

Introduction to spatial point process and its Fourier analysis

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Fundamentals

Point pattern data

Spatial locations of things or events

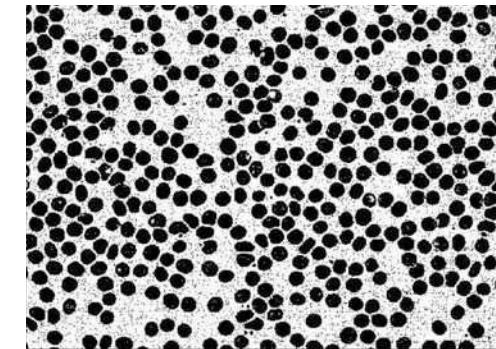
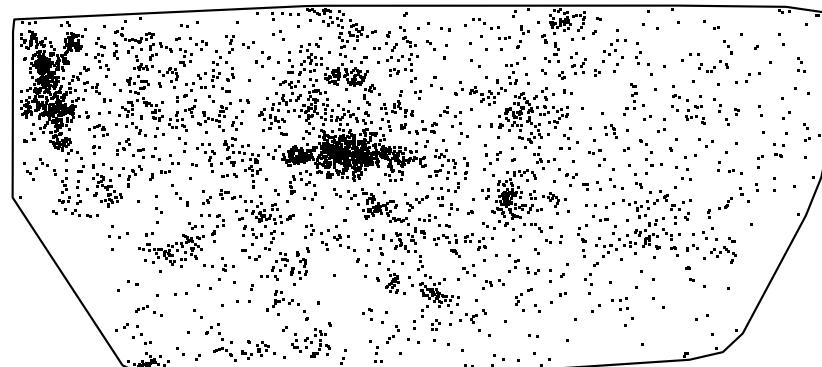
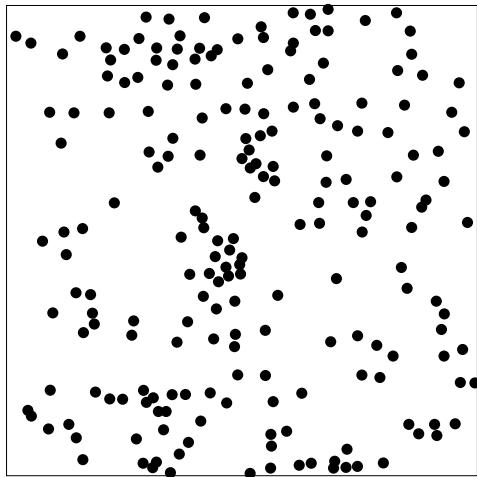


For a study area, **all locations are observable!**

Locations without a point = observed but no event happened!

Point pattern data

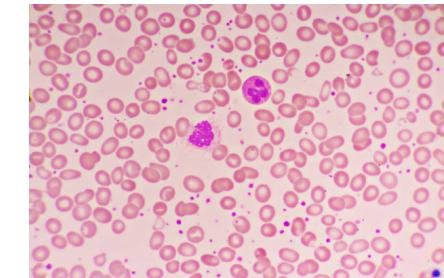
Spatial locations of things or events



Japanese black pine seedlings



Sky positions of 4215 galaxies in the Shapley Supercluster



Red blood particles

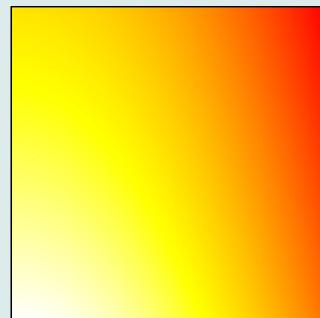
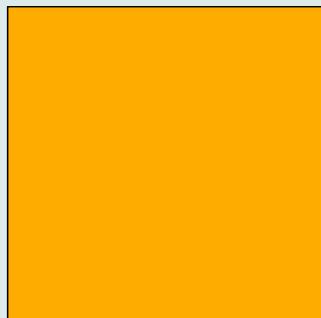
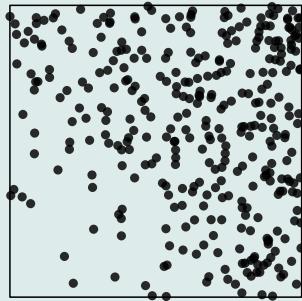
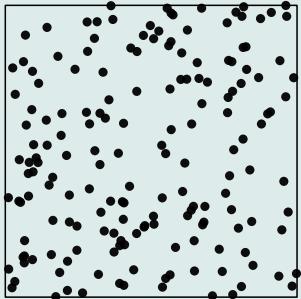
For a study area, **all locations are observable!**

Locations without a point = observed but no event happened!

Characteristics of point process

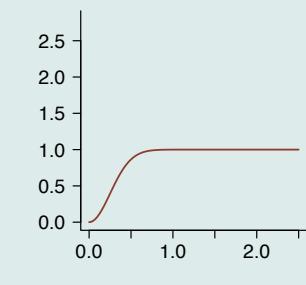
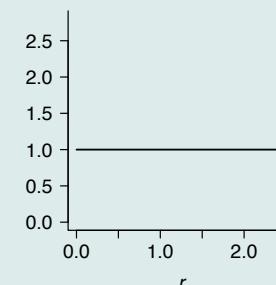
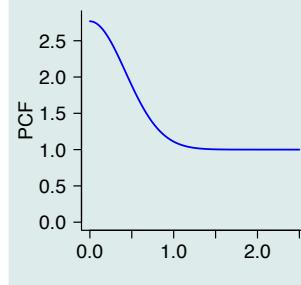
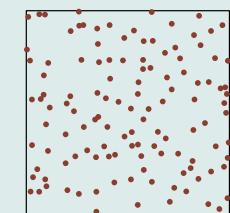
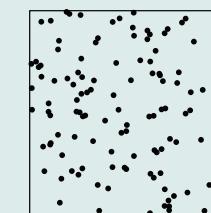
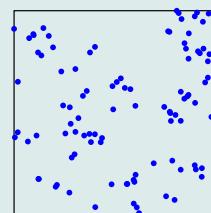
Intensity function: $\lambda(x)$

$\propto \mathbb{P}(\text{Having a point at location } x)$

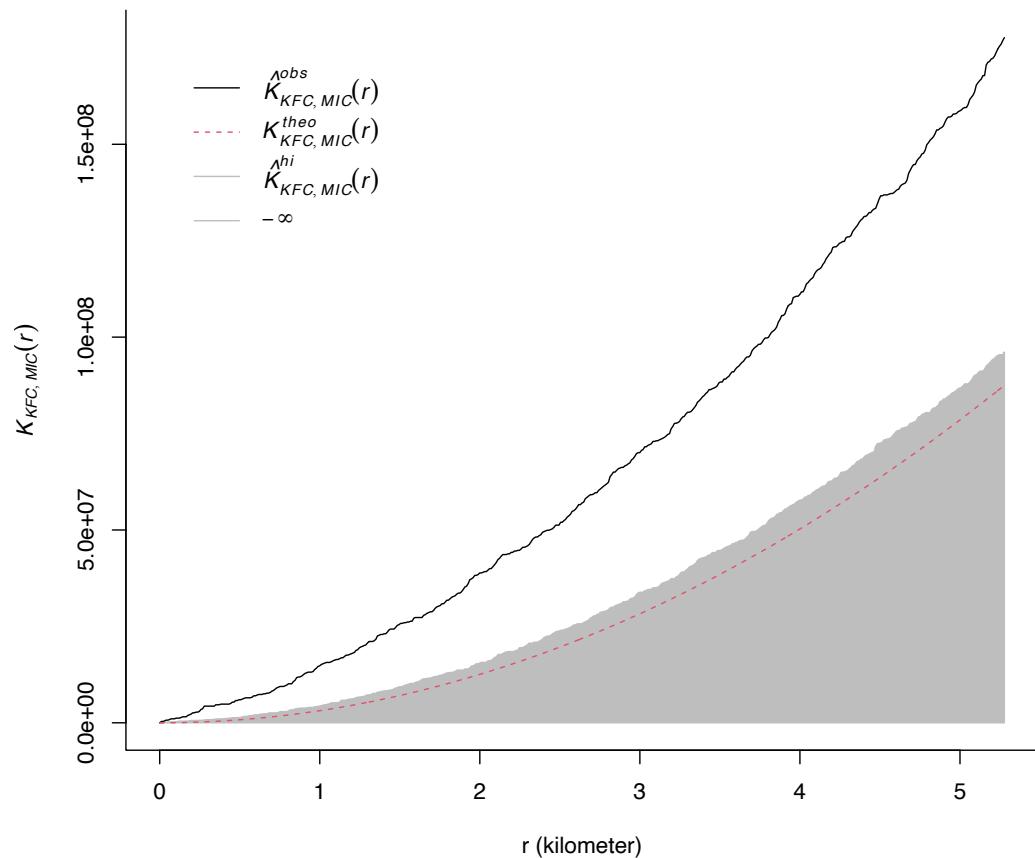
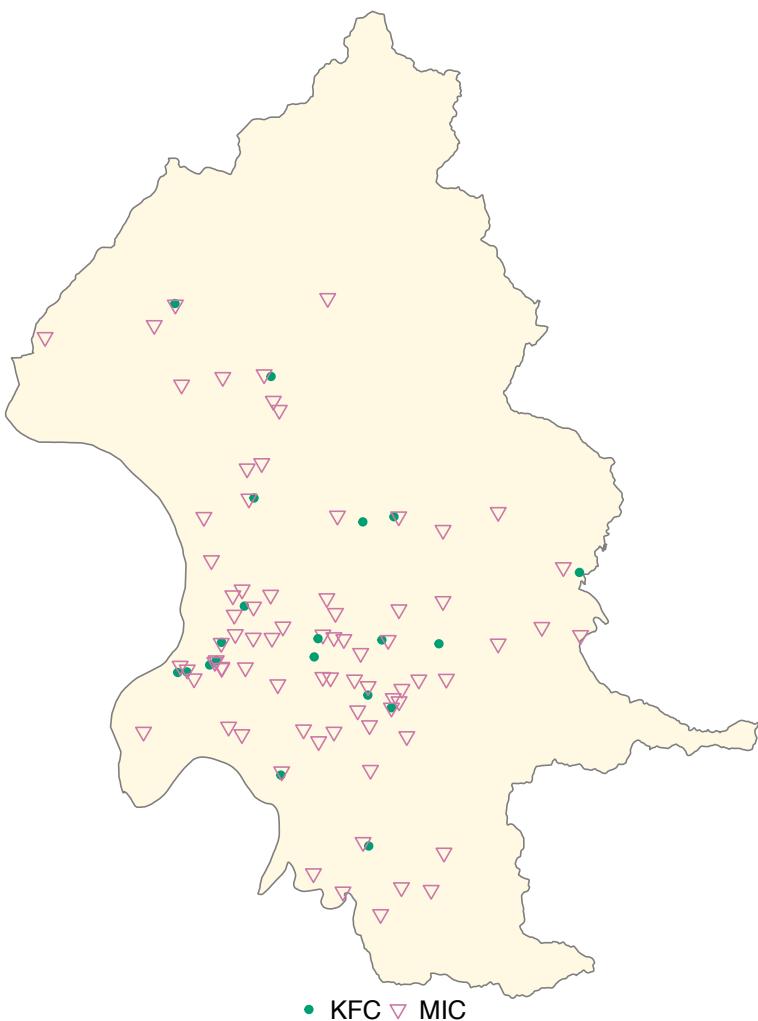


Pair correlation function: $g(r)$

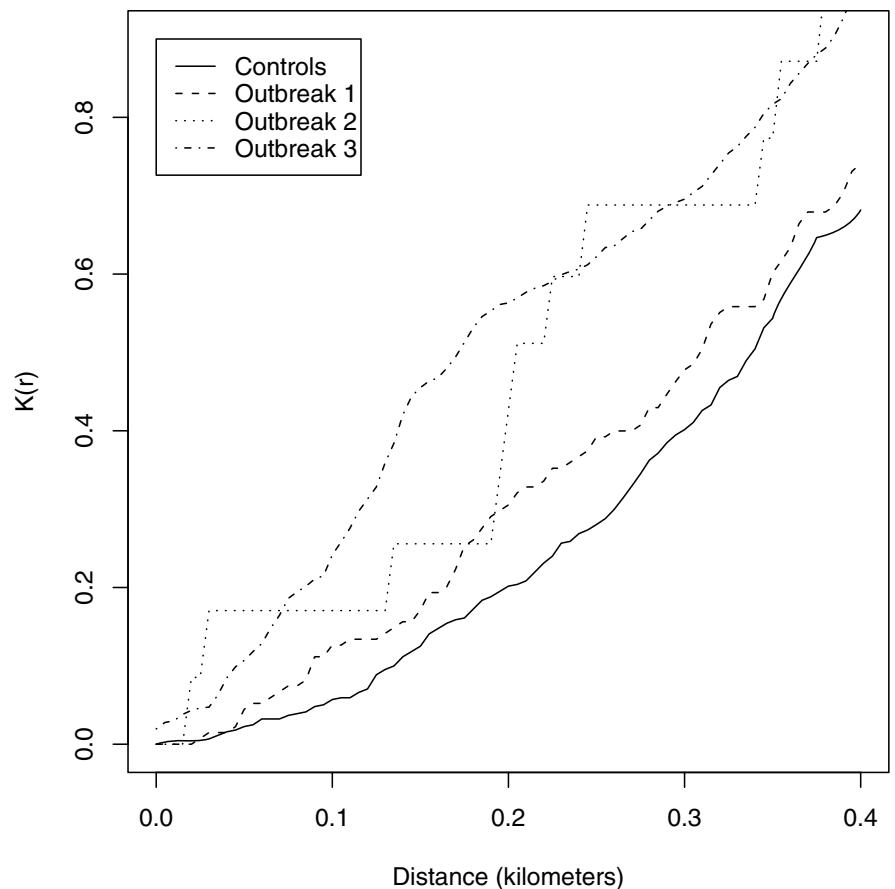
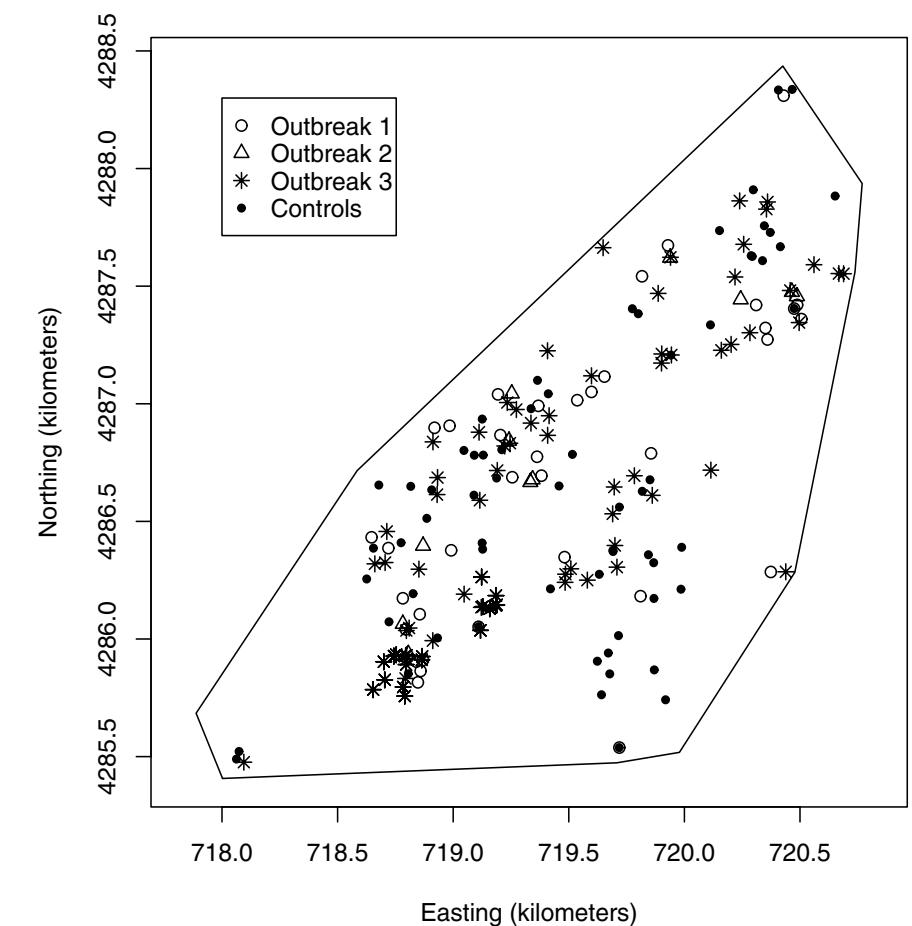
How events interact at radius r



Example 1: Type interaction



Example 2: Source detection of infectious disease⁷



Fourier analysis of point processes

Time series vs. spatial point processes

Time series model

- White noise : $e_t \stackrel{\text{iid}}{\sim} \mathcal{N}(0, \sigma^2)$
- MA(1) : $X_t = e_t + \theta e_{t-1}$
- AR(1) : $X_t = \alpha X_{t-1} + e_t$

ACF

- $\gamma(k) = \sigma^2 \mathbb{1}\{k = 0\}$
- $\gamma(k) = \theta \sigma^2, k = \pm 1$
- $\gamma(k) = \alpha^{|k|} \sigma_X^2$

Spectral density

- $f(\omega) = \sigma^2 / (2\pi)$
- $f(\omega) = \sigma^2 (1 + \theta^2 + 2\theta \cos \omega) / (2\pi)$
- $f(\omega) = \frac{\sigma^2}{2\pi(1 - 2\alpha \cos \omega + \alpha^2)}$

Point process model

- Homogeneous Poisson process
- Thomas cluster process
- Determinantal point process

PCF

- $g(r) = 1$
- $g(r) = 1 + \frac{e^{-r^2/4\sigma^2}}{4\pi\kappa\sigma^2}$
- $g(r) = 1 - \left(e^{-r^2/\sigma^2}\right)^2$

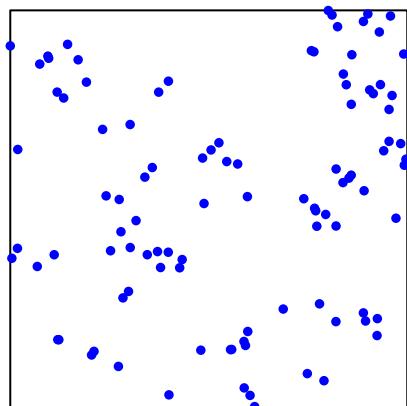
Spectral density

- $f(\omega) = (2\pi)^{-d} \lambda$
- $f(\omega) = (2\pi)^{-d} \kappa \mu \left[1 + \mu e^{-\sigma^2 \|\omega\|^2} \right]$
- $f(\omega) = (2\pi)^{-d} \left[\lambda - \lambda^2 \left(\frac{\pi\sigma^2}{2} \right)^{\frac{d}{2}} e^{-\frac{\sigma^2 \|\omega\|^2}{8}} \right]$

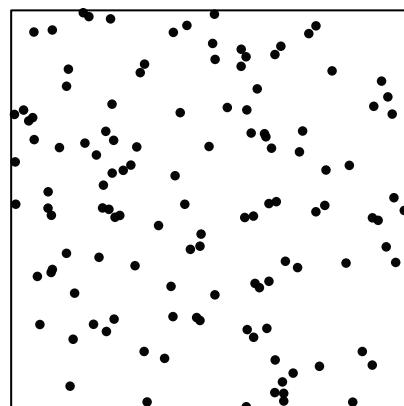
For stationary and isotropic case, $g(\mathbf{x}_i, \mathbf{x}_j) = g(\|\mathbf{x}_i - \mathbf{x}_j\|) = g(r)$.
Parameter: $\boldsymbol{\theta}_{\text{Thomas}} = (\kappa, \mu, \sigma^2)^T$, $\boldsymbol{\theta}_{\text{Determinantal}} = (\lambda, \sigma^2)^T$.

PCF and spectral density

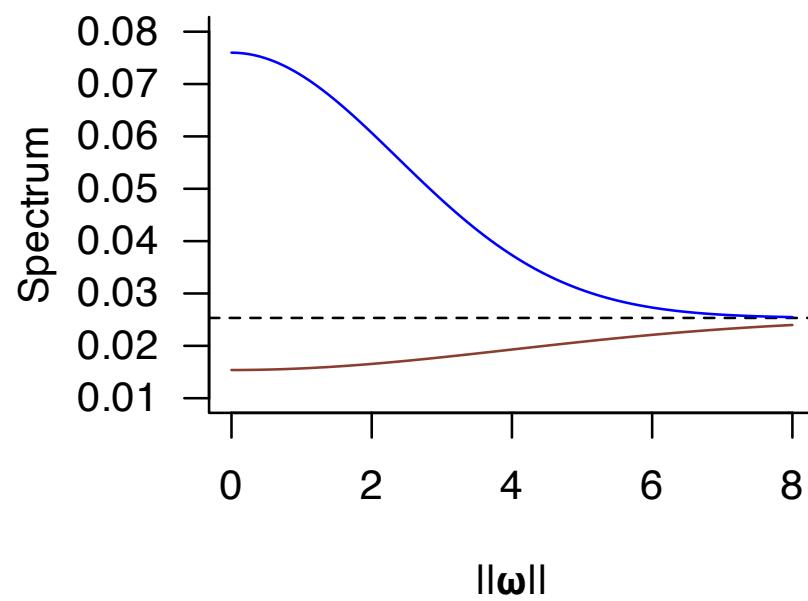
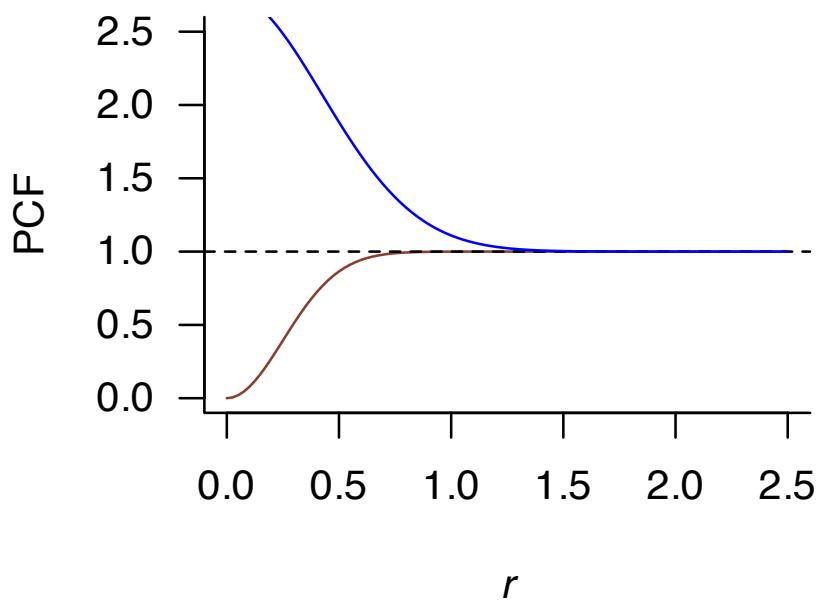
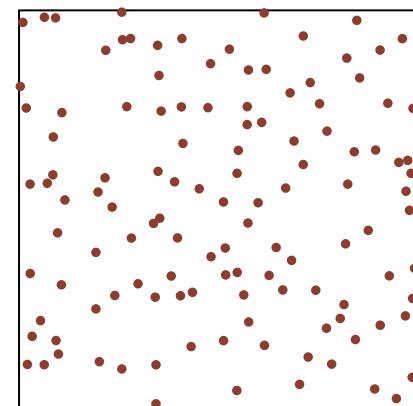
Thomas process
 $(\kappa = 0.5, \sigma = 0.3, \mu = 2)$



Poisson process
 $(\lambda = 1)$



DPP with Gaussian kernel
 $(\lambda = 1, \sigma = 0.5)$



Frequency domain parameter estimation

Whittle-type likelihood

Let $\{X_\theta\}$ be a family of 2nd-order stationary point processes with parameter $\theta \in \Theta$. The associated spectral density is denoted as f_θ . Then, we fit the model using the pseudo-likelihood

$$L(\theta) = \sum_{\omega_k \in D} \left\{ \frac{\hat{I}(\omega_k)}{f_\theta(\omega_k)} + \log f_\theta(\omega_k) \right\}.$$

Intuition

- $\hat{I}(\omega)$ can be regarded as the “truth” since $\mathbb{E}[\hat{I}_n(\omega)] \rightarrow f(\omega)$.
- $f_\theta(\omega)$ are the parameter family of spectral densities.
- $L(\theta)$ is the **spectral divergence between the truth and our guess. The smaller the better!**

Proposed model parameter estimator

$$\hat{\theta} = \arg \min_{\theta \in \Theta} L(\theta)$$

Frequency domain parameter estimation

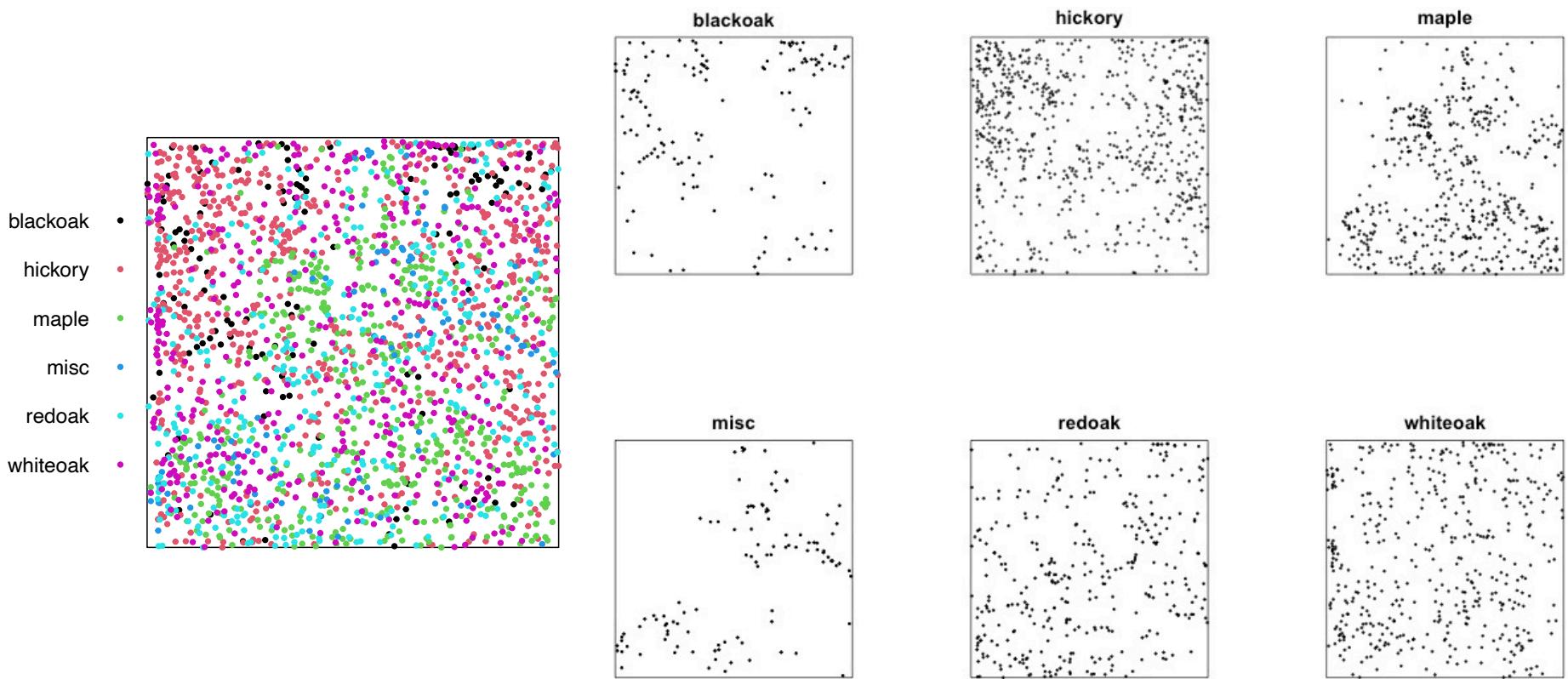
Model	Window	Parameter	Method		
			Ours	ML	MC
TCP	[-5, 5] ²	κ	-0.04 (0.11)	-0.02 (0.11)	-0.04 (0.10)
		μ	0.72 (3.52)	-0.24 (5.93)	-
		σ^2	0.02 (0.07)	-0.04 (0.22)	0.01 (0.10)
	[-10, 10] ²	Time (sec)	0.74	0.38	0.07
		κ	-0.02 (0.05)	-0.02 (0.05)	-0.01 (0.05)
		μ	0.60 (1.77)	0.33 (2.79)	-
	[-20, 20] ²	σ^2	0.01 (0.02)	-0.01 (0.11)	0.00 (0.06)
		Time (sec)	2.38	5.67	0.23
		κ	-0.01 (0.04)	0.00 (0.03)	0.00 (0.03)
		μ	0.25 (1.03)	0.15 (1.23)	-
		σ^2	0.01 (0.02)	0.00 (0.03)	0.00 (0.03)
		Time (sec)	9.15	173.66	1.95

The bias and the standard errors (in parentheses) of the estimated parameters based on three different approaches for the Thomas clustered process (TCP)

Future directions

Multivariate point pattern

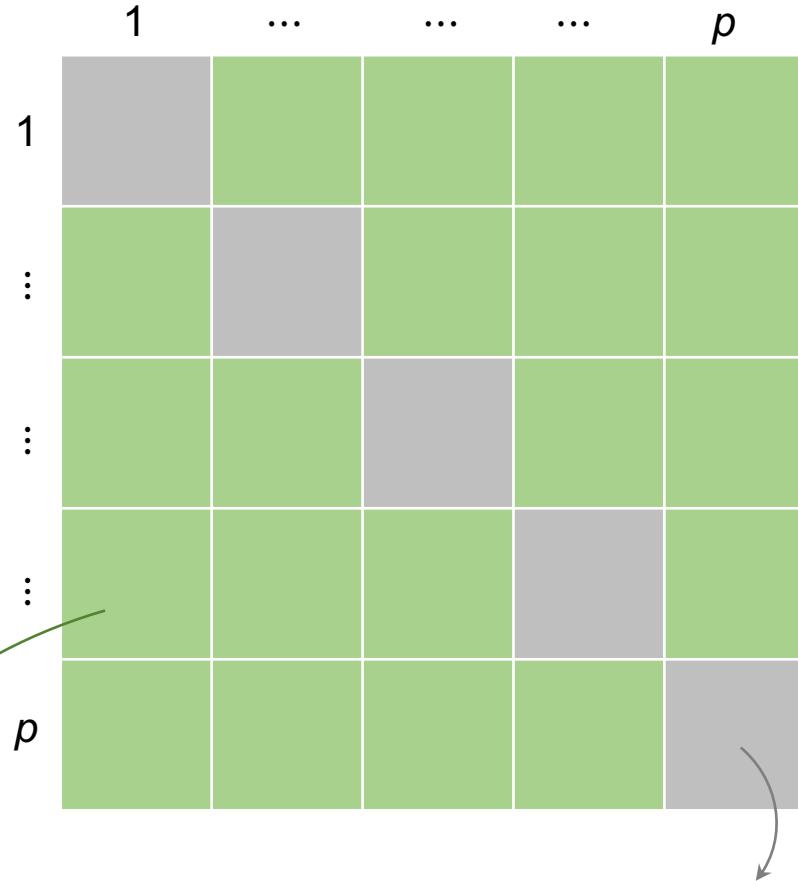
Multivariate = each point belongs to some **category**



Location of trees in Lansing woods, **marked** by their **species**

Multitype point pattern

Consider a p -variate process: $i, j \in \mathcal{V} = \{1, 2, \dots, p\}$



Spectral coherence:

$$R_{ij}(\boldsymbol{\omega}) = \frac{f_{ij}(\boldsymbol{\omega})}{[f_{ii}(\boldsymbol{\omega})f_{jj}(\boldsymbol{\omega})]^{\frac{1}{2}}}$$

Cross-spectrum:

$$f_{ij}(\boldsymbol{\omega}) = (2\pi)^{-d} \int_{\mathbb{R}^d} C_{ij}(\mathbf{x}_1 - \mathbf{x}_2) e^{-i\mathbf{x}^\top \boldsymbol{\omega}} d\mathbf{x}$$

Marginal spectrum:

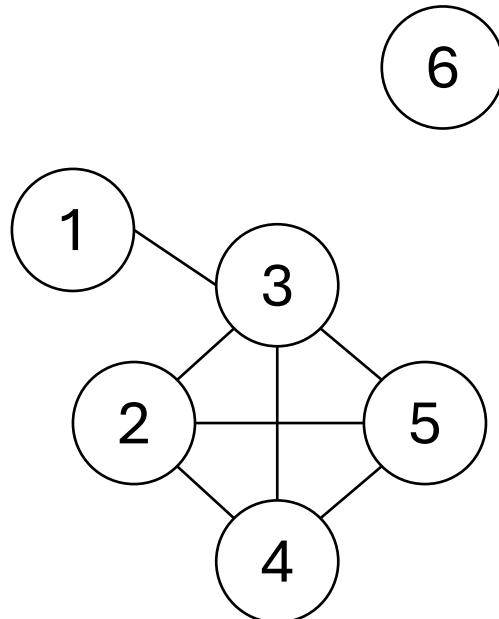
$$f_{ii}(\boldsymbol{\omega}) = (2\pi)^{-d} \int_{\mathbb{R}^d} C_{ii}(\mathbf{x}_1 - \mathbf{x}_2) e^{-i\mathbf{x}^\top \boldsymbol{\omega}} d\mathbf{x}$$

Spatial dependence graph model (SDGM)

SDGM (Eckardt, 2016)

Let \mathbf{N}_ν be a multivariate spatial counting process. A SDGM is an **undirected graphical model** $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where any $v_i \in \mathcal{V}(\mathcal{G})$ encodes a component of \mathbf{N}_ν and $\mathcal{E}(\mathcal{G}) = \{(v_i, v_j) : R_{ij|\mathcal{V}\setminus\{i,j\}}(\boldsymbol{\omega}) \neq 0\}$ such that

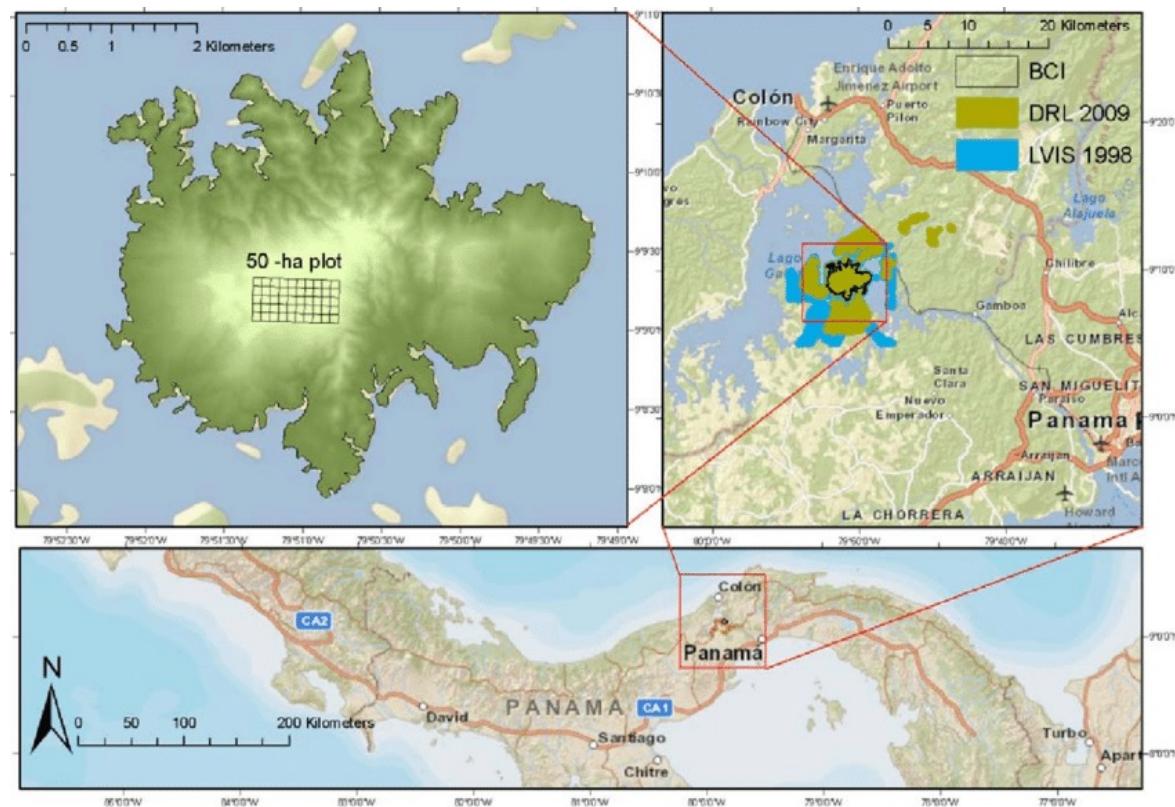
$$\{N_i\} \perp\!\!\!\perp \{N_j\} | \{N_{\mathcal{V}\setminus\{i,j\}}\} \Leftrightarrow (v_i, v_j) \notin \mathcal{E}(\mathcal{G}).$$



For $\{N_i : i \in I \subset \mathbf{N}_\nu\}$, $\{N_j : j \in J \subset \mathbf{N}_\nu\}$, and $\{N_h : h \in H \subset \mathbf{N}_\nu\}$,

$$\begin{aligned} N_I \perp\!\!\!\perp N_J | N_H &\Leftrightarrow f_{I,J|H}(\boldsymbol{\omega}) = 0, \forall \boldsymbol{\omega} \\ &\Leftrightarrow R_{I,J|H}(\boldsymbol{\omega}) = 0, \forall \boldsymbol{\omega} \\ &\Leftrightarrow \text{Missing edges between } N_I \text{ and } N_J \end{aligned}$$

Barro Colorado Island (BCI) data



207,718 alive trees

310 species

7 censuses



Figure 1 in Fricker et al. (2012)

Barro Colorado Island (BCI) data

cappfr



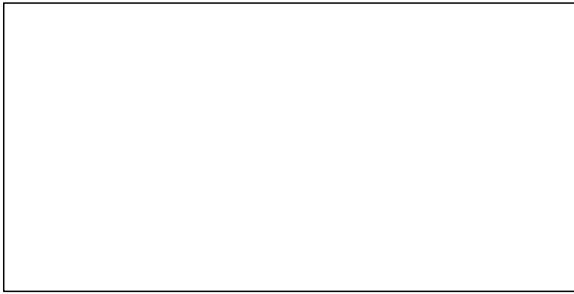
hirttr



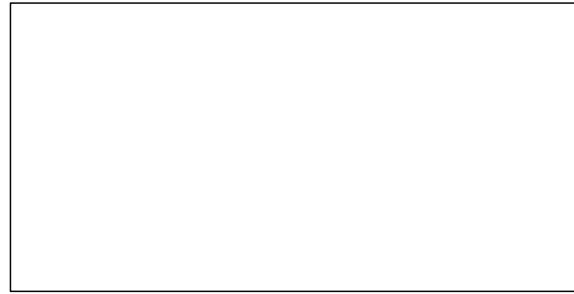
protpa



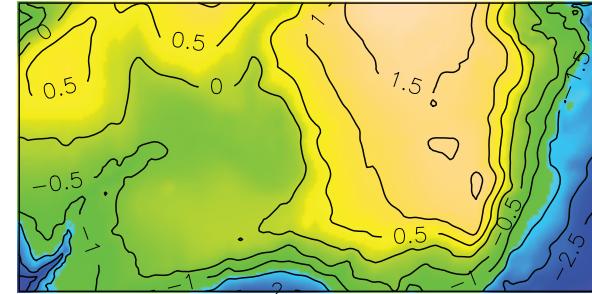
protte



tet2pa



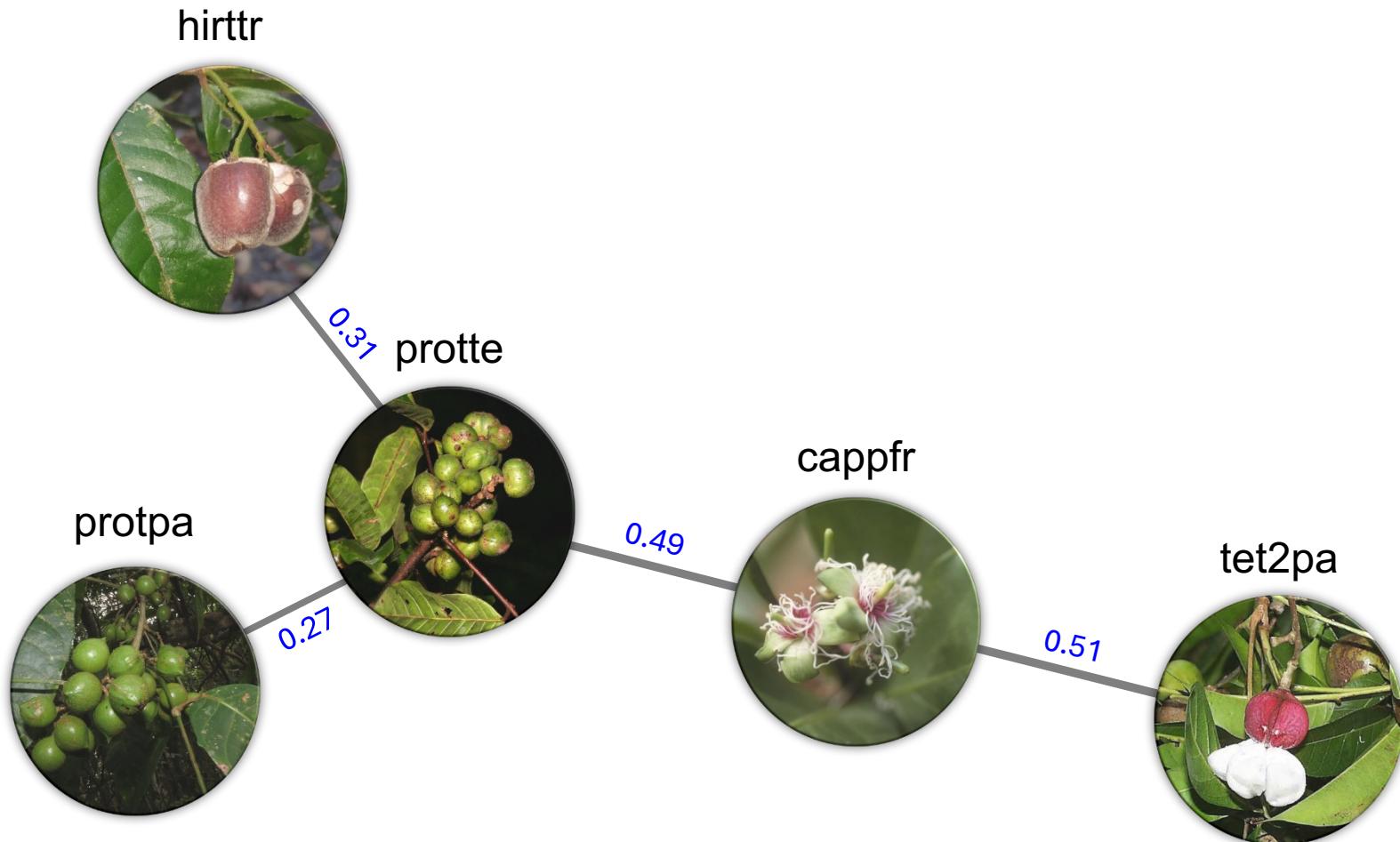
elevation



Point patterns of five species in the BCI dataset and image of elevation in the study region.

BCI data: Graphical model

Threshold = 0.2



Value = max squared partial coherence