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Spatial identification of tributary impacts in river networks

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Introduction

The ability to assess spatial patterns of ecological conditions in river networks has been confounded by difficulties of measuring and perceiving features that are essentially invisible to observers on land and to aircraft and satellites from above. The nature of flowing water, which is opaque or at best semi-transparent, makes it difficult to visualize fine-scale patterns in habitat and biota at close range, and the linear topology of river networks complicates the process of scaling up to detect coarse-scale patterns. This spatially incomplete perspective limits our understanding of lotic systems because the scaled character of biotic and abiotic patterns produces different results depending on the method of data collection (Fausch *et al.*, 2002; Hildrew and Giller, 1994).

Recent changes in the way river scientists collect data are now filling in these gaps to reveal patterns that raise new questions about the structure and function of riverine mosaics and networks. The recent identification of tributary influences on stream channel morphology (Benda *et al.*, 2004b; Benda *et al.*, 2003) and associated data (Fernandes *et al.*, 2004; Kiffney *et al.*, 2006; Rice *et al.*, 2001) has been made possible, in part, by the use of spatially explicit sampling approaches. This chapter focuses on contributions of such approaches to recognizing and describing the impacts of tributaries in river networks. The emphasis here is on identifying patterns as opposed to explaining the processes underlying such patterns. Other sections of this book elucidate the functional impacts of tributaries on spatial heterogeneity in fluvial morphology, water quality, biological response, network topology, hydrology, sediment delivery and contaminant transport. This chapter explains how to see patterns amidst this heterogeneity.

We illustrate various approaches for identifying impacts of tributaries along the receiving channel (hereafter referred to as the main stem) in a river network. Literature examples are drawn from a range of disciplines that apply different sampling designs, data types and data-collection methods. Many of the studies cited in this chapter do not state an explicit intent to evaluate tributary impacts, but their methods hold promise for addressing important questions in this area. Except for terrain analysis of available digital elevation data (e.g. Benda *et al.*, in press), broad-scale, spatially explicit investigations of tributary effects on fluvial features and aquatic biota are uncommon. Therefore, we demonstrate graphical (longitudinal analysis and smoothing) and geostatistical (one-dimensional and network variograms) methods of identifying tributary impacts through specific case studies of (1) remotely sensed summer water temperature in the North Fork John Day River in north-eastern Oregon, USA and (2) coastal cutthroat trout distribution in a headwater stream network of Camp Creek, a tributary to the Umpqua River in western Oregon, USA.

Data and measurement

The detection of tributary influences requires information on the locations of confluences and spatial variation in the response variables of interest. In this respect, the task of spatial identification of tributary impacts is as much cartographic as it is geomorphologic and ecological. The first challenge in designing a study to identify tributary impacts is to locate the tributaries themselves. Without walking the entire length of the river network, it is difficult – if not impossible – to map first-order tributary junctions in densely forested watersheds. However, analytical tools are now available to automate recognition of tributary junctions from relatively high-resolution digital elevation data ($< 10\,\text{m}^2$) over broad spatial extents ($> 10\,000\,\text{km}^2$) (Benda *et al.*, in press). The ability to locate tributary confluences may depend on the size and intermittency of the

tributaries relative to the main stem (Benda *et al.*, 2004a; Clarke and Burnett, 2003; Wigington *et al.*, 2005). Thus, it is essential to specify the source, scale and date of the map or digital data used to identify the location and relative size of confluences in relation to the main stem. In forested headwater streams, tributaries of 1–2 m in width are very difficult to detect using aerial photography, on which topographical maps are based. The error in maps of various types and scales can often be quite significant. For example, in a forested landscape, a commonly available US Geological Survey (USGS) topographic map with a scale of 1:24 000 represents the best estimate of an aerial photo interpreter on the location and extent of a tributary that is not visible from above due to overhanging riparian vegetation. The USGS standard for horizontal positional accuracy in 1:24 000 data is that 90 per cent of mapped points lie within approximately 12 m of their true positions (USGS, 2007). However, no such standard exists for mapping the occurrence or spatial extent of streams. Errors in spatial accuracy cannot be quantified without field verification. Digital elevation models (DEM) of various resolutions (e.g. 10–30 m for USGS 7.5 minute topographic quadrangles) may give the impression of greater accuracy than the hand-drawn maps from which they were derived. However, these data by definition incorporate additional error during translation from analogue to digital form. Therefore, 10- and 30-metre DEM data must be viewed critically as tools for locating tributary junctions that cannot be viewed in aerial photographs (Clarke and Burnett, 2003; Stock and Dietrich, 2003). Light detection and ranging (LiDAR, or lidar) offers the most promising potential for mapping fine-scale topography of fluvial features in both forested and non-forested landscapes. (Power *et al.*, 2005).

Sampling design

In the past, traditional sampling methods attempted to avoid biases caused by discontinuities at tributary confluences rather than focus on such discontinuities in physical and biological gradients (Bruns *et al.*, 1984). This was a reasonable approach for pursuing objectives of detecting dominant gradients in environmental conditions and biological communities. For example, broad-scale longitudinal patterns in water temperature are more accurately represented by avoiding sampling locations immediately downstream of confluences, where temperature measurements are likely to be viewed as outliers. However, with rising interests in exploring discontinuities along the river continuum (Poole, 2002), traditional sampling techniques (sensu Cochran, 1977) are being adapted (see Hirzel and Guisan, 2002) to address scientific questions that are fundamentally spatial in nature.

Investigations of tributary impacts in river networks employ two kinds of sampling designs that differ in the scale and the spatial arrangement of sample units. In the nomenclature of statistical design in aquatic resource monitoring and assessment, these
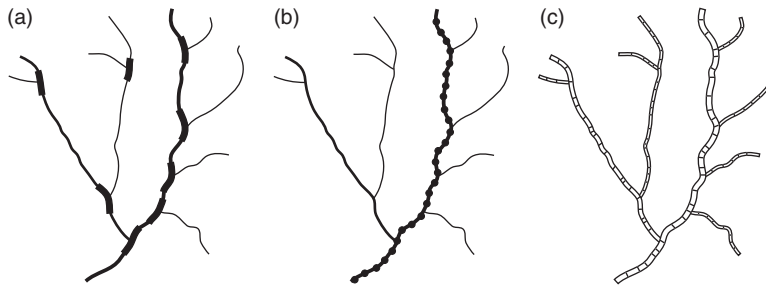
Figure 9.1   Intensive and extensive sampling approaches for identifying tributary impacts in fluvial networks. An intensive design employs a limited number of (a) sites positioned upstream and downstream of tributary confluences. Extensive designs use (b) sample points or (c) sample areas (pool/riffle units and reaches) that are distributed along the entire main stem or throughout the river network.

types of study designs are termed 'intensive' and 'extensive' (Conquest and Ralph, 1998). Simplified graphical representations of these approaches are depicted in Figure 9.1.

Intensive sampling

Intensive surveys employ methods that meet specific data requirements at a limited number of sites distributed within and among catchments (Figure 9.1(a)). This survey method focuses sampling effort at sites in the main stem upstream, adjacent to and downstream of tributary confluences. Measurements of biological and physical parameters are collected at a single site, often with an emphasis on establishing long-term records of change. Techniques employed in intensive surveys may be time consuming but offer an advantage in that they usually quantify accuracy and precision. The spatial scale of an intensive survey may range in resolution from 0.1 to 10 m (i.e. the minimum dimension of an individual measurement in terms of length of stream) and in extent from 10 to 1000 m (i.e. the site or length of stream within which individual samples are taken). Within a site, sampling may be conducted hierarchically at points, along transects or over areas to assess variation at microhabitat, pool/riffle and reach scales individually or, using a nested design, collectively (Armitage and Cannan, 1998; Frissell *et al.*, 1986). The number and spatial dimensions of sites in an intensive survey are generally limited by the time it takes to sample multiple parameters accurately and precisely at each site. Thus, considerable effort must be expended to identify sites where tributary impacts are most likely to be detected. Any determination of the appropriate sampled length requires a knowledge or estimation of the downstream and upstream extent of the tributary effects before data are collected and analysed – a difficult task in remote or poorly studied regions where tributary impacts typically occur. In spite

of these logistical challenges, the intensive approach has been used effectively in several studies that have identified tributary impacts on aquatic biota (Bruns *et al.*, 1984; Fernandes *et al.*, 2004; Kiffney *et al.*, 2006; Osborne and John Wiley & Sons, 1992; Stevens *et al.*, 1997).

Extensive designs

Extensive surveys are designed to characterize spatial variation contiguously across many sites to obtain a picture of entire river segments. The distinguishing feature of an extensive survey is the relatively high resolution (0.1–100 m) and density of samples distributed over a relatively large extent of the main stem (> 1000 m) (Figure 9.1(b)). To identify longitudinal patterns in aquatic habitat and biota, data are typically gathered only in the main stem (Rice *et al.*, 2001). Recent recognition that network structure can influence fluvial systems has led aquatic scientists to collect spatially continuous data throughout entire headwater catchments (Figure 9.1(c)) (Gresswell *et al.*, 2006). As in intensive surveys, samples in extensive surveys may be collected at point locations or along transects, but areal sample units, such as geomorphologically defined pools and riffles, are most commonly employed to map aquatic habitat in linear networks (Radko, 1997). The size of the sample unit (i.e. micro-, meso- or macro-habitat features) determines the degree of variability in the data and the patterns observed. For example, extensive surveys typically exclude micro-scale variability by targeting geomorphically defined meso-scale habitat features, such as pools and riffles. Nested sampling designs have potential for evaluating longitudinal patterns in fluvial characteristics and biota at multiple spatial scales, but such approaches are often not combined with extensive surveys (Torgersen and Close, 2004). Certain types of data lend themselves better to point- or area-based sampling techniques. For example, continuous data types – including elevation, water temperature, chemistry, and channel width and depth – may be measured effectively using a point-based sampling technique. Discrete data types, such as counts of fish, invertebrates, sediment particles and logs, are usually quantified in linear or areal units. Counts can be estimated over large areas with point sampling methods (Barker and Sauer, 1995), but these methods are not widely used in rivers (Persat and Copp, 1990).

In spite of the apparent advantages for quantifying spatial pattern in rivers, three key trade-offs are associated with extensive surveys: (1) contiguous sampling along a main stem or a river network, rather than among catchments, generally limits studies to a smaller sampling extent, (2) including a large number of samples can increase data subjectivity if methods are used that rely on indirect measurement and estimation, as opposed to direct measurement with defined levels of accuracy and precision and (3) the large number of observers needed to sample many kilometres of river in a short period increases the cost of field data collection for synoptic assessments.

Data collection

Spatially extensive, high-resolution data are useful for identifying spatial patterns of geomorphological and biological responses (Cooper *et al.*, 1997). Data of this nature have recently become available in fluvial geomorphology and lotic ecology (Fausch *et al.*, 2002; Power *et al.*, 2005; Walsh *et al.*, 1998), but traditional, intensive approaches for sampling fluvial systems are still the dominant method of data collection. Riverine scientists are beginning to weigh the known precision and accuracy of traditional measurement methods against newer methods with greater capacity to quantify spatial patterns but with less-well-known performance. The continued experimentation and development of such approaches is essential for improving our understanding of tributary confluences and their role in structuring the biotic and abiotic properties of fluvial networks.

The following examples of data collection illustrate techniques across disciplines that have been used successfully to evaluate tributary impacts or have high potential for development and application. The methods are presented according to the nature of data collection: (1) samples that are collected in the field and (2) remotely sensed images that are sampled in the laboratory. The distinction between the two methods is important because field sampling requires an observer to travel to and collect data at a site and so is more time consuming. Moreover, the scales of spatial and temporal variation in some types of field data are not suited for extensive data collection. For example, data types that require near-simultaneous sampling or complicated collection protocols, such as pH and turbidity, cannot be sampled in large numbers of sites without increasing the number of field personnel. The requirement that the observer be present – on the ground – makes it difficult to collect spatially extensive data at a high resolution in river networks. Remotely sensed data, in contrast, can be collected from a variety of platforms (ground, airborne or space) in a short period and offers the advantage that sampling can be streamlined, and even automated, using a computer in the laboratory. As a general rule in collecting data to quantify spatial patterns, the time in the field collecting and processing samples is minimized to increase the number of samples and the distance over which they are collected (Hirzel and Guisan, 2002; Schneider, 1994a).

Field measurement

Data-collection methods for measuring spatial variation in river channel dimensions, substrate composition, water temperature and chemistry, and fish and macroinvertebrate distribution can be modified to increase the spatial resolution and extent of sampling. Using the technique developed by Hankin and Reeves (1988), visual estimates of channel width, depth and pool/riffle length can be corrected for observer bias based on a systematic selection of verified measurements. This dramatically reduces

the time required to map spatial patterns in river morphology so that over 10 km per day may be surveyed by a two-person crew (McIntosh *et al.*, 2000). A similar approach has been developed for visually characterizing and validating gravel-cobble river-bed sediments at the scale of kilometres (Latulippe *et al.*, 2001). In navigable rivers, water temperature, depth and conductivity can be measured in an extensive manner by towing probes behind a boat and continuously logging temperatures every one to three seconds while a global positioning system (GPS) records spatial coordinates. Using this method, Vaccaro and Maloy (2006) mapped thermal patterns and groundwater discharge areas over distances of 5–25 km.

Measurements of water-nutrient concentrations cannot be estimated visually, and it is difficult to collect samples sequentially along a main stem to quantify spatial heterogeneity at the scale of kilometres. However, Dent and Grimm (1999) employed up to 14 different people arrayed along a 10-km stream segment and collected nearly simultaneous water samples every 25 m. The samples were then processed in the laboratory to quantify nutrient concentration (nitrate-nitrogen and soluble reactive phosphorus) and conductivity. This technique provided data of sufficient resolution and extent to identify discontinuities in longitudinal patterns associated with tributary confluences; however, no attempt was made to relate spatial patterns in the measured variables to the positions of tributary junctions.

Quantifying spatial patterns of biological organisms in fluvial systems presents a new set of sampling challenges in addition to those just described. Field equipment required for observing and collecting aquatic organisms and measuring important variables, such as algal biomass and chlorophyll, is bulky and heavy. Moreover, some organisms, such as fish, amphibians and large macroinvertebrates, avoid detection by terrestrial observers and snorkellers. In spite of these difficulties, various techniques have been developed to approximate spatial patterns and thus help identify tributary impacts. Macroinvertebrates are particularly difficult to sample at high spatial resolution and over long distances because collection and laboratory processing techniques are time consuming, and traditional sampling equipment, such as Surber samplers and drift-collection devices, are not easily transportable if one intends to traverse multiple kilometres along a stream (Hauer and Lamberti, 1998). Nevertheless, quantifying patchiness in macroinvertebrate distribution is important for understanding abiotic factors influencing community organization (Downes *et al.*, 1993). Rice *et al.* (2001) employed a two-person crew to collect 10-minute kick samples at 10 different subsamples per site and was able to gather data in 43 sites over 12 days. The distribution of large-bodied macroinvertebrates, such as freshwater mussels, can be mapped also by snorkelling (Howard and Cuffey, 2003). Similar methods are currently being developed for quantifying spatial patterns of large-bodied arthropods, such as stonefly larvae (C.V. Baxter, Idaho State University, USA, *personal communication*).

Stream fishes have long been observed and counted by divers with mask and snorkel (Cunjak *et al.*, 1988; Mullner *et al.*, 1998; Roni and Fayram, 2000). However, only recently have spatially continuous distributions of fish abundance and species composition

been mapped by visual surveys. Such methods are particularly suited for small- to medium-sized rivers that have good visibility due to low turbidity and high water quality (Torgersen *et al.*, 2006). Although visual surveys are considerably more time consuming for quantifying fish than physical habitat, multiple two-person crews, with each mapping up to 4 km per day, can cover tens of kilometres per week. In contrast to snorkelling, electrofishing techniques involve heavy equipment and are generally not employed to map spatially continuous fish distributions, but these methods also have been adapted to increase the resolution and extent of sampling (Bateman *et al.*, 2005).

Remote sensing

Remote-sensing technology is revolutionizing the study of fluvial networks (Hauer and Lorang, 2004; Power *et al.*, 1999; Walsh *et al.*, 1998). New methods have developed at a rapid rate since sensor technology and computer processing capability improved dramatically in the mid-1990s. The remote sensing of rivers and streams is still primarily an airborne application, particularly with regard to identifying tributary impacts in small rivers and streams. However, this is merely a technical challenge of spatial resolution and may be solved in the next decade by improved space-borne sensors. The list of biotic and abiotic features that may be remotely sensed is rapidly growing, and the most comprehensive review of these techniques applied to rivers was compiled by Mertes *et al.* (2004). Remote sensing can now obtain digital data that – with calibration – are nearly identical to field measurements for a variety of parameters used to identify tributary impacts, including topography, surface-suspended sediment concentration, water-surface height, bed material grain size, bathymetry and surface temperature. Moreover, remote sensing data, once considered too costly due to the expense of contracting both a sensor and aircraft, are increasingly recognized as more economical than collecting, entering and processing similar field-collected analogue data.

Airborne remote-sensing methods that have been particularly helpful for quantifying fine-scale spatial patterns over long distances in small- to medium-sized rivers include lidar (Charlton *et al.*, 2003; Reutebuch *et al.*, 2005), multi- and hyperspectral sensors (Legleiter *et al.*, 2004; Lorang *et al.*, 2005; Marcus *et al.*, 2003) and thermal infrared imaging (Cherkauer *et al.*, 2005; Handcock *et al.*, 2006; Torgersen *et al.*, 2001). Direct observations from a helicopter have also been used to map spawning habitat for salmon over hundreds of kilometres (Isaak and Thurow, 2006).

Significant advances have also resulted from very high-resolution digital aerial photography and an automated sampling algorithm to generate a spatially continuous record of the median grain size of substrates in an 80-km river section (Carbonneau *et al.*, 2005). A major limitation of these airborne methods – with the exception of lidar – is that they are effective only when the vertical view of the stream is unobstructed by riparian vegetation. Thus, in some instances it may be necessary to employ

remote-sensing approaches on the ground, underneath the riparian canopy. Traditional methods for characterizing the size of river-bed sediments involve a time-consuming, manual collection of particles (Diplas and Sutherland, 1988; Wolman, 1954), but various ground-based photographic methods can reduce the time spent at each site and thereby increase sampling resolution or extent. Graham *et al.* (2005) developed a transferable ground-based technique using a hand-held digital camera and automated image processing to quantify grain-size variability in rivers and streams that are not suited for airborne applications. In summary, digital imaging and computerized-processing techniques have produced major advances that are just beginning to help establish a spatially explicit template for identifying tributary impacts. Thus, much fertile ground remains for exploring remote-sensing technology and applying it to the study of main-stem–tributary dynamics in fluvial networks.

Analytical tools

In the section on sampling design, intensive and extensive approaches for identifying tributary impacts were differentiated. Intensive studies, with widely dispersed sample sites, are not spatially explicit in the strictest sense because the gradient across all sites is evaluated, not the actual spatial patterns among sites. Hildrew and Giller (1994) eloquently describe this problem in relation to environmental gradients determined by the statistical analysis of intensive survey data: 'These gradients are not "real" gradients in space, such as those which might exist along a single river, but are abstracts from all of the sites surveyed.' A recent study by Kiffney *et al.* (2006 and Chapter 11, this volume) addressed this problem by collecting nested samples in transects spaced along the main stem 500 m upstream and downstream of tributary confluences. Responses of multiple-habitat, water-quality and biological variables to tributary confluences were then averaged among sites, but the spatial locations of transects with respect to the confluence were maintained and included in statistical analysis. In another intensive study, Fernandes *et al.* (2004) statistically identified impacts of tributaries by plotting fish species diversity upstream of tributary confluences against fish diversity downstream; departures from a 1:1 regression relationship provided evidence of tributary effects. Both methods were appropriate and instructive, but they provided limited information about the spatial gradients in species–habitat relationships between confluences, which would, potentially, provide additional insights.

The next sections on analytical tools for identifying tributary impacts focus primarily on the analysis of data acquired through extensive rather than intensive surveys. Additional information on the statistical analysis of intensive survey data can be obtained from a standard statistical text (Sokal and Rohlf, 1995). Extensive survey data, however, require non-traditional approaches to analysis because they are spatially

autocorrelated, non-normally distributed and generally inappropriate for traditional statistical tools, such as least squares regression and analysis of variance (ANOVA) (Legendre and Fortin, 1989).

Graphical methods

The most basic method for identifying tributary impacts in fluvial systems is graphical analysis of longitudinal data sets, which can be readily generated with new GIS-based analytical tools (Benda *et al.*, in press). Heterogeneity associated with tributary confluences has been effectively characterized in physical attributes (e.g. boulders and wood) through graphical approaches to examining field data (Benda *et al.*, 2003; Bigelow *et al.*, 2007; Macnab *et al.*, 2006). Spatially continuous data from extensive surveys are instructive for evaluating associations between locations of tributary junctions and biotic and abiotic patterns, but certain data types are easier to interpret than others. Measurements of variables, such as water temperature, are relatively stable over short distances and produce plots that are directly interpretable. For example, remotely sensed water-temperature data are well suited to longitudinal analysis in a 80-km section of the North Fork John Day River, a medium-sized wilderness stream (5–30 m in width) (Figure 9.2).
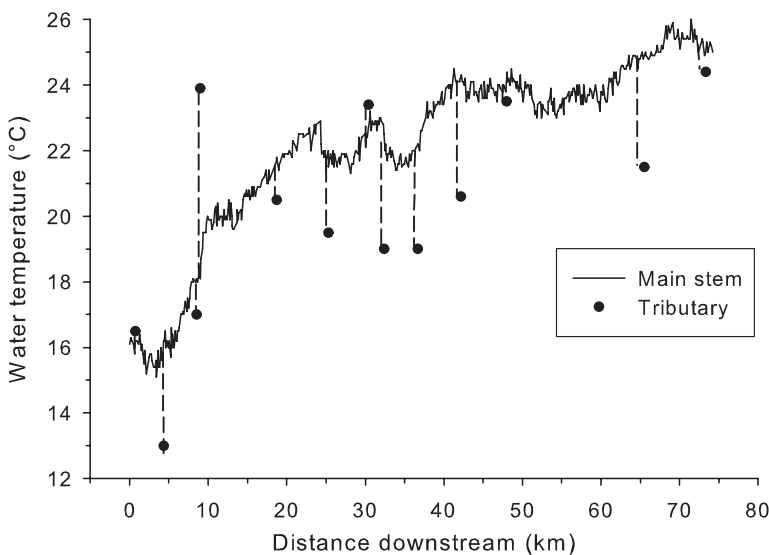

Figure 9.2   Remotely sensed water temperature in the main stem and tributary confluences of the North Fork John Day River, north-eastern Oregon, USA. Airborne thermal infrared remote sensing was conducted on 4 August 1998. Dashed vertical lines indicate the spatial locations of tributaries with respect to main-stem water temperature.

The fine-scale variation in water temperature in Figure 9.2 is the result of measurement error of approximately 0.5 °C (Torgersen *et al.*, 2001), and broad-scale variation is caused by multiple landscape factors influencing solar inputs, groundwater–surface-water exchange and channel morphology (Poole and Berman, 2001). As with other methods of airborne remote sensing of streams, the aircraft flew upstream and collected overlapping imagery sequentially along the main stem. Geographic coordinates for each image were recorded in flight with a GPS and were used to create maps linking water temperature to locations in the river. Individual temperatures were sampled digitally ($n = 10$) in each image, and the median was calculated and plotted versus distance upstream. Water temperatures measured from the imagery were not corrected for diel changes during the aerial survey, but the duration of the flight was short, approximately 45 minutes. The depiction of the location and temperature of tributaries relative to the main stem facilitated analysis of potential tributary impacts. The precise magnitude of tributary effects on main-stem water temperature was identified in individual high-resolution (< 1 m) thermal images. Thermal variations in main-stem water temperature downstream of river km 25 suggested a cooling influence of some tributaries. The utility of simple graphical representations such as Figure 9.2 is that they provide a broad-scale perspective on longitudinal patterns and the magnitude of the tributary effects.

Graphical analyses of spatial variation in counts of biological organisms and measurements of channel morphology in rivers can be difficult to interpret due to the high degree of heterogeneity in these variables over short distances (sensu Downes *et al.*, 1993). Data-smoothing techniques can help sort this fine-scale variation from ecologically meaningful coarse-scale variation. To demonstrate data smoothing in a longitudinal graphical analysis of fish counts, data were selected from Camp Creek, a headwater stream in western Oregon, USA that was surveyed extensively to evaluate spatial and temporal patterns in trout distribution (Gresswell *et al.*, 2006). Counts of trout were obtained using single-pass electrofishing in all pool and cascade habitats throughout the entire fish-bearing sections of the stream network (Bateman *et al.*, 2005) (Figure 9.3). Locations of sampled units were geographically positioned and mapped in a geographical information system (GIS) based on field-measured distances between mapped landmarks, such as tributary junctions and road crossings (Torgersen *et al.*, 2004). The main stem of Camp Creek has eight fishless tributaries and four fish-bearing tributaries. Hydrography for the stream network was derived from 7.5-minute USGS topographic maps.

Similar to spatially continuous counts of other organisms, trout counts in Camp Creek were highly variable among sample units (range 0–22 trout) and gave the appearance of being randomly distributed (Figure 9.4(a)). Such a distribution requires smoothing techniques to identify patterns amidst the heterogeneity. Locally weighted scatterplot smoothing (LOWESS) is a robust, unbiased nonparametric regression technique for identifying trends in 'noisy' data (Trexler and Travis, 1993). Many statistical packages
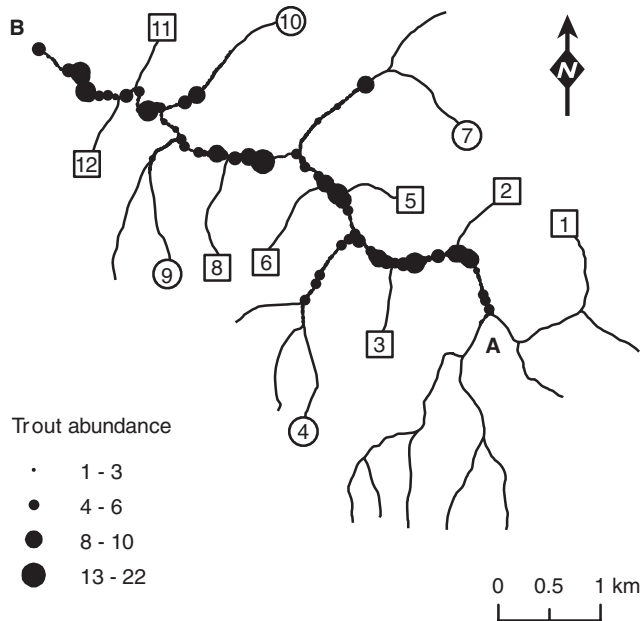
Figure 9.3   Distribution of fish-bearing (open circles) and fishless (squares) tributaries and counts of coastal cutthroat trout in Camp Creek, western Oregon, USA. The size of the black dots indicates the relative abundance of trout sampled in all pools and cascades in the fish-bearing portion of the stream network. The direction of flow in the main stem (plotted in Figure 9.4) is from A to B.

can perform LOWESS, but SigmaPlot (SPSS, 2004) is particularly flexible in allowing the user to specify two parameters that determine the fit of the model: (1) a smoothing factor that corresponds to the fraction of data points used for each regression and (2) the polynomial degree of the model (SPSS, 2004).

For Camp Creek data, a smoothed trend line of trout counts along the main stem was created with a sampling fraction of 0.2 and a second-order polynomial. The locations of fish-bearing and fishless tributaries were overlaid on the LOWESS trend line to graphically evaluate the correspondence between peaks and valleys in trout abundance and the locations of tributary confluences (Figure 9.4(a)). Fish-bearing and fishless tributaries showed a weak association with valleys and peaks in trout abundance respectively (e.g. tributaries 2, 3, 4 and 5). However, using scaling techniques (Schneider, 1994b; Schneider and Piatt, 1986), counts of trout were smoothed by modifying the bin size of the analysis to 100 m as opposed to plotting raw counts (Figure 4(b)). When LOWESS with the same smoothing factor and polynomial degree was applied to the binned data, the correlation between tributary junctions and the spatial structure of trout distribution became apparent (Figure 9.4(b)). No statistical tests were employed to test the relationship between tributary locations and the distribution of trout because
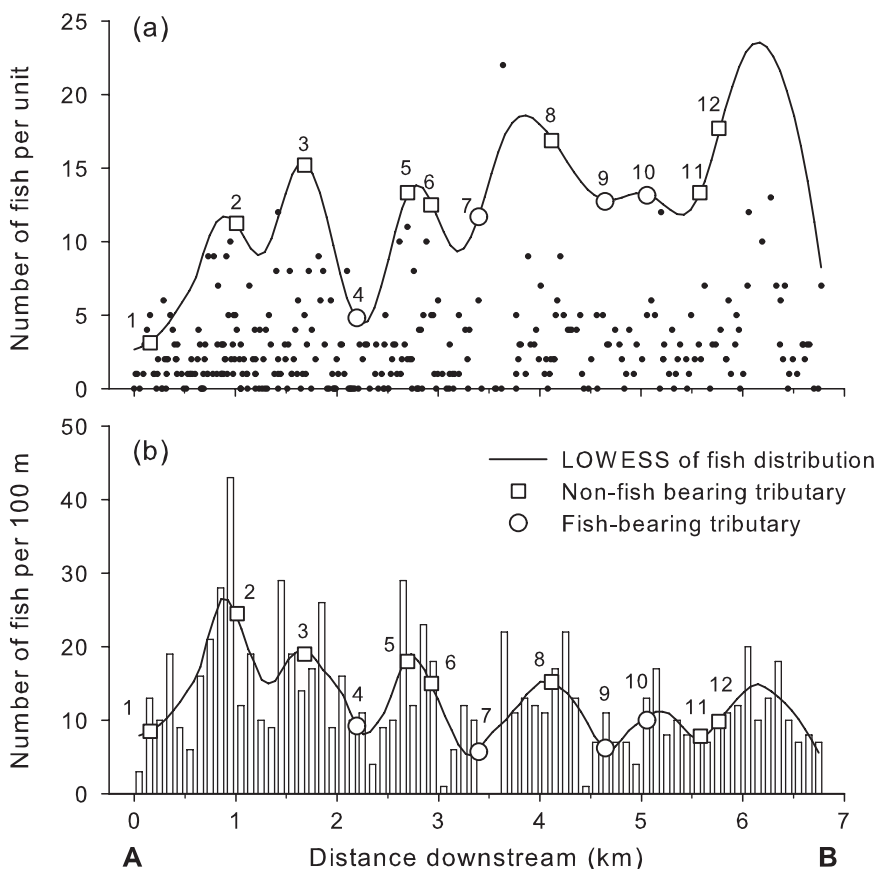
Figure 9.4 Longitudinal variation in trout counts, and locations of fish-bearing and fishless tributaries in the main stem of Camp Creek (see Figure 9.3). Tributary locations (circles and squares) are overlaid on locally weighted scatterplot smoothing (LOWESS) of trout counts and 100-m bins of trout counts to facilitate graphical analysis. The labels 'A' and 'B' refer to the positions indicated in Figure 9.3.

a complete census of trout was conducted in the study stream. Nine tributary junctions corresponded precisely with peaks and valleys in the LOWESS trend line, and only two of the tributary junctions were not aligned with a peak or a valley. Of particular interest is the association between *fishless* tributaries and *peaks* in trout distribution and the association between *fish-bearing* tributaries and *valleys* in trout distribution.

Trout distribution in headwater streams, such as Camp Creek, reflects complex interactions between physical habitat structure and biological requirements for trout growth and reproduction (Connolly and Hall, 1999; Gresswell *et al.*, 2006; Hicks and Hall, 2003). Further verification of the patterns identified here and their relevance to cutthroat trout ecology require similar analyses in multiple headwater streams. This

is the subject of ongoing work at the present time on multiscale determinants of cut-throat trout distribution, diet and growth in western Oregon (see Gresswell *et al.*, 2006). Examples from the literature in similar headwater streams of the Pacific Northwest suggest that fishless tributary junctions function as localized conduits of invertebrate prey and may be associated with higher densities of fish in the main stem (Wipfli and Gregovich, 2002; Wipfli, 2005). Additionally, fishless streams, although small in drainage area and channel width, can contribute substantially to large wood accumulations transported by debris flows from steep, forested hillslopes of headwater catchments (May and Gresswell, 2003). These large accumulations of wood in the main stem at tributary junctions contribute to channel complexity and may help to explain localized peaks in trout abundance.

Statistical methods

Graphical analysis of longitudinal patterns may not be sufficient for detecting subtle tributary–main-stem interactions. Therefore, statistical methods may be required to compare multiple longitudinal data sets or explore patterns of within- and between-site variability in stream networks. The careful application of standard statistical tests, such as ANOVA, can be used to parse out sources of variation associated with tributary impacts (Rice and Church, 1998). However, the assumptions of independence and equal variances make ANOVA a problematic tool for analysing closely spaced geographic data (Legendre and Fortin, 1989; Rice and Church, 1998). Geostatistics provides an alternative means to directly evaluate spatial autocorrelation among samples (Rossi *et al.*, 1992). Spatial autocorrelation is the tendency of samples that are collected near to one another to be more similar than samples that are further apart. A semivariogram depicts the variance (y-axis) between sample points versus the distance at which they are separated (x-axis) (Palmer, 2002). The shape of the semivariogram provides insights into the spatial structure of the variable of interest (Ettema and Wardle, 2002). Variograms may be calculated for one-dimensional data (x-coordinate only) and also for two-dimensional data (x- and y-coordinates). The Camp Creek data demonstrate how the shape of a semivariogram can provide information on the spacing of peaks and valleys in fish counts.

   The semivariograms in Figure 9.5, calculated using the statistical package GS+ for the data depicted in Figure 9.4 (GDS, 2004), illustrate two important phenomena: (1) spatial structure was not discernible from the semivariogram of either the raw fish counts (Figure 9.5(a)) or the binned data (Figure 9.5(b)), but (2) semivariograms of the data smoothed with LOWESS summarized the average spacing between peaks and valleys. The x-axis location of the first peak in the semivariogram (Figures 9.5(c) and 9.5(d)) indicates the average spacing between peaks and valleys in the smoothed data, and the
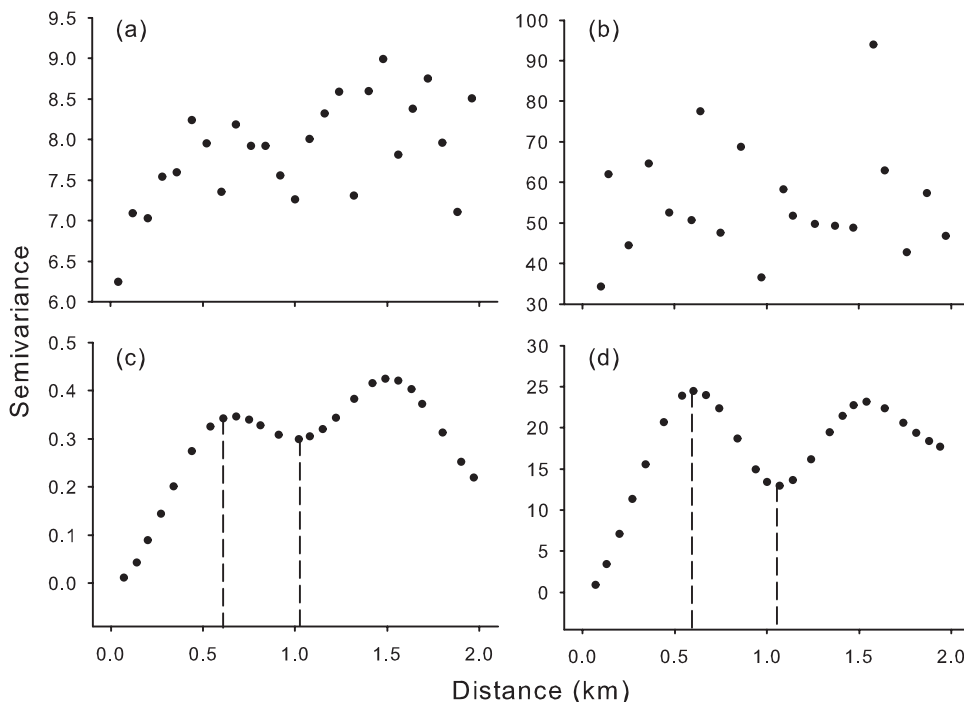
Figure 9.5 Semivariograms of (a) trout counts, (b) 100-m bins of counts, (c) locally weighted scatterplot smoothing (LOWESS) of counts and (d) LOWESS of 100-m bins in the main stem of Camp Creek (see Figure 9.4). Dashed vertical lines indicate the locations of peaks and valleys in semivariance with respect to the x-axis.

x-axis location of the first valley indicates the average spacing between successive peaks and valleys (Legendre and Fortin, 1989). The shapes of the variograms from the raw counts (Figure 9.5(c)) and from the binned data (Figure 9.5(d)) differed little. Thus, the underlying spatial structure of fish counts was the same whether it was derived from the LOWESS of the raw counts or the LOWESS of the binned data. Statistical tests were not necessary to evaluate the significance of the variograms of fish counts in the main stem of Camp Creek because the patterns confirmed the results of graphical analysis.

Extending this analysis into the fish-bearing tributaries (Figure 9.3; tributaries 4, 7, 9 and 10) required an automated approach for testing the statistical significance of patterns observed in the semivariogram (Ganio *et al.*, 2005). A network semivariogram was used to simultaneously compare spatial autocorrelation throughout the entire fish-bearing portion of the stream network shown in Figure 9.3. The semivariogram provided a means to compare the patterns of fish counts in the network to

a hypothetical random spatial distribution. If the data are randomly distributed in space, the semivariogram depicts a horizontal cloud of points with no trend in semivariance with increasing separation distance between sample points. Such a pattern confirms that the data are spatially independent (i.e. sample points that are close to one another are not more similar than sample points that are far apart). To determine whether the spatial structure of fish counts depicted in the network semivariogram differed from a random distribution, 5000 permutations of the fish counts were generated, and 2.5th and 97.5th percentiles were calculated. A statistical routine in the S-PLUS statistical package (S-PLUS, 2002) was used to randomly reassign the fish counts to different locations in the stream network for each permutation (Ganio *et al.*, 2005). The characteristic shape and inflection point of the semivariogram in Figure 9.6 indicates that fish counts were non-randomly distributed in the stream network. The departure of semivariance values outside of the horizontal 'random' band defined by the percentile boundaries indicated statistically significant spatial structure in the semivariogram at a scale of approximately 1 km – the mean distance between fish-bearing tributaries. This distance is greater than the corresponding peak-to-valley distance (0.5 km) in the main stem alone (Figure 9.4(b)) because it incorporates the entire fish-bearing portion of the stream network. These analyses indicate the potential value of geostatistical techniques for identifying tributary impacts (Torgersen *et al.*, 2004), but more work is needed across multiple stream networks to test specific hypotheses on the role of tributaries in structuring biotic and abiotic gradients in river networks.
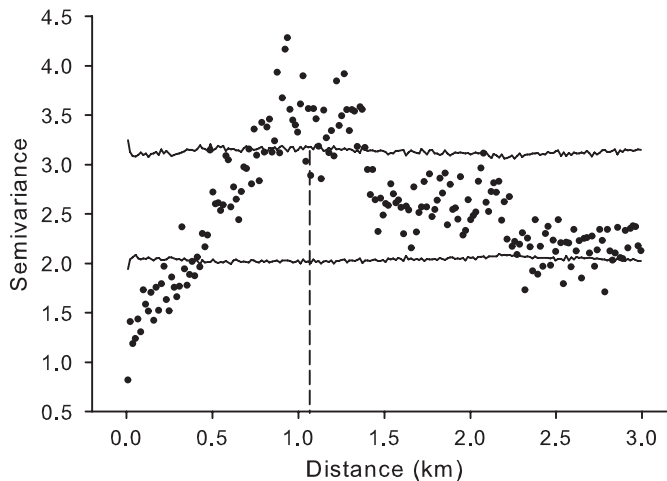
Figure 9.6 Network semivariogram of trout counts in Camp Creek (see Figure 9.3). Dashed vertical line indicates the location of the peak in semivariance with respect to the *x*-axis. Horizontal lines are 2.5th and 97.5th percentiles generated from 5000 permutations.

Future developments and challenges

Methods for identifying tributary impacts in fluvial networks have advanced rapidly due to improvements in sampling, mapping and automated analysis techniques. However, the increasing availability of high-resolution data over long reaches of stream will require riverine scientists to draw upon analysis tools and approaches developed by other disciplines. Intensive approaches to data collection and statistical analysis, which have traditionally derived relationships from a limited number of sites, will need to be adapted to handle large, spatially autocorrelated data sets. Sophisticated statistical tools for pattern detection, such as wavelet analysis, are perfectly suited to evaluating complex spatial patterns but are not commonly applied in rivers (Csillag and Kabos, 2002). These methods were designed for decomposing hierarchical structure in time series and one-dimensional data, which are similar in spatial configuration to the nested spatial pattern of biotic and abiotic features along river channels. An advantage of wavelets over semivariograms is that the wavelet transform function preserves locational information along a transect (i.e. the main stem) (Bradshaw and Spies, 1992). Thus, in wavelet analysis the positions of tributary junctions can be evaluated directly with respect to any hierarchical spatial structure in the data. In contrast, the semivariogram loses locational information due to the averaging of variances across all data points. These two different methods of analysis are complementary but seldom have been used together to elucidate spatial heterogeneity associated with tributary effects (Torgersen *et al.*, 2004).

The spatial analysis of river networks is currently a major focus of environmental monitoring and assessment at local and regional scales and can provide useful tools for understanding and modelling tributary impacts in a network context (Peterson and Urban, 2006; Theobald *et al.*, 2006; Ver Hoef *et al.*, 2006). Other disciplines, such as transportation geography, have developed specialized techniques for studying point patterns in road networks (Yamada and Thill, 2004). Kernel density estimates use a set of probabilities to represent the intensity of spatial point patterns and have been used to examine the spatial clumping of plant species in road networks (Spooner *et al.*, 2004).

The analytical tools and approaches described in this chapter constitute a first step towards understanding tributary impacts using spatially explicit data sets. The application of these and other state-of-the-art methods has significant potential for identifying tributary impacts and developing a better understanding of complex spatial patterns in fluvial networks. Next steps involve the development, testing and transfer of models that predict tributary impacts in systems where data are limited or difficult to collect over large areas (Benda *et al.*, 2004b; Rice, 1998). Recent modelling work on sediment routing at tributary junctions illustrates that longitudinal discontinuities in physical and biological diversity can be predicted at network scales (Ferguson *et al.*, 2006; Rice *et al.*, 2006). Such predictive models can be tested against empirical patterns revealed through the methods outlined in this chapter. The ultimate goal of a combined approach to empirical pattern analysis and modelling is to simulate the spatially dynamic

physical and biological mosaic of tributary–main-stem interactions unfolding through time.

Acknowledgements

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