

# Spatiotemporal prediction of wildfire size extremes with Bayesian finite sample maxima

## Appendix S1: Prior specifications

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Prior distributions were chosen to regularize coefficients on the distribution specific means  $\beta^{(\mu)}$  and structural zero parameters  $\beta^{(\pi)}$ . We used a regularized horseshoe prior on these coefficients, which shrinks irrelevant coefficients towards zero, while regularizing nonzero coefficients (Piiironen, Vehtari, and others 2017). For zero-inflated models, we used a multivariate version of the regularized horseshoe (Peltola et al. 2014):

$$\begin{pmatrix} \beta_j^{(\mu)} \\ \beta_j^{(\pi)} \end{pmatrix} \sim \text{N} \left( \mathbf{0}, \begin{pmatrix} \tau_1^2 \tilde{\lambda}_{1,j}^2 & \rho \tau_1 \tau_2 \tilde{\lambda}_{1,j} \tilde{\lambda}_{2,j} \\ \rho \tau_1 \tau_2 \tilde{\lambda}_{1,j} \tilde{\lambda}_{2,j} & \tau_2^2 \tilde{\lambda}_{2,j}^2 \end{pmatrix} \right),$$
$$\tilde{\lambda}_{m,j}^2 = \frac{c_m^2 \lambda_j^2}{c_m^2 + \tau_m^2 \lambda_j^2},$$

for each response dimension  $m = 1, 2$  and coefficient  $j = 1, \dots, p$ . Here  $\rho$  is a correlation parameter,  $\tau_1$  and  $\tau_2$  are global variance hyperparameters,  $c_1$  and  $c_2$  are hyperparameters that determine the amount of shrinkage on the largest coefficients, and  $\lambda_j$  is a local scale parameter drawn from a half-Cauchy distribution that control the amount of shrinkage applied to coefficient  $j$  (Piiironen, Vehtari, and others 2017). With this prior specification, information can be shared across the two response dimensions through the correlation pa-

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parameter  $\rho$ , and/or through the local scale parameters  $\lambda_j$ . For count models without structural zeros (the Poisson and negative binomial models), this multivariate prior simplifies to a univariate regularized horseshoe prior.

Spatiotemporal random effects were constructed using a temporally autoregressive, spatially intrinsically autoregressive formulation (Besag and Kooperberg 1995; Banerjee, Carlin, and Gelfand 2014). Temporarily suppressing the superscript that indicates whether the effects are on  $\mu$  or  $\pi$ , and denoting column  $t$  from an  $S \times T$   $\Phi$  as  $\phi_t$  we have:

$$\phi_{t=1} \sim N(\mathbf{0}, (\tau^{(\phi)}(\mathbf{D} - \mathbf{W}))^{-1})$$

$$\phi_t \sim N(\eta\phi_{t-1}, (\tau^{(\phi)}(\mathbf{D} - \mathbf{W}))^{-1}), \quad t = 2, \dots, T$$

where  $\eta$  is a temporal dependence parameter,  $\tau^{(\phi)}$  is a precision parameter,  $\mathbf{D}$  is an  $S \times S$  diagonal matrix with entries corresponding to the number of spatial neighbors for each spatial unit, and  $\mathbf{W}$  is an  $S \times S$  spatial adjacency matrix with nonzero elements only when spatial unit  $i$  is a neighbor of spatial unit  $j$  ( $w_{i,j} = 1$  if  $i$  is a neighbor of  $j$ , and  $w_{i,j} = 0$  otherwise, including  $w_{i,i} = 0$  for all  $i$ ).  $\tau^{(\phi)}$  is a precision parameter. We imposed a soft identifiability constraint that places high prior mass near  $\sum_{s=1}^S \phi_{t,s}^* = 0$  for all  $t$ .

We applied a univariate regularized horseshoe prior to all  $\beta$  coefficients in burned area models (Piironen, Vehtari, and others 2017):

$$\beta_j \sim N\left(0, \tau^2 \tilde{\lambda}_j^2\right), \quad \tilde{\lambda}_j^2 = \frac{c^2 \lambda_j^2}{c^2 + \tau^2 \lambda_j^2},$$

Spatiotemporal random effects were constructed in the same way as for the count models.

## Literature cited

Banerjee, Sudipto, Bradley P Carlin, and Alan E Gelfand. 2014. *Hierarchical Modeling and Analysis for Spatial Data*. CRC Press.

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