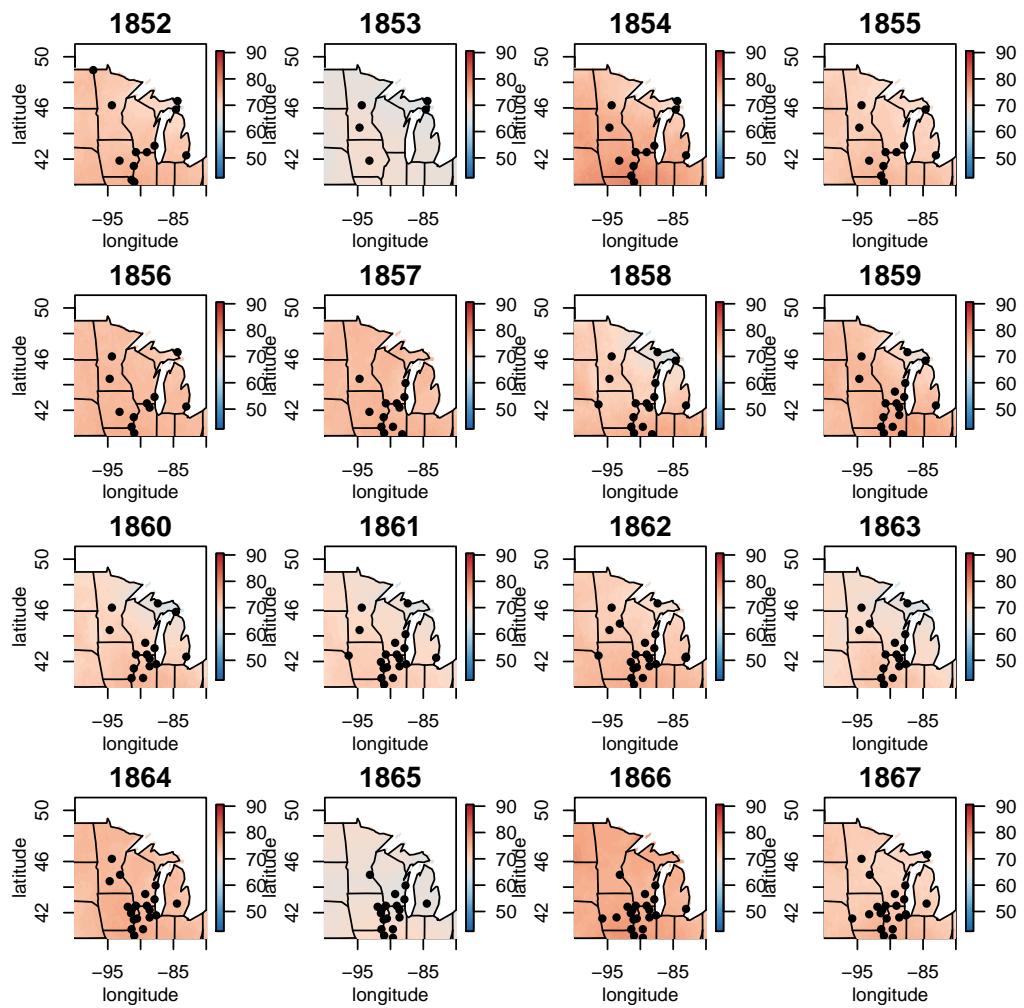


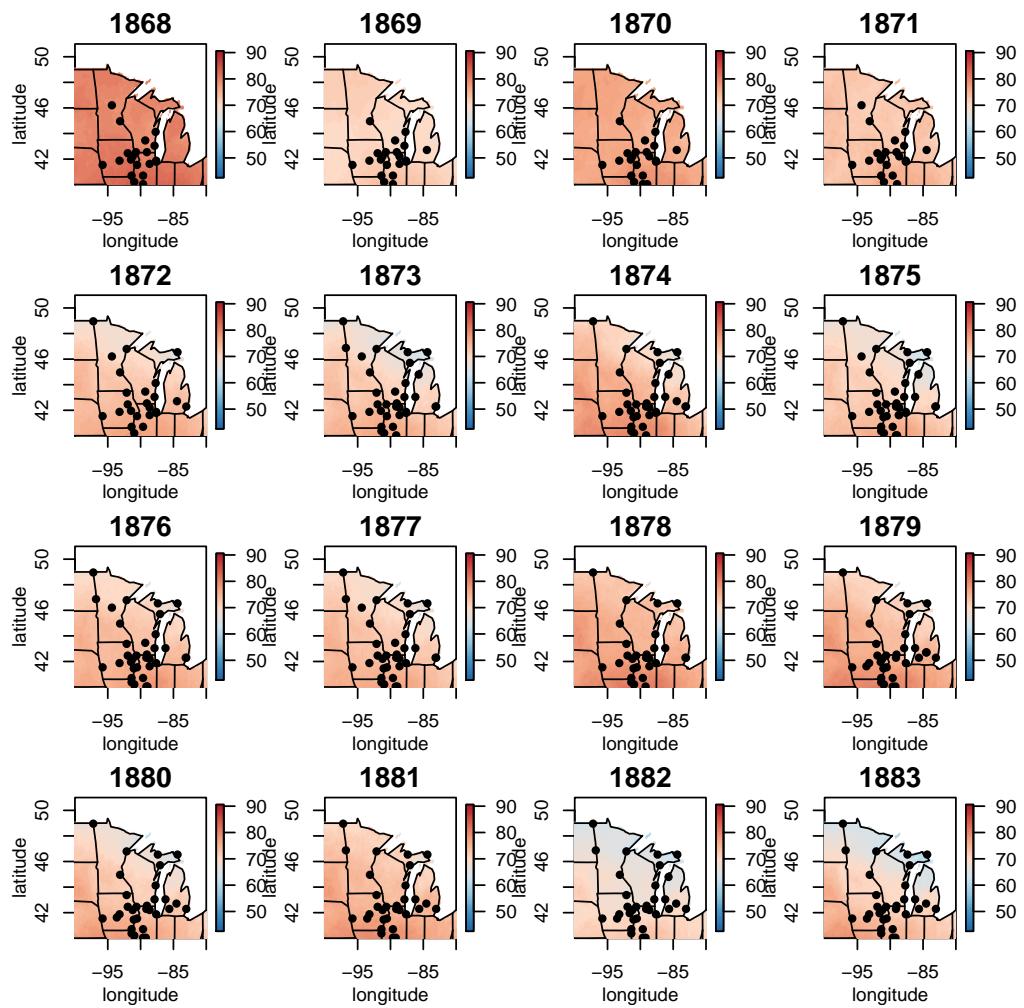


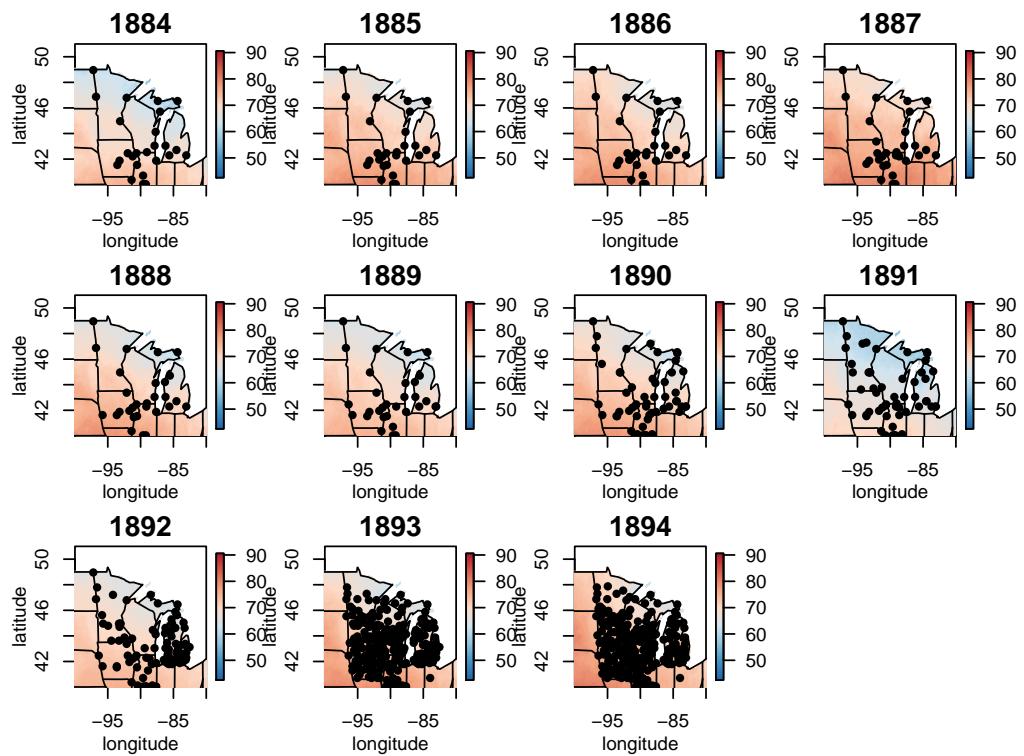
50 S.4 Robust Probabilistic PCR Model Posterior Mean July Temperature











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S.5 Robust Probabilistic PCR Model July Temperature Posterior Standard Deviations

