A Raster-Based Neighborhood Model for Evaluating Complexity in Dynamic Maps

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ABSTRACT: The cartographic community has taken a renewed interest in evaluating the effectiveness of automated map displays, given their increasing prevalence among general map users. The changing values of the mapped area from frame to frame in a dynamic thematic map constitute its main element of visual complexity, while many of the peripheral map components often change little (titles) or not at all (scale bars, color ramps). Building on recent research into visual complexity as it relates to dynamic thematic mapping, this study developed a raster-based GIS model for evaluating the graphical variability between sequences of choropleth maps as they would appear as scenes in a dynamic map. The evaluation of visual complexity is based on two previously established metrics, Basic Magnitude of Change (BMOC) and Magnitude of Rank Change (MORC), for describing the variability and average class 'jump' for enumeration units across map scenes. The model presented in this paper uses a neighborhood focal operator that sequentially moves across the entire map, replicating the user's viewing perspective as it divides the scene to instantaneously focus only on the part of the map within the foveal viewing area, a zone of enhanced visual-cognitive acuity. This model accepts a single vector map, uses its class membership attribute data as inputs, computes the BMOC and MORC variability, and writes the value to the focus. The model output is two smoothed map images depicting relative visual complexity values for the sequence of maps. While the neighborhood paradigm can theoretically be used to quantify change on either a vector or raster map, the raster-based approach suggests several improvements over one based on vector polygons. These include a potentially higher degree of accuracy in modeling the user's perspective, especially if enumeration units vary widely in size within the foveal area and map itself, plus the ability to use (with minimal customization) existing image-processing software such as ERDAS Imagine, ArcGIS Spatial Analyst and ENVI to perform analysis of dynamic map complexity.

KEYWORDS: dynamic maps, foveal area, change blindness, neighborhood operators

Introduction

Visualization and dynamic map design are two of the most active research fields in modern cartography. This is not surprising, given the prevalence of increasingly sophisticated hardware and software, access to cloud-computing resources via the Internet , and the immense quantities of geographic data that are currently being collected, such as high-resolution remotely-sensed datasets. Today, while technological capabilities exist for processing these datasets, what is now needed is investigation into improved ways to synthesize these spatial data into forms that allow scientists to effectively analyze and model complex systems such as global-scale atmospheric circulation models. The need for advanced visualization techniques for exploratory data analysis, and for scientific research such as epidemiological mapping is great, and has driven visualization research since its early days (DiBiase et al. 1992).

However, there is an emerging area of visualization research that is tailored to a different audience – that of the casual map user. 'Casual' refers here to non-scientists such as the citizen accessing the local municipal online GIS service, the high-school student researching a term paper, the voter interested in past election returns, or the visitor to the US Census website. While variation does exist within this group with respect to age, socioeconomic status, education level and other characteristics, its members tend to have two things in common. These are a) the probable lack of a specialized background in data analysis or the sciences, and b) a limited amount of time to devote to the task (i.e., they are not being paid to analyze the data, as a researcher may be). For these users, the Internet is the medium through which most digital spatial data is accessed, and thus the digital web map, in either static or animated form, is often the method of spatial data presentation most commonly encountered by these users in their investigations. It has been argued that map animations more congruently depict change in spatial phenomena with respect to time than do static maps (Slocum et al., 2009). While researchers and data analysts typically explore the complex interrelationships among numerous variables in the course of their work, casual map readers are more often exposed to displays that map a single variable. To be effective in communicating both general trends and specific information to these casual users, cartographic complexity may have to be sacrificed for the sake of clarity and ease of interpretation. One method does not ‘fit all’ users when it comes to dynamic geovisualization.

Since this paper focuses on using raster-based GIS modeling to evaluate complexity in dynamic choropleth maps, a distinction must be made here: the term ‘dynamic map’ or interactive map can also refer to other types of non-static maps, such as digital thematic displays in which the user clicks on or ‘mouses’ over a polygon to access more detailed information about a specific area, often in the form of a ‘bubble’ or small data table. These are fundamentally different from the type of map animation examined in this study.

Due to the fact that dynamic – or animated – maps are often (although not always correctly) the medium of choice for communication with casual users, the topic of designing effective animated maps has received increasing attention in the literature, especially during the past decade. This research has begun addressing the issue of temporal constraints, cognitive load and complexity with respect to these animations’ interpretability by map users. It appears possible that rapidly advancing technology for creating animations (plus wider access to these techniques by non-specialist amateur cartographers) risks conflicting with what has been termed the ‘bottleneck’ of the map user’s finite cognitive capacity (Harrower, 2007). This is exacerbated by the very nature of animation, since each scene follows the previous one at a fixed pace that is often not directly controllable by the user. Some have suggested that VCR-type controls can give users more control over the animation’s pace (Harrower, 2003), but others argue that this control – pausing the animation to allow fuller absorption of information – degrades or removes altogether animation’s chief benefit of temporal congruence, effectively turning the animation into little more than a set of small multiples (Harrower and Fabrikant, 2008). Still others have questioned the general effectiveness of animation (Tversky et al., 2002).

Although the most recognizable animated web map is probably the weather map, the choropleth map is also a common dynamic map type in web displays, and is a popular means of presenting a single geospatial theme to users. Interestingly, its use in dynamic displays presents several important issues that must be addressed (it is outside the scope of this paper to address the questionable usage of choropleth maps - static or dynamic - to depict inappropriate data distributions.). One notable aspect of the dynamic choropleth map is that, unlike an animated isoline, dot-density or proportional symbol map, its spatial arrangement (i.e., its polygon structure) is usually fixed throughout the animation, while the values of the mapped variable change or persist according to their spatio-temporal distribution. Thus, the change in the class (which here means lightness or hue) of the polygons that represent the enumeration units of its mapped area is the animated choropleth map's chief element of inter-scene complexity. While it could be argued that reducing the number of volatile elements may make choropleth animations easier to understand, static choropleth maps have in fact been found to be slightly more 'complex' than isoline maps for representing identical datasets, especially for communicating general spatial trends (MacEachren, 1982b). Moreover, both cartographic research (Fish et al., 2011) and the cognitive psychology literature (Levin et al., 2000; Rensink 2002) have shown that humans are susceptible to 'change blindness,' or the inability to detect surprisingly large graphical changes from one scene to the next. The topic of change blindness is especially germane to the study of choropleth map complexity since, with polygonal extent fixed and no visual cues present other than (the sometimes-subtle) lightness change, it is possible that polygons may change class during an animation without the reader's noticing. This is especially important in animations containing both large and small polygons, whether regionally stratified or intermixed. On the other hand, it is also possible for animated choropleth maps to show the movement of a cluster over time, and, if visually salient, this movement may attract a viewer's attention. This allows the anticipation and prediction of its next location in each successive frame in an animation (Griffin et al, 2006).

It seems reasonable to assume that a map viewer can visually attend to only a limited number of change events or mini-scenes during even a short animation, particularly if the extent of the mapped area is large. One example of this would be a web map of US states that occupies half of a typical-size computer screen – in this case, a user focusing on class change in New England may not notice similar change in Oregon, since it is likely taking place in the user's peripheral, vs. foveal, vision. Obviously, this is not a major issue if either of the following is true: a) the viewer focuses on one area (such as a home state's population change) during the entire animation to the deliberate exclusion of all other areas, or b) the viewer has prior knowledge of the data's distribution or temporal trend, and is viewing the animation only to confirm this knowledge. In either case, the viewer's cognitive load is significantly diminished. Scale plays a role here since, to continue with the example given above, changes in both New England and Oregon might achieve a similar level of visual and cognitive salience if the map's extent was instead shrunk to 7 cm across. For this paper, it is assumed that the map reader is a casual user viewing an animation to learn the general trends in a dataset rather than specific values, and the complexity of animated choropleth displays is here evaluated specifically for these users.

Issues of change blindness, cognitive load and general pattern recognition have led researchers to create two magnitude of change (MOC) metrics for quantifying localized inter-scene complexity of animated choropleth maps, and to propose models that evaluate adjacent animation scenes using these metrics in a vector-based modeling environment (Goldsberry and Battersby, 2009). Their work with these metrics forms the starting point for this paper, and will be reviewed in more detail below. Building upon their work, the purpose of this study is twofold: 1) it applies the same MOC metrics, but in a raster environment, and 2) it uses ArcGIS's Model Builder to make the model easier to use, requiring less input from the user, and thus, less potential for user error. The format of this paper will be as follows: section one introduces the topic, then a brief review of relevant literature in section two will be followed in section three by an outline of the requirements and methods of developing the raster model. Section four discusses the differences between the results of the vector and raster output for similar datasets as well as ways to compare these results, and section five concludes by summarizing key points and suggesting paths for future research.

Literature Review

Static Map Complexity

While study into designing effective animated maps began at least as far back as Norman Thrower's brief 'how-to' guide (Thrower, 1959), the bulk of research into map complexity prior to the late 1990s involved the study of static maps. This reflects the technical limitations of the nascent digital era, which resulted in the relative scarcity of animated maps. The static map literature's importance in the current discussion cannot be understated, however, since all map animations can be understood as being composed of sequences of static maps, punctuated by transitions such as 'tweens' or 'wipes' (Battersby and Goldsberry, 2010). Moreover, the MOC metrics are deployed by the raster model on a static 'difference' map between two frames; this intermediate, 'imaginary' map is the actual input to the GIS model. Finally, many of the studies on map complexity have tended to focus largely on choropleth maps, making a comparison between these findings and those of the current study more meaningful.

What is complexity? MacEachren (1982a) distinguishes between two different sub-types: 1) graphical complexity, or how difficult it is for the map reader to visually decode the information presented in the map display, and 2) conceptual complexity, or how intellectually challenging the mapped variable is to comprehend. For example, an unclassed choropleth map representing burglary rates for the 50 states is one example that ranks rather high in graphical complexity (unclassed schemes generally take more time to interpret), but low in conceptual complexity (most people understand the concept of a burglary rate, and the term itself - as well as potential spatial patterns - is familiar to them). On the other hand, a classed choropleth map for the 50 states depicting ordinal classes of low, medium and high levels of out-of-wedlock pregnancies to women under age 30 as a percent of all such pregnancies presents exactly the opposite scenario. While such a map with three non-numeric classes of 'low', 'medium' and 'high' is easy to interpret graphically, its variable is more conceptually demanding – it takes a bit of time for many people to grasp. This study focuses mainly upon graphical complexity.

Castner and Eastman (1984, 1985), approaching complexity from a slightly different angle, employed eye-movement tracking of human subjects in a series of studies seeking to discover what drew a viewer's attention to a particular part of a map. Their methodology evaluated a set of simple choropleth maps using graph theory. Graph theory classifies objects or shapes according to the number of faces, edges and vertices in a graphical display, and provides a conceptually simple yardstick for comparing choropleth maps, since their vector polygon format uses these same topological elements. Castner and Eastman's metric of a map's complexity was entropy, and they compared highly-entropic regions within a map to higher 'hit' rates and longer dwell times from the eye-tracking analysis. Their research only considered the geometry of a map object (such as an enumeration unit), and did not address issues relating to color differences. Because much of the literature cited here combines geometry and color, this focus on graphical entropy is helpful in singling-out these effects (*inter*-scene complexity) from simple color changes (*intra*-scene complexity) in capturing the map reader's attention. Research into entropy was continued by Bjork (1996). Eye-movement research into dynamic map complexity using ‘gaze-maps’ has recently been performed by Fabrikant and colleagues (2008, 2010).

Steinke and Lloyd (1981, 1983) conducted a series of studies to compare three measures of a choropleth map’s graphical variability: correlation (‘similarity of overall map patterns’), blackness (‘similarity of the spatial units within greyscale map classes’) and complexity (‘class similarity of the neighboring spatial units’) (Steinke and Lloyd 1981, p. 13). The authors’ complexity coefficient measured the size of neighboring polygons of different class memberships, a methodology with roots in graph theory. Test subjects were found to judge map pairs’ similarity based first on blackness, then on correlation and complexity, using these researchers’ narrow definitions of the terms. It is assumed that the ‘blackness’ metric is not exclusive to greyscale maps, but could be applied to any monochromatic choropleth map as tonal ‘darkness’. The present study’s use of the term ‘complexity’ is semantically broader, encompassing all three of the above graphical attributes; however, by statistically quantifying graphical differences *between* choropleth maps, Steinke and Lloyd’s work probably has the most immediate relevance to the present study of the pre-animation research reviewed.

Distinct from the vector, choropleth map research trend, Olson (1975) used 10-by-10 grids of greyscale raster cells, in a study which compared their levels of spatial autocorrelation to human test subjects’ perceptions of their complexity. Based upon her study’s mixed results, she hypothesized that an objective quantification of map complexity may be difficult. Due to variability between individuals’ visual acuity and perceptive-cognitive capacity, arriving at measures of a graphic’s interpretability or complexity has proven elusive, and Olson’s cautionary opinion on the subject of seeking a use-anywhere quantitative yardstick of map complexity is significant.

More recently, Fairbairn (2006) took a new approach to investigating graphical complexity. Under the assumption that the more homogeneous the detail in the map, and the higher its proportion of ‘white space’, the more compressible it is as digital file, he created several vector and raster maps at three different scales apiece, and compared each map’s respective file compression ratio (using several lossless algorithms) to several measures of the intra-map variation. These measures included Shannon’s diversity and evenness indices, Moran’s I autocorrelation coefficient, and, for the panchromatic images, the ratio of black to white area. Using principal components analysis to narrow his results, he found that run-length encoding (RLE) file compression and spatial autocorrelation showed the strongest relationship (-0.91). One improvement to his study would be to see whether map readers’ opinions also were in agreement. However, file compression as a metric seems unlikely to work well for a choropleth animation’s individual frames, since whatever their level of complexity, compression ratios would probably be fairly constant since only the fill colors change from scene to scene.

At its time of publication, each of these studies significantly advanced cartographic knowledge, and each of them informs the current study. Although focused on static maps, they have much to offer in evaluating dynamic choropleth map complexity, since an animation ‘frame’ contains many of the same elements as a static map. However, of even greater value to this study is more recent scholarship in the field of animated map design.

Complexity of map animations

DiBiase and colleagues (1992) proposed the addition of three ‘dynamic visual variables’ to the seven developed by Bertin (1983) for static maps. These new variables were 1) Duration (how long each scene persists on-screen), 2) Rate of Change (the relationship between magnitude of scene change and the duration of that scene), and 3) Order (chronological, attribute or other). The MOC metrics under evaluation here measure Rate of Change. Duration and Order may influence interpretability and therefore the perceived complexity of an animation, but are not the focus of this paper.

The present study of animated maps’ complexity is largely based on the research of Goldsberry and Battersby (2009). Three aspects of their work merit particular attention. First, as stated in this paper’s introduction, they have developed a pair of metrics for evaluating change between choropleth maps - Basic Magnitude of Change (BMOC), and Magnitude of Rank Change (MORC). Second, they distinguished between three levels of change detection for choropleth animations: Level 1 (polygon changes class – corresponds to BMOC), Level 2 (polygon’s class membership increases or decreases), and Level 3 (the magnitude of the positive or negative change is detected – corresponds to MORC). Third, their research was the first to localize the study of graphical complexity, by considering limitations on the visual perspective of the map reader. This was done by evaluating the MOC for each enumeration unit (EU) of a choropleth map (as part of a continuous display) in relation to its surrounding polygons in the frame only within the foveal area, the region of a human’s highest visual and perceptual acuity (Williams 1982, Goldstein 2007). The foveal area (FA) is defined based on an angle of 1.5 to 2° on either side of a point directly in front of a viewer’s eyes, and thus its diameter varies as a function of viewing distance. If this page is viewed from 50 cm (arm’s length or average eye-screen distance, the foveal area is about 3 cm in diameter. Assuming a classed choropleth map animation, for any pair of scenes:

$$\text{BMOC} = \frac{\boldsymbol{count}\ of\ EUs\ that\ change\ class\ in\ instantaneous\ FA}{count\ of\ EUs\ in\ instantaneous\ FA}$$

$$\text{MORC} = \frac{\boldsymbol{sum}\ of\ total\ class\ changes\ in\ instantaneous\ FA}{count\ of\ EUs\ in\ instantaneous\ FA}$$

For two adjacent map animation frames, these metrics’ outputs differ from each other only in cases where enumeration units change by more than one class. The output is a map with polygon decimal values ranging from 0.0 to a maximum of either 1.0 for BMOC (i.e., every EU in the FA changed), or [(# classes) * (# EUs in the FA)] for MORC (every EU in the FA changed by the maximum # of classes in the map). In their study, a Python script was written which computed the metrics using the shapefile’s attribute table. The resulting value is stored in the polygon at the center of the instantaneous foveal area, and the program moves on, visiting each polygon in the change map via the attribute table.

Methods

The goal of this study is two-fold: 1) to apply the Magnitude of Change (MOC) metrics to a raster data model, in order to discover whether these metrics produce significantly different results when the data type of the enumeration units is altered from indivisible vector polygons to rasterized symbolization that (depending on the cell size chosen) has the same graphical appearance but can be subdivided, and 2) to automate this functionality by constructing a GIS model within ArcGIS's Model Builder. Doing so has the advantage of making the process more user-friendly, by eliminating most of the Python programming involved in the existing vector model. The model's specific requirements are as follows:

1) Accept any pair of choropleth maps with identical classification schemes and polygons / EUs

2) Compute MOC statistics for each pixel's neighborhood, as defined by the foveal area

3) Size the foveal area / neighborhood automatically using typical eye-screen distance, and the scale and units of the input map as currently displayed in ArcMap. This should require no computation or other input from the user.

Since the basics of the MOC computation (vector and raster) have been detailed above, this section will briefly outline the differences between the functionality of the two models, by describing each model step sequentially.

Model Input

Both models accept a vector shapefile as initial input; in the vector model, the shapefile's full path reference is a hard-coded model attribute, while the raster model, as a Model Builder process within an active ArcMap .mxd document, allows input selection via a parameter pop-up dialog. (To take advantage of the automated computation of the foveal area below, the shapefile must be open in the map document while the model is in use.) Both require that each polygon's class membership (1,2,3…*N* for an *N*-class map) for each of the two map frames being compared exist in a separate column of the attribute table. The raster model then uses this information and the desired analysis cell size to re-create the two maps under comparison via a Vector-to-Raster conversion.

The other important input is the extent of the foveal area, which is coded as a local variable in the vector model, where the user must perform this computation 'by hand' and embed the value in the code. However, in the raster model, this is computed with no user input, via a script that reads the scale and map units from the current data frame, assumes standard eye-screen distance (50 cm), and computes the radius of the foveal area in map units as a local variable. A conditional statement applies the appropriate conversion factor (map units can be meters or feet, but not degrees), since the Focal Statistics operator accepts a window radius in map units, not centimeters. The expression for the computation of the foveal area radius for input to the Neighborhood operator is given below.

$$FA_{radius} = \tan(1.5) * dist_{ES} * scale_{map} * CF$$

Where:

$\boldsymbol{dist_{ES}}$ is the eye-to-computer screen distance for the map user, in cm

$\boldsymbol{CF}$ is the appropriate conversion factor to change radius from cm to map units

Determination of Inter-scene Class Change

The vector model uses basic value subtraction in a loop structure to derive the absolute difference of the class membership attributes, while the raster model obtains this result via a map algebra function. A new difference ('imaginary') raster map is thus created at this step, which incidentally may or may not resemble the mental image of change used by viewers of the original animation.

Derivation of Change Metrics

As part of the loop structure, the vector model uses the Select By Location function and the foveal area's radius (as the search distance) to compute metrics for each record and write the result to a new column in the attribute table. The raster model uses the Neighborhood toolset's Focal Statistics tool to visit each cell in the difference map, perform the calculation and write the result to the cell. It accepts the previously-derived foveal area as the radius of a circular neighborhood window. The main difference in the result is that, provided the cell size is small enough, the raster model computes metrics for cells precisely within the foveal area, while the vector model includes all polygons of which any portion falls within the foveal area. This difference is detailed further in the Discussion section, and illustrated in Figure 2.

Model Output and Visual Comparison

The output of the vector model is the input shapefile, with added fields for the two MOC metrics. These decimal fields can be symbolized in ArcMap, either classified or as continuous greyscale. The raster model's MOC output is two new raster map-images.

The models' respective output can be symbolized several ways. One way to compare the results of the vector output is to create a pseudo-stretched greyscale effect (to imitate the raster's continuous output) by symbolizing the MOC metrics using quantiles and the maximum number of classes in ArcMap (32), and turning off the polygon outlines. Figure 1 compares the two outputs using this method, showing the source 'difference' map as well, in which blue represents counties that changed class between two adjacent animation frames. Insofar as the whiter areas represent polygons or pixels of high MOC, while darker parts of the map changed little, these map-images somewhat resemble a single band of remotely-sensed data. The areas marked by red circles indicate areas with limited change according to the 'difference' map, but which are labeled in the output as regions of very high change. For more on this behavior, the reader is referred to the Discussion section, below.

Conversely, the raster output can be scaled to more closely resemble that of the vector maps by level-slicing, or classifying its continuous, smoothed images (not shown). However, this type of analysis must be carried out carefully, as the classification method chosen will greatly affect the appearance of the result, and thus its usefulness in determining the location(s) of highly complex areas in the animation.

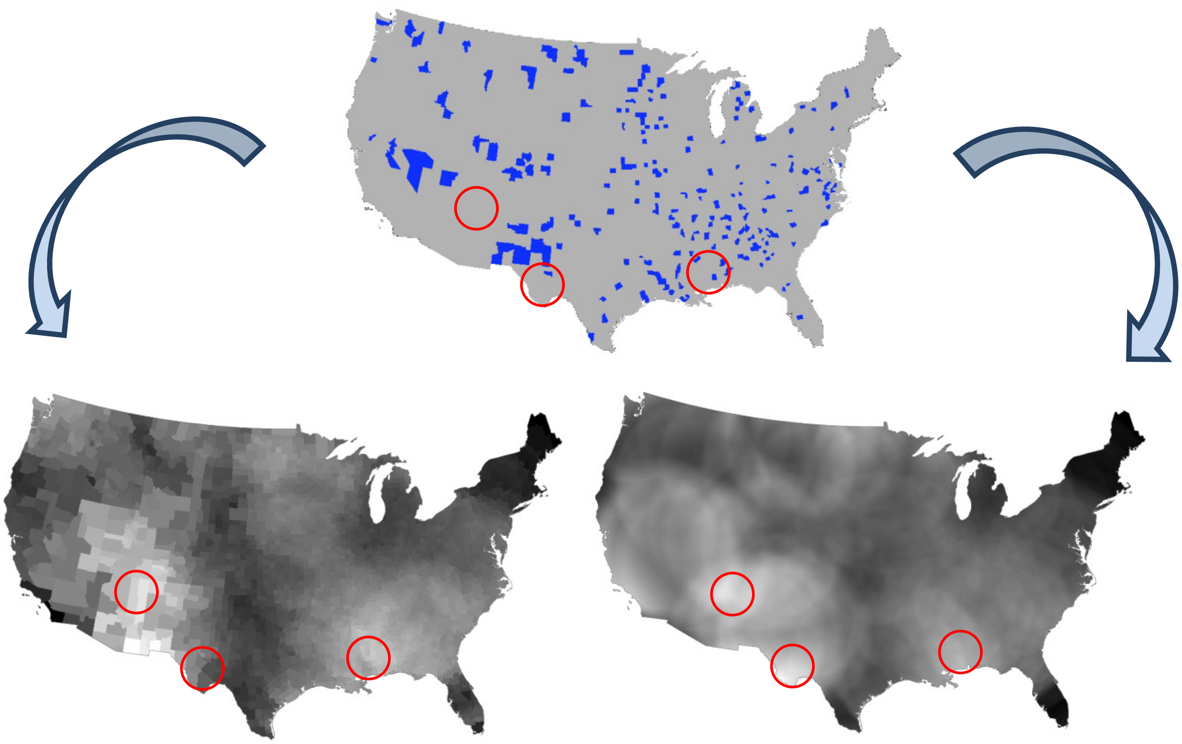

Figure 1: MOC complexity model graphical output (clockwise from top): the source difference map, vector-based MORC, and raster-based MORC. Source dataset is a four-class equal interval classification of US county population for 1990 and 2000. Raster cell size is 5 km. Under close examination, the foveal area's diameter becomes apparent.

Discussion

Limitations of vector-based focal analysis

When viewed within a GIS, choropleth maps are fundamentally vector-based data displays. The geographic area in question is represented as a polygon layer (often a feature class or shapefile), with the enumeration units colored an appropriate tint. However, these units cannot be subdivided, and the phenomenon being mapped is assumed to uniformly fill the entire area of each unit. Indeed, this is often seen as one shortcoming of choropleth maps for mapping certain types of spatial distributions.

Figure 2 depicts the variation in the size of the instantaneous foveal area, when processing is constrained by a vector data structure. Elko, Nevada and Hancock, Kentucky were selected as examples of two enumeration units (here, counties) of vastly different sizes and environments, whose comparison using foveal area-based MOC metrics poses significant problems when comparing the 'complexity' of the two regions in a single choropleth map animation. Two different problems exist which are compounded when combined. First, since the instantaneous foveal area is derived by the vector model by using a fixed radius from the boundary of the polygon currently under investigation (here, a county), the foveal area for any polygon will of necessity be larger than it ideally should be. Unless the foveal area were computed for a dimensionless point (which removes choropleth maps from consideration), this holds true. In the example below, the transparent red buffer shows the effective 200 km 'search radius' for each county. This issue could be removed by using county centroids (black dots) as a preprocessing step in the analysis.

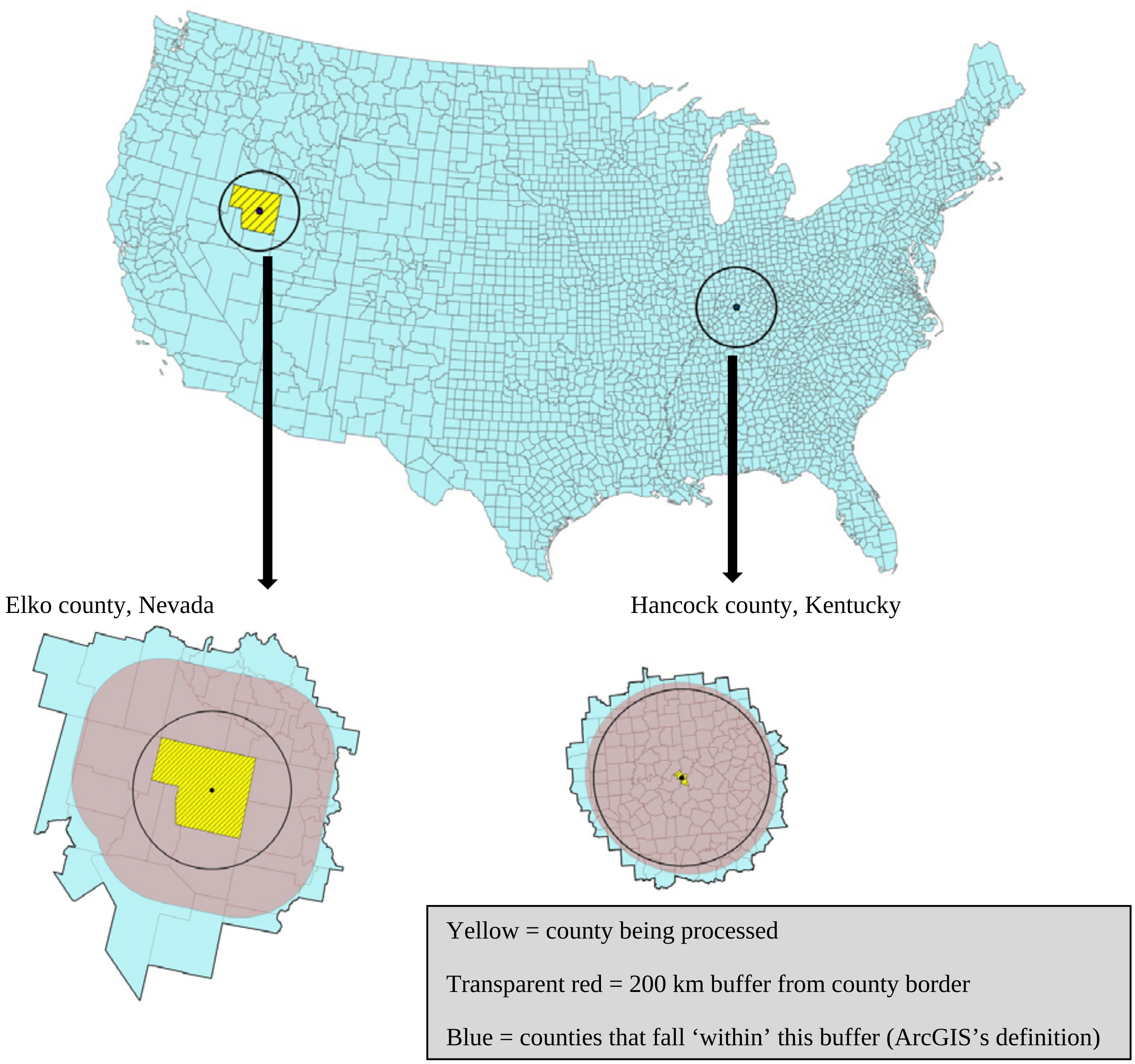

Figure 2: Variation in polygons counted as belonging to instantaneous foveal area as a function of polygon size, shape and arrangement. Solid black line is 200 km buffer from county centroid (vector) or cell (raster).

However, a further problem lies in the fact that the model uses the 'Within' option in Select by Location, and any county of which even a tiny portion lies within this irregular radius is counted in its entirety. Of course, other Select options could be used, such as 'completely within' or 'centroid within,' but the problem posed by large, irregular counties would persist, albeit less noticeably. Although only count, not area, is used in the MOC metric derivation, the model's inclusion of counties that changed but which are over 450 km from the edge of a county (as in the Elko example in Figure 2) can have a significant, artificial, MOC-inflating effect in animated maps which consist of enumeration units of different sizes, and / or significantly irregular shapes. In this example, the light blue counties' class change or lack of it can impact the MOC value assigned to the county being processed, shown here with yellow hatching.

This means that large, oddly-shaped counties in the test dataset surrounded by other large, oddly-shaped counties (such as those found in Nevada, Arizona and other western states) may be coded with disproportionately high MOC values. While it is to be expected that larger polygons will have higher MOC values due to their higher visual salience, this advantage is augmented by 'drawing on' neighboring units, even if only a small portion of these units fall within the search radius for the polygon whose MOC is being computed. This advantage is problematic when comparing these regions to others within the same animation which have exactly the opposite characteristics, of which Hancock, Kentucky (right) is one example. Due to the small size and uniform shape of most of Hancock's neighboring counties within the foveal area, the match between the counties truly within the instantaneous foveal area and those within a 200 km search radius used in its MOC computation are much more similar than in the case of Elko, Nevada.

This issue is significantly reduced by using the raster model, since each unit is no longer structurally a polygon, but a polygon-shaped mass of individual cells. Assuming that the cell size chosen is small enough, the raster-based foveal area closely resembles the circular buffer pictured in Figure 2 by the solid black line, and favorably compares with the 'zero-dimensional point' buffering situation mentioned earlier in this section. The result is a more equal treatment of all units regardless of size during the scanning and MOC-computation process.

A second limitation is one of convenience. Few, if any, commercial software packages are currently able to perform moving window calculations as part of a pre-packaged *vector*-based routine, since such analysis methods are fundamentally a raster construct. Of course, scripting languages such as Python offer flexibility to developers in customizing applications, but this is dependent upon programming skill. This approach has been used by Goldsberry and Battersby (2009) in modeling the complexity of change within the county-level population change dataset from the US Census described earlier. ArcGIS's Model Builder module contains a Feature Class Iterator function that can 'visit' each enumeration unit, but any statistical measures for windows or 'kernels' centered on these areas must be custom-programmed within the Python environment. However, there is only the illusion of a true moving window.

A raster model using existing software

This study instead developed a raster-based model – one that accepts the same input map as in the case of the vector model, converts class membership values stored in its attribute table into a pair of raster map-images, generates a difference map via map-algebra, and uses a focal GIS operator to scan each cell in the difference map. The window is set to the size of the user's foveal viewing area as a function of the scale of the map and the eye-screen distance. BMOC and

MORC is computed for all cells within the window, and the resulting value is written to the center cell. The only major functional difference between this model and its vector predecessor is that this one uses cells and not irregular units. Two greyscale maps are output, with individual pixel values replacing vector polygons in depicting which EUs changed and which persisted across the animation pair.

A prototype model was developed that used 'out-of-the-box' ArcGIS Model Builder and ArcToolbox Focal Statistics functions (e.g., the MEAN operator). As part of computing BMOC, the Reclass function was also used. Key variables set to parameters allowed a dialog box to open upon initial execution of the model, asking the user to supply the reference of the input map, the workspace for the project, the names of the two fields in the attribute table to be used to create the raster map pair, and the cell size. However, the user is relieved of defining the parameters of the Neighborhood window. This window's shape is locked to 'circular,' based on research that has found (Williams, 1982) that the human foveal area is best approximated by a circle or slightly elliptical shape, and its radius is computed assuming a standard eye-screen distance of 50 cm.

Comparison of the two models' output

The dataset used in this paper is US county-level population change by decennial Census year, and the adjacent frames (if it were displayed in animated form) depict 1990 - 2000 population shifts. It reveals a pattern whose general trend will be familiar to many readers; the South and Southwest are growing in population at the expense of the Northeast. A visual comparison of the two model's graphical outputs in Figure 1 shows general agreement between the models on which counties saw sufficient population change between 1990 and 2000 to effect a change in class membership. However, the two outputs are far from identical; while the vector map shows class change as more specific and identifiable, but with sharp discontinuities at political boundaries, the raster's representation of the same difference map using the foveal area filter greatly smoothes the MOC data. It is this behavior that may cause the raster modeling framework to more closely resemble what a map reader subconsciously 'sees' when locating and interpreting class change among choropleth polygons.

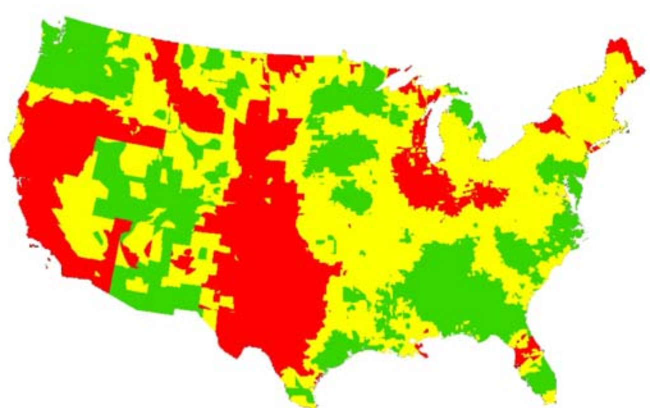

Figure 3: Result of subtracting MORC vector output from raster output (Figure 1). Yellow indicates areas where the two models were in general agreement about the magnitude of perceived change as measured by the localized metrics.

One way to compare these outputs is to subtract one from the other. Figure 3 shows the result of subtracting the vector output (rasterized after the model finished processing, to permit map algebra) *from* the raster output. The cell size used in this study is 5 km, which at the scale of the dataset, was sufficiently small to avoid visible pixilation. This method yields positive values (red) where the raster model over-indicated the level of class change relative to that shown by the vector model, and negative values (green) where raster under-indicated change. Yellow indicates areas within ½ standard deviation of the mean, which was close to zero; due to the normal distribution of brightness values, these class breaks were chosen in order to highlight areas where both models predicted about the same amount of perceived change.

A second way that the raster output can be analyzed is to perform histogram stretching on the image-maps. This can be done with the vector model output as well, provided that it has first been rasterized. Doing so can increase understanding of the MOC maps in Figure 1 by graphically enhancing MOC in some areas of the map as an aid to regional analysis, or it can isolate 'hot spots' or zones of highest inter-scene change complexity. When used this way, histogram manipulation can define various 'resolutions'. Figure 4 shows examples of both actions.

Figure 4: Histogram contrast stretching as applied to the raster model's output. Two standard deviations (left), 0.5 standard deviation (right).

A final observation should be made here: it is readily apparent from Figure 1 and Figure 4 (especially the 2 standard deviation map) that the zones of highest complexity as indicated by either model often do not contain the highest number of polygons that changed class (compare the areas in Figure 1 circled in red). For example, a region along the Gulf coast in Mississippi and Louisiana is shown as a very complex region, and is thus colored bright white in the output. However, an examination of the 'difference' map shows that this area contains only a few scattered counties that changed class during the ten-year period: most of the change occurs around the periphery of a foveal area centered on this region. A similar behavior is apparent in the Southwest, where high-intensity change areas are found, particularly in the raster output, offset from change areas in the difference map by a significant amount. This is a result of the interplay between the focal MOC operation and the size of the foveal area. Since the focus of the moving window has no precedence in the calculation, i.e., change (or the lack of it) in the focus county (vector) or cell (raster) can be trumped by a lot of changing units near the edges of the foveal area. The result seems to be a possible shift in the focus of change; whether this is an accurate representation of the viewer's perspective has yet to be seen.

Conclusion

This paper outlines an improved framework for evaluating the complexity of animated map displays. The raster version of the MOC animated map complexity model shows promise. It is easier to create and modify, has a shorter processing time than the vector model at all but the very smallest cell sizes, and uses a consistent-sized instantaneous foveal area during the focal analysis and metric generation.

However, further research is necessary to address questions raised by both this project and the research of Goldsberry and Battersby (2009). How well do the MOC metrics agree with a map reader's cognitive process? How well do they measure complexity as experienced by such a map reader interpreting an animated choropleth map? What about the concept of the foveal area, and of its size and shape? While it seems that the regularly-shaped circular window generated by the raster model (Figure 2) would more closely imitate an organic process of the human eye-brain system, perhaps this is not true.

Questions of a more psychological nature include, What attracts the eye's attention to one part of an animation rather than to another? Is it related to a single large polygon that changes significantly, causing the eye to search its vicinity because 'something is happening here?' Or does a cluster of changing polygons have more of an effect in this situation? Does the difference map really replicate an ephemeral mental image instantaneously created by the map reader? While these types of questions have been partially addressed by cognitive scientists, among them Nothdurft (2002), the cartographic literature has only recently begun to focus upon them.

Neither the raster model developed in this paper nor its vector predecessor have yet been validated with human subjects. Doing so may begin to answer some of these questions, but a wide variety of test animations will need to be presented to large, representative samples of map readers before any definite verdict on MOC effectiveness can be reached. Comparison of MOC output maps with eye-tracking analysis and 'gaze maps' would be one possible validation step.

Modern GIS and image-processing systems offer an substantial toolkit for research into these questions and others yet to be raised, while a growing body of existing research exists in both dynamic mapping and related fields. Work on validating these models using human-subject testing is ongoing, and the results promise to offer new insights into ways of quantifying the cognitive inter-scene complexity of map animations.

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