Geospatial big data and cartography: research challenges and opportunities for making maps that matter

Anthony C. Robinson[1*], Urška Demšar[2], Antoni B. Moore[3], Aileen Buckley[4], Bin Jiang[5], Kenneth Field[4], Menno-Jan Kraak[6], Silvana P. Camboim[7], Claudia R. Sluter[7]

[1]*GeoVISTA Center, Department of Geography, The Pennsylvania State University, University Park, USA*

[2]*School of Geography and Geosciences, University of St Andrews, St Andrews, Scotland*

[3]*School of Surveying, University of Otago, Dunedin, New Zealand*

[4]*Esri, Inc, Redlands, USA*

[5]*Division of GIScience, University of Gävle, Gävle, Sweden*

[6]*Department of Geoinformation Processing, Faculty of Geoinformation Science and Earth Observation, University of Twente, Enschede, the Netherlands*

[7]*Department of Geomatics, Universidade Federal do Paraná, Curitiba, Brazil*

*Corresponding author: arobinson@psu.edu, 302 Walker Building, University Park, PA 16802

Geospatial big Data and Cartography: Research Challenges and Opportunities for Making Maps that Matter

Geospatial big data present a new set of challenges and opportunities for cartographic researchers in technical, methodological, and artistic realms. New computational and technical paradigms for cartography are accompanying the rise of geospatial big data. Additionally, the art and science of cartography needs to focus its contemporary efforts on work that connects to outside disciplines and is grounded in problems that are important to humankind and its sustainability. Following the development of position papers and a collaborative workshop to craft consensus around key topics, this article presents a new cartographic research agenda focused on making maps that matter using geospatial big data. This agenda provides both long-term challenges that require significant attention as well as short-term opportunities that we believe could be addressed in more concentrated studies.

Keywords: big data; cartography; geovisualization; visual analytics; research agenda

Introduction

The emergence of big data presents a call to action for cartographers. The process of making a map is, at its core, an act of generalization to make sense out of an infinitely complex world. As data sources creep closer toward the ability to describe every detail, all the time, for every place, the ways in which we make maps to make decisions must adapt to handle this data windfall. New sources of information, including streaming imagery from satellites and millions of conversations via location-enabled social media, are examples which stretch the limits of what and how we map. These new data sources are of limited utility if we cannot find meaning in them, therefore an overarching goal for cartographers is to find a way to use these data to make maps that matter to people.

In this article we present a new research agenda for making maps that matter from big data. Maps that matter are those that pique interest, are tacitly understandable, and are relevant to our society. Achieving any one of these goals with a given map is non-trivial, and achieving them together is even more difficult. And yet cartography and geographic visualization are uniquely placed to develop tailored representations and methods of interaction that can help humans to visually discover the hidden content of big spatiotemporal data (MacEachren & Kraak, 2001, p. 3). Many of the challenges outlined in previous cartographic research agendas remain relevant (G. Andrienko et al., 2007; Fairbairn, Andrienko, Andrienko, Buziek, & Dykes, 2001; MacEachren, 1994; MacEachren & Kraak, 2001; MacEachren & Kraak, 1997; Virrantaus, Fairbairn, & Kraak, 2009), but we focus here on new challenges posed by the emergence of big data. To develop this focus for a research agenda and associated key challenges and opportunities, we followed a multi-phase collaborative ideation process. Members of four International Cartographic Association (ICA) Commissions collaborated using Google Moderator to propose, comment on, and vote to promote key research issues in cartography. Twenty-nine research needs emerged from this activity, which were then categorized into three major areas; research methods in cartography, designing for human ability and map use contexts, and leveraging geospatial big data. Each research aim was further expanded upon through the development of fifteen position papers for an ICA workshop titled *Envisioning the Future of Cartographic Research* held in 2015. At this workshop, the challenges and opportunities described in this agenda were iteratively refined and elaborated. A complete description of the agenda development process is described in (Griffin, Robinson, & Roth, Submitted).

Since the emergence of the concept in recent years, big data have been discussed in many disciplines and a number of research agendas for big data have appeared, generating ample new scholarship. The definition of big data is nebulous, however. It was not so long ago that one megabyte of data was seen as ‘big’ and which required vast computational power to explore.

While there is no widely accepted common definition for what constitutes big data, the most commonly cited definition suggests that big data is characterized by large volumes, high velocity, and a high degree of variety (Laney, 2001). Additional dimensions have been subsequently proposed to include veracity (Li et al., In Press; Thatcher, 2014; Tsou, 2015), high resolution, a high degree of flexibility, relational nature, and an exhaustive scope. For the purposes of this agenda, we focus on big data volume, velocity, variety, and veracity. Recent research agendas on big data in GIScience have focused on methods and algorithmical complexities (Jin, Wah, Cheng, & Wang, 2015), on social media (Li et al., In Press; Tsou, 2015) and on defining geospatial big data (Lee & Kang, 2015; Li et al., In Press). Researchers are also pondering what big data really mean (Jagadish, 2015) or how to contextualize them within the traditional disciplines, such as geography (Graham & Shelton, 2013; Kitchin, 2013).

Our agenda contributes to this discussion to identify what cartography and geovisualization can do to efficiently and effectively visualize complex spatial data to make decisions and support reasoning. Cartography and geovisualization can support exploratory as well as confirmatory analysis of big data, serving a role to help users identify patterns worthy of analysis as well as to interrogate previously known problems. We also emphasize the critical need for interdisciplinary knowledge transfer between various data sciences, given the complexity of geospatial big data in its current and anticipated future forms. Each of the research aims in this article deserves collaborative attention between cartographers and experts from allied domains such as computer science, human-computer interaction, game design, virtual reality, information visualization, data mining, and the visual arts.

We begin by highlighting core concepts in cartography that provide a basis for cartographic research with big data, many sources of which are location-based (or have location as an attribute) which makes mapping them essential. Then we present our research agenda in two major sections. First we present the long-term and large-scale *research challenges* that face cartography and geovisualization in relation to big data and its four primary dimensions. To go further, we look at potential approaches informed by Art, an essential component of cartography. In the second part of this agenda we introduce short-term *research opportunities* that we believe can be achieved in more concentrated investigations. We structure these around the development of new visual, computational, and artistic methods for geospatial big data. Finally, we explain how cartography and geovisualization can tackle research challenges and opportunities to make maps that matter; maps that generate insights from complex, large, unstructured, varied data on problems that have broad impacts to society and our environment.

Core Concepts

Geospatial big data, a special type of big data, can be categorized into two classes. The first is *geolocalized* big data in which location is an additional, accessory attribute. These data are often points, such as GPS locations from smartphones or customer addresses from business intelligence systems. The other category of geospatial big data are *spatially-grounded*, in which location, shape, size, orientation, and spatial relationships are integral to the data. These data come from sources such as sensor networks, collections of text reports with spatial references, high-resolution imagery from drones and satellites, and 3D laser scans. In the context of geospatial big data, space and time are inherently linked as many big data sources include temporal information. In the following sections, we outline five crosscutting themes that provide key perspectives on cartographic research with geospatial big data.

Place, Space, and Time

A core theme concerns an understanding of space and place so that we can appreciate the cartographic complexity of representing geospatial big data. Space might be regarded as abstract while place is something more tangible that people can identify with, model and map as part of a space (Seamon & Sowers, 2008; Tuan, 1977). A place gives a space meaning. It is those features of a place that can be captured, modelled and mapped. In this sense, geospatial big data allow us to model a place. Geospatial big data can go beyond mapping of individual places and features and begins to allow us to define combinations of places. Perhaps this will lead to a mechanism to better characterize the linkages of places that form a space. We therefore envision the potential that mapping big data may lead to *big cartography* which conceptualizes and visualizes complex representations of place and space. Coupled with the important but poorly researched temporal dimension (Kraak, 2014; Rosenberg & Grafton, 2010) this has the promise of making it possible for cartographers to tackle pressing and non-trivial issues in visualization concerned with references to place.

Representation

In the context of cartography, representations are the constructions we develop to signify features and concepts in reality in a simplified form for interpretation via maps (Dodge, Kitchin, & Perkins, 2011; Fairbairn et al., 2001; MacEachren, 1995). In the context of big data, advances in representation are necessary to produce graphics, including maps, that help people see patterns and outliers, as well as derive meaning from massive, complex datasets (and computational results derived from them). It is also essential to craft new means for representation in computational structures, as complex data and their interrelations will need to be carefully modelled so that we can effectively and efficiently compute on massive data collections.

Interaction

Maps as overviews to big data can provide a powerful visual gateway for analysis, but only if their interactive affordances are carefully designed and evaluated. Interaction is the essential mechanism by which users can navigate, search, filter, and compare (among other actions) using geographic data sources. The wide range of form factors for digital maps today presents a new set of challenges to support user interaction, including touch, voice, and gesture-based interfaces. We have much to learn yet to determine best practices for manipulating maps via digital interaction (Andrienko & Andrienko, 1999; Roth, 2013). Interaction also plays a key role now in determining what data is captured or emphasized in the future, as evidenced by new predictive computational approaches by industrial giants like Google and Amazon. It is possible that interaction with a digital map today could influence what is collected and/or emphasized tomorrow – highlighting a new age for map use in which map interaction itself can influence which data we can map later.

Scale

Map scale is the relationship between distances on the map and their corresponding ground distances (Kimerling, Buckley, Muehrcke, & Muehrcke, 2011). Geographic or spatial scale is the operational level at which the analyses are conducted, for example, from cities to continents. In other sciences such as physics, biology, and mathematics (Mandelbrot, 1982), scale is primarily defined in a manner in which a series of extents are related to each other in a hierarchy. These concepts of scale overlap in interesting ways with big data. The degree of resolution (map scale) associated with big data can influence types of operational scales for analysis. Both present challenges associated with showing detail on maps. Requirements for cartographic abstraction (generalization, simplification, classification, and symbolization) are exacerbated for big data, and while there are well-known issues associated with abstracting to smaller-scale representations (Fotheringham & Wong, 1991), new approaches are providing promising avenues for exploration, such as those that support visual analysis across multiple scales of social statistics (Dykes & Brunsdon, 2007; Goodwin, Dykes, & Slingsby, 2014).

Users and Usability

Understanding users and prioritizing their needs is key to helping people make sense of geospatial big data. A major goal is to support a high degree of usability in the tools and techniques for mapping big data, as these are increasingly complicated in terms of their form and function (Brown et al., 2013). This challenge is not a new one (Andrienko et al., 2002; Robinson, Chen, Lengerich, Meyer, & MacEachren, 2005; Slocum et al., 2001), but it retains importance today as users expect real-time interaction and the ability to manipulate model parameters to explore outcomes. This need challenges existing computational and rendering capabilities, and requires that complex algorithms and their parameters are readily understandable to non-experts. The emergence of crowdsourcing as a mechanism for conducting user studies (Liu, Bias, Lease, & Kuipers, 2012) and cognitive testing (Klippel et al., 2013) also suggest the potential for evaluating *usability at scale* to help refine cartographic approaches to geospatial big data.

Context

Every map is situated within a specific context of use, which is frequently defined as the information that can be used to describe the situation of an entity (Brézillon, 1999; Dey, 2001; Tomaszewski & MacEachren, 2012). Contextual factors impact the interface between cartography and big data because the scientific challenges associated with mapping big data are inextricable from the relevance of real-world problems. Context may also determine whether or not we consider a specific dataset to be *big*. Advances in knowledge and technology must be linkable to contexts that matter for society, for example, via connection to global goals for sustainable development (General Assembly, 2015). The type of visualization a user might need will depend on the context in which it is used, and little is known regarding which visualization types are best suited to which contexts.

Research Challenges

Here we outline key long term research challenges for cartography and geospatial big data, organized into six broad areas; making sense of geospatial big data, volume, variety, velocity, veracity, and art and geospatial big data (Figure 1).

Research Challenges for Cartography and Geospatial Big Data	
Making sense of geospatial big data	▪ Develop visual analytical reasoning systems that help users add meaning to and organize what they discover from geospatial big data ▪ Design effective map-based interfaces to support long-term analytical engagement with complex spatiotemporal problems and geospatial big data ▪ Develop new approaches for supporting collaborative decision making using the map as a mutual interface for analyzing geospatial big data ▪ Develop techniques that allow users to express and match a spatiotemporal pattern they have in mind using the map as an interface for analyzing geospatial big data ▪ Understand when, how and if maps can help us understand geospatial big data
Volume	▪ Identify effective methods for creating overviews of geospatial big data ▪ Develop methods that embody the volume of geospatial big data
Variety	▪ Design and develop cartographic interfaces that can handle the complexity of geospatial big data ▪ Develop techniques for understanding change over time in geospatial big data ▪ Craft new approaches to support predictive analytics of dynamic phenomena with maps leveraging geospatial big data ▪ Develop spatiotemporal visualization methods for geospatial big data that support a variety of uses and users
Velocity	▪ Develop methods that embody the velocity of geospatial big data ▪ Create maps and map-oriented interfaces that prompt attention to important changes in dynamic geospatial big data sources
Veracity	▪ Characterize the quality and certainty of geospatial big data ▪ Develop new approaches for visualizing the quality and certainty of geospatial big data
Art and Geospatial Big Data	▪ Encourage and maximize creative contributions for expressing geospatial big data ▪ Build a library of artistic methods and techniques for representing geospatial big data ▪ Generate artistic renderings of geospatial big data ▪ Dynamically link artworks to conventional geospatial big data representations

Figure 1: An overview of major research challenges for cartography and geospatial big data.

Making sense of geospatial big data

Big data has become a buzzword that carries different meanings in a variety of contexts (Jagadish, 2015). Consequently, there is a need to define what we actually mean when we consider big data in the context of cartography. Further, a known challenge lies in how to find the hidden knowledge inherent in big data; to make sense of big data. This challenge is not unique to big data per se, but big data's attributes make revealing knowledge more difficult to achieve. Progress made toward the development of better map overview methods, pattern analysis techniques, and dynamic spatial visualizations will set the stage for research to improve methods and interfaces for synthesizing results and for analytical reasoning about space and geography. Map users need the ability to add meaning to individual findings in mapping interfaces, to ensure that results provenance is maintained, and to develop sharable stories to support decisions (Robinson, 2011). In this section we present challenges that refer to these issues in the context of cartography, geovisualization, and visual analytics.

Challenge: Develop visual analytical reasoning systems that help users add meaning to and organize what they discover from geospatial big data

To support visual analytics with geospatial big data, we have to move beyond naïve exploration and focus attention on tools that help people reason about what they are seeing. It is not enough to build systems that help users find patterns. Those same users need to be able to save, annotate, and compare their findings as they work on complex problems. This action of information synthesis was proposed early on by DiBiase (1990) and expanded upon by MacEachren (1995), but has received relatively little attention since that time. One thing we do know is that once analysts have made discoveries using analytical systems, many turn to generic office productivity software to collect, organize, and add meaning to their results (Robinson, 2009). Supporting information synthesis will require significant advances in how we help users capture insights and maintain provenance (Gotz & Zhou, 2009; Morisette et al., 2013; Ragan, Endert, Sanyal, & Chen, 2016) while telling stories about data using geovisual analytics tools (Eccles, Kapler, Harper, & Wright, 2008).

Challenge: Design effective map-based interfaces to support long-term analytical engagement with complex spatiotemporal problems and geospatial big data

Support for analytical reasoning with geospatial big data must enable long-term engagement on complex societal and environmental problems. Many research efforts on evaluating geovisual support for analytical reasoning focus on short-term, tactical problems that are easier to observe and compare (Robinson, 2011). However, many problems that have broad impacts on society and the environment will require months, years, or even decades of concerted effort to solve (Kang & Stasko, 2011). We do not yet know how best to support long-term, collaborative analytical engagement (Jeong, Ji, Suma, Yu, & Chang, 2015), effective recall of past spatiotemporal insights, or the use of structured analytic techniques with geospatial big data.

Challenge: Develop new approaches for supporting collaborative decision making using the map as a mutual interface for analyzing geospatial big data

Decision making is almost always a collaborative task, yet guidelines for designing effective maps and map-based interfaces to support collaborative decision making are missing (Gennady Andrienko et al., 2007). Supporting collaborative analysis using map-based interfaces (Brewer, MacEachren, Abdo, Gundrum, & Otto, 2000; Rinner, 2001) has been mentioned in most of the previous research agendas in our field. Much of the published research on this area was conducted in the early days of web-mapping, and does not account for mobile devices, high performance touch/gesture/voice interfaces, cloud computing, augmented reality, and other significant advancements.

Challenge: Develop techniques that allow users to express and match a spatiotemporal pattern they have in mind using the map as an interface for analyzing geospatial big data

Exploratory spatial data analysis typically seeks to reveal new patterns in complex datasets to prompt engagement and (hopefully) new discoveries. Pattern detection methods are abundant today, employing a wide range of quantitative techniques for uncovering clusters and outliers. The next generation of techniques and tools must also support users who wish to seek examples for what they already have in mind. This should build on work initiated as early as 1990 by cartographers who proposed a cognitive framework for how humans explore data on maps which relies on the recognition of patterns (MacEachren & Ganter, 1990). We need to provide users with effective visualizations that show interesting spatiotemporal patterns, and we also must give them the ability to provide their own concept of a relevant pattern and have the system find examples of similar patterns in their data. To support the latter we must design and evaluate approaches that support the flexible expression of a user-desired multivariate spatiotemporalspatiotemporal pattern. An expressed pattern could come in the form of a verbal or written description, or via a graphical depiction, as demonstrated by Shao et al. (2016).

Challenge: Understand when, how and if maps can help us understand geospatial big data

The final challenge we highlight in this section is that as cartographers we have a natural thirst to find a way to map something. It is rare that anyone asks for a map of something, yet we make them nevertheless. We value the cartographic perspective and the way in which mapping something brings us insight. It remains entirely possible that for many situations, maps of big data are not the ideal solution. Knowing *when to make a map* is just as important and knowing how to make a map. We need to determine in which situations maps help people make decisions, just as much as we need to understand what qualities aid (or hinder) effectiveness in terms of map design.

Volume

Volume refers to data size (Gandomi & Haider, 2015), and depending on the discipline, these sizes can vary considerably, from several million data points in a movement dataset (Stienen et al., 2016), to petabytes in imagery sources. What these definitions have in common is that the volume of the data exceeds the handling capabilities of current computational systems. We focus here on how the challenges associated with big data volume prompt new directions for cartographic research.

Challenge: Identify effective methods for creating overviews of geospatial big data

Maps remain one of the best ways to reduce complexity and render actionable complex spatial datasets. However, we routinely come up against the limits of traditional map-based overviews of big data, for example when we attempt to show millions of social media conversations (MacEachren et al., 2011) or movement trajectories captured from mobile phone users (Andrienko & Andrienko, 2011). We need new approaches for generating overviews and we need to know which overview methods work better than others. We also need to know more about user requirements for interaction with displays of big data, for example, controls for manipulating overview maps and linking them to other visualizations. Coordinated-view systems (Roberts, 2005) may provide solutions for visualizing big data, and a significant amount of work has focused on their development in the field of information visualization (Shneiderman, 1996), but we know relatively little about their limits (Andrienko & Andrienko, 2007) in generating insight about geographic phenomena.

Challenge: Develop methods that embody the volume of geospatial big data

In terms of data volume, we need cartography that can intelligently process and display big data at a size and in a format that users can realistically handle. We need methods that can highlight the most salient aspects of the data to reveal something useful for a user. Fortunately, a number of researchers are working on geospatial visual analytics, which focuses on this area of cartographic inquiry (Andrienko et al., 2016). To embody large volumes, we need mapping methods that handle volume at each phase in the analysis and visualization pipeline: collation and categorization of vast collections of data into constituent parts; processing and analysis to draw out essential characteristics; and graphical display and manipulation of the results to reveal insights. This will require solutions that support coupled analysis and visualization, as big data often needs to be analyzed before it is visualized (this order is reversed in exploratory visualization).

Variety

Traditionally, variety refers to data heterogeneity (Gandomi & Haider, 2015), that is, data lie in different formats and representations that can be structured, semi-structured, or unstructured. Most existing visual exploratory and analytical systems are only able to deal with geospatial big data of particular types, such as trajectory data from animal tracking or phone records that include location information. Geospatial big data is diverse, often less structured, includes a temporal component, and will feature qualitative and quantitative dimensions. While integration of geospatial big data is a problem, location can be used as a common denominator, and the linked data concept (Heath, Bizer, & Hendler, 2011) is also promising. Additionally, we recognize the significant analytical potential that can come from diverse data representing different perspectives on a problem.

We also propose that it is not only the data that have this property, but that the variety dimension should be considered in the terms of users of mapping systems, and this needs to be addressed through user-centered design. We are still quite far from the goal of developing walk-up-and-use geovisual systems that are accessible for first-time users (Thomas & Cook, 2005).

Challenge: Design and develop cartographic interfaces that can handle the complexity of geospatial big data

Data are becoming cheaper to acquire and can be sensed in automated ways to provide live feeds that populate repositories with vast quantities of information with varying degrees of structure. Traditional database frameworks are ill-equipped to do analytical work with these sources, but distributed computing provides a framework to support their use with geospatial big data. To expose the variety within geospatial big data, we need front-end visualization methods that integrate and synchronize disparate displays to provide multiple windows into data (Agrawal et al., 2012). Synchronized displays, often referred to as Coordinated Multiple View systems (Roberts, 2005), include a variety of forms (for example, maps, graphs, tables, and reports), in which an operation (for example, zoom or filter) on one display automatically applies to all other displays. Such approaches are not novel, but we do not yet know how best to design coordinated geovisual environments in the context of geospatial big data. Recent work to define new types of data structures around spatial dimensions (Bédard, Proulx, Rivest, & Badard, 2006) and trajectories (Leonardi et al., 2013) could help support rapid interaction with new cartographic interfaces to big data.

Because big data are collected in a variety of formats and the data represent a variety of phenomena, cartographic methods should be developed that directly link visualization methods with the format of the data and the phenomena they represent. For example, temporal data could be displayed dynamically to leverage intuitive connection between dynamic processes and data that describe them (Buckley, 2013). Similarly, virtual reality (VR) could be used to explore geospatial big data in an immersive environment that simulates a physical presence in real (or imagined) places (Olshannikova, Ometov, Koucheryavy, & Olsson, 2015). We need to evaluate the potential utility of VR in the context of geospatial big data and cartographic representation.

Challenge: Develop techniques for understanding change over time in geospatial big data

In the geographic context, change in geospatial big data can not only refer to changes in location or in character but also include dynamic processes over time. From a temporal perspective events might occur at changing time intervals; they might occur only once, or they might return in irregular overlapping and different cycles (Andrienko & Andrienko, 2012). The advantage of sensors continuously providing data means that there is less chance we might miss events entirely due to intervals between collections.

So how do we detect changes over time? Finding spatial patterns at one moment in time is not a problem. Finding temporal patterns and subsequent changes over time can be done with existing algorithms. Examples include the analysis of changing temperature over the last 30 years at one particular weather station (Wu, Zurita-Milla, & Kraak, 2015). Another example could be the changing wind pattern over multiple years at a particular location observed at different heights (Yusof, Zurita-Milla, Kraak, & Retsios, 2016). For both examples the complexity will increase if we consider multiple locations with observations. Data mining algorithms alone will not suffice. Visual interfaces to guide and support their action as well as understanding their results will be necessary.

Challenge: Craft new approaches to support predictive analytics of dynamic phenomena with maps leveraging geospatial big data

Solving problems associated with recognizing change on maps is an essential step toward tackling the larger issue of prompting change prediction using maps. Effective situational awareness requires knowledge of the key spatiotemporalspatiotemporal elements, understanding their meaning, and making predictions about their status into the future (Endsley, 1995). Most dynamic mapping and visualization systems are only designed to support the first two priorities of identifying key elements and understanding their meaning. Predictive analytics can use past patterns and modelled outcomes to alert users to important changes in data streams and to suggest potential future outcomes (Maciejewski et al., 2011).

Challenge: Develop spatiotemporal visualization methods for geospatial big data that support a variety of uses and users

Once big data has been analyzed, it needs to be presented in meaningful visualizations that assist interpretation and build understanding. In doing so one has to consider the potential tasks that user might have to address in respect to the spatiotemporal data (Roth, 2012). Geospatial big data visualization systems should include a rich palette of display options that convey the significance of analytical results. These displays must be presented in a way that is best understood by users within their particular domains, or, in some cases, by the general public. Cartographers can draw upon Bertin's concept of the Map-to-See, which is "a clear graphic representation which can be comprehended in a short moment", and as such is "the most efficient means to communicate a message" (Kraak, 1989). At the same time, the messy nature of big data may be more effectively expressed in a "messy map", which is an example of a more complex Map-to-Read (Kraak, 1989).

Geospatial big data visualizations are used in a wide variety of applications and domains: science and research; education; intelligent transportation; environmental preservation; business intelligence; personalized health care; urban planning; homeland security; and more (Jiang, 2013b). Our challenge is to provide cartographic visualization solutions that can be applied across these domains for users at varying levels of expertise. Alternative approaches such as spatialization may be intuitive for some users (Fabrikant, 2000). For non-expert audiences, intelligent automated mapping may provide solutions through dashboards (Few, 2013) or via interfaces that incorporate storyboarding techniques from the cinematic arts to convey a broader understanding of big data (Roth, Hart, Mead, & Quinn, In Press), and could also support data-driven journalism (Lewis, 2015).

Velocity

Velocity is the speed at which geospatial big data are generated and at which they should be analyzed (Gandomi & Haider, 2015). Recent technological developments in data creation have led to fast, continuous and ubiquitous data streams that exceed capabilities of contemporary computing systems to map and analyze in real-time.

Challenge: Develop methods that embody the velocity of geospatial big data

In many situations, the results of geospatial big data analysis and visualization are required immediately—to detect the locations of fraudulent credit card transactions, for example. In these cases the ideal solution is to flag the activity before the event has ended. A full analysis of all relevant data in this sort of situation is not feasible in real-time—nor is it necessary. Instead, we need to produce predictive partial results, presented in personalized displays, so that incremental computation with new data can be used to make quick decisions.

Challenge: Create maps and map-oriented interfaces that prompt attention to important changes in dynamic geospatial big data sources

The dynamic behavior of people and their environments is now captured and streamed in real-time (Andrienko et al., 2010). Although there are a range of representation techniques for showing change, maps suffer well-known issues associated with change blindness (Fish, Goldsberry, & Battersby, 2011). Yet it is more important than ever for users to recognize change when it is occurring in their datasets, and to be able to anticipate future changes through the use of predictive techniques. Designing visualizations that are able to handle data generated at high velocity is not necessarily a problem if the changes to trends and patterns in those data are limited. However, if the data changes frequently and/or with high magnitudes, traditional graphics will not suffice. Further development in cartographic animation techniques could be one direction to take, however, its success will depend on the nature of changes and the scale at which they occur. We will need to work with global changes, local changes, and combinations across scales. In addition, if we display every possible change at once, then the graphical displays become cluttered. Creating summaries of change may be the solution, but we do not yet know how to select important patterns and generalize to something that a user can understand.

A dashboard with streaming visual summaries of geospatial big data's vital statistics could be part of the solution (Few, 2013). It could offer a selective (analytical) overview, including the data's spatial extent, the range and variability of the attributes, and time interval, as well as information about its geographic context. Although dashboards are supposed to be simple in design, at times they may become complex due to the nature of the data at hand (Andrienko, Andrienko, Fuchs, Rinzivillo, & Betz, 2015). Embedded within this challenge is the need for design guidelines for summary maps that can readily characterize geospatial big data.

Veracity

In data analytics, veracity refers to the inherent unreliability of data (Gandomi & Haider, 2015) in terms of precision and other aspects of uncertainty. For example, social media data, which contain human judgements, are subjective in their basic nature and may refer only vaguely to places and times. This however is not novel to cartography, which has a long tradition of dealing with uncertainty in spatial data (Zhang & Goodchild, 2002).

Challenge: Characterize the quality and certainty of geospatial big data

Maps can claim to be authoritative and the more fuzzy, dubious, or nefarious the data, the more the map's message is brought into question. With increasingly large spatial datasets that are distilled into a simplistic metric for reporting, the potential for over-simplification is clear. What may be more problematic is quality in terms of the bias that the data may contain. For instance, many have mapped dimensions of social media feeds (Field & O'Brien, 2010; MacEachren et al., 2011), but the resulting maps, which at first glance may appear to reveal insights, are rarely representative of what they purport to show. Their ability to be representative of a societal view is fundamentally flawed given what we know about which people use (and don't use) social media. This requires map readers to be cautioned and aware of the limits of what they are seeing.

The same could be said of datasets captured and published by non-traditional sources. We are no longer limited to making maps with official data gathered by National Mapping and Census agencies (Goodchild, 2007). Anyone can capture, store, and publish data from their mobile devices. The many situations that these sensor networks operate within can also create problems. Error and uncertainty undoubtedly exist, sometimes in unknown ways and quantities.

Challenge: Develop new approaches for visualizing the quality and certainty of geospatial big data

In Kinkeldey et al. (2014) the authors reviewed decades of efforts to find a way to communicate data quality information on maps, and have concluded that the task to retrieve quality values can still be achieved using traditional cartographic methods. However, analytical and exploratory tasks, such as those involved in analyzing big data, need dynamic approaches for application in real time. MacEachren (2015) presents a new and complementary perspective; claiming that the role of uncertainty in decision making, reasoning, and outcomes is often overlooked in the research of visual methods to represent uncertainty in maps.

Use and interpretation caveats could become commonplace on maps based on geospatial big data to highlight aspects of uncertainty. Such a future approach might lead not to a single map but a set of maps, or an interactive component that reveals the extent of uncertainty. While mapping uncertainty is not new to academic cartography (MacEachren et al., 2005), representing it on maps in the public realm would be novel to many map readers who are used to seeing one map and considering one message. Engendering an ethos of caution through appreciating error and uncertainty could become a major goal for effective mapping of geospatial big data.

Art and Geospatial Big Data

The potential of art (including aesthetics and beauty) in the context of exploring spatial data has not been fully realised, despite calls for investigation into “non-conventional graphics” in earlier agendas (Fairbairn et al., 2001). Geospatial big data highlights the increased need for this investigation to take place. Art has always been present in the history of maps, assuming a major but decorative aspect early on (Casey, 2005), taking a background role in the 19th and 20th centuries (Cosgrove, 2005) before recent recognition within cartography that art is a powerful representation of the world that is different in kind to maps (Caquard & Fraser Taylor, 2005; Cartwright, Gartner, & Lehn, 2009). Furthermore, art is a key component of the ICA's definition of cartography (Rystedt et al., 2003), described as the, "…discipline dealing with the art, science and technology of making and using maps."

There are many reasons to explore artistic approaches towards understanding big data. Artistic methods have the flexibility to represent multiple scales, dimensions, uncertainty and variety (Laney, 2001; MacEachren & Kraak, 2001) in a single representation. Cartwright (2004) uses the analogy of the soft pencil, for vague, impressionistic and artistic representations that foster exploration and makes serendipitous discoveries more likely. Art is also a natural representation for the narratives and stories implicit in big data, being able to convey underlying meaning, as well as representing process and phenomenon, potentially with emotional heft. The linkage between cartographic design principles to emotions and ideas has been considered, as well as the role of the map relative to mood (Buckley & Jenny, 2012). Here we focus on the potential of creative expression, artistic rendering methods and their generation, and linked artistic methods with conventional spatial and aspatial displays for big data analysis.

Challenge: Encourage and maximize creative contributions for expressing geospatial big data

There is an acknowledged overlap of fine art in particular with cartography, sharing aspects of form, composition, framing and perspective, as well as content selection, emphasis, line, colour, medium and symbolization aspects (Ehrensvärd, 1987). There has also been an increased number of artists using map content or mapping processes in their work, possibly because artists recognise that maps are very flexible (Watson, 2009). An example is the "flowing city maps" by Istvan (2015) which conveys their dynamic and chaotic essence by digitally extending flow lines from map features to artistic effect. In art, complex information can be represented in a readily consumed way, which makes it ideal for communicating the broad sense of geospatial big data. This shared basis must be built upon further, but how do we engage artists to visually address this new order of spatial data, quite unlike the geospatial subject matter that they have tackled up to now? And what can we learn from art's attempts at geospatial expression and cartography so far? Examples include artworks with a realistic content (Priestnall & Hampson, 2008) to abstracted works, even those that are maps themselves (Patterson, 1992).

Challenge: Build a library of artistic methods and techniques for representing geospatial big data

Despite the observed commonalities in the respective technical methods and approaches of fine art and cartography (Ehrensvärd, 1987), there is large scope to exploit geometric and technical aspects that have not yet made it into map making, from common processes (e.g. generalization) to what would be completely new aspects for cartography (e.g. 'messy maps'). To initiate this, we can learn from examples in recent visualization work which use types of artistic expression as a starting point for the development of new techniques (Etemad, Carpendale, & Samavati, 2014; McCurdy, Lein, Coles, & Meyer, 2016). Likewise, there are aspects of cinematic and aural art processes that also have great potential in the visualization of geospatial big data. We need to know the full scope of potential artistic methods and techniques, drawing from fine, illustrative, cinematic and music/audio that can be co-opted to represent geospatial big data.

Challenge: Generate artistic renderings of geospatial big data

The first challenge points to solutions that would have a heavy reliance on the output of artists, which is hardly a real-time solution, so it is not a good approach for the velocity aspect of big data (Laney, 2001). The second challenge at least would facilitate identification of artistic techniques for depicting big data, effectively packaging them for easy reuse computationally, which could enable real-time visualization. However, before this can happen, a solution needs to be found for the digital generation of artworks that are both meaningful wholes and are somehow a true representation of a big dataset. This is aesthetics as “the science of the beautiful in nature and art” (Merriam-Webster, 2014). Recent neurological research indicates that there is a systematic basis for our cognitive processing of art and its attributes, despite its apparent subjectivity and variability (Zeki, 2001), paving the way towards generation of artworks. For example, the aesthetic properties of beauty in art are processed by the same area of the brain, regardless of genre (landscape or portrait, for example) (Kawabata & Zeki, 2004) or medium (painting or music, for example) (Ishizu & Zeki, 2011). Given this, how can we semi-automatically generate artistic renderings of big data?

Challenge: Dynamically link artworks to conventional geospatial big data representations

Artworks that have been created or generated from big data may be effective in isolation but are likely to realize a greater potential if put into a context that enables dynamic exploration. Such a connection could be effective for dealing with the dynamism of big data, adopting the standard overview, zoom and filter, details-on-demand visualization approach (Shneiderman, 1996) and coupling this with new artistic methods for cartographic design (Christophe & Hoarau, 2012). New artistic interfaces should be able to be manipulated visually in real time, connecting standard tools (choropleth maps, scatterplots, etc.) and non-conventional tools (abstracted and virtual representations) via linking and brushing. There is a clear challenge in engineering the linkages needed to build such an interface: how do we determine the meaningful linkages from created artworks and artistically rendered maps to ‘conventional’ spatial and non-spatial representations in a visual analytics context?

Research Opportunities

In the sections that follow, we highlight key research opportunities in the broad categories of visual, computational, and artistic methods (Figure 2). We distinguish opportunities from challenges based on our estimation that they can be solved in the near term, rather than long term.

Research Opportunities for Cartography and Geospatial Big Data	
Visual methods for geospatial big data	▪ Systematically evaluate the ability of existing visual methods in thematic cartography to support analysis of geospatial big data ▪ Adapt cartographic generalization principles and techniques to support visual analysis of geospatial big data ▪ Couple computational methods and cartographic representation best practices into an automated framework that suggests appropriate design decisions on-the-fly for geospatial big data ▪ Leverage what we know about map animation and interactive cartography to construct visual solutions for dynamic sources of geospatial big data
Computational methods for geospatial big data	▪ Leverage knowledge about patterns across scales in the development of new computational methods for geospatial big data ▪ Use what we know about human dynamics to find patterns in geospatial big data ▪ Connect concepts from complexity science to new visual analytics methods for geospatial big data
Adapting artistic methods for geospatial big data	▪ Facilitate engagement of artists with geospatial big data and the creation of an artistic geospatial language ▪ Co-opt artistic methods and techniques to represent geospatial big data ▪ Generate artistic renderings of geospatial big data ▪ Link artworks to conventional representations in a visual analytics context to leverage geospatial big data

Figure 2: An overview of key research opportunities for cartography and geospatial big data.

Visual Methods for Geospatial Big Data

The common refrain of "…a picture is worth a thousand words" is only worthy when the picture in question is understandable. Bertin (1983) states that "the most efficient constructions are those in which any question, whatever its type or level, can be answered in a single instant of perception, in a single image." MacEachren (1995) proposed that "maps that connote truth (or even reality) are likely to work better than those that do not." While we propose a research agenda for creating and developing new visual methods for big data, we must not ignore lessons learned from these and other predecessors.

Opportunity: Systematically evaluate the ability of existing visual methods in thematic cartography to support analysis of geospatial big data

An overarching goal for cartographers is to develop techniques for processing and manipulating geospatial big data that make it possible to generalize and symbolize geographic results through graphics and visualizations that match or exceed quality we already achieve with smaller data sources and analytical methods. Rather than focusing solely on the development of *new* visual methods, we propose to first evaluate current thematic mapping solutions to characterize their strengths and limitations when it comes to their application with geospatial big data. To accomplish this goal we need to connect big data characteristics and the visual affordances of existing cartographic approaches. In addition to cartographic approaches, it is important to look at how allied fields have approached similar problems. Solutions for visualizing large data sets have been proposed in statistics, computer science, psychology, and related domains (Wills & Wilkinson, 2010).

Opportunity: Adapt cartographic generalization principles and techniques to support visual analysis of geospatial big data

Key considerations for visual designs include the number of the spatial phenomenon occurrences and the variation of their spatial density and accuracy; the variation of related dataset semantics, and the spatiotemporal dynamics of data streams. The core characteristics of geospatial big data can influence the level of generalization, both geometric and semantic, that may be possible. In terms of Bertin's (1983) framework for graphics, the components that must be considered for map generalization are: invariant information and components; the organization of information components (qualitative, ordered, and quantitative); and the level of retinal variations (association, selection, order, and quantity). Additionally, decisions about generalizing geospatial big data must take into consideration the variation of data representations from discrete elements to continuous phenomena (MacEachren, 1992). This concern is also present for situations in which temporal resolution must be considered.

Opportunity: Couple computational methods and cartographic representation best practices into an automated framework that suggests appropriate design decisions on-the-fly for geospatial big data

When the information component is quantitative, there are two well-known situations that have been studied in Cartography. One of them is when the data can be represented as choropleth maps or proportional symbol maps. The other is related to continuous phenomena that can be represented as a smoothed surface. For choropleth or proportional symbol representations, we propose the development of computational solutions to automatically evaluate the characteristics of the phenomenon, in terms of both spatial and semantic dimensions, in order to render decisions on the level of generalization, and the appropriateness of representing the data with these kinds of maps. For continuous surface representations the level of generalization also depends on the spatial density of samples, including the variation in quality within the study area. A computational solution could assess the variation of the spatial density of the data sample and calculate various levels of accuracy. Such a computational solution must also include the means to dynamically generate a surface as data streams change.

When the information component is qualitative, the phenomenon is discrete and known at point locations, and the study region is large enough to be depicted on a scale that requires semantic generalization, the decisions about attribute classification can be based on the geographic relations between data attributes and key geographic features, and the maximum level of generalization possible. The qualitative level always involves two perceptual approaches: associative and dissociative. At a dissociative level, it is not possible to combine information components because they are different from each other. On the other hand, at the associative level, components can be grouped.

There are some solutions in statistics that have attempted to automate design decisions for data graphics (Wills & Wilkinson, 2010). One potential way forward is to evaluate the applicability of Wilkinson's *Grammar of Graphics* (2005) for displaying geospatial big data.

Opportunity: Leverage what we know about map animation and interactive cartography to construct visual solutions for dynamic sources of geospatial big data

Conventional solutions for interactive mapping, animated mapping or geovisual analytics can be used for representing big data. However, because of the high velocity characteristic of big data it is necessary to develop solutions that can automate map design decisions to support interactive design solutions that respond (or potentially precede based on modelled outcomes) as the data changes. New mapping solutions could allow users to understand different aspects of phenomena by reviewing multiple alternative scenes from the same dataset. Animated mapping solutions could be developed specifically to target geospatial big data velocity, volume, variety, and veracity aspects. These approaches could be incorporated into dashboards and virtual environments to support new avenues for user engagement. Efficient interaction in such systems will of course depend on concomitant advances in computational methods to drive such tools.

Computational Methods for Geospatial Big Data

Maps appear to be a perfect means for showing things that are too big and/or too complex to readily perceive in raw form. As a result, maps and map metaphors have received significant attention in information visualization and visual analytics (Aggarwal, 2011; Andrienko & Andrienko, 2011; Chen, 2013; Dykes, Wood, & Slingsby, 2010; Guo, Chen, MacEachren, & Liao, 2006). However, in most analytical settings, maps must be combined with statistical methods or computational methods to explore or uncover underlying patterns or structure. Computational methods constitute the third scientific paradigm (Hey, Tansley, & Tolle, 2009), and in the field of geography, computational geography and geoinformatics have been well developed since the 1960s (Openshaw, 1998). Today, computational geography is data-driven (Miller & Goodchild, 2014) or data-intensive (Jiang, 2013b). In addition to volume concerns, there are other big data aspects to be addressed, including veracity and variety. The former is closely related to uncertainty modelling (Zhang & Goodchild, 2002), while the latter illustrates an underlying scaling pattern of far more small things than large ones. Big data is likely to include diversity and heterogeneity – highlighting the problem of spatial heterogeneity (Jiang, 2014). Here we describe several key research opportunities focused on advances in computation to support cartography with geospatial big data.

Opportunity: Leverage knowledge about patterns across scales in the development of new computational methods for geospatial big data

Computational methods are particularly important for uncovering underlying patterns. One such universal pattern is the *scaling* or *fractal* pattern (Mandelbrot, 1982), in which a pattern repeats at every scale. In this regard, head/tail breaks (Jiang, 2013a) demonstrates an alternative approach to conventional clustering techniques such as k-means for showing underlying scaling patterns, and could be employed for cartographic visualization through recursively filtering out data in the tail (Jiang, 2015). Conventional clustering techniques, for example k-means or natural breaks, are based on the premise that variance within classes should be minimized, and variance between classes should be maximized. However, these assumptions do not necessarily make sense for big data, which often demonstrate a long tail distribution because of their diversity and heterogeneity. New efforts should be made to integrate computational and visual methods that can help develop new insights into geospatial big data (Endert, Chang, North, & Zhou, 2015).

Opportunity: Use what we know about human dynamics to find patterns in geospatial big data

It has been claimed that 95% of big data is unstructured (Gandomi & Haider, 2015). As more and more big data are becoming georeferenced and time stamped, geographic features such as cities and temporal rhythms become an implicit means for structuring the data. Because big data can be structured geographically and/or temporally, maps will play an important role in visualizing the underlying patterns and toward developing new insights. For example, the notion of natural cities has been applied to location based social media data to uncover how users aggregate spatially and temporally (Jiang, 2015).

Opportunity: Connect concepts from complexity science to new visual analytics methods for geospatial big data

Conventional science or Newtonian science is simple science focused on the correlation between two parameters, or causality, and represents a longstanding paradigm under which geography and cartography have been significantly influenced. Complexity science focuses on individual interactions from the bottom up, and is interested in emergence rather than simple correlation or causality (Balcan et al., 2010). Complexity science has developed a range of tools including discrete models such as cellular automata and agent-based modeling, complex networks such as small-world and scale-free networks, scaling hierarchies; e.g., Zipf's law, fractal geometry, self-organized criticality, and chaos theory. All of these approaches attempt to reveal underlying mechanisms, linking complex surface forms to underlying mechanisms (or deep simplicity) through agent-based simulations from the bottom up. To date relatively little has been accomplished to design cartographic solutions for representing phenomena through complexity science approaches.

Adapting Artistic Methods for Geospatial Big Data

Opportunity: Facilitate engagement of artists with geospatial big data and the creation of an artistic geospatial language

There is a need for new work which introduces artists to geospatial big data as well as creating artworks that could be used as part of a geovisual analysis of a big dataset. One such investigation would be to simply ask artists to draw overviews for datasets that are quite well known already. These artwork overviews could then be examined for commonalities in how data characteristics are expressed; these common elements would become the start of a language which we could use in future investigations of big data. This language would be added to by mining geospatial concepts that are semantically depicted in existing “map” artworks. A similar process could be applied to sonic works, realising the potential of sound (Cartwright et al., 2001; Krygier, 1994). Art and science collaborations can be engineered through joint art shows, such as those featured at SIGGRAPH and IEEE VIS conferences. Digital creativity support tools (Shneiderman, 2007) or similar e.g. COSTART (Candy & Edmonds, 2000) could provide a platform for collaboration between artists and scientists.

Opportunity: Co-opt artistic methods and techniques to represent geospatial big data

We can look to fine art, cinema, and music and the techniques they employ to represent spatiotemporal data, compiling these techniques into a library through which geospatial big data can be expressed. A further step would be to organize this resource into a “grammar of artistic methods”, inspired by Wilkinson’s (2005) grammar of graphics. Prominent in such a library would be the methods of caricaturing in illustrative art, being analogous to cartographic generalization (Jones, 1997), an approach used by Döllner (2007) in non-photorealistic rendering of 3D objects. Simplicity in drawing makes for effective communication to a greater audience (McCloud, 1994), a powerful aspect for depicting big data whilst addressing its volume aspect. Alternatively, certain styles of modern art such as Jackson Pollock’s drip maps can be used to create ‘messy maps’ for revealing spatial and attribute veracity (Field, 2015).

Another prime example is storyboarding, an essential visual planning tool in cinema (Caquard, 2013) and one that has seen previous use in various geospatial and HCI contexts (Cartwright, 1994; Dix, Finlay, Abowd, & Beale, 2004; Riedl, 2012). The goal here is to depict the spatiotemporal narratives that may be implicit in big data. Narratives can also be spatially vague (Caquard, 2013), speaking to the aspect of the veracity in big data. This is a continuation of the observed convergence of maps and narratives, manifesting itself as ‘story maps’, and enabled by technologies such as geoparsing (Caquard, 2013). The technique is also similar to comic strips (Moore, 2009), given knowledge of the narrative. Synthesized discoveries from the geovisual analytics process will also lend themselves to storyboarding.

Opportunity: Generate artistic renderings of geospatial big data

In fractal geometry we have a way of generating a complex artifact of an aesthetic, or even artistic value from simple global inputs. Jiang and Sui (2014) build upon this and Alexander's living geometry (Alexander, 2002), stressing that fractals have structural beauty, presenting fifteen properties of beautiful representations across geographic scale. Therefore, fractals could be used to create artworks from geospatial big data. How we translate attributes of geospatial big data to fractal parameters is a particular research challenge. There have been projects to generate artworks from simple initial rules (Sundararajan, 2014) and artificial intelligence (Koch, 2015). Another potential method of artistic rendering is to adapt highly abstracted spatiotemporal representations (Bertin, 1981; Guo et al., 2006) with aesthetic qualities that have attractive geometries and/or colour schemes, such as those found in Adaptive Relative Motion (Moore & Rodda, 2015).

Opportunity: Link artworks to conventional representations in a visual analytics context to leverage geospatial big data

To identify meaningful linkages from artworks to typical spatial and aspatial representations as a path towards artistically-enabled geovisual analytics, we have a starting point with the map: anti-map (i.e. art) category of art and cartography manifestations (Caquard & Fraser Taylor, 2005). This linkage between artwork and map (Moore, Marinescu, & Tenzer, 2011) can be built upon by establishing links from art to other graphical representations (e.g. scatterplots).

Finally, agents should be a part of future research too. For example, agents could guide users through the bewildering amount of possible representations, setting their parameters, and managing possible combinations with other representations (Fairbairn et al., 2001). AutoVis, an automatic visualization system (Wills & Wilkinson, 2010) builds on Wilkinson's grammar of graphics and has similar aims to what we propose here. Agents could also have a role in using geocomputation to uncover structure in complex representations (Gahegan, Wachowicz, Harrower, & Rhyne, 2001; MacGill & Openshaw, 1998). Cartwright (2004) proposes "engineered serendipity", a combination of free exploration and engineered guidance to information that may have been missed. If the artwork, whether created or generated, and flexible links with other representations (Thudt et al. (2012) present an interface that encourages serendipity in discovering books) can foster serendipity, then agents can help direct attention to overlooked visual elements, representations, and linkages between them.

Making Maps That Matter From Geospatial Big Data

In this article we have presented a series of key research challenges and opportunities associated with mapping geospatial big data with the intention of spurring the next wave of forward-thinking cartographic research. Cartographers in concert with experts in allied domains such as computer science, visual arts, human-computer interacting, and data mining have the ability to contribute new solutions to pressing problems that require novel approaches. In particular, cartographers have the ability to provide effective visual products that leverage what we know about how people see and make sense out of geographic information. In addition to the research imperatives we have outlined in this article, we call attention in this concluding section to the critical need for cartographic research on big data to focus on relevance to society, and we specifically suggest the development of close connections to the global goals set forth by the

United Nations through their 2030 Agenda for Sustainable Development (General Assembly, 2015). We also draw inspiration from earlier work to theorize visual analytics and connect its aims to key application areas (Keim, Mansmann, Schneidewind, Thomas, & Ziegler, 2008).

For example, the United Nations 2030 Agenda includes Goal 6, which aims to “Ensure availability and sustainable management of water and sanitation for all.” A way to support this goal via future cartographic research would be to ground a project on geospatial big data veracity, for example, in the context of water modelling results under a range of potential climate change scenarios. Taken one step further, one could include an effort to explore artistic representations and their affordances for communicating such model results via maps.

A concerted effort must take place to define potential linkages across research goals in cartography and tackle grand societal challenges. As the recognized international scientific body of cartography, we recommend that the International Cartographic Association (ICA) should coordinate and host workshops and web-based collaborative efforts to pursue these goals. We also suggest that the ICA should compile a repository of exemplary maps and visualizations that can be easily reproduced with other data, have demonstrated success in use and interpretation, and are well understood in terms of their effectiveness for explaining key dimensions of big data. In order to make progress on collecting, sharing, and promoting such things, we have to define what we mean by best practices for the cartography of big data as a community.

We believe that solutions to the challenges and opportunities we present here will result in cartographic contributions to big data that will deliver maps that matter to society and the environment. To enact those solutions, cartographers will need to explore each key dimension of geospatial big data and develop clever solutions for overcoming their complexity and dynamism.

The authors wish to thank Alan MacEachren and Gennady Andrienko for their feedback on an early version of this manuscript.

References

Aggarwal, C. C. (Ed.). (2011). *Social Network Data Analytics*. New York, NY: Springer US.

Agrawal, D., Bernstein, P., Bertino, E., Davidson, S., Dayal, U., Franklin, M., . . . Widom, J. (2012). Challenges and Opportunities with Big Data: A community white paper developed by leading researchers across the United States.

Alexander, C. (2002). *Book 1 - The Phenomenon of Life*. Berkeley, CA: Center for Environmental Structure.

Andrienko, G., & Andrienko, N. (1999). Interactive maps for visual data exploration. *International Journal of Geographical Information Science, 13*(4), 355-374

Andrienko, G., & Andrienko, N. (2007). *Coordinated Multiple Views: a Critical View*. Coordinated & Multiple Views in Exploratory Visualization, Zurich, Switzerland.

Andrienko, G., Andrienko, N., Demsar, U., Dransch, D., Dykes, J., Fabrikant, S. I., . . . Tominski, C. (2010). Space, time and visual analytics. *International Journal of Geographical Information Science, 24*(10), 1577-1600

Andrienko, G., Andrienko, N., Dykes, J., Kraak, M. J., Robinson, A., & Schumann, H. (2016). GeoVisual analytics: interactivity, dynamics, and scale. *Cartography and Geographic Information Science, 43*(1), 1-2. doi: 10.1080/15230406.2016.1095006

Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M.-J., MacEachren, A. M., & Wrobel, S. (2007). Geovisual analytics for spatial decision support: setting the research agenda. *International Journal of Geographical Information Science, 21*(8), 839-857

Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M. J., MacEachren, A. M., & Wrobel, S. (2007). Geovisual analytics for spatial decision support: setting the research agenda. *International Journal of Geographical Information Science, 21*(8), 839-857

Andrienko, G. L., Andrienko, N. V., Voss, H., Bernardo, F., Hipolito, J., & Kretchmer, U. (2002). Testing the Usability of Interactive Maps in CommonGIS. *Cartography and Geographic Information Science, 29*(4), 325-342

Andrienko, N., & Andrienko, G. (2011). Spatial generalization and aggregation of massive movement data. *IEEE Transaction on Visualization & Computer Graphics, 17*(2), 205-219

Andrienko, N., & Andrienko, G. (2012). A visual analytics framework for spatio-temporal analysis and modelling. *Data Mining and Knowledge Discovery, 27*(1), 55-83. doi: 10.1007/s10618-012-0285-7

Andrienko, N., Andrienko, G., Fuchs, G., Rinzivillo, S., & Betz, H. D. (2015). Detection, tracking, and visualization of spatial event clusters for real time monitoring *Data Science and Advanced Analytics (DSAA), 2015. 36678 2015. IEEE International Conference on* (pp. 1-10).

Balcan, D., Gonçalves, B., Hu, H., Ramasco, J. J., Colizza, V., & Vespignani, A. (2010). Modeling the spatial spread of infectious diseases: The GLobal Epidemic and Mobility computational model. *Journal of Computational Science, 1*(3), 132-145. doi: http://dx.doi.org/10.1016/j.jocs.2010.07.002

Bédard, Y., Proulx, M.-J., Rivest, S., & Badard, T. (2006). Merging Hypermedia GIS with Spatial On-Line Analytical Processing: Towards Hypermedia SOLAP. In E. Stefanakis, M. P. Peterson, C. Armenakis & V. Delis (Eds.), *Geographic Hypermedia: Concepts and Systems* (pp. 167-187). Berlin, Heidelberg: Springer Berlin Heidelberg.

Bertin, J. (1981). *Graphics and Graphic Information Processing*. Berlin: De Gruyter.

Bertin, J. (1983). *Semiology of Graphics: Diagrams, Networks, Maps* (W. Berg, Trans. (translation from French 1967 edition) ed.). Madison, WI: University of Wisconsin Press.

Brewer, I., MacEachren, A. M., Abdo, H., Gundrum, J., & Otto, G. (2000). Collaborative geographic visualization: enabling shared understanding of environmental processes *Information Visualization, 2000. InfoVis 2000. IEEE Symposium on* (pp. 137-141).

Brézillon, P. (1999). Context in Artificial Intelligence II. Key Elements of Contexts. *Computers and Artificial Intelligence, 18*(5), 425-446

Brown, M., Sharples, S., Harding, J., Parker, C. J., Bearman, N., Maguire, M., . . . Jackson, M. (2013). Usability of Geographic Information: Current challenges and future directions. *Applied Ergonomics, 44*(6), 855-865. doi: http://dx.doi.org/10.1016/j.apergo.2012.10.013

Buckley, A. (2013). Guidelines for the effective design of spatio-temporal maps *26th International Cartographic Congress*. Dresden, Germany: International Cartographic Association.

Buckley, A., & Jenny, B. (2012). *Letter from the Guest Editors*.

Candy, L., & Edmonds, E. (2000). Creativity enhancement with emerging technologies. *Commun. ACM, 43*(8), 63-65. doi: 10.1145/345124.345144

Caquard, S. (2013). Cartography I: Mapping narrative cartography. *Progress in Human Geography, 37*(1), 135-144. doi: 10.1177/0309132511423796

Caquard, S., & Fraser Taylor, D. R. (2005). Chapter 12 Art, maps and cybercartography: Stimulating reflexivity among map-users. In D. R. F. Taylor (Ed.), *Modern Cartography Series* (Vol. Volume 4, pp. 285-307): Academic Press.

Cartwright, W. (1994). Chapter 5 - Interactive Multimedia for Mapping. In M. Alan M & T. D.R. Fraser (Eds.), *Modern Cartography Series* (Vol. Volume 2, pp. 63-89): Academic Press.

Cartwright, W. (2004). Engineered Serendipity: Thoughts on the Design of Conglomerate GIS and Geographical New Media Artifacts. *Transactions in GIS, 8*(1), 1-12. doi: 10.1111/j.1467-9671.2004.00164.x

Cartwright, W., Crampton, J., Gartner, G., Miller, S., Mitchell, K., Siekierska, E., & Wood, J. (2001). Geospatial Information Visualization User Interface Issues. *Cartography and Geographic Information Science, 28*(1), 45-60. doi: 10.1559/152304001782173961

Cartwright, W., Gartner, G., & Lehn, A. (Eds.). (2009). *Cartography and Art*. Berlin: Springer-Verlag.

Casey, E. S. (2005). *Earth-Mapping: Artists Reshaping Landscape*. Minneapolis, MN: University of Minnesota Press.

Chen, C. (2013). *Mapping Scientific Frontiers: The Quest for Knowledge Visualization*. London, UK: Springer-Verlag London.

Christophe, S., & Hoarau, C. (2012). Expressive Map Design Based on Pop Art: Revisit of Semiology of Graphics? *Cartographic Perspectives, 73*(2012), 61-74

Dey, A. K. (2001). Understanding and Using Context. *Personal Ubiquitous Comput., 5*(1), 4-7. doi: 10.1007/s007790170019

DiBiase, D. (1990). Visualization in the Earth Sciences. *Earth and Mineral Sciences, Bulletin of the College of Earth and Mineral Sciences, The Pennsylvania State University, 59*(2), 13-18

Dix, A., Finlay, J., Abowd, G. D., & Beale, R. (2004). *Human-Computer Interaction* (3rd ed.). Upper Saddle River, NJ.: Prentice Hall.

Dodge, M., Kitchin, R., & Perkins, C. (Eds.). (2011). *The Map Reader: Theories of Mapping Practice and Cartographic Representation*. Chichester, UK: John Wiley & Sons, Ltd.

Döllner, J. (2007). Non-Photorealistic 3D Geovisualization. In W. Cartwright, M. P. Peterson & G. Gartner (Eds.), *Multimedia Cartography* (pp. 229-240). Berlin, Heidelberg: Springer Berlin Heidelberg.

Dykes, J., & Brunsdon, C. (2007). Geographically Weighted Visualization: Interactive Graphics for Scale-Varying Exploratory Analysis. *IEEE Transactions on Visualization and Computer Graphics, 13*(6), 1161-1168. doi: 10.1109/TVCG.2007.70558

Dykes, J., Wood, J., & Slingsby, A. (2010). Rethinking Map Legends with Visualization. *Visualization and Computer Graphics, IEEE Transactions on, 16*(6), 890-899. doi: 10.1109/TVCG.2010.191

Eccles, R., Kapler, T., Harper, R., & Wright, W. (2008). Stories in GeoTime. *Information Visualization, 7*(1), 3-17

Ehrensvärd, U. (1987). Color in Cartography. In D. Woodward (Ed.), *Art and Cartography: Six Historical Essays* (pp. 123-146). Chicago: Chicago University Press.

Endert, A., Chang, R., North, C., & Zhou, M. (2015). Semantic Interaction: Coupling Cognition and Computation through Usable Interactive Analytics. *IEEE Computer Graphics and Applications, 35*(4), 94-99

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 37*(1), 32-64

Etemad, K., Carpendale, S., & Samavati, F. (2014). Node-Ring Graph Visualization Clears Edge Congestion *IEEE VIS Arts Program*. Paris, France.

Fabrikant, S. I. (2000). Spatialized browsing in large data archives. *Transactions in GIS, 4*(1), 65-78

Fairbairn, D., Andrienko, G., Andrienko, N., Buziek, G., & Dykes, J. (2001). Representation and its relationship with cartographic visualization. *Cartographic and Geographic Information Sciences, 28*(1), 13-28

Few, S. (2013). *Information Dashboard Design: Displaying Data for At-a-Glance Monitoring*. Berkeley, CA: Analytics Press.

Field, K. (Cartographer). (2015). Pollock-style election map. Retrieved from http://www.arcgis.com/apps/webappviewer/index.html?id=661d96be9fe64b3db4124546b67b2f39

Field, K., & O'Brien, J. (2010). Cartoblography: experiments in using and organising the spatial context of micro-blogging. *Transactions in GIS, 14*(1), 5-23

Fish, C., Goldsberry, K. P., & Battersby, S. (2011). Change blindness in animated choropleth maps: an empircal study. *Cartographic and Geographic Information Sciences, 38*(4), 350-362

Fotheringham, A. S., & Wong, D. W. S. (1991). The Modifiable Areal Unit Problem in Multivariate Statistical Analysis. *Environment and Planning A, 23*(7), 1025-1044. doi: 10.1068/a231025

Gahegan, M., Wachowicz, M., Harrower, M., & Rhyne, T.-M. (2001). The Integration of Geographic Visualization with Knowledge Discovery in Databases and Geocomputation. *Cartography and Geographic Information Science, 28*(1), 29-44. doi: 10.1559/152304001782173952

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management, 35*(2), 137-144. doi: http://dx.doi.org/10.1016/j.ijinfomgt.2014.10.007

General Assembly, U. N. (2015). Transforming our world: The 2030 agenda for sustainable development. In U. Nations (Ed.), (Vol. A/RES/70/1). Geneva: United Nations.

Goodchild, M. F. (2007). Citizens as voluntary sensors: spatial data infrastructure in the world of Web 2.0. *International Journal of Spatial Data Infrastructures, 2*(1), 24-32

Goodwin, S., Dykes, J., & Slingsby, A. (2014). Visualizing the effects of scale and geography in multivariate comparison *Visual Analytics Science and Technology (VAST), 2014 IEEE Conference on* (pp. 251-252).

Gotz, D., & Zhou, M. X. (2009). Characterizing Users' Visual Analytic Activity for Insight Provenance. *Information Visualization, 8*(1), 42-55. doi: 10.1057/ivs.2008.31

Graham, M., & Shelton, T. (2013). Geography and the future of big data, big data and the future of geography. *Dialogues in Human Geography, 3*(3), 255-261. doi: 10.1177/2043820613513121

Griffin, A. L., Robinson, A. C., & Roth, R. E. (Submitted). Envisioning the Future of Cartographic Research. *International Journal of Cartography*

Guo, D., Chen, J., MacEachren, A. M., & Liao, K. (2006). A Visualization System for Space-Time and Multivariate Patterns (VIS-STAMP). *Visualization and Computer Graphics, IEEE Transactions on, 12*(6), 1461-1474

Heath, T., Bizer, C., & Hendler, J. (2011). *Linked Data*: Morgan & Claypool Publishers.

Hey, T., Tansley, S., & Tolle, K. (Eds.). (2009). *The fourth paradigm: data intensive scientific discovery*. Redmond, WA: Microsoft Research.

Ishizu, T., & Zeki, S. (2011). Toward A Brain-Based Theory of Beauty. *PLoS ONE, 6*(7), e21852. doi: 10.1371/journal.pone.0021852

Istvan. (2015). *Flowing City Maps*.

Jagadish, H. V. (2015). Big Data and Science: Myths and Reality. *Big Data Research, 2*(2), 49-52. doi: http://dx.doi.org/10.1016/j.bdr.2015.01.005

Jeong, D. H., Ji, S.-Y., Suma, E. A., Yu, B., & Chang, R. (2015). Designing a collaborative visual analytics system to support users' continuous analytical processes. *Human-centric Computing and Information Sciences, 5*(1), 1-20. doi: 10.1186/s13673-015-0023-4

Jiang, B. (2013a). Head/Tail Breaks: A New Classification Scheme for Data with a Heavy-Tailed Distribution. *The Professional Geographer*, *65*(3), 482-494. doi: 10.1080/00330124.2012.700499

Jiang, B. (2013b). Volunteered Geographic Information and Computational Geography: New Perspectives. In D. Sui, S. Elwood & M. Goodchild (Eds.), *Crowdsourcing Geographic Knowledge* (pp. 125-138): Springer Netherlands.

Jiang, B. (2014). Geospatial analysis requires a different way of thinking: the problem of spatial heterogeneity. *GeoJournal, 80*(1), 1-13. doi: 10.1007/s10708-014-9537-y

Jiang, B. (2015). Head/tail breaks for visualization of city structure and dynamics. *Cities, 43*, 69-77. doi: http://dx.doi.org/10.1016/j.cities.2014.11.013

Jiang, B., & Sui, D. Z. (2014). A New Kind of Beauty Out of the Underlying Scaling of Geographic Space. *The Professional Geographer*, *66*(4), 676-686. doi: 10.1080/00330124.2013.852037

Jin, X., Wah, B. W., Cheng, X., & Wang, Y. (2015). Significance and Challenges of Big Data Research. *Big Data Research, 2*(2), 59-64. doi: http://dx.doi.org/10.1016/j.bdr.2015.01.006

Jones, C. B. (1997). *Geographical Information Systems and Computer Cartography*. New York, NY: Routledge.

Kang, Y. a., & Stasko, J. (2011). Characterizing the intelligence analysis process: Informing visual analytics design through a longitudinal field study *Visual Analytics Science and Technology (VAST), 2011 IEEE Conference on* (pp. 21-30).

Kawabata, H., & Zeki, S. (2004). Neural Correlates of Beauty. *Journal of Neurophysiology, 91*(4), 1699-1705. doi: 10.1152/jn.00696.2003

Keim, D. A., Mansmann, F., Schneidewind, J., Thomas, J., & Ziegler, H. (2008). Visual Analytics: Scope and Challenges. In S. J. Simoff, M. H. Böhlen & A. Mazeika (Eds.), *Visual Data Mining: Theory, Techniques and Tools for Visual Analytics* (pp. 76-90). Berlin, Heidelberg: Springer Berlin Heidelberg.

Kimerling, A. J., Buckley, A. R., Muehrcke, P. C., & Muehrcke, J. O. (2011). *Map Use: Reading, Analysis, Interpretation* (Seventh ed.). Redlands, CA: Esri Press.

Kinkeldey, C., MacEachren, A. M., & Schiewe, J. (2014). How to Assess Visual Communication of Uncertainty? A Systematic Review of Geospatial Uncertainty Visualisation User Studies. *The Cartographic Journal, 51*(4), 372-386. doi: 10.1179/1743277414Y.0000000099

Kitchin, R. (2013). Big data and human geography: opportunities, challenges and risks. *Dialogues in Human Geography, 3*(3), 262-267. doi: 10.1177/2043820613513388

Klippel, A., Wallgrün, J. O., Yang, J., Mason, J. S., Kim, E.-K., & Mark, D. M. (2013). Fundamental Cognitive Concepts of Space (and Time): Using Cross-Linguistic, Crowdsourced Data to Cognitively Calibrate Modes of Overlap. In T. Tenbrink, J. Stell, A. Galton & Z. Wood (Eds.), *Spatial Information Theory: 11th International Conference, COSIT 2013, Scarborough, UK, September 2-6, 2013. Proceedings* (pp. 377-396). Cham: Springer International Publishing.

Koch, C. (2015). Do Androids Dream? *Scientific American Mind, 26*, 24-27

Kraak, M. J. (1989). Computer-assisted cartographical 3D imaging & techniques. In J. Raper (Ed.), *Three-dimensional Applications in Geographical Information Systems* (pp. 99-114). London: Taylor & Francis.

Kraak, M. J. (2014). *Mapping Time*. Redlands, California: Esri Press.

Krygier, J. B. (1994). Chapter 8 - Sound and Geographic Visualization. In M. Alan M & T. D.R. Fraser (Eds.), *Modern Cartography Series* (Vol. Volume 2, pp. 149-166): Academic Press.

Laney, D. (2001, February 6, 2001). 3D Data Management: Controlling Data Volume, Velocity, and Variety. Retrieved from http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf

Lee, J.-G., & Kang, M. (2015). Geospatial Big Data: Challenges and Opportunities. *Big Data Research, 2*(2), 74-81. doi: http://dx.doi.org/10.1016/j.bdr.2015.01.003

Leonardi, L., Orlando, S., Raffaetà, A., Roncato, A., Silvestri, C., Andrienko, G., & Andrienko, N. (2013). A general framework for trajectory data warehousing and visual OLAP. *GeoInformatica, 18*(2), 273-312. doi: 10.1007/s10707-013-0181-3

Lewis, S. C. (2015). Journalism In An Era Of Big Data. *Digital Journalism, 3*(3), 321-330. doi: 10.1080/21670811.2014.976399

Li, S., Dragicevic, S., Castro, F. A., Sester, M., Winter, S., Coltekin, A., . . . Cheng, T. (In Press). Geospatial big data handling theory and methods: A review and research challenges. *ISPRS Journal of Photogrammetry and Remote Sensing*. doi: http://dx.doi.org/10.1016/j.isprsjprs.2015.10.012

Liu, D., Bias, R. G., Lease, M., & Kuipers, R. (2012). Crowdsourcing for usability testing. *Proceedings of the American Society for Information Science and Technology, 49*(1), 1-10. doi: 10.1002/meet.14504901100

MacEachren, A. M. (1992). Visualizing uncertain information. *Cartographic Perspectives*(13), 10-19. doi: 10.14714/cp13.1000

MacEachren, A. M. (1994). Visualization in modern cartography: Setting the agenda. In A. M. MacEachren & D. R. F. Taylor (Eds.), *Visualization in modern cartography* (pp. 1-12). Oxford, England: Pergamon.

MacEachren, A. M. (1995). *How Maps Work: Representation, Visualization and Design*. New York: Guilford Press.

MacEachren, A. M. (2015). Visual Analytics and Uncertainty: It's Not About the Data *EuroVis Workshop on Visual Analytics (EuroVA)* (pp. 55-60). Cagliari, Italy: Eurographics Association.

MacEachren, A. M., & Ganter, J. H. (1990). A pattern identification approach to cartographic visualization. *Cartographica, 27*(2), 64-81

MacEachren, A. M., Jaiswal, A., Robinson, A. C., Pezanowski, S., Savelyev, A., Mitra, P., . . . Blanford, J. (2011). *SensePlace2: Geotwitter Analytics Support for Situation Awareness*. IEEE Conference on Visual Analytics Science and Technology, Providence, RI.

MacEachren, A. M., & Kraak, M.-J. (2001). Research Challenges in Geovisualization. *Cartography and Geographic Information Science, 28*(1), 3-12

MacEachren, A. M., & Kraak, M. J. (1997). Exploratory cartographic visualization: advancing the agenda. *Computers & Geosciences, 23*(4), 335-343

MacEachren, A. M., Robinson, A. C., Hopper, S., Gardner, S., Murray, R., & Gahegan, M. (2005). Visualizing geospatial uncertainty: what we know and what we need to know. *Cartography and Geographic Information Science, 32*(3), 139-160

MacGill, J., & Openshaw, S. (1998). The use of flocks to drive a geographic analysis machine *Third International Conference on Geocomputation*. Bristol, UK.

Maciejewski, R., Hafen, R., Rudolph, S., Larew, S. G., Mitchell, M. A., Cleveland, W. S., & Ebert, D. S. (2011). Forecasting Hotspots—A Predictive Analytics Approach. *Visualization and Computer Graphics, IEEE Transactions on, 17*(4), 440-453. doi: 10.1109/TVCG.2010.82

Mandelbrot, B. (1982). *The fractal geometry of nature*: W.H. Freeman.

McCloud, S. (1994). *Understanding Comics*. New York, NY: William Morrow Paperbacks.

McCurdy, N., Lein, J., Coles, K., & Meyer, M. (2016). Poemage: Visualizing the Sonic Topology of a Poem. *Visualization and Computer Graphics, IEEE Transactions on, 22*(1), 439-448. doi: 10.1109/TVCG.2015.2467811

Merriam-Webster. (2014). Webster's New World College Dictionary (5th ed., pp. 1728). Boston, Massachusetts: Webster's New World.

Miller, H. J., & Goodchild, M. F. (2014). Data-driven geography. *GeoJournal, 80*(4), 449-461. doi: 10.1007/s10708-014-9602-6

Moore, A., Marinescu, D., & Tenzer, R. (2011). A Visual Art Interface to an Embedded Sequence of Maps. *Cartography and Geographic Information Science*, *38*(2), 184-191. doi: 10.1559/15230406382184

Moore, A. B. (2009). Maps as Comics, Comics as Maps *International Cartographic Conference* (pp. 1-13). Santiago, Chile: International Cartographic Association.

Moore, A. B., & Rodda, J. (2015). Adaptive Relative Motion Representation of Space–Time Trajectories. *The Cartographic Journal, 52*(2), 204-209. doi: 10.1080/00087041.2015.1119463

Morisette, J. T., Jarnevich, C. S., Holcombe, T. R., Talbert, C. B., Ignizio, D., Talbert, M. K., . . . Young, N. E. (2013). VisTrails SAHM: visualization and workflow management for species habitat modeling. *Ecography, 36*(2), 129-135. doi: 10.1111/j.1600-0587.2012.07815.x

Olshannikova, E., Ometov, A., Koucheryavy, Y., & Olsson, T. (2015). Visualizing Big Data with augmented and virtual reality: challenges and research agenda. *Journal of Big Data*, *2*(1), 1-27. doi: 10.1186/s40537-015-0031-2

Openshaw, S. (1998). Towards a More Computationally Minded Scientific Human Geography. *Environment and Planning A, 30*(2), 317-332. doi: 10.1068/a300317

Patterson, S. (1992). The Great Bear.

Priestnall, G., & Hampson, D. (2008). Landscape Visualization: Science and Art. In M. Dodge, M. McDerby & M. Turner (Eds.), *Geographic Visualization* (pp. 241-258): John Wiley & Sons, Ltd.

Ragan, E. D., Endert, A., Sanyal, J., & Chen, J. (2016). Characterizing Provenance in Visualization and Data Analysis: An Organizational Framework of Provenance Types and Purposes. *IEEE Transactions on Visualization and Computer Graphics, 22*(1), 31-40. doi: 10.1109/TVCG.2015.2467551

Riedl, A. (2012). State-of-the-art of Tactile Hyperglobes. In M. Buchroithner (Ed.), *True-3D in Cartography* (pp. 215-226): Springer Berlin Heidelberg.

Rinner, C. (2001). Argumentation Maps: GIS-Based Discussion Support for On-Line Planning. *Environment and Planning B: Planning and Design*, *28*(6), 847-863. doi: 10.1068/b2748t

Roberts, J. (2005). Exploratory visualization with multiple linked views. In J. Dykes, A. M. MacEachren & M. J. Kraak (Eds.), *Exploring Geovisualization*. Amsterdam: Elsevier.

Robinson, A. C. (2009). Needs assessment for the design of information synthesis visual analytics tools *IEEE International Conference on Information Visualization* (pp. 353-360). Barcelona, Spain.

Robinson, A. C. (2011). Supporting Synthesis in Geovisualization. *International Journal of Geographical Information Science, 25*(2), 211-227

Robinson, A. C., Chen, J., Lengerich, G., Meyer, H., & MacEachren, A. M. (2005). Combining usability techniques to design geovisualization tools for epidemiology. *Cartography and Geographic Information Science, 32*(4)

Rosenberg, D., & Grafton, A. (2010). *Cartographies of Time*. New York, New York: Princeton Architectural Press.

Roth, R. E. (2012). Cartographic Interaction Primitives: Framework and Synthesis. *The Cartographic Journal, 49*(4), 376-395. doi: 10.1179/1743277412y.0000000019

Roth, R. E. (2013). Interactive Maps: What we know and what we need to know. *The Journal of Spatial Information Science, 6*, 59-115

Roth, R. E., Hart, D., Mead, R., & Quinn, C. (In Press). Wireframing for interactive & web-based mapping: Designing the NOAA Lake Level Viewer. *Cartography and Geographic Information Science*

Rystedt, B., Ormeling, F., Konecny, M., Li, L., Liebenberg, E., McMaster, R., . . . Wood, M. (2003). *A Strategic Plan for the International Cartographic Association, 2003-2011*. I. C. Association.

Seamon, D., & Sowers, J. (2008). Place and Placelessness, Edward Relph. In P. Hubbard, R. Kitchin & G. Vallentine (Eds.), *Key Texts in Human Geography* (pp. 43-51). London: Sage.

Shao, L., Sacha, D., Neldner, B., Stein, M., & Schreck, T. (2016). Visual-Interactive Search for Soccer Trajectories to Identify Interesting Game Situations. *Electronic Imaging, 2016*(1), 1-10

Shneiderman, B. (1996). The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations *1996 IEEE Conference on Visual Languages* (pp. 336-343). Boulder, CO.

Shneiderman, B. (2007). Creativity support tools: accelerating discovery and innovation. *Commun. ACM, 50*(12), 20-32. doi: 10.1145/1323688.1323689

Slocum, T., Blok, C., Jiang, B., Koussoulakou, A., Montello, D., Fuhrmann, S., & Hedley, N. (2001). Cognitive and usability issues in geovisualization. *Cartography and Geographic Information Systems, 28*(1), 61-75

Stienen, E. W. M., Desmet, P., Aelterman, B., Courtens, W., Feys, S., Vanermen, N., . . . Lens, L. (2016). GPS tracking data of Lesser Black-backed Gulls and Herring Gulls breeding at the southern North Sea coast. *ZooKeys*, *555*, 115-124. doi: 10.3897/zookeys.555.6173

Sundararajan, L. (2014). Mind, Machine, and Creativity: An Artist's Perspective. *The Journal of Creative Behavior*, *48*(2), 136-151. doi: 10.1002/jocb.44

Thatcher, J. (2014). Living on Fumes: Digital Footprints, Data Fumes, and the Limitations of Spatial Big Data. *International Journal of Communication, 8*(2014), 1765-1783

Thomas, J. J., & Cook, K. A. (Eds.). (2005). *Illuminating the path: the research and development agenda for visual analytics*. New York: IEEE CS Press.

Thudt, A., Hinrichs, U., & Carpendale, S. (2012). *The bohemian bookshelf: supporting serendipitous book discoveries through information visualization*. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Austin, Texas, USA.

Tomaszewski, B., & MacEachren, A. M. (2012). Geovisual analytics to support crisis management: information foraging for geo-historical context. *Information Visualization, 11*(4), 339-359. doi: 10.1177/1473871612456122

Tsou, M.-H. (2015). Research challenges and opportunities in mapping social media and Big Data. *Cartography and Geographic Information Science*, *42*(sup1), 70-74. doi: 10.1080/15230406.2015.1059251

Tuan, Y.-F. (1977). *Space and place: The perspective of experience*: University of Minnesota Press.

Virrantaus, K., Fairbairn, D., & Kraak, M. J. (2009). ICA Research Agenda on Cartography and GI Science. *The Cartographic Journal*, *36*(2), 209-222

Watson, R. (2009). Mapping and Contemporary Art. *The Cartographic Journal, 46*(4), 293-307

Wilkinson, L. (2005). *The Grammar of Graphics* (2nd ed.). New York: Springer-Verlag.

Wills, G., & Wilkinson, L. (2010). AutoVis: Automatic Visualization. *Information Visualization, 9*(1), 47-69. doi: 10.1057/ivs.2008.27

Wu, X., Zurita-Milla, R., & Kraak, M.-J. (2015). Co-clustering geo-referenced time series: exploring spatio-temporal patterns in Dutch temperature data. *International Journal of Geographical Information Science, 29*(4), 624-642. doi: 10.1080/13658816.2014.994520

Yusof, N., Zurita-Milla, R., Kraak, M.-J., & Retsios, B. (2016). Interactive discovery of sequential patterns in time series of wind data. *International Journal of Geographical Information Science*, 1-21. doi: 10.1080/13658816.2015.1135928

Zeki, S. (2001). Artistic Creativity and the Brain. *Science, 293*(5527), 51-52. doi: 10.1126/science.1062331

Zhang, J., & Goodchild, M. (2002). *Uncertainty in Geographical Information*. New York, NY: CRC Press.