Introduction to Spatial Stream-Network Models

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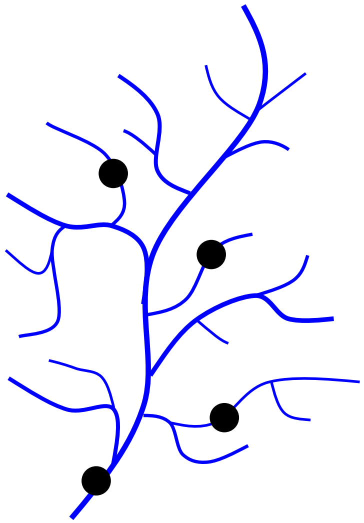
Conceptualization of Stream Systems

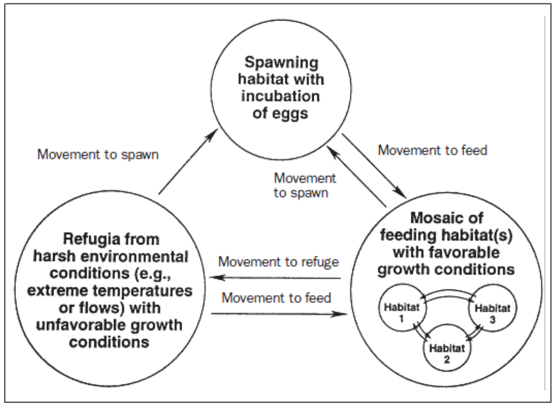
- Dendritic ecological networks (DENs)
  - Highly connected, directed dendritic networks (Grant et al. 2007)



- Seminal papers: Schlosser & Angermeier 1995; Fisher 1997; Ward 1997,1998; Fausch et al. 2002; Power & Dietrich 2002; Wiens 1999, 2002; Allan 2004; Benda et al. 2004; Fisher et al. 2004

- 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

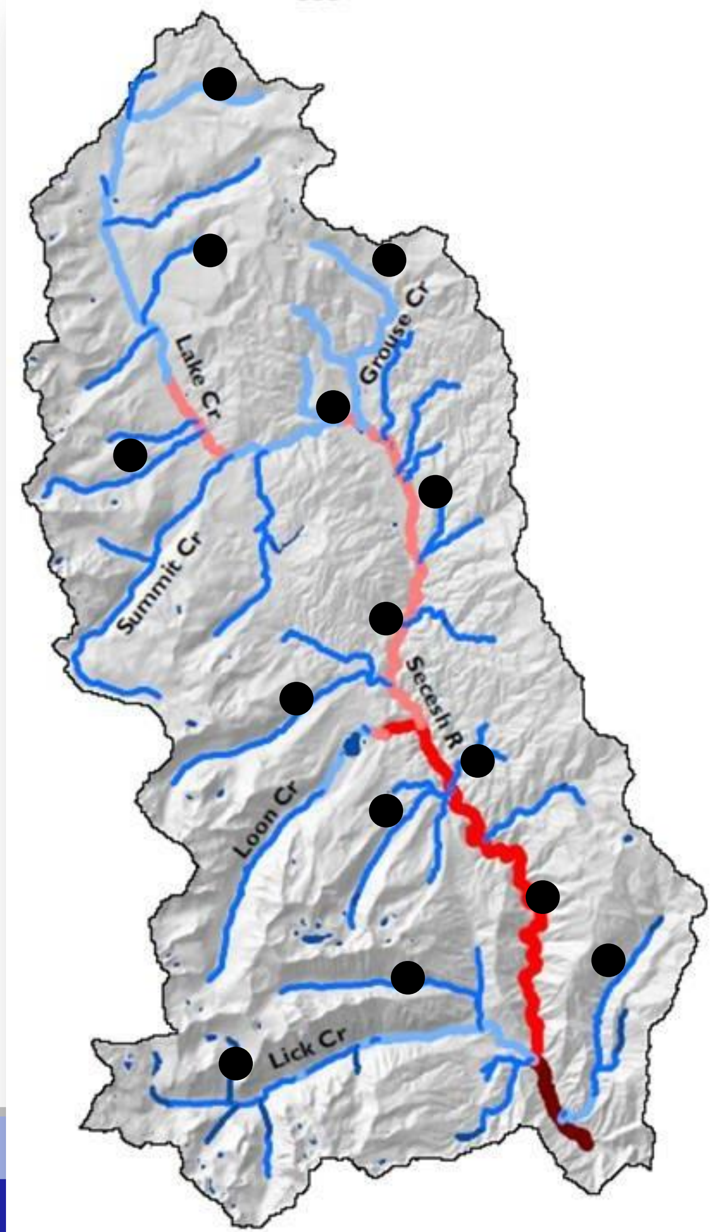
- Lateral: Catchment-Floodplain-Channel
- Longitudinal: Flow & in-stream processes

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 (ε) is assumed to be uncorrelated
    - ε = *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**

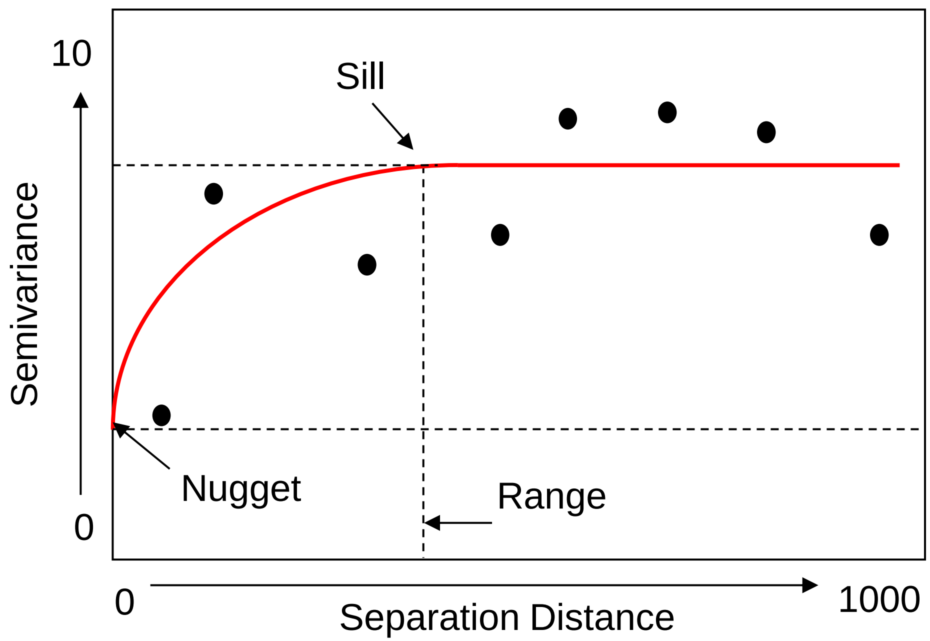
What is a Spatial Statistical Model?

Fit an autocovariance function to data

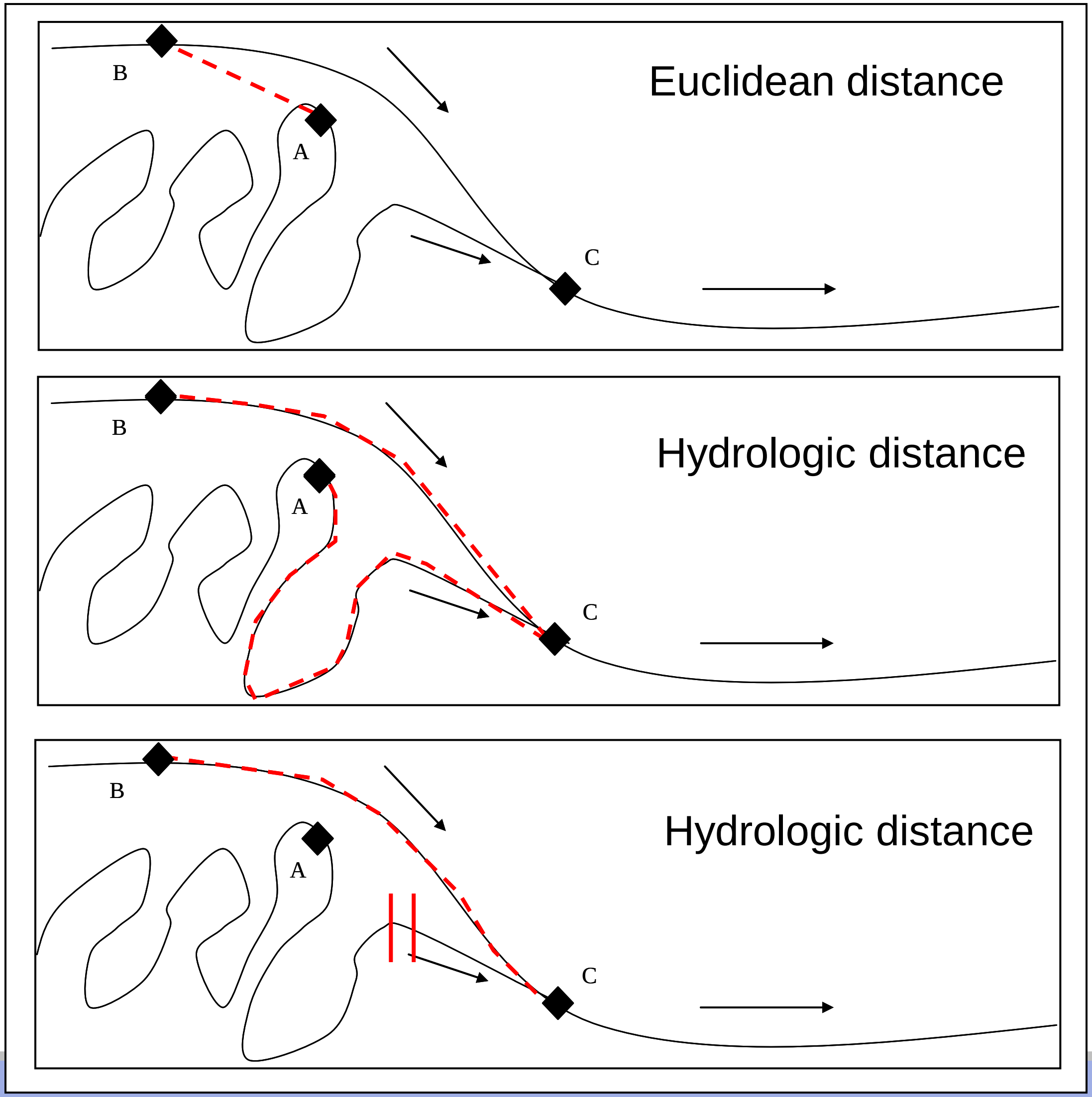
- Describes relationship between observations based on separation distance

Distances and spatial relationships

- Represented differently depending on the distance measure



Spatial Relationships in Streams



Euclidean

- As the crow flies

Flow-unconnected

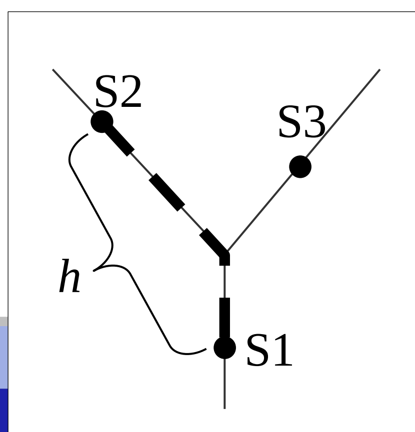
- As the fish swims

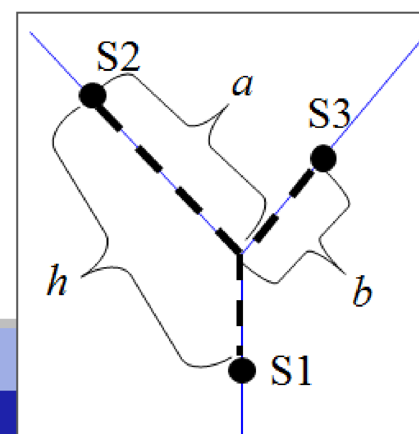
Flow-connected

- As the water flows

Autocovariance Models for Streams

Tail-up	Tail-down
Hydrologic distance	Hydrologic distance
Flow-connected relationships	Flow-connected & Flow-unconnected relationships
Spatial weights used to split function	Spatial weights not necessary





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

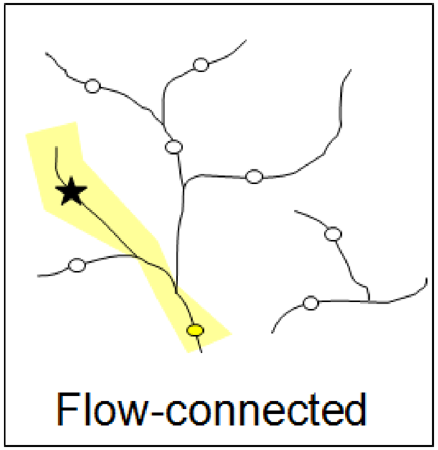
- Measured and unmeasured variables at multiple scales
- Spatial-weighting schemes for Tail-up models

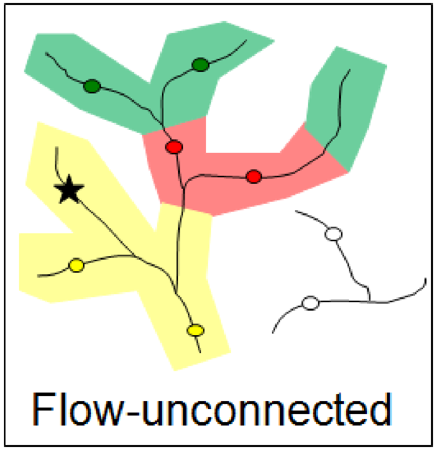
$$\mathbf{\Sigma} = \sigma^2_{Euc}\mathbf{R}_{Euc} + \sigma^2_{down}\mathbf{R}_{down} + \sigma^2_{up}\mathbf{R}_{up} + \sigma^2_{nug}\mathbf{I}$$

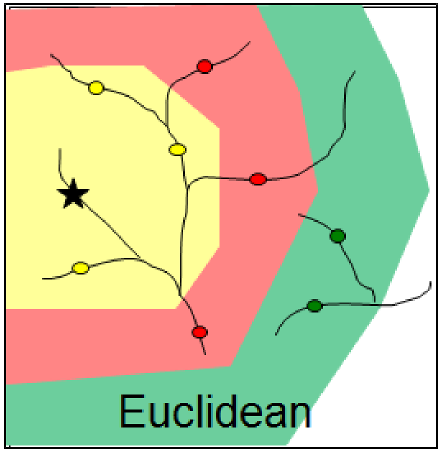
where

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

$\sigma^2_{Euc}, \sigma^2_{down}, \sigma^2_{up}, \sigma^2_{nug}$ are the variance components.



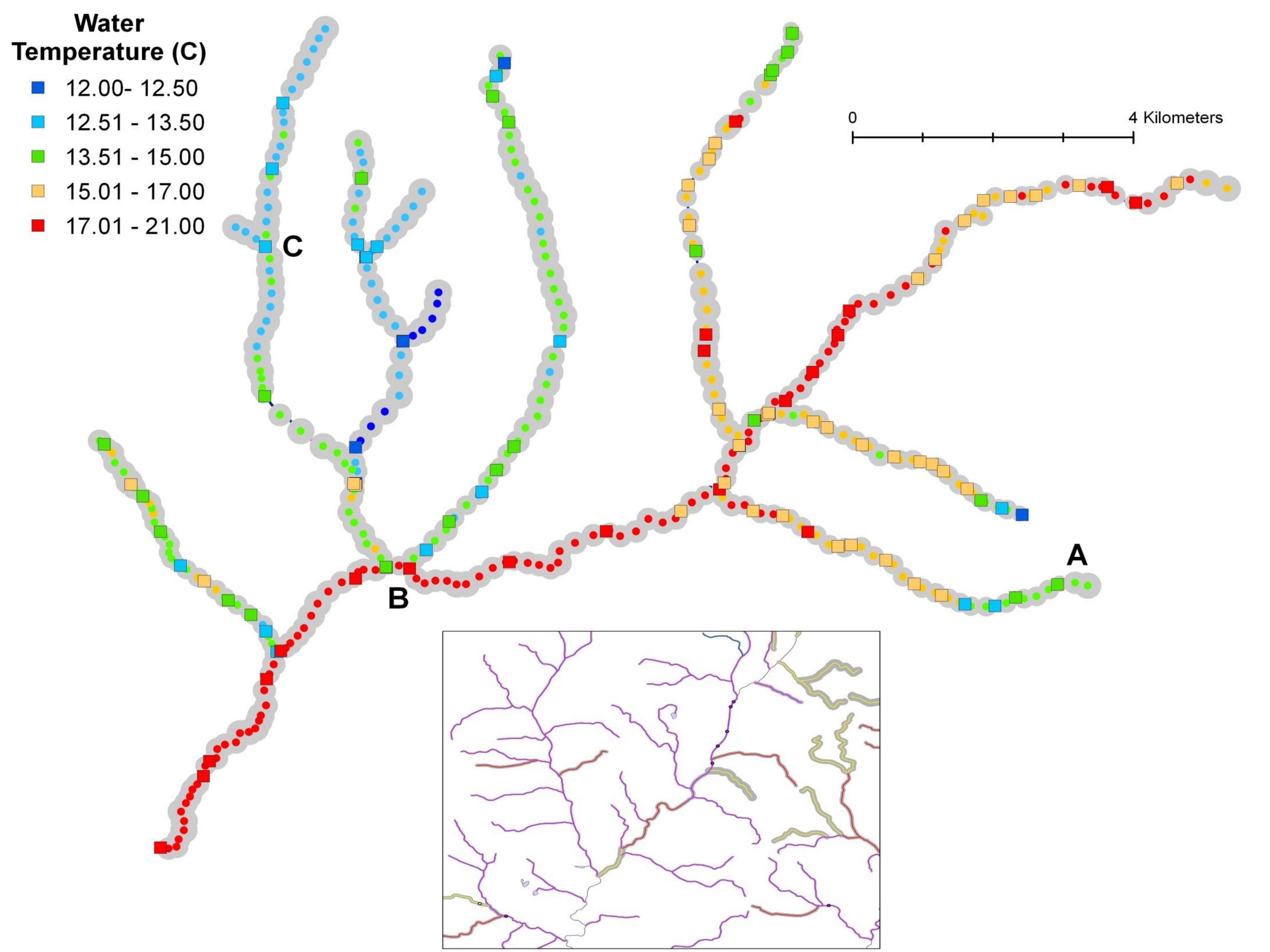




Spatial Autocorrelation and Parameter Estimates

Model	Covariate	Estimate (SE)	p-value	p	AIC	r^2	RMSPE (˚C)
Non-spatial	Intercept	31.2 (0.918)	$p < 0.01$	6	3912	0.46	2.99
	Elevation (100 m)	-0.754 (0.0512)	$p < 0.01$				
	Glacial valley (%)	-3.04 (0.574)	$p < 0.01$				
	Valley bottom (%)	3.06 (0.631)	$p < 0.01$				
	Stream slope (%)	-6.62 (2.92)	$p = 0.02$				
	Contributing area (100 km^2)	0.124 (0.0048)	$p = 0.01$				
Spatial	Intercept	30.5 (1.69)	$p < 0.01$	13	3161	0.85	1.58
	Elevation (100 m)	-0.767 (0.0881)	$p < 0.01$				
	Glacial valley (%)	-1.51 (0.797)	$p = 0.06$				
	Valley bottom (%)	2.95 (0.645)	$p < 0.01$				
	Stream slope (%)	-0.0929 (3.57)	$p = 0.98$				
	Contributing area (100 km^2)	0.0495 (0.0864)	$p = 0.57$				

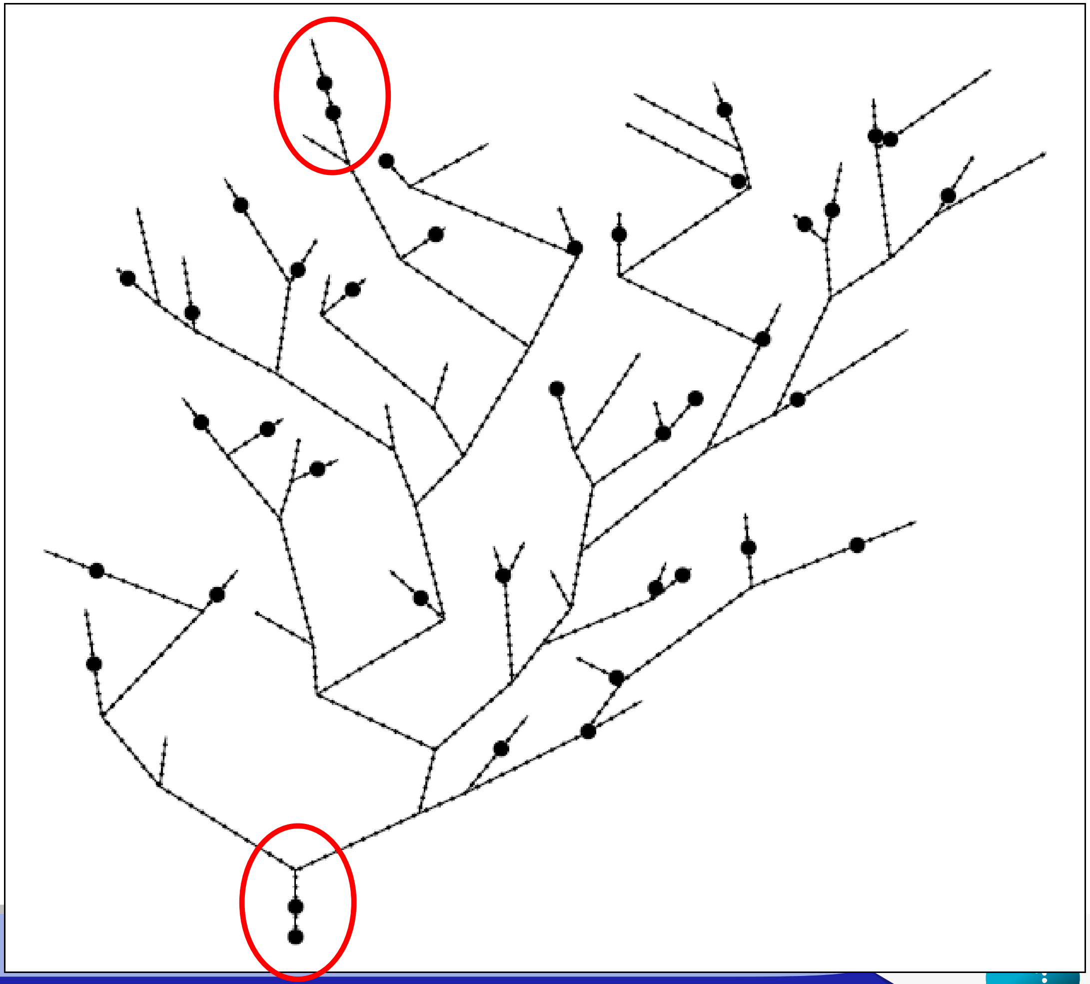
Table 2 from Isaak et al. (2014), WIRES Water


Water Temperature (C)
12.00- 12.50
12.51 - 13.50
13.51 - 15.00
15.01 - 17.00
17.01 - 21.00
0
4 Kilometers
A
B
C

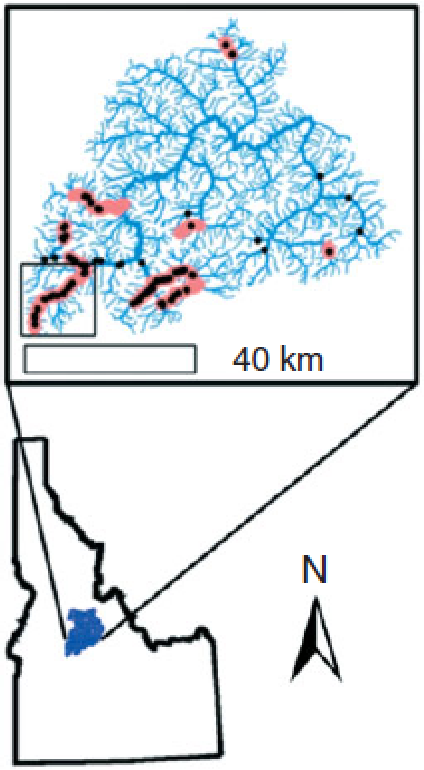
Survey Design on Streams

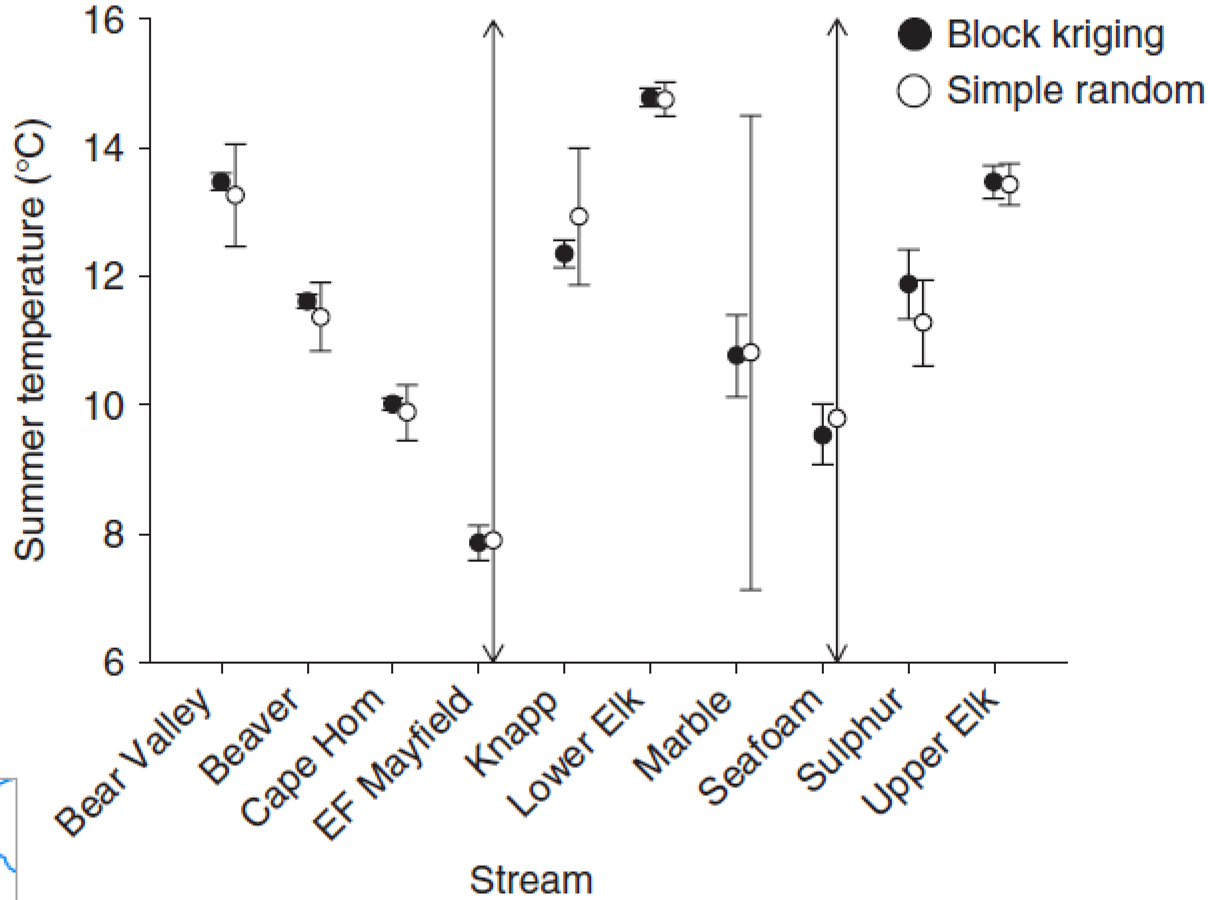
Prediction or fixed effects estimation, with an unknown covariance structure

- Good spatial coverage
- Clusters
  - Headwater segments
  - Outlet Segment
- Singles
  - Headwater segments
  - Trend



Summarizing Over Area: Block Kriging





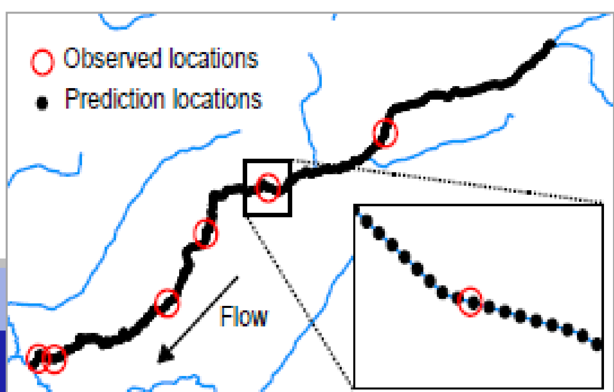
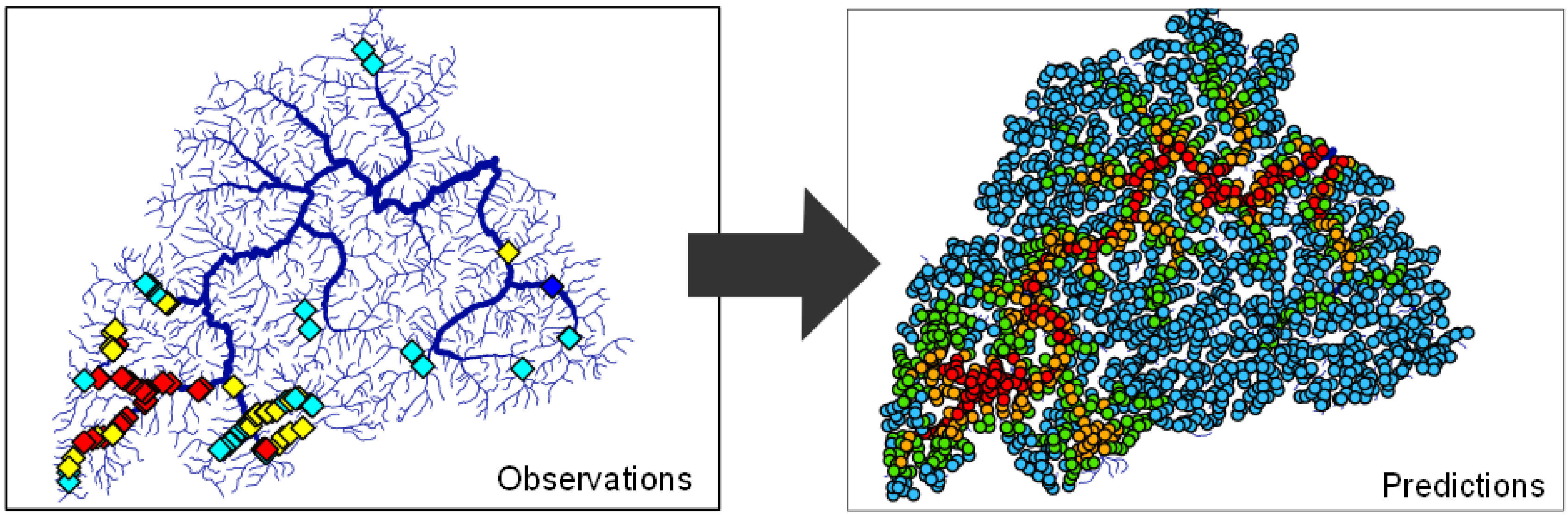


Figure 7: Modified from Isaak et al. (2014) WIRES Water

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

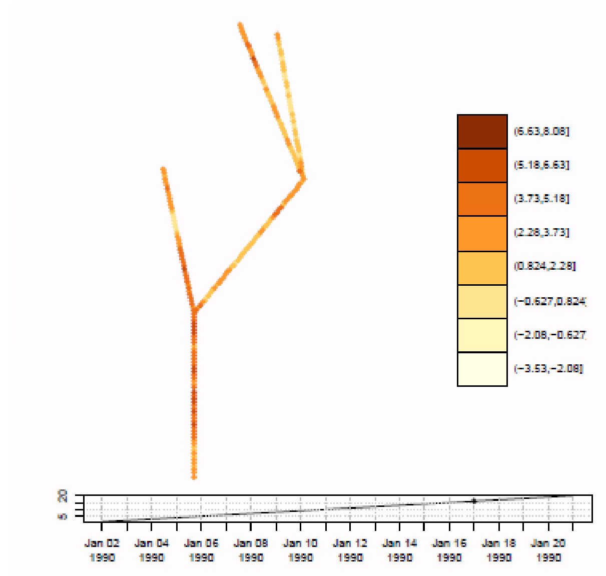
- Promote the development of new methods for stream networks

http://www.fs.fed.us/rm/boise/AWAE/projects/SpatialStreamNetworks.shtml

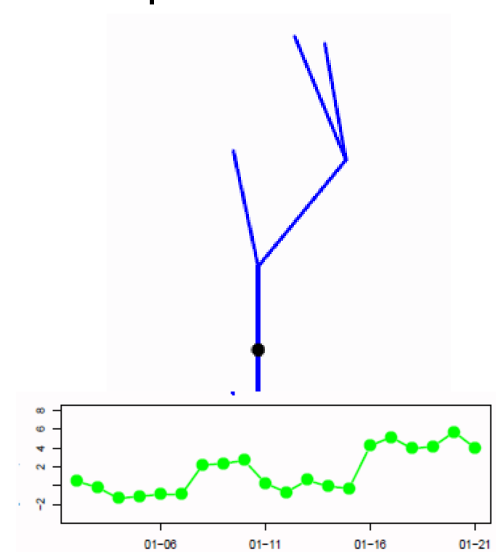
Spatio-temporal Visualization

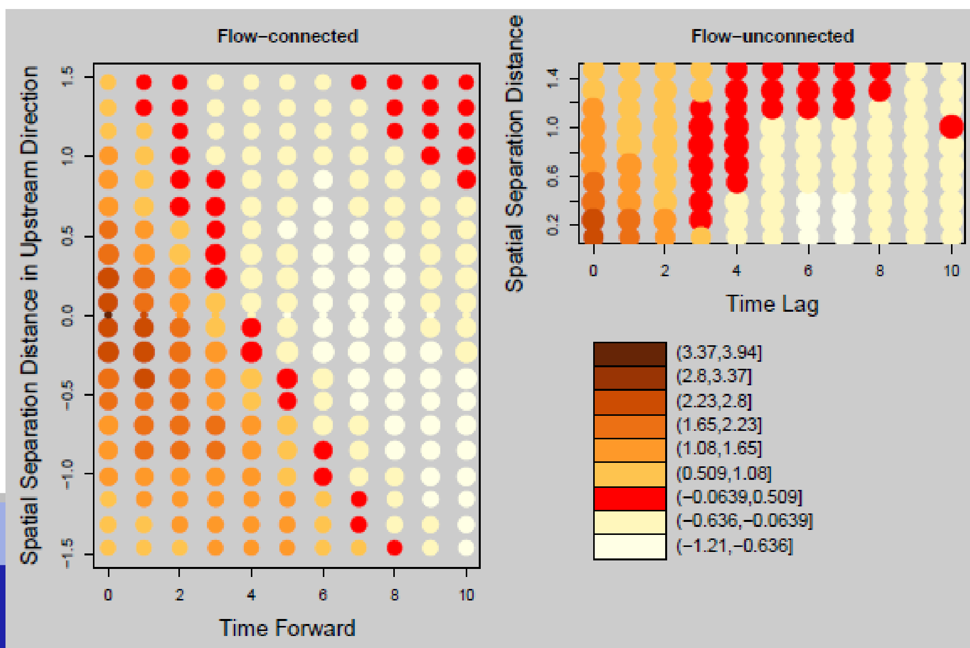
- In-situ sensors produce massive space-time datasets
- Spatio-temporal patterns are difficult to visualize
- R package STSN
  - Provides data structure to promote methods development

Spatial Animation



Temporal Animation





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