FEATURE

Three Visualization Approaches for Communicating and Exploring Passive Integrated Transponder Tag Data

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As the number, size, and complexity of ecological data sets have increased, narrative and interactive raw data visualizations have emerged as important tools for exploring and understanding these large data sets. As a demonstration, we developed three visualizations to communicate and explore passive integrated transponder tag data from two long-term field studies. We created three independent visualizations for the same data set, allowing separate entry points for users with different goals and experience levels. The first visualization uses a narrative approach to introduce users to the study. The second visualization provides interactive crossfilters that allow users to explore multivariate relationships in the data set. The last visualization allows users to visualize the movement histories of individual fish within the stream network. This suite of visualization tools allows a progressive discovery of more detailed information and should make the data accessible to users with a wide variety of backgrounds and interests.

INTRODUCTION

In recent years, millions of passive integrated transponder (PIT) tags have been implanted in fish (Prentice et al. 1990; Zydlewski et al. 2006). Every PIT tag is unique, providing individual identification of tagged fish. This allows researchers to track histories of individuals over time and space. Tagging efforts may range from laboratory studies of a few individual fish to the massive numbers (>40 million) of fish tagged in the Columbia River basin, USA (http://ptagis.org). In all cases, PIT tag data are complex because individuals can be observed and recaptured repeatedly in different locations over time and detection rates of tagged fish are almost always less than 100%. A number of modeling approaches have been developed to accommodate these issues (Lebreton et al. 1992; Williams et al. 2002; Schaub and Royle 2014), resulting in a better understanding of the ecology (movement, growth, survival) and evolution (selection, gene flow, genetic drift) of fish (e.g., Baerum et al. 2013; Vincenzi et al. 2014; Bassar et al. 2016). However, models are abstractions of their underlying data and necessarily result in the loss of information, particularly when dealing with individual tagging data. In PIT tag studies, variation in individual performance is often as interesting as the population-level average, and though this variation may be modeled directly (Royle 2008; Bonner et al. 2010), it can still be difficult to fully characterize individual-level variation when using models. For example, we have found modeling individual trout movements in small streams to be difficult as movement patterns and their drivers can be diverse and difficult to characterize or identify.

When using tag data, one alternative way to learn about variation in individual performance is to explore the raw data. Data exploration is often conducted prior to modeling to identify general patterns in the data and facilitate hypothesis formation. However, we suggest that new approaches to raw data visualization, utilizing Web-based, interactive visualization platforms, can become integral to the data analysis process, leading to improved understanding of the data as well as enhanced communication with both technical and general audiences.

Recent developments in free and open source software frameworks and libraries (e.g., Shiny [shiny.rstudio.com], d3.js [https://d3js.org]) provide new opportunities to visually represent and explore complex data sets through dynamic interaction while also making these data more accessible to general audiences through distribution on the World Wide Web. Data visualizations fall somewhere between author-driven and user-driven applications. In purely author-driven applications, a narrative "data story" is presented to the user in a linear, step-by-step progression that culminates in a clear, predefined message. These author-driven narratives use a specific sequence of data transitions with no truly interactive steps (Segel and Heer 2010). The opposite is true in user-driven applications, which allow users to explore the data on their own by choosing which data they wish to view and how it will be visualized. This interactivity can enhance learning by allowing individual users to identify patterns in the data and formulate their own questions (Yi et al. 2007).

An example of a strong author-driven narrative is the "What's warming the world?" application from Bloomberg (www.bloomberg.com/graphics/2015-whats-warming-the-world). This story presents a series of animated charts and short captions describing how different factors contribute to rising global temperatures. The author's clear intention is to show that anthropogenic factors (i.e., greenhouse gas emissions) make the strongest contribution to temperature increases relative to other natural factors (e.g., volcanic emissions, solar fluctuations). The limited interactivity at the end of the story aims to reinforce the intended narrative by allowing filtering of the possible contributions. In contrast, a good example of a user-driven application is the neural network tutorial of TensorFlow (playground.tensorflow.org). Users can explore how model complexity influences the predictive capability of a neural network with no predetermined narrative or enforced sequence to the exploration.

Highly interactive applications can amplify learning and understanding by promoting the formation of a "mental model" of a given system as users explore relationships in the data (Card et al. 1999). However, interactivity can also lead to cognitive overload if the visual output or user interface is too complex (Sweller et al. 1998). Effective interactive visualizations therefore require a balance between providing enough information to promote learning (i.e., mental model formation) while preventing or minimizing cognitive overload.

To demonstrate the utility of interactive visualizations, we first present long-term PIT data sets that we collected in two New England, USA streams. We then develop several visualizations from the PIT data, emphasizing different levels of interactivity and complexity.

PIT TAG STUDY OVERVIEW

We assembled large PIT tag databases from two primary study sites: West Brook in Whately, Massachusetts, USA (1997–2016) and Stanley Brook on Mount Desert Island in Maine, USA (2006–2013). West Brook is a typical New England headwater stream in forested uplands and Stanley Brook is a coastal stream where fish have access to the sea. The 1-km-long West Brook study area included the main stem and three-second-order tributaries. The Stanley Brook study area (2 km) consisted of a main stem with a lower tidal portion (approximately 240 m long) and one-second-order tributary. Both streams contain Brook Trout *Salvelinus fontinalis* but West Brook also supports Brown Trout *Salmo trutta* and Atlantic Salmon *S. salar* (stocked as 25-mm fry in spring until 2004). Four seasonal samples were collected each year in West Brook and twice per year in Stanley Brook. Maps and images of the study sections are available at http://pitdata.ecosheds.org. Further details can be explored using the data visualizations described below.

The PIT tag data were collected for three primary reasons: (1) to gain a deeper understanding of Atlantic Salmon life histories, (2) to learn how environmental variation affects trout population dynamics, and (3) to understand how access to estuarine and coastal environments affects Brook Trout life histories and population dynamics. Over the course of the study, we have conducted analyses and modeling exercises to identify drivers of population dynamics and life history patterns, resulting in 43 publications to date. For example, we identified variation in Atlantic Salmon body size (Letcher and Gries 2003), growth (Sigourney et al. 2012, 2013), survival (Letcher et al. 2002; Horton et al. 2009), and morphometry (Letcher 2003; Pearlstein et al. 2007) for fish with different eventual freshwater life histories. Fish with earlier smolt ages (2+ versus 3+) and males that were mature or not in the stream were different sizes and shapes as early as their first year. Combining PIT data with parentage analysis, we then determined that early emerging fish maintained a size advantage over later emerging fish and that early fish also smolted a year earlier (Letcher et al. 2004). These types of retrospective life history analyses were made possible by our continuing, seasonal PIT tag sampling efforts.

Our PIT tag data have also been used in capture–recapture analyses (Lebreton et al. 1992) to estimate Brook Trout survival across seasons and ages (Carlson and Letcher 2003), to identify environmental drivers of seasonal and age variation (Xu et al. 2010), and to develop an integrated model of movement, growth and survival (Letcher et al. 2015). This integrated model was subsequently incorporated in a population projection model (Easterling et al. 2000) that allowed us to study the relative importance of environmental factors and Brook Trout density on population dynamics (Bassar et al. 2016) and to identify life history shifts that might promote persistence of a fragmented population (Letcher et al. 2007). Combining PIT data with parentage assignment has also yielded important information on heritability (Letcher et al. 2011) and on cross-generation movement among stream segments (Kanno et al. 2014).

GOALS AND DESIGN CONSIDERATIONS FOR THE VISUALIZATIONS

When designing the PIT tag data visualizations, our overarching goals were to facilitate broad communication and to create a series of engaging and intuitive tools for individual investigations of the data. We sought to help viewers quickly understand the scope of the data, then to provide a means of exploring complex patterns and relationships within the data. At the outset, we recognized that audiences would associate with the data in different ways, based upon their previous experiences and questions. For instance, viewers with little or no prior training in fisheries science might simply wish to see where PIT tag data have been collected while seasoned researchers may wish to know how siblings are distributed in space. We therefore developed three separate visualizations of the PIT tag data set, each of which was created to serve a specific target audience and to address specific types of questions (see Table 1). The first visualization is designed to introduce the PIT tag data set, the second uses crossfilters to examine multivariate relationships within the data, and the third explores movement and performance of individual fish.

To achieve a balance between mental model formation and minimizing cognitive overload when designing the visualizations (see Introduction), we adopted Shneiderman's (1996) visual information seeking mantra (VISM) of "overview first, zoom and filter, then details-on-demand." This general approach to visual design is also known as progressive disclosure, where only the necessary or requested information is displayed at any given time (Lidwell et al. 2010). In our visualizations, an overview of the entire data set is first provided, zooming and filtering are used to focus on a particular subset of interest, and detailed information on any data points of interest can be generated on demand.

Additional design criteria for the visualizations included application speed, exclusive use of open-source software, and free access to the source code and underlying PIT tag data sets. To address application speed, we minimized server-side operations by loading the data set into the user's browser at the beginning of a session and relying on client-side libraries to manipulate the data and update the visualizations. Once the data set is loaded, no additional calls are made to the server and all remaining operations are performed locally in the user's Web browser. This initial download may slow the application at start-up (depending on connection speed), but it allows the user to take full advantage of the local memory for very fast operations during use, with greater responsiveness and interactivity than traditional server-side applications (Walker and Chapra 2014).

Open-source software was used exclusively so that others could replicate or modify our applications as needed. This included Hypertext Markup Language (HTML; the standard language to define the structure and position of individual elements on a Web page) and Cascading Style Sheets (CSS; rules that define the stylistic elements of a Web page, such as color, font size, etc.), in addition to base JavaScript and the JavaScript libraries D3 (Data-Driven Documents), jQuery, CrossFilter, Leaflet, and Intro.js. JavaScript is the most common programming language used in modern Web browsers to add interaction, animation, and application logic to a Web site. The D3 library was used to link data to objects on the Web page, then to interactively transform these objects by changing their styles (e.g., color, shape, size) or locations. D3 was particularly useful in creating dynamic transitions or animations within the visualizations. The jQuery library was used to simplify some blocks of JavaScript code and to ensure consistency across different Web browsers. The Crossfilter library was used to add cross-filtering, the ability to filter across multiple variables simultaneously. The Leaflet library was used to generate interactive maps of the study sites. And the Intro.js library was used to create a guided introduction to some of the Web page objects.

In full disclosure, developing the visualizations was a significant technical challenge. Learning to use D3 was particularly difficult as the functions and underlying data structure are substantially different from more familiar languages like R and Python. Mastering D3 is a good time investment for anyone that requires a high level of flexibility in Web visualization, and many online resources are available to help (e.g., https://github.com/d3/d3/wiki/Tutorials; www.dashingd3js.com), but the process will likely require several months to a year of focused effort. Learning to use D3 will be faster with solid knowledge of Web design and application principles based on HTML, CSS, and JavaScript (a good place to start is www.w3 schools.com). As an alternative, some D3 functions can now be reproduced

Table 1. Overview of the three visualizations, including objectives, intended audiences, and example questions.

Application	Objective	Intended audience	Example questions
Study overview	Introduce the study	General public	Where was the study?
			How many species were in the study?
			How many fish did you tag?
			How many streams were in the study area?
			How often did you sample?
			How long did the study last?
Multi-dimensional crossfilter	Explore relationships in the data	Resource managers	Where were the fish in the study area?
			Is the population declining?
			Do species overlap in space?
			What is the body size distribution?
			Where are the large fish?
Individual-based visualization	Explore details of individual performance	Collaborators, researchers	How do individual fish move in the stream network? Is there variation by species and season?
			What is the shape of the dispersal kernel?
			How many fish move among streams?
			How many fish emigrate?
			Which fish were not captured each sample?
			Which fish were never seen again?
			How do stream flow and temperature influence movement and survival?
			How are families distributed in space?

in R. For example, the R package Shiny can be used to create interactive Web applications, providing an easier entry point when the full functionality of D3 is not required. Learning to maintain servers to distribute our code and data to client-side users was also a significant challenge. Fortunately, this does not have to limit visualization opportunities because many application hosting services are now available.

Finally, embracing the concept of reproducible research (Goodman et al. 2016), we posted the complete code for our applications at our public GitHub page (https://github.com/Conte-Ecology/shedsPitData). The complete PIT tag data set is also available from the GitHub repository.

USING THE THREE VISUALIZATIONS

Landing page

Users are first greeted with an overview page (pitdata.ecosheds.org) that provides a quick introduction to PIT tagging studies as well as maps of our two study areas. Users can hover the mouse cursor over a study section on the map to open a pop-up window with a photo of that section. The landing page also provides links and short descriptions for each of the three visualizations described below.

Visualization 1: study overview [pitdata.ecosheds.org/overview]

The study overview is a narrative visualization that summarizes how many fish fall into different categories (Figure 1). Users can see how many fish were tagged among three species, which rivers they occurred in, and numbers of captures among seasons and years. At the end of the narration, users can further explore the data by grouping observations in space and assigning colors to different variables. The study overview is primarily an author-driven application designed to lead users through a high-level overview of the data. It has proven useful in providing colleagues and the general public with an introduction to our PIT tag research.

Visualization 2: multi-dimensional crossfilter [pitdata.ecosheds.org/crossfilter]

Each record in the PIT tag data set is appended with several categorical (species, river branch, and season) and continuous variables (fish length, section within a river branch, and year). Using the multi-dimensional crossfilter application (Weaver 2010), viewers will first see histograms of select variables with a map of the number of observations at each stream segment (Figure 2). The data set can then be filtered by either selecting one or more values for a categorical variable (e.g., selection by species) or by clicking and dragging over a continuous variable histogram to select a range of values (e.g., a specific range of years). When one or more filtering criteria are specified, the histograms of all other variables, as well as the map and time series, are instantly updated to reflect the new subset of data. For example, by selecting and unselecting a species, users can quickly see in which locations and in what year a species was captured or whether that species is larger or smaller than other species. This interactivity allows the user to easily explore relationships within the data and to focus exclusively on data subsets of interest.

Notably, the multi-dimensional crossfilter is completely user-driven. An author-defined narrative is not used to guide the viewer through sequential visualizations of the data; the user must pose questions and explore the data autonomously. However, this application provides no information on individual PIT tag identities. Thus, the full content of the individual-based data set cannot be explored with the multi-dimensional crossfilter.

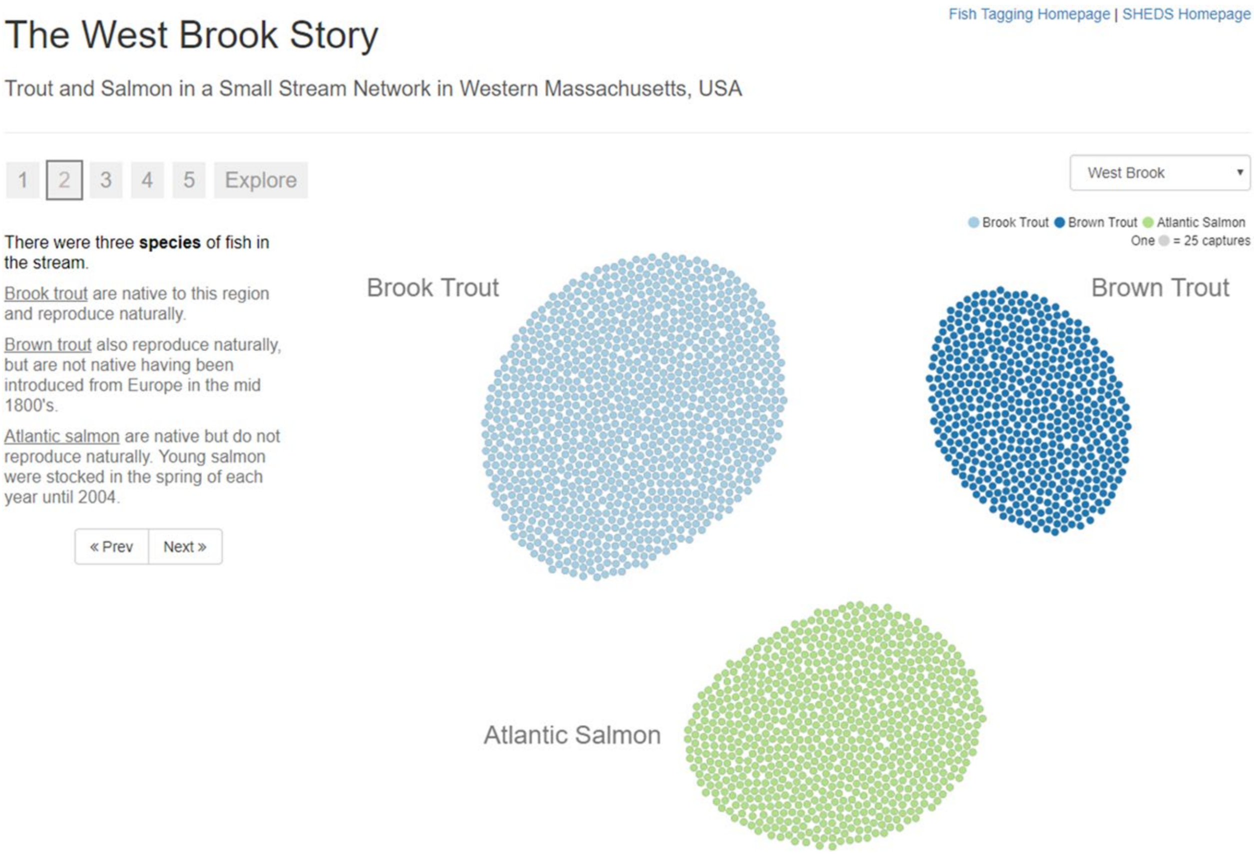

Figure 1. Snapshot of the *Study Overview* visualization, providing a broad overview of the PIT tag data.

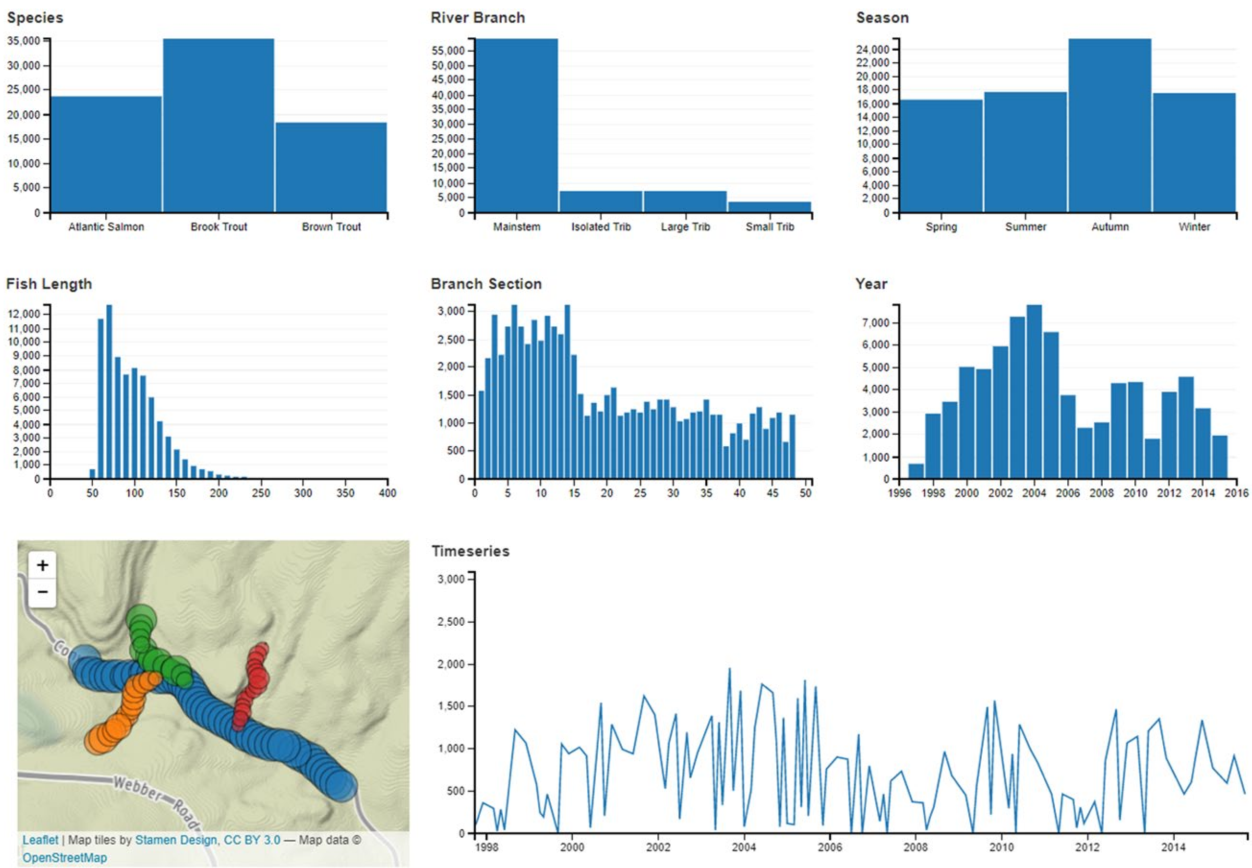

Figure 2. Initial view of the *Multi-dimensional Cross-filter* visualization, a tool for exploration of patterns in multi-variate data.

Visualization 3: individual-based movement [pitdata.ecosheds.org/fish-movements]

This application was designed to aid in studying individual movements, which are difficult to characterize with traditional statistical summaries and models. It shows the locations of individual fish within the steam network for each sampling occasion (Figure 3). To illustrate individual movements over time, users can click the “next” or “previous” buttons and individual fish (represented as colored dots) will transition to their new locations (if they moved). Information on individual body size can also be explored; the sizes of individual dots are proportional to individual length and hovering over a dot with the cursor will show that fish’s capture history with date, location, length, and estimated age.

Because large numbers of individuals were captured in some years, large aggregations of dots will sometimes appear on the screen, making it difficult to identify patterns and promoting cognitive overload. Users can therefore filter the individual data into subsets based on family identity, discrete stream section, or river. Individual fish can also be selected. Filters gray out unselected fish, allowing the user to focus on selected fish and to more easily visualize fish movements throughout the stream network.

The individual-based movement application can also depict the addition or loss of individuals within the database. Known emigrants (i.e., individuals that were detected outside of the study area) are indicated by dots that move beyond the mapped study area. Individuals that were never observed again are represented by an open dot at the beginning of an interval, indicating the last observation of that fish; these lost fish are removed entirely from the visualization at the beginning of the next movement interval. Newly tagged fish appear in their respective stream section at the end of a movement interval. In this way, users can easily see how many and which fish exited (or were otherwise undetected; see Letcher et al. 2015) or entered the population in each interval.

Complementing the visualizations of individual fish movements, the application can also summarize aggregate movements by overlaying distributions of movement distances for a given sampling interval and season on the combined distribution for all years and by plotting probabilities of fishes transitioning among stream segments. Finally, distributions of daily stream temperature and flow can be plotted for the current time interval or for seasons (across years) to show users if a given interval was relatively hot/cold or wet/dry.

EXAMPLE INSIGHTS FROM THE VISUALIZATIONS

These visualizations can enhance learning by providing easy, graphical access to summarized (Visualizations 1 and 2) or individual-level data (Visualization 3). For instance, working with the crossfilter visualization, we learned quickly that Brook Trout were generally smaller than Brown Trout and that Brown Trout were more abundant than Brook Trout in downstream reaches. We also identified stream sections with consistently high abundances of large fish and low abundances of small fish. Based on habitat surveys (not represented in the visualizations), these are known pool sections. Interestingly, abundances of large fish appeared to decline over time in pools with decreasing depths. In Stanley Brook, we observed that large fish are relatively abundant in the tidal section and that low abundances over time were correlated with low flow summers. While these observations certainly would be possible using standard graphical and statistical approaches, our interactive visualizations streamlined the discovery process and minimized the need for expert training in data analysis.

Exploring the individual-based movement visualization, we were impressed by the high degree of variation in individual movements. General movement patterns did emerge, however, including a strong and unexpected downstream salmon emigration in the autumn (salmon typically emigrate to the sea in spring), emigrants originating from the full range of the study area for salmon and trout, and very few fish leaving

Figure 3. Image of the *Individual-based* visualization, showing the locations of individually-tagged fish in a stream network. Users can visualize fish movements by clicking “previous” or “next” to change the sampling interval. Individual fishes (dots) will move to capture locations at the end of the selected interval.

the small, isolated stream in West Brook. We also observed that fish from the same family were found together when they were age 0+ and that families tended to disperse following age 0+. In Stanley Brook, we observed that summer mortality was higher than winter mortality, that most movements were in the downstream direction, and that many of the individuals that moved to the tidal portion originated from the most upstream sections of the study area.

DISCUSSION AND CONCLUSIONS

Like many ecological data sets, PIT tag data can be complex and difficult to draw inferences from. Formal training in statistical modeling and data analysis are normally required to utilize these data, making them inaccessible to general audiences, as well as other researchers. Effective data visualizations can overcome some of these limitations by providing high-level summaries, as well as detailed representations of the underlying data, in ways that are intuitive and broadly accessible.

We developed three visualizations to help present and explore two long-term PIT tag data sets. Hopefully, these visualizations will serve to demonstrate new ways of working with PIT tag data and encourage other researchers to consider similar approaches when analyzing and sharing their data. Furthermore, our applications could easily be adapted to other study sites if the raw data include similar attributes. Indeed, the first two visualizations, the study overview and the multidimensional crossfilter, do not require data with individual identifiers and could therefore be applied to many different data sets. The individual-based movement visualization does require individual identifiers but could accommodate virtually any spatial structure, including other stream networks.

Designing our visualizations involved trade-offs between an emphasis on clear, simple patterns and the ability to gain more complex insights. Although we solicited feedback from colleagues and used their comments to improve the visualizations, a focus group consisting of different end users would likely provide new ideas to improve our designs. For example, one trade-off that we considered was the decision to build one large application, allowing for multiple views of the data set, or to create three separate applications, each designed to meet a specific goal. We decided on the latter, both for ease of development and to demonstrate differences between author-driven and user-driven narratives. But we acknowledge that a single, integrated application may be more effective for some purposes.

In summary, data visualization tools are rapidly becoming more sophisticated. Powerful new software libraries and visualization frameworks can generate engaging, esthetic representations of complex data and make these representations instantly accessible on the World Wide Web. And a basic understanding of design principles can help to ensure that users will be able to engage with visualizations without being overwhelmed by complexity and cognitive overload. The three PIT tag data visualizations presented here provide a modest glimpse of these capabilities. We hope they will prove useful to new audiences and motivate other researchers to communicate and explore their own data in new ways.

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