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Comparative Study on Continuous and Discontinuous Dorling Maps

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ABSTRACT

The Dorling map, a special type of thematic map, is a widely employed tool for visualizing geospatial statistical data. It transforms regions into circles with areas proportionate to statistical values while endeavoring to maintain regional spatial relationships. Notably, two types of Dorling maps emerge, distinguished by their consideration of regional continuity: continuous and discontinuous Dorling maps. However, as of yet, the discrepancies between these two types remain inconclusive. In this paper, we employ an eye-tracking method to investigate the efficacy of Dorling maps in two common application scenarios, namely unpurposed browsing tasks and purposeful reading tasks. To this end, we administer tasks involving region search, attribute comparison/recognition/memory, conditional selection, relationship judgment, summary, and subjective evaluation. Subsequently, we perform a statistical analysis of the eye movement data of participants when they complete the above tasks in the continuous and discontinuous Dorling maps. The results indicate that the discontinuous Dorling maps are significantly better than the continuous ones in interpretation time for forward and reverse region search, selecting conditions, and judging adjacent relationships. Continuous Dorling maps significantly outperform discontinuous maps in terms of search efficiency during attribute comparison. Moreover, continuous maps significantly outperformed discontinuous maps in terms of cognitive supplementation or reprocessing of previous regions during conditional selection. This study can help users choose the right form of Dorling map visualization according to their needs.

1 | Introduction

With the contemporary simplification of data visualization production facilitated by computer technology, researchers have increasingly focused on evaluating and enhancing existing visualization design practices (Shi et al. 2020). Area cartograms, a widely applied visualization technique with relatively few design guidelines, have recently recaptured researchers' attention (Gastner, Seguy, and More 2018; Hogräfer, Heitzler, and Schulz 2020; Wei et al. 2024). For example, Nusrat, Alam, and Kobourov (2016) evaluated the effectiveness of four types of area cartograms (contiguous, non-contiguous, rectangular, and Dorling cartograms). Duncan et al. (2020) explored the effectiveness of interactive contiguous area cartograms based on designed tasks, and Fung, Perrault, and Gastner (2023) assessed the effectiveness of legends in contiguous area cartograms.

These studies offer valuable insights into the effectiveness of various types of cartograms, yet there remains a gap in our understanding regarding a specific cartogram method. Building upon this, our focus shifts to Dorling maps, a distinctive category of area thematic cartograms. Dorling map transforms regions into circles with areas proportionate to statistical values while endeavoring to maintain regional spatial relationships

(Dorling 2011). Based on whether the continuity of regions in the generated Dorling map is preserved, they can be classified into continuous and discontinuous types. For instance, Dorling's 1996 map was discontinuous, but subsequent research has indicated that maintaining regional continuity enhances the visualization effect of cartograms (Sun and Li 2010; Nusrat and Kobourov 2016). Therefore, algorithms for both continuous and discontinuous Dorling maps have been developed in later studies (Inoue 2013; Satyanarayan et al. 2017; Wei, Ding, et al. 2023; Wei, Xu, et al. 2023). While these works primarily focus on algorithmic research and quantitative analyses for specific types of Dorling maps, there is a notable absence of an objective evaluation of the visual cognitive effectiveness of different Dorling map variants. This gap in knowledge makes it challenging for users to select the most suitable visualization form according to their specific needs.

Hence, this study endeavors to assess the effectiveness of two frequently employed Dorling map types, namely continuous and discontinuous, as their focal points. We incorporate tasks similar to those devised by Duncan et al. (2020) and Fung, Perrault, and Gastner (2023) into our research design. In a departure from their methodologies, we augment our approach by integrating eye movement tracking methods, aiming to provide additional insights into cognitive effectiveness.

2 | Related Works

2.1 | Previous Research on the Usability of Dorling Maps

Dorling maps are a significant type of cartogram, and previous studies on their usability often focus broadly on cartograms rather than specifically on Dorling maps, which are sometimes included in these broader evaluations. The first evaluation of the cartograms can be traced to 1975 (Dent 1975). He conducted a user study and reported that participants perceived cartograms as "confusing and difficult to read," while concurrently finding them "interesting, generalized, innovative, unusual." Subsequent studies also positioned cartograms against other thematic maps, such as choropleth maps and proportional symbol maps. For instance, Kaspar, Fabrikant, and Freckmann (2011) evaluated how well map readers made spatial inferences comparing cartograms to choropleth maps. With advancements in computer technology, researchers have rekindled their focus on evaluating and refining existing visualization design practices and many studies have been reported recently. Nusrat, Alam, and Kobourov (2016) examined the effectiveness of four types of area cartograms—contiguous, non-contiguous, rectangular, and Dorling map. Their experimental results first indicated the difference between continuous and discontinuous cartograms and hinted at contiguous area cartograms leading to the lowest error rate during area comparison. Duncan et al. (2020) explored the efficacy of interactive contiguous area cartograms, emphasizing the potential of interactivity to make contiguous cartograms accessible to readers unfamiliar with interactive computer graphics, and animations emerged as the most impactful interactive feature. Furthermore, Fung, Perrault, and Gastner (2023) delved into the assessment of legends in contiguous area cartograms, while Wei, Xu, et al. (2023) conducted a user study on the effectiveness of visual stability in visualizing time-varying data using Dorling maps.

In summary, these studies provide valuable insights into the effectiveness of various cartograms, including Dorling maps. Specifically, as indicated by Nusrat, Alam, and Kobourov (2016) and Duncan et al. (2020), continuous and discontinuous cartograms each have distinct advantages. As a popular type of cartogram, Dorling maps also come in both continuous and discontinuous forms. However, there remains a notable gap in our understanding of the effectiveness of the two types of Dorling maps. Moreover, while these studies included user evaluations, they did not specifically observe cognitive effectiveness. It is necessary to employ cognitive methods to evaluate the effectiveness of continuous and discontinuous Dorling maps.

2.2 | Previous Research on the Usability of Thematic Maps Using Eye-Tracking

Eye-tracking technology can record users' visual behaviors in real-time during the reading, providing researchers with a direct method for exploring visual behavior (Rayner 1998). Consequently, it has been widely used in psychology and neurobiology since the twentieth century (Duchowski 2017). As maps are also user-oriented products, some researchers adopted eye-tracking technology into cartography to evaluate thematic map usability from a cognitive perspective since the 1970s (Dobson 1977; Castner and Eastman 1984; MacEachren and Kraak 2001; Slocum et al. 2001). Kiik, Nyström, and Harrie (2017) used eye-tracking to explore whether map boundaries, transparency, shaded lines, and icon designs facilitated recognizing the extent of polygons and whether the designs interfered with the reading of background maps, and the study showed that shaded lines were more effective than the other designs in polygon recognition. Wu and Qiao (2022) used eye-tracking to compare which of three visual variables, hue, luminance, and transparency, in a moving map best directs visual attention to the correct encoding of geographic correlations on a small display, showing that "Darker is more" is only partially understood and the traffic light metaphor is unsuitable for encoding ordered geographic relevance on mobile maps. He et al. (2023) produced GeoEye, a geospatial remote sensing image dataset containing thematic maps, remote sensing images, and street view images, and confirmed that the dataset could promote the intelligence and customization of geographic information services by utilizing it for the prediction of geospatial image saliency and the identification of map users. Olivieri and Reichenbacher (2023) used eye-tracking to explore the coupling of three metaphor types (orientational, ontological, and structural) with symbols at three levels of iconicity, the results indicate that, compared with bin-packing and multi-view symbols, metaphorical symbols significantly improved effectiveness and efficiency, and reduced participants' cognitive load. Vojtechovska and Assoc (2024) used the GazePoint HD 3 eye tracker in the leaflet.js map application to develop a framework for incorporating gaze-based interactions into digital mapping, thereby improving the effectiveness of digital map mapping.

Beyond overall map evaluation, eye-tracking technology has also been employed to assess specific map elements such as labels (Liao et al. 2019; Ooms et al. 2012), color schemes, and fonts (Brychtova and Coltekin 2016; Yang et al. 2023). For example, Liu, Dong, and Meng (2017) used eye-tracking to analyze the shapes, hues, sizes, and visual consistency of 3D symbols in various locations. Yang et al. (2023) analyzed the usability of color strategy and font size strategy to express the values in tag maps through eye movement experiments and questionnaire surveys.

In summary, eye-tracking technology is a highly effective methodology for assisting cartographers in the design process (Fairbairn and Hepburn 2023). Therefore, in our approach, we also employ eye-tracking technology to investigate the efficacy of continuous and discontinuous Dorling maps.

3 | Design of Eye Movement Experiment

3.1 | Participants

To ensure the independence of the data samples, participants were divided into two groups, each completing the user experiment for either the continuous Dorling map or the discontinuous Dorling map. The experiment was completed in early July 2023. A total of 69 participants, aged between 19 and 25, with educational backgrounds at the undergraduate or graduate level, took part in the study. All participants had no eye diseases (such as high myopia, color weakness, or astigmatism), and their vision or corrected vision was 1.0. Data from participants with an eye movement sampling rate lower than 70% were excluded, resulting in valid eye movement data from 63 participants (31 for the continuous Dorling map and 32 for the discontinuous Dorling map). Their self-identified gender (given the options of male or female) was 16 males and 15 females for the continuous Dorling map and 16 males and 16 females for the discontinuous Dorling map. The statistical results for the participants are shown in Table 1, with a similar number of male and female participants in each experimental group.

3.2 | Experimental Stimulus

The experiment was divided into two groups, using continuous and discontinuous Dorling maps as stimulus materials, as shown in Figure 1a,b. Both types of maps were generated based on the same algorithm proposed by Wei, Ding, et al. (2023); the difference lies in the algorithm's constraint settings, which consider regional continuity and non-continuity, respectively. The dataset used was the proportion of the obese population in each state of the United States (excluding Alaska and Hawaii), sourced from the open-source visualization tools Protovis and Vega to display Dorling map examples, ensuring a certain level of universality (VEGA 2022). Each state is represented by a corresponding circle, with the text on the circle indicating the state's abbreviation. The size of the circle represents the proportion of the obese population in that state, and the distribution of the circles aims to maintain the spatial adjacency relationship of each region.

TABLE 1 | The statistical results for the participants.

Experimental group name	Number of participants	Male/female	Age
Continuous	31	16/15	19–25
Discontinuous	32	16/16	19–25

3.3 | Experimental Tasks

The tasks for the two experimental groups were designed identically to closely resemble real-world map reading scenarios. These tasks were divided into two parts: unpurposed browsing tasks and purposeful reading tasks (Yang et al. 2023). An overview of these tasks is provided in Table 2, with specific design details available in the Supporting Information. The unpurposed browsing tasks are designed to examine user behaviors when reading maps without a specific objective. Participants are required to freely browse the Dorling maps displayed on the screen, without performing any clicking operations or completing specific tasks. Following this, participants will proceed to the 11 purposeful reading tasks. These tasks cover common map reading needs such as target search, attribute comparison/identification/memory, conditional selection, relationship judgment, and overall interpretation, and the tasks are arranged from easy to difficult in terms of completion difficulty. Then familiarity with the stimulus can aid users in completing more challenging tasks as they progress. Among them, to avoid the impact of circle size (AOI) on the experimental results, tasks 1–7 are performed in small, medium, and large areas according to the size of the circle. The division of circle size is based on the natural breakpoint method (Jenks 1963). Specifically, small-sized circles correspond to areas with a low obesity ratio (10%–14.6%), medium-sized circles correspond to areas with a medium obesity ratio (15%–17.2%), and large-sized circles correspond to areas with a high obesity ratio (17.5%–20.1%). Furthermore, to avoid familiarity with the same stimuli, the selected areas in each task are also located in different regions.

3.4 | Experimental Equipment

The experiment collected eye movement data through the Tobii Pro X3-120 eye tracker, recording various eye-tracking metrics such as information processing, visual search, and cognitive load when users use Dorling maps. The eye tracker has a sampling rate of 120 Hz, an accuracy of 0.4°, a precision of 0.24°, and a tracking distance of 50 to 90 cm. All subject data were recorded through Tobii Pro Lab 1.138 software.

3.5 | Experimental Procedure

The experiment was conducted in a quiet and well-lit office, with participants positioned approximately 70 cm from the eye tracker. Before the experiment began, participants were briefed on the experimental precautions, research objectives, and procedures. They also completed a background information survey, providing details such as age, gender, and relevant experience or knowledge. Before starting the tasks, participants were

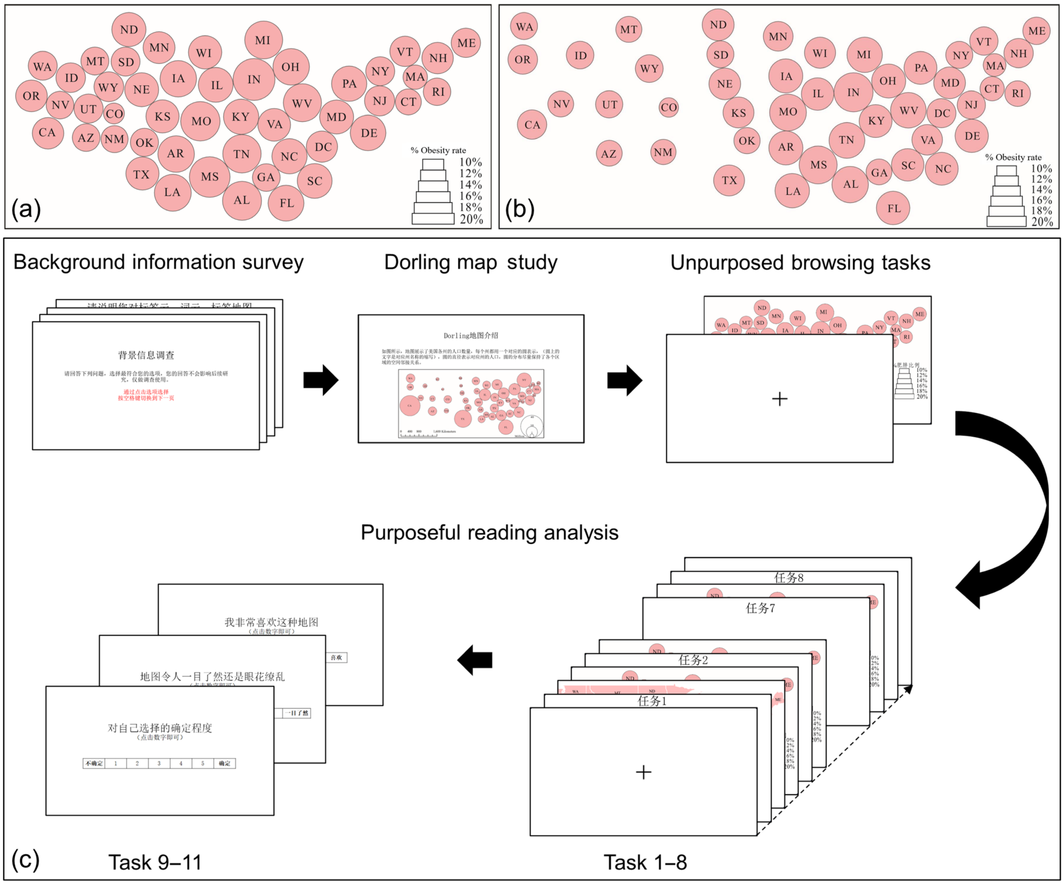

FIGURE 1 | Experimental stimulus material and experimental procedure. Continuous and discontinuous Dorling maps of the percentage of obese population in each state of the United States are shown separately in (a) and (b), (c) shows the experimental procedure. *Note:* During the experiment, the texts in the figure are displayed in Chinese, and the content of the above figure is translated by its corresponding Chinese.

familiarized with the Dorling map and the meanings of its symbols through an example map. Following this, they began completing the two parts of the task.

The first part involved unpurposed browsing tasks. It started with a blank calibration page, which switches to the Dorling map after 2 s. The map was displayed for 20 s, allowing participants to browse without a specific objective. Upon completion, the tasks automatically transitioned to the second part.

The second part involved purposeful reading tasks. This part also started with a blank calibration page. Participants performed a series of visual search tasks (tasks 1 to 8 in Table 2), with task instructions appearing on the screen first. After confirming they understood the task requirements, participants pressed the space bar to view the Dorling map and completed the tasks by clicking the corresponding areas with the mouse. Tasks either switched automatically or by pressing the space bar (as in tasks 4 and 8 in Table 2). Following the visual search tasks, participants proceeded to subjective evaluation tasks (tasks 9 to 11 in Table 2), using a 5-point Likert scale to complete them by clicking score options on the screen. The entire process is detailed in Figure 1c. To minimize familiarity with the same stimuli, the stimulus presentation time was limited to 20 s, ensuring that participants concentrated on the specified areas of interest on the map.

3.6 | Data Collection and Processing

As we divided the experimental tasks into unpurposed browsing tasks and purposeful reading tasks (Yang et al. 2023). Consequently, we also collected and analyzed data based on these two categories. The metrics and data collection process are describe as follows.

3.6.1 | Metrics for Unpurposed Browsing Tasks

The unpurposed browsing tasks are designed to examine user behaviors when reading maps without a specific objective. Therefore, we collected information processing metrics using eye-tracking for analysis. The metrics for unpurposed browsing tasks are listed in Table 3. Each circle in a stimulus is designated as an area of interest (AOI), and we recorded four metrics for each AOI. The metrics for circles of the same type, such as small-sized circles (defined in Section 3.3), are calculated based on their average values.

3.6.2 | Metrics for Purposeful Reading Tasks

The purposeful reading tasks aim to evaluate the effectiveness, efficiency, and satisfaction of users as they complete specific tasks. Each task is limited to 20 s, and we collected metrics

TABLE 2 | Overview of experimental tasks.

Task	User tasks	Purpose	Related tasks in Supporting Information
1	Given the name of a region in a regular map, locate its corresponding region in a Dorling map	Forward region search	Tasks 1–3
2	Given the name of a region in a Dorling map, locate its corresponding region in a regular map	Reverse region search	Tasks 4–6
3	Given the names of two regions in a Dorling map, compare their obesity rates	Attribute comparison	Tasks 7–9
4	Find the three regions with the highest obesity rates in a Dorling map	Conditional selection	Tasks 10
5	Given the names of three regions in a Dorling map, determine their obesity rates	Attribute recognition	Tasks 11–13
6	Give the region names in turn, and judge whether It is adjacent to the other four surrounding regions according to the Dorling map	Adjacent judgment	Tasks 14–17
7	Determine the area with the highest obesity rates in a Dorling map (east, west, south, north, or central)	Summary	Tasks 18
8	Recall the obesity rates of the three regions in task 5 and rank them	Attribute memory	Tasks 19
9	Assess the degree of confidence in one's own choices	Confidence	Tasks 20
10	Is the map easy to understand or confusing?	Readability	Tasks 21
11	I like this kind of map	Satisfaction	Tasks 22

TABLE 3 | Metrics in unpurposed browsing tasks and their definitions (Dong et al. 2019; Yang et al. 2023).

Type	Metrics	Cognitive meaning
Information processing metrics	Fixation frequency	A higher fixation frequency metrics more interest in a target
	Total fixation duration	The longer the total fixation duration, the greater the interest in the target
	Time to the first fixation	The shorter the time, the stronger the target salience
	First fixation duration	The longer the duration, the stronger the attractiveness of the target

involving general performance, information processing, visual search, and cognitive load. The metrics are listed in Table 4.

Different metrics were collected for different tasks. For tasks 1–7 (corresponding to tasks 1–18 in the Supporting Information), the circles involved in the task stimuli are considered as AOIs. For example, in the task "Search region MA," the circle named MA is an AOI. Eye-tracking metrics related to these tasks, as shown in Table 4. If a task involves several circles, the metrics for the task are calculated based on their average values. For tasks 3–8 (corresponding to tasks 7–19 in the Supporting Information), we additionally calculated the accuracy rates. In tasks 3–6, each task was performed three times. For example, in task 3 (corresponding to tasks 7–9 in the Supporting Information), if a participant answers *n* tasks correctly, the accuracy rate is n/3. In tasks 7 and 8, each task was performed once, so the accuracy rate for these tasks is either 0 or 1, depending on whether the participant provided the correct answer. For tasks 9–11 (corresponding to tasks 20–22 in the Supporting Information), we collected participants' scores on a 5-point Likert scale.

3.6.3 | Data Collection and Analysis

According to the metrics defined in Sections 4.1 and 4.2, we collected data related to each task. The number of eye-tracking metrics counted in the experimental tasks resulted in the same number of eye movement data sets. For example, if task 1 counts four eye-tracking metrics, four data sets will be obtained. A total of 48 data sets (excluding the accuracy rate) were collected from

TABLE 4 | Metrics in purposeful reading tasks and their definition.

Type	Metrics	The definition or cognitive meaning	Related tasks
General performance	Accuracy	The rate of correct answers in the same type of task	Tasks 3–8 in Table 2
	Confidence score	The five-point Likert score for task 9	Task 9 in Table 2
	Readability score	The five-point Likert score for task 10	Task 10 in Table 2
	Satisfaction score	The five-point Likert score for task 11	Task 11 in Table 2
Information interpretation	Total fixation duration on involved AOI	The longer the total fixation duration, the longer the time to interpret information related to the AOIs	Tasks 1–7 in Table 2
Visual search	Saccade frequency	The higher the saccade frequency, the higher the search efficiency	Tasks 1–7 in Table 2
	Average saccade amplitude	The longer the saccade amplitude, the more information obtained per single fixation, and the higher the reading efficiency	Tasks 1–7 in Table 2
	Regression count	Cognitive supplementation or reprocessing of previous areas	Tasks 3, 4, 6, 7 in Table 2
Cognitive load	Average pupil diameter change	The smaller the change, the lower the cognitive load	Tasks 1–7 in Table 2

Note: The circles involved in a task are considered as area of interests (AOIs) (Dong et al. 2019; Yang et al. 2023).

the unpurposed browsing tasks and tasks 1–7 of the purposeful reading tasks. The data meet the criteria for normality and homogeneity of variance, making them suitable for analysis using variance analysis (le Cessie, Goeman, and Dekkers 2020). We analyzed these data on the SPSSPRO platform using a one-way analysis of variance (ANOVA). The post hoc multiple comparison analysis used the least significant difference (LSD) method (Orcan 2020). For the accuracy rate metrics in tasks 3–7 of the purposeful reading tasks and scores of tasks 8–11, since both the original data and the transformed data do not meet the assumptions of variance analysis, we used the Kruskal–Wallis non-parametric test for statistical analysis.

4 | Experimental Results

4.1 | Unpurposed Browsing Tasks

Using the Dorling map type as the independent variable, and the average values of total fixation duration, time to first fixation, first fixation duration, and fixation frequency as the dependent variables, we applied a single-factor variance analysis method to examine the eye movement data in areas with low, medium, and high obesity proportion during unpurposed browsing tasks. The results are shown in Table 5, where the gray highlight represents significant differences, and the significance level is 0.05 (the same below, no longer redundant in the text).

TABLE 5 | Results of the variance analysis of the unpurposed browsing tasks.

Level	Dependent variable	*F*	*p*
Low	Total fixation duration	1.580	0.215
	Time to the first fixation	0.005	0.947
	First fixation duration	0.074	0.787
	Fixation frequency	0.333	0.567
Medium	Total fixation duration	9.523	0.003
	Time to the first fixation	0.102	0.751
	First fixation duration	0.551	0.461
	Fixation frequency	0.190	0.665
High	Total fixation duration	0.388	0.536
	Time to the first fixation	0.524	0.474
	First fixation duration	0.438	0.511
	Fixation frequency	0.019	0.890
Overall	Total fixation duration	7.230	0.010
	Time to the first fixation	0.105	0.748
	First fixation duration	0.181	0.672
	Fixation frequency	0.016	0.899

Note: The shaded values indicate 'statistical significance'.

As shown in Table 5, for the low-level and high-level areas, there is no statistically significant difference in the total fixation duration, time to first fixation, first fixation duration, and fixation frequency metrics of participants. This suggests that during unpurposed browsing, there is no significant difference in target prominence, target attractiveness, or the interest aroused by low-level and high-level areas between continuous and discontinuous Dorling maps.

However, for medium-level areas, a statistically significant difference is found only in total fixation duration. Participants' total fixation duration on the continuous map (2602.462 ms) is significantly longer than on the discontinuous map (1551.792 ms). This implies that users may find continuous maps more engaging than discontinuous ones in medium-level areas. This may be because the medium-level area's graphic size lacks the visual significance of low-level or high-level areas, and symbols of larger or smaller size are more likely to be noticed due to contrast differences (Yang et al. 2023). There are no statistically significant differences in time to first fixation, first fixation duration, and fixation frequency, indicating no significant difference in target prominence and attractiveness between the two map types for medium-level areas.

In terms of the overall results, participants only showed statistically significant differences in total fixation duration, with the total fixation duration on the continuous map (8168.080 ms) being significantly longer than the discontinuous (5714.417 ms). This suggests that participants are more interested in the continuous map compared to the discontinuous one. There are no statistically significant differences in time to first fixation, first fixation duration, and fixation frequency, indicating no significant difference in target prominence and attractiveness for the overall area between the continuous and discontinuous Dorling maps.

4.2 | Purposeful Reading Tasks

Using the type of Dorling map as the independent variable and the eye-tracking metrics corresponding to each task in Table 4 as the dependent variables, we performed a one-way ANOVA for tasks 1–7 in Table 2. For tasks 8–11, as well as the accuracy of participants completing tasks 3–7, we conducted a Kruskal–Wallis non-parametric test. The results of these statistical analyses are summarized in Table 6.

4.2.1 | Task 1. Forward Region Search Result Analysis

As can be seen from Table 6, participants only have a statistically significant difference in the total fixation duration. The total fixation duration of participants on the continuous map (2371.378 ms) is significantly longer than that on the discontinuous map (1289.705 ms). This implies that when participants search for targets from the conventional map to the Dorling map, the time to interpret information on the continuous map is significantly more than that on the discontinuous map.

There is no statistically significant difference among participants in terms of saccade frequency, average saccade amplitude, and average pupil diameter change. This implies that when participants search for targets from the conventional map to the Dorling map, there is no significant difference in search efficiency, reading efficiency, and cognitive load between the continuous and discontinuous Dorling maps.

4.2.2 | Task 2. Reverse Region Search Results Analysis

As can be seen from Table 6, participants only have a statistically significant difference in the total fixation duration. The total fixation duration of participants on the continuous map (3098.745 ms) is significantly longer than that on the discontinuous map (1999.763 ms). This implies that when participants search for targets from the Dorling map to the conventional map, the time to interpret information on the continuous map is significantly more than that on the discontinuous map.

There is no statistically significant difference among participants in terms of saccade frequency, average saccade amplitude, and average pupil diameter change metrics. This implies that when participants search for targets from Dorling maps to regular maps, there is no significant difference in search efficiency, reading efficiency, and cognitive load on both continuous and discontinuous types of Dorling maps.

4.2.3 | Task 3. Attribute Comparison Results Analysis

As shown in Table 6, participants only showed statistically significant differences in saccade frequency. The saccade frequency of participants on the continuous map (1.523 num/ms) was significantly higher than that on the discontinuous map (1.135 num/ms). This implies that when comparing attributes, the search efficiency of participants on the continuous map is significantly higher than that on the discontinuous map.

Participants showed no statistically significant differences in total fixation duration, average saccade amplitude, regression count, and average pupil diameter change. This implies that when comparing attributes, there is no significant difference in the time to interpret information, reading efficiency, cognitive supplementation or reprocessing of previous areas, and cognitive load of participants on continuous and discontinuous Dorling maps.

In addition, when participants read the continuous and discontinuous Dorling maps, there was no statistically significant difference in the accuracy of the attribute comparison task.

4.2.4 | Task 4. Conditional Selection Results Analysis

As shown in Table 6, there is a statistically significant difference among participants in terms of total fixation duration and regression count. The total fixation duration of participants on continuous maps (7353.034 ms) is significantly longer than that on discontinuous maps (4948.607 ms), and the regression count on continuous maps (41.704 num) is significantly more than that on discontinuous maps (32.500 num). This implies that when making conditional selection, the time to interpret information by participants on continuous maps is significantly more than that on discontinuous maps, and the cognitive supplementation or reprocessing of previous areas when participants read

TABLE 6 | Results of the variance analysis of the purposeful reading tasks.

	Total fixation duration		Saccade frequency		Average saccade amplitude		Average pupil diameter change		Regression count		Accuracy		Score	
Task	***F***	***p***	***F***	***p***	***F***	***p***	***F***	***p***	***F***	***p***	***F***	***p***	***F***	***p***
Task 1	8.020	0.006	0.056	0.815	0.342	0.563	1.209	0.277	—	—	—	—	—	—
Task 2	4.483	0.038	3.170	0.082	0.019	0.892	1.147	0.289	—	—	—	—	—	—
Task 3	3.020	0.089	4.939	0.031	0.302	0.586	2.412	0.126	1.138	0.291	1.469	0.225	—	—
Task 4	5.161	0.027	1.696	0.199	0.289	0.593	1.864	0.177	4.195	0.046	0.010	0.920	—	—
Task 5	3.831	0.056	3.710	0.060	0.288	0.594	2.258	0.138	—	—	0.001	0.970	—	—
Task 6	9.544	0.003	0.325	0.571	0.080	0.778	0.874	0.354	1.623	0.209	2.545	0.111	—	—
Task 7	0.016	0.900	0.016	0.900	0.837	0.365	0.515	0.476	0.001	0.977	0.006	0.939	—	—
Task 8	—	—	—	—	—	—	—	—	—	—	0.719	0.396	—	—
Task 9	—	—	—	—	—	—	—	—	—	—	—	—	0.875	0.350
Task 10	—	—	—	—	—	—	—	—	—	—	—	—	2.524	0.112
Task 11	—	—	—	—	—	—	—	—	—	—	—	—	2.587	0.108

Note: "—" indicates no statistical data available. The shaded values indicate 'statistical significance'.

continuous maps is significantly more than that on discontinuous maps.

There is no statistically significant difference among participants in terms of saccade frequency, average saccade amplitude, and average pupil diameter change. This implies that when making conditional selection, there is no significant difference in search efficiency, reading efficiency, and cognitive load on both continuous and discontinuous types of Dorling maps among participants.

Additionally, when participants read the two types of Dorling maps, continuous and discontinuous, they did not show a statistically significant difference in the accuracy of the conditional selection task.

4.2.5 | Task 5. Attribute Recognition Results Analysis

As shown in Table 6, there is no statistically significant difference among participants in the total fixation duration, saccade frequency, average saccade amplitude, and average pupil diameter change. This implies that when identifying attributes, there is no significant difference in the time to interpret information, search efficiency, reading efficiency, and cognitive load on both continuous and discontinuous types of Dorling maps among participants.

Additionally, when participants read the two types of Dorling maps, continuous and discontinuous, they did not show a statistically significant difference in the accuracy of the attribute recognition task.

4.2.6 | Task 6. Adjacent Judgment Results Analysis

As can be seen from Table 6, participants only have a statistically significant difference in the total fixation duration. The total fixation duration of participants on the continuous map (3740.965 ms) is significantly longer than that on the discontinuous map (2349.033 ms). This implies that during adjacent judgment, the time to interpret information by participants on the continuous map is significantly more than that on the discontinuous map.

There is no statistically significant difference among participants in terms of saccade frequency, average saccade amplitude, regression count, and average pupil diameter change. This implies that during adjacent judgment, there is no significant difference in search efficiency, reading efficiency, cognitive supplementation or reprocessing of previous areas, and cognitive load of participants when reading the two types of Dorling maps, continuous and discontinuous.

Additionally, when participants read the two types of Dorling maps, continuous and discontinuous, there is no statistically significant difference in the accuracy of the adjacent judgment task.

4.2.7 | Task 7. Summary Results Analysis

As can be seen from Table 6, there is no statistically significant difference in the total fixation duration, saccade frequency, average saccade amplitude, regression count, and average pupil diameter change among participants. This implies that during the summary task, there is no significant difference in the time to interpret information, search efficiency, reading efficiency, cognitive supplementation or reprocessing of previous areas, and cognitive load of participants when reading the two types of Dorling maps, continuous and discontinuous.

Additionally, when participants read the two types of Dorling maps, continuous and discontinuous, there is no statistically significant difference in the accuracy of the summary task.

4.2.8 | Task 8. Attribute Memory Results Analysis

Participants need to recall the obesity rate values of the three areas in task five and sort them by size, with the accuracy of completing this task as the dependent variable. Since the original data and the transformed data here did not meet the prerequisite conditions for variance analysis, the Kruskal–Wallis non-parametric test method was used for analysis. The results show (see Table 6) that there is no statistically significant difference in the accuracy of participants, indicating that the accuracy is not affected by the type of map. There is no significant difference in attribute memory when participants read the two types of Dorling maps, continuous and discontinuous.

4.2.9 | Task 9–11. Subjective Evaluation Results Analysis

After completing all the above tasks, this study also statistically analyzed participants' subjective evaluations of the two types of Dorling maps from three aspects: confidence, readability, and satisfaction. Participants' scores on the 5-point Likert scale were used as the dependent variable. Firstly, the reliability of the results of the two types of map Likert scale was tested. The results showed that Cronbach's α of the continuous scale was 0.841, Cronbach's α of the discontinuous scale was 0.736, and Cronbach's α of the overall scale was 0.79. The data reliability coefficient values of the above results are all higher than 0.7, which indicates that the data reliability quality is high and can be used for further analysis. Secondly, since the data did not meet the prerequisite conditions for variance analysis, the Kruskal–Wallis non-parametric test method was also used for analysis. The results show (see Table 6) that there is no statistically significant difference among participants in the three metrics of confidence, readability, and satisfaction level. This implies that there is no significant difference in participants' confidence, readability, and satisfaction when reading the two types of Dorling maps, continuous and discontinuous.

5 | Discussion

5.1 | What Is New and What Is Not New?

The Dorling map offers an intuitive approach for map readers to grasp spatial data quantity with an aesthetically pleasing presentation (Sun and Li 2010). Our findings partially align with these results, as evidenced by instances such as the noteworthy average satisfaction for the Dorling map in task 10, scoring 3.4. Additionally, the average accuracy for attribute comparison and recognition in tasks 3 and 4 attains commendable scores of 0.91 and 0.84, respectively. In addition, the satisfaction for continuous Dorling maps may be attributed to their inherent emphasis on adjacencies, as evidenced by the compelling results in adjacent judgment (task 6). Continuous Dorling maps outperform their discontinuous counterparts significantly in assessing adjacent relationships.

Contrary to prior research demonstrating the enhanced visualization impact of cartograms through the preservation of regional continuity (Nusrat and Kobourov 2016), our subjective evaluation (tasks 9–11) reveals no significant difference in participants' confidence, readability, and satisfaction when comparing the two types of Dorling maps—continuous and discontinuous. This nuanced insight adds a layer of complexity to the existing understanding of the visual effectiveness of Dorling maps, highlighting the need for a more nuanced consideration of map design factors.

5.2 | So, Which Dorling Map Is Best?

While the selection of a cartogram type should be tailored to the anticipated tasks (Nusrat, Alam, and Kobourov 2016), our findings suggest that discontinuous Dorling maps exhibit superior performance over continuous Dorling maps in specific aspects, as summarized in Table 6. The table reveals that discontinuous Dorling maps excel significantly in interpreting information time during forward and reverse region searches, selecting conditions, and judging adjacent relationships. Additionally, continuous Dorling maps outperform discontinuous ones in search efficiency during attribute comparison. Furthermore, continuous maps demonstrate a notable advantage over discontinuous maps in terms of cognitive supplementation or reprocessing of previous regions during conditional selection. This may be attributed to the closer proximity of circles in continuous Dorling maps, facilitating easier search and recognition for users.

These results provide valuable guidance for users in selecting an appropriate visualization form based on their specific needs. For instance, when prioritizing interpretation time, discontinuous Dorling maps are recommended, while when prioritizing search efficiency, continuous Dorling maps are recommended. However, it is crucial to note that, despite the advantages of both continuous and discontinuous Dorling maps in certain aspects, Table 6 reveals that there is no significant difference between continuous and discontinuous Dorling maps in various other aspects. Hence, users can choose their preferred option based on their practical preferences and requirements (Figure 2).

5.3 | Limitations

While our evaluation encompassed 11 tasks to analyze the utility and usability of continuous and discontinuous Dorling maps, it is crucial to acknowledge its limitations.

1. The participants, aged 19–25, predominantly possessed a background in cartography, rendering them well-acquainted with the tasks. Subsequent experiments should aim for a more diverse participant pool, considering a broader age range and incorporating individuals with varying knowledge backgrounds.
2. The experimental stimuli in our study were subject to constraints that might introduce disparities between the results and real-world scenarios. Variables such as the standard deviation of circular symbol sizes, the color or locations of symbols, contour features of expressed areas, annotation settings, and spatial distribution differences in circular symbols could all influence the outcomes. Although we performed tasks 1–7 using small, medium, and large symbols located in different regions to mitigate the impact of position

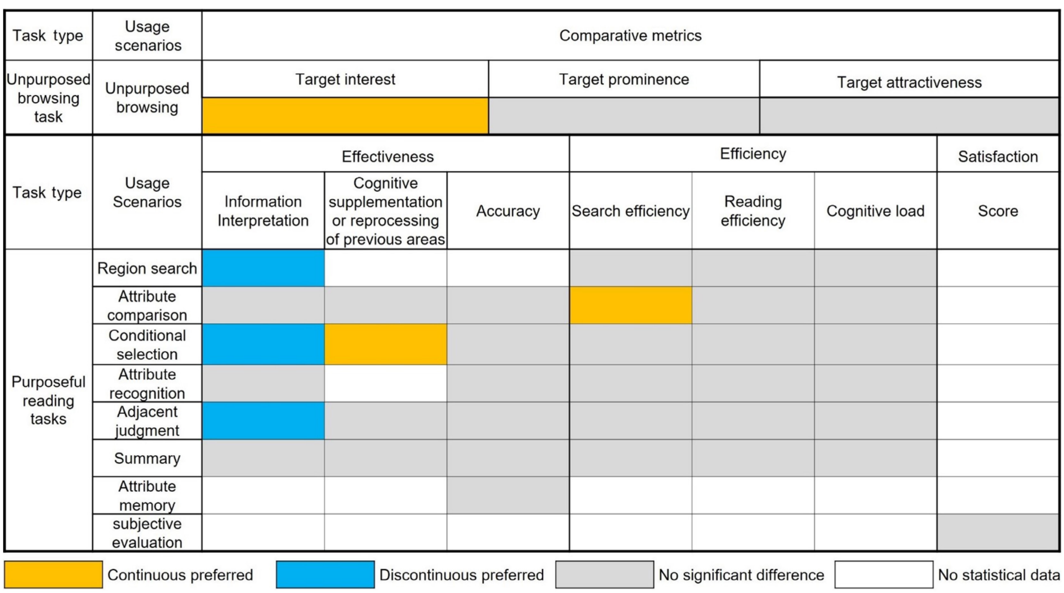

FIGURE 2 | Summary of experimental results. *Note:* "Comparative Metrics" corresponds to the definitions or cognitive meanings in Tables 3 and 4.

and size on the results, a detailed analysis of these factors may still be necessary. For example, our results indicate that accuracy in attribute recognition may be higher for larger symbols. However, the influence of these factors is beyond the scope of this work. Future research should explore these variables to enhance the robustness and applicability of the findings, recognizing the need for continued exploration in this domain.

6 | Conclusion

This study represents, to the best of our knowledge, the pioneering application of eye-tracking methodology to assess the efficacy of Dorling cartograms. Employing eye-tracking experiments, we objectively evaluated the effectiveness of Dorling maps across two application scenarios involving 11 tasks, encompassing unpurposed browsing and purposeful reading. The independent variable in our analysis was the type of Dorling map. Results revealed that, in forward and reverse region searches, conditional selection, and relationship judgment, discontinuous Dorling maps exhibited significantly superior performance over continuous ones in terms of interpretation time. For attribute comparison, the continuous Dorling maps outperformed the discontinuous in search efficiency. Notably, during conditional selection, the cognitive supplementation or reprocessing of previous areas on continuous Dorling maps surpassed that on discontinuous ones. In other aspects, however, no significant differences emerged between continuous and discontinuous Dorling maps. This study contributes to the nuanced cognitive evaluation of the continuity expression in Dorling maps, offering insights to assist users in selecting the appropriate visualization form based on their specific needs. For instance, continuous Dorling maps are recommended when users prioritize effective reading or search efficiency considerations.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

References

Brychtova, A., and A. Coltekin. 2016. “An Empirical User Study for Measuring the Influence of Colour Distance and Font Size in Map Reading Using Eye Tracking.” *Cartographic Journal* 53, no. 3: 202–212. https://doi.org/10.1179/1743277414Y.0000000103.

Castner, H. W., and R. J. Eastman. 1984. “Eye-Movement Parameters and Perceived Map Complexity—I.” *American Cartographer* 11, no. 2: 107–117. https://doi.org/10.1559/152304084783914768.

Dent, B. D. 1975. “Communication Aspects of Value-By-Area Cartograms.” *American Cartographer* 2, no. 2: 154–168. https://doi.org/10.1559/152304075784313278.

Dobson, M. W. 1977. “Eye Movement Parameters and Map Reading.” *American Cartographer* 4, no. 1: 39–58. https://doi.org/10.1559/152304077784080022.

Dong, W., H. Liao, Z. Zhan, B. Liu, S. Wang, and T. Yang. 2019. “New Research Progress of Eye Tracking-Based Map Cognition in Cartography Since 2008.” *Acta Geographica Sinica* 74, no. 3: 599–614. https://doi.org/10.11821/dlxb201903015.

Dorling, D. 2011. “Area Cartograms: Their Use and Creation.” *Map Reader* 59: 252–260. https://doi.org/10.1002/9780470979587.ch33.

Duchowski, A. T. 2017. *Eye Tracking Methodology: Theory and Practice*. Cham, Switzerland: Springer.

Duncan, I. K., S. Tingsheng, S. T. Perrault, and M. T. Gastner. 2020. “Task-Based Effectiveness of Interactive Contiguous Area Cartograms.” *IEEE Transactions on Visualization and Computer Graphics* 27, no. 3: 2136–2152. https://doi.org/10.1109/TVCG.2020.3041745.

Fairbairn, D., and J. Hepburn. 2023. “Eye-Tracking in Map Use, Map User and Map Usability Research: What Are We Looking for?” *International Journal of Cartography* 9, no. 2: 231–254. https://doi.org/10.1080/23729333.2023.2189064.

Fung, K. L. T., S. T. Perrault, and M. T. Gastner. 2023. “Effectiveness of Area-To-Value Legends and Grid Lines in Contiguous Area Cartograms.” *IEEE Transactions on Visualization and Computer Graphics* 30: 4631–4647. https://doi.org/10.1109/TVCG.2023.3275925.

Gastner, M. T., V. Seguy, and P. More. 2018. “Fast Flow-Based Algorithm for Creating Density-Equalizing Map Projections.” *Proceedings of the National Academy of Sciences of the United States of America* 115, no. 10: E2156–E2164. https://doi.org/10.1073/pnas.171267411.

He, B., W. H. Dong, H. Liao, et al. 2023. “A Geospatial Image Based Eye Movement Dataset for Cartography and GIS.” *Cartography and Geographic Information Science* 50, no. 1: 96–111. https://doi.org/10.1080/15230406.2022.2153172.

Hogräfer, M., M. Heitzler, and H.-J. Schulz. 2020. “The State of the Art in Map-Like Visualization.” *Computer Graphics Forum* 39: 647–674. https://doi.org/10.1111/cgf.14031.

Inoue, R. 2013. “A New Construction Method for Circle Cartograms.” *Cartography and Geographic Information Science* 38: 146–152. https://doi.org/10.1559/15230406382146.

Jenks, G. F. 1963. “Generalization in Statistical Mapping.” *Annals of the Association of American Geographers* 53, no. 1: 15–26. https://doi.org/10.1111/j.1467-8306.1963.tb00429.x.

Kaspar, S., S. I. Fabrikant, and P. Freckmann. 2011. *Empirical Study of Cartograms*. https://www.zora.uzh.ch/id/eprint/51344/.

Kiik, A., M. Nyström, and L. Harrie. 2017. “Cartographic Design Matters—A Comparison of Thematic Polygon Design.” *Cartographic Journal* 54, no. 1: 24–35. https://doi.org/10.1080/00087041.2016.1147191.

le Cessie, S., J. J. Goeman, and O. M. Dekkers. 2020. “Who Is Afraid of Non-normal Data? Choosing Between Parametric and Non-parametric Tests.” *European Journal of Endocrinology* 182, no. 2: E1–E3. https://doi.org/10.1530/eje-19-0922.

Liao, H., X. Wang, W. Dong, and L. Meng. 2019. “Measuring the Influence of Map Label Density on Perceived Complexity: A User Study Using Eye Tracking.” *Cartography and Geographic Information Science* 46, no. 3: 210–227. https://doi.org/10.1080/15230406.2018.1434016.

Liu, B., W. Dong, and L. Meng. 2017. “Using Eye Tracking to Explore the Guidance and Constancy of Visual Variables in 3D Visualization.” *ISPRS International Journal of Geo-Information* 6, no. 9: 274. https://doi.org/10.3390/ijgi6090274.

MacEachren, A. M., and M. J. Kraak. 2001. “Research Challenges in Geovisualization.” *Cartography and Geographic Information Science* 28, no. 1: 3–12. https://doi.org/10.1559/152304001782173970.

Nusrat, S., M. J. Alam, and S. Kobourov. 2016. "Evaluating Cartogram Effectiveness." *IEEE Transactions on Visualization and Computer Graphics* 24, no. 2: 1077–1090. https://doi.org/10.1109/TVCG.2016.2642109.

Nusrat, S., and S. Kobourov. 2016. "The State of the Art in Cartograms." *Computer Graphics Forum* 35, no. 3: 619–642.

Olivieri, M., and T. Reichenbacher. 2023. "A Study on the Aptitude of Color Hue, Value, and Transparency for Geographic Relevance Encoding in Mobile Maps." *Cartography and Geographic Information Science* 51: 674–686. https://doi.org/10.1080/15230406.2023.2283063.

Ooms, K., P. D. Maeyer, V. Fack, E. V. Assche, and F. Witlox. 2012. "Investigating the Effectiveness of an Efficient Label Placement Method Using Eye Movement Data." *Cartographic Journal* 49, no. 3: 234–246. https://doi.org/10.1179/1743277412Y.0000000010.

Orcan, F. 2020. "Parametric or Non-Parametric: Skewness to Test Normality for Mean Comparison." *International Journal of Assessment Tools in Education* 7: 236–246. https://doi.org/10.21449/ijate.656077.

Rayner, K. 1998. "Eye Movements in Reading and Information Processing: 20 Years of Research." *Psychological Bulletin* 124, no. 3: 372–422. https://doi.org/10.1037/0033-2909.124.3.372.

Satyanarayan, A., D. Moritz, K. Wongsuphasawat, and J. Heer. 2017. "Vega-Lite: A Grammar of Interactive Graphics." *IEEE Transactions on Visualization and Computer Graphics* 23, no. 1: 341–350. https://doi.org/10.1109/TVCG.2016.2599030.

Shi, T., I. K. Duncan, Y. N. Chang, and M. T. Gastner. 2020. "Motivating Good Practices for the Creation of Contiguous Area Cartograms." *arXiv preprint arXiv:2006.00285*. https://arxiv.org/abs/2006.00285.

Slocum, T. A., C. Blok, B. Jiang, et al. 2001. "Cognitive and Usability Issues in Geovisualization." *Cartography and Geographic Information Science* 28, no. 1: 61–75. https://doi.org/10.1559/152304001782173998.

Sun, H., and Z. Li. 2010. "Effectiveness of Cartogram for the Representation of Spatial Data." *Cartographic Journal* 47, no. 1: 12–21. https://doi.org/10.1179/000870409X12525737905169.

VEGA. 2022. https://vega.github.io/vega/examples/Dorling-cartogram/.

Vojtechovska, M., and C. M. Assoc. 2024. Beyond Evaluation: Utilizing Gaze-Based Interactions for Digital Cartography PROCEEDINGS OF THE 2024 ACM SYMPOSIUM ON EYE TRACKING RESEARCH & APPLICATIONS, ETRA 2024. 16th Annual ACM Symposium on Eye Tracking Research and Applications (ETRA).

Wei, Z., S. Ding, W. Xu, L. Cheng, S. Zhang, and Y. Wang. 2023. "Elastic Beam Algorithm for Generating Circular Cartograms." *Cartography and Geographic Information Science* 50: 371–384. https://doi.org/10.1080/15230406.2023.2196732.

Wei, Z., W. Xu, S. Ding, S. Zhang, and Y. Wang. 2023. "Efficient and Stable Circular Cartograms for Time-Varying Data by Using Improved Elastic Beam Algorithm and Hierarchical Optimization." *Journal of Visualization* 26, no. 2: 351–365. https://doi.org/10.1007/s12650-022-00878-z.

Wei, Z., N. Yang, X. Wenjia, and D. Su. 2024. "Generating Grid Maps via the Snake Model." *Transactions in GIS* 28: 1156–1174. https://doi.org/10.1111/tgis.13174.

Wu, M. G., and L. G. Qiao. 2022. "Designing Metaphorical Multivariate Symbols to Optimize Dockless Bike Sharing." *Cartographic Journal* 59, no. 3: 220–238. https://doi.org/10.1080/00087041.2022.2097759.

Yang, N., G. Wu, A. M. MacEachren, X. Pang, and H. Fang. 2023. "Comparison of Font Size and Background Color Strategies for Tag Weights on Tag Maps." *Cartography and Geographic Information Science* 50, no. 2: 162–177. https://doi.org/10.1080/15230406.2022.2152098.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.