

Chapter 13

From Data–Centered to Activity–Centered Geospatial Visualizations

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ABSTRACT

As geospatial visualizations grow in popularity, their role in human activities is also evolving. While maps have been used to support higher-level cognitive activities such as decision-making, sense making, and knowledge discovery, traditionally their use in such activities has been partial. Nowadays they are being used at various stages of such activities. This trend is simultaneously being accompanied with another shift: a movement from the design and use of data-centered geospatial visualizations to activity-centered visualizations. Data-centered visualizations are primarily focused on representation of data from data layers; activity-centered visualizations, not only represent the data layers, but also focus on users' needs and real-world activities—such as storytelling and comparing data layers with other information. Examples of this shift are being seen in some mashup techniques that deviate from standard data-driven visualization designs. Beyond the discussion of the needed shift, this chapter presents ideas for designing human-activity-centered geospatial visualizations.

INTRODUCTION

Geospatial visualizations are digital geographic and/or spatial maps to which users or designers can link their data. Due to the widespread availability of map application programming interfaces

(e.g., Google Maps, Google Earth, Bing Maps, OpenStreetMap, and others), geospatial visualizations have become common tools in many human activities. Climatologists, biologists, linguists, literary researchers, business analysts, real-estate agents, journalists, historians, librarians,

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archivists, geologists, social scientists, educators, archaeologists, health and medical professionals, and others have adopted various types of maps for data visualization (Shandler, 2012; Bailey et al., 2012; Boggs et al., 2012; Nunn & Bentley, 2012; Xie & Pearson, 2010; Skiba, 2007). Broadly, designers create geospatial visualizations using three approaches. First approach is taken by those who design simple Web 2.0 tools such as Fusion Tables, Flickr, Historypin, or SIMILE Widgets. Second approach is taken by those who, having more advanced programming skills, use data-centered models, developed by geovisualization and information visualization researchers, to design time maps, coordinated displays, and dynamic query interfaces. Third approach is taken by those who design activity-centered geospatial visualizations—examples of which include Historypin, an online, user-created archive of historical photos and personal recollections (Historypin, n.d.) and Marine Map decision support tool (South Coast Regional Stakeholder Group, n.d.). These visualizations are geared towards supporting user tasks and activities. The first two approaches result in more-or-less data-centered visualizations, and the third approach is intended to produce human-activity-centered visualizations. The distinction between data-centered and activity-centered visualizations lies in the focus of their designs. Whereas data-centered visualizations are primarily focused on and concerned with representing empirically or mathematically derived data values, activity-centered visualizations focus on representations and interactions that support user's goals, needs, and real-world tasks and activities. As there is scarcity of research with regard to how to design activity-centered geospatial visualizations, in this chapter, we discuss how geospatial visualizations can be made more activity-centered and suggest some ideas and techniques.

In this chapter, human activities refer to “clusters of actions and decisions that are done for a purpose” (Saffer, 2010). Tracing one's genealogy,

deciding about a real-estate purchase, making sense of medical records, or finding the cause of a disease outbreak are examples of human activities. Activities may range from simple ones, such as finding a specific location or retrieving driving directions, to complex ones, such as determining the cause and effect in natural phenomena or drawing conclusions about the data coming from multiple sensors or map layers. A single activity may involve many tasks and subtasks (Sedig & Parsons, 2013). For example, determining the causes of some social activities (e.g., riots or strikes) may involve a number of visual comparisons of several map layers with the locations of riots and strikes, reading newspaper articles and social media messages about them, and determining proximity to some important landmarks. As such, it can be seen that there are differences between the complexity of higher-level activities that people perform and the less complex lower-level computational and preparatory tasks that help them complete these activities.

Understanding user tasks and activities is essential for the effective design of activity-centered visualizations. Geospatial visualizations should be designed such that they support users to tell spatio-temporal stories, to make comparisons between different data, to draw extrapolations from data, to generate hypotheses, to observe trends in data, and to perform other tasks that collectively give rise to more complex activities at hand. Ideally, these visualizations should create conditions whereby users would not assume that maps can only provide limited “snapshots of reality” (Cartwright, 2009), nor that they are not able to support high-level sense-making activities (Elias et al., 2008). Sedig and Parsons (2013) suggest that one of the main roles that computational tools, such as these interactive visualizations, can play is epistemic—that is, they should support, extend, partner, and supplement the cognitive functionings and activities of their users, activities, such as decision-making, learning, problem

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