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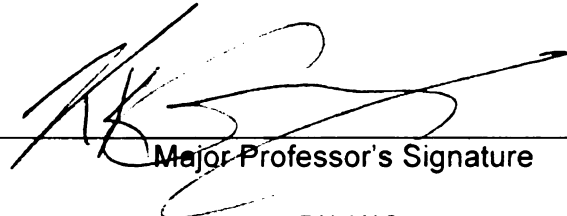
CHANGE DETECTION IN ANIMATED CHOROPLETH MAPS

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CHANGE DETECTION IN ANIMATED CHOROPLETH MAPS

By

Carolyn Fish

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ABSTRACT

CHANGE DETECTION IN ANIMATED CHOROPLETH MAPS

By

Carolyn Fish

Computer animation enables cartographers to visualize time-series data as never

before; we can build dynamic map sequences that congruently depict change over time.

However, map readers have difficulty comprehending these animations, and they often

fail to detect important changes between adjacent scenes, this is called change blindness.

These potentially overwhelming perceptual burdens, such as change blindness, threaten

the effectiveness of animated maps in which several important changes can occur

simultaneously throughout the display. Animated maps also require viewers not only to

notice changes but also understand the transitions within these dynamic displays. Graphic

interpolation between display frames, also known as "in-betweening" or "tweening",

smoothes transitions and lengthens the duration of the transition between scenes in an

animated map series. Previous cartographic literature suggests tweening as one potential

solution for change blindness in animated cartography. This thesis tested the influence of

change blindness on animated choropleth map reading and evaluated the influence of

tweening to increase change detection abilities of map readers. Empirical results from

this research indicate that map readers, 1) have difficulty detecting changes in these types

of maps, 2) often fail to comprehend these maps fully, and 3) are influenced by the use of

tweening between the scenes of the animated map.

ACKNOWLEDGEMENTS

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Chapter 1
INTRODUCTION

1.1 Introduction

Computer animation enables cartographers to depict change over time congruently by visualizing time-series data more realistically. We can use dynamic temporal displays to mimic the passage of time. However, while animation is advantageous for the depiction of time, viewers have difficulty apprehending the changes that occur in dynamic displays (Tversky *et al.*, 2002), and often fail to detect important changes between adjacent scenes. This phenomenon is known as change blindness (Grimes, 1996; Rensink, 2002a; Harrower, 2003; Simons and Rensink, 2005; Fabrikant *et al.*, 2008; Goldsberry and Battersby, 2009). One inherent problem with animated thematic map displays is that they require users to notice, attend to, and decode many simultaneous change signals during rapid scene transitions. Since several important changes can occur simultaneously throughout the display during a single scene transition, cartographic animation demands potentially overwhelming perceptual requirements of map readers that threaten the effectiveness of animated maps (Harrower, 2007; Fabrikant, 2008; Goldsberry and Battersby, 2009).

In a more artistic context, Lasseter (1987) suggests that animators control changes on the display so only one important change occurs at a time. Unfortunately, cartographic animations are representations of underlying geographic information, and unlike more artistic animations, their appearance cannot be completely controlled by the cartographer.

Cartographic animations also offer a second additional perceptual burden to readers. To comprehend map animations fully, it not only is important to notice a change

between scenes of a map animation, readers must also *understand the meaning of the change*. To comprehend a change in an animated map, a reader must first notice the change, take notice of the geographic pattern before and after the change, and decode the meaning of the transformation. Goldsberry and Battersby (2009) identified these tasks as a part of the three levels of change detection applicable to thematic map reading:

- **Change Detection Level 1:** the reader notices the presence or absence of a change, the persisting or shifting behavior of the map,

- **Change Detection Level 2:** the reader understands whether the change was an increase or decrease in the mapped phenomena (only in quantitative thematic maps),

- **Change Detection Level 3:** the reader apprehends the origin state of the map and makes the connection between the origin and destination states to understand the meaning of the visual transformation.

To achieve the highest level of change detection and to understand the meaning of the cartographic animation fully (Level 3), map designs need to afford readers time not only to notice the origin and destination states, but also perceive the transition between the two. This represents an important emerging cartographic challenge.

Finally, animated maps are vulnerable to the phenomenon of "change blindness blindness", which involves the overestimation of one's own change detection ability (Levin *et al.* 2000, 2002). Change blindness blindness literature has shown that often people believe they will notice a change when they see one, yet often they still miss important changes (Levin *et al.* 2000, 2002). Serious implications could occur if map readers overestimate their change detection abilities. For example, dynamic cartographic

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literature has suggested that interactivity can help map readers to read animated maps more accurately (Tverksy *et al.*2002; Harrower, 2007; Fabrikant *et al.*, 2008); however, change blindness blindness may mean that map readers are less likely to use the interactivity available because they believe they have completely comprehended the animated map.

Recent research has suggested one option to help mitigate change blindness in animated thematic maps: gradual transitions (Goldsberry, 2004; Fabrikant *et al.*, 2008). By graphically interpolating between scenes, cartographers can smooth and lengthen the duration of the transition in an animation this process is known as tweening. Tweening can extend the amount of display time dedicated to the transition, consequently affording readers with more time to view the change between display scenes. However, it remains unclear to what extent gradual transitions will facilitate or impede the map reader's understanding of changes in these dynamic displays. This thesis investigates how well map readers detect changes in dynamic thematic maps.

1.2 Research Goals

The goals of this thesis are to 1) determine to what extent change blindness affects animated map reading and 2) examine how different transition designs affect change detection.

1.3 Research Questions

To investigate the impact of change blindness on animated map reading, this research attempts to answer three main questions:

1. **How well do map readers detect changes between scenes in animated maps?**

2. **Do map readers have greater difficulty detecting changes at higher levels of change detection (Goldsberry and Battersby, 2009)?**

3. **Does the design of map transitions influence the change detection abilities of animated map readers?**

4. **How will map readers' confidence in their own change detection abilities differ from their accuracy in detecting changes?**

1.4 Hypotheses

Hypothesis 1. Rates of change blindness in animated choropleth maps will be high

Studies in psychology have shown that humans are innately blind to change (for review, Simons and Rensink, 2005). Animated maps present additional perceptual burdens to their viewers because change cannot be completely controlled by the cartographer and thus many changes occur across the display at once.

Hypothesis 2. Map readers will have increased difficulty detecting changes at higher levels. Higher levels of change detection require that map readers not only simply notice the change, but also perceive its cartographic meaning by apprehending both the origin and destination states of the map before and after a cartographic transition. It currently remains unknown how well humans detect changes at different change detection levels.

Hypothesis 3. Utilizing tweening while still allowing participants to view the static map scene before the change will allow participants to best comprehend changes between map scenes. Previous research has suggested that tweening and smooth transitions may mitigate change blindness by elongating durations of the transitions between scenes, and afford map readers time to scan the display during a transition (Goldsberry, 2004; Fabrikant *et al.*, 2008). A combination of these longer transitions with static scene display will allow map readers time both to read the map, and perceive the transition.

Hypothesis 4. Despite missing many of the changes in animated thematic maps, map readers would be highly confident in their change detection abilities. Previous research in psychology has shown that while viewers often believe they would notice a change, more often than not they failed to detect the change. The same results are expected in this experiment.

1.5 Research Relevance

As a means to inform cartographic design, it is necessary to investigate how perceptual limitations affect contemporary map reading tasks. Cartographic literature, specifically Robinson's *The Look of Maps* (1952), has called for empirical studies to investigate the influence of cartographic design on map cognition. With the rapid emergence of dynamic displays as medium to communicate spatial and temporal information, it is necessary to

investigate how the design of animated maps may influence the effectiveness of animated maps.

It remains unknown how well map readers comprehend animated maps, and more specifically how well they detect changes in these maps. Without this knowledge, it is impossible for cartographers to improve the design of animated maps. Results from this research will inform future design strategies that may potentially increase change detection and indicate whether these types of animated maps are useful to their readers. This study aims to uncover how well map readers detect changes, and how different design strategies affect map readers' abilities to detect change.

Chapter 2
LITURATURE REVIEW

In 1952, Arthur Robinson, published *The Look of Maps*, the seminal work of academic cartography in the United States. The goal of the book was to establish that maps are communication devices and research is needed to understand how best to communicate cartographic ideas. Robinson specifically called for empirical research as a means to reveal how cartographic design influences cognition of cartographic displays. Specifically, Robinson argued that map quality should be judged according to user performance opposed to aesthetic subjective opinions. This review aims to outline the animation, psychology, and cartographic literature as it applies to how map readers comprehend animated maps and how geographic information is communicated in these displays.

2.1 Experimental Cartography

Robinson's suggestions that maps should be developed based on map readers' performance could be argued as the beginning of experimental cartographic research in the United States. Robinson's graduate student, J.J. Flannery, following Robinson's suggestion tested human subjects and their estimation of graduated symbols on maps. Flannery's (1971) findings indicate that generally, map readers underestimated the size of these symbols. Over the next half a century, academic cartographic research became synonymous with experimental cognitive psychological research on maps and map readers. Robinson mentored and advised many academic cartographers many of who

continued his tradition, such as Flannery, to evaluate the effectiveness of maps based on the user and not the map maker.

Montello (2002) indicated that the "heyday" of academic cartography was during the 1970s based on the number of PhDs awarded during that time; as technology has improved, it has allowed cartographers to investigate many of the cognitive map design issues more easily by assessing speed, accuracy, and eye movements, which have all become part of this academic cartographic research. Finally, many cartographers argue that the rise of Geographic Information Science has decreased the interest in cognitive map design research, but others argue that GIS and other new technological developments may become new fodder for cognitive cartographic research in the future. For example, little research has empirically investigated interactive and animated maps and the perceptual abilities of the map readers who use them.

2.2 Representation of Spatial-Temporal Change

Cartographers have a multitude of ways to represent spatial-temporal change. In the static domain, cartographers can depict change over time with a single map or a series of maps, called small multiples (Campbell and Egbert, 1990; Tufte, 1983). With animation, cartographers can display time series geographic data dynamically by simulating changes of time, space, and attributes.

With a single map, a cartographer can represent temporal changes in attributes using a "change map" (Monmonier, 1990) or with a map that depicts change using the visual variables (Bertin, 1983). A change map illustrates attribute differences between two time periods on a single map. For example, in a choropleth map, a map made up of

polygonal units (e.g. counties) colored or shaded based on a value or range of values in the data, each enumeration unit is colored based on the attribute difference between the two time periods. Using a sequential color scheme, ranging from light to dark, one could imagine areas with high rates of change represented with dark hues, while areas with little change represented with light hues. The visual variables also offer cartographers additional ways to represent change on a single map. One example is the U.S. Geological Survey's 24,000 scale map series (Campbell and Egbert, 1990). In these topo quads, urban areas are depicted in pink, and in the revised versions of these maps, areas of newer urban growth are depicted in purple. Map readers can easily interpret how an urban area has changed between two or more time periods using this type of map (Campbell and Egbert, 1990).

Cartographers can also depict change over time as a series of static graphics called "small multiples". Tufte (1983) is often credited with popularizing this type of data representation. Cartographically, small multiples present a chronologically ordered map sequence of the same geographic area at different time periods. These types of graphics allow users to identify how one place has changed over time. Users can internally interact with small multiples, by viewing the graphic at their own pace in their own preferred order (Fabrikant *et al.*, 2008).

While static maps can effectively illustrate change over time, dynamic illustrations of spatiotemporal phenomena, specifically animated maps, offer one significant advantage by allowing the cartographer to *congruently* represent change over time. Using computer animation we can now depict temporal processes using temporally dynamic representations. Several researchers have recognized the advantages of animated

maps as ways to provide new insights into dynamically changing data (Thrower, 1959; Tobler, 1970). For example, perhaps the first computer animated map was designed by Waldo Tobler in the early 1970s to visualize and understand urban growth in the Detroit, Michigan region. However, researchers have also suggested that more research is needed to provide insight into the power of these types of graphics (Cornwell and Robinson, 1966). Until the 1990s, however, little empirical research examined the utility and practicality of animated maps. Previously, the costs and limitations of computing, along with labor intensity, prevented cartographers from creating animated maps, but as technology and computing have improved, creating animated maps has become "more practical than ever" (MacEachren and DiBiase, 1991, p.221; Harrower, 2007).

Despite these remarkable technological developments, an important set of new challenges has emerged. Since cost and access are less of an obstacle, contemporary cartographic research questions have less to do with computation and more to do with the design, perception, and cognition of animated maps. "When it comes to animated maps, the bottleneck is no longer the hardware, the software, or the data - it is the limited visual and cognitive processing capabilities of the map reader" (Harrower, 2007, p. 269). In this way, animated maps present human beings with amplified map reading burdens. Recent research has revealed, for example, that readers have difficulty understanding animated graphics (e.g. Goldsberry and Battersby, 2009; Fabrikant *et al.*, 2008; Harrower, 2003, 2005; Tversky *et al.*, 2002). One problem is that, human beings have difficulty comprehending changes within these animations, and regularly fail to detect important changes between adjacent scenes. This is particularly troubling because advocates of

cartographic animations argue that the power of animated maps is their ability to depict change over time.

Animated displays are fleeting by design; as a consequence, one inherent problem with animated displays is that they require users to notice, attend to, and decode multiple simultaneous change signals during rapid scene transitions. These potentially overwhelming perceptual requirements threaten the effectiveness of animated maps because several important changes can occur simultaneously throughout the display during a single scene transition. The goal of this chapter is to summarize previous relevant research as a means to give context to the content of this thesis.

2.3 Characteristics of Animation

2.3.1 The Congruence Principle

Computer animation enables cartographers to visualize time-series data as never before; we can build dynamic sequences that congruently depict change over time. A graphic is said to adhere to the *congruence principle* when the format and content of the graphic corresponds to the format and content of the concepts to be conveyed (Tversky *et al.*, 2002). Animations are congruent in their ability to mimic the passage of world time with the congruent passing of display time. Map animations allow us to illustrate change dynamically in the same way as changes occur in the natural world. Fabrikant *et al.* (2008) suggest that well-designed animations that adhere to the congruence principle will allow their viewers to more easily understand complex spatiotemporal geographic phenomena.

2.3.2 Informational Equivalence

Several studies in psychology and educational psychology have compared animated and static graphics to identify the benefits of using the two different types of representations (e.g. Rieber, 1990; Thompson and Riding, 1990; Rieber, 1991a; Rieber, 1991b; Large et al., 1996). These studies identified that animation fostered learning and insight better than static graphics versions of the same ideas; however, when comparing animated and static graphics these studies did not compare *informationally equivalent* graphics (Tversky *et al.* 2002). Two representations are said to be informationally equivalent when the same information can be inferred from both representations (Larkin and Simon, 1987). When two graphical representations are *informationally inequivalent*, one graphic is believed to present the viewer with more information than the other. In other words, one graphic is superior to the other because it allows the viewer greater inference leading to better apprehension when viewing the superior graphic. For example, Thompson and Riding (1990) designed a program to teach the Pythagorean theorem to junior high school students. The participants were divided into three groups, one group viewed a static diagram, the second group viewed a discrete animation, and the third group viewed a continuous animation. The third group, viewing the continuous animation performed the best in learning the theorem. In the experiment, the authors state that the paper graphic and the discrete animation illustrated the same information, while the continuous animation was not informationally equivalent and included additional information that lead to successful comprehension of the Pythagorean theorem. In the cartographic domain, one might argue that small multiples and animated maps are not informationally equivalent graphics because the two graphics present different

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information to readers. Tversky *et al.* (2002) argue that informationally inequivalent graphics cannot be compared because different information is presented to the users.

2.3.3 The Apprehension Principle

The goal of scientific visualization is to communicate complex ideas. In some cases, these representations facilitate readers understanding; however, poorly designed maps and graphics can be misunderstood and difficult to read. The *apprehension principle* states that external representations must be "readily and accurately perceived and comprehended" (Tversky *et al.*, 2002, p 256). Humans have difficulty perceiving motion, preventing accurate apprehension of animated displays that are informationally equivalent to their static counterparts (Tversky *et al.* 2002). As a means to achieve apprehension, often animations present viewers with different and perhaps more information than static graphics; however, by presenting more information in the animated domain the two graphical forms become informationally inequivalent. For example, interactivity is one known way to increase apprehension; however, interactivity renders animated and static graphics informationally inequivalent by allowing the user to interact with the animated graphic differently than they would with a static graphic.

2.3.4 Computational Equivalence

Fabrikant *et al.* (2008) argue that maintaining informational equivalence for "good experimental control for comparisons may actually mean degrading [animation's] potential power for certain tasks" (Fabrikant et al., p. 202). *Computational equivalence*, instead of informational equivalence, provides a better way to compare two different representations of the same concept. Two representations are said to be computationally equivalent when both representations allow the viewer to infer the same concepts and

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ideas "quickly and easily" from explicitly designed information (Larkin and Simon, 1987). For example, in a map the cartographer can use a scale bar or a map scale ratio to express the scale in a particular map, however, these two different representations of the same idea are computationally equivalent because they both lead to the same inference without difficulty for the viewer.

While Tversky *et al.* believe that interactivity in animation creates informational inequivalence, Fabrikant *et al.*, (2008) suggest there is internal interactivity in static graphics. Users are able to go back and forth with their eyes to examine the various scenes of a set of small multiples for any duration of time. The external interactivity of animated displays, however, is more obvious and requires users to view the animation in a specific order with developer specified buttons. Sweller (1994) suggests that this external interactivity may not be as helpful to viewers as the internal interactivity of static displays and may add cognitive load onto a viewer's working memory.

2.4 Perceptual Obstacles

2.4.1 Change Blindness

Change blindness, the "surprising difficulty observers have in noticing large changes to visual scenes" may be one perceptual difficulty map viewers face when reading animated maps and graphics (Simons and Rensink, 2005, p. 16). Change detection, the opposite of change blindness, is the "apprehension of change in the world around us" (Rensink, 2002, p. 246). Recent research in psychology indicates that observers often fail to notice or perceive seemingly important changes, in both the real world and on a display screen (for overview: Rensink, 2002; Simons and Rensink, 2005).

While change blindness/detection studies have changed over the years, the overall experimental design has remained similar. In nearly all change blindness studies, an observer is shown a scene, a change is made to the stimuli, and the accuracy of detection or the response time of the observer is recorded (Rensink, 2002).

In the early change blindness studies, the changes to the visual stimuli were small and thus changes understandably went unnoticed. These early studies identified that people were surprisingly poor at detecting changes when the change occurred after a visual occlusion or during an eye movement (saccade) (Rensink, 2002). For example, in 1953, Robert French tested how well participants in his study were able to detect when small dots were displaced within a display of two to seven dots. He found that participants were most successful at detecting the change when there were only a few (two to three) dots in the display and were less successful at change detection as the number of dots increased (French, 1953).

By the early 1990s, change blindness and detection research no longer focused on small changes within the visual field, but instead used large realistic stimuli changes. Even when observers were presented with large magnitudes of change, the alteration remained unnoticed (Rensink, 2002). For example, one study presented participants with a photograph that changed to a similar, but slightly altered photo during a visual disruption (Grimes, 1996). Participants had a surprising difficulty noticing the change between the two pictures. Once the change was pointed out, participants had no difficulty recognizing the difference between the two photos. In another study, observers were shown a movie clip where an actor was swapped with another actor (Levin and Simons, 1997). Once again participants had difficulty noticing the change. Finally, even when

participants were asked to engage in conversation with another person, they often failed to notice when their conversation partner was replaced by a different person during a visual occlusion (Simons and Levin, 1998; Levin *et al.*, 2002)!

Rensink (2002) identified several stimuli contingencies of change that lead to change blindness.

1. *Gap contingent-* change occurs during a visual gap between the first and second (altered) scene, also called the flicker paradigm (for reviews: Simons, 2000 and Simons and Levin, 1997),

2. *Saccade contingent-* change occurs during an eye movement (e.g. Henderson and Hollingworth, 1999),

3. *Shift contingent-* change occurs during a movement (shift) of the entire stimuli (Blackmore et al., 1995),

4. *Blink contingent-* change occurs during an eye blink (e.g. O'Regan *et al.* 2000),

5. *Splat contingent-* change occurs when a distracter change, often resembling a "mud splat" appears on the display at the same time as the change occurs. Observers are distracted by the visual onset of the "splats" and they miss the change (e.g. O'Regan *et al.* 1999),

6. *Occlusion contingent-* change occurs during a brief occlusion (e.g. Simons and Levin, 1998),

7. *Cut contingent-* change occurs during a change in viewing position (e.g. Levin and Simons 1997). For example, movie directors rely on this type of change blindness during camera cuts and movements,

8. *Gradual change*- change occurs slowly and gradually between scenes resulting in change blindness (e.g. Simons *et al.*, 2000).

Each of these contingencies have been tested and it has been determined that each leads to some level of change blindness.

Animated maps present map readers with similar obstacles that may inhibit change detection. Five of the eight change contingencies that have been proven to lead to change blindness in psychology may also apply to animated map reading. Animated maps are subject to change blindness for the saccade and blink contingencies because at any point while viewing an animated map people may blink or move their eyes and miss the change. The splat contingent also relates to animated map reading because often many changes occur at one point in time on an animated map and have the possibility of producing the same change blindness effect as the splat contingent. Observers may be distracted by the onset of change in another place on the map and miss the change. The cut contingent relates to 3-D fly though maps, or any map where viewing position may change during the animation. During these types of cartographic animations, cuts may occur between scenes and the viewer may miss the change. Finally, it has been suggested that smooth transitions may mitigate change blindness (Fabrikant *et al.*, 2008), however, Simons *et al.* (2000) has shown that a gradual change may cause change blindness instead of reducing it.

While participants in all of the change blindness studies mentioned were surprisingly blind to change even when the salience of change was large (conversation partner changes), studies have shown that salience of change does have an effect on the accuracy of change detection (Williams and Simons, 2000). The results indicate that

participants were best at correctly identifying persistence, followed by highly salient changes, and performed the worst at detecting changes when the change was not salient. The results of their experiments suggest that change detection is dependent on the saliency of change that occurs between scenes. In animated maps, map readers are often required to detect changes that may not always be the most salient on the map, and may be blind to these changes.

2.4.2 Change Blindness Blindness

Despite the large rates of change blindness in both controlled and real-world environments two studies identified that most people believed they would see these changes within their visual field. This is called *change blindness blindness* (Levin *et al.* 2000, 2002). Levin *et al.* (2000 and 2002) tested this phenomenon using stimuli from previous change blindness experiments (Levin and Simons, 1997 and Simons and Levin, 1998). In all of the experiments, participants overestimated their change detection abilities. In one experiment, 76% of participants rated that they believed they would see a change, yet 0% of the population actually noticed the change (Levin *et al.*, 2000). Because of this problem, people may believe they have noticed everything in their visual field, but in reality they may have missed a significant amount of changes in the world around them.

This metacognitive error of overestimating change detection abilities has large implications not only for cognitive science, but also for the real world (Simons and Rensink, 2005). Change blindness blindness also has serious implications for scientific visualization including map reading, where missing display changes can result in misinterpretation of the data presented by the map. For example, if a viewer were to miss

the extreme increase in unemployment during the 1930s in an animated map of unemployment in the United States during the 20th century, one would assume that the viewer would go back and review the animation again. However, because of the change blindness blindness phenomenon, and the overestimation of change detection abilities, viewers might miss an important change such as this, yet would be less inclined to review the animation. In short, people believe they are better map readers than they actually are.

2.4.3 Attention and Its Impact on Change Detection

Results from empirical studies on change detection (Rensink, 2002) suggest that observers should be alerted of upcoming changes because focused attention is needed to perceive changes in the visual field. Attention allows observers to keep a "memory" of the scene before the change during a scene transition (Wolfe, 1999). Inattentional blindness is then the inability to see objects within the area of fixation because attention is focused somewhere else (Mack and Rock, 1998). Studies testing inattentional blindness aim to answer the question, why do we sometimes look, but fail to see? Simons and Chabris (1999) tested inattentional blindness in an experiment where participants watched a video of several people passing a ball to each other. The experimental participants were instructed to count the number of times the ball was tossed. During the ball passing activity, a person in a gorilla costume walked directly through the center of the display. Despite this activity in the area of fixation, 46% of participants, failed to notice the unexpected person walking across the display.

Inattentional and change blindness studies beg the question, what captures attention? Studies have shown that visual salience within the visual field captures attention more than any other factor (Yantis, 2005). However, other research also

indicates that both abrupt onsets (Yantis and Jonides, 1984) and abrupt luminance (Theeuwes, 1995) help to capture attention, allowing viewers to attend to changes more easily.

Finally, while humans have the ability to attend to multiple things, four to five different items at the same time, only one change can be perceived at a time (Rensink, 2002b). Animated maps present a special case of animation, where changes can occur at multiple places throughout the display at the same time and thus potentially overwhelm our perceptual system.

2.5 Animated maps

2.5.1 Perceptual Issues of Animated Maps

While the primary utility of animated maps is to depict change over time (Harrower, 2007), perceptual limitations like change blindness and inattentional blindness obstruct map reading tasks and threaten the effectiveness of these maps. As cartographers embrace the ease of creating animated graphics, the perceptual difficulties associated with apprehending their message become more noticeable. In animated maps, time-series geographic information changes constantly across the map display; thus, several important changes can occur simultaneously throughout the display during a single scene transition. For example, in an animated dot map, where dots represent the occurrence of an event in time, (e.g. an earthquake) dots appear and disappear on the map display as the data changes over time. In some instances, many dots may appear or disappear at once. Because of the complexity of change that may occur at the same time, viewers may have difficulty noticing the appearance or disappearance of a particular dot

(Harrower, 2003). French's (1953) stimuli was not unlike an animated dot map and his study revealed the difficulty people have in detecting these types of changes. Lasseter (1987) indicates "it is important… that only one idea be seen by the audience at a time. If a lot of action is happening at once, the eye does not know where to look and the main idea of the action will be [missed]" (Lasseter, 1987, p. 38). Because in animated maps, multiple important changes occur at many places at one time, change blindness, inattentional blindness, and change blindness blindness each represent potentially serious concerns for animated map reading.

2.5.2 The Dynamic Variables

To create effective animated maps, DiBiase et al. (1992) identified the dynamic visual variables, which attempted to mirror, function as, and extend Bertin's (1983) visual variables for static displays. In other words, the cartographer can use the dynamic variables to create an animated map in the same way as they would use Bertin's visual variables to create static graphics. The dynamic variables are: 1) *duration* 2) *rate of change*, and 3) *order* (DiBiase et al., 1992). The dynamic variables are intended to help cartographers create effective displays allowing the cartographer to "treat display time as a controllable dimension of the map" (Goldsberry and Battersby, 2009, p. 206).

The dynamic variable, rate of change is defined as m/d, where m is the magnitude of change and d is the duration. The cartographer can adjust the rate of change by adjusting either magnitude of change or duration. The rate of change determines the pace of the animation. "As m is increased (while holding d constant), the apparent rate of change … in the animation increases and the character of the illusory motion becomes less smooth and more abrupt" (DiBiase et. al., 1992, p.206). Magnitude of change (m),

however, is directly related to the dynamic nature of the underlying data, and can only be controlled by the cartographer to a certain extent. On the other hand, it is easier to adjust duration. If duration (d) is increased and m is held constant, rate of change will decrease and the animation will become smoother and less abrupt.

There are two key components to an animated map, a scene and an event. A *scene* is a representation of an instant in time called a *situation*. A scene can be represented as a static map or as a frame in an animation. An *event* is composed of a series of situations (Szego, 1987; DiBiase *et al.*, 1992). Multiple scenes can be displayed as a set of small multiples to portray an *event* in static form (DiBiase et al., 1992). In the dynamic domain, an *event* is represented as a series of scenes or frames played one after another.

The dynamic variable *duration* or *scene duration* is defined as the length of a scene in time (DiBiase et al., 1992). For example, a scene displayed for ten seconds would have a longer duration than a scene displayed for one second. The amount of time a scene is displayed affects the pace and temporal scale of the animation. Fast-paced animations have short scene durations, while slow-paced animations have long scene durations. When transitions are elongated in an animation, duration is defined as the amount of time devoted to the transition (Goldsberry, 2004). Thus, an animation with long transitions has a longer duration than an animation with short transitions. In the context of this research, Goldsberry's definition is a more appropriate indicator of duration in a map with elongated transitions.

The quantification of the amount of change between frames in an animation is known as the *magnitude of change* (Goldsberry and Battersby, 2009). In effect, magnitude of change describes the amount of change that occurs between scenes in a

dynamic map display (DiBiase *et al.*, 1992, Goldsberry and Battersby, 2009). The design of the static map frames, the dynamics of the mapped phenomena, and the sampling interval of the phenomena (DiBiase *et. al.*, 1992) typically determine the magnitude of change. For example, the United States Census is conducted every ten years, while mean daily temperatures are collected everyday, thus the magnitude of change is different between the two because the sampling method and the dynamics of the phenomena are different. Magnitude of change, however, can also be quantified by the amount of display change from scene to scene. In thematic map animations, the classification scheme and the number of classes, influence the magnitude of change between display frames (Goldsberry and Battersby, 2009). For example, a five class animated choropleth map will typically have a higher magnitude of change than a three class animated choropleth map because more enumeration units are likely to change between scenes when there are a greater number of classes. As a result, readers would have to notice and attend to more changes throughout the animation.

2.5.3 Tweening

Animation software offers the designer several other dynamic capabilities beyond the dynamic variables, including tweening. Tweening or "in-betweening" is a process first used for hand-drawn animations, and was one of the first uses of the computer for early computer animations. In hand-drawn animations, the "master" animator would draw the important "keyframes" and a less experienced animator would fill in the "in-between" frames (Kochanek and Bartels, 1984). In contemporary animation computers are used not only to create the "tweens", but also to adjust and even draw the keyframes.

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In dynamic thematic maps, the keyframes of animation are usually a set of static maps that could be displayed as a set of small multiples in the static domain. The keyframes in these maps are often associated with the temporal sampling interval. While many geographic phenomena are temporally continuous in nature, this data can only be collected at discrete times and places. Tweening allows the cartographer to interpolate graphically between temporal samples (keyframes) and smooth the transitions between the static maps to produce a continuous effect. For example, in a map based on United States Census data, the keyframes would correspond to the first year of each decade, when the Census was conducted. Tweening can be used to smooth the transition between decades. This technique is similar to the spatial interpolation techniques used by geographers to develop Digital Elevation Models (DEMs). A DEM is created by interpolating from a few survey points to create a continuous 2.5 dimensional model of elevation on the Earth's surface. Tweening is the graphic and temporal interpolation between known keyframes.

2.5.4 Influence of Smoothed Transitions

It has been suggested that tweening and "applying smooth transitions" (p.202) may even help to reduce change blindness (Fabrikant *et al.*, 2008) when the transition stages are just long enough but not too long (Heer and Robertson, 2007). However, two studies using the gradual change contingent of change blindness (Simons *et al.*, 2000; Seeber, 2003) concluded that smoothed transitions did not result in better change detection. Simons *et al.* (2000) tested change detection by altering a photograph over a 12 second gradual transition. The authors concluded that gradual transitions resulted in the same rate of change blindness as the flicker paradigm used on the same photograph.

Goldsberry and Battersby (2009), however, attribute this to the length of the transition used in the experiment; however, Simons *et al.* note that while the transition was slow, it was not unnoticeable.

In 2003, Joanna Seeber was the first to investigate the benefits of smoothing in the cartographic domain empirically with her study on animated dot maps for her Masters thesis at the University of Wisconsin-Madison. The goals of her research were to "ascertain if pattern recognition [was] more accurate with smooth or abrupt animations" and to determine the type of transition users preferred (Seeber, 2003, p. 33). Because DiBiase *et al.* (1992) suggested that people find smooth animations more visually appealing, she hypothesized that users would perform better with abrupt animations on more difficult map reading tasks, but users would prefer smooth animations (Seeber, 2003)

Seeber (2003) tested her hypothesis on two groups of 30 subjects, mostly graduate students in geography. The groups viewed two dot map animations of the same dataset, one smooth and one abrupt, in different orders. The abrupt animation played for 28 frames at a rate of 1 frame per second over 28 seconds. The smooth animation was created with tweening and the dots faded in and out with transparency during the animation. This "animation played at a frame rate of 5 frames per second, was 145 frames long, and thus played for a total of 29 seconds" (p. 28). Twenty-eight of the frames were data collection points and the remainder of the frames were created with tweening.

The experiment consisted of quantitative and qualitative multiple-choice and short-answer questions of three difficulty levels: easy, medium, and hard. The questions

were aimed to ascertain performance on several different map reading tasks from specific to general. Seeber's results for the quantitative questions indicated that there was little difference between the smooth and abrupt animations for task performance. On the qualitative questions, participants indicated the smooth animations were "too fast", but found the abrupt animations to be "just right". However, she stated that map viewing order had an impact on her results. Participants preferred the abrupt maps to answer questions about the map, but preferred the smooth map for overall aesthetics (Seeber, 2003).

Finally, Seeber's animated maps included interactive buttons. Each map (abrupt and smooth) had the same buttons, play, stop, step forward, and step backward. In her conclusion, Seeber (2003) noted that participants relied heavily on the step buttons and suggested that future similar experiments exclude interactive elements such as buttons.

2.5.5 Animated choropleth maps

A choropleth map is a map made up of polygons called enumeration units colored or shaded based on the data values or qualitative phenomena associated with each unit (Slocum et al., 2009). The famous "Red-State, Blue-State" map, illustrating majority political affiliation by state, is perhaps the most popular and recognized choropleth map in the United States. An animated choropleth map is often made up of a time-series of choropleth maps depicting different time periods, shown one after the other. For example, one could imagine an animated "Red-State, Blue-State" map to illustrate changes in political affiliation over time.

The primary utility of animated choropleth maps is to depict geographic change, aggregated to enumeration units, over time and space (Harrower, 2007). Readers of

animated choropleth maps may use the maps to locate three different geographic extents:

1) a single enumeration unit, 2) a region of the map, or 3) the entire extent of the map.

Users of these maps must apprehend if a particular place is changing and the magnitude

of change in comparison to the surrounding enumeration units (Goldsberry and Battersby,

2009).

Goldsberry and Battersby (2009) describe three levels of change detection in

animated choropleth maps. All three levels are needed for the map reader to comprehend

the dynamics of these maps fully. The three levels of change detection are:

1. The reader simply *noticed* there was a change between scenes in the
   animated choropleth map but cannot identify how exactly the map
   changed,

2. The reader noticed the change and was able to detect that the change
   resulted in an increase or decrease from the original state (only
   applicable for quantitative maps),

3. The reader noticed the change and is able to recall the origin state of the
   map after the transition, the highest level of change detection.

To apprehend the geographic information encoded within animated choropleth maps, the

reader must achieve the highest level of change detection.

Finally, one reason animated choropleth maps are difficult to read is due to

classification (Harrower, 2007; Goldsberry and Battersby, 2009). Data values for

choropleth maps depicting quantitative data by enumeration unit are typically divided

into groups called classes. The cartographer determines the grouping of these data values.

In a choropleth map, enumeration units within the same class are shaded the same color.

However, technological advances have allowed cartographers to create unclassed maps more easily, where each individual data value is represented by a unique color value (Slocum *et al.*, 2009). In classed animated choropleth maps, some units may shift in color many times throughout an animation when the data values associated with those units fall near class breaks. Thus the changes in these maps give a flicker illusion (Figure 1). On the other hand, other units remain the same color or persist through time when data values only change within a class and never cross class breaks (Harrower, 2007). Some of this is due to classification, which may hide changes in the data.
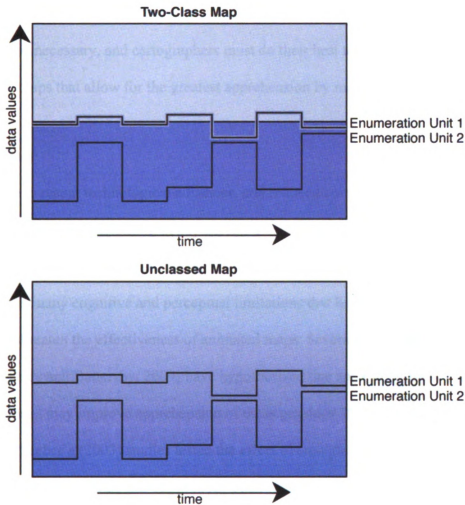
Figure 1. Demonstration of possible data changes by enumeration unit for classed and unclassed maps. Enumeration Unit 1 changes subtly over time, however according to Harrower, this unit "flickers" by switching back and forth between classes in the classed map, while Enumeration Unit 2 changes drastically over time, but remains in one class in the classed map. Harrower argues that in the unclassed map, the changes in the map more congruently represent the changes in the data (graphic modeled after Harrower 2007 and Goldsberry and Battersby, 2009).

Harrower suggests using unclassed animated choropleth maps because they do not

'flicker' as much and slight changes are more easily apprehended in unclassed maps. The

prior notion (Monmonier, 1985; Dykes and Unwin, 1998) that classed maps are more

desirable than unclassed maps does not hold true for animated choropleth maps because

of the availability of interactivity which gives the user the ability to click or mouse-over

an enumeration unit for its data value (Harrower, 2007). However, Goldsberry and

Battersby (2009) state that there are still instances when classed animated choropleth maps may be necessary, and cartographers must do their best to create animated choropleth maps that allow for the greatest apprehension by map readers.

2.6 Summary

Due to recent technological advances, and reduced computing costs, animated scientific graphics are increasing in popularity. However, whether or not these new kinds of visual representations offer advantages over their static counterparts remains unknown. For instance, many cognitive and perceptual limitations that have only recently been uncovered threaten the effectiveness of animated maps. Several researchers (Fabrikant *et al.*; Goldsberry and Battersby, 2009) have hypothesized that smoothing transitions in animated maps may improve apprehension of these graphics. However, Simons *et al.* (2000) and Seeber's (2003) studies tested the effect of smooth transitions on change and pattern detection and refute this suggestion. Their results indicate that smooth transitions did not facilitate change and pattern detection. This thesis investigates the incidence of change blindness in animated choropleth maps and how different design strategies influence change detection in these types of maps.

Chapter 3
METHODS

3.1 Overview and Goals

An experiment was designed to investigate the influence of change blindness on animated choropleth map reading. In the experiment, map readers were asked to detect changes in animated choropleth maps. Accuracy, bias criterion, and discriminability of the changes were each assessed. There were several goals of the study:

1. To assess human change detection abilities for animated choropleth map reading,

2. To evaluate human change detection performance for different levels of change detection (Goldsberry and Battersby 2009),

3. To explore how different transition designs influence map readers abilities to detect changes,

4. To investigate change detection performance for different "change characterizations",

5. To investigate the relationship between participants' confidence and their abilities to detect changes in animated choropleth map reading tasks.

3.2 Overall Change Detection in Animated Choropleth Maps

Participants in the study saw 108 total questions. In each question, a choropleth map was shown. Following a transition, one unit, of the total 64-unit map, was highlighted, and the participant was asked to indicate whether the highlighted unit had changed between the two scenes (Figure 2). Participants were assessed on whether they correctly or incorrectly detected changes.

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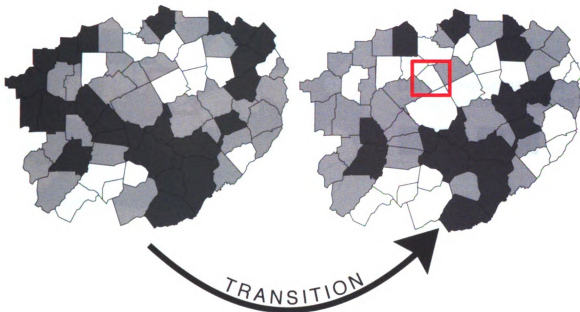
Figure 2. Example of a transition between two scenes. The red rectangle was intended to highlight an enumeration unit of the map. The participant was required to determine whether the highlighted unit changed in lightness between the two scenes.

3.3 Change Detection Levels and Question types

Two question types were asked to correspond with the different levels identified by Goldsberry and Battersby (2009). In Question Type #1, the participant was asked a simple yes/no question about whether he or she was able to detect a change in the unit highlighted with the red rectangle (Figure 3). These questions were designed to understand accuracy for Change Detection Level. The first level of change detection is the ability simply to notice that a change has occurred. Goldsberry and Battersby (2009) classify it as the lowest level of detection. Half of the questions in the test were of Type #1, for a total of 54 questions.

Figure 3. Example of Question Type #1. In this question, participants simply had to indicate whether they had noticed a change or not. This question was designed to understand how well participants were able to detect changes at Level 1.

For Question Type #2, the participant was asked to recall the origin state of the highlighted unit prior to the scene change by selecting "high", "medium", or "low" from the answer choices (Figure 4). If the participant wished to indicate that the unit had persisted, he or she could select the current color of the unit from the options. This type of change detection is considered an advanced level of detection; the reader is able not only to notice the change, but is also able to recall the origin state of the map prior to the change (Goldsberry and Battersby, 2009). This level of change detection is necessary to understand the fully meaning encoded in the map. Fifty-four questions of the total 108 question test were of Question Type #2.

Please indicate the color of the highlighted unit before the scene change:

Figure 4. Example of Question Type #2. In this question, participants were instructed to indicate the shade of highlighted unit before the scene change. This question was designed to understand how well participants were able to detect changes at Level 3. Participants not only had to grasp whether the unit had changed, but also the origin state of the unit before the change.

3.4 Design Conditions

Previous research suggests that transitional designs variables might influence change detection accuracy in animated maps(Goldsberry, 2004; Fabrikant *et al.*, 2008). Fabrikant *et al.* (2008) suggested that gradual transitions created with tweening may allow map readers more time to view the transitions and thus more easily apprehend the changes that occur during a transition state. In this experiment, performance was assessed for three different transition design conditions. The three conditions were:

1. Abrupt (Figure 5),

2. Delayed Smooth (Figure 6),

3. Continuous Smooth (Figure 7).

In all three conditions participants saw a two second map animation; however, duration of the transition and duration of the static scene before the transition differed across conditions. In the "Abrupt Condition", the static map (origin state) was shown for two seconds then abruptly transitioned to the second scene (destination state) of the map (Figure 5). The second scene remained visible for 250 milliseconds before the red highlight rectangle appeared to highlight one enumeration unit within the second scene. The 250-millisecond delay was added to ensure that subjects focused on the change within the map and not the appearance of the question and the red rectangle. In other words, the experiment was designed to avoid problems like the splat contingent of change blindness (O'Regan *et al.*, 1999). The participant could view the second scene for as long as he or she wished until answering the question. Once the question was answered, the next map would appear. Thirty-six questions were asked about maps within the Abrupt Condition.
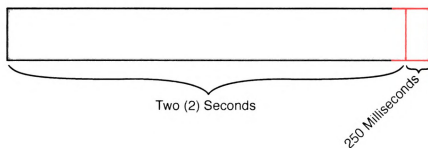
Figure 5. The Abrupt Condition schematic. In this condition, the static first scene (purple) was shown for two (2) seconds, followed by the second scene (orange) which was shown for 250 milliseconds before the highlight rectangle and question appeared.

In the "Delayed Smooth Condition", a static map (origin state) was shown for one second and the map gradually transitioned for one second to the second scene

(destination state) through the use of tweening (Figure 6). The red highlight rectangle and the question appeared immediately after the transition ended and the second scene was shown. Once again, participants had an unlimited amount of time to view the second scene and answer the question. Thirty-six questions were asked about maps within the Delayed Smooth Condition.
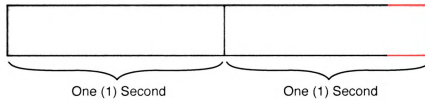
Figure 6. The Delayed Smooth Condition schematic. In this condition, the static first scene (purple) was shown for one (1) second, followed by a one (1) second transition between the first and second scene. Once the transition ended, the highlight rectangle and question appeared.

In the "Continuous Smooth Condition", no static map was shown. This transition design was most congruent to the passage of world time. The map was in a perpetual state of transition from the onset of the first scene (origin state) to the transition to the second scene (destination state) of the map upon appearance on the display (Figure 7). The map transitioned for a total of two seconds. This condition adheres to the congruence principle by mimicking the passage of time with a continuous transition (Tversky *et al.* 2002). Immediately following the transition, the red highlight rectangle and the question appeared. Thirty-six questions were asked about maps within the Continuous Smooth Condition.
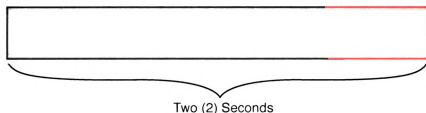
Two (2) Seconds

Figure 7. The Continuous Smooth Condition schematic. In this condition, no static scene was shown, the map immediately began to transition upon appearance on the screen and continued to transition for two (2) seconds. Once the transition ended, the highlight rectangle and question appeared.

Each participant saw all three conditions. The conditions were ordered in six different ways for a total of six different test forms to ensure that learning effects did not play a role in the experiment. An equal number of participants took each of the six test forms.

3.5 Change Characterization Accuracy

Changes within an animated choropleth map can be effectively categorized using cross-change characterization arrays (Monmonier, 1975; Goldsberry 2004). In the array, the diagonal elements from upper left to lower right indicate the units that did not change while the off-diagonals indicate the units that did change and how they changed. The maps used in this experiment were three class maps with "high", "medium", and "low" categories. A three-class map has nine possible transition behaviors shown in a 3 x 3 matrix (Figure 8). In the experiment, 12 questions were asked about each of the possible change detection behaviors, with the exception of the "low" to "medium" transition and the "high" to "medium" transition. Fifteen questions were asked about units transitioning from "low" to "medium", while only nine questions were asked about units transitioning from "high" to "medium"
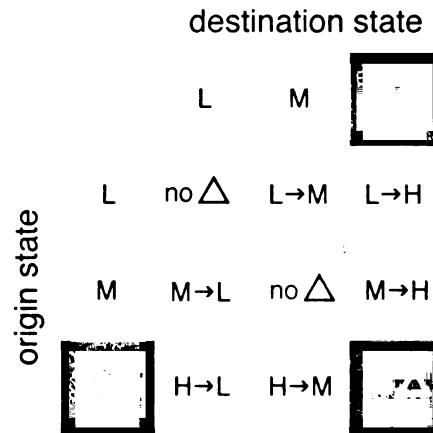
Figure 8. A change characterization array for a pair of three (3) class animated choropleth maps. In a three-class map, there are nine (9) potential change behaviors. Three of these behaviors are examples of persistence, while the other six change in various ways. The persistent behaviors are represented by the diagonals from top left to bottom right on the array.

3.6 Participant Confidence of Personal Performance

Following each of the 108 questions, participants were asked to indicate their

confidence on the previous question by indicating "confident", "neutral", or "unsure"

(Figure 9). There were a total of 108 confidence questions.

How confident are you about your answer?

.   .

Confident   Neutral   Unsure

.

Figure 9. Example of confidence question. Participants were able to indicate that they were "confident", "neutral", or "unsure" of their answer on the previous question. There were 108 confidence questions, one following each of the change detection questions.

3.7 Expected Results

Previous change detection research in psychology has shown that humans have

great difficulty detecting changes in dynamic displays (for review: Rensink, 2002;

Simons and Rensink, 2005). Since animated maps present a uniquely complex stimulus,

it was predicted that participants would have difficulty detecting and apprehending messages encoded within the animations.

3.7.1 Change Detection Level Expectations

Due to the assumption that it would be easier for participants simply to detect whether an enumeration unit within the map shifted or persisted during a transition, than to comprehend both the origin and destination state of a particular unit, it was predicted that participants would perform better on Question Type #1. In this question type, participants were asked simply to indicate whether the unit changed, or remained the same. There are two bases for this prediction: 1) participants would have an easier time answering questions about Change Detection Level 1 because they had a 50% chance of guessing correctly and 2) because it was assumed that it would be easier simply to notice the presence of a change, than both to notice it and recall the unit's initial origin state (Question Type #2).

3.7.2 Transition Type Expectations

By elongating transitions between scenes, tweening can reduce the rate of change, and lengthen the amount of time devoted to cartographic transitions. This increase in the duration of the transition results in a lower rate of change. *Rate of change*, defined by DiBiase *et al.* (1992), is the *magnitude of change* (*m*) divided by the *duration* of the static scene (*d*). However, duration of the static scene does not account for transitions between scenes, thus a second definition can be used. *Duration of change* (*D*) is the duration of the transition between two scenes. In a non-tweened animation, the duration of change is the amount of time between the two frames, and in a tweened animation it is the "length of time devoted to the tween" (Goldsberry, 2004, p. 52).

It was predicted that the Delayed Smooth condition would elicit the highest change detection accuracy because it affords the reader enough time to view the static scene before the transition as well as the gradual change between the two scenes. Participants would have time to 1) view the static map for one-second and 2) view the transition for another second. This design would more likely allow participants to notice, attend to, and perceive a greater number of changes within the map, making it possible to perceive the specific change of the highlighted enumeration unit.

3.7.3 Change Behavior Expectations

Accuracy for each type of change behavior, as shown in the change characterization arrays, was expected to vary. Because changes where the unit transitioned between the "highest" and "lowest" class are more salient, it was expected that these types of changes would elicit higher change detection performance scores.

3.7.4 Participant Confidence Expectations

Previously perceptual research has indicated that while many times people miss changes within their visual field, they firmly believe that they would see the changes within their visual field (Levin *et al.*, 2000, 2002); this phenomenon is known as *change blindness blindness*. In this study, it was expected that participants would be more confident than accurate. While participants would not always be highly accurate, it was predicted that questions with higher accuracy scores would also have higher confidence ratings. Because of the expectation that participants would perform better when asked about lower levels of change detection, it was predicted that participants would be more confident on these types of questions. Finally because it was predicted that participants

would perform better on the Delayed Smooth Condition, it was also expected that participants would rate these questions with higher confidence.

3.8 Participants

A total of eighty-one students at Michigan State University participated in the study. The participants signed up for the study voluntarily in several Geography and Integrative Social Science classes; however, only three of the total 81 participants were Geography majors. The other 78 participants were made up of 46 different majors from across campus. Each participant was compensated $10 for about 30 minutes of his or her time. An equal number of males and females participated in the study, 39 of each gender. The age of the participants ranged from 18 to 29 (mode: 20). All of the participants were students; they indicated that they were freshmen, sophomores, juniors, seniors, other, or grad students in school (mode: sophomore).

3.9 Materials

3.9.1 Hardware

The study was conducted on Dell Precision 690 Computers with Dell 1907 FPt computer displays with a screen resolution of 1280 x 1024, and a refresh rate of 60 Hertz. The brightness was set to 100 and the contrast was set to 50 on all of the displays. The questions in the study were designed in *Adobe Flash CS3* (Adobe Systems, Inc., 2007) using the default frame rate of 12 frames per second. The experiment was administered using *Mozilla Firefox* (Mozilla Corporation, 2009) in "full-screen" mode.

3.9.2 Map Data

Sixty-four of the total 154 counties of the state of Georgia were used to create the animated stimuli maps (Figure 10).

Figure 10. The sixty-four counties used for the stimuli are highlighted in purple; the other counties of the state of Georgia were excluded from the stimuli.

The stimuli maps depicted average yearly unemployment rates in Georgia counties between 1990 and 2008. This data is freely available from the United States Bureau of Labor Statistics for all of the counties in the United States. Nineteen keyframes were used to represent each year between 1990 and 2008, thus there were 18 total transitions.

The geographic area used in the animations was unfamiliar to the participants of the study. Due to the demographics of the participants, the geographic area selected for this study was located outside the Great Lakes region. To avoid biases from participants, they were not informed of the geographic area or underlying data. In addition, the counties used for the study were rotated in four different directions throughout the experiment (Figure 11).
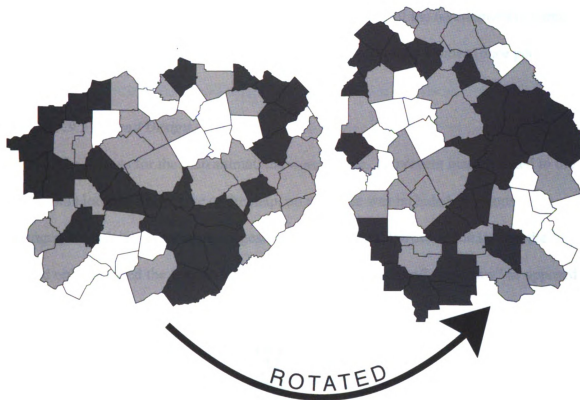
Figure 11. Illustration of the rotation of the choropleth map stimuli. In the experiment, each of the questions used the same basemap. To avoid having participants "memorize" the basemap, the map was rotated in one of four directions.

To create the animations for the stimuli, the data was first manipulated in *Microsoft Excel* (Microsoft Corporation, 2008), joined to a shapefile in *ArcMap 9.2* (Environmental Systems Research Institute, Inc., 2006), rotated in *Adobe Illustrator CS3* (Adobe Systems Inc., 2007), and then imported directly into *Adobe Flash CS3* (Adobe Systems Inc., 2007) where the set of small multiples was animated into a sequence.

There were a total of 19 maps and 18 transitions. These maps were repeated six times throughout the test, once per condition type and once per question type. Within each set of maps, the years were randomly ordered using a random number generator. Within each condition, the different question types were inter-mixed. For example, the participant might see three Question Type #1's followed by two Question Type #2's.

Throughout the 108 questions of the experiment, 36 of the 64 enumeration units

of the map were highlighted, thus the same unit was highlighted 3 times (once per

condition).

3.9.3 Legend Design

The layouts for the map animations were simple. To prevent biases related to the

geographic location and theme of the map, no map title was included. Previous

cartographic animation research suggests simple legends (Harrower, 2003), thus the

legend only included the legend definitions of: "high", "medium", and "low" as opposed

to more detailed numerical definitions (Figure 12).

High

Medium

Low
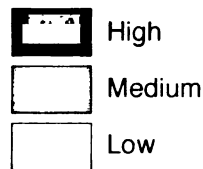
Figure 12. The legend used in the experiment was simple and only included: "high", "medium", and "low".

3.9.4 Classification Scheme

Several different classification schemes can be used in choropleth mapping;

however, no one classification scheme works optimally for all data. Different

classification schemes result in a different number of data points or observations within

each class. The scheme also has the ability to emphasize or de-emphasize different

characteristics within the data.

According to Harrower (2003), additional issues of classification come into play

in animated mapping. The classification scheme can lead to empty classes and skewed

distribution and must be heeded when choosing how to class the data. It is also important

to have a matched legend throughout an animated choropleth map sequence to avoid

confusing map readers. In other words, the classification scheme chosen should attempt to avoid the problems noted by Harrower (2003).

Brewer and Pickle (2002) suggest that quantiles are the best classification scheme for map comparison. The quantile classification scheme places the same number of observations into each class. The time series used in this experiment consisted of 1,216 observations (19 years of data for 64 counties). The three-class quantile classification results in about 405 observations in each class. Often class breaks occurred between two observations of the same value and the classification was altered slightly to move class breaks between different observation values.

Because of the additional perceptual requirements necessary to read animated choropleth maps, cartographers must design these maps differently than traditional static choropleth maps. In static choropleth maps, five to seven classes are often considered an appropriate number of classes to use (Slocum *et al.*, 2009). However, five to seven classes are too many for animated choropleth maps (Harrower, 2003), where users have a limited amount of time to view each scene of the animation. To reduce complexity, Harrower (2003) suggests using only two to three classes for animated choropleth maps. Because animated map displays are fleeting by nature, users often do not have much time to view the display and must apprehend important geographical distributions in a matter of moments. Goldsberry and Battersby (2009) also indicate that increases in the number of classes result in higher complexities and magnitudes of change. The stimuli in this thesis experiment have three classes to reduce strain on working memory as well as to reduce magnitude of change.

3.9.5 Color Schemes

Choosing an appropriate color scheme is very important for choropleth maps. In these maps, a gray color scheme was used to avoid color effects and protect biases against colorblind participants; a lightness-based sequential color scheme was used to imply a unipolar data distribution (Brewer, 1994). Specifically, because the maps in this experiment utilized tweening, the colors ranged from dark to light and when a unit transitioned between light and dark, the color passed through the middle gray color. The differences in lightness between the shades of gray used were salient enough that even between just two frames of the animation, it was a noticeable difference for the map reader. This way, participants could distinguish even the slightest color shift that occurred between two single frames.

3.9.6 Interactivity

Although research suggests interactivity can help users better comprehend animated maps, and that users often get frustrated with maps they cannot control (Harrower, 2003), these maps did not include any interactivity. The reason for this is two-fold: 1) interactivity would allow each participant to view the animation differently and would no longer be controlled for time, and 2) in Seeber's study (2003), interactivity was available and her participants' tended to rely too much on the buttons to move between scenes. In her study, each condition included the same buttons, play, stop, step forward, and step backward. After noting the reliance on the buttons, Seeber stated, "it would be useful to design future experiments so that the animations had no step buttons" (p. 66).

DiBiase *et al.* defined magnitude of change, *m*, as the difference in position and attributes between scenes. Goldsberry and Battersby (2009) extended this definition, as the amount of symbology change between two scenes. In a classed animated choropleth map, *m* is the number of enumeration units that shift between classes (Goldsberry, 2004). Overall this dataset included many maps with relatively high magnitudes of change (Figure 13). For example, the highest magnitude of change between two scenes was 50 of the 64 units, while the lowest magnitude of change between was when 11 of the 64 units changed between scenes.
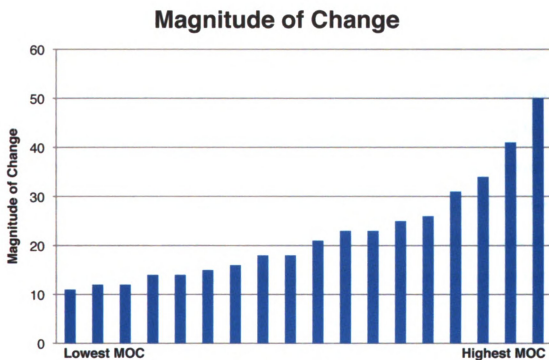
Figure 13. Graph illustrating the magnitudes of change for all of the 18 transitions used in the experiment. The lowest MOC is 11, while the highest MOC is 50. In all cases, the MOC is relatively high because unemployment in Georgia was very dynamic.

3.10 Procedure

Each participant completed the experiment in the Windows computer lab in the Geography Building at Michigan State University, and spent between 25 and 45 minutes participating in the study. Between one and eight subjects participated at the same time. Cardboard tri-folds were used to block the participants from disturbing each other.

During the study, subjects were asked to enter the testing room, were assigned computers (8 of the total 16 computers in the lab were used for testing), and were thanked for their participation. The computers screens were set 30 centimeters from the edge of the desk; however, participants were allowed to sit at whatever distance from the screen they felt was comfortable.

The participants were handed two consent forms following the Michigan State University Institutional Review Board protocol. They were instructed to read, sign, and date one copy of the consent form (see Appendix A) and keep the second copy for his or her records. Following the completion of the consent form, each participant was given the "pretest" (see Appendix B). The pretest consisted of questions about age, gender, school year, and the participants' familiarity with animated and interactive maps. The goal of the pretest was to gather basic information about each of the participants' background and abilities.

Upon completion of the pretest, before starting the actual test, each participant took part in a training session on the computer. In the training the participants practiced the questions they would be asked and were given general information about the study (see Appendix C). The goal of the training was to familiarize the participants with the questions they would see during the test. The training did not inform the participants

about the different transition types they would see. Each participant had to navigate through the training before starting the test. Forward and back buttons were used to move through the training to allow participants to go back if necessary; however these buttons were not available during the actual experimental test.

Immediately following the training, the experimental test began. Participants had to answer all 108 questions to complete the test. Upon completion, participants were handed the posttest (see Appendix D). The posttest consisted mostly of open-ended opinion questions about their feelings towards the test, the transitions, and the training. The goals of the posttest were to 1) determine if the participants felt the test was effective, 2) assess whether participants had different opinions about the different types of transitions they saw, and 3) ascertain whether the training was adequate at familiarizing the participants with the types of questions they would see. Once all of the participants in the room had finished the test, the participants were allowed to collect their $10 compensation and leave the testing room. The response data was immediately recorded and stored in a spreadsheet for analysis.

Chapter 4
RESULTS AND ANALYSIS

4. 1 Change Detection Performance

Change detection performance was evaluated for all 108 questions of the study.

Accuracy was evaluated for:

1. The entire study (108 questions),

2. By change detection level (54 questions of each),

3. For each transition design (36 questions of each),

4. For each change characterization.

Participants were also evaluated on their abilities to detect changes as well as

persisting behaviors between map scenes. The ability to detect a change is classified as a

hit, while the ability to detect persistence is called a correct rejection. Accuracy in this

study is defined as hits plus correct rejections.

Signal detection theory (SDT) was also used to investigate the decision-making

strategies of the participants. SDT is widely used by psychologists, but in recent years has

been used to assess decision making for geographic information tasks (Griffin and Bell,

2009). Decision responses specifically for "yes/no" type questions can be categorized

into four types of potential responses; hits, correct rejections, false alarms, and misses

(Macmillian and Creelman, 1991). Both hits and correct rejections have been discussed

above and are each important for comprehending animated maps. False alarms in this

experiment occur when a participant indicates seeing a change when there was no

change. Misses occur when there is a change, but the participant indicates no change.

These four possible outcomes are shown in (Table 1).

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	Participant Decision	
Reality	*Change*	*No Change*
Change	Hit (H)	Miss (M)
No Change	False Alarm (FA)	Correct Rejection (CR)

Table 1. The SDT outcome array. Categorization of map readers potential decisions based on what they were shown.

In this study, SDT was used to measure discriminability of a change and

participant bias to indicate either "yes" or "no". The measure of discriminability is d'

which is defined as:

$$d' = z(H) - z(FA)$$

As d' increases the discriminability of a change increases.

There are several ways to measure participant bias, however in this study the

formula used was:

$$criterion\ (c) = \frac{1}{2}\ (z\ (H) + z\ (FA))$$

A positive c indicates a tendency to say "no" while a negative c indicates a tendency to

say "yes". A zero c indicates no bias toward either "yes" or "no".

4.1.1 Overall Change Detection Performance

Table 2 summarizes the overall performance of all participants. The mean score

out of 108 was 57.26. The median was similar to the mean at 57.5 correct responses. The

minimum was 45 of 108 questions and corresponds to chance for the entire experiment.

The maximum was 72 of 108 question or two-thirds correct (Figure 14).

Total Performance Accuracy	
Total Possible	108 (100%)
Mean	57.26 (53.02%)
Median	57.5 (53.24%)
Minimum	45 (41.67%)
25th Percentile	54 (50%)
75th Percentile	60 (55.56%)
Maximum	72 (66.67%)
Standard Deviation	5.17 (4.79%)

Table 2. Descriptive statistics of total change detection performance accuracy for all 108 questions for all 78 participants (hits plus correct rejections).
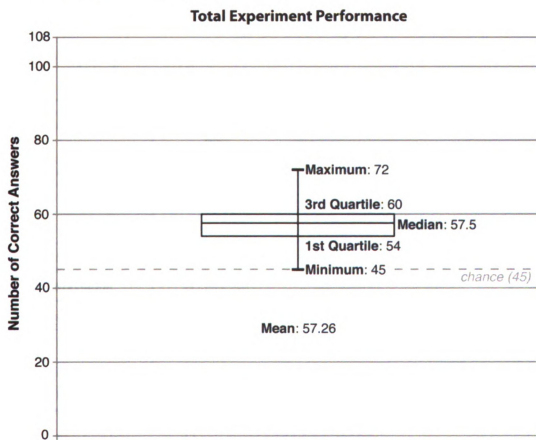
Figure 14. Box and whisker plot of total performance accuracy on all 108 questions for all participants (hits plus correct rejections). The chance score is equivalent to the minimum number of correct answers (45) for all participants for the entire test.

Overall participants in the study commonly failed to detect changes between map scenes. Chance for the entire experiment (all 108 questions) was evaluated as the chance for Change Detection Level 1 questions (Question Type #1) plus chance for Change Detection Level 3 questions (Question Type #2). For Change Detection Level 1 questions, with two options for responses, chance was 50% (27 of 54 questions). For Change Detection Level 3 questions, with three choices, chance would be expected to result in an accuracy of 33.3% (18 of 54 questions). The chance accuracy score for the total 108 question test would then be 41.67% (45 of 108 questions). Participants averaged 57.26/108 (53.02%) questions correct. A one-sample t-test at a 0.05 significance level was used to determine whether accuracy was significantly different from chance. The mean accuracy score of the entire experiment was significantly different from the chance score of 45, $t(77) = 20.933$, p<0.0001.

Total Performance			
	Hits	**Correct Rejections**	**False Alarms**
Total Possible	**72** (100%)	**36** (100%)	**36** (100%)
Mean	**32.69** (45.41%)	**23.62** (65.60%)	**12.38** (34.39%)
Median	**33** (45.83%)	**24.5** (68.06)	**11.5** (31.94%)
Minimum	**17** (23.61%)	**6** (16.67%)	**4** (11.11%)
Maximum	**51** (70.83%)	**32** (88.89%)	**30** (83.33%)
Standard Deviation	**7.02** (9.75%)	**4.78** (13.27%)	**4.78** (13.27%)
Mean d'	**0.31**		
Mean criterion c	**0.27**		

Table 3. Descriptive statistics of hits and correct rejections for the entire experiment for the entire population (all 108 questions).

The participants in this study maintained higher correct rejection rates (65.6%) than hit rates (45.41%) (Table 3). A paired t-test at a 0.05 significance level was used to

test if the hit and correct rejection rates were significantly different. The paired t-test indicated that the two rates were significantly different at $t(77) = -8.444$, $p<0.0001$. The d' was 0.31, indicating that overall it was hard to distinguish between noise and the signal (the change). The criterion c indicates there was a bias to say there was no change rather than change.

4.1.2 Change Detection Level Performance

Participants were evaluated on their abilities to detect changes at the different levels of change detection (Table 4, Figure 15). Level 1 Change Detection refers to questions where participants were asked simply to notice the change, while Level 3 Change Detection refers to questions where participants were required to recall the origin state of the highlighted unit. Change detection accuracy was determined as hits plus correct rejections. A total of 54 questions were asked about each change detection level. It was expected that participants would perform better when asked whether they had simply noticed the change than when they were required to recall *how* the unit changed over time.

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	Change Detection Level 1	Change Detection Level 3
Total Possible	**54** (100%)	**54** (100%)
Mean	**34.49** (63.87%)	**22.77** (42.17%)
Median	**34.5** (63.89%)	**23** (42.59%)
Minimum	**22** (40.74%)	**13** (24.07%)
25th Percentile	**32** (59.26%)	**21** (38.89)
75th Percentile	**37** (68.52%)	**25** (46.30%)
Maximum	**45** (83.33%)	**30** (55.56%)
Standard Deviation	**4.03** (7.45%)	**3.24** (6.01%)

Table 4. Population level change detection performance for both levels 1 and 3 of change detection (hits plus correct rejections). Change Detection Level 1 corresponds to Question Type #1 where participants were asked simply to indicate whether the highlighted unit changed or remained the same. Change Detection Level 3 corresponds to Question Type #2 where participants were asked to indicate the class of the origin state of the highlighted unit.

Change Detection Levels Performance
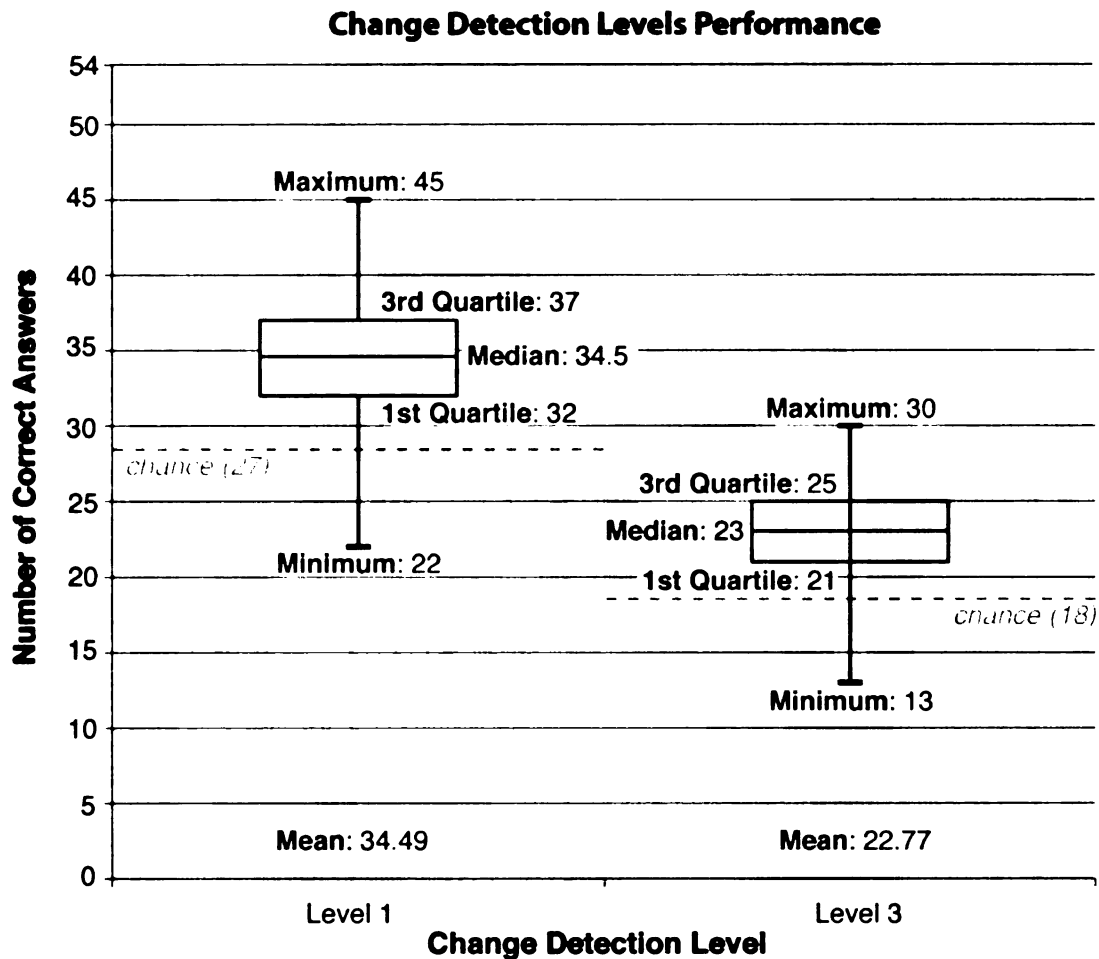
Figure 15. Box and whisker plot illustrating change detection performance by Change Detection Level. Participants performed better on Change Detection Level 1 questions, by simply noticing the change. Performance was not as high on Change Detection Level 3, when participants needed to recall the origin state of the highlighted unit.

Participants performed better at Change Detection Level 1 (mean: 34.39) than Change Detection Level 3 (mean: 22.77). The accuracy scores for the two question types were significantly different from each other, $t(77)=20.029$, $p<0.0001$.

When simply noticing the change, the mean accuracy score (34.49 of 54 questions) was within two standard deviations of chance (50%, 27 of 54 questions). When asked to identify how the unit changed, the mean accuracy score (22.77 of 54 questions) was within 1.5 standard deviations of chance (33.3%, 18 of 54 questions). Two one-sample t-tests were used to determine if accuracy scores were significantly

different than chance. For Change Detection Level 1 questions, $t(77)=16.428$, p<0.0001 indicates that the scores were significantly different than chance. The accuracy scores were also significantly different than chance for Change Detection Level 3, $t(77)=12.988$, p<0.0001.

	Change Detection Level 1		
	Hits	Correct Rejections	False Alarms
Total Possible	36 (100%)	18 (100%)	18 (100%)
Mean	22.45 (62.36%)	11.09 (61.61%)	6.91 (38.39%)
Median	22 (61.11%)	11 (61.11%)	7 (38.89%)
Minimum	11 (30.56%)	3 (16.67%)	3 (16.67%)
Maximum	34 (94.44%)	15 (83.33%)	15 (83.33%)
Standard Deviation	4.71 (13.07%)	2.39 (13.29%)	2.39 (13.29%)
Mean d'	0.65		
Mean criterion c	-0.02		

Table 5. Hits, correct rejections and false alarms for all Change Detection Level 1 questions

	Change Detection Level 3		
	Hits	Correct Rejections	False Alarms
Total Possible	36 (100%)	18 (100%)	18 (100%)
Mean	10.24 (28.45%)	12.53 (69.59%)	5.47 (30.41%)
Median	10 (27.78%)	13 (72.22%)	5 (27.78%)
Minimum	2 (5.56%)	1 (5.56%)	0 (0%)
Maximum	19 (52.78%)	18 (100%)	17 (94.44%)
Standard Deviation	3.34 (9.27%)	3.25 (18.06%)	3.25 (18.06%)
Mean d'	-0.03		
Mean criterion c	0.58		

Table 6. Hits, correct rejections and false alarms for all Change Detection Level 1 questions

Hits and correct rejection rates differed for the two question types (Table 5, Table 6). Hi rates were highest for Change Detection Level 1 questions. Correct rejections rates were higher for Change Detection Level 3 questions than Change Detection Level 1. Thus false alarm rates were higher for Change Detection Level 1 questions than for Change Detection Level 3 questions. A paired t-test was used to distinguish differences between hits for both question types at a 0.05 significance level. The hit rate differences were significant, $t(77)=25.910$, $p<0.0001$. The difference between correct rejection rates for the two detection levels were also significant, $t(77)=-4.060$, $p<0.0001$.

The d' indicates it was easier to distinguish a change for Change Detection Level 1 than Change Detection Level 2 with the higher d' for Change Detection Level 1. There also was a stronger bias for Change Detection Level 3, and participants tended to say there was no change rather than change. The criterion c value, which is very close to 0 for Change Detection Level 1, indicates very little bias for that level.

4.1.3 Change Detection Performance across Design Conditions

To test the influence of different transition types on animated choropleth map reading tasks, participants' were evaluated on their abilities to detect changes with three different transition types: Abrupt, Delayed Smooth, and Continuous Smooth. In the Abrupt Condition, one scene abruptly transitioned to a second map scene. In the Delayed Smooth Condition, the map remained static for one second and then smoothly transitioned to the second map scene for another second. In the Continuous Smooth Condition, the map immediately began to transition from the first map scene to the second over two seconds. It was hypothesized that participants would perform best in the

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Delayed Smooth Condition. This condition allows the participants to view the static

scene and also watch the transition.

4.1.3.1 Change Detection Level 1

Change Detection Level 1			
	Abrupt	**Delayed Smooth**	**Continuous Smooth**
Total Possible	**18** (100%)	**18** (100%)	**18** (100%)
Mean	**11.21** (62.25%)	**11. 68** (64.89%)	**11.60** (64.46%)
Median	**11** (61.11%)	**12** (66.67%)	**11** (61.11%)
Minimum	**6** (33.33%)	**7** (38.89%)	**6** (33.3%)
25th Percentile	**10** (55.56%)	**11** (61.11%)	**10** (55.56%)
75th Percentile	**12** (66.67%)	**12** (72.22%)	**13** (72.22%)
Maximum	**16** (88.89%)	**16** (88.89%)	**17** (94.44%)
Standard Deviation	**1.93** (10.72%)	**1.96** (10.91%)	**2.24** (12.42%)

Table 7. Participant accuracy for all three conditions for Change Detection Level 1. To answer these questions correctly, the participant only needed to notice whether a change occurred in the highlighted unit.

Change Detection across Design Conditions (CD Level 1)

Maximum: 17

Maximum: 16

Maximum: 16

3rd Quartile: 13

3rd Quartile: 13

3rd Quartile: 12

Median: 12

Median: 11

Median: 11

1st Quartile: 11

1st Quartile: 10

1st Quartile: 10

chance (9)

Minimum: 7

Minimum: 6

Minimum: 6

Number of Correct Answers

Minimum: 6

Mean: 11.21

Mean: 11.68

Mean: 11.60

Abrupt

Delayed Smooth

Continuous Smooth

Condition Type

Figure 16. Box and whisker plot illustrating change detection performance for all three conditions for Change Detection Level 1. Participant performance was similar for all three conditions for the lowest level of Change Detection.

60
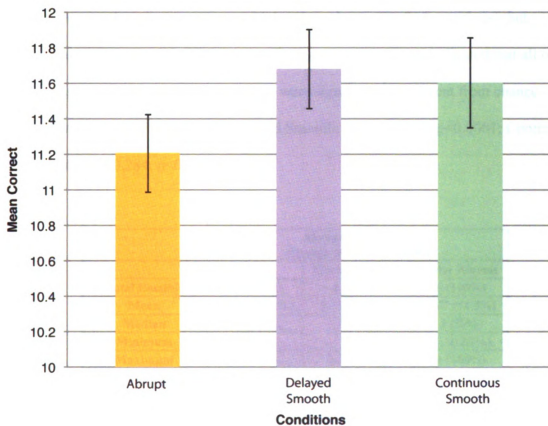
Figure 17. Mean performance and standard error bars for Change Detection Level 1. The accuracy results indicate there were no large differences between the three conditions.

Based on the mean scores for Change Detection Level 1 (Abrupt: 11.21; Delayed Smooth: 11.68; Continuous Smooth: 11.60), participants performed best on the Delayed Smooth Condition, as expected (Figure 17, Table 7). However, performance in all of the conditions was similar and median scores only varied by 1 question (Figure 16). The Continuous Smooth Condition had the highest maximum score of all three conditions (17 of 18 questions answered correctly). A one-way repeated measures ANOVA indicated that differences in accuracy for all three conditions were not significantly different from each other. $F(2, 154) = 1.409$, p=0.248

Mean and median scores were higher than chance (9 of 18 questions), but minimum scores were all below chance. Three one-sample t-tests indicated that all of the accuracy scores for each of the conditions were significantly different from chance (Abrupt: $t(77)=10.093$, p<0.0001; Delayed Smooth: $t(77)=12.050$, p<0.0001; Continuous Smooth: $t(77)=10.284$, p<0.0001).

	Abrupt Condition: Change Detection Level 1		
	Hits	Correct Rejects	False Alarms
Total Possible	12 (100%)	6 (100%)	6 (100%)
Mean	7.53 (62.71%)	2.73 (45.51%)	3.27 (54.5%)
Median	8 (66.67%)	3 (50%)	3 (50%)
Minimum	3 (25%)	0 (0%)	1 (16.67%)
Maximum	12 (100%)	5 (83.33%)	6 (100%)
Standard Deviation	2.02 (16.87%)	1.05 (17.55%)	1.05 (17.5%)
Mean d'	0.27		
Mean c	-0.23		

Table 8. Hits, correct rejections and false alarms for the Abrupt Condition for Change Detection Level 1.

	Delayed Smooth Condition: Change Detection Level 1		
	Hits	Correct Rejects	False Alarms
Total Possible	12 (100%)	6 (100%)	6 (100%)
Mean	7.77 (64.74%)	3.91 (65.17%)	2.09 (34.83%)
Median	8 (66.67%)	4 (66.67%)	2 (33.3%)
Minimum	3 (25%)	0 (0%)	0 (0%)
Maximum	12 (100%)	6 (100%)	6 (100%)
Standard Deviation	2.20 (18.36%)	1.21 (20.13%)	1.21 (20.17%)
Mean d'	0.86		
Mean c	-0.01		

Table 9. Hits, correct rejections and false alarms for the Delayed Smooth Condition for Change Detection Level 1.

	Continuous Smooth Condition: Change Detection Level 1		
	Hits	Correct Rejects	False Alarms
Total Possible	12 (100%)	6 (100%)	6 (100%)
Mean	7.15 (59.62%)	4.45 (74.15%)	1.55 (25.83%)
Median	7 (58.33%)	5 (83.33%)	1 (16.67%)
Minimum	1 (8.33%)	2 (33.33%)	0 (0%)
Maximum	12 (100%)	6 (100%)	4 (66.67%)
Standard Deviation	2.40 (19.97%)	1.17 (19.49%)	1.17 (19.5%)
Mean d'	0.97		
Mean c	0.19		

Table 10. Hits, correct rejections and false alarms for the Continuous Smooth Condition for Change Detection Level 1.

Hit rates were similar across conditions, while correct rejection rates varied (Table 8, Table 9, Table 10). The highest hit rate was in the Delayed Smooth Condition, while the highest correct rejection rate was for the Continuous Smooth Condition. Dividing accuracy into hits and correct rejection can help to understand how the different condition types affect change detection. A one-way repeated measures ANOVA was used to distinguish differences between hits for all three conditions at a 0.05 significance level. The hit rate differences were not significant, $F(2, 154)=2.049$ p=0.132. The differences between correct rejection rates for the three conditions were significant, $F(2, 154)=59.366$ p<0.0001. To understand how the conditions were different, a comparison of the main effect using a Bonferroni corrected paired comparison indicated there was a significant difference between all of the conditions (Abrupt and Delayed Smooth, p<0.0001; Abrupt and Continuous Smooth, p<0.0001; Delayed Smooth and Continuous Smooth, p=0.003).

The d' measure was highest for the Continuous Smooth condition because of the large amount of false alarms in the Abrupt Condition. This indicates that it was easier to

discriminate a change for the Continuous Smooth Condition than for the Abrupt

Condition. The criterion c indicates that participants were the least biased in the Delayed

Smooth Condition. Thus SDT indicates that both the smoothly changing conditions were

better than the Abrupt Condition.

4.1.3.2 Change Detection Level 3

Change Detection Level 3			
	Abrupt	**Delayed Smooth**	**Continuous Smooth**
Total Possible	18 (100%)	18 (100%)	18 (100%)
Mean	8.21 (45.66%)	7.68 (42.66%)	6.87 (38.18%)
Median	8 (44.44%)	8 (44.44%)	7 (38.89%)
Minimum	3 (16.67%)	4 (22.22%)	3 (16.67%)
25th Percentile	7 (38.89%)	7 (38.89%)	6 (33.33%)
75th Percentile	10 (55.56%)	8.75 (48.61%)	8 (44.44%)
Maximum	13 (72.22%)	13 (72.22%)	12 (66.67%)
Standard Deviation	1.94 (10.81%)	1.78 (9.87%)	1.61 (8.92%)

Table 11. Participant accuracy for all three conditions for Change Detection Level 3, the highest level of change detection. In these questions, participants were asked to recall the origin state of the unit following the transition.
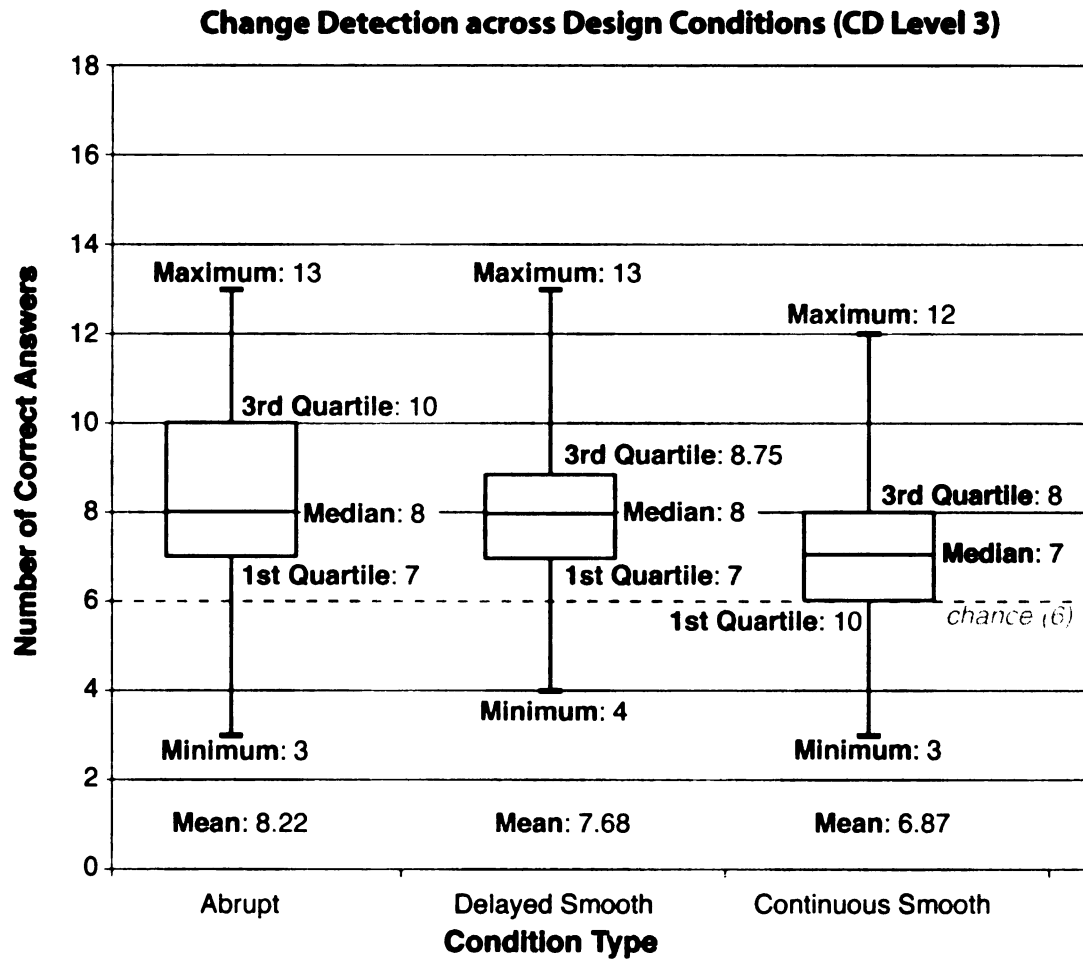
Figure 18. Box and whisker plot illustrating change detection performance for all three conditions for Change Detection Level 3. Participant performance varied depending on the transition condition for this higher level of change detection.
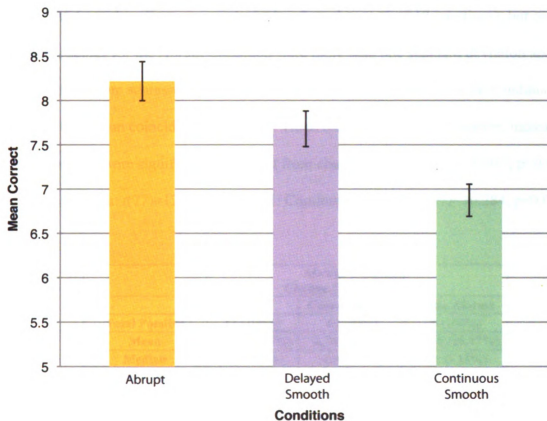
Figure 19. Mean performance and standard error bars for Change Detection Level 3. The accuracy results indicate that participants were more accurate in the Abrupt Condition than the other two conditions.

Mean performance scores for Change Detection Level 3 were highest in the

Abrupt Condition (mean: 8.22) (Figure 19, Table 11). However, performance in all of the

conditions was similar and median scores only varied by 1 question (Figure 18). There

was a significant difference between the three conditions, F (2, 154)=35.808, p<0.0001.

To understand fully how the conditions were different for Change Detection Level 3

questions, a comparison of the main effect using a Bonferroni corrected paired

comparison indicated no significance between the Abrupt and Delayed Smooth

conditions (p=0.187), but did indicate significant differences between the Delayed

Smooth and the Continuous Smooth conditions (p= 0.007) and the Abrupt and the

Continuous Smooth conditions (p<0.0001).

Mean and median scores were higher than chance (6 of 18 questions), but only accuracy scores for the Abrupt Condition were more than one standard deviation above chance. Minimum scores were all below chance, and the 1st quartile for the Continuous Smooth Condition coincided with chance. Three one-sample t-tests, however, indicated that the scores were significantly different from chance (Abrupt: $t(77)$=10.093, p<0.0001; Delayed Smooth: $t(77)$=12.050, p<0.0001; Continuous Smooth: $t(77)$=10.284, p<0.0001).

	Abrupt Condition: Change Detection Level 3		
	Hits	Correct Rejects	False Alarms
Total Possible	12 (100%)	6 (100%)	6 (100%)
Mean	4.44 (36.97%)	3.78 (63.03%)	2.218 (36.97%)
Median	4 (33.33%)	4 (66.67%)	2 (33.33%)
Minimum	0 (0%)	0 (0%)	0 (0%)
Maximum	8 (66.67%)	6 (100%)	6 (100%)
Standard Deviation	1.83 (15.23%)	1.58 (26.41%)	1.58 (26.41%)
Mean *d'*	-0.01		
Mean *c*	0.37		

Table 12. Hits, correct rejections and false alarms for the Abrupt Condition for Change Detection Level 3.

	Delayed Smooth Condition: Change Detection Level 3		
	Hits	Correct Rejects	False Alarms
Total Possible	12 (100%)	6 (100%)	6 (100%)
Mean	3.40 (28.31%)	4.28 (71.37%)	1.72 (28.63%)
Median	3 (25%)	4 (66.67%)	2 (33.33%)
Minimum	0 (0%)	0 (0%)	0 (0%)
Maximum	9 (75%)	6 (100%)	6 (100%)
Standard Deviation	1.78 (14.79%)	1.25 (20.79%)	1.25 (20.79%)
Mean *d'*	-0.03		
Mean *c*	0.61		

Table 13. Hits, correct rejections and false alarms for the Delayed Smooth Condition for Change Detection Level 3.

	Continuous Smooth Condition: Change Detection Level 3		
	Hits	Correct Rejects	False Alarms
Total Possible	12 (100%)	6 (100%)	6 (100%)
Mean	2.41 (20.09%)	4.46 (74.36%)	1.54 (25.64%)
Median	2 (16.67%)	5 (83.33%)	1 (16.67%)
Minimum	0 (0%)	0 (0%)	0 (0%)
Maximum	6 (50%)	6 (100%)	6 (100%)
Standard Deviation	1.38 (11.51%)	1.44 (23.98%)	1.44 (23.98%)
Mean d'	-0.29		
Mean c	0.79		

Table 14. Hits, correct rejections and false alarms for the Continuous Smooth Condition for Change Detection Level 3.

Participants produced the most hits in the Abrupt Condition and the most correct rejections in the Continuous Smooth Condition (Table 12, Table 13, Table 14). The hypothesized Delayed Smooth Condition was the second best in both cases. Two one-way repeated measures ANOVA's were used to detect differences between hits and correct rejections across conditions. Hits were significantly different across conditions, $F(2,154)=34.177$, $p<0.0001$. A comparison of the main effect with Bonferroni corrected paired comparison indicated that all conditions were significantly different from each other ($p<0.0001$ for all conditions). Differences were also significant for correct rejections across conditions, $F(2,154)=7.398$, $p<0.0001$. A comparison of the main effect using a Bonferroni corrected paired comparison indicated no difference between the two gradual transition conditions ($p=0.728$). However, differences were significant between the Abrupt and the Delayed Smooth ($p=0.035$) and the Abrupt and the Continuous Smooth Conditions ($p=0.004$).

Signal detection theory is designed to understand differences between noise and signals and is typically used for two-choice answers. For Change Detection Level 3, all

wrong answers were lumped into misses and false alarms, while all correct answers were denoted as hits or correct rejections. Using these measures, d' was greatest for the Abrupt Condition and smallest for the Continuous Smooth Condition. Although d' was small for all three conditions. There was also the least bias for the Abrupt Condition with a c of 0.37 and there was the greatest bias to indicate no change for the Continuous Smooth condition with a c of 0.79.

4.1.4 Change Characterization Accuracy- Cross Classification Arrays

Overall Performance

destination state

	L	M	H
L	0.72 n=936	0.47 n=1170	0.46 n=936
M	0.43 n=936	0.6 n=936	0.56 n=936
H	0.4 n=936	0.41 n=682	0.73 n=936

origin state

Figure 20. Cross-classification array of accuracy rates for all 108 questions in the experiment. These rates indicate how well participants performed on questions for each of the nine possible transitions. The results indicate that the highest rates of detection occurred when the unit remained the same, the diagonals from top left to bottom right. For example, participants were 73% accurate on detecting the absence of a change when the unit remained "high" between the two scenes.

The overall performance accuracy was highest for correct rejections, when participants identified a persisting behavior between map scenes (the diagonals from top left to bottom right on the cross-classification array) (Figure 20). Participants were least accurate when the unit shifted from "high" to "low" with only a 40% accuracy rate. Hit rates, where participants correctly identified there was a change, however, were similar for all types of change, ranging from 40% to 56%.

Change Detection Level 1

destination state

	L	M	H
L	0.68	0.71	0.67
	n=468	n=468	n=468
M	0.49	0.54	0.62
	n=468	n=468	n=468
H	0.69	0.56	0.78
	n=468	n=468	n=468

origin state

Change Detection Level 3

destination state

	L	M	H
L	0.76	0.27	0.24
	n=468	n=782	n=468
M	0.37	0.65	0.49
	n=468	n=468	n=468
H	0.12	0.09	0.68
	n=468	n=214	n=468

origin state
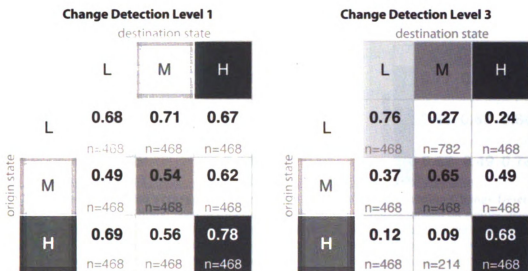
Figure 21. Cross-classification arrays of accuracy rates for all questions for the two question types. The rates for Change Detection Level 1 indicate how well participants performed on simple change detection for each of the nine possible transition behaviors, while Change Detection Level 3 indicates how well participants identified the origin state of the highlighted unit.

Accuracy rates for Change Detection Level 1 were highest when the mapped unit persisted within the "high" class between two scenes. Participants were also highly accurate (71%) when the unit transitioned from the "low" class to the "middle" class between scenes. Overall, rates of change detection were higher for Change Detection Level 1 than for Change Detection Level 3; however, chance was also higher for Change Detection Level 1 questions than Level 3 questions (Figure 21). For Change Detection Level 3, participants remained highly accurate at detecting persistence behavior, however, when changes were more substantial (a larger class shift) participants often failed to detect the change correctly. The differences between hit rates of the two types of change detection were different, especially when the unit changed *from* the "highest" class. Hit rates for the change of "high" to "low" and "high" to "medium" for Change Detection Level 1 were 69% and 56%, respectively, while for Change Detection Level 3 hit rates were only 12% and 9%, respectively. A paired t-test indicated that the two matrices were significantly different from each other, $t(8) = 2.780$, p= 0.024.

Abrupt Condition				**Delayed Smooth Condition**				**Continuous Smooth Condition**		
destination state				destination state				destination state		
	L	M	H		L	M	H		L	M	H
L	0.69	0.76	0.51	L	0.58	0.69	0.72	L	0.77	0.68	0.78
	n=156	n=156	n=156		n=156	n=156	n=156		n=156	n=156	n=156
M	0.54	0.39	0.62	M	0.58	0.56	0.59	M	0.35	0.68	0.66
	n=156	n=156	n=156		n=156	n=156	n=156		n=156	n=156	n=156
H	0.72	0.60	0.76	H	0.73	0.58	0.81	H	0.62	0.49	0.78
	n=156	n=156	n=156		n=156	n=156	n=156		n=156	n=156	n=156

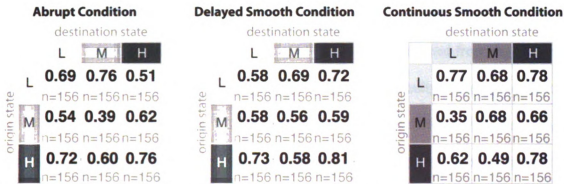**Figure 22. Cross-classification arrays of accuracy rates for all questions regarding Change Detection Type 1 for each of the conditions.** The rates indicate how well participants performed on simple change identification. In the Abrupt Condition, the map transitioned abruptly from one scene to the next. In the Delayed Smooth Condition, the map remained static for one second followed by a smooth transition for one second. The Continuous Smooth Transition maps began to transition immediately after the map was presented.

Correct rejection rates, the rate of correctly identifying persisting behaviors, were typically higher than hit rates, the rate of correctly identifying there *was* a change, for Change Detection Level 1 across conditions (Figure 22). The highest correct rejection rate was in the Delayed Smooth Condition when the highlighted unit remained in the "highest" class (81%). The lowest correct rejection rate was in the Abrupt Condition, when the unit remained in the "middle" class (39%). The highest hit rate was in the Continuous Smooth condition when the highlighted unit changed from "low" to "high" (78%). The lowest hit rate was when the unit transitioned from the "middle" class to the "lowest" class (35%).

There were some notable differences across conditions depending on the nature of the change. First, the correct rejection rate was 39% for the Abrupt Condition when the highlighted unit remained in the "middle" class. While for the two smoothly changing conditions, correct rejection rates were 56% and 68% for the Delayed Smooth and Continuous Smooth Conditions, respectively. For the transition from the "middle" class to the "lowest" class, hit rates were over 50% for the Abrupt (54%) and Delayed Smooth (58%) conditions while participants seemed to have difficulty identifying this same

change in the Continuous Smooth condition and only had a hit rate of 35%. Finally, there were also differences in hit rates when the highlighted unit transitioned from the "lowest" to the "highest" class. Hit rates were over 70% for the two gradually changing conditions (78% for Continuous Smooth and 72% for Delayed Smooth) while hit rates were only 51% for the Abrupt Condition. Despite these differences, the Friedman non-parametric repeated measures ANOVA, indicated no significant differences between the means of the matrices for the three conditions, $p < 0.905$.
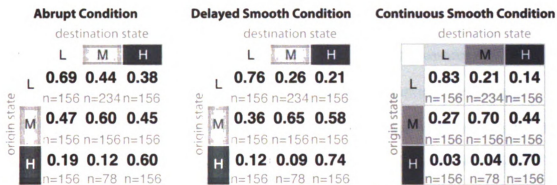
Figure 23. Cross-classification arrays of accuracy rates for all questions regarding Change Detection Type 3 for each of the conditions. The rates indicate how well participants performed on the highest level of change identification, where participants were required to recall the origin state of the highlighted unit. In the Abrupt Condition, the map transitioned abruptly from one scene to the next. In the Delayed Smooth Condition, the map remained static for one second followed by a smooth transition for one second. The Continuous Smooth Transition maps began to transition immediately after the map was presented.

There was a greater gradation between accuracy rates for each of the nine types of change by condition type for Question Type #2 (Figure 23). Participants were consistently more accurate at correct rejections than hits. Correct rejection rates for Change Detection Level 3 were similar to those in Change Detection Level 1, despite the participant having three choices to choose from instead of two. Hits, however, were lower than for Change Detection Level 1. The highest correct rejection rate was 83% in the Continuous Smooth condition when the unit remained in the highest class. The lowest correct rejection rate was 60% in the Abrupt Condition, when the unit remained in the "middle" and "highest" classes.

There are several notable differences between the three conditions made apparent by the cross-classification array. The greatest gradation between the three conditions was for the change from the "lowest" class to the "highest" class. The rate of accuracy for this particular type of change was highest for the Abrupt Condition (39%) and lowest for the Continuous Smooth Condition (14%). Differences were also evident for the transition from the "lowest" class to the "middle" class and from the "middle" class to the "lowest" class. In these two cases, with large differences between the three conditions, participants performed best in the Abrupt Condition and worst in the Continuous Smooth Condition. Despite these differences, the Friedman non-parametric repeated measures ANOVA, indicated no significant differences between the means of the matrices for the three conditions, $p < 0.19$. Finally, the transition from the "high" to the "middle" class for all three conditions had an overall low rate (12% for the Abrupt Condition, 9% for the Delayed Smooth Condition, and 4% for the Continuous Smooth Condition).

4.2 Confidence

Following each change detection question, participants were asked to rate their confidence on the presiding question as either "confident", "neutral", or "unsure", for a total of 108 confidence questions.

Participant Confidence for Entire Test
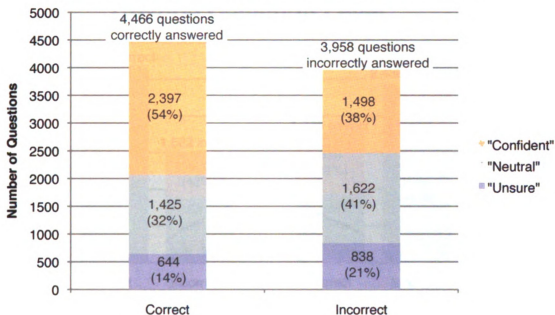
Figure 24. Stacked bar graph of correct and incorrect answers for the entire test (108 questions for 78 participants) categorized by participants' confidence ratings.

When participants correctly identified a change or persisting behavior, more than half of the time they indicated that they were "confident" about their answer (Figure 24). Of the total 4,466 correct answers, the "confident" choice was chosen 2,397 times (53.67%). Participants chose "neutral" or "unsure" only 47.33% of the time they answered correctly. For the 3,958 incorrect responses, participants indicated they were "neutral" (40.98%) more than "confident" and "unsure". However, despite answering the questions incorrectly, participants indicated they were more "confident" (37.85%) than "unsure" (21.17%). The percentage of correct answers did significantly differ by confidence rating, $\chi^2(2, N = 8424) = 215.78$, $p < 0.0001$.
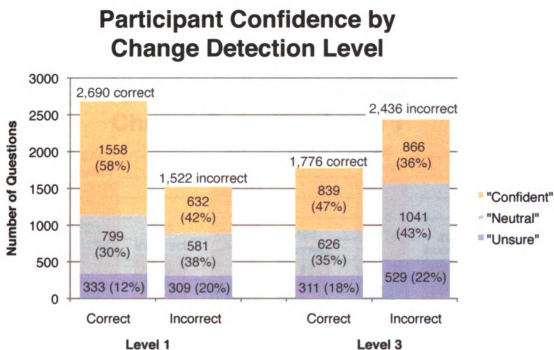
Figure 25. Column graph of correct and incorrect answers for each of levels of change detection categorized by participants' confidence ratings. Level 1 is the lowest level of change detection while Level 3 is the highest level of change detection identified by Goldsberry and Battersby (2009). In the experiment, for Change Detection Level 1, the participants were asked simply if they noticed the change, while for Change Detection Level 3, the participants were asked to identify the origin state of the highlighted unit.

Participants' confidence ratings varied between question types (Figure 25). Participants were more accurate on Level 1 Change Detection, and were also more confident when they answered these questions correctly (57.92% for 2,690 correct answers). When asked to detect changes at the highest level of change detection, participants were less confident and less accurate (47.24% for 1,776 correct answers) than they were for lower levels of change detection. In all cases, except incorrect responses for Change Detection Level 3, "confident" was the most popular answer. For incorrect responses for Change Detection Level 3, participants selected "neutral" more than any other possible confidence rating (42.73%). In all cases, "unsure" was the least popular answer. Correct answers significantly differed by confidence rating for Change

Detection Level 1, $\chi^2(2, N = 4212) = 111.57$, $p < 0.0001$ as well as for Change Detection

Level 3, $\chi^2(2, N = 4212) = 58.33$, $p < 0.0001$.

4.3.3 Confidence Ratings for Change Detection Level 1 Across Conditions
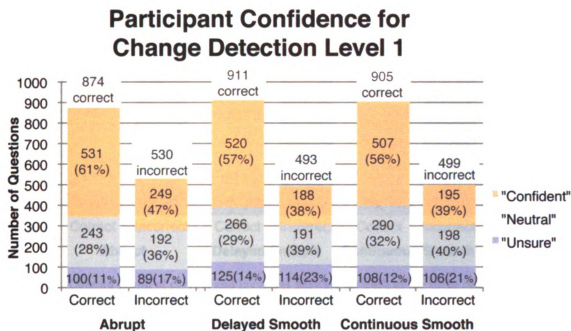
Figure 26. Column graph of correct and incorrect answers for each of the three conditions for Change Detection Level 1 categorized by participants' confidence ratings.

Between conditions, confidence ratings were similar for Change Detection Level

1 (Figure 26). Participants were more confident when answering questions in the Abrupt

Condition even when they answered incorrectly (47%), while confidence ratings for the

other two conditions were 38% (Delayed Smooth) and 39% (Continuous Smooth). In all

cases correct answers significantly differed by confidence rating (Abrupt: $\chi^2(2, N = 1404)$

$= 25.84$, $p < 0.0001$; Delayed Smooth: $\chi^2(2, N = 1404) = 48.34$, $p < 0.0001$; Continuous

Smooth: $\chi^2(2, N = 1404) = 42.15$, $p < 0.0001$).

Figure 27. Column graph of correct and incorrect answers for each of the three conditions for Change Detection Level 3 categorized by participants' confidence ratings.

Confidence ratings were similar between the three conditions for Change Detection Level 3 (Figure 27). The percentage of correct answers where participants chose the "confident" choice ranged from 46.41% to 48.21%. Participants chose "confident" between 34.21% and 36.27% of the time when they answered the question incorrectly. The two widest ranges between conditional confidence ratings were when participants answered questions correctly and selected either "neutral" or "unsure". Neutral ratings ranged between 34% and 37% and unsure ratings ranged between 16% and 20%. In all cases correct answers significantly differed by confidence rating (Abrupt: $\chi^2(2, N = 1404) = 28.42, p < 0.0001$; Delayed Smooth: $\chi^2(2, N = 1404) = 20.61, p < 0.0001$; Continuous Smooth: $\chi^2(2, N = 1404) = 49.79, p < 0.0001$)

DISCUSSION

5.1 Change Detection Abilities

The results from this experiment suggest that map readers have difficulty

detecting changes between scenes in animated choropleth maps. Participants averaged

53% accuracy at detecting a change or a persisting behavior, meaning nearly half of the

responses were incorrect. Finally, the results of SDT indicate that, in general, participants

had a bias to believe there was less change in the maps than in reality. This finding

supports the first hypothesis of this thesis, that rates of change blindness would be high

for basic map reading tasks.

Maps graphically depict geographic information, and cartographers, unlike other

animators, cannot fully control the look and behavior of dynamic maps. Consequently,

many changes may occur across the display at a single moment in time. This is

problematic because humans are unable to perceive more than one change at a time

(Rensink, 2002) and thus many changes are left unnoticed in an animated map.

Furthermore, the primary utility of animated maps is their ability to portray changes over

time and space (Harrower, 2007), meaning the potential implications of cartographic

change blindness could be substantial. When map readers miss changes they fail to

comprehend the meaning encoded within the map. The inherent complexity of animated

maps requires readers to see more than just a gorilla in a basketball game (Chabris and

Simons, 1999). For example, in an animated choropleth map of unemployment changes

over time, failing to detect the change from the lowest class to the highest class indicates

a significant failure to understand the dynamics of unemployment over space and time.

Because of the meaningful data these maps represent, map readers must complete more

burdensome perceptual tasks in limited periods of time. Unlike movies or other stimuli used in psychology change blindness literature, simply noticing the changes is only part of the map reading task at hand.

5.2 Different Levels of Change Detection

The results of this study indicate that map readers are better at detecting changes at Change Detection Level 1 than Change Detection Level 3. Participants were more accurate at detecting lower levels of change when they simply needed to identify whether the highlighted unit had changed. These results support the hypothesis that people would perform better on Question Type #1, Change Detection Level 1 than Question Type #2, Change Detection Level 3. Using the calculations for d' and c as noted in the Results section, the SDT results indicated that it was easier to distinguish a change for Change Detection Level 1 than for Level 3 and there was a greater bias to indicate no change for Level 3, however there are limitations to the d' and c measures for Change Detection Level 3 questions where there were three possible answers.

To comprehend the meaning of an animated choropleth map completely, the reader must not only notice a change in a particular unit, but also must understand and recall *how* that unit changed over time. Map readers are able to deduce that if a map symbol has changed, it must have changed from a different symbol, however, the full meaning of the transition is lost if the reader is not able to identify the origin state of that symbol. While it is important to detect changes at Level 3 to apprehend an animated choropleth map fully, this research indicates that this task is very difficult in the way it has been currently presented to our readers.

The disparity between the accuracy rates of the two levels of change detection

may be linked to the two different questions types. Participants had a 50% chance on

Change Detection Level 1 questions compared to a 33.3% chance on Change Detection

Level 3 questions. However, it is clear that Level 3 Change Detection is more difficult

because it requires the participant to notice, attend to, and perceive more information

about map transitions.

While complete comprehension of animated choropleth maps requires the map

reader to achieve Change Detection Level 3, this is not to demean the necessity of

detecting changes at lower levels. Lower levels of change detection are essential to

understanding these types of maps because detection of a simple change can lead to

further exploration that, upon reviewing, leads to Change Detection Levels 2 and 3.

Finally, this research did not specifically explore Change Detection Level 2, the detection

of whether change in a particular area increased or decreased, however, Figure 28 may

help visually to understand Level 2 Change Detection by exploring participants responses

for Change Detection Level 3 questions in more detail.
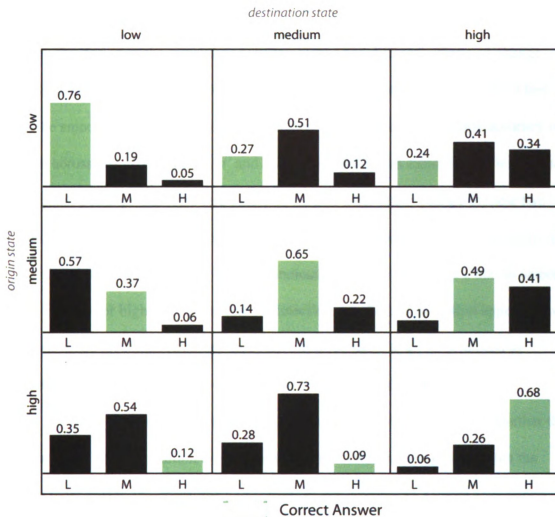
Figure 28. Illustration of participants responses to Change Detection Level 3 questions. Often the correct answer is not always the most popular choice. This graphic may help to understand Change Detection Level 2, the detection of an increase, decrease, or persistence between origin and destination states.

The Signal Detection analysis in this thesis does not take into account the apparent bias to believe that if there was a change, it was from the adjacent class and not the more distant class. For example, when the unit transitioned from "high" to "low", there was a large bias to select "medium" instead of "low". Once again, when the unit transitioned from "low" to "high" more participants selected "medium" as the possible answer than either of the other two possible answers.

5.3 Transitional Design

The design of the transitions between scenes had different effects on change detection accuracy. For lower levels of change detection, participants performed best with the smoothly changing conditions based on the results of SDT. While accuracy was similar across design conditions, d' and c indicated that it was easier for participants to distinguish a change and were less biased to assume there was a change in these two conditions. Basically, while the Abrupt Condition had the highest accuracy in terms of hits, false alarms were also very high and indicate that participants had a bias to select the "yes" option. For higher levels of change detection, the Abrupt Condition appeared to be superior based on simple accuracy analysis, however, more analysis is needed to understand SDT for this type of question with three potential answers.

In the posttest (see Appendix D) participants were asked to indicate whether they felt that some of the condition types helped them to detect the changes between the scenes more easily. In general the participants in this study were divided over which condition they felt helped them the most. Some participants indicated that the Abrupt Condition was the best because the time devoted to the static scene before the transition was the longest. Those who preferred the Abrupt Condition also indicated that because the change was so sudden it drew their attention to places where the map had changed. However, participants who felt they performed better with the smoothly changing transitions typically believed that the time devoted to the transition allowed them to apprehend the transitional behavior of the map more effectively.

It was expected that the Delayed Smooth Condition would elicit the highest change detection accuracy because it allowed for an equal duration of time devoted to the

transition and the static scene before the change. Participants in the study were not told

explicitly about the different condition types they would see although they did see

questions during the training of each of the different transition designs. Thus, in general,

responses on the posttest did not directly refer to the Delayed Smooth Condition, perhaps

because they did not notice the difference between this condition and the Continuous

Smooth Condition. However, one participant did refer directly to this condition and felt

that it would result in their highest score by condition type.

One reason participants may have produced a large number of false alarms in the

Abrupt condition may be related to the salience of overall change in the Abrupt

Condition. Because all of the change occurs in a fraction of a second, it may affect the

participants' bias to indicate "yes"; the abruptness of the change seems to make it appear

to the reader that there is change even when there was no change in the highlighted unit.

The abrupt condition seems to induce Harrower's idea of animated simultaneous contrast.

One problem with the smoothly changing transition designs may be related to the

Rensink's (2002) two types of change that a person may perceive: dynamic and

completed change. Dynamic change is a change that the viewer sees during a transition

event. For example, in this experiment, in the smoothly changing conditions, it was

possible for the participant to catch the change while it was occurring, called dynamic

change detection. However, the Abrupt Condition represented an example of completed

change detection; it is possible for map readers to become confused when watching the

smoothly changing transition because they may only notice the change during a dynamic

change and misread the transition. For example, when a unit transitioned from the "low"

class to the "high" class, it was possible that a map reader may have noticed the change

during the midpoint of the transition (while the unit was in the "middle" class) and

thought that the unit changed from the "middle" class to the "high" class instead from the

"low" class. In effect, this explicit representation of change may lead to confusion of map

readers especially when they are not watching the *entire* transition event.

One issue with tweened maps is that tweened transitions produce colors on the

map that differ from those in the legend (Battersby and Goldsberry, 2010). This

experiment was designed with this in mind thus the shade of gray during the tween from

the "low" class to the "high" class matched the "middle" class shade of gray. Battersby

and Goldsberry (2010) suggest using color schemes that are appropriate for tweening,

such as the one used in this experiment. Map readers may misread maps if the transition

does not progress through the colors of the middle classes. For instance, sequential color

schemes using a combination of both hue *and* lightness do not transition through the

middle classes of the scheme (Figure 29). For example, when a transition occurs between

the highest and lowest classes using a yellow, green, blue color scheme, the color that

occurs during the transition does not "travel" through the middle class color (green).

Basically, a transition between the yellow color and the dark blue color in this particular

color scheme is not the green color that is shown on the legend as the middle class, but as

the graphical interpolation of color between yellow and blue.
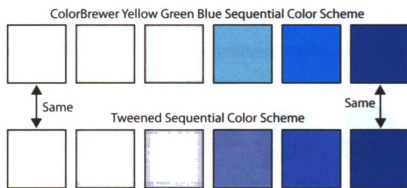
Figure 29. Illustration of the differences between the ColorBrewer color schemes and the in-between states of a tweened color scheme with the same origin and destination states.

Because additional colors are presented on the map, map readers may be able to identify the differences and may be more likely to detect changes at higher levels. It may be easier for map readers to identify *how* the unit is changing during dynamic change detection if tweened colors do not visually "pass through" the colors of the middle classes. More colors are shown on the map then on the legend during a transition and thus each unique color during a transition could correspond to a unique transition event. Finally, non-tweened or abruptly changing maps do not suffer from this same effect because no interpolated colors are shown on the map. Several participants indicated that it was difficult to identify whether the unit had changed from the neighboring class or not because in a tweened map a unit that changed from black to white or vice versa must visually progress through gray.

Tweened maps also suffer from a lack of congruence between the legend and the transition (Figure 30). In this study, the maps had three classes: "high", "medium", and "low", however during a transition event in the smoothly changing conditions, the intermediary colors on the map did not correspond to any of the three colors shown on the legend and is technically meaningless. For example, if a unit transitioned between middle gray and white, the light gray color that occurs during the transition was not

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shown on the legend. This could lead to confusion for the map reader when viewing these tweened maps. A gradient legend may be less confusing for the map reader.
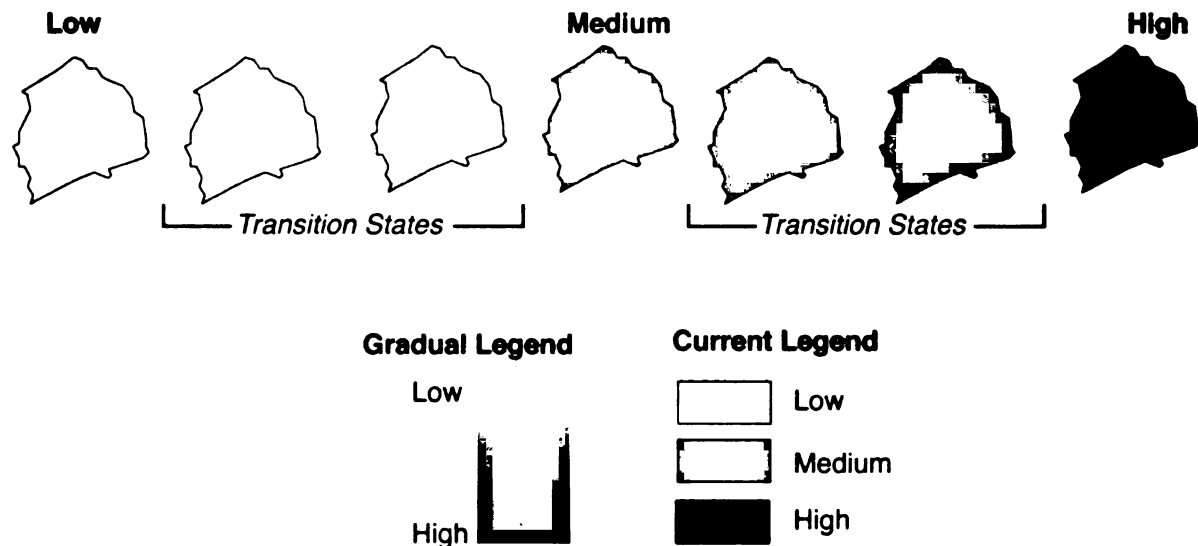
Figure 30. Illustration of how the current legend design differs from what the map reader sees during a transition state. Using a gradual legend may make this less confusing to the map reader.

Finally, based on the results of SDT, it appears that the smoothly changing conditions were superior for Change Detection Level 1. Specifically, the continuous tween outperformed the other two conditions because participants had an easier time distinguishing a choroplethic shifting behavior from persisting behavior and participants were less biased to select a particular answer. The Continuous Smooth Condition was also the most congruent to the passage of time. This supports previous research by Fabrikant *et al.* (2009) that says that more congruent representations would be more easily understood and comprehended.

5.4 Transitional Salience

The cross-classification change arrays enable the exploration of the different types of shifting that elicits the highest change detection rates. The results suggest that correct

rejections (detection of a persistence behavior) were easier to detect. Hit rates (detection of a class shift) varied depending on the question type and the condition. However, throughout entire experiment, hit rates were similar across all six shifting behaviors. This finding refutes the hypothesis that more drastic shifting behaviors would be more easily apprehended.

There was no clear pattern as to which shifting behaviors were the most perceptually salient. Previous literature suggests that persistent and more salient changes are more easily noticed than less salient changes (Williams and Simons, 2000), however, it is currently unknown what changes are most salient in these types of maps. The previous research tested how easily people noticed changes when only one change happened after a transition and it was believed that more drastic changes were more perceptually salient. Specifically in the Williams and Simons study (2000), the researchers tested participants' abilities to detect whether a change had occurred on a small fictional character developed for the study. The participants were instructed to try to detect a change to this character in several ways. For example, arms and legs were removed or added to the character and participants were asked whether they were able to detect the change of the character. In this thesis study, changes were less obvious than those presented in the Williams and Simons experiment and this may be why there is no clear pattern as to which types of change were the most easily detected.

Figure 28 illustrates the responses given to Question Type #2. In cases where enumeration units changed drastically, from the "high" class to the "low" class or vice versa, participants incorrectly believed the unit was changing from the neighboring class (the "middle" class). This is related to dynamic vs. completed change detection,

discussed in the previous section. The results may indicate that map readers in this study assumed that changes would not be drastic between scenes. Map readers may have a bias to think the unit persisted or only changed from the neighboring class. This prejudice may stem from a prior notion that more drastic change may seem unlikely. If map readers already assume that drastic changes are unlikely, what does this mean for this type of map reading? In other words, if people are assuming a particular change will happen, what is the point of this type of visualization? More research is needed to attempt to break this bias habit especially in highly dynamic geographic data.

5.5 Tendency toward Change Blindness Blindness

Finally, this research attempted to understand to what extent animated map readers experience change blindness blindness. Participants in this study were generally over confident, but not very accurate. One participant even noted, "it was very easy" (although many participants indicated it was very difficult and appreciated not being graded on the task). More importantly, participants rarely choose the "unsure" choice when rating their confidence, despite the overall failure to detect changes in many of the maps. This result supports the hypothesis that people would be highly confident but not highly accurate when detecting changes in animated choropleth maps.

This result is consistent with other change blindness blindness research. Levin and his colleagues (2000 and 2002) found that viewers believed they would see a change, even when 100% of viewers failed to notice the change. In Levin's experiments, participants were asked to indicate whether they believed they would see a change before they saw it. In this study, participants were asked to rate their confidence in change

detection after each change detection question. However, even when asked *after* failing to detect the change, participants were confident they saw it correctly.

The bias towards selecting "confident" may indicate that participants had a prior notion to believe they saw a change. This bias may undermine the effectiveness of these types of maps and from a cartographic standpoint is difficult to combat. In general, participants in this study underestimated the dynamics of the geographic information presented in the maps they saw, and were confident that they knew how the data changed over time despite missing many of the changes. More research is needed to explore how cartographers can indicate to their readers that while they may believe they understand the underlying data presented in the map, in fact, they probably did not fully understand the meaning of the geographic information presented.

One known method that helps map readers avoid change blindness is to incorporate interactivity and allow users to replay the scenes of an animation. However change blindness blindness may cause map readers to believe they have correctly identified changes between scenes, despite missing them, and thus map readers may be reluctant to use the available interactivity to its full potential. Basically, map readers who are sure they know what happened are not going to use a replay button, because they think they understand the underlying data better than they actually do.

The map task in this experiment was fairly difficult. It has been noted that this particular task of noticing whether a specific unit has changed between two moments in time, is probably more difficult then other types of animated choropleth map reading tasks such as detecting the overall change trend over time, but this remains unknown. Despite the difficulty of the task at hand, participants still felt "confident" in their change

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detection abilities. However, difficult tasks, such as the one tested in this thesis, may help

map readers to realize that they are missing important changes. Many of the participants

noted that they were glad they were not graded and apologized for being particularly bad

at this type of task.

5.6 Implicit Representations of Change

One problem with animated maps as compared to their static counterparts is that

often the differences between map scenes are implicit and only implied. Therefore much

of the problem with these types of displays stems from the map readers' failure to

apprehend the implied transitions buried within the animation. Basically, the map reader

is forced to "read between the lines" to apprehend the change in the map. In contrast,

static maps such as small multiples allow map readers to internally interact and scan the

maps in a different way (Fabrikant *et al.*, 2008), and may make it easier to comprehend

the changes between the scenes.

Cartographers have many possible ways to increase performance on different

change detection levels in animated maps. Two choices to help improve detection are:

interactivity, and explicit representations of change. Interactivity is commonly cited as a

way to assist map readers with complex dynamic map tasks (Tversky *et al.*, 2002;

Harrower, 2007; Fabrikant *et al.*, 2008). Maps that enable users to click or mouse over a

particular place to identify how the unit changed, or have buttons that allow the user to go

back and review the previous state of the map may help to improve performance on both

levels of change detection. Similarly, explicit representations of spatial-temporal change

such as change maps or cross-classification arrays may also assist map readers to detect

changes at higher levels. The addition of change maps and cross-classification arrays within the map display during an animation may also help make changes more salient by depicting them explicitly. Currently, if map readers do not achieve the first level of change detection, there will be no reason for the map reader to go back to investigate the higher levels of change detection. By explicitly representing change in more than one way (animation, change maps, *and* cross-classification arrays) map readers may be more likely to understand the changes presented.

5.7 Static Cartographic Conventions

As cartographers continue to use the dynamic domain for portraying spatiotemporal data, the concepts and conventions that are "tried and true" in the static domain may not be acceptable for use in the dynamic domain. One example of this is the number of classes used in an animated choropleth map. In the static domain, it has been convention to use five to seven classes to design maps appropriately for the map reader's perceptual system (Slocum *et al.*, 2009). However, Harrower (2003) and Goldsberry and Battersby (2009) note that when using this number of classes, 1) the reader only has a limited amount of time to take note of the geographic pattern in the animated map before a change (Harrower, 2003) and 2) the number of possible transition behaviors increases exponentially with the number of classes in the animated choropleth map (Goldsberry and Battersby, 2009).

Similarly, ColorBrewer (Brewer and Harrower, 2002) color schemes have been proven to allow cartographers to create visually appealing maps, as well as account for colorblindness, the color limitations of different visual media, black and white

conversion, and allow map readers to distinguish between the different colors easily. However, these colors were also designed to allow for map labels and thus the color schemes do not span the entire lightness ramp (from the darkest version of a hue to the lightest version of a hue). Differences between the colors may not be as noticeable as they need to be in the dynamic domain. For example, in a tweened map there must be enough difference between the colors for the map reader to notice, attend to, and perceive the change, also called a *just noticeable difference* (JND). More research is needed to explore JND's to create more effective tweened animated displays.

5.8 Attention and its Impact on Change Detection

Previous change blindness research in psychology suggests that attention is needed for change detection (e.g. Rensink, 2002). In this thesis research, participants were not given any cues as to where a change would occur. One possible solution would be to alert map readers of an upcoming change. In fact, one participant indicated that she would appreciate being told where to look in the map to help identify and decode the changes. Similar to the highlight rectangle used in this thesis experiment, one could imagine several of these rectangles appearing prior to the change to direct the map reader's attention to places in the map where change will occur.

Robinson (2009) has suggested seven methods to highlight specific display elements within interactive displays (Figure 31). Although, these ideas were designed to direct attention across displays with multiple views, they could also be used to represent change in dynamic cartographic displays explicitly. Of the seven highlighting techniques

that can be used to direct attention in multi-view displays, six of these methods could potentially be used to signify change in these animations explicitly:

1. **Color-** can be used to symbolize change with the adjustment of the fill or the stroke color,

2. **Depth of Field-** used in photography to adjust areas in and out of focus. Gives a pop-out effect of the in-focus/highlighted unit,

3. **Transparency-** adjustment of the alpha value for non-highlighted units. Gives the effect of pop-out of the highlighted unit,

4. **Color Desaturation-** desaturation of non-highlighted units. This works in color maps by "graying out" all non-highlighted units,

5. **Contouring-** applies contour lines to the outside of the highlighted unit. This produces a similar effect as the color highlight but potentially decreases the impact of simultaneous contrast,

6. **Style Reduction-** can be used when all units have a particular style applied to them by removing that style from non-changing units when a change is about to occur. Robinson uses the example with labeling where all the units of a choropleth map are labeled and to highlight a particular unit, all of the labels are removed except from the "highlighted" unit.
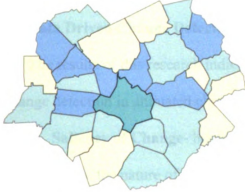
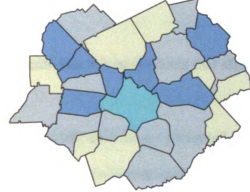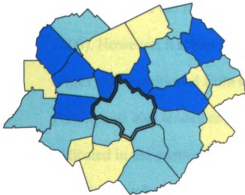# Robinson's Highlighting Methods
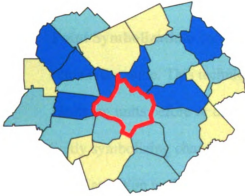
1. Color

2. Depth of Field

3. Transparency

4. Color Desaturation

5. Contouring

6. Style Reduction

Figure 31. Robinson's highlighting methods. These methods could potentially be used to direct attention to specific changes to help mitigate cartographic change blindness.

One additional method can be used to denote a change not included in Robinson's (2009) set of highlighting methods:

7. **Point Symbolization-** can also explicitly denote whether a unit will change or remain the same. This technique works by placing a point symbol on each of the changing units before or during a change.

By explicitly symbolizing change during transitions, cartographers may be able to direct map readers' attention to the changes and increase change detection.

5.9 Data Driven Change Detection Effects

The results of this research indicate that several data driven elements that affect change detection in animated choropleth maps:

1. **Saliency of Change-** based on the cross-classification arrays presented in this thesis, the nature of a given change affects detection in animated choropleth maps. It was expected that more drastic changes would elicit higher change detection rates because of the indications from previous research (Williams and Simons, 2000). However, it seems that map readers often are confused as to whether the origin unit transitioned from the adjacent class or from a more distant class. Participants also tended to look at the dark areas more often than the light areas as indicated in the posttests and tended to notice an onset or offset of the darkest color in the scheme during a transition event. While cartographers cannot fully control this data driven effect, they should beware of the implications of using lightness based color schemes and realize that darker colors appear more salient to map readers against a white background.

2. **Spatial Location-** some participants in the study noted that during the experiment they spent their time focusing on the center of the map or at least a specific region within the map. Cartographers must realize that only one change can be detected at a time (Rensink, 2002), and only four to five places can be attended to at any given time making change detection outside of the attended area difficult. If changes occur outside of this area of fixation, cartographers must determine a way to direct attention to those changes.

3. **Relative Size of Changing Area-** the size of the unit compared to its surrounding units could potentially affect change detection in animated choropleth maps. For example, it may be easier to notice a change in a large unit surrounded by several small units, than to see change in a small unit surrounded by several larger units, or when all the units are the same size. Attention must be directed to units that are smaller than surrounding units or else changes may go unnoticed.

4. **Overall Direction of Change-** this is the effect of the overall change in the map on change detection in a particular unit of the map. For instance, if most units in the animated choropleth map increase, it may imply to the reader that in general the data increased across the map. In this experiment, there were several years where the magnitude of change was high and many of the units changed in the same way. One would assume then that all of the units changed in the same direction (all increased or all decreased), however, in some cases, this was not always true. Map readers may have a bias to answer a question in a certain way based on the overall direction of the change. Participants also seemed to find it

easier to detect changes when there was one prominent color change on the map based on posttest responses.

5. **Change in Neighboring Areas-** Harrower's (2007) animated simultaneous contrast indicates that changes in neighboring units of an animated choropleth map affect the apparent change in a particular unit. This problem affects overall change detection as well as the different levels of change detection noted by Goldsberry and Battersby (2009). If apparent motion or changes in surrounding units affect the perception of change in a neighboring area, it might be safe to assume that this also affects the perception of *how* a particular place is changing.

6. **Magnitude of Change-** in animated choropleth maps, many changes can occur during a single scene transition. The number of changes that occur during one transition event is defined as the magnitude of change. Despite the multiple changes that occur during a transition event in an animated choropleth map, map readers can only perceive one change at any given moment (Rensink, 2002). One participant in this study noted that it was very difficult to identify the particular change of the highlighted unit because so many changes happened at once. In animated thematic maps cartographers can limit the magnitude of change by choosing a limited number of classes. Harrower (2003) suggests using between two and three classes because of the limited amount of time the map reader has to encode the information.

5.10 Duration Effects

Along with testing change detection in animated choropleth maps, this study also evaluated the components of animated maps the cartographer can control. Cartographers have full control of the pace and speed of the animated through the use of duration. In these types of maps there are two types of duration available to the cartographer: duration of static scene and duration of the transition. DiBiase *et al.* (1992) defined duration as the amount of time devoted to static scene display. However, as tweening and smooth transitions become easier to implement in animated maps, it has become the cartographer's job to take into account both duration of the static scene as well as duration of the transition. The results of this thesis indicated that duration of the transition may be important for change detection, limited duration of the static scene may not give our map readers enough time to view the static scene.

1. **Duration of Transition** - the duration of the transition affects animated choropleth map reading and specifically change detection. In this thesis, when the duration of the transition was increased, SDT indicated that participants had an easier time distinguishing a change. Smooth transitions may not always allow for the greatest accuracy of detection; however, these congruent representations of some spatiotemporal data, do not elicit the same bias to indicate there was a change, thus false alarms were lowest for these types of transitions. It still remains unknown how these smooth transitions affect accuracy of detecting a change at higher levels.

2. **Duration of Static Scene-** the duration of transition also has an effect on change detection in animated maps. The results indicate that transitional design affected

apprehension of change in animated choropleth maps. All of the conditions in this experiment had an equal amount of time devoted to the entire animation from initial onset to the appearance of the question; however, duration of the static scene varied for each of the condition designs. Research in psychology has shown that the time given to encode the information before the change affects the amount of information that is encoded (Hollingworth *et al.*, 2001). It is important that map readers are given adequate time to view the static scene before the change due to the effects of this type of duration on change detection abilities, although the SDT analysis indicates that this may not affect map reading as much as the psychological literature suggests.

5.11 Limitations

This study included some important limitations, however the results still provide valuable incite into the change detection abilities of animated choropleth map readers.

5.11.1 The Splat Contingent of the Highlight Rectangle

The visual onset of the red rectangle at the end of the transition in this study may *cause* change blindness. In the Abrupt Condition, a delay of 250 milliseconds was added between the onset of the second map scene and the onset of the rectangle. However, this delay may not be enough time to avoid the "splat contingent" of change blindness (O'Regan, *et al*, 1999). Finally, no delay was added for either of the smooth transition conditions.

5.11.2 Spatial Location of the Highlighted Unit

In this experiment, 36 of the 64 units in the map were highlighted three times after a transition. The experiment was designed so these 36 units were not clustered in one particular area of the map. Instead, the goal was to have the highlighted unit appear in many different places across the map. However, the cross-classification arrays indicate that some change characterizations had relatively high accuracy rates while some had very low rates. Low rates may be related to the spatial location of the highlighted unit. For example, the transition from the "highest" class to the "lowest" class resulted in a 12% accuracy rate for Question Type #2 (Change Detection Level 3). The highlighted unit for these particular questions was located on the periphery of the map and none of the questions about this type of change were located in the center of the map.

5.11.3 Transitional Behaviors

During the experiment, only one question was asked about the transition from the "high" class to the "middle" class for Change Detection Level 3 questions. The change detection rate was only 9% for all participants for Change Detection Level 3 and may be explained by the lower n for this type of change ("high" to "middle") than for all of the other types of change. The particular unit highlighted for this type of change was also on the periphery of the map and thus could be easily missed. It would be ideal in future experiments, to have more questions about each of the nine possible transition behaviors to avoid problems such as this in similar experiments.

5.11.4 Static Scene Duration

This experiment was controlled for the total duration of the animation from first onset to the appearance of the highlight rectangle and question (Figure 32). However, the

time given to view the static scene before the transition varied by condition. The Abrupt Condition had the longest static scene duration (two seconds), followed by the Delayed Smooth Condition (one second), and finally the Continuous Smooth Condition (nearly zero). According to previous research in psychology, the amount of time given to encode information is directly related to the amount of information the map reader is able to retain after the change took place (Hollingworth *et al.*, 2001). It would be useful to design a future study where duration of the static scene was equivalent across conditions (Figure 33).
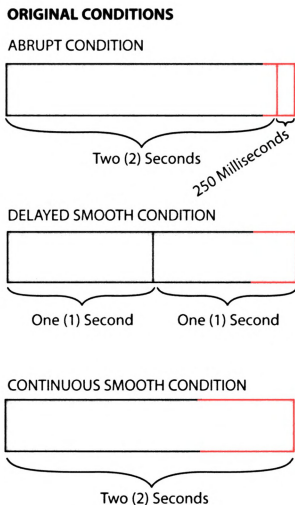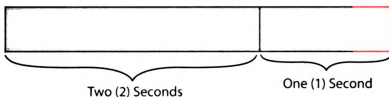

Figure 32. Original conditions. Total duration for all conditions was equal, but duration of the static scene and the transition were unequal.

PROPOSED CONDITIONS

DELAY WITH SHORT TWEEN

Two (2) Seconds   One (1) Second

DELAY WITH LONG TWEEN
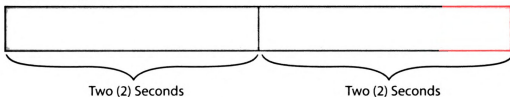

Two (2) Seconds   Two (2) Seconds

Figure 33. Proposed conditions. Total duration for all conditions was unequal, but duration of the static scene was unequal.

5.11.5 Hits versus Correct Rejections

In this study, the results indicated that there was a difference in accuracy when there was a change to detect (hits) versus when the participant was required to detect a persisting behavior (correct rejections). In similar psychology studies, correct rejections are often ignored and only hits are counted. However, in this type of change detection, it is not only important to notice a change, but also to notice a persistence behavior between map scenes. For example, in an animation of the Red-State, Blue-State map, between the years 2000 and 2004, only three states changed from red to blue or vice versa. However, while these three states changed, it is also important to note that 47 states did not change. In these types of maps, persistence is meaningful. In this particular example, it means that 47 states did not have a significant change in political affiliation to change the electoral votes for those states. This study suggests that persistence between map scenes (correct rejection) was easier to distinguish than when there is a change (hit). However, in this

study there were more questions were the correct answer was a hit rather than a correct rejection. This could have an effect on the results because a blindly guessing participant would be more likely to get a higher correct rejection score than hit score. This also may account for the high false alarm rate across the entire experiment.

5.11.6 Magnitude of Change and Map Complexity

This experiment tested change detection when viewing an animated choropleth map with 64 enumeration units each exhibiting one of nine unique transition behaviors. Several participants found it difficult to detect changes with the high number of units in the map, as well as the large magnitude of change that occurred between many of the map scenes. In this experiment, the lowest magnitude of change was 11 units, and the highest magnitude of change was when 41 of the 64 units changed. These high magnitudes of change are a result of the underlying data as well as the classification scheme and the number of classes used. The data used to create these maps was yearly average unemployment data between 1990 and 2008. Unemployment can change dramatically in short periods of time, and in these particular years for this geographic place, unemployment was very dynamic. The data was classed using a quantile classification scheme where the same number of data points are placed into each the classes. This scheme was appropriate to avoid empty classes and a skewed distribution, but may have been a major factor influencing the high magnitude of change in these animations. Finally, it would have been more appropriate to limit the overall size and complexity of the map by limiting the number of units in the map to a number less than 64.

5.11.7 Congruent Data Representations

Battersby and Goldsberry (2010) argue that classed maps should not be tweened because it implies there is a smooth transition between the two classes, when in fact there no gap between two classes of a classed choropleth map, thus interpolation is unnecessary. This study used tweening for a classed map and may have caused confusion for the study participants.

5.11.8 Animated Simultaneous Contrast

Harrower (2007) extended the idea of simultaneous contrast a well-known problem in static maps to the animated domain. This idea of simultaneous contrast occurs when a particular unit in a choropleth map perceptually shifts in color due to the different colors of the surrounding units. For example, dark units tend to appear darker when surrounded by light units, and light units appear lighter when surrounded by dark units. Harrower suggests the idea of "animated simultaneous contrast" is when a particular unit may look as though it is changing more or changing less because of the apparent change in the units surrounding it. For example, one unit may persist throughout an animation, but if many drastically changing units surround that unit, it may appear as though the persisting unit is changing too. In Harrower's study, participants evaluated change in a small area of a choropleth map. His participants noted how the change in the surrounding areas affected their abilities to answer the questions in his study. Animated simultaneous contrast can lead to misinterpretation of changes in the map.

In the case of this experiment, the maps were created with real unemployment data, thus there were instances where some units persisted throughout the 18 years used in the animation. In other cases these units were surrounded by drastically changing units

that may have affected the change detection abilities of the participants in this study. Basically, map readers may not understand how unemployment shifted or persisted because the enumeration unit in question may be surrounded by units that change differently from it.

5.11.9 Map Tasks

It should be noted that this study only tested one particular map task; participants were required to notice change in one enumeration unit during a singular complex transition. This map task may be more difficult than some other map tasks for animated choropleth maps and could in part explain the low detection rates presented here. Other map tasks include evaluating one unit over many transitions times, many units between two times, or many units over many times. Detection rates may differ when readers are asked to perform other map tasks. In general, however, as a form of geovisualization, the goal of these maps should be to allow users to search for unknown patterns that would not be apparent in any other way. Change blindness, however, may seriously limit to the goal of these types of geovisualizations.

5.11.10 Signal Detection Theory for Three Choice Answers

Finally, signal detection theory as it was used in this thesis is designed for only two- choice answers. In the yes/no questions, d' and c were conclusive that the Continuous Smooth Condition allowed for the easiest discriminability of the change from the noise, while the Abrupt Condition produced too much noise for the participants to correctly select the answer. Instead in the Abrupt Condition, participants were biased to select "yes" because of the amount of noise leading to the large amount of correct rejections for this condition. In the three-choice questions, d' and c did not give a clear

answer because SDT failed to take into account the differences in wrong answers.

Basically, as it was calculated, all wrong answers were lumped together, however, Figure

28 illustrates that it seems that participants had a bias to indicate that the enumeration

unit had transitioned from the neighboring class. Further SDT analysis is needed to fully

understand how participants were biased in these questions.

Chapter 7
CONCLUSION

Change blindness is a serious problem that limits the effectiveness of dynamic geovisual displays. As cartographers we are unable to control the actions and transitions in animated maps completely because of the inherent tie to underlying geographic data. Thus many changes may occur during a single scene transition. However, the realistic depiction of real world data changes may require more cognitive power of map readers than humanly possible. As Harrower (2007) states, the limits of computing are no longer a problem for the development of these types of displays, it is the limited cognitive capacity of our map readers that potential undermines these new ways to represent data. Finally, it is the connection to underlying spatiotemporal data that requires map readers to perceive more than just simple changes between scenes of a map animation. In other words, map readers must fully comprehend the meaning of the change to understand the change in the worldly phenomena it is depicting.

The results of this empirical study have revealed that people are surprisingly poor at detecting changes in animated choropleth maps. This thesis has also shown that map readers are not only poor at detecting basic changes, but also are unable to detect changes at higher levels. In recent years, several researchers have suggested gradual transitions as a potential strategy to mitigate change blindness (Goldsberry, 2004; Fabrikant *et al.*, 2008); however, more analysis is needed to understand how gradual transitions affect change detection especially at higher levels.

More research is needed to understand how to design these maps to allow for better apprehension of cartographic change. Previous research suggests that interactivity may help to alleviate problems such as change blindness. However, these findings

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suggest that interactivity may not solve these problems because map readers are not only

missing changes in these displays, they are confident they did *not* miss them. In effect,

interactivity may not be enough to make these types of displays understandable. Based on

the findings in this thesis research, these questions deserve further attention:

- **Can change detection be improved by cueing map readers to a particular place within a dynamic display?** Previous research suggests that attention is necessary for accurate change detection (e.g. Rensink, 2002). By cuing our readers where to look we are directing their attention to where a change may or may not occur. This way our readers are not fruitlessly searching for a potential change in a relatively large visual area. Robinson's (2009) highlighting methods may provide potential ways to cue our readers' attention to a specific place within these types of displays.

- **What is the effect of changing the duration of the static scene?** In this study, each condition controlled for duration of the entire animation from the onset of the first scene of the animation to the onset of the question and the red highlight rectangle. However, research suggests that the amount of time given to encode information affects how much of the scene before the change can be retained after the change (Hollingworth *et al.*, 2001).

- **Could stabilizing the rate of change (Goldsberry, 2004) affect change detection in animated choropleth maps, by adjusting the duration of the transition based on the magnitude of change?** Many participants felt they would more easily apprehend changes in the display if less changes happened at once. In other words, they felt the magnitude of change was too high. Often the cartographer cannot adjust magnitude of change, however, by increasing the duration of the transition when there is a higher magnitude of change may help to improve change detection in these types of maps.

- **How well do map readers apprehend changes in other types of dynamic maps?** While animated choropleth maps present a fairly obscure mapping technique, this change blindness phenomena could also extend to maps where missing a change has more serious consequences. The use of static navigation maps has decreased significantly as use of electronic in-vehicle navigation units have increased. These devices require the user to be aware of display changes that occur to make key way finding decisions. In-vehicle navigation units also cannot always be the focus of the user's attention. If a driver is confused because of change blindness, wrong turns could be made, and potentially life-threatening consequences could ensue. Testing change detection abilities for these types of maps and others may provide insight into how changes in different types of maps are comprehended.

- **Can we create maps that express the difficulty of perceiving the changes for our map readers?** This study indicates that despite missing a large percentage of changes in these types of maps, confidence in change detection was still high. This potentially undermines the use of interactivity, allowing map readers to go back and replay the animation. There may be better ways to design these maps so our map readers understand how unlikely it is that they have correctly comprehended the full meaning of these types of maps.

Perception of change in animated map displays is fundamental to map cognition and understanding. As cartographers and map readers continue to use these types of maps to portray spatiotemporal information, it is essential that map designers attempt to alleviate some of the stress on the cognitive limits of map readers by creating more easily understood and perceived animated maps. Cartographers must generate more effective animations and make an effort to reduce change blindness in animated choropleth maps.

APPENDICES

CONSENT FORM

Research Participant Information and Consent Form

You are being asked to participate in a research project on animated map reading. This study is being conducted by Carolyn Fish under the direction of Drs. Kirk Goldsberry and Judy Olson. Participation in this study is completely voluntary. This document provides information about the study so you can make an informed decision about whether you would like to participate. You should feel free to ask the researchers any questions you may have.

Evaluating Human Change Detection in Animated Maps

Carolyn Fish, Graduate Student
Kirk Goldsberry, Assistant Professor
Judy Olson, Professor Emeritus

Department of Geography
Michigan State University

116 Geography Building
Michigan State University
East Lansing, MI 48824

1. PURPOSE OF RESEARCH:

This study evaluates how well humans detect changes in animated maps. Often humans miss the changes between two scenes in a map animation. From this study, the researchers hope to learn how different ways of animating may allow for you to better see those changes. Your participation in this study will take about 30 minutes of your time.

2. WHAT YOU WILL DO:

You must be 18 years of age or older to participate. If you agree to participate in this study, you will be asked to complete: a pretest, training session, test, and a posttest. In the pretest you will be asked simple questions about your age and gender. In the training, you will learn about map animations, the types of questions you will be asked in the test, and how to answer these questions using the software. In the test you will answer approximately 100 questions about the changes you saw in the simple map animations. In the posttest you will indicate to the researcher what you thought of the test and how you think it could be improved.

3. POTENTIAL BENEFITS:

You will not directly benefit from your participation in this study. However, your participation in this study may contribute to the understanding of human change detection in animated maps.

4. POTENTIAL RISKS:

The potential risk to you is minimal. At the most, participation in this study will result in fatigue, due to the number of questions and the length of time it will take you to complete this study.

5. PRIVACY AND CONFIDENTIALITY:

In this study, your name will not be connected with your answers. Only the consent form will contain your name and it will not be connected with the answers you give in the test. Your answers in the test may be presented at professional meetings or used in publications, but your identity will remain anonymous.

6. COSTS AND COMPENSATION FOR BEING IN THE STUDY:

You will not incur any cost for participating in this study. You will be compensated $10 for completing your participation.

7. YOUR RIGHTS TO PARTICIPATE, SAY NO, OR WITHDRAW:

Participation in this research project is completely voluntary. You have the right to say no. You may change your mind at any time and withdraw. Your answers will then be destroyed and will not be included in the data for the study. If you chose to withdrawal from the study, before completion, you will not receive the $10 compensation. You will not, however, be penalized in any other way.

8. CONTACT INFORMATION FOR QUESTIONS AND CONCERNS:

If you have concerns or questions about this study, such as scientific issues, please contact the researcher Carolyn Fish (Graduate Student, Department of Geography, Michigan State University, 116 Geography Building, East Lansing, MI 48824, cfish11@msu.edu, 517-353-9940) or Dr. Kirk Goldsberry (Assistant Professor, Department of Geography, Michigan State University, 116 Geography Building, East Lansing, MI 48824, kg@msu.edu, 517-353-0308) or Dr. Judy Olson (Professor Emeritus, Department of Geography, Michigan State University, 116 Geography Building, East Lansing, MI 48824, olsonj@msu.edu, 517-353-8757).

If you have questions or concerns about your role and rights as a research participant, would like to obtain information or offer input about those rights, or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, Fax 517-432-4503, or e-mail irb@msu.edu or regular mail at 202 Olds Hall, MSU, East Lansing, MI 48824.

9. DOCUMENTATION OF INFORMED CONSENT

Your signature below means that you voluntarily agree to participate in this research study.

_____

Print Name

_____   _____

Signature   Date

Please keep one copy of this form for your records.

Map Study- Pretest questions

1. Have you taken this test before? If yes, please raise your hand and inform the researcher. If no, please continue on to the next question.

2. Please indicate your gender (circle 1):   Male / Female

3. What year are you in school:

   a. Freshman

   b. Sophomore

   c. Junior

   d. Senior

   e. Grad Student

   f. I am not in school

   g. Other

4. Do you wear glasses or contacts? (Circle one) : Yes / No

5. Are you colorblind?

   a. Yes

   b. No

   c. Unsure

6. Do you play video games?

   a. Often (more than 5 times a week)

   b. Sometimes (between 2 and 5 times a week)

   c. Rarely (less than once per week)

   d. Never

7. How often do you use the computer?

    a. Often (more than 5 times a week)

    b. Sometimes (between 2 and 5 times a week)

    c. Rarely (less than once per week)

    d. Never

8. What is your age: _____

9. What is your major? _____

An animated map is a map that shows change over time. The most popular type of animated maps are TV weather maps like you might see on your local news channel. These maps show how the weather is changing in a given place over a period of time. These maps can be interactive, such as those you might see on a weather website, which allow you to stop, slow or adjust the animation. However, not all animated maps are interactive. Also interactive maps are not necessarily animated. For example, online navigation maps (e.g. GoogleMaps or MapQuest) are often interactive and allow you to adjust them, but do not move on their own. (The maps you will see in this test will be animated but not interactive).

10. Have you ever seen an animated map?

    a. I have never seen an animated map

    b. I am familiar with animated maps

    c. I have made animated maps

11. If yes, where have you seen animated maps? (circle all that apply)

    a. TV weather maps

    b. news media

    c. online (world wide web)

    d. as a part of course material

    e. other, explain: _____

12. Have you ever used an interactive map?

    a. Yes

    b. No

    c. Unsure

13. If yes, where did you use one? (circle all that apply)

    a. online (world wide web)

    b. as a part of course material

    c. other, explain: _____

Thank you for your participation!

| Continue |

This is a test designed to understand how people read and see changes in animated maps.

| Go Back | | Continue |

You will not recognize the geographic place used for this test.

Do not worry about trying to figure this out, it is unimportant for this study.

| Go Back | Continue |

This training session will introduce you to the maps you will see and the types of questions you will encounter during the test.

| Go Back | Continue |

You will see three different question types
throughout the test.

For each question, you will see a map and will
be asked a question about the change you
saw while viewing the animation.

The map you will see will look similar to the
county map shown below, however, it will
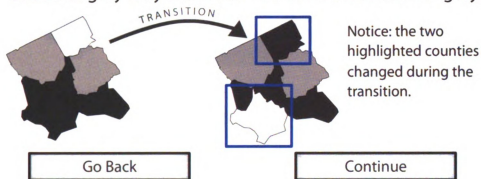have more counties.

While you watch the county map, some of
the counties will transition in **color**.

For example, a county that starts out as the lightest
shade of grey may transition to the darkest shade of grey.

TRANSITION

Notice: the two
highlighted counties
changed during the
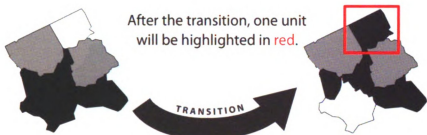transition.

| Go Back |
| Continue |

After each transition, you will be asked a
question about the changes that you see
after the transition.

Make sure to try your best in answering
all of the questions.

| Go Back |
| Continue |

Question Type #1

After the transition, one unit will be highlighted in red.

Then you must decide whether the unit changed color by selecting "Yes" or "No".

Go Back		Continue

Now let's try a practice question.

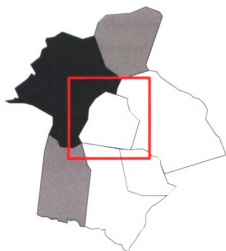| Go Back		Continue

Practice Question #1
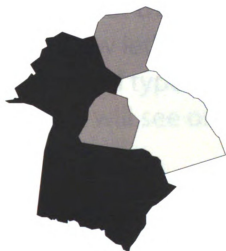
Practice Question #1

Did the highlighted unit change between scenes?

Yes   **No**

Great that's correct!
Now let's look at the
second type of question
you will see on the test.
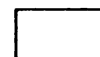
Go Back	Continue

Question Type #2

This question type is the similar to question type 1, except that the question is a little more complex.

After the transition, you must decide how the unit changed color by selecting one of the three possible colors

Please indicate the color of the highlighted unit before the scene change:

Go Back	Continue

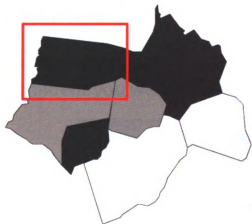Now let's try another practice question.

Practice Question #2

Please indicate the color
of the highlighted unit
before the scene change:

Great that's correct!
Now let's look at the
third type of question
you will see on the test.

| Go Back | | Continue |

Question Type #3

The third question will consist of a confidency scale and will follow every question in the test.

After each of the questions, you will be asked to rate how confident you were about your answer.

Confident   Neutral   Unsure

Go Back	Continue

Now, let's try a couple more questions that are more similar to the type you will see on the test.
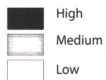
Go Back	Continue

Did the highlighted unit change between scenes?

Yes   No

High
Medium
Low

How confident are you about your answer?

Confident   Neutral   Unsure

Great, you are correct!
Let's try just one more practice question.

Go Back	Continue

Please indicate the color
of the highlighted unit
before the scene change:

High
Medium
Low

High
Medium
Low
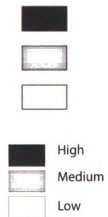
How confident are you about your answer?

Confident   Neutral   Unsure

Great,
now you are ready to begin the test.

| Go Back | | Continue |

Map Study- Posttest questions

1. Have you ever taken a test like this before?

    a. Yes

    b. No

    c. Unsure

2. Did you feel that the training session of this test was useful to you in learning how to take the test and introducing you to the types of questions you answered?

    a. Yes

    b. No

    c. Neutral

3. Was it easy to navigate through the test program?

    a. Yes

    b. No

    c. Neutral

4. What was your overall strategy to try to identify the changes?

    _____

    _____

    _____

5. Did you feel that there were some maps that allowed you to detect the change between scenes easier? Describe.

_____

_____

_____

6. Did you feel that some of the maps transitioned slower than others? If so, do you think that some of these maps allowed you to more easily detect the changes?

_____

_____

_____

7. Did you feel that some of the maps had smoother transitions than others? If so, do you think that some of these maps allowed you to more easily detect the changes?

_____

_____

_____

8. Do you have any other comments that might help to improve the test or the design of the maps?

_____

_____

_____

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