Delineating cohesive ecological boundaries across scales

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† Deceased
Outline

• Cohesive Ecological Boundaries

• Effects of Spatial Autocorrelation on Detection of Boundaries

• Boundary Detection
  Local Edge Detector
  Global Edge Detector

• Patch Growing
  Local Spatial Statistics
Boundaries may be surrounding an area (A) or not (open: B and C).

Boundaries may be sharp (A and B) or gradual/soft (C).

They may be natural (forest edge) or artificial (road).
Cohesive Boundaries

- Patch A
- Patch B
- Patch C

Cohesive Boundary: Connected Edges

Edges
Boundaries at Multiple Scales

Gosz 1993
Landscape Spatial Heterogeneity

Stationary over the entire landscape but not locally
Patch or Boundary
Spatial Partition

- **Quantitative Data**
  - Yes
    - **Contiguous Data**
      - Yes
        - Spatial Clustering (L-PG)
        - Lattice-Wombling (L-ED)
        - Wavelets (G-ED)
        - Scale-Space (G-ED)
      - No
        - Spatial Clustering (L-PG)
        - Categorical-Wombling (L-ED)
  - No

L-PG: Local Patch-Growing
L-ED: Local Edge Detector
G-ED: Global Edge Detector
Boundary Detection

Sharp

Soft/Gradual
Boundary Detection

Edge Detectors

Local
- Laplacian
  - Lattice-Womble
- Sharp/Gradual
  - Open/Close
- Boundary Detected

Global
- Wavelets
  - Scale-Space
- Sharp
  - Close
Local Edge Detector

Edge/Boundary = Local High Rate of Change

Highest rates = Boundaries
Arbitrary threshold
Lowest rates = Patches
Effects of Spatial Autocorrelation

Value (z)

High Variance

Highest Rate of Change

Mean of Patch A
Mean of Patch B
Mean of Patch C

Location (x)

Low Variance

Low Variance

Spatial Autocorrelation
Effects of Spatial Autocorrelation

Two-patch landscapes (50 × 50 cells) based on conditional autoregressive model:

\[ P[z(s_i)]: \sim \text{Gauss}(\rho_i \cdot \text{ave}(z(N_i)), t_i) \]

where:
- \( \text{ave}(z(N_i)) = \) the average of the neighbors of location \( s_i \)
- \( t = \) conditional variance
- \( \rho = \) spatial autocorrelation
Number of Boundaries (20 replicates)
\[\Delta \text{Mean} = 1, \text{Variance} = 1\]

Spatial Autocorrelation: \(r_1\) and \(r_2\)
Number of Boundaries (20 replicates)

\[ \Delta \text{Mean} = 2, \text{Variance} = 1 \]

Spatial Autocorrelation: \( r_1 \) and \( r_2 \)
Number of Boundaries (20 replicates)

\[ \Delta \text{Mean} = 10, \text{Variance} = 1 \]

Spatial Autocorrelation: \( r_1 \) and \( r_2 \)

<table>
<thead>
<tr>
<th>( r_1 )</th>
<th>( r_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>0.0</td>
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</tr>
<tr>
<td>0.95</td>
<td>0.99</td>
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<tr>
<td>0.99</td>
<td>0.99</td>
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</tbody>
</table>
Scalable Wombling

2 × 2  

4 × 4  

8 × 8
Scalable Womble

Number of Boundaries (20 replicates)

$\Delta$ Mean = 2, Variance = 1

Spatial Autocorrelation: $r_1 (0.0)$ and $r_2 (0.99)$
Scale-Space

Second-order derivatives indicate changes in the gradient

Multiscale edge detector using a Gaussian smoothing filter
Scale-Space

\[ \Delta \text{Mean} = 2, \text{Variance} = 1 \]

Spatial Autocorrelation: \( r_1 (0.0) \) and \( r_2 (0.99) \)
Scale-Space (green) + Womble (purple)
Global Edge Detectors

Scale-Space

Wavelet
Local Spatial Statistic: Getis

Hot Spots and Cold Spots

Lag 1

Lag 2

Lag 3
Vector Data
Topological Distances

- $p_i$
- Lag 1 neighbourhood
- Lag 2 neighbourhood
Boundary Detection at Multiple Scales

Boundary Strength Through Lags 1 to 3

Lag 1

Lag 2

Lag 3

Boundary Strength
Strongest (upper quantile)
Weakest (lower quantile)
Forest Stand Height
>22m
17m-22m
12m-17
<7
References


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