

The Trustree for the Visualisation of Attribute and Spatial Uncertainty: Usability Assessments

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ABSTRACT

Attribute and spatial uncertainty are defined and put into context for this research. This paper then extends on a research programme which has designed a visualisation of attribute and choropleth spatial uncertainty using the Hexagonal or Rhombus (HoR) hierarchical spatial data structure. Using the spatial data model in this fashion is termed – the *trustree*. To understand this progression, a brief explanation of this research programmes past history must be covered. The New Zealand 2001 census is used as an exemplarity dataset to express attribute uncertainty and choropleth boundary uncertainty (termed spatial uncertainty). An internet survey was conducted to test the usability of the trustree, which was used as a transparent tessellation overlay and a value-by-area (VBA) display within a population choropleth map. Two other visualisation of attribute uncertainty methods – blinking areas and adjacent value were also incorporated into the survey. Participants were required to rank, from 1 to 6, six grid cells which overlaid the uncertainty visualisations, in order from the most accurate to the most uncertain cell, respectively. These ranking results were correlated with the actual ranks, providing a metric of usability for each visualisation method. The blinking areas method was the most effective, followed by adjacent value, VBA trustree and the transparent HoR trustree. The time taken for a participant to rank each visualisation's cells was collected – there is an 82% correlation between the time taken and the final usability results obtained.

Keywords and phrases: Uncertainty, Visualisation, Attribute, Spatial, Trustree, Usability.

1.0 INTRODUCTION

New intuitive methods for the representation of attribute and spatial uncertainty can greatly increase the validity of a decision when spatial data is utilised. Therefore, the scope for such methods is broad and sorely needed to ensure time and money is not lost pursuing a wrong decision avenue. Expressing uncertainty in spatial data is currently a key research challenge on the geovisualization agenda put forward by Fairbairn et al. (2001) in a special issue of Cartography and Geographic Information Science on Geovisualization (MacEachren & Kraak 2001). Fairbairn et al. (2001, 20) state, 'Making information available about data uncertainty, [and ensuring] the suitability of a representation for a particular task is essential, if users are to make informed decisions and we are to extend the visualisation toolkit. A comprehensive program of research is needed to ensure the development and test (in a variety of circumstances) efficiency of quality or uncertainty indicators for new methods of representation.' This key research challenge was the driving force behind this research programme. A new visualisation of uncertainty research programme has been defined to express attribute and spatial uncertainty utilising the HoR quadtree (which here after its use in this manner will be termed the *trustree*) by the current authors (Kardos, Benwell & Moore in press), and by briefly explaining this method in *The trustree to visualise attribute and spatial uncertainty* section of this paper, readers will be able to understand the trustree evolution

put forward there after. The main focus of this research paper is to test the usability of the trustree – which can be visualised in two forms, as a transparent overlay (termed *HoR trustree*) or as a value-by-area map (termed *VBA trustree*) when used in conjunction with a choropleth map.

2.0 UNCERTAINTY

Uncertainty in spatial applications can be diverse. This research is concerned with two types of uncertainty – attribute and spatial uncertainty. Temporal uncertainty does exist, but it is chosen to be disregarded for discussion (see Tøssebro and Nygård 2003 for further detail). To condense this uncertainty section, attribute and spatial uncertainty will only be discussed from a population census perspective – the dataset used for this research programme.

2.1 Attribute Uncertainty

Attribute uncertainty is the difference between collected data and the actual values exhibited in the real world. Goodchild (1995) explains that all attributes can be uncertain; this is due to factors like measuring instrument inaccuracies (due to scale and calibration for example). Gross blunders can occur; a user can misread an instrument or mistype data into a spreadsheet, also names can be confused and they are subject to historical uncertainty. On areal imagery, one operator's interpretation of a land use class can differ from another. Similar uncertainty and many other forms can arise when an operator assigns attribute data to locations in a database, especially if the data is complex.

Attribute uncertainty for census data can come from numerous sources. Data can be miscalculated; people may have their information collected twice or not at all. Some census collection agencies attempt to gauge the amount of attribute uncertainty associated with a particular census. As an example, Statistics New Zealand provides an additional post enumeration survey (Statistics New Zealand. 2002) about the quality of their published results from the New Zealand 2001 census dataset. The information provides actual undercount figures for geographic location (used in previous work by Kardos et al. in press) and other quantitative variables. It is not assumed that all datasets have additional attribute uncertainty information, but fortunately for this research program such data can be utilised.

2.2 Spatial Uncertainty

Spatial uncertainty can be considered the locational difference between a model stored in a geographic information system (GIS) and the actual location exhibited in the real world (Drummond 1995). Also, spatial uncertainty will become prevalent when generalisation from reality into a GIS model occurs. Certain spatial aspects and relationships become lost. Currently, it would be near to impossible to collect all real world locational data and model it within a GIS (Zhang & Goodchild 2002); therefore locational (or spatial) uncertainty will exist. This research programme deals indirectly with spatial uncertainty; moreover it is concerned with the spatial uncertainty associated with boundaries (for the continuation of this paper where spatial uncertainty is referenced, it refers to spatial boundary uncertainty).

2.2.1 Choropleth Spatial Uncertainty

Census datasets are typically viewed using choropleth maps (Martin 1996). There are a number of spatial uncertainty issues, aside from the definition explained above, which will arise from using choropleth maps to express census data. Martin (1989) and others (Wright 1942; Jenks & Caspall 1971) discussed problems mapping population data in choropleth form. Martin explained that uncertainty arises when aggregated data is assigned to areal units which are designed for ease of enumeration and administrative containment (Blakemore 1983; Chrisman 1989); and therefore, are not designed to be data driven. This means that data within an areal unit is basically a function of boundary definitions, rather than the underlying data distribution. Using imposed zonal boundaries applies a single geography to all variables rather than an appropriate geographic settlement pattern. Martin (1989, 91) continued that “the areal units are frequently least appropriate for areas displaying the most extreme socio-economic characteristics, giving them disproportionate and misleading visual impact in the map image”. Moreover, many users believe printed and computer display maps to be ‘true’ (Jenks & Caspall 1971; Mark & Csillag 1989), thus when selecting areal units, planning, consideration and caution is vital.

Also, on a choropleth map homogeneity is implied within geographic units (i.e. – census tracts) and between units in the same category (i.e. – colour hue). This implies a visual assumption that all areas within the same category are equal (which is obviously not true – see Wright 1942), and if areas are adjacent in this same category, then the whole area is assumed homogenous and different from other (Jenks & Caspall 1971; Mark &

Csillag 1989; MacEachren 1995). Clearly, this would not be the case for population data, which is more likely to be a semi-continuous phenomenon. People are not continuously linked in space, unlike population census data which is collected by household. Population data approaches continuity through the linking of house sections or boundaries. Still, there are breaks between household boundaries in the form of roads, shops, parks, rivers or institutions etc. Therefore, this research program argues that population data exhibits semi-continuous spatial dispersion. Census household data is collated into subjectively assigned census tracts (or uses roads, rivers, lakes etc. to separate boundaries) which additionally provides privacy for individuals, but the original semi-continuous spatial dispersion of the phenomenon digresses towards discrete spatial units. Also, the choropleth map can be divided into any number of equally acceptable areal sizes and/or shapes, but depending on how these areas are divided, differing patterns and values for a location will be seen. This is commonly known as the modifiable areal unit problem (MAUP) (Openshaw & Taylor 1981). Also, there are many ways to collate data into categories for choropleth mapping. Common examples include: Natural Breaks (Alexander & Zahorchak 1943), Standard Deviation (Armstrong 1969), Counting Numbers or Manual Definition (Jenks & Caspall 1971), Equal Interval (Jenks & Coulson 1963), Nested Means (Scripter 1970) and Minimum Boundary Error. Depending on the data collection method used, different results will visually appear. There are potential ways to visualise uncertainty, as it is expressed in this section, of which will now be discussed.

3.0 THE VISUALISATION OF UNCERTAINTY

The visualisation of uncertainty is a relatively new topic in GIS research, even though the importance of accuracy, data error and uncertainty has been known for some time (Goodchild 1992). Even current GIS do not have built in means to view uncertainty (Hunter 2000), despite there being numerous techniques available. Some of these methods will be covered in the next two sections, particularly to express attribute uncertainty and then spatial uncertainty.

3.1 Visualising Attribute Uncertainty

MacEachren (1992) provided a good practical background to using graphical variables (as Bertin 1983 outlines) which could be used to depict attribute uncertainty. The author stated that out of Bertin's seven graphical variables (location, size, value, texture, colour, orientation, and shape), size and shape (which are utilised in this research programme) are the most appropriate for numerical information. MacEachren also expressed that saturation of colour – see also (MacEachren, Brewer & Pickle 1998; Leitner & Buttenfield 2000; De Cola 2002; Drecki 2002; Hengl, Walvoort & Brown 2002; Aerts, Clarke & Keuper 2003), the focus of an image (including fill clarity or opacity and obscuring fog) and lowering spatial resolution might be ideal ways to represent attribute uncertainty. The latter was proposed to convey uncertainty whereby the map graphic detail would change to correspond with the attributes. Adjusting resolution to visualise uncertainty is used by the trustee, explained in section 4 of this paper.

Other methods to visualise attribute uncertainty have been proposed. Two adjacent maps can together show data uncertainty; one shows the data whilst the other shows the uncertainty information (MacEachren 1992; Schweizer & Goodchild 1992; Evans 1997; Leitner & Buttenfield 2000; Aerts, Clarke & Keuper 2003). This is otherwise known as *adjacent value* and is tested for usability in section 5 of this paper. A texture can overlay a map display and depending on the texture used, varying degrees of uncertainty can be expressed (Monmonier 1990; Beard, Buttenfield & Clapham 1991). The use of sound as a medium to represent uncertainty has been explored (Krygier 1994; Fisher 1994a; Fisher 1994b). Possible sound variables are outlined by Krygier (1994). Animation has also been explored (Davis & Keller 1997; Ehlschlaeger, A.M. Shortridge & Goodchild 1997; Bastin, Fisher & Wood 2002).

3.2 Visualising Spatial Boundary Uncertainty

Expressing spatial uncertainty for this research programme generally means expressing uncertainty around fixed boundaries – either between spatial units or category classes. Techniques to show boundary uncertainty typically exploit the crispness or fuzziness of boundary edges.

The epsilon band (initially designed to combat sliver polygons) (Perkal 1956) or confidence band (McGranaghan 1993) around boundaries can show a level of spatial uncertainty. Further extensions of this include using the width of a line to express spatial uncertainty (McGranaghan 1993), a broken line to misrepresent contour lines or uncertain boundaries (Muehrcke & Muehrcke 1992; Pang 2001), and varying contour widths to represent uncertainty (Dutton 1992). MacEachren (1992) proposed areas to have no boundaries, but instead fade from the centre to its outer limits. Also, by using varying degrees of fill clarity for

features a sharp and distinct pattern could indicate certainty, whilst a less defined pattern could express uncertainty. MacEachren (1992) also addressed spatial uncertainty using a semi-transparent fog to overlay a map; hiding uncertain parts where thicker fog represented more uncertain areas. Fisher (1994b) explained that animation can show areas where spatial data is uncertain using individual map pixels which constantly change. Realizations for each pixel can be generated, determining the accuracy of a classified pixel. For example, uncertain pixels use the temporal dimension by swapping back and forth between applicable categories. Therefore, animated pixels highlight uncertain areas which can have many valid categories.

4.0 THE TRUSTREE TO VISUALISE ATTRIBUTE AND SPATIAL BOUNDARY UNCERTAINTY

A recent research article by these authors (Kardos, Benwell & Moore in press) proposed to use the output from the hexagonal or rhombus (HoR) quadtree spatial data structure (Bell, Diaz & Holroyd 1989) for the expression of attribute and spatial uncertainty. This method will be briefly explained, allowing readers to grasp the concepts put forward in this paper thereafter.

The HoR quadtree (a spatial data structure), designed to divide a spatial representation, is based on the successive subdivision of a bounded image into four equal-sized quadrants (Bell, Diaz & Holroyd 1989). This research programme proposed to take the HoR quadtree out of its original context and utilise its inherent variable resolution and graphical structure to exhibit a degree of attribute and choropleth spatial uncertainty (where spatial uncertainty is mentioned for the continuation of this work, it refers to choropleth spatial uncertainty). Instead of using the HoR quadtree to decompose a bounded image array, the HoR quadtree was used to decompose census tract polygons. When representing spatial data, the output of the HoR quadtree could be used as a metaphor for uncertainty showing levels of detail. Fairbairn et al. (2001, 14) stated that “levels of detail as a cartographic concept similar to generalisation is now accepted [in visualisations]”. In particular, the HoR quadtree output could be used to show varying levels of detail which in turn is analogous to varying levels of detail. The visual use of the HoR quadtree in this way will be termed ‘The Representation of Uncertainty using Scale-unspecific Tessellations in Tree form’ – the Trustree and can be seen in Figure 1. The trustree is similar to the highly regarded resolution and fog metaphors (MacEachren 1992), but instead of changing or hiding detail, the spatial data structure is a transparent layer over the top. The trustree is also a multi-resolution display because more resolution is gained the more the tree structure divides. A display of uncertainty is achieved using a tree structure of varying detail. The trustree provides an ability to impose many variable tessellation sizes (i.e. coarse, average, fine, etc.); all able to represent a measure of uncertainty. Attribute uncertainty is represented by the size of a quadrature or cell. Spatial boundary uncertainty (i.e. for census datasets) is expressed by spreading a linear boundary into areal tessellations. This shows an area associated with a tessellation of a certain size has the effect of distributing the boundary over space, reducing subjectivity and fixed boundaries associated with census tracts.

The Representation of Uncertainty using Scale-unspecific Tessellations or TRUST is a plug-in for the ArcMap GIS software suite which is responsible for producing the trustree visualizations. TRUST obtains a measure of attribute uncertainty using Monte Carlo (MC) statistical techniques. Other uncertainty researchers utilise and express the benefits of MC simulations (Burrough & McDonnell 1998; Heuvelink 1998; Zhang & Goodchild 2002), for MC is a simple approach to modelling statistical errors in data using ordinary statistics and random variables. MC simulations help identify errors associated with an attribute using arithmetical operations. There is an assumption that each attribute’s error has a Gaussian (normal) probability distribution function (PDF), and by continuously repeating the arithmetical operation the PDF variation will be removed (see Heuvelink 1998 for a detailed discussion). The final results from a MC simulation are mean error and standard deviation values for each attribute. By dividing the standard deviation layer by the mean layer, TRUST produces a layer of relative error. This provides TRUST with a numerical attribute uncertainty layer which can be fed into the trustree visualization engine, producing uncertainty visualizations as its output (as seen in Figure 1).

4.1 The Trustree to Denote both Attribute and Spatial Boundary Uncertainty

In summary, this research programme chose to generate attribute uncertainty for population census data using the MC statistical technique, and rather than generate figures for choropleth boundary uncertainty, the same data was utilised. This was done because (a) there is an inherent relationship between attribute and spatial uncertainty which the tessellation can show. For example, if there are two neighbouring census tracts with markedly different attribute uncertainties then the area of transition shown through the tessellation will normally be greater, as you pass from small cells through medium sized cells to the largest cells that denote the greatest attribute uncertainty. This would imply that the greater the difference between neighbouring census tracts, the

more spatial boundary uncertainty there is, as expressed by a greater area of transition. Also, (b) the choropleth arbitrarily separates space; whilst a tessellation can show attribute uncertainty by tessellation size and spatial uncertainty by the tessellation location. This, in short is not a pure representation of spatial uncertainty, but rather implied by the attribute uncertainty creating a good overall approach to contribute meaning to arbitrary choropleth boundaries.

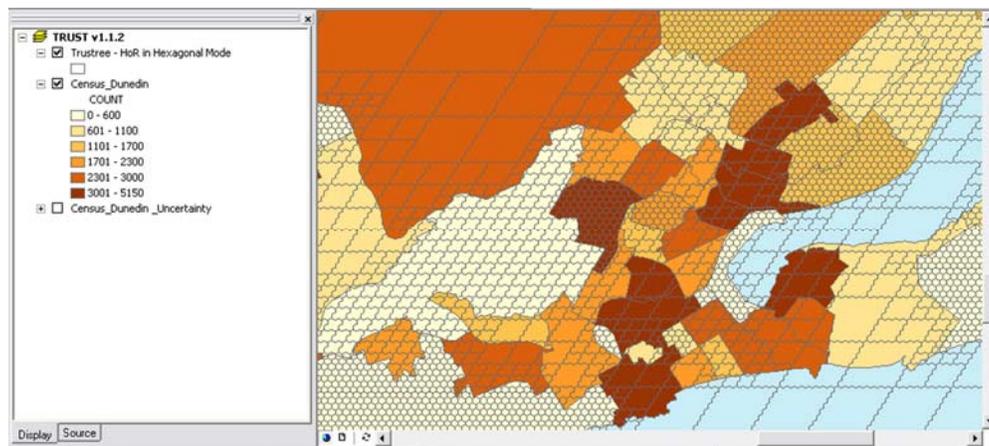


Figure 1: Screenshot of TRUST v1.1.2 – the HoR trustree over Dunedin City. The original census data is still visible whilst the HoR trustree tessellation represents uncertainty in the data. Smaller tessellations represent accurate areas and vice versa.

5.0 THE USABILITY OF UNCERTAINTY VISUALISATIONS

Usability testing of four uncertainty visualisations was performed. To effectively test the usability of the HoR and VBA trustree (using the HoR boundaries to separate choropleth colours) as well as blinking areas and adjacent value, it is possible to provide tasks for participants to perform which could determine whether or not they can ‘spot’ and rank areas in a visualisation display which are uncertain. Also, by recording the time taken for a participant to perform this ranking task, it can provide a speed of understanding associated for each of the trustree visualisations tested. In effect, the result set provided proficiency metrics for each visualisation. A simple task was put forward to the participants, whilst two variables – uncertainty rankings and time taken were collected.

5.1 Assessing the Usability of Four Uncertainty Visualisations

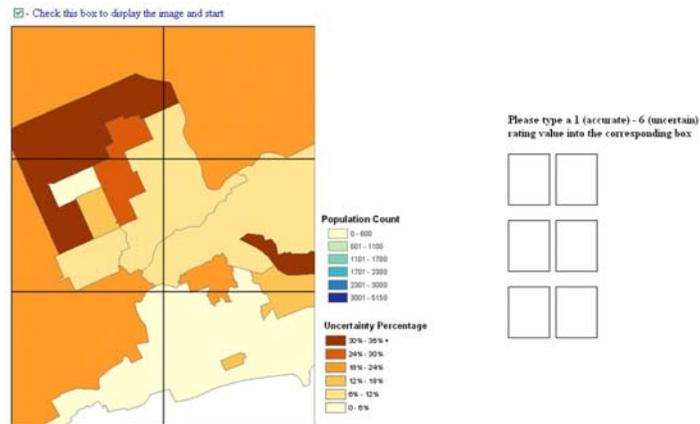
A survey was created on the Internet to assess usability of four uncertainty visualisations. Using the Internet as a medium was done for a number of reasons. The Internet provides an excellent ability to convey visualisations through (which Drecki 1997 and Aerts et al. 2003 also use), and also easily record responses using database technologies. The Internet also provides worldwide access to individuals in the GIS community. The survey was created in two sections; the first section was called **General Information** and the second, **Usability**. As an example, the general information section questions included: (do you use geographic information (GI)?, if so what for?; your experience using GI - which was self assessed: beginner, intermediate, advanced or expert?; your occupation?; did you know that uncertainty can exist in GI visualisations and how would you visualise uncertainty?).

The participants were then required to complete the usability section. This section was designed to show a participant each uncertainty visualisation, which were divided into six grid cells. Participants were asked to rank each cell on the following scale:

1 - cell containing the most accurate information <==> 6 - cell containing the most uncertain information

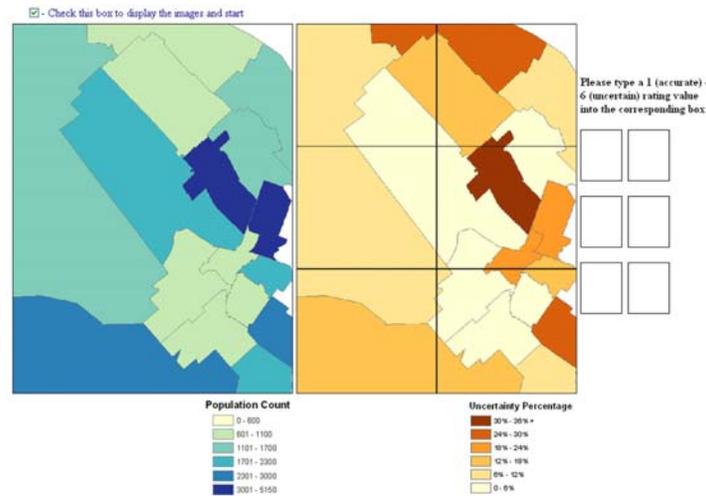
Uncertainty and population legends were provided for the participant to use when deciding the uncertainty of the six grid cells. Corresponding boxes adjoining the visualisations were provided for the participant to enter their grid cell rankings. An explanation of the usability selection process and a visual example provided participants with an indication of how to successfully complete the survey. All of the four usability uncertainty visualisations can be seen in figure 2. It should be noted that the blinking areas example shown in figure 2a (the uncertainty map is shown) cannot blink in paper form – the population map would be exchanged by the uncertainty map every 1.5 seconds. The time taken to perform the rankings was recorded allowing the periods between visualisations to be examined.

2.1 Blinking Areas



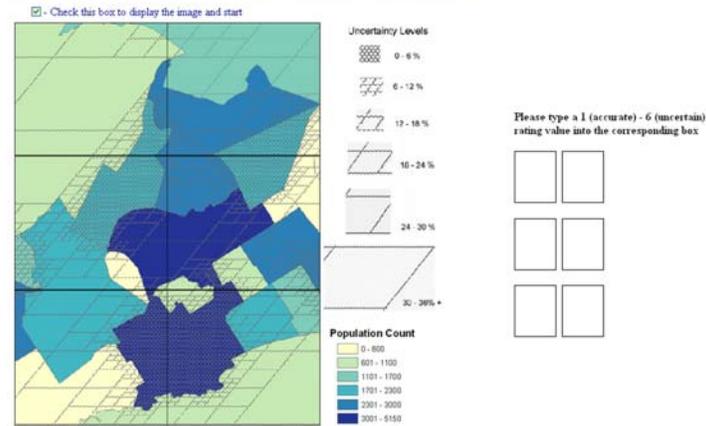
a)

2.2 Adjacent Value Uncertainty Maps



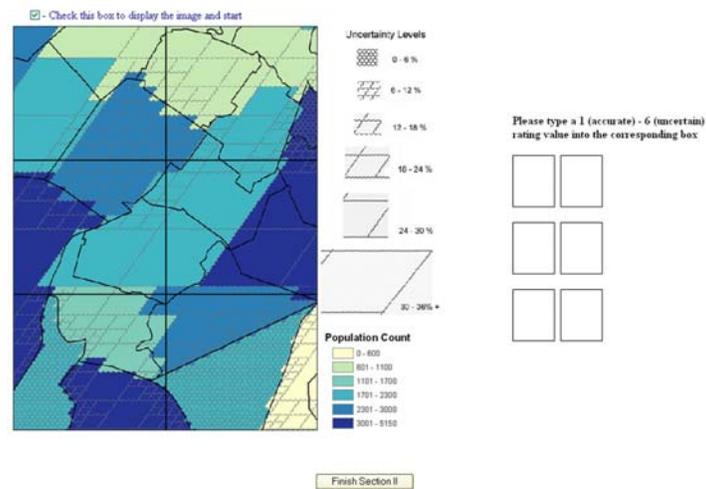
b)

2.3 Hexagonal or Rhombus (HoR) Trustree Tessellation Overlay



c)

2.4 Value-by-Area Trustree with Census Boundaries



d)

Figure 2: The four uncertainty visualisations surveyed for usability, a) blinking areas, b) adjacent value, c) HoR trustree and d) VBA trustree. An uncertainty and population legend was provided for each visualisation and boxes to the right for participants to insert their grid cell rankings.

5.2 Spearman's Rank Correlation Coefficient

To assess how well each participant did, a Spearman's rank correlation coefficient (Siegel 1956) was performed. This allowed a proper evaluation of responses to be obtained. Drecki (2002) performed a similar usability study that also used the Spearman rank correlation coefficient test to check true uncertainty rankings against the participant's rankings. A true uncertainty ranking for each visualisation method was obtained using an areal interpolation. As an example, if within a grid cell, 50% of the area exhibits the highest degree of uncertainty (6), whilst 30% exhibits the 5th level and the last 20% exhibits the 1st level or lowest degree of uncertainty. An arbitrary uncertainty indicator for this grid cell could be determined using the following as an example:

$$50\% \text{ at level } 6: 50 * 6 = 300$$

$$30\% \text{ at level } 5: 30 * 5 = 150$$

20% at level 1: $20 * 1 = 20$

Uncertainty indicator = 470

Therefore, by performing the areal interpolation for each of the six grid cells within a visualisation, an uncertainty indicator (U_i) relating to each cell was acquired. This generated a ranking order which could be used for the Spearman rank correlation coefficient testing. Spearman's rank correlation coefficient provides a rank coefficient – r_s of which the value must be between -1 (inverse correlation) and 1 (full correlation) using the following formula in equation 1:

$$r_s = 1 - \left[\frac{6 \sum d^2}{n^3 - n} \right]$$

Equation 1

where n is the number of ranks in the sample and d the disparity between two rankings. As an example, in table 1, after running the areal interpolation for each of the cells (on the left) the *blinking areas* ranking order (on the right) was:

Cell 1: $U_i = 450$	Cell 2: $U_i = 370$	→	6	4
Cell 3: $U_i = 400$	Cell 4: $U_i = 273$		5	2
Cell 5: $U_i = 345$	Cell 6: $U_i = 90$		3	1

Table 1: Using areal interpolation to determine an uncertainty indicator (U_i) whereby a greater U_i exhibits larger uncertainty. This provided each technique with a grid cell ranking order – this example shows the U_i values and grid cell ranking order for the *blinking areas* visualisation.

This provided the true rank order values to be used in the Spearman's rank correlation coefficient test. Let's say as a continuation to this example, three subjects provide cell rankings for the *blinking areas* visualisation. The rank correlation coefficient outputs can be seen in table 2. Respondent one (R1) ranked each of the six cells correctly and therefore obtains perfect correlation with an r_s value of 1. Unfortunately, respondent two (R2) did not read the scale rating system correctly and has reversed the uncertainty rank order acquiring a near perfect negative correlation value for r_s of -0.90887. Respondent three did get one ranking correct and was close to getting all other rankings correct; therefore, the r_s value of 0.771429 is reasonably close to 1.

True Rank Order	R1	R2	R3
Cell 1 - 6	6	1	6
Cell 2 - 4	4	5	5
Cell 3 - 5	5	2	3
Cell 4 - 2	2	5	1
Cell 5 - 3	3	4	4
Cell 6 - 1	1	6	2
$r_s =$	1	-0.90887	0.771429
Average $r_s = 0.287$			

Table 2: An example of Spearman's rank correlation coefficient whereby each respondents ranking is assessed against the true rank order for correlation.

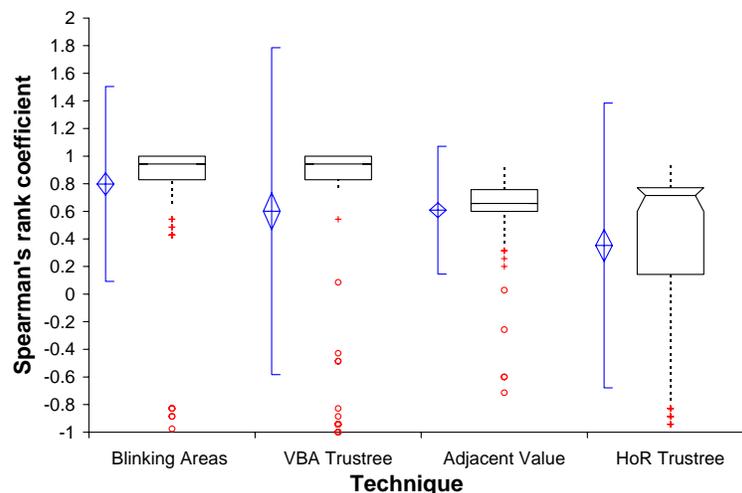
Unfortunately, in the example given in table 2, the average r_s value of 0.287 is dramatically reduced because one of the respondents reversed the scale ordering. Therefore, R_2 could be considered an outlier to the other results.

6.0 RESULTS AND CONCLUSION

The study group consisted of around 110 participants throughout the world that used GIS and had an understanding about uncertainty in GIS. These participants subscribed to a variety of GIS group email lists (contact author for a complete list). Participants were asked to provide a self-assessed GIS experience rating; overall, their experience was high with 26% experts, 40% advanced and 17% intermediate. More than half of the respondents were in a profession using GIS or involved with GIS in government or education & training. Most participants used geographic information to view, manipulate and present, whilst a majority also created, researched, managed and made decisions from geographic information.

6.1 Spearman's Rank Correlation Coefficient Results

Box and whisker graphs were used to show the Spearman's rank correlation coefficient results. To determine what kind of influence outliers can have on the average r_s resultant, a standard deviation and 95% confidence interval (CI) statistical tests were run. The outliers were not removed because using the 95% CI can give a clear indication where the r_s could lie without manipulating the original dataset.



	Blinking Areas	VBA Trustree	Adjacent Value	HoR Trustree
n	109	114	108	115
Mean	0.798	0.601	0.609	0.352
SD	0.4290	0.7199	0.2812	0.6269
SE	0.0411	0.0674	0.0271	0.0585
95% CI of Mean	0.717 to 0.879	0.467 to 0.735	0.555 to 0.662	0.237 to 0.468
Median	0.943	0.943	0.657	0.714
IQR (inter-quartile range)	0.171	0.171	0.157	0.629
95% CI of Median	0.943 to 0.943	0.943 to 0.943	0.657 to 0.657	0.600 to 0.771

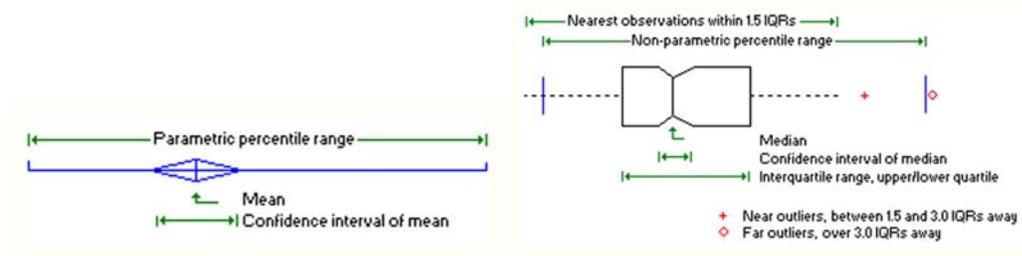


Figure 3: The four visualisation of uncertainty methods tested for usability. The Spearman rank correlation coefficient results are plotted into the box and whisker chart – whereby the r_s values closer to one have the greatest correlation.

6.2 Timer Results

To further these results, a timer variable was collected whilst the participants ranked the uncertainty visualisations. This determined the amount of time a participant spent ranking each visualisation. The timer started when a participant clicked on the ‘display image to start’ checkbox. The timer stopped when the next checkbox was selected or a button to finish the usability survey. The timer results for all the uncertainty visualisations are displayed in figure 4.

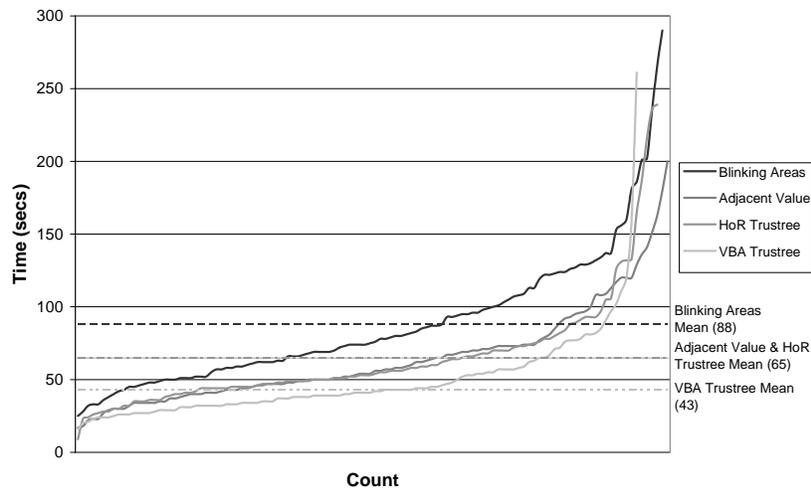


Figure 4: A time graph for all visualisations assessed for usability with mean value lines (ordered by time taken).

6.3 Discussion of the Results

This survey was designed to provide an actual usability metric value for four uncertainty visualisations, two current methods (blinking areas and adjacent value) and two TRUST suite visualisations – the HoR trustree from TRUST v1.1.2 and the VBA trustree from TRUST v1.2. By asking participants to use a cell ranking system and then checking their answers against the model answers, a ranking correlation coefficient value could determine how well each participant performed. The results for the HoR trustree are not very strong, with a mean r_s value of 0.35 from a range between 1 and -1. Therefore, to put the HoR trustree into a more realistic usability category, the r_s value can be converted into a usability percentage. The HoR trustree ranked 65% usable, whilst the VBA trustree with a mean r_s value of 0.60 ranked 80% usable. This was just off the adjacent value usability rank of 81%, but still 10% off blinking areas, which ranked at 90% usable. There are a number of reasons why the results might be arranged in this manner. The uncertainty indicator (U_i) values which determine the amount of uncertainty within each cell (the U_i values are explained in detail in section 5.2 – Spearman’s

rank correlation coefficient) had markedly less separation for the HoR trustree and VBA trustree, than the blinking areas method. All of the U_i values for the four methods can be seen in table 3. It would be expected that participants are able to differentiate between grid cell uncertainty levels easier when a method has a high U_i value. By putting the U_i ranks against the usability ranks in a Spearman's rank correlation coefficient test, there is a 70% correlation ($r_s = 0.4$). The adjacent value method performs slightly better than the two trustree visualisations, but otherwise the trend matches. This means that there is a 70% chance that the larger average U_i values would help participants differentiate between and select the correct cell rank order.

Visualisation Method	Usability Rank	U_i Average Separation	U_i Rank
Blinking Areas	1	72	1
Adjacent Value	2	22	4
VBA Trustree	3	46.5	2
HoR Trustree	4	39	3

Table 3: The average U_i separation between the six grid cells within each visualisation.

Unfortunately, since the trustree visualisations had to be split into six grid cells, the boundary lines tended to clutter over the uncertainty visualisation display. Since the HoR trustree and VBA trustree both use a form of overlay to express uncertainty, the grid cell boundaries hid the full thrust behind these methods. Both the blinking areas and adjacent value method had two line forms within its display, whilst the HoR trustree and VBA trustree had three line forms – census tract boundaries, HoR tessellation boundaries and grid cell boundaries.

The timer results are semi indicative of the usability, participants spent most time ranking the blinking areas visualisation method, whilst equal mean times were recorded for the HoR trustree and adjacent value methods and the least amount of time was spent on the VBA trustree method. To assess if there is a correlation between usability and time spent ranking the different visualisation methods, a Spearman's rank correlation coefficient test was done, using data from table 4. The adjacent value and HoR trustree both had a mean timer value of 65 seconds; therefore their ranking was averaged between 2 and 3, providing a ranking of 2.5 each. The correlation results show that there is an 82% correlation between the time taken to rank each visualisation and their overall usability ranking results ($r_s = 0.63$).

Visualisation Method	Usability Rank	Mean Time	Timer Rank
Blinking Areas	1	88	1
Adjacent Value	2	65	2.5
VBA Trustree	3	43	4
HoR Trustree	4	65	2.5

Table 4: Assessing if there is correlation between the mean time taken for a participant to rank an uncertainty visualisation and the usability results obtained.

The timer and usability correlation results mean that there is a significant chance that there is a correlation between how long a participant took to rank a visualisation and the usability rank obtained. Moreover the longer a participant spent deliberating the uncertainty within cells, the higher chance the participant ranked the cells correctly.

6.4 Conclusion

The paper presented here has defined attribute and spatial uncertainty in the context of this research programme. In particular, attribute uncertainty for the New Zealand 2001 census dataset was obtained using MC statistical simulations, whilst spatial choropleth boundary uncertainty was expressed by spreading a linear boundary into areal tessellations. This, in short is not a pure representation of spatial uncertainty, but rather implied by the attribute uncertainty creating a good overall approach to contribute meaning to arbitrary choropleth boundaries. The trustree was briefly defined, allowing readers to understand the previous research undertaken in this

uncertainty visualisation programme. Two versions of the trustree: the HoR trustree and the VBA trustree were assessed for usability along with two other popular uncertainty visualisation methods, blinking areas and adjacent value. Grid cell lines were placed over each visualisation presenting 6 separate cells for each participant to rank in order from accurate to uncertain. The participant rankings were compared against the actual ranking answers (obtained using areal interpolation) using a Spearman's rank correlation coefficient test. Results show the TRUST visualisations do not perform as well as the blinking areas or adjacent value methods. Blinking areas ranks at 90% usable, adjacent value at 81%, VBA trustree at 80% and the HoR trustree at 65% usable. This could be because the degree of separation between the amounts of uncertainty separating grid cells is low for the TRUST visualisations and higher for the blinking areas visualisation. There is a 70% chance that the larger average U_i values would help participants differentiate between and select the correct cell rank order. Also, timer results indicate that there is an 82% correlation for: the longer a participant spent deliberating the uncertainty within the grid cells, the greater chance the participant ranked the cells correctly. The trustree visualisations had three forms of texture-like overlay (census tract boundaries, HoR tessellation boundaries and grid cell boundaries), whilst the blinking areas and adjacent value methods only had two (census tract boundaries and grid cell boundaries). This could reduce the full thrust behind the trustree, making the visualisations cluttered.

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