How Do People Parse Dynamic Maps? Insights from Event Segmentation Experiments

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Abstract

Dynamic thematic maps can visualize spatiotemporal phenomena but have been found to be perceptually and cognitively challenging for users. The cognitive process of event segmentation describes how people parse the complex and continuous experiences of everyday life into discrete events, facilitating further processing. This research explores how segmentation processes impact the perception of dynamic thematic maps. Specifically, we investigate if conceptual and perceptual influences on segmentation generalize to depictions of spatiotemporal data on dynamic maps. In two within-subjects experiments, participants (N = 125, 176) segmented 32 maps displaying insect population densities over time. We manipulated participants' expectations of the trend in population density and the salience of the direction of the trend. The results show that viewers' expectations, as well as change salience (both through color scale and spatial pattern of change), impact how similarly participants place event boundaries. Our research on the interindividually shared processing of dynamic map data extends key event segmentation findings to the field of spatial cognition. At the same time, it takes a step towards researching design measures for facilitating the processing of dynamic maps rooted in cognitive theories.

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1 Introduction

Visuospatial displays support cognition by decreasing the demand for memory resources, organizing information and allowing the replacement of cognitive with perceptual processes and action [5]. Dynamic thematic maps can be a powerful way to communicate complex spatiotemporal data patterns. However, due to the dense information presentation, recognition of those patterns is not always effective [3]. Psychological research has shown that animating learning content does not necessarily facilitate learning per se but can be overwhelming or distracting if not designed well [9]. A better understanding of the cognitive processes involved in deciphering dynamic maps is therefore crucial for designing dynamic maps that meet their communication goals. This research investigates how individuals mentally structure dynamic maps during observation, building upon the cognitive theory of event segmentation [12].

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2 Event Segmentation Theory

Event segmentation refers to the automatic discretization of a continuous experience. As one step in the processing of experiences, it has been shown to influence the memory thereof [12]. A common paradigm to assess this process is the segmentation task, in which participants are presented with a continuous visual or auditory stimulus and press a button whenever they perceive a boundary between two meaningful units [12]. To compute the intersubjective segmentation agreement, the button presses are transformed into a time series of 1-second bins containing information on whether a participant gave a segmentation response in a given bin or not [8]. That time series is correlated with the group norm of all other participants. The group norm is defined as the percentage of participants who gave a segmentation response in each bin. To avoid confounding by the number of button presses, this observed correlation r_{obs} is scaled by using the maximal and minimal possible correlation given the number of button presses. The resulting measure (Eq. 1), therefore, can range from 0 to 1.

$$segmentation\ agreement\ = \frac{r_{obs} - r_{min}}{r_{max} - r_{min}} \tag{1}$$

Both conceptual influences, such as inferred goals of the observed actors and event schemata, and perceptual influences, such as movement, have been shown to influence the segmentation agreement in everyday scenes [7]. Dynamic thematic maps typically feature neither identifiable actors nor movement of objects but convey information through color changes. It can also be assumed that people do not have strong schemata for what they observe in such maps. The two experiments presented here investigate if the same processes also come into play when people observe dynamic maps.

3 Experiment 1: Influence of Framing and Color Scale

To tackle this research question, we produced maps showing changes in insect population density on fictional islands. To create opposing expectations in the participants, we labeled the insect populations as being either endangered or invasive. To independently vary the perceptual features of the maps, namely the salience of the direction of change, we used hue-based and saturation-based color scales to depict the change. We expect the saturation scale to make the direction of change more salient [2] and hypothesize that the agreement will be higher if the shown change matches the expectation the framing encourages in the high salience but not in the low salience condition.

3.1 Methods

Participants and experimental design. We recruited 125 participants (43 women and 82 men) between 18 and 63 years old (mean age = 30.56, SD = 9.9) via Prolific. All participants reported being fluent in English and having normal or corrected-to-normal vision. Two participants had to be excluded for failing the attention checks included in the experiment. All participants received 5.13£ as compensation. The sample size was predetermined by power simulation. It yields a power of 0.8 to detect an effect of the hypothesized three-way interaction of 0.02 at the 5% significance level. The experiment used a within-subjects design. The three independent variables were trend, framing, and color scales. Variable expressions (8 trend values, two framings, and two color scales) were combined orthogonally to produce the 32 stimuli.

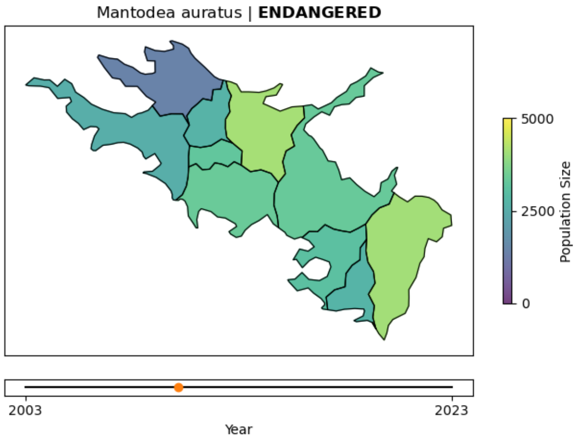

Figure 1 Example stimulus frame.

Materials. In this experiment, we produced 32 animated unclassed choropleth maps [2] that each lasted 30 seconds. An example frame is shown in Figure 1. Each base map was drawn using a randomly selected island shape file obtained from `https://www.naturalearthdata.com/` and dividing it into 10 regions with a Voronoi diagram seeded by 10 randomly selected points. The data dynamic to be shown on the map was explicitly manipulated as an independent variable in 8 steps from -1 to 1: -1.00 -0.71 -0.43 -0.14 0.14 0.43 0.71 1.00. The start value of the map was drawn randomly from the range of values that still allowed the map values to remain in the range between 0 and 1 after applying the slope. Hence, a map with a slope of -1 can only start with 1, whereas a map with a slope of -0.43 can start at any value between 0.43 and 1. To this global trend, noise drawn from a normal distribution with a mean of zero and a standard deviation of 0.1 was added to each of the 10 regions. The color scales used to depict the resulting values were also manipulated as an independent variable for this experiment. Specifically, we varied between hue-based and saturation-based color scales. Purples, Greens, Oranges, and Blues were used as the saturation scales. Summer, Winter, Viridis, and Wistia were used as the hue-based scales [6]. Titles were added to the maps to manipulate the third independent variable. Each title contained the name of the made-up insect species whose population density was to be depicted. The species names were produced by ChatGPT. Next to the species name, the information on whether the insect was considered invasive or endangered was presented to participants – the two values of the independent variable framing. The map videos were animated with 24 frames per second. Two sets of stimuli, using the same shapes but a different shape assignment to the combination of values of the independent variables, were produced, and each was shown to half of the participants. The experiment was shown in a window with a minimal width of 1000 pixels and a minimal height of 600 pixels.

Procedure. The participants were asked to imagine themselves as an insect researcher reviewing data on insect population numbers on different remote islands. The role of insects in functioning ecosystems was explicitly stressed. It was explained that the data had been processed to be reviewed in the form of color-coded maps. It was further described that the maps showed the population development of different endangered and invasive species. In order to ensure the framing had similar effects regardless of the participants' prior knowledge, they were provided with definitions of endangered and invasive species. Participants were instructed to press their spacebar key whenever they perceived that a meaningful event unit had ended and a new one had begun [7].

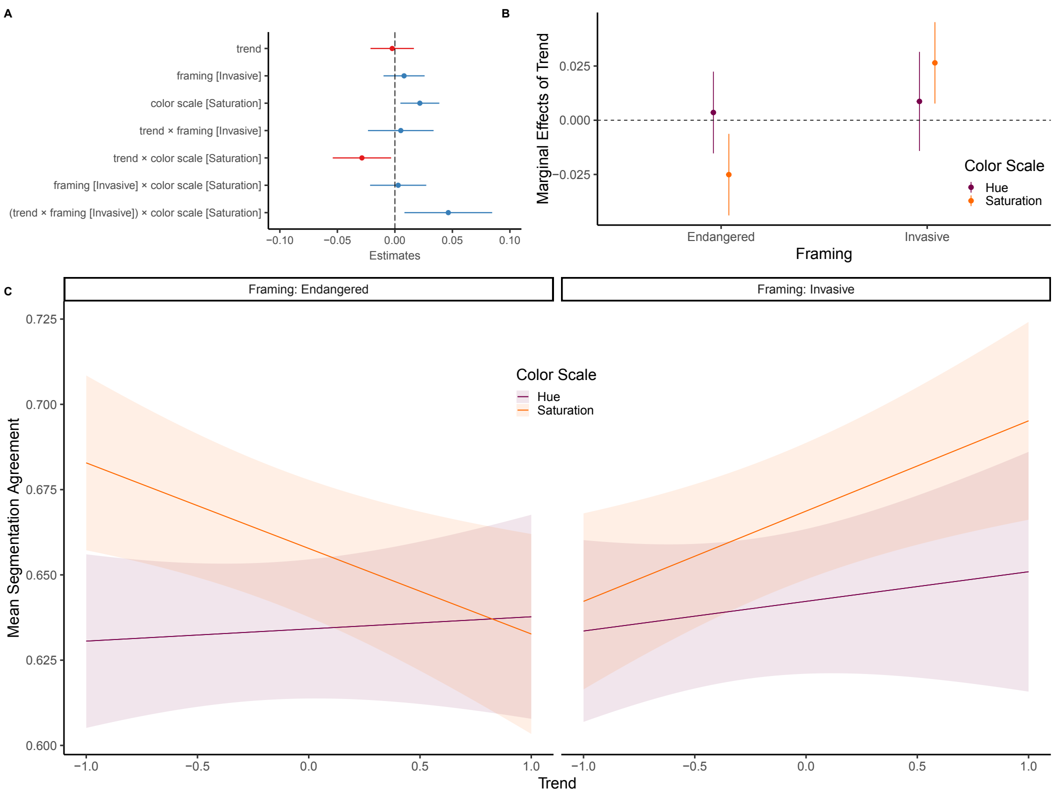

Figure 2 **A** Parameter estimates, **B** Marginal effects of trend, **C** Model predictions All with 95 % confidence intervals.

The experiment's main block consisted of presenting the 32 map stimuli in a randomized order. The participants decided when to progress to the next map. Before each map, an announcement with the following format was shown to draw attention to the framing variation: "The next map shows the population development of *Species* on the *Island*. *Species* is classified as *Framing*."

3.2 Results

The analysis plan was preregistered (see 2nd study under this link)[2]. After excluding incomplete data sets, 117 subjects entered the analysis. On average, participants gave 6.34 segmentation responses ($SD = 5.41$) per stimulus. The mean duration of event units was 8.17 seconds ($SD = 11.51$). We observed a mean segmentation agreement of 0.59 ($SD = 0.2$). A linear mixed-effects model including random intercepts and random slopes for the three independent variables per subject was fit to the data [1]. As can be observed in Figure 2A, we find a significant interaction effect between trend, framing and color scale ($\beta = 0.046$, $95\%CI = [0.008, 0.084], d = 0.147$) on segmentation agreement. The marginal effects noted in Table 1 and depicted in Figure 2B specify the pattern of this interaction. The marginal effect of trend on segmentation agreement is negative for the endangered condition and positive for the invasive condition, but only in combination with the saturation scale. When a hue scale is used, the marginal effect of trend does not differ between the two framing conditions. The model predictions are shown in Figure 2C.

[2] https://osf.io/v9n3m/?view_only=614bcbdcefec4850b79af44bf0500978

3.3 Discussion

The framing of the species elicited expectations in the participants regarding which development the maps would show – namely, a decreasing population size for endangered species and an increase in population size for invasive species. The results indicate that participants segment the map stimuli more similarly when the depicted trend matches those expectations only if the trend's direction is made salient through a saturation color scale. The finding that both conceptual (framing) and perceptual (salience) features impact segmentation behavior extends established findings in event segmentation research [11, 12] to the special case of dynamic maps.

Table 1 Estimates for the marginal effects of Trend.

Experiment 1					
Framing	Color Scale	Estimate	Std. Error	z	p
Endangered	Hue	-0.00142	0.00963	-0.147	0.88292
Endangered	Saturation	-0.03005	0.00959	-3.134	0.00173
Invasive	Hue	0.00394	0.01166	0.338	0.73567
Invasive	Saturation	0.02136	0.00958	2.229	0.02581
Experiment 2					
Framing	Spatial Pattern	Estimate	Std. Error	z	p
Endangered	Distributed	-0.00686	0.00436	-1.571	0.11611
Endangered	Clustered	-0.01370	0.00436	-3.140	0.00169
Invasive	Distributed	-0.01809	0.00436	-4.146	< 0.001
Invasive	Clustered	0.00161	0.00436	0.369	0.71244

4 Experiment 2: Influence of Framing and Spatial Pattern

The first experiment used maps showing a uniform, albeit noisy, trend across all regions. But dynamic maps are especially useful to communicate patterns across time *and* space [3]. Consequently, the second experiment investigates the influence of different spatial patterns on segmentation agreement. This experimental manipulation takes a step toward the spatiotemporal complexity expected to be found in real dynamic maps. It additionally allows us to test whether the effect of the salience of the trend's direction also appears if manipulated through the spatial pattern of the data themselves rather than the color scales used to depict them. We expect the marginal effect of the trend on segmentation agreement to be negative if the species is framed as endangered and positive if it is framed as invasive in the high salience condition showing clustered change.

4.1 Methods

Participants and experimental design. We recruited 176 participants (56 women, 118 men, 2 non-disclosed) between 18 and 71 years old (mean age = 33.79, $SD = 11.81$) via Prolific. All participants reported being fluent in English and having normal or corrected-to-normal vision. Two participants had to be excluded for failing the attention checks included in the experiment. All participants received 5.13 £ as compensation. The sample size was predetermined by power simulation [10]. It yields a power of 0.85 to detect an effect of the hypothesized three-way interaction of 0.02 at the 5 % significance level. The experiment used a within-subjects design. The three independent variables were trend, framing, and spatial pattern. Variable expressions (four values of trend, two framings, and two spatial patterns) were combined orthogonally once with 3 and once with 4 changing regions to produce the 32 stimuli. The procedure was identical to the one used in the previous experiment.

Materials. In this experiment, we again produced 32 maps that lasted 30 seconds. The slope of the map – or the trend – was varied in 4 steps from -1 to 1: -1.00 -0.5 0.5 1. Different from the prior experiment, the trend defines the change of a selected subset of 3 or 4 map regions instead of the whole map. The number of changing regions was varied to mask the manipulation of spatial pattern. In both conditions, a random first region was selected, and additional regions were selected according to the corresponding pattern. The data was depicted using only the saturation scales. The addition of noise, the legends, map titles including the framing manipulation, as well as the frame rates, were identical to the previous experiment.

4.2 Results

The analysis plan was preregistered (see 3rd study under this link)[3]. Participants gave 5.94 segmentation responses ($SD = 6.02$) per stimulus on average. The mean duration of event units was 8.65 seconds ($SD = 11.59$). We observed a mean segmentation agreement of 0.59 ($SD = 0.19$). A linear mixed-effects model assessing the relationship between segment agreement and the three independent variables (trend, framing, and spatial pattern) and their interactions was fit to the data [1]. The model included random intercepts and random slopes for the predictors per participant.

The parameter estimates (shown in Figure 3A) indicate a significant interaction effect between trend, framing and spatial pattern ($\beta = 0.024$, $95\%CI = [0.023\ 0.0309], d = 0.073$) on segmentation agreement. Agreement was overall higher for spatially clustered change ($\beta = 0.011$, $95\%CI = [0.0002\ 0.022]$, $d = 0.073$). The marginal effects (Figure 3B and Table 1) of trend on segmentation agreement is negative for endangered species only when the change is spatially clustered. It is also negative for invasive species only when the change is spatially distributed. The model predictions are shown in Figure 3C.

4.3 Discussion

The results show an interaction between the viewer's expectations and the salience of the change elicited by its spatial pattern on segmentation agreement. However, the pattern of the marginal effects of the trend is more difficult to interpret than in the previous experiment. This can potentially be due to the fact that the maps showed the trend only in a subset of their regions. Prior research on the perception of animated choropleth maps has shown that detecting spatial patterns can be challenging and depends on the visual behavior [3], which we neither measured nor controlled. It has even been shown that participants perceive a change in map regions that do not change their color value [4]. Seeing that Gaussian noise was also applied to the regions that did not exhibit the underlying trend in the used stimuli, it seems plausible that the segmentation task was more difficult in this experiment than in experiment 1.

[3] `https://osf.io/v9n3m/?view_only=614bcbdcefec4850b79af44bf0500978`

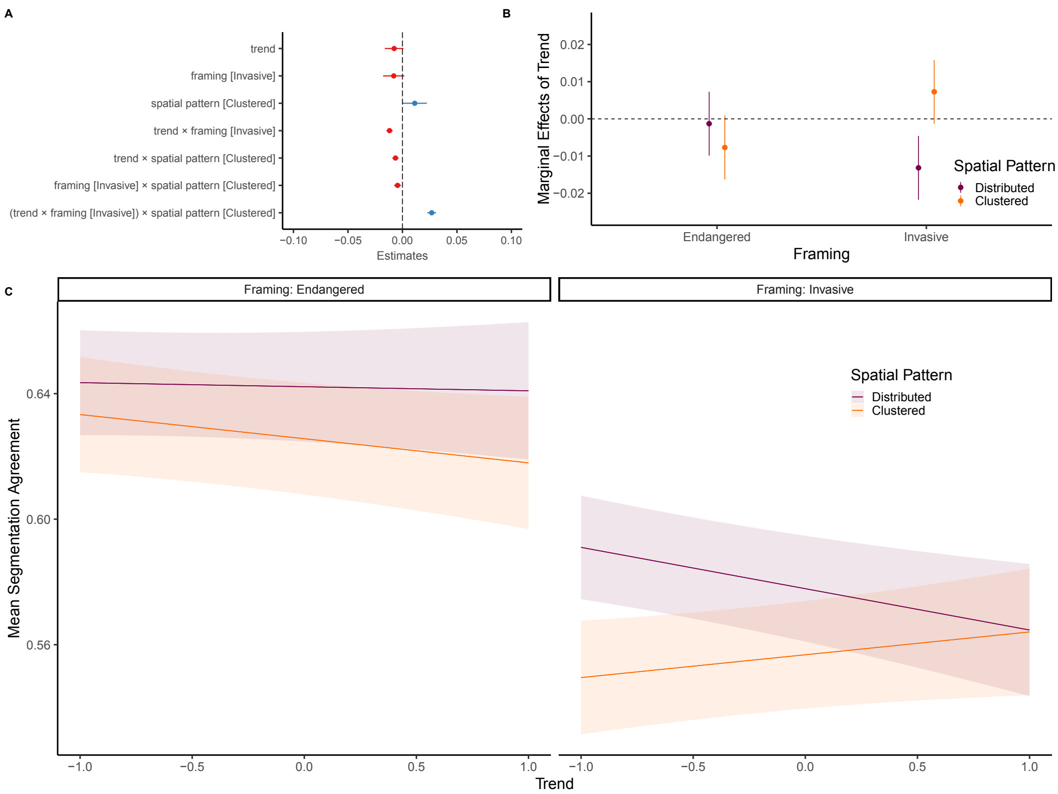

Figure 3 **A** Parameter estimates, **B** Marginal effects of trend, **C** Model predictions All with 95 % confidence intervals.

5 General Discussion and Conclusion

Across the two experiments, we replicated the interaction of the depicted trend, the viewer's expectations concerning the trend, and the salience of the trend's direction on segmentation agreement. The observed effect sizes are relatively small, with substantial variance between subjects. This shows that segmentation can be a noisy process, but can also be attributed to the less controlled experimental conditions when collecting data online. Even so, these conditions might resemble conditions in which people encounter data presented on dynamic maps in everyday life.

Overall, the results demonstrate the suitability of the event segmentation paradigm for researching the cognitive processing of dynamic maps. Showing that both conceptual and perceptual manipulations influence segmentation agreement extends key results of event segmentation research with everyday scenes to dynamic maps as a novel stimuli class. At the same time, we show the importance of considering viewers' expectations, e.g., when embedding dynamic maps into narratives, and of making the spatiotemporal patterns that are to be communicated salient through the maps' design. Overall, the results once again highlight the complexity of designing effective dynamic maps while showing how cognitive theories can help guide research in this area.

Further research is needed to explore whether the way dynamic maps are segmented also influences how they are processed and remembered.

References

1 Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. Fitting Linear Mixed-Effects Models Using **lme4**. *Journal of Statistical Software*, 67(1), 2015. doi:10.18637/jss.v067.i01.

2 Sarah E. Battersby and Kirk P. Goldsberry. Considerations in Design of Transition Behaviors for Dynamic Thematic Maps. *Cartographic Perspectives*, pages 16–32, March 2010. doi:10.14714/CP65.127.

3 Paweł Cybulski. An Empirical Study on the Effects of Temporal Trends in Spatial Patterns on Animated Choropleth Maps. *ISPRS International Journal of Geo-Information*, 11(5):273, April 2022. doi:10.3390/ijgi11050273.

4 Paweł Cybulski and Vassilios Krassanakis. The Role of the Magnitude of Change in Detecting Fixed Enumeration Units on Dynamic Choropleth Maps. *The Cartographic Journal*, 58(3):251–267, July 2021. doi:10.1080/00087041.2020.1842146.

5 Mary Hegarty. The Cognitive Science of Visual-Spatial Displays: Implications for Design. *Topics in Cognitive Science*, 3(3):446–474, July 2011. doi:10.1111/j.1756-8765.2011.01150.x.

6 John D. Hunter. Matplotlib: A 2D Graphics Environment. *Computing in Science & Engineering*, 9(3):90–95, 2007. doi:10.1109/MCSE.2007.55.

7 Christopher A. Kurby and Jeffrey M. Zacks. Segmentation in the perception and memory of events. *Trends in Cognitive Sciences*, 12(2):72–79, February 2008. doi:10.1016/j.tics.2007.11.004.

8 Frank Papenmeier, Annika E. Maurer, and Markus Huff. Linguistic Information in Auditory Dynamic Events Contributes to the Detection of Fine, Not Coarse Event Boundaries. *Advances in Cognitive Psychology*, 15(1):30–40, March 2019. doi:10.5709/acp-0254-9.

9 Barbara Tversky, Julie Bauer Morrison, and Mireille Betrancourt. Animation: can it facilitate? *International Journal of Human-Computer Studies*, 57(4):247–262, October 2002. doi:10.1006/ijhc.2002.1017.

10 Florian Wickelmaier. Simulating the Power of Statistical Tests: A Collection of R Examples, March 2022. arXiv:2110.09836 [stat]. URL: http://arxiv.org/abs/2110.09836.

11 Jeffrey M. Zacks. Using movement and intentions to understand simple events. *Cognitive Science*, 28(6):979–1008, November 2004. doi:10.1207/s15516709cog2806_5.

12 Jeffrey M. Zacks. Event Perception and Memory. *Annual Review of Psychology*, 71(1):165–191, January 2020. doi:10.1146/annurev-psych-010419-051101.