CyberGIS-Vis for Democratizing Access to Scalable Spatiotemporal Geovisual Analytics: A Case Study of COVID-19

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Abstract

The COVID-19 pandemic underscored the critical need for effective disease mapping tools, essential for tracking infectious diseases. Following the WHO's pandemic declaration in March 2020, numerous technological solutions emerged to map cases, assess risk factors, and monitor mobility. However, there remains a shortage of reusable, open-source geovisual analytics tool for rapid response to future pandemics. To address this gap, we developed an innovative open-source JavaScript-based geovisual analytics tool as part of the CyberGIS-Vis project. This paper introduces two visualization modules of CyberGIS-Vis, showcasing their use in visualizing spatiotemporal COVID-19 data by integrating advanced cyberGIS and online visualization with robust analytics for geospatial knowledge discovery.

CCS Concepts

• **Human-centered computing → Geographic visualization**; • **Information systems → Geographic information systems**.

Keywords

CyberGIS, COVID-19, Geovisual Analytics, Visualization

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1 Introduction

Disease mapping tools have been crucial in public health for tracking infectious diseases over time and space. During the COVID-19 pandemic, these tools became vital for monitoring the virus's spread and identifying severely impacted regions. Following the WHO's pandemic declaration in March 2020, numerous technological solutions were rapidly developed to map cases, assess risk factors, and monitor mobility (e.g., [2, 4, 6, 12–15]), drawing significant attention from researchers, health officials, and policymakers. However, despite their widespread adoption, there has been a notable lack of effort to create reusable, open-source geovisual analytics tool, which is essential for swift responses to future pandemics.

On the technical front, the visualization of spatiotemporal dynamics, especially in disease datasets, has experienced a remarkable surge in the development and accessibility of web-based online data visualization tools in recent years. However, there remains a notable scarcity of open-source JavaScript-based tools that support Coordinated and Multiple Views (CMV) within the domain of geovisual analytics. CMV focuses on linking user interactions, such as cross-filtering, brushing, and highlighting, so that actions in one view can immediately affect others, facilitating more dynamic data exploration. CMV enables dynamic visual interfaces where various data representations are interactively linked, allowing for comprehensive analysis of spatiotemporal data—crucial for making well-informed decisions based on thorough data analysis. [17].

Traditional GIS software like GeoViz Toolkit [11] , CommonGIS [3], GeoVISTA Studio [18], and Cartographic Data Visualizer [5] have supported CMV but are mainly Java-based and designed for offline desktop use, making them challenging to integrate into modern web-based environments that use JavaScript libraries like D3, Plotly.js, and Leaflet. This creates a gap in integrating CMV systems into current geovisualization tools that require real-time, web-based analytics.

To bridge this gap, we developed a novel open-source JavaScript-based geovisual analytics tool within the CyberGIS-Vis project. This paper introduces two visualization modules within CyberGIS-Vis, demonstrating their application in visualizing spatiotemporal COVID-19 data. CyberGIS-Vis combines advanced cyberGIS and online visualization capabilities with robust analytical methods, enabling comprehensive geospatial data analysis. The tool enables comparative visualization of spatiotemporal patterns with dynamic choropleth maps linked to charts and offers reproducible analytics through CyberGIS-Jupyter [16].

2 Implementation of CyberGIS-Vis ST

Open-Source. We developed web-based spatiotemporal modules, CyberGIS-Vis ST, using open-source libraries like Leaflet (https:

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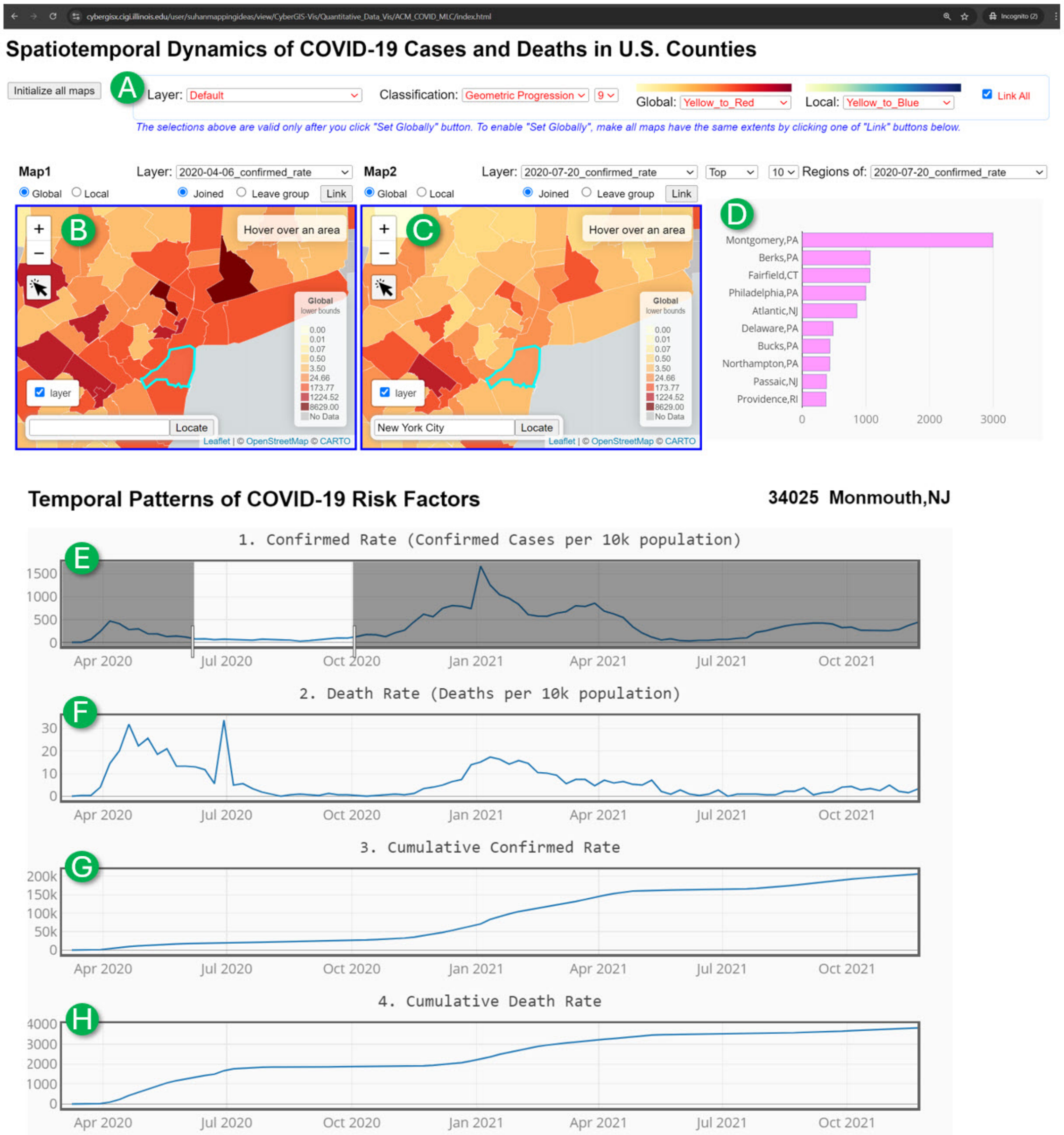

Figure 1: An example visualization using CyberGIS-Vis ST's Multiple Linked Chart (MLC) functionality. Step-by-step demos are available at https://su-gis.org/vis/mlc, and a larger image can be viewed a https://github.com/su-gis/CyberGIS-Vis/blob/master/images/Fig_1.jpg.

//leafletjs.com), D3 (https://d3js.org), PlotlyJS (https://plotly.com), Geostats [7], Simple Statistics [1], and jQuery (https://jquery.com). CyberGIS-Vis ST consists of an HTML file with a JavaScript-based main algorithm, a CSS file for styling, a JavaScript configuration file, and two JavaScript files for input data on variables and geometry. Users generate visualizations by replacing the example data, and the HTML file runs in a web browser, with the configuration file allowing parameter customization.

CyberGISX Environment. Users can create visualizations with Python code on the CyberGISX platform, a scalable framework for geospatial analysis through JupyterLab (https://cybergisxhub.cigi.illinois.edu;[16]). Unlike standard JupyterLab, where users must install libraries, CyberGISX provides pre-installed geospatial libraries like SciPy, scikit-learn, GeoPandas, Shapely, and PySAL, streamlining the setup process and allowing them to focus directly on their analysis and visualization tasks. Key advantages of CyberGISX include: (1) enabling users without JavaScript experience to create visualizations in Jupyter notebooks using Python, (2) providing a pre-installed library environment, and (3) allowing users to publish Jupyter Notebooks with CyberGIS-Vis ST visualization settings, making them publicly accessible and easily reproducible [9]. This accessibility benefits non-programmers and allows advanced users to modify code to extend functionality.

Creating and Sharing Visualizations. To create visualizations with CyberGIS-Vis ST, users can start with a template on the CyberGISX website [8], input their data, adjust parameters, and run a single line of code. Input details are on GitHub (https://github.com/su-gis/CyberGIS-Vis). Visualizations can be accessed privately via a URL or shared by publishing the notebook on CyberGISX. Full guidance is available at https://su-gis.org/vis/start.

3 Key Features and Functionalities

This section showcases the core functionalities of CyberGIS-Vis ST, a geovisual analytics tool for analyzing and visualizing datasets with spatiotemporal dimensions. Using COVID-19 data from the New York Times (https://github.com/nytimes/covid-19-data) as a case study, we demonstrate how CyberGIS-Vis ST uncovers hidden patterns and relationships through in-depth data exploration. The tool integrates Coordinated and Multiple Views (CMV) [17], which allows interactions in one view to dynamically update others. CyberGIS-Vis ST offers several visualization modules, including choropleth maps, bar charts, multiple linked charts, and comparison line charts. We present two examples: one combining choropleth maps, bar charts, and linked charts (Fig. 1), and another integrating choropleth maps, and comparison line charts (Fig. 3). Step-by-step guides for these visualizations are available at https://su-gis.org/vis/mlc and https://su-gis.org/vis/clc. The following sections detail each module.

Adaptive Choropleth Mapper (ACM). We utilized the Adaptive Choropleth Mapper (ACM) and incorporated bar and time series charts to create coordinated views for spatiotemporal datasets. ACM, an open-source tool for visualizing multiple choropleth maps, allows users to set the number of maps; here, two maps are shown in Figs. 1 and 3. For key features of ACM, see [10]. Fig. 1, panels A, B, and C, shows two choropleth maps using ACM with confirmed rates for April 6th (left) and July 20th (right). The "Link All" feature unifies class intervals for consistent comparison, while separate intervals allow for exploring variations within each map. The maps show a decline in confirmed rates from April to July, particularly in New York and nearby areas, indicating improvement.

Multiple Linked Chart (MLC). we developed MLC in our platform, allowing users to display multiple time series charts by specifying chart numbers and relevant variables. For example, we visualized trends in confirmed rates, death rates, and cumulative rates (Fig. 1 E, F, G, H). Cumulative charts help visualize whether rates are accelerating or decelerating, while weekly charts detect sudden changes for quick response. The MLC feature allows users to select a region on a map, and multiple time series charts dynamically update to reflect data for that area (Fig. 1E, F, G, H).

A key MLC feature is dynamic Y-axis adjustment when zooming into a specific time range, allowing detailed analysis of temporal changes. For example, zooming into a period in Fig. 1E refines the Y-axis, revealing previously unnoticed variations (Fig. 2A). Additionally, synchronized zooming across charts ensures all charts display corresponding data for the same period, facilitating comprehensive analysis (Figs. 2B, C, D).

Bar Chart. The bar chart feature helps identify regions with high or low values or impacts of specific events within the current map view. Users can customize the chart to show the top or bottom values. For example, Fig. 1D displays the top 10 counties by COVID-19 confirmed rate on July 20, 2020, within the current map extent in Fig. 1C. The bar chart is linked to the map, updating dynamically to show the top 10 values for the selected variable based on the

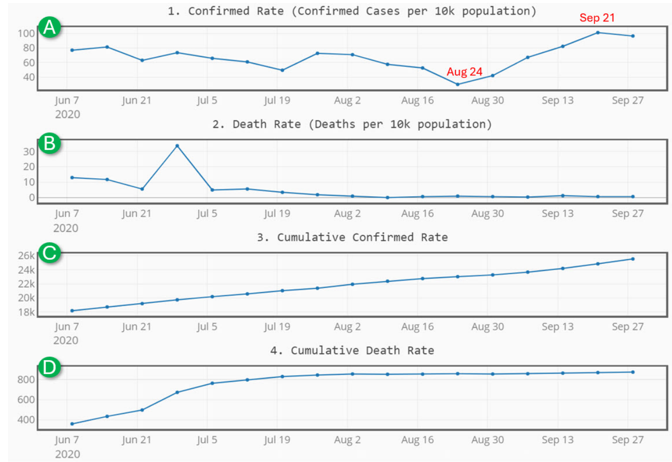

Figure 2: A zoomed-in view from Fig. 1.E shows the selected period, with grayed-out areas representing data outside the focus. A larger version is available at: https://github.com/su-gis/CyberGIS-Vis/blob/master/images/Fig_2.jpg

current map view. When the map changes, the chart adjusts in real-time, ensuring relevant data is always highlighted. Additionally, hovering over a bar highlights the corresponding region on the map, allowing users to connect numerical data with its spatial location.

Comparison Line Chart (CLC). CLC allows users to analyze and compare COVID-19 confirmed rates over time across regions (Fig. 3C). Selecting a region, like Los Angeles County on the left map (Fig. 3A), updates the blue line on the chart to show its trends. Similarly, selecting Miami-Dade County on the right map (Fig. 3B) updates the orange line, enabling a direct visual comparison of trends between the two areas (Fig. 3C). The CLC (Fig. 3C) allows users to examine individual temporal trend lines or compare them simultaneously using the buttons at the top. The "Trend Comparison" function normalizes data between 0 and 1, allowing clearer trend comparisons across two datasets with different ranges. For example, after selecting Hardee County, Florida, on the right map, it becomes evident that Los Angeles County consistently exhibits a higher confirmed rate throughout the timeline, with significant peaks during the first, second, and third waves (Fig. 3D). Hardee County, however, displays relatively stable trends with a consistently lower confirmed rate and minimal fluctuations. When using the "Trend Comparison" feature, the normalized view reveals distinct temporal patterns (Fig. 3E); Los Angeles County shows a pronounced second wave, while Hardee County's third wave appears most significant compared to its first and second waves. This normalization approach facilitates a straightforward comparison of temporal trends, allowing for a more nuanced understanding of regional differences in COVID-19 confirmed rates.

4 Conclusion

This article shows how CyberGIS-Vis ST can analyze and visualize infectious disease data like COVID-19, emphasizing its reproducibility and reusability for future pandemics. Its versatility allows it to handle a wide range of spatiotemporal datasets— from other diseases and disaster casualties to crime rates and human mobility—enabling researchers and policymakers to quickly analyze patterns and enhance preparedness and response for future

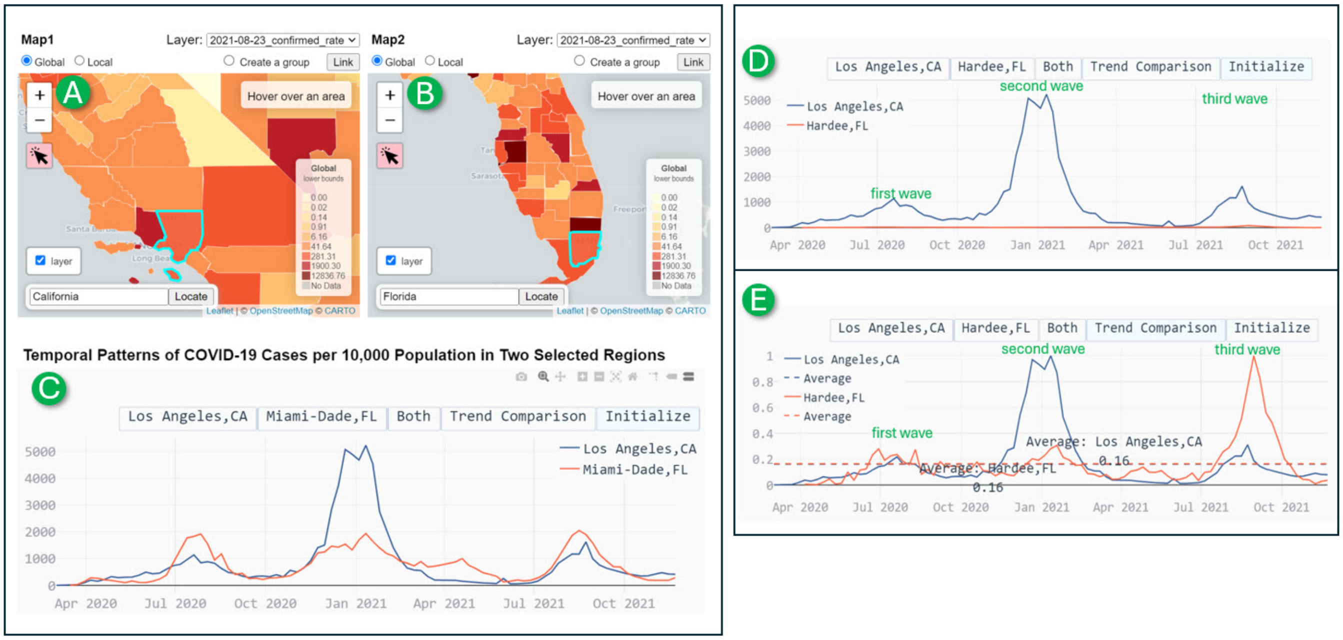

Figure 3: An example visualization using CyberGIS-Vis ST's Comparison Line Chart (CLC). Step-by-step demos are available at https://su-gis.org/vis/clc. A larger version is available at: https://github.com/su-gis/CyberGIS-Vis/blob/master/images/Fig_3.jpg

events. In future studies, we plan to enhance CyberGIS-Vis ST by adding more visualization modules to explore relationships between datasets. This will involve linking the adaptive choropleth mapper with various advanced charts from state-of-the-art data visualization libraries like D3 and Plotly, including scatter plots, parallel coordinate plots, violin plots, correlograms, and box plots. These enhancements will offer robust tools for exploratory data analysis that are accessible, reproducible, and publicly available.

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