

Solar DEM Model

$$Y \approx \text{Poisson}(\lambda) + N(0, \sigma_b^2)$$

$$Y = I_{ijb} \cdot \tau_b \quad \lambda_{ijb} = \sum \beta_t \cdot M_{ijbt} \cdot \tau_b$$

I_{ijb} : A solar image in color band b , $m \times n$ pixels, containing a particular solar feature, for $b = 1, 2, \dots, B$

$M_{bt} = M_{ijbt}$: The expected *Emission Measure in color band b originating at temperature t* , for $t = 1, 2, \dots, T$.

Solar DEM Model

$$Y \approx \text{Poisson}(\lambda) + N(0, \sigma_b^2)$$

$$Y = I_{ijb} \cdot \tau_b \quad \lambda_{ijb} = \sum \beta_t \cdot M_{ijbt} \cdot \tau_b$$

β_t : the proportion of the total volume at temperature t .

σ_b : computed from the magnitude of the negative values of I_b in the data.

New Solar DEM Model

$$Y \approx Y_1 + Y_2 + 1/4$$

$$Y = I_{ijb} \cdot \tau_b \quad Y_1 = Z^2 \quad Y_2 \sim N(0, \sigma_b^2)$$

$$Z \sim N(\sqrt{\lambda_{ijb}}, \varepsilon^2) \quad \lambda_{ijb} = \sum \beta_t \cdot M_{ijbt} \cdot \tau_b$$

This will ensure that Y will never be negative, and using the Normal distribution will help with implementing the Gaussian Random Field model on the spatial correlations.

EM for This Model

$$Y \approx Y_1 + Y_2 + 1/4$$

$$Y = I_{ijb} \cdot \tau_b \quad Y_1 = Z^2 \quad Y_2 \sim N(0, \sigma_b^2)$$

$$Z \sim N(\sqrt{\lambda_{ijb}}, \varepsilon^2) \quad \lambda_{ijb} = \sum \beta_t \cdot M_{ijbt} \cdot \tau_b$$

E-Step: $E(Z|Y\dots)$

M-Step 1: Given σ_b^2 to maximize $\mu = \sqrt{\lambda_{ijb}}$

M-Step 2: Given μ to maximize β_t

EM for This Model

$$Y \approx Y_1 + Y_2 + 1/4$$

$$Y = I_{ijb} \cdot \tau_b \quad Y_1 = Z^2 \quad Y_2 \sim N(0, \sigma_b^2)$$

$$Z \sim N(\sqrt{\lambda_{ijb}(t)}, \varepsilon^2) \quad \lambda_{ijb}(t) = \sum \mu_t \cdot M_{ijbt} \cdot \tau_b$$

Problem:

The M-step can't go well.

M-Step1: goes slow because of too many pixels;

M-Step2: We use Fisher Scoring, and it converges poorly because of positive constraints of $\lambda_{ijb}(t)$

MCMC for This Model

$$Y \approx Y_1 + Y_2 + 1/4$$

$$Y = I_{ijb} \cdot \tau_b \quad Y_1 = Z^2 \quad Y_2 \sim N(0, \sigma_b^2)$$

$$Z \sim N(\sqrt{\lambda_{ijb}(t)}, \varepsilon^2) \quad \lambda_{ijb}(t) = \sum \mu_t \cdot M_{ijbt} \cdot \tau_b$$

Step 1: $f(Z | Y, \beta, M, \varepsilon^2, \sigma_b^2)$

Step 2: $Y_1 = Z^2$ Step 2': $f(\beta | Z, M, \varepsilon^2)$

Step 3: $f(\sigma_b^2 | Y, Y_1)$ Step 3': $f(\varepsilon^2 | Z, M, \beta)$

MCMC for This Model

$$Y \approx Y_1 + Y_2 + 1/4$$

$$Y = I_{ijb} \cdot \tau_b \quad Y_1 = Z^2 \quad Y_2 \sim N(0, \sigma_b^2)$$

$$Z \sim N(\sqrt{\lambda_{ijb}(t)}, \varepsilon^2) \quad \lambda_{ijb}(t) = \sum \mu_t \cdot M_{ijbt} \cdot \tau_b$$

I use both Gibbs Sampling and Metropolis-Hastings Algorithm.

Problem:

1. Each iteration costs too much time.
2. Acceptance Rate is too low.