

# Bayesian Estimation of Modified ETAS Model for Invasive Species

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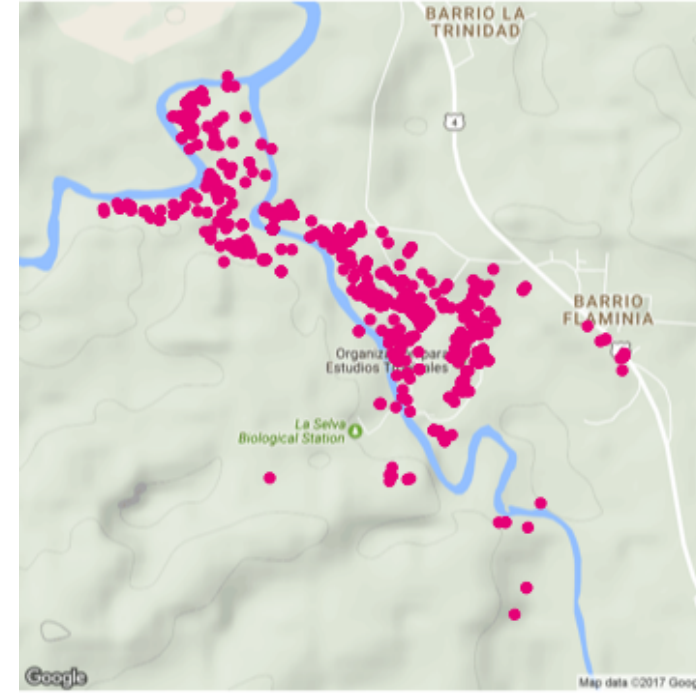
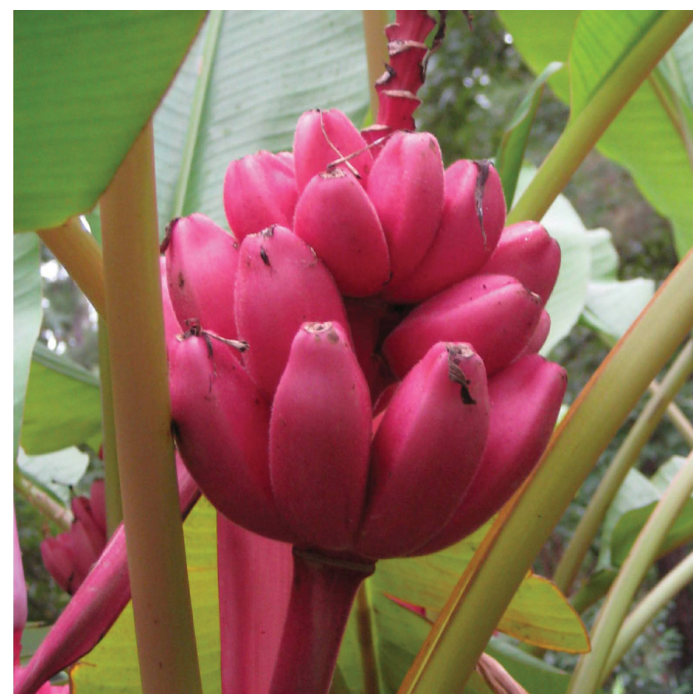


## Motivation

- **Invasive Plant:** Invasive alien species of plants can destroy the habitat of native species and disturb the natural evolution that takes place in the environment in which they spread.
- **ETAS Model:** Epidemic-Type Aftershock Sequence (ETAS) model, a **spatial-temporal marked point process model**, is the most popular stochastic model used to **describe earthquake occurrence**, to forecast earthquakes and to detect fluid/magma signals or induced seismicity.
- **Adjusted ETAS model** is applied onto the study of red banana tree to **characterize its spatial-temporal spreading patterns**.

## Data

- **Red Banana Tree:** An invasive plant in Costa Rican rainforest have been observing in recent few years. Heights of 1008 red banana plants were observed and **longitude and latitude** coordinates were recorded by GPS. The **age** of plants was estimated according to the growth rate.
- **788 plants have complete location and origin times data, and were used for the subsequent analyses.**



## Epidemic-Type Aftershock Sequence (ETAS) Model

- The spatial-temporal ETAS model (Ogata, 1998) is a point process model where **the rate of an earthquake of magnitude-M occurring at time  $t$  and location  $(x, y)$  depends on the histroy of occurrences  $H_t$** , characterized by the conditional intensity function:

$$\lambda(t, x, y|H_t) = \mu(x, y) + \sum_{\{i: t_i < t\}} \frac{K_0}{(t - t_i + c)^p} \cdot \frac{e^{\alpha(M - M_0)}}{((x - x_i)^2 + (y - y_i)^2 + d)^q}$$

$\mu(x, y)$  : A non-homogeneous background rate.

$\sum$  : Triggering function defined in the earthquake context.

$K_0, \alpha, c, p, d, q$  : Parameters to be estimated.

- **The ETAS model for red banana plants** by Balderama (2012) is

$$\lambda(t, x, y|H_t) = (1 - \rho)\mu(x, y) + \frac{\rho\alpha\beta}{\pi} \sum_{\{i: t_i < t\}} e^{-\alpha(t-t_i)-\beta\{(x-x_i)^2+(y-y_i)^2\}}$$

$\frac{\alpha\beta}{\pi}$  : A normalizing constant so that  $\sum$  integrates to unity.

$\alpha$  : Exponential decay rate due to **temporal distance apart**.

$\beta$  : Exponential decay rate due to **spatial distance apart**.

$\rho$  : **Proportion of events** attributed to triggering by other events.

- The **log-likelihood function** for the occurrence of red banana plants is

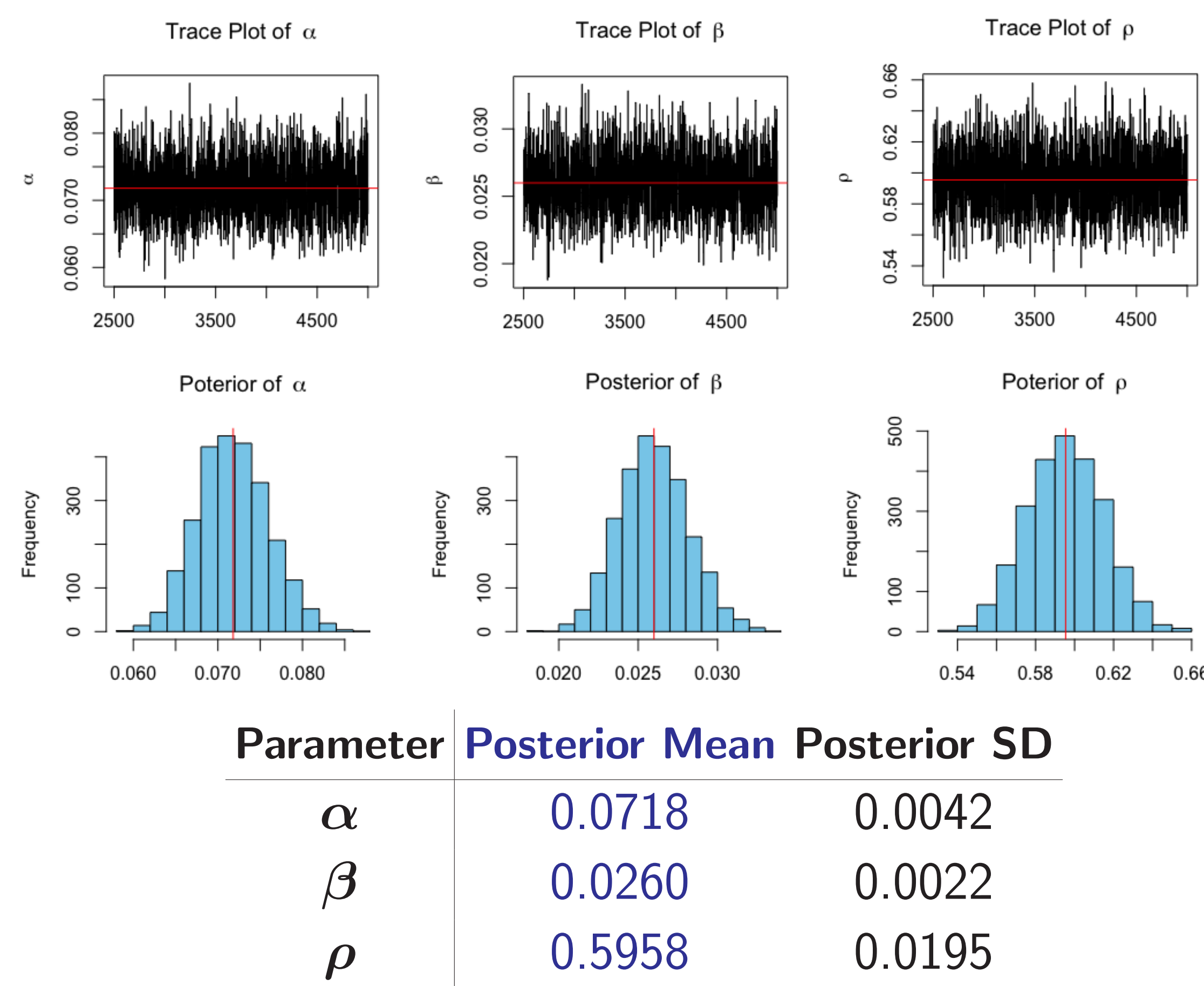
$$\begin{aligned} \log L &= \sum_{i=1}^n \log \lambda(t_i, x_i, y_i) - \iint_A \int_0^\infty \lambda(t, x, y) dt dx dy \\ &= \sum_{i=1}^n \log \lambda(t_i, x_i, y_i) - (1 - \rho)T \iint_A \mu(x, y) dx dy - \rho N \end{aligned}$$

## Bayesian Estimation

- **Bayesian Analysis:** A statistical paradigm that answers research questions about unknown parameters using probability statements.
- **Prior Distribution:** A probability distribution with respect to **current knowledge about parameters**, written as  $p(\theta)$ .
- **Likelihood:** **The information regarding parameters** contained by new data  $y$ , which is proportional to  $p(y|\theta)$ .
- **Posterior Distribution:** An updated probability distribution, on which all Bayesian inference is based, produced by **the combination of likelihood and the prior**, written as  $p(\theta|y)$ .
- The posterior is proportional to the prior times the likelihood:

$$p(\theta|y) = \frac{p(\theta)p(y|\theta)}{\int p(\theta)p(y|\theta)d\theta}, \text{ where } \theta = \{\alpha, \beta, \rho\}$$

## Results of Bayesian Estimation



- $\alpha$ : The intensity of triggering events **decays at a rate of  $1 - e^{-0.0718} = 6.93\%$  for every week that passes.**
- $\beta$ : The intensity of triggering events **decays at a rate of  $1 - e^{-0.026} = 2.57\%$  for every squared distance (in meters) away.**
- $\rho$ : **59.58% of events were triggered** by previous events. Thus, **40.42% is the background rate**, i.e., percentage of immigrant events.

## Bayesian Estimate Versus MLE

Maximum Likelihood Estimates obtained by Newton-Raphson algorithm:

Parameter	MLE	Standard Error
$\alpha$	0.0761	0.0045
$\beta$	0.0292	0.0022
$\rho$	0.5767	0.0193

- **Estimates from Bayesian MCMC are very close to MLEs.**
- **Bayesian estimates have such small standard deviations that can be considered as excellent estimates.**

## Markov Chain Monte Carlo (MCMC Algorithm)

- **Goal of MCMC:** Draw samples from a posterior distribution without having to know its exact height (probability) at any point.
- **Monte Carlo Methods:** A class of algorithms relies on repeated random sampling to obtain numerical results.
- **Markov Chain:** A type of Markov Process that has either discrete state space or discrete index set (often representing time).
  - ▷ The state of the chain after a number of steps is then used as a sample of the desired distribution.
- **MCMC Algorithm:**
  1. Set up prior distributions and proposal distributions

Parameter	Prior Distribution	Proposal Distribution
$\alpha$	Gamma(1,10)	Normal( $\alpha_0, 0.1$ )
$\beta$	Gamma(1,10)	Normal( $\beta_0, 0.1$ )
$\rho$	Uniform(0,1)	Beta( $\rho_0, 1 - \rho_0$ )

  2. Initialize  $\theta$  by randomly picking a **initial state** from each prior.
  3. For  $t$  in (1:50000), **update  $\theta$** :
    - ▷ **Propose a candidate  $\alpha_1$**  (randomly pick a candidate state from the proposal distribution based on current state  $\alpha_0$ ).
    - ▷ Compute **Metropolis-Hastings ratio  $R$** , which is  $\frac{p(\alpha_1|y)}{p(\alpha_0|y)}$ .
    - ▷ **Accept  $\alpha_1$  and replace  $\alpha_0$  at probability  $R$ .**
    - ▷ Proceed the same procedure above on  $\beta$  and  $\rho$ .
    - ▷ **Record  $\theta$**  after each iteration.
  4. After 50,000 iterations, return all states for parameters. **The 50,000 samples of each parameter make the posterior distributions.**
  5. Compute **the means of samples** as the estimates of parameters.
- **Thinning:** **Discard all but 10<sup>th</sup> observations** to get rid of autocorrelation to guarantee the independency of samples.
- **Burn-in:** **Throwing away first 2500 observations** to minimize the effect of initial values on the posterior inference.

## Future Work

- **Simulation** needs to be done to check if the adjusted ETAS model fits the actual red banana plants data.
- **More environment covariates and variables** should be considered into the spreading pattern of red banana plants, such as the distance from rivers, the amount of sunlight, elevation of plants etc.
- The adjusted ETAS model needs to be **applied on other invasive species or point-process natural events** to assess its effectiveness.

## Reference

- Ogata, Y.(1988), "Statistical Models for Earthquake Occurrences and Residual Analysis for Point Processes," *Journal of the American Statistical Association*, 83, 9-27.
- Balderama, E.(2012), "Spatial-Temporal Branching Point Process Models in the Study of Invasive Species," *University of California, Los Angeles*