

## Visualizing Data Certainty: A Case Study Using Graduated Circle Maps

Several techniques have been proposed for displaying data certainty on maps, but few have been empirically tested for effectiveness. While it is important to make data certainty information easily accessible, the addition of such data should not unduly increase map complexity. Thus, it becomes important for cartographers to examine the available methods for displaying this aspect of metadata and to test each for its effectiveness. The focus of this study was the display of data certainty information on graduated circle maps. Four types of accuracy indicators were evaluated for their effectiveness in communicating data certainty information. Two were traditional accuracy indicators: reliability diagrams and legend statements. Two were bivariate in form, one using a value-size combination and the other mimicking the idea of *focus* by varying the line value of the graduated circles to suggest a fading of symbolization for least certain data. The study was designed to assess whether subjects could identify data certainty information on test maps, and evaluate how accurately and confidently they could extract and interpret both thematic and data certainty information. Mean accuracy and confidence rates were compared for maps using different accuracy indicators to evaluate their relative effectiveness. Results suggest that subjects had most difficulty identifying and extracting data certainty information using maps that employed legend statements. They were most successful when data certainty was wedded to thematic data on the map using the bivariate accuracy indicator that mimicked the concept of focus. Identification and extraction of thematic data values were not significantly affected by choice of accuracy indicator.

Map accuracy is often equated with graphic quality. As noted by both Wright (1942) and McGranaghan (1993), well-drawn, precise maps are typically taken as scientifically authentic, regardless of the quality of their underlying data. Aesthetically pleasing maps, however, can conceal problems with the data and methods used in their creation. Wright (1942:527) provides perhaps the most interesting analogy on this subject: "A map may be like a person who talks clearly and convincingly on a subject of which his knowledge is imperfect." Always a problem cartographically, this particular issue has become even thornier as we have moved from manual, hand-drawn maps into the digital environment where nearly anyone who can master a software package can be a "mapmaker". Technology provides us with amazing capabilities in creating, editing, and displaying spatial data, capabilities that are offset by the fact that many of these maps are inappropriately used given the data upon which they are based. Since the validity of the underlying data is the key to making credible decisions, it makes sense that reporting and spatially depicting data certainty information should be addressed in a contemporary cartographic framework. Yet, as MacEachren (1994:67) points out: "The cartographic literature has largely ignored the question of depicting uncertainty. Insuring viewer understanding of uncertainty, then, will depend on developing a means to represent it."

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### INTRODUCTION

*"Since data validity is the key to making credible decisions, it makes sense that reporting and spatially depicting data certainty information should be addressed in a contemporary cartographic framework."*

*“The ease of extracting and processing both thematic and data certainty information are likely to be affected by the cartographer’s symbolization choices.”*

*“Inherent in the mapmaking process is cartographic abstraction . . . Abstraction, however, introduces uncertainty . . .”*

## BACKGROUND

*“Information regarding variation in the certainty of spatial data has been most often given using either legend statements or reliability diagrams.”*

The objective of this study was to assess several methods for displaying data certainty, using the graduated circle map as a case study for displaying this information in the thematic mapping arena. While there has been a wealth of theoretical publications on the subject, there has been surprisingly little empirical research published on this topic. In spite of this dearth of research, the choice of symbolization technique used may have a profound effect on map use. Both the ease of extracting and processing thematic data, as well as the ease of extracting and processing data certainty information are likely to be affected by the cartographer’s symbolization choices (Buttenfield, 1993). Our goals with this study were basic. We sought to answer whether or not one could, by manipulating symbolization design parameters:

- understand that some information on the map varies in certainty
- interpret that information in the context of the thematic data presented on the map

Data from this study contributes to cartography because it provides information on the integration of data certainty symbolization with traditional graduated circle symbolization. It also presents empirical evidence outlining workable ways of wedding data certainty information with quantitative information in a thematic mapping context. The experiment was designed to test four unique display techniques. Each was evaluated using accuracy rates and confidence ratings. These measures were used to assess the effectiveness of each technique for:

- displaying data certainty information
- enhancing one’s ability to answer questions about both the thematic data and the data certainty information displayed on the map

Inherent in the mapmaking process is *cartographic abstraction*, without which we would not be able to graphically portray the complexity of the real world. Abstraction, however, introduces uncertainty - uncertainty about data quality and about the relationships between variables, both of which can affect location and attribute quality on the map (MacEachren, 1994).

Discussion on the topic of data certainty is often complicated by terminology. Several terms have been bandied about and used interchangeably in the literature: *uncertainty/certainty*, *error*, *quality*, and *reliability* are typical examples. Although these terms tend to vary in scope of definition, they are usually taken to encompass not only the completeness of the data mapped, but also temporal variability and the spatial and attribute variability due to aggregation processes. Perhaps the actual term we use is less important than *how* we choose to portray the consequence of abstraction. Ultimately, the goal is to provide a tool in which the portrayal of data certainty is adequate enough to give the map user a sense of how much faith to put into the information extracted from the map (MacEachren, 1994).

## Visualizing Data Certainty

Traditionally, information regarding variation in the certainty of spatial data has been most often given using either textual information, such as a *legend statement*, or by a graphic known as a *reliability diagram*, usually located in the map’s margins (van Der Wel, et al., 1994). These types of *traditional accuracy indicators* are the most non-intrusive. An example of a

legend statement, which is typically a simple verbal description of data certainty variation, can be found in Figure 1a. Reliability diagrams, more graphically oriented, consist of outline maps or abstract block diagrams that provide a visual sense of the spatial variation of data certainty associated with the source data mapped (Muehrcke and Muehrcke, 1992). Figure 1b shows an example of this type of accuracy indicator. The primary risk with both of these indicators, however, is that data certainty information may be ignored, as it is separated from the thematic data.

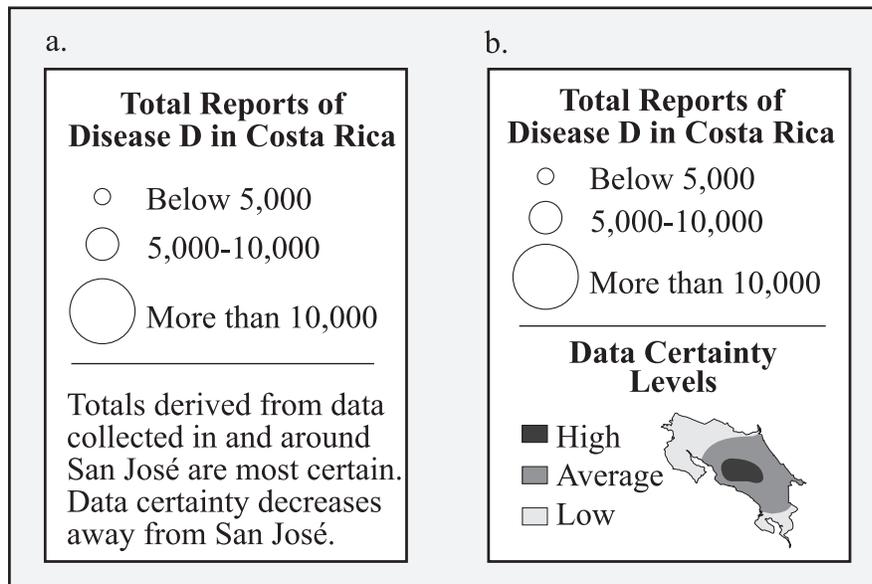


Figure 1. Traditional accuracy indicators: (a) Legend statement, (b) Reliability diagram

Cartographic research, in recent years, has extended the above options by establishing a broader set of theoretical guidelines regarding the visualization of data certainty on maps and in GIS (Buttenfield, 1991; MacEachren, 1992; van Der Wel, et al., 1994). These guidelines address both the wedding of data certainty information to the actual mapped spatial data using *bivariate accuracy indicators* (Figure 2), as well as newer techniques, such as animation and sound, resulting in accuracy indicators that we might categorize as *novel*. The starting point for the development of both of these groups of indicators has generally been Bertin's (1983) set of six visual variables (shape, size, orientation, hue, value, and pattern), which has provided the discipline of cartography with its basic structure for visualizing spatial data. To these six, several other variables have since been added, providing an even larger taxonomy from which to draw symbolization choices (MacEachren, 1992; Muehrcke and Muehrcke, 1992; Fisher, 1994). Few of these guidelines, however, have been tested in empirical studies that would either confirm these ideas or suggest the most appropriate framework for visualizing data certainty (Leitner and Buttenfield, 2000).

One study that does examine these guidelines from an empirical perspective is Schweizer and Goodchild (1992). They tested the potential of bivariate choropleth maps for displaying quantitative thematic data using saturation, coupled with variation in value to indicate differing levels of data certainty. Value is one of Bertin's visual variables that has been most often mentioned as being potentially effective for displaying variation in data certainty (Buttenfield, 1991; MacEachren, 1992; van Der Wel, et al.,

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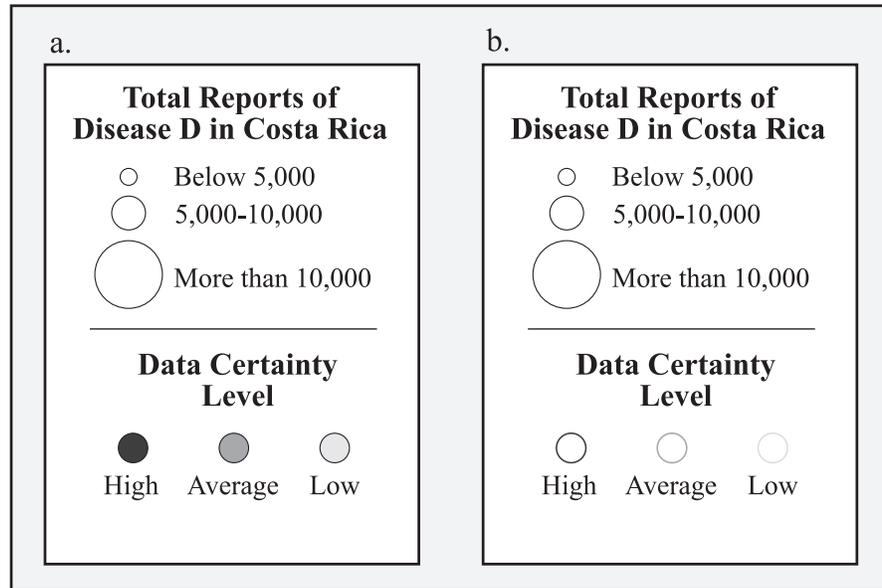


Figure 2. Bivariate accuracy indicators tested in the study: (a) Value-size, (b) Focus

*“Four unique accuracy indicators were evaluated in the context of displaying data certainty information on graduated circle maps.”*

1994). Results from this study led the authors to conclude that at least in the case of a value-saturation combination, we tend to combine the two dimensions in decision-making processes. Instead of focusing on variation in value alone to determine data certainty levels, subjects tended to assume a “darker is more, lighter is less” maxim that relied on a combination of value and saturation and caused incorrect interpretations of the maps.

Saturation is often considered a logical extension of Bertin’s original six, and has been suggested as another possible alternative in the display of data certainty (MacEachren, 1992). Leitner and Bittenfield (2000) tested this variable, along with texture and value, in their study. Their research focused on spatial decision support systems; one emphasis was on evaluating how the timing, accuracy, and confidence of decisions could be affected by choice of visual variable used to represent data certainty information in the map display. Results of the study suggest that the addition of data certainty information can increase the number of correct responses in a decision-making task, provided that the information is symbolized using either lighter values or finer textures for more certain information. Saturation may also be used, but is ranked a distant third choice by the authors.

#### THE EXPERIMENTS

Four unique accuracy indicators were evaluated in the context of displaying data certainty information on graduated circle maps. Two accuracy indicators, legend statements (Figure 1a) and reliability diagrams (Figure 1b), were chosen because they represent the traditional means of communicating data certainty. To these were added two variations of a bivariate accuracy indicator, representing the implementation of some of the newer theoretical guidelines that have been proposed in the literature. One bivariate indicator was comprised of variation in values and sizes of the circles, with value representing variation in data certainty (Figure 2a). The other was designed to mimic the idea of *focus*, a means of visualizing data certainty by varying value to suggest a fading effect (van Der Wel, et al., 1994). Here data certainty was symbolized by varying the value of the lines defining the graduated circle sizes (Figure 2b). More novel tech-

niques were not tested, as we chose to work in a printed environment for the study.

### Research Questions

Heading into the experiments, we anticipated that the traditional accuracy indicators - legend statements and reliability diagrams - would be the most difficult for subjects to use effectively. Muehrcke and Muehrcke (1992) lend support to this expectation, as does Fisher (1994: 185), who states the problem perhaps the most succinctly: "... embedding the error in the display makes it impossible to ignore it, which is otherwise the tendency of the user." We also expected, however, to see a difference in subject performance between the legend statement and reliability diagram. Although in both cases data certainty information is separated from the mapped thematic data, we anticipated that subjects would be more likely to notice and process the information provided by a graphic than by a comparable verbal statement.

Bivariate accuracy indicators are more complex, and may reach a complexity threshold quickly (McGranaghan, 1993), but we expected that subjects would find data certainty information easier to notice and process when it was wedded to the actual thematic information in the map. Results of the Leitner and Bittenfield (2001:14) study support this: "... the inclusion of certainty information is not associated by map viewers as an addition of map detail ... It would seem that map certainty is understood as clarification rather than adding complexity to a map display." Of the two bivariate accuracy indicators tested, we expected that the more typical value-size indicator would be most effective, as it was more familiar and had the most graphic "punch". The indicator mimicking *focus*, in which the value of the line surrounding each circle varied, appeared much more subtle from a figure-ground perspective. With these thoughts in mind, the following research questions were posed:

- What effect does the type of accuracy indicator have on one's ability to recognize the existence of data certainty information on the map?
- What effect does the type of accuracy indicator have on one's ability to comprehend data certainty variation in the context of mapped thematic data?

These questions can be answered by comparing how accurately and how confidently one can

- identify data certainty patterns on maps using these types of accuracy indicators
- answer questions about the spatial variation of data certainty displayed on maps using these types of accuracy indicators

### Maps

Sixteen graduated circle maps, an example of which can be seen in Figure 3, were prepared for use in two related experiments. All maps utilized the same base. They differed in the manner in which data certainty was symbolized and in spatial complexity (Table 1). Each of the sixteen maps displayed one of four fictitious data sets tied to spatial complexity and one of four accuracy indicators. For graphic examples of the spatial patterns

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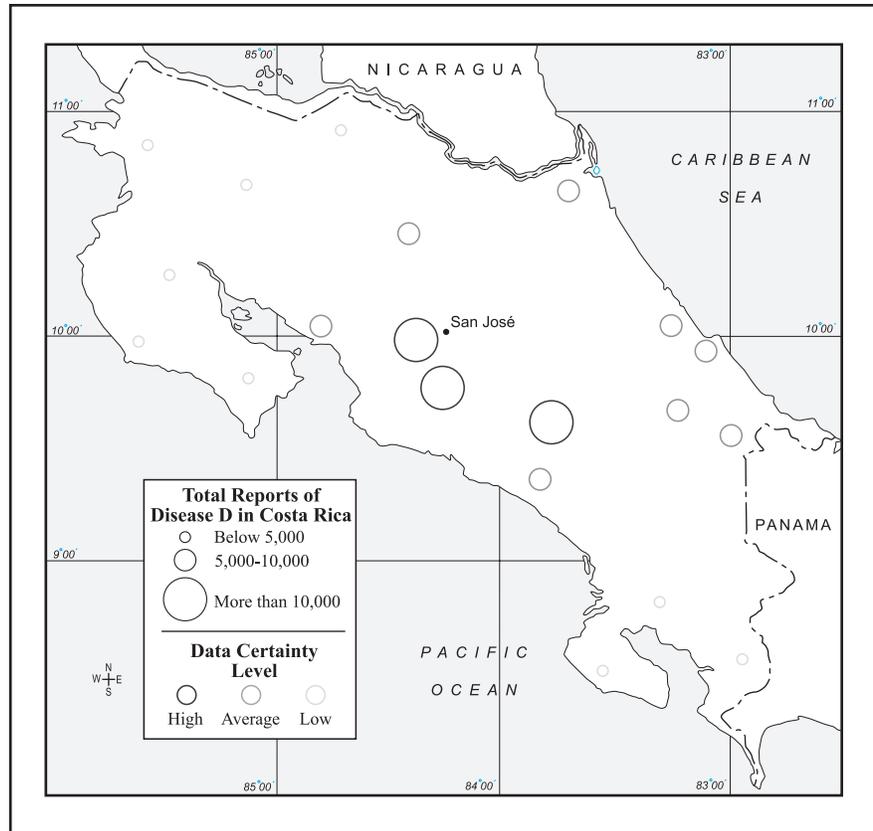


Figure 3. Example of a test map used in the experiments.

Accuracy Indicator	Spatial Pattern: Thematic Data	Correlation with Data Certainty Information
<i>Legend Statement</i>	Clustered I	Yes
<i>Legend Statement</i>	Clustered II	No
<i>Legend Statement</i>	Random	No
<i>Legend Statement</i>	Systematic	Yes
<i>Reliability Diagram</i>	Clustered I	Yes
<i>Reliability Diagram</i>	Clustered II	No
<i>Reliability Diagram</i>	Random	No
<i>Reliability Diagram</i>	Systematic	Yes
<i>Bivariate Value-Size</i>	Clustered I	Yes
<i>Bivariate Value-Size</i>	Clustered II	No
<i>Bivariate Value-Size</i>	Random	No
<i>Bivariate Value-Size</i>	Systematic	Yes
<i>Bivariate Focus</i>	Clustered I	Yes
<i>Bivariate Focus</i>	Clustered II	No
<i>Bivariate Focus</i>	Random	No
<i>Bivariate Focus</i>	Systematic	Yes

Table 1. Characteristics of the sixteen test maps.

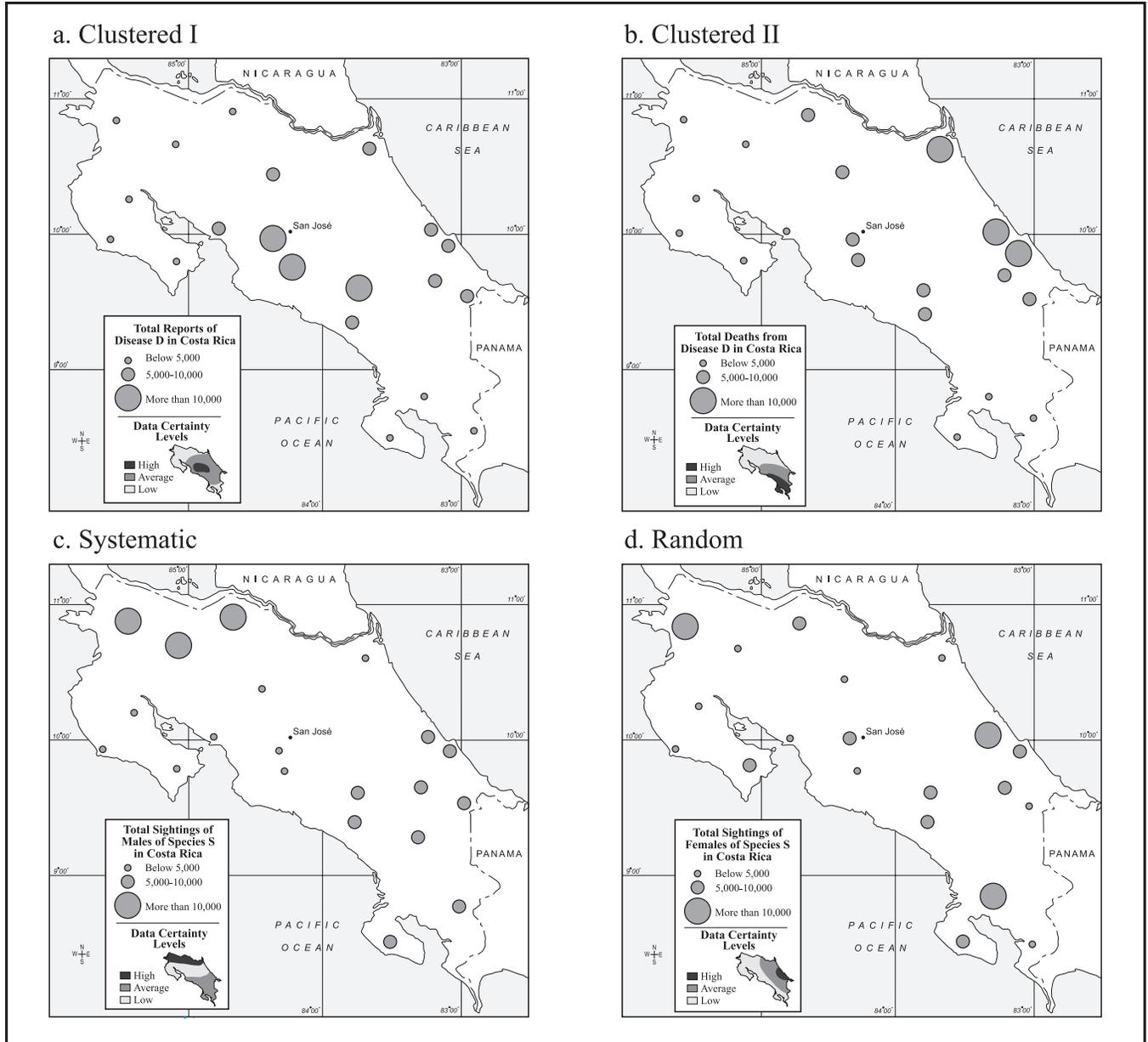


Figure 4. Four spatial patterns used to test the effectiveness of accuracy indicators. These examples use reliability diagrams to symbolize data certainty variation.

used, see Figure 4. The different data sets with varying levels of spatial complexity were necessary to prevent subjects from memorizing mapped conditions over the course of using several test maps. They were also useful for mimicking a variety of real world conditions.

**Assessing map complexity.** MacEachren (1982) defined map complexity as being composed of the nature of the distributions being mapped, along with the symbolization used to display those distributions. In our case, the distribution of data values and correlation of data values with data certainty information were used to determine spatial complexity, since symbolization was already a variable being studied independently. A distribution should be easier to remember when the data is grouped or chunked, so in theory, those distributions in which the data are clustered and in which the data certainty information is correlated with data values

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*“Variation in spatial complexity should affect ease of map use, but since this was not a variable we were interested in studying, we opted to quantify it and use it as a covariate in our analysis.”*

*“On each map, the symbolization used to communicate data certainty was defined in the legend below the graduated circle information.”*

*“Subjects were instructed in the use of graduated circles . . . they were also given an explanation of data certainty and . . . participated in a practice test prior to taking the actual experiments.”*

should result in distributional patterns that are less complex. Variation in spatial complexity should affect ease of map use, but since this was not a variable we were interested in studying, we opted to quantify it and use it as a covariate in our analysis.

To establish a measure, a panel of five experienced cartographers was asked to rank the levels of complexity used in producing the maps. Each cartographer on the panel individually ranked the maps on the basis of ease of extracting both data values and data certainty information. Rankings were then averaged across all cartographers to arrive at an average ranking for each map. Those maps in which the thematic data values were correlated with data certainty information were judged to be the least complex (Figure 4a and c, Table 2). Those in which data certainty information was not correlated with data values were judged the most complex (Figure 4b and d, Table 2).

Spatial Pattern: Thematic Data	Correlation with Data Certainty Information	Complexity Rankings*	Complexity Measure
<i>Clustered I</i>	Yes	1,1,1,2,2	1.4
<i>Systematic</i>	Yes	1,1,2,2,2	1.6
<i>Clustered II</i>	No	3,3,3,3,4	3.2
<i>Random</i>	No	3,4,4,4,4	3.8

\*1 = least complex, 4 = most complex

Table 2. Complexity rankings and resulting measures for the four spatial complexity patterns used in the test maps.

**Symbolizing Data Certainty.** On each map, the symbolization used to communicate data certainty was defined in the legend below the graduated circle information. For the legend statement method, for example, there was a verbal description of how data certainty varied across the mapped region (Figure 5a). Reliability diagrams, on the other hand, were small copies of the base map in which categories of data certainty were symbolized using a light to dark areal shading scheme (Figure 5b). For the bivariate focus indicator (Figure 5c) and bivariate value-size indicator (Figure 5d), a light to dark shading scheme was again used to depict the change in certainty occurring across the map. In all cases where value was manipulated to represent changes in data certainty, lighter values represented lower levels of data certainty and darker values represented higher levels of data certainty.

### Subjects

Eighty students taking geography classes at San Diego State University were recruited for testing. All subjects volunteered for the experiments; none were compensated with extra credit or money. Subjects were instructed in the use of graduated circle maps prior to the experiments. They were also given an explanation of data certainty and how it relates to mapped data. Prior to actual testing, they participated in a practice test using a different base map and data. This familiarized the subjects with the experimental procedures and map symbology and exposed them to the types of questions they would be required to answer. Subjects were not required to have previous cartographic courses or experience to take the experiments. Testing occurred in a group environment, with 6 groups of 7 - 16 students participating at any given time. Subjects ranged in age from

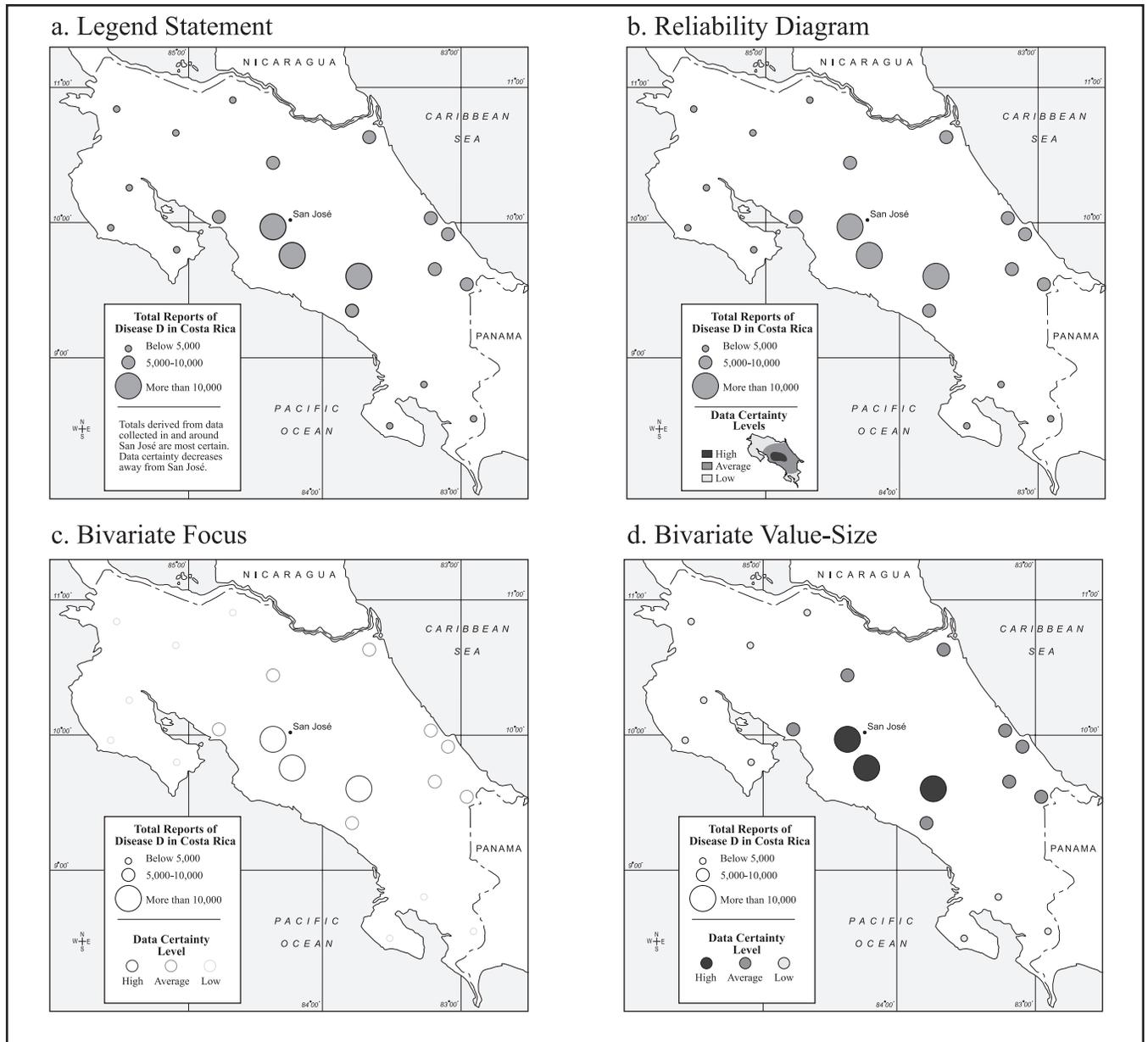


Figure 5. Four accuracy indicators used to symbolize data certainty information.

21 to 52 years, with the average age being 28.5 years. Two-thirds were male; three-quarters were geography majors.

**Procedures and Analyses**

Eighty printed test packets were prepared for the study, one for each subject tested. Each packet included eight maps. Four of these maps, each portraying data certainty with a unique accuracy indicator and using a unique spatial complexity pattern, were evaluated in Experiment I. The remaining four maps, used in Experiment II, were also comprised of four unique accuracy indicators and used unique spatial complexity patterns, with the additional caveat that the combinations tested here were distinct from those tested in Experiment I. For example, if a subject worked with a map using a reliability diagram as the first map in the Experiment I, s/he

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*“The selection of the eight maps from the sixteen and the order in which they were presented to each subject was determined using the method of Latin Squares.”*

would see no other maps using reliability diagrams in Experiment I, and that particular map would also not be used in Experiment II. S/He would evaluate a map using a reliability diagram in Experiment II, but the spatial complexity of the data mapped would be different to minimize subject familiarity with the spatial patterns being assessed. The selection of the eight maps from the sixteen and the order in which they were presented to each subject was determined using the method of Latin Squares (Bogomolny, 1996). This procedure, which minimized the effect that map order would have on subjects' performances, also insured that each of the 16 maps would be evaluated by 20 of the 80 subjects for each experiment. See Table 3 for an example of the map contents of a typical test packet.

Experiment	Accuracy Indicator	Spatial Pattern: Thematic Data	Correlation with Data Certainty Information
I	<i>Reliability Diagram</i>	Clustered I	No
	<i>Legend Statement</i>	Clustered II	Yes
	<i>Bivariate Value-Size</i>	Random	No
	<i>Bivariate Focus</i>	Systematic	Yes
II	<i>Bivariate Value-Size</i>	Clustered I	No
	<i>Legend Statement</i>	Random	No
	<i>Bivariate Focus</i>	Clustered II	Yes
	<i>Reliability Diagram</i>	Systematic	Yes

Table 3. An example of the map contents and order presented for one test packet.

*“... subjects performed a rapid pattern detection task for each of the first 4 maps in the test packet.”*

**Experiment I - Procedure.** In this experiment, patterned after that performed in DiBiase, et al. (1994), subjects performed a rapid pattern detection task for each of the first 4 maps in the test packet. Subjects examined a map for 15 seconds. They then turned the page to an outline map of the same area and were given 15 seconds to:

- mark the area(s) in which they believed data values to be the highest with a circle or circles
- mark the area(s) in which they believed the data to be most certain with an X or Xs

A time limit of 15 seconds for each step was established during a pilot test of the methodology. Time pressure was used to test symbolization effectiveness for discerning data patterns quickly. This sequence of steps was then repeated for 3 other maps, where each map used a different accuracy indicator and a different level of spatial complexity.

*“The data collected from this experiment were first subjected to a visual analysis . . .”*

**Experiment I - Analysis.** The data collected from this experiment were first subjected to a visual analysis similar to the one performed by DiBiase, et al. (1994) in the assessment of their rapid pattern data. As the first step in the process of informally identifying which accuracy indicator did the best job of alerting map users that data certainty information was part of the map display and available for interpretation, we created two composite figures for each of the sixteen maps. The first figure for each map depicted all the circles drawn by subjects to indicate areas of highest data values. The second figure depicted all the X marks drawn by subjects to indicate areas of highest data certainty for each of the maps. The composite figures were created by scanning in subject response maps, registering

these maps to an outline base map, and transferring the center points of the circles and Xs to the digital bases. Patterns extracted from these figures were then used to informally assess differences in responses for each accuracy indicator and spatial complexity pattern represented.

Composite results for patterns of data values showed relatively little visual variation in amount of clustering across the test maps. Circles were almost always clustered around the area of highest data values, regardless of the accuracy indicator used or the pattern of spatial complexity imposed on the map. The same, however, was not true for the composite results depicting variation in perceived areas of highest data certainty. In these cases, 3 of the 4 maps using legend statements as the accuracy indicator showed relatively weak visual clustering compared to maps using other accuracy indicators (see Figure 6 for examples). Maps with areas of strong visual clustering were also easy to identify for data certainty information, but they do not seem to be consistently tied to any particular accuracy indicator.

It is also possible to assess the *sparseness* of subject responses for the composite figures by tallying the number of blank responses for Experiment I. The number of blank responses per accuracy indicator provides

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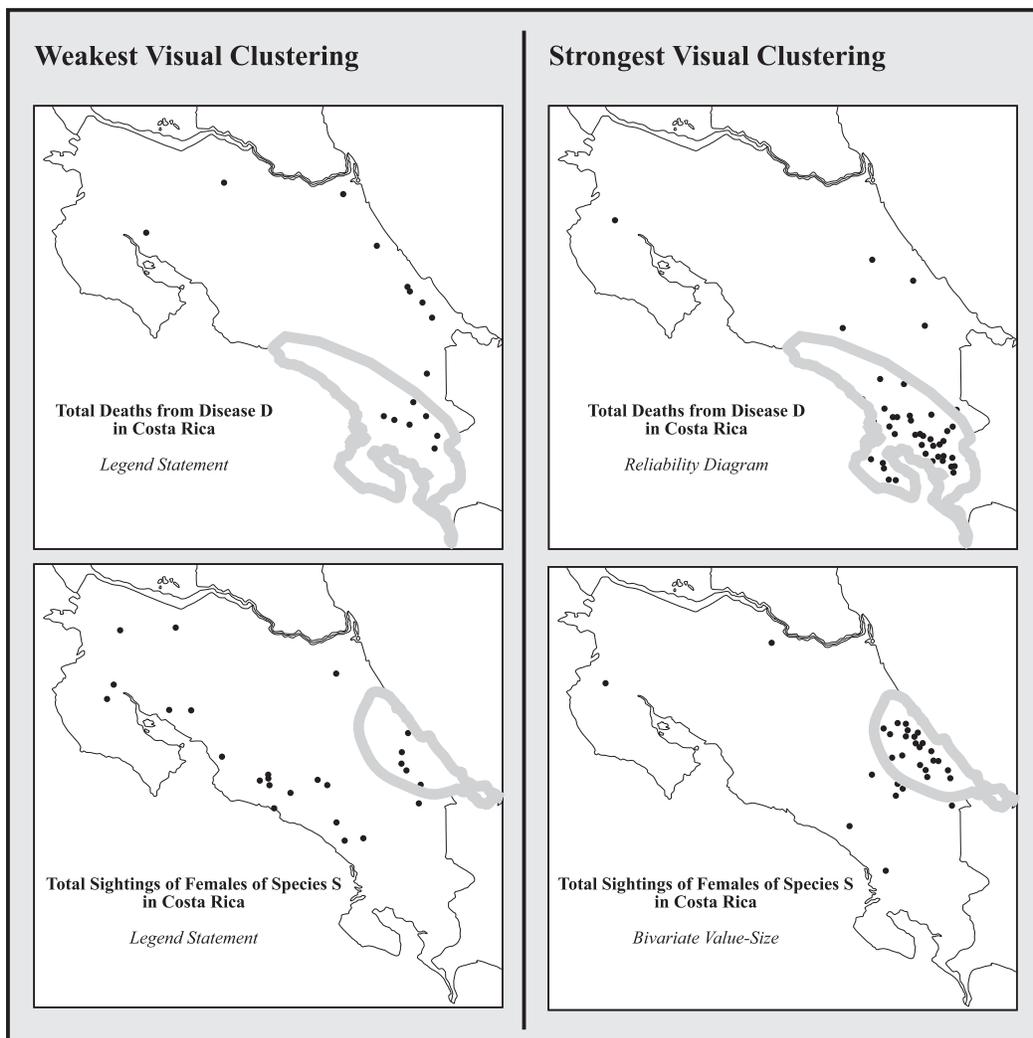


Figure 6. Examples of composite drawings showing the weakest and strongest visual clustering of perceived areas of highest data certainty for 5 of the 16 test maps. Gray outlines indicate the true areas of highest data certainty for each map.

*“Maps using legend statements accumulated the highest number of blank responses.”*

additional clues as to whether subjects could identify and extract data certainty information from the maps. Theoretically, if all accuracy indicators portray data certainty information equally well, there should be no significant difference in the number of subjects who do not identify an area of highest perceived data certainty for any given map. As can be seen in Table 4, however, the number of blank responses for the task varies quite considerably from one type of accuracy indicator to another. A chi-square

Accuracy Indicator	Total Number of Blank Responses	Percentage of all Blank Responses
<i>Legend Statement</i>	39	40%
<i>Reliability Diagram</i>	36	37%
<i>Bivariate Value-Size</i>	12	12%
<i>Bivariate Focus</i>	11	11%

Table 4. Number of blank responses per accuracy indicator for Experiment I.

*“The final 4 maps in the test packet were evaluated . . . using a memory/recall task . . .”*

analysis in which the observed frequencies were the number of blank responses for each accuracy indicator and the expected frequencies were the total number of blank responses divided by 4 (the number of accuracy indicators tested), shows that these differences are indeed significant ( $= 21.607, p < 0.0001$ ). Maps using legend statements accumulated the highest number of blank responses. These are followed closely by maps using reliability diagrams. The bivariate accuracy indicators accumulated the least number of blank responses.

**Experiment II - Procedure.** The final 4 maps in the test packet were evaluated in this experiment, using a memory/recall task to assess the influence of the accuracy indicator on one's ability to comprehend data certainty variation over the mapped data. This experiment required subjects to examine a map for 30 seconds. Subjects were then instructed to turn the page to an outline map of the same region with 2 labeled areas (Figure 7). They were given thirty seconds to:

- answer a multiple-choice question about the variation in mapped data values
- rate their level of confidence in their answer by circling a number between 1 and 7
- answer a multiple-choice question about the variation in data certainty across the map
- rate their level of confidence in their answer by circling a number between 1 and 7

*“Mean accuracy rates and mean confidence ratings for each of the four accuracy indicators were analyzed using analyses of covariance models . . .”*

A time limit of 30 seconds for each step was established during a pilot test of the methodology. This sequence of steps was then repeated for 3 other maps, where each map used a different data certainty indicator and a different level of spatial complexity.

**Experiment II - Analysis.** Mean accuracy rates and mean confidence ratings for each of the four accuracy indicators were analyzed using analyses of covariance models (ANCOVA) to determine whether statistically significant differences existed between the indicators when used to

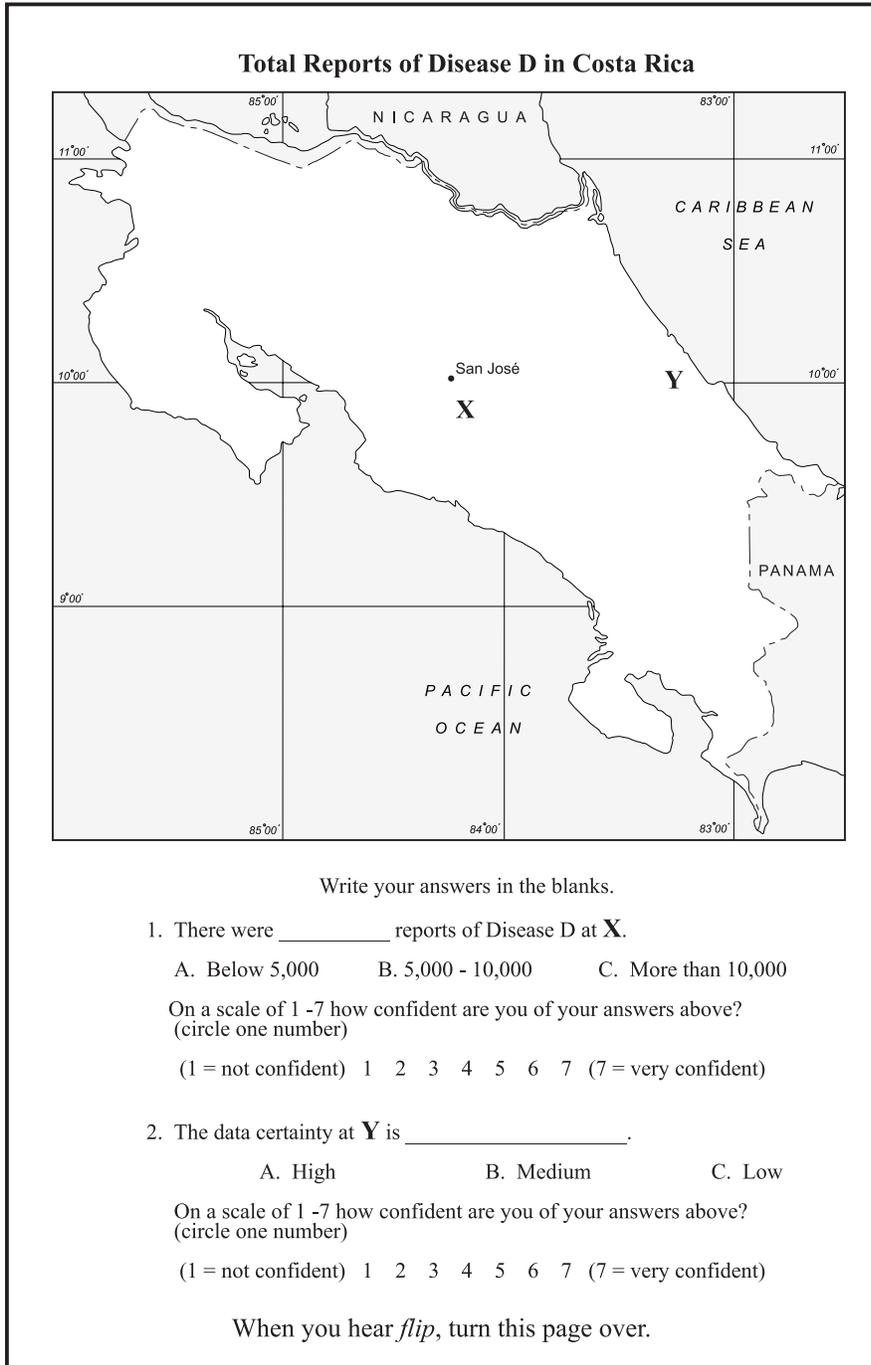


Figure 7. Example of testing material used in Experiment II.

assess spatial variation in data values and patterns of data certainty on a map. Mean Accuracy Rates and Mean Confidence Rates served as the dependent variables in these analyses; the independent variable in each analysis was Accuracy Indicator. The covariate for all analyses was Map Complexity Level. An ANCOVA model is often used when it is not possible to control a covariate directly in an experiment. In this study, Map Complexity Level is a covariate because it is significantly correlated with the dependent variables. By using an ANCOVA, the variation in map complexity associated with Mean Accuracy Rates and Mean Confidence Rates can be removed for the error variance. This allows for more precise estimates and more

*“An ANCOVA model is often used when it is not possible to control a covariate directly in an experiment. In this study, Map Complexity Level is a covariate . . .”*

*“The accuracy indicator used on the map did not significantly affect one’s ability to answer questions about mapped data values . . .”*

powerful statistical testing (Stevens, 1992).

A total of four models were run, one for each of the dependent variables tested:

- mean accuracy rates for questions targeting data value variations
- mean accuracy rates for questions targeting data certainty variations
- mean confidence rates for questions targeting data value variations
- mean confidence rates for questions targeting data certainty variations

Confidence ratings were weighted following a procedure used by Nelson (1996) prior to analysis. This procedure, which multiplies all incorrect responses by -1, then adds 7 to all responses, results in a rating system that gives less weight to confidence levels associated with incorrect responses.

Although the ANCOVA models for *Mean Accuracy Rates* and *Mean Confidence Rates* associated with **data value variations** on the maps were significant, the main effect of *Accuracy Indicator* was not significant for either mean accuracy rates ( $p > F(0.475) = 0.700$ ) or mean confidence rates ( $p > F(0.801) = 0.494$ ). Thus, the accuracy indicator used on the map did not significantly affect one’s ability to answer questions about mapped data values or significantly affect one’s confidence in these answers (Figure 8a).

*“. . . one’s ability to answer questions about data certainty variation accurately and confidently did vary by accuracy indicator . . .”*

The ANCOVA models for *Mean Accuracy Rates* and *Mean Confidence Levels* associated with **data certainty variations**, on the other hand, suggest quite the opposite. Both of these models were significant, as were the main effects of *Accuracy Indicator* used in both models. Both the mean accuracy rates ( $p > F(9.051) = 0.0001$ ) and mean confidence ratings ( $p > F(7.165) = 0.0001$ ) for accuracy indicators were significantly different at the 0.05 level, suggesting that one’s ability to answer questions about data certainty variation accurately and confidently varied with the accuracy indicator used to symbolize data certainty. (Figure 8b). In these instances, responses tied to legend statements were shown to be significantly less accurate. Subjects were also significantly less confident of their answers for this method of data certainty representation.

## DISCUSSION

*“Subject agreement on areas of highest data certainty varied the most for maps that used legend statements . . .”*

The results from both experiments that stand out most prominently - both visually and statistically - are those that separate legend statement effectiveness from the effectiveness of the other accuracy indicators tested. Subject agreement on areas of highest data certainty varied the most for maps that used legend statements to communicate information about data certainty. These maps also resulted in more blank responses for Experiment I, further suggesting that data certainty information was less easily identified and extracted from these maps. If all accuracy indicators had been equally effective at portraying data certainty information, then the number of blank responses should have been evenly distributed between the maps. As the chi-square analysis indicated, this was clearly not the case. These particular results should not surprise most of us, as noted previously by both Fisher (1994) and Muehrcke and Meuhrcke (1992). In the first place, this mode of portraying data certainty information requires map users to process and integrate two distinctly different forms of information: verbal and graphic. Secondly, the information from both must be mentally overlaid to create a composite picture from which one can answer questions about the spatial patterns of data certainty. The men-

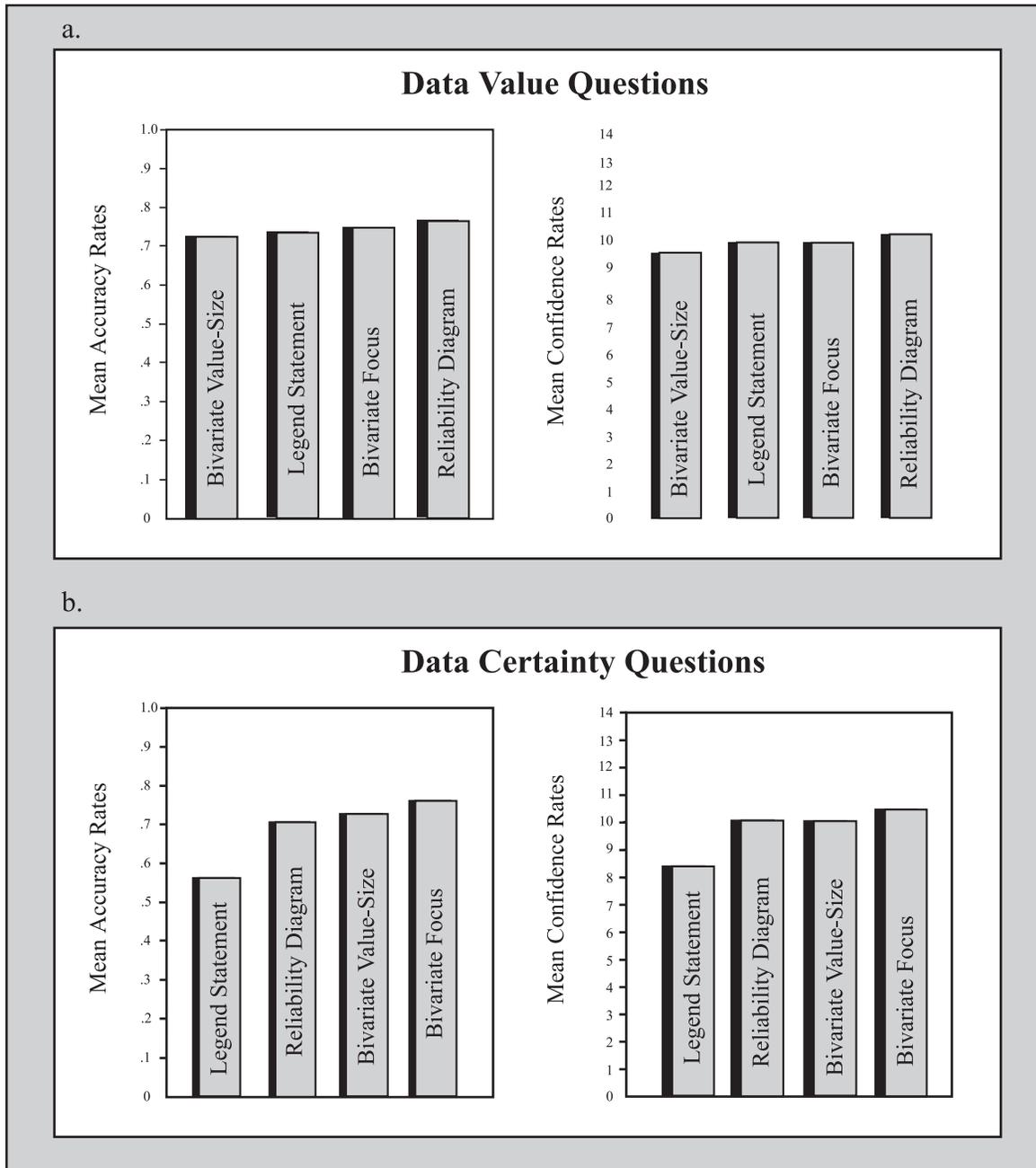


Figure 8. Mean accuracy rates and confidence rates for (a) data value questions and (b) data certainty questions for each type of accuracy indicator tested.

tal overlay process is also problematic for reliability diagrams, although perhaps less so since the information is already in graphic format. This traditional accuracy indicator did perform better than the legend statement, with the increase in performance most likely attributable to the graphic nature of the indicator.

Although not statistically significant, there are definite trends in the data that also warrant discussing the differences in effectiveness of the other accuracy indicators. The bivariate accuracy indicators, for example, resulted in more accurate and more confident interpretations of data certainty information (Table 5). Despite, then, the increased complexity of symbolization, subjects were not only able to effectively process these

*“The bivariate accuracy indicators . . . resulted in more accurate and more confident interpretations of data certainty information.”*

Accuracy Indicator	Mean Accuracy Rates	Mean Confidence Rates*
<i>Legend Statement</i>	0.56	8.4
<i>Reliability Diagram</i>	0.70	10.0
<i>Bivariate Value-Size</i>	0.72	10.0
<i>Bivariate Focus</i>	0.77	10.5

\*Confidence rates range from 0 – 14

Table 5. Mean Accuracy and Confidence Rates for Data Certainty Questions in Experiment II.

symbols, but to process them more efficiently than the traditional means of displaying data certainty information. These results confirm those of Leitner and Battenfield's (2000), which suggest that subjects do not find the addition of data certainty information embedded in the thematic data symbolization to negatively affect map interpretation. Apparently, the collocation of the two datasets does, instead, offer significant advantages: eye movements are reduced, and the mental overlay required of traditional accuracy indicators is eliminated.

*“... the bivariate focus indicator, much to our surprise, out-performed the bivariate value-size indicator.”*

Perhaps the most important findings in this context are the differences noted between the bivariate value-size indicator and the bivariate focus indicator. Both of these means of displaying data certainty performed particularly well, but the bivariate focus indicator, much to our surprise, out-performed the bivariate value-size indicator. We found this particularly interesting for the following reasons:

- It is not one of the more common forms of bivariate symbolization in graduated circle mapping
- It seems to violate one of cartography's principle design rules, which is to always have the thematic information - all of it - at the top of the visual hierarchy

Is it possible that this very violation is what makes the symbolization so effective for processing data certainty information? More certain data gets the graphic punch, at the expense of the less certain data, so much so that perhaps it becomes a more effective means of displaying the two data sets in tandem.

## CONCLUSIONS

Information on data certainty is a vital component of metadata. It is also a component that should be easily accessible to the map user to facilitate effective decision-making. This study has empirically examined the effectiveness of displaying data certainty on printed graduated circle maps using both traditional accuracy indicators and bivariate accuracy indicators. Results from both experiments indicate that subjects perform pattern identification and interpretation tasks more accurately and more confidently when data certainty is symbolized using bivariate indicators. Legend statements and reliability diagrams separate the two data sets and require not only extra eye movements, but also a mental overlay process to complete the map tasks. This particular finding does not provide new information for guiding the symbolization process, but is instead confirmatory. It gives us empirical evidence that points to the need for developing and testing new forms of accuracy indicators, both bivariate and novel.

The most interesting result from the study was the better task performance seen with the bivariate focus indicator as opposed to the bivariate

value-size indicator. This finding strongly suggests the continued need to assess new ways of combining visual variables in bivariate symbolization specifically for displaying data certainty in combination with thematic data. Perhaps data certainty information is unique and will require a new type of framework for designing symbolization. Although this is a controversial viewpoint, the results of our study suggest this may be the case, and there are others in cartography that also believe this may hold true (Buttenfield and Beard, 1991; Buttenfield, 1993). If so, then it will be very important for cartographers to continue work in expanding visualization research to accommodate new and updated frameworks for data symbolization.

We gratefully acknowledge the insights and constructive comments made by the anonymous reviewers and Dr. Patricia Gilmartin of the University of South Carolina. Their input was essential to the final product seen here. We would also especially like to thank Dr. Richard Wright and Dr. Sandra Marshall of San Diego State University for their contributions, support, and encouragement in the development of this research.

Bogomolmy, A. 1996. Latin Squares. <http://www.cut-the-knot.com/arithmetric/latin-intro.html>. Accessed May 1999.

Buttenfield, B.P. 1991. Visualizing Cartographic Metadata. *NCGIA Research Initiative 7: Visualization of Spatial Data Quality*. Scientific Report for the Specialist Meeting (Castine, ME). NCGIA Technical Paper: 91-126.

Buttenfield, B.P. 1993. Representing Data Quality. *Cartographica*, 30(2):1-7.

DiBiase, D., Sloan II, J. L. and Paradis, T. 1994. Weighted Isolines: An Alternative Method for Depicting Statistical Surfaces. *Professional Geographer*. 46(2):218-229.

Fisher, P. 1994. Animation and Sound for the Visualization of Uncertain Spatial Information. In *Visualization in Geographic Information Systems*, ed. D. Unwin and H. Hearnshaw, pp. 181-185. New York: John Wiley.

Leitner, M. and Buttenfield, B. P. 2000. Guidelines for the Display of Attribute Certainty. *Cartography and Geographic Information Science*. 27(1):3-14.

MacEachren, A.M. 1982. Map Complexity: Comparison and Measurement. *The American Cartographer*. 9(1):31-46.

MacEachren, A.M. 1992. Visualizing Uncertain Information. *Cartographic Perspectives*. 13:10-19.

MacEachren, A.M. 1994. *Some Truth with Maps: A Primer on Symbolization & Design*. Washington, D.C.: Association of American Geographers.

McGranaghan, M. 1993. A Cartographic View of Spatial Data Quality. *Cartographica*. 30(2):8-19.

Muehrcke, P.C. and Muehrcke, J.O. 1992. *Map Use: Reading, Analysis, and Interpretation*. 3rd edition. Madison, Wisconsin: JP Publications.

*"This finding strongly suggests the continued need to assess new ways of combining visual variables in bivariate symbolization."*

#### ACKNOWLEDGMENTS

#### REFERENCES

Nelson, E.S. 1996. Cognitive Maps: Encoding and Representing Spatial Information within the Mind. *Cartography and Geographic Information Systems*. 23(4):229-247.

Schweizer, D.M., and Goodchild, M.F. 1992. Data Quality and Choropleth Maps: An Experiment with the Use of Color. *Proceedings, GIS/LIS*. 2:686-699.

Stevens, J. 1992. *Applied Multivariate Statistics for the Social Sciences*. 2nd edition. Hillsdale, New Jersey: Lawrence Erlbaum Associates, Inc.

Wright, J.K. 1942. Map Makers are Human: Comments on the Subjective in Maps. *Geographical Review*. 32(4):527-544.

van der Wel, F.J.M., Hootsmans, R.M. and Ormeling, F. 1994. Visualization of Data Quality. In *Visualization in Modern Cartography*, ed. A.M. MacEachren and D.R.F. Taylor, pp. 313-331. New York: Pergamon/Elsevier Science.