Conceptualization of Stream Systems

- Dendritic ecological networks (DENs)
  - Highly connected, directed dendritic networks (Grant et al. 2007)


- Key physicochemical & biological processes operate at the ‘network scale’ (1-100 km)
  - e.g. Metapopulation dynamics and disturbance regimes

- Goal: Investigate relationships between a set of locations, rather than treating discrete locations independently

Schlosser’s dynamic landscape model of stream fish life history (Figure 2 from Schlosser and Angermeier 1995).
Challenges of Modelling Streams Data

Dendritic network structure
• Form semi-restricted corridors
• In-stream dispersal & species interactions
• Position within the network affects food web composition & structure

Dual spatial representation
• Networks are embedded in the terrestrial environment

Connectivity
• Lateral: Catchment-Floodplain-Channel
• Longitudinal: Flow & in-stream processes

Directional flow
• Flowing water influences processes
• Passive versus active movement

Spatio-temporal variability of habitat and flow
• Evolutionary or ecological niche
What is a spatial statistical model?

- Traditional statistical models (non-spatial)
  - Residual error ($\varepsilon$) is assumed to be uncorrelated
    - $\varepsilon = unexplained$ variability in the data

$$Y = X\beta + \varepsilon$$

- Spatial statistical models
  - Residual errors are **correlated through space**
    - Spatial patterns in residual error resulting from unidentified process(es)
  - Model spatial structure in the residual error
    - Explain additional variability in the data
  - **Generate predictions at unobserved sites with estimates of uncertainty**

$$Y = X\beta + \delta + \varepsilon$$

- Spatial patterns in the residual error are traditionally described using **Euclidean distance**
What is a Spatial Statistical Model?

Fit an autocovariance function to data
• Describes relationship between observations based on separation distance

Distances and spatial relationships
• Represented differently depending on the distance measure

![Graph showing semivariance and separation distance with annotations for sill, nugget, and range.](image-url)
Spatial Relationships in Streams

Euclidean
• As the crow flies

Flow-unconnected
• As the fish swims

Flow-connected
• As the water flows
## Autocovariance Models for Streams

<table>
<thead>
<tr>
<th>Tail-up</th>
<th>Tail-down</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hydrologic distance</td>
<td>Hydrologic distance</td>
</tr>
<tr>
<td>Flow-connected relationships</td>
<td>Flow-connected &amp; Flow-unconnected relationships</td>
</tr>
<tr>
<td>Spatial weights used to split function</td>
<td>Spatial weights not necessary</td>
</tr>
</tbody>
</table>

- **Tail-up Diagram:**
  - Nodes: S1, S2, S3
  - Edges: S1-S2, S2-S3, S3-S1
  - **h**

- **Tail-down Diagram:**
  - Nodes: S1, S2, S3
  - Edges: S1-S2, S2-S3, S3-S1
  - **a**
  - **b**
  - **h**
Mixture Models

Variance component approach
• Single model fit using a mixture of covariances based on different spatial relationships
• Sum of positive-definite covariance matrices
  • Models: Tail-up, Tail-down, Euclidean

Flexible Modelling Approach
• Measured and unmeasured variables at multiple scales
• Spatial-weighting schemes for Tail-up models

\[ \Sigma = \sigma_{Euc}^2 R_{Euc} + \sigma_{down}^2 R_{down} + \sigma_{up}^2 R_{up} + \sigma_{nug}^2 I \]

where

\[ R_{Euc}, R_{down}, R_{up} \]

matrices of autocovariance values for Euclidean (Euc), tail-down (down), and tail-up (up) models.

\[ \sigma_{Euc}^2, \sigma_{down}^2, \sigma_{up}^2, \sigma_{nug}^2 \]

are the variance components.
Spatial Autocorrelation and Parameter Estimates

<table>
<thead>
<tr>
<th>Model</th>
<th>Covariate</th>
<th>Estimate (SE)</th>
<th>p-value</th>
<th>p</th>
<th>AIC</th>
<th>r²</th>
<th>RMSPE (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-spatial</td>
<td>Intercept</td>
<td>31.2 (0.918)</td>
<td>p &lt; 0.01</td>
<td>6</td>
<td>3912</td>
<td>0.46</td>
<td>2.99</td>
</tr>
<tr>
<td></td>
<td>Elevation (100 m)</td>
<td>-0.754 (0.0512)</td>
<td>p &lt; 0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Glacial valley (%)</td>
<td>-3.04 (0.574)</td>
<td>p &lt; 0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Valley bottom (%)</td>
<td>3.06 (0.631)</td>
<td>p &lt; 0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Stream slope (%)</td>
<td>-6.62 (2.92)</td>
<td>p = 0.02</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Contributing area (100 km²)</td>
<td>0.124 (0.0048)</td>
<td>p = 0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial</td>
<td>Intercept</td>
<td>30.5 (1.69)</td>
<td>p &lt; 0.01</td>
<td>13</td>
<td>3161</td>
<td>0.85</td>
<td>1.58</td>
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<tr>
<td></td>
<td>Elevation (100 m)</td>
<td>-0.767 (0.0881)</td>
<td>p &lt; 0.01</td>
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<tr>
<td></td>
<td>Glacial valley (%)</td>
<td>-1.51 (0.797)</td>
<td>p = 0.06</td>
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</tr>
<tr>
<td></td>
<td>Valley bottom (%)</td>
<td>2.95 (0.645)</td>
<td>p &lt; 0.01</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>Stream slope (%)</td>
<td>-0.0929 (3.57)</td>
<td>p = 0.98</td>
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</tr>
<tr>
<td></td>
<td>Contributing area (100 km²)</td>
<td>0.0495 (0.0864)</td>
<td>p = 0.57</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table 2 from Isaak et al. (2014), WIRES Water
Spatial Models for Stream Networks

Water Temperature (°C)
- 12.00 - 12.50
- 12.51 - 13.50
- 13.51 - 15.00
- 15.01 - 17.00
- 17.01 - 21.00

C
B
A

0 4 Kilometers
Survey Design on Streams

Prediction or fixed effects estimation, with an unknown covariance structure

- Good spatial coverage
- Clusters
  - Headwater segments
  - Outlet Segment
- Singles
  - Headwater segments
  - Trend
Summarizing Over Area: Block Kriging

Figure 7: Modified from Isaak et al. (2014) WIRES Water
Disjunct to Spatially Explicit Management

Provides a semi-continuous view of conditions, with estimates of uncertainty, across relatively broad spatial scales.
Making Methods Accessible

Tools:

• STARS: Spatial tools for the Analysis of River Systems
  • Custom toolset for ArcGIS versions 9.3, 10.1, and 10.2
• SSN: R package for spatial statistical stream-network modeling
  • Data structure: modification of the spatial data structures used in sp package

Learning materials:

• Tutorials, vignettes, example datasets, papers

Example datasets for statisticians

• Promote the development of new methods for stream networks

Spatio-temporal Visualization

- In-situ sensors produce massive space-time datasets
- Spatio-temporal patterns are difficult to visualize
- R package STSN
  - Provides data structure to promote methods development
Where to from here...

Spatial statistical stream-network models

Engage with statisticians to develop/adapt spatial statistical methods for streams

- Occupancy models
- Models for extremes
- Big data
- Spatio-temporal models
- Multivariate data
- Nonstationarity
- Visualization tools