

Spatial correlation and deconvolution: (attempting to) estimate spatial process from pattern

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Biomath seminar

20 November 2009

Outline

- 1 Overview & motivation: landscapes and models
- 2 Correlations & correlation equations
- 3 Deconvolution
- 4 Example # 2: estimating habitat preferences

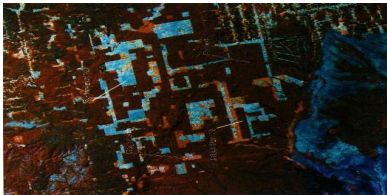
Ecological landscapes



endogenous/exogenous?



endogenous: foci



anthropogenic patches



fractal?

Interactions in ecological landscapes

Geometries:

- endogenous vs. exogenous
- continuous vs. discontinuous
- disorganized vs. coherent/deterministic

Interactions:

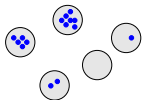
- competition
- local dispersal
- social aggregation
- predator/prey (host/pathogen)
- disturbance

Case study: spatial synchrony

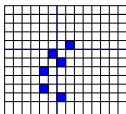
- Many (animal) populations display population fluctuations in *synchrony* across broad geographic regions: grouse, voles, butterflies, lynx and hares . . . e.g. Eastern spruce budworm, *Choristeroneura fumiferna*
- Driving process(es): correlated environmental variation (the *Moran effect*), dispersal, nomadic predators?
- “you can’t subtract thunderstorms from lemmings spruce budworms”



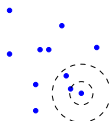
Geometries for spatial ecology



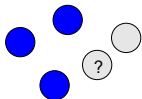
patch/metapopulation



lattice



point process/IBM



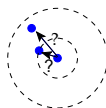
patch occupancy models
 ("classical" metapops)

$$p' = cp(1-p) - mp$$



pair approximation

$$p([n0])' = \dots$$



PDEs or spatial moment equations

$$\frac{\partial c(r)}{\partial t} = \dots$$

Spatial correlation/covariance

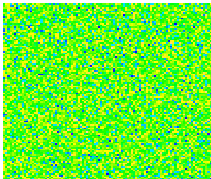
- Describe the relationship between conditions at two points a given distance apart
- Spatial covariance:

$$c_{ij}(|\mathbf{x} - \mathbf{y}|) \propto \langle (n_i(\mathbf{x}) - \bar{n}_i) \cdot (n_j(\mathbf{y}) - \bar{n}_j) \rangle$$

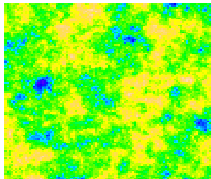
- Correlation is a scaled version ($\in [-1, 1]$)

Spatial patterns

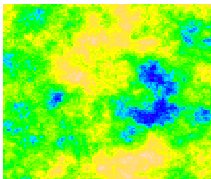
Random



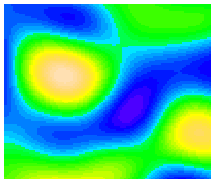
Short-range



Long-range

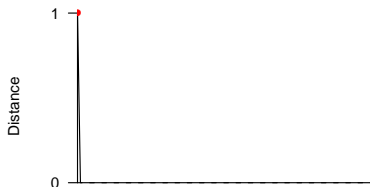


Even

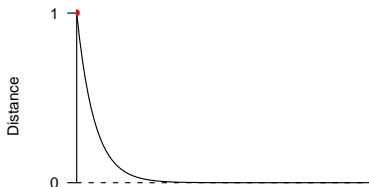


Spatial correlations as a function of distance

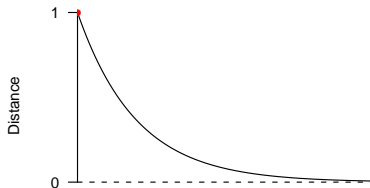
Random



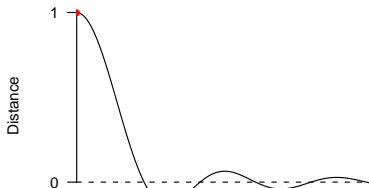
Short-range



Long-range



Even



Correlation equations

Define individual-based spatial process
Write down transition rules

Moment equations

Derive expected changes in mean
density and spatial correlation

Assume (second-order) spatial
homogeneity

Moment closure

Continuous equations

Derive expected changes in density

Assume continuous densities

Linearize around equilibrium

Fourier transform correlation equations
Solve for equilibrium correlations/power spectrum

Correlation equations: alternate derivations

via moment equations:

- small-scale patterns
- allows/requires detailed consideration of interactions
- noise terms emerge naturally from dynamics

via continuous equations:

- large-scale patterns
- simple extension of existing models
- allows arbitrary scaling of noise terms

Correlation equations: *via* moment equations

$$\frac{\partial c_{\mu n}(\rho)}{\partial t} = \underbrace{f(D * c_{\mu n})}_{\text{clustering}} - \underbrace{\bar{n} c_{\mu\mu}}_{\text{habitat association}} - \underbrace{\bar{\mu} c_{\mu n} - \alpha \bar{n} (U * c_{\mu n} + c_{\mu n})}_{\text{thinning}}$$

$$\frac{1}{2} \cdot \frac{\partial c_{nn}(\rho)}{\partial t} = \underbrace{f(D * c_{nn} + D\bar{n})}_{\text{clustering}} - \underbrace{\bar{n} c_{\mu n}}_{\text{habitat association}} - \underbrace{\bar{\mu} c_{nn} - \alpha \bar{n} (c_{nn} + U * c_{nn} + U\bar{n})}_{\text{thinning}}$$

Correlation equations: *via* continuous eqns

cf. Lande et al. 1999, Engen et al. 2002:

$$\frac{\partial N(\mathbf{x}, t)}{\partial t} = \underbrace{F(N(\mathbf{x}, t), E(\mathbf{x}, t))}_{\text{pop. growth}} - \underbrace{mN(\mathbf{x})}_{\text{emigration}} + \underbrace{m \int D(\mathbf{y}, \mathbf{x}) N(\mathbf{y}) d\mathbf{y}}_{\text{immigration}}$$

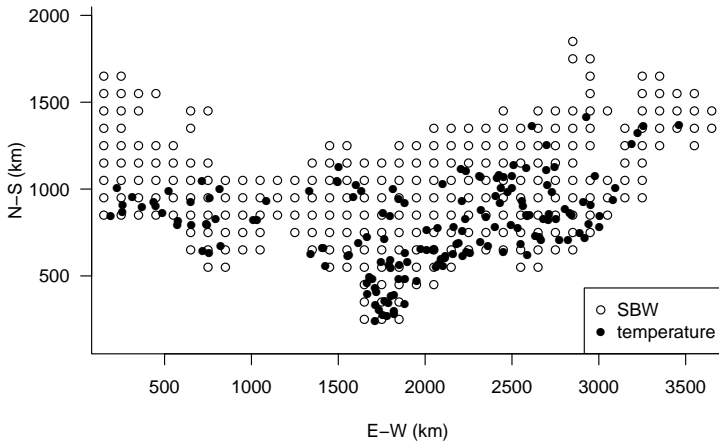
$$\frac{\partial n}{\partial t} \approx \underbrace{-rn(\mathbf{x}, t)}_{\text{regulation}} + \underbrace{m(D * n - n)}_{\text{redistribution}} + \underbrace{\sigma_E^2 e(\mathbf{x}, t)}_{\text{noise}}$$

$$2(r + m)c^* = m(D * c^*) + \sigma_E^2 \text{Cor}(e)$$

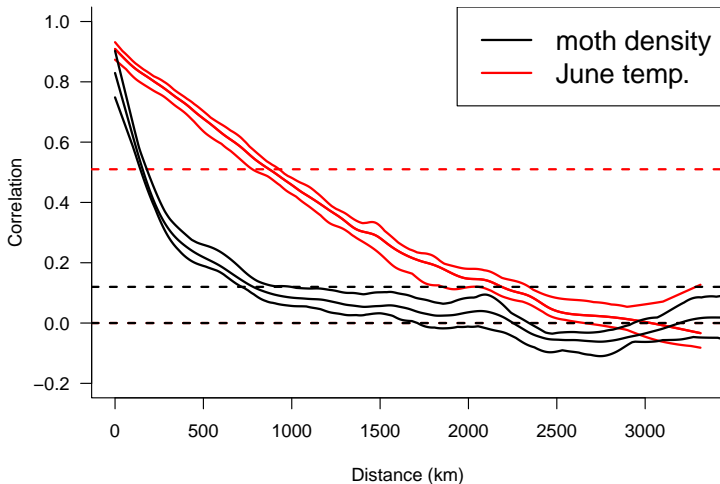
Combining theory and data

- Classical approach: *empirical* and/or *qualitative* predictions (strong inference)
- Instead, *decompose* spatial patterns by multiple processes: estimation rather than hypothesis testing
- Technical challenge of quantifying spatial patterns and drivers
- ...

Moth sampling locations



Spatial correlations of moth data



Spatial logistic: solution

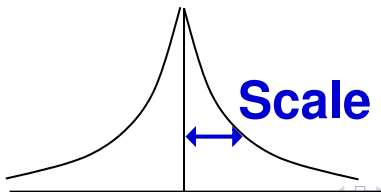
At equilibrium, the power spectrum of the population densities obeys

$$\tilde{S} = \left| \left(\tilde{N}^* \right) \right|^2 = \frac{\sigma_E^2 \tilde{e}}{2(r + m(1 - \tilde{D}))}$$

where $\tilde{\cdot}$ denotes the Fourier transform. Therefore:

$$\text{Scale}^2(p) = \text{Scale}^2(e) + \frac{m}{r} \text{Scale}^2(d)$$

(Lande et al. 1999) where Scale represents the standard deviation of the autocorrelation function *with respect to space*



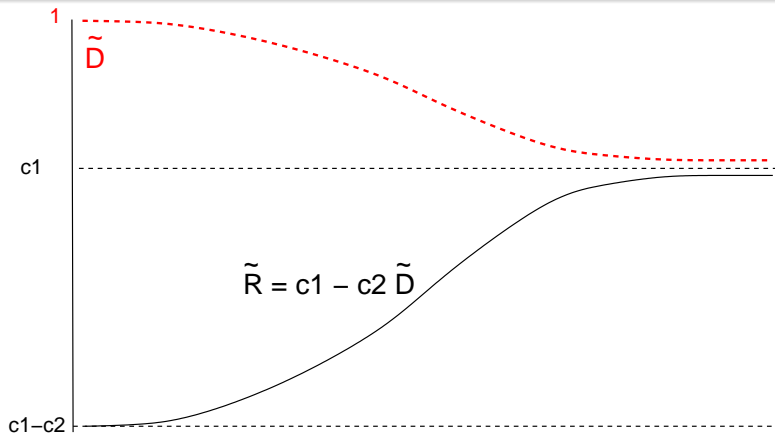
Spectral ratios

Alternatively, we can calculate the *spectral ratio*:

$$\tilde{R} = \frac{\tilde{e}}{\tilde{S}} = \frac{2}{\sigma_E^2}(r + m(1 - \tilde{D})) = c_1 - c_2\tilde{D}$$

Re-inverting this corresponds to *deconvolving* the effects of environmental variability from the population pattern ...

Reconstructing the dispersal curve



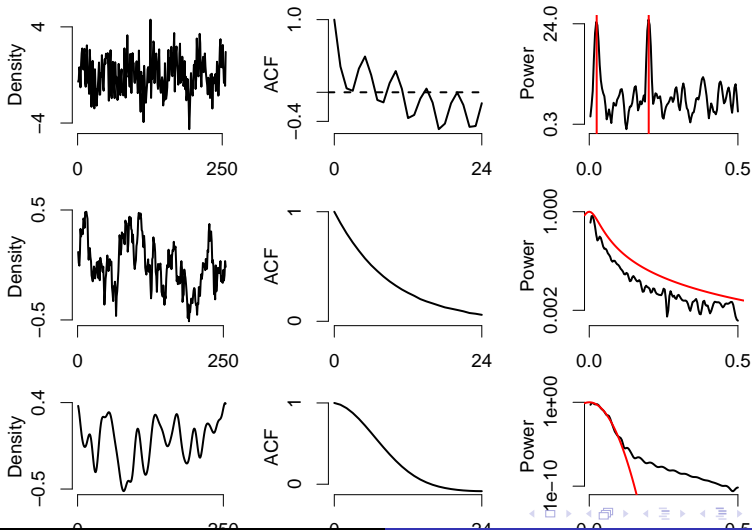
We know the limits $\tilde{D}(0) = 1$, $\tilde{D}(\infty) \rightarrow 1$: thus

$$\tilde{D}_{\text{est}}(\omega) = \frac{\tilde{R}(\infty) - \tilde{R}(\omega)}{\tilde{R}(\infty) - \tilde{R}(0)}$$

Spatial power spectra

- Measure variance or *power* accounted for by a given *spatial frequency*
- May be familiar from time series: emphasize different features than correlation analysis (e.g. periodicity)

Landscapes, correlations, and power spectra



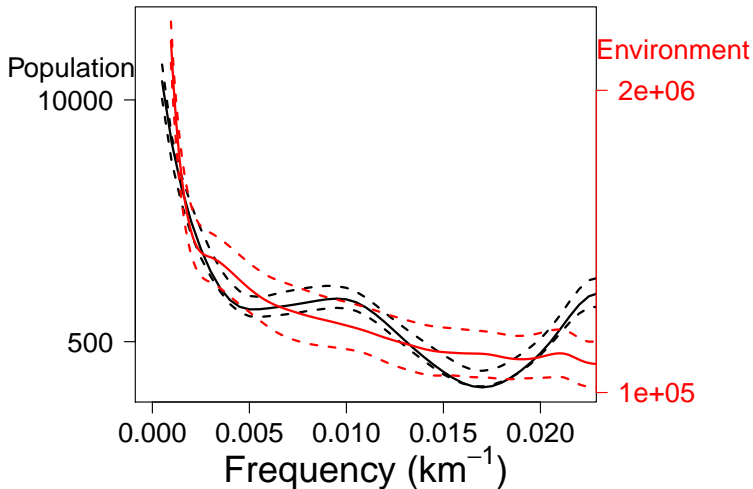
Spatial power spectra: methods

Challenge: unevenly sampled, 2D data

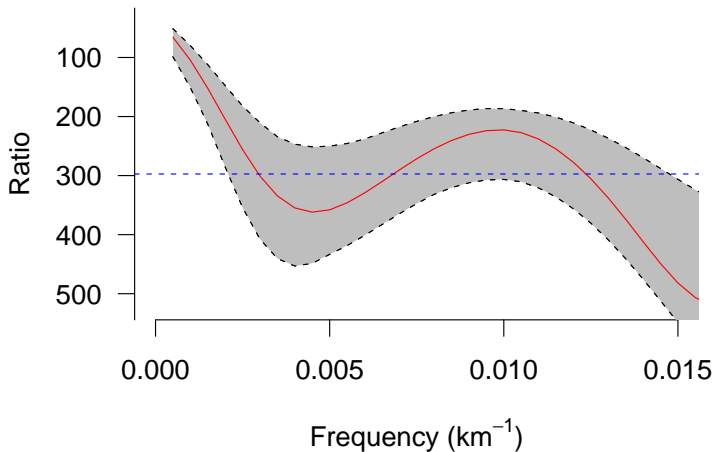
- Nonparametric models (direct Fourier/Hankel transform)
- Geostatistics: simple parametric models (exponential, spherical, etc.)
- Spatial ARMA models

Tradeoff between generality and simplicity/statistical power: biases in nonparametric estimates?

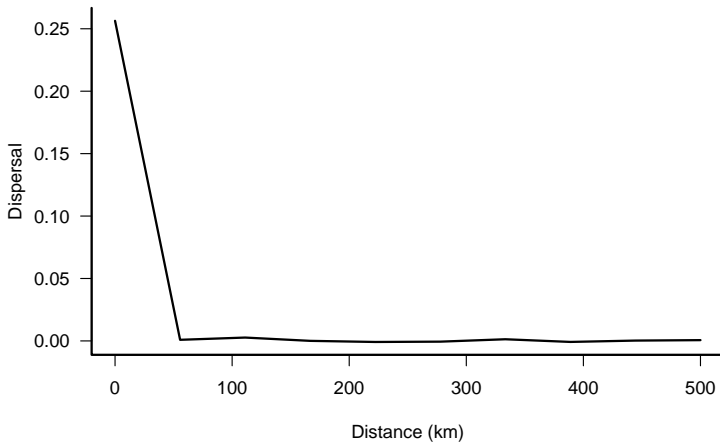
Moth data: spectra



Moth data: spectral ratios



(Putative) moth dispersal curve



- We often want to estimate the effects of some *local* environmental variable (e.g. habitat, competitor density) on an ecological response (population density, fecundity)
- but not sure about the spatial scale of the relationship
- existing methods:
 - regress response on local averages at different scales
 - inverse methods
- what if (1) data are not measured in commensurate ways, (2) we want a nonparametric estimate?

Model

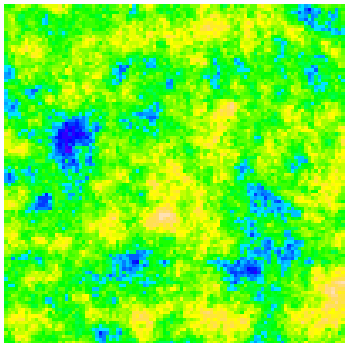
We can think of this as (surprise!) a convolution:

$$N(x) \propto (E * H)(x)$$

where E is the environmental variable (water?) and H is the *habitat kernel*

example: habitat selection

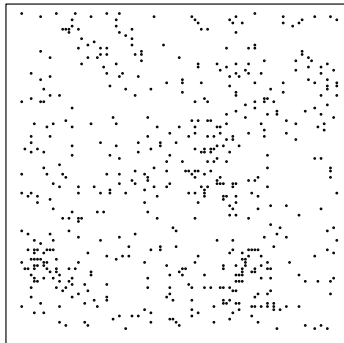
habitat



0

100

population

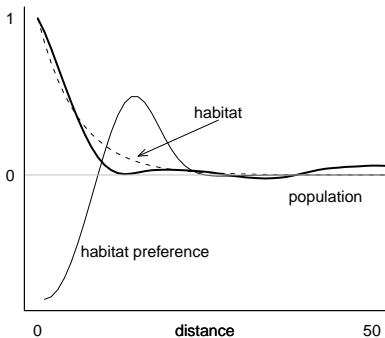


0

100

drivers

correlations & preference



Solution

If $N(x) \propto (E * H)(x)$ then

$$C_{EN}(r) = (C_{EE} * H)(r)$$

and ...

$$\tilde{C}_{EN}(\omega) = \tilde{C}_{EE}(\omega)\tilde{H}(\omega)$$

$\tilde{H} = (\tilde{C}_{EN}/\tilde{C}_{EE})(\omega)$ is hence the ratio of the cross-spectrum of (environment \times population) divided by the power spectrum of the environment ...

Caveats, limitations, & challenges

- Fluctuating populations (synchrony vs. population correlation)
- Strongly nonlinear dynamics: *linearization*
- Non-normal responses
- Numerical stability of ratios
- Nonparametric (or flexible) spectral estimates

Correlation equations: applications

- Theoretical analyses of plant competition
- Evolution of dispersal
- Synchrony
- Separating spatial processes in plant competition (esp. step-by-step)

Acknowledgements

Ottar Bjørnstad, Sandy Leibhold, Stephen Cornell, NCEAS

photo credits:

<http://www.crh.noaa.gov/mkx/slide-show/tstm/>

http://www.pfc.forestry.ca/biotechnology/posters/optical_e.html