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Geovisualization: Past, Present, and Future

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Introduction

Geovisualization, initially defined by its emphasis on user interaction and multiple views of the same data, has undergone significant evolution over time (Fitzpatrick and Hedley, 2024). The integration of visual analytics (Andrienko et al., 2010) has been particularly transformative, expanding geovisualization from a primarily cartographic field into a comprehensive approach for exploring, analyzing, and understanding geospatial phenomena. This integration has introduced advanced analytical capabilities, interactive and dynamic visualizations, and improved handling of big data. Consequently, the focus has shifted toward knowledge construction, decision support, and collaborative analysis while fostering a more multidisciplinary and user-centered approach to geospatial data visualization and analysis (Christophe, 2020).

Over the past decade, geovisualization has been driven by the increasing availability of diverse, large-scale geospatial data and advances in visualization techniques. It plays a crucial role in helping people interpret complex spatial data, generate insights, and make informed decisions. As a field at the intersection of cartography, computer science, and data science, geovisualization has embraced new technologies, ranging from open-source tools to machine learning. These advancements have fundamentally transformed how spatial data is represented, analyzed, and understood.

This essay reflects on the progress made in geovisualization over the past ten years, highlights the current state of the field, and outlines future directions for research and practice. [We primarily draw upon literature from ICA-related journals published since 2015.](#) Particular attention is given to how modern challenges, such as handling big data, representing uncertainty, and integrating real-time data, are addressed through evolving tools and techniques. Finally, we explore how emerging technologies, especially Artificial Intelligence (AI), are shaping the future of geovisualization.

Reflecting on the Past 10 Years

Over the past decade, geovisualization has evolved significantly as a multidisciplinary field, incorporating advancements from cartography, geoinformatics, computer science, data science, and machine learning (Krassanakis et al., 2023). As the demand for interpreting vast amounts of geospatial data continues to grow, researchers and practitioners have developed increasingly sophisticated tools and methods to augment human cognitive capacities with computational power.

Conceptualization and Research Agendas

[Over the past decade, early efforts to define and structure the field of geovisualization set the stage for much of its subsequent evolution. A notable contribution in this regard is Çöltekin et al. \(2017\), which uniquely combined top-down analyses of existing research agendas with bottom-up insights gathered](#)

from over 70 experts across various subdomains of geographic information science and technology. Their approach highlighted the areas of convergence between established research priorities and emerging practitioner concerns and revealed several enduring challenges.

Central to Çöltekin et al.'s findings were three major issues: first, the need for a clearer delineation of the geovisualization domain and more effective engagement with related disciplines; second, a systematic exploration of human factors—particularly the perceptual and cognitive dimensions that influence how visual information is processed; and third, the development of practicable guidelines that bridge the gap between visualization types and the tasks they are meant to support. Additionally, the study raised concerns regarding knowledge transfer, suggesting that best practices and design principles often struggle to reach the wider community responsible for producing geovisualizations.

These foundational perspectives have not only influenced subsequent research trajectories, especially with the advent of AI and advanced computational methods, but have also underscored persistent gaps that continue to challenge the field. In reflecting on the past 10 years, revisiting these early conceptualizations helps to frame both the progress made and the enduring issues that inform current and future research agendas.

While these conceptual frameworks set the stage for understanding geovisualization's persistent challenges, the field has also made notable practical advances. In the following subsections, we turn to these developments, examining the impact of dynamic data sources, emerging analytical tools, evolving representation techniques, and innovative interaction paradigms.

Data

The rise of the Internet of Things, satellite imagery, and the explosion of real-time data from sensors, social media, and other sources have resulted in increasingly diverse and complex datasets. This has necessitated new approaches for handling diverse data types and managing large volumes, structural complexity, and dynamic characteristics (Robinson et al., 2017). Various computational methods are now employed to transform these data into digestible information that humans can interpret and reason about. As a result, machine learning (ML) has become widely used for identifying patterns in large geospatial datasets. Automated techniques can now detect spatial trends, classify regions, and forecast changes (Li et al., 2016).

The inherent complexity of geospatial data—often incorporating temporal and multidimensional aspects—demands advanced data modeling techniques. Researchers continue to develop novel methods for representing and analyzing spatio-temporal data, emphasizing the importance of integrating both spatial and temporal dimensions into models and visualizations (Gautier et al., 2021).

Additionally, handling uncertainty has become a core concern in geovisualization, particularly as datasets grow more complex and involve predictions, estimates, and incomplete information. Beyond simple visual representations, uncertainty is increasingly incorporated into analytical processes (MacEachren, 2015). This includes accounting for probability distributions, confidence intervals, and sensitivity to parameter changes. The use of Bayesian networks (Chuprikova and Meng, 2019) exemplifies how uncertainty can be modeled and visualized probabilistically. By integrating uncertainty information, analysts and modelers can provide a more comprehensive and reliable basis for understanding complex systems, enabling decision-makers to assess outcomes with varying levels of confidence.

Table 1 summarizes recent developments in data handling.

Aspect	Early works	Recent progress
Data Types	Structured data (such as census data)	Diverse data (IoT, social media, satellite imagery)
Volume	Small singular datasets from a single source	Big data, real-time, multiple diverse datasets from multiple sources
Handling Complexity	Static models, limited handling of complexity	ML-based models for handling structural complexity and dynamic data
Handling Uncertainty	Visual representation of uncertainty in data	Incorporation of uncertainty information in analysis and modeling

Table 1: Developments in Data Handling Over the Past Decade

Tools

The proliferation of open-source libraries has transformed the landscape of geovisualization tools. Libraries like D3.js¹, Leaflet², GeoPandas³, and CesiumJS⁴ have allowed a wide range of users to analyze and visualize geospatial data. These tools support real-time data processing and sophisticated map visualizations, often through web-based platforms, eliminating the need for proprietary software.

Web-based geovisualization has become the dominant paradigm, driven by the growing demand for real-time, collaborative mapping tools. WebGL⁵, WebGIS, and cloud-based platforms such as ArcGIS Online⁶ and Google Earth Engine⁷ have simplified the creation and sharing of interactive maps, making them accessible across various devices and platforms. These tools facilitate complex analyses and simulations, allowing multiple stakeholders to collaborate in real time.

Geovisualization research and practice also benefits from employing existing opensource tools for data integration and processing, statistical analysis, scientific and technical computations, particularly, to deal with multidimensional data. Moreover, the wide availability of machine learning techniques, e.g., in Python libraries, such as Scikit-learn⁸, TensorFlow⁹, and PyTorch¹⁰, has enabled development of geovisualization systems capable of predicting patterns and simulating scenarios.

¹ <https://d3js.org/>

² <https://leafletjs.com/>

³ <https://geopandas.org/en/stable/>

⁴ <https://cesium.com/platform/cesiumjs/>

⁵ <https://www.khronos.org/webgl/>

⁶ <https://www.arcgis.com/home/index.html>

⁷ <https://earth.google.com/web/>

⁸ <https://scikit-learn.org/stable/>

⁹ <https://www.tensorflow.org/>

¹⁰ <https://pytorch.org/>

Computational notebooks such as Jupyter notebook¹¹ and Observable¹² have further transformed the geovisualization landscape, making it easier for users to create, iterate on, and share geospatial analyses. These platforms enable the rapid generation of geovisualizations with minimal effort, allowing for real-time data validation and exploration.

The evolution of tools that can be used for geovisualization applications is reflected in Table 2, whereas Table 3 groups the opensource tools regarding the purposes of their use.

Tool Type	Earlier practices	Recent progress
Mapping Libraries	Google Maps API, Mapbox	Leaflet, CesiumJS, GeoPandas, D3.js
Data Analysis	ArcGIS, QGIS	Opensource ML tools like TensorFlow, Scikit-learn
Web-Based Visualization	Static web maps with traditional GUIs (point-and-click and menu-based)	WebGIS with real-time data updates, WebGL-based interactivity
Interactive Platforms	Desktop GIS	Cloud-based platforms (ArcGIS Online, Google Earth Engine)

Table 2: Geovisualization Tools: Past vs. Present. Note: ‘early works’ here are limited to developments from 2015 to 2025, distinct from earlier geovisualization frameworks.

Category	Opensource Tools	Purpose
Data Visualization Libraries	D3.js, Leaflet, CesiumJS	Create interactive, web-based geospatial visualizations
Data Analysis	GeoPandas, Scikit-learn, TensorFlow, PyTorch	Process and analyze geospatial data, enable ML and predictive analysis
Computational Notebooks	Jupyter, Observable	Rapid prototyping of geovisualizations, live coding for analysis

Table 3: Summary of Opensource Libraries and Tools

In Table 2, ‘early works’ refers specifically to developments from 2015 onward rather than the broader history of geovisualization. While web mapping tools such as Google Maps and Mapbox were widely used during this period, it is important to recognize that advanced geovisualization frameworks existed well before 2015. Platforms such as GAV Flash (Ho 2011), GeoVISTA Studio (Gahegan et al. 2002), and CommonGIS (Andrienko et al. 2003) demonstrated sophisticated interactive visualization capabilities in earlier decades, some of which remain unmatched in current web-based implementations. The distinction made in the table highlights the shift over the past decade toward real-time WebGIS, WebGL-based interactivity, and cloud-integrated systems.

Representation

Representation techniques have evolved significantly, expanding from 2D maps and coordinated multiple views to immersive, interactive environments. Virtual Reality (VR) and Augmented Reality (AR) are

¹¹ <https://jupyter.org/>

¹² <https://observablehq.com/>

beginning to reshape how geospatial data is represented and experienced (Hruby et al., 2018). There is also growing interest in **sonification** (representing data through sound) (Hruby, 2019) and **physicalization** (representing data with tangible objects) (Jansen et al., 2015). Though still experimental, these methods offer novel ways to interpret and interact with geospatial data, engaging multiple human senses and expanding how users understand spatial patterns and trends.

Effectively representing space and time, including transformations that enhance interpretation, is crucial for uncovering complex, higher-order patterns in geovisualization. For example, Andrienko et al. (2021) introduce an innovative approach in the analysis of soccer tactics. Building on earlier work in aviation and vessel movement (Andrienko and Andrienko, 2018), their method segments the game into discrete episodes, defining time relative to key events and transforming spatial coordinates from absolute pitch positions into a “**team space**” that captures the relative arrangements of players. This transformation not only enhances analytical clarity but also enriches visual representation, illustrating a methodology applicable across various domains.

Another key trend is the **personalization of geovisualizations**. Personal geospatial data, such as tracking individual movements through mobile apps, is increasingly visualized in ways that are meaningful to the data creator (Nelson, 2023). This trend opens possibilities for fitness tracking, travel diaries, and personalized urban experiences but also raises concerns regarding privacy and data ownership.

Uncertainty remains a critical aspect of geospatial data (MacEachren, 2015), and researchers continue to develop more effective ways to visualize and communicate it. These include probabilistic surfaces, fuzzy boundaries, novel visual variables (blur, opacity, sketchiness), and explicit representations of probability distributions or confidence intervals. Such techniques allow users to grasp not only the data itself but also its variability and potential errors. A major focus remains on conveying uncertainty in a way that supports decision-making (Goodwin et al., 2024).

Interaction

User interaction has evolved significantly, moving beyond traditional WIMP-based interfaces (windows, icons, menus, and pointers) to embrace multimodal interaction. Touch, gestures, and speech recognition now provide more natural and intuitive ways to engage with geospatial data. These techniques are particularly important for immersive technologies such as virtual reality (VR) and augmented reality (AR) (Hruby et al., 2018; Çöltekin et al., 2020). These technologies enable a spatially embedded interaction experience, allowing users to “step into” a map or data space and manipulate elements with their hands or voice.

At the other end of the spectrum, the widespread use of smartphones and tablets has popularized gesture-based controls and voice interfaces in mobile geovisualization applications. These interaction methods allow users to engage with geospatial data in real-world contexts, further enhancing the accessibility and practicality of geovisualization tools in everyday life (Li et al., 2016).

Researchers have also explored eye-tracking as an interaction technique in geovisualization (Brägger et al., 2022), where machine learning algorithms adapt visualizations based on user behavior. A gaze-aware interactive map system (GAIMS) can create personalized experiences, allowing users to engage more intuitively with complex geospatial data (Keskin et al., 2023). This research reflects the ongoing effort to refine human-data interaction by integrating machine learning and adaptive user interfaces (Mezhoudi and Vanderdonckt, 2020).

Table 4 summarizes recent progress in interaction techniques.

.Interaction Method	Early works	Recent progress
User Interface (UI)	GUI, mouse, keyboard	Multimodal interfaces (touch, gestures, speech, eye-tracking)
Immersive Technologies	Static 2D/3D maps	VR, AR environments (step into the data, manipulate data spatially)
Personalization	General-purpose, one-size-fits-all	User-centered (adaptive to user preferences, gaze-aware, personalized maps)
Mobile Interaction	Limited touch controls	Gesture-based, voice-assisted, adaptive to mobile devices

Table 4: Recent Evolution of Interaction Methods

Current status

oday, geovisualization stands at the intersection of multiple disciplines, combining the spatial reasoning of traditional cartography with the analytical power of modern machine learning and data science (Andrienko et al., 2016; Andrienko et al., 2020). Geovisualization has advanced in its ability to handle large-scale, real-time datasets, represent uncertainty, and support collaborative decision-making. However, challenges remain, particularly in the areas of user-friendly interfaces for managing massive datasets and effectively communicating uncertainty in ways that support informed decision-making.

The integration of AI and machine learning into geovisualization tools is an especially prominent current trend (Robinson et al., 2023; Chen et al., 2023). *It is worth noting that, even more than 10 years ago, geovisualization systems were already incorporating machine learning techniques (e.g., Guo et al., 2005, 2012; Andrienko et al., 2010). Over the past decade, however, these approaches have shifted from pioneering to mainstream.*

AI is now used to automate tasks such as land-use classification, detecting patterns in satellite imagery, and making predictions based on historical data. For example, Esri's ArcGIS platform has incorporated AI and machine learning tools to enhance spatial analysis. Esri integrates deep learning models to analyze imagery, automatically identify features like roads, vegetation, and buildings, and detect changes over time. AI is also used to predict traffic patterns, identify optimal routes, and model the spread of diseases. *Beyond automating or facilitating data processing and computational analyses, contemporary AI offers enhanced personalization and natural language interfaces that extend established interaction paradigms and techniques.*

While significant progress has been made in democratizing access to geovisualization tools, further work is needed to ensure that these tools are accessible to non-experts while retaining their analytical power for professionals. The ongoing challenge lies in balancing complexity with usability, ensuring that powerful geospatial analyses are not only technically feasible but also user-friendly and actionable for decision-makers at all levels (Çöltekin et al., 2017).

Future

The future of geovisualization will be heavily influenced by the increasing integration of artificial intelligence and machine learning into geospatial analysis and visualization. AI will play a central role in enabling more intelligent, automated, and personalized geovisualizations, where machines assist users in hypothesis generation, testing, and decision-making.

Geovisualization research and practice will increasingly exploit AI's capabilities to facilitate every stage of the data pipeline—from data acquisition, integration, and cleaning, to transformation and computational analysis. AI will enable the automated discovery of patterns, trends, and anomalies within complex geospatial datasets, which would be difficult or impossible for humans to detect unaided. It will support the development of descriptive and predictive models of complex phenomena, simulate geospatial scenarios under diverse conditions, and compare the potential consequences of alternative decisions.

AI-powered geovisualization systems will become increasingly capable of adapting to users' knowledge, skills, preferences, habits, and behaviors. These systems will not only personalize the interaction experience but will also respond dynamically to the real-time context of use, such as a user's location and surrounding environment. This will enable the delivery of contextually relevant information and analytical services in various scenarios, such as fieldwork, emergency response, or travel.

Conversational interfaces using speech, gestures, and sketching will become standard interaction paradigms. Such interfaces will allow users—whether experts or novices—to communicate naturally with geovisualization systems. Through these interactions, an AI system will be capable of explaining its own capabilities, recommending appropriate analytical techniques, and interpreting visualizations and computational results, making complex geospatial analysis more accessible to a broader audience.

Table 5 summarizes the possible uses of AI at different stages of an analytical workflow.

Stage	Traditional Approach	AI Contributions
Data Acquisition	Manual data collection	Automated, real-time acquisition
Data Cleaning and Preparation	Manual data wrangling, feature engineering and selection	Automated cleaning, structuring, feature extraction
Pattern Detection	Human-driven analysis	AI-assisted pattern recognition and pattern discovery
Visualization	Human-designed, fixed	Personalized, adaptive, dynamic
User Interaction	GUI-based (mouse, keyboard)	Conversational interfaces, multimodal (speech, gestures, gaze)
Decision-Making	Human interpretation only	AI-aided hypothesis testing, proactive suggestions

Table 5: Potential use of AI at different stages of geovisualization workflow

From the perspective of visual analytics, which focuses on the synergistic collaboration between humans and computers, with each side employing its unique strengths, the most exciting developments will be in the creation of mixed-initiative systems (Andrienko et al., 2022). These systems will enable humans and AI to act as equal intelligent partners engaged in a shared analytical process (Toniolo et al., 2023). The AI partner will not be a passive tool waiting for commands but an active participant, proactively generating relevant analytical artifacts, such as supplementary visualizations, suggestions, or comparisons, without being explicitly instructed by the user.

In this collaboration, the human partner will employ their perceptual and cognitive abilities to interpret visualizations, link them to prior knowledge, and generate hypotheses. Simultaneously, the AI partner will interpret the user's spoken words, gestures, and annotations, storing these inputs as explicit information objects. The AI will immediately test hypotheses, make inferences, and offer implications, providing material for the human partner to think through and refine their understanding of the data. Additionally, the AI will strive to reconstruct the user's evolving mental model of the phenomenon under study and explicitly represent the knowledge that emerges from the analysis. This explicit representation of evolving

knowledge will improve transparency, ensure traceability, and allow for the documentation of how each piece of information was obtained.

An AI-driven system will be capable of maintaining a detailed history of the analysis process, preserving all relevant data, hypotheses, visualizations, and insights. This will enable users to pause and resume their work at any stage or explore alternative analytical paths, revisiting and branching off from previous stages of the analysis. Furthermore, in collaborative settings, such systems will facilitate asynchronous work by multiple users. For example, if a team is conducting a complex analysis, each member can contribute knowledge, perspectives, and insights, and the AI will update collaborators on the current state of the analysis, new contributions, unresolved questions, and remaining tasks.

Table 6 summarizes the vision of human-AI partnership within a mixed-initiative system.

Task	Human Contribution	AI Contribution
Data processing	Domain-specific transformations	Automating and scaling transformations
Visualization	Contextual interpretation, interactive exploration	Updating visualizations to accommodate new data in real time, adapting to users and tasks
Pattern Recognition	Leveraging domain knowledge, perceptual detection of patterns and anomalies, discovery of unexpected patterns and facts	Processing large datasets quickly, automated identification of predefined patterns and anomalies
Hypothesis Generation	Analogical reasoning, intuition, creative insights	Testing multiple hypotheses rapidly, proactive suggestion of additional hypotheses
Collaborative Work	Teamwork, sharing knowledge and insights, discussing, arguing, finding common ground	Storing and organizing contributions, enabling asynchronous collaboration
Decision-Making	Strategic thinking, judgment, soft and tacit criteria	Generating data-driven alternatives, computational optimization
Documentation and reporting	Comments, explanations, justification of decisions	Automatic recording of analysis steps and conversation history, provenance tracking, report generation

Table 6: Mixed-Initiative Human-AI Systems in Geovisualization

For professional analysts and domain experts, AI will serve as a sophisticated partner for collaborative problem-solving, offering advanced analytical capabilities, predictive modeling, and dynamic simulations. At the same time, end users such as policymakers, planners, and even the general public will benefit from AI in the role of geospatial advisors—interactive systems that can generate personalized visualizations, answer questions, verify conjectures, and assist users in interpreting complex geospatial data.

The ultimate goal of AI-driven geovisualization systems is to empower users with unprecedented analytical capabilities, transforming geospatial data into actionable knowledge while ensuring that humans remain at the center of the decision-making process.

It is also important to note that the integration of AI raises significant challenges, including ethical considerations related to copyright, energy consumption, and the transparency of algorithmic decision-

making (Jobin et al., 2019; Kanungo, 2023; Larsson and Heintz, 2020). Addressing these challenges is crucial for the responsible integration of AI, ensuring that technological advancements align with ethical standards and societal values.

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