ATMOSPHERIC SCIENCE LETTERS
Atmos. Sci. Let. **14**: 220–226 (2013)
Published online 21 June 2013 in Wiley Online Library
(wileyonlinelibrary.com) **DOI:** 10.1002/asl2.443

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Using sound to represent uncertainty in UKCP09 data with Google Maps API

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Received: 8 February 2012
Revised: 15 May 2013
Accepted: 18 May 2013

Abstract

The UK Climate Projections 2009 (UKCP09) dataset contains future climate projections for the UK and a measure of uncertainty for these values. Understanding both types of data is important for scientific interpretation, but just presenting information visually has limitations because of the amount of data involved. This study evaluates the use of sound to represent uncertainty using a survey tool developed with Google Maps API (Application Programming Interface) ($n = 72$). Use of sound to reinforce visual information results in significantly better performance for participants ($p = 0.006$), and participants also performed more effectively with pre-existing knowledge of the dataset and with practice.

Keywords: sonification; uncertainty; UKCP09; Google Maps API; data representation

1. Introduction

Much work involving future climate projections produces voluminous data which is shown to the end user on a map. Multiple data values for the same spatial location are difficult to show on one map and therefore are often shown as a set of maps. This can be effective for two or three variables, but for more it soon becomes unwieldy. This paper examines the use of sound as a complementary means of presentation. Using projections from the UKCP09 dataset as an example, sonification methods are compared with a visual method to see whether the sounds help the data to be understood more effectively.

2. What is sonification?

Sonification is defined as using sound to represent data (Hermann *et al.*, 2011) with the earliest example from ancient Egypt (*ca* 3500 BC) where two independent logs of grain transactions from the silos were recorded. These were read out (i.e. sonified) in front of the Pharaoh and any discrepancies between the records were quickly spotted (Worrall, 2009). One of the most widely recognized forms of sonification is the Geiger counter, where a repeating pulse is emitted, and the frequency of the pulse varies with the intensity of the radiation detected. With technical developments over the last 20 years, sonification has grown significantly in terms of the sounds that have been used (with a focus on non-speech sounds) and availability of data to be sonified.

Sonification has been applied in a wide range of situations, but few with spatial data and none using sound to represent climate data over a large area as far as the authors are aware. Flowers *et al.* (2001) sonified daily weather records for Lincoln (Nebraska, USA) to allow comparisons of different months and the ability to pick out trends over different years. While not using explicitly spatial data, it was an interesting attempt to represent the data in a different way. A number of successful sonification prototypes have been created using spatial data (Fisher, 1994, Jeong and Gluck, 2003), but they have not had significant user evaluations to see whether the sonification method increases the amount of data that can be displayed to the user effectively.

3. UK Climate Projections 2009 (UKCP09)

The UKCP09 dataset provides a wide range of future climate projections for the UK up to 2100 (Jenkins *et al.*, 2009, Sexton *et al.*, 2011), and this is the first future climate projections dataset that provides information on the uncertainty of the projections to the end users. The data is targeted at policy and decision makers, whose policies will be impacted by the changing climate, but the data are complex and often the users are not experts in climate change. To assist potential users a set of training materials and resources are available from the UKCP09 website (http://ukclimateprojections.defra.gov.uk).

The main climate variables available in UKCP09 are temperature (mean, daily max. and min. and temperature of the warmest/coldest day and night), precipitation (mean and wettest day), air pressure, cloud cover and humidity (relative and specific). This study used the mean daily summer temperature (mean of maximum daily temperature of June, July and August) and temperature of the warmest day. The temperature data were used in preference to precipitation data because the uncertainty surrounding future precipitation projections is much higher than temperature and only the summer season was used to limit the complexity of the evaluation. For each of these variables, the time period, temporal averages, emissions scenario and spatial location can be selected. The time periods are a series of 30 year periods, centred around seven decades of the 21st century (e.g. 2050s which is 2040–2069) and the temporal averages used relate to a seasonal average (e.g. summer). The medium emissions scenario was chosen, which relates to the SRES emissions scenarios, A1B (IPCC, 2000). The data for the whole of the UK were used in this evaluation, downloaded as a grid of 440 25 km × 25 km cells.

Future temperatures are usually shown using a blue-red colour scale with blue for lower increases and red for higher increases in temperature. The UKCP09 dataset now contains information on the projected uncertainty of each grid cell of data; there are visual ways of representing this (such as hatching or shading for each cell), but any visual method may be complex to view and risks obscuring the underlying data. One alternative visual method (as used in the UKCP09 supporting documentation) shows the 10% probability level, the 50% probability level and the 90% probability level on three different maps (Figure 1). This allows the user to see how the uncertainty varies spatially, with the range between 10 and 90% probability levels being the projected uncertainty and the 50% probability level being the median, also known as the central estimate. This represents the data but can be complex to interpret because of the need to look at three separate maps at the same time.

All probability levels from 1 to 99% are available within the UKCP09 data, but to provide a basis for evaluation it was necessary to simplify this. For this research, a range value was calculated for each grid cell which was used to represent the projected uncertainty, by subtracting the 10% probability value from the 90% probability value. The data were downloaded from the UKCP09 site using the CDF (cumulative distribution frequency) option which provided the temperature values for the probability of the increase being less than 10, 50 or 90% as appropriate. The data are also available as a PDF (probability density function) which shows the relative probability for different temperature increases (see Jenkins *et al.*, 2009, fig. 8 for details). The CDF data were accessed using the raw data option, rather than the sampled data as only the three values were required from the CDFs (see Murphy *et al.*, 2009, section 3.2 and annex 4 for details on sampled data).

4. Evaluation

Participants ($n = 72$) consisted of staff from Ordnance Survey and the UK Climate Impacts Programme, MSc Climate Change students, PhD students and staff from University of East Anglia. All participants were given a briefing document 24 h before and a consent form at the evaluation. Opportunity was given for the participants to ask questions before and during the evaluation. As well as a map evaluation exercise, participants were asked a variety of background questions on knowledge of geographical information systems (GIS), the UKCP09 dataset and preferred learning style to

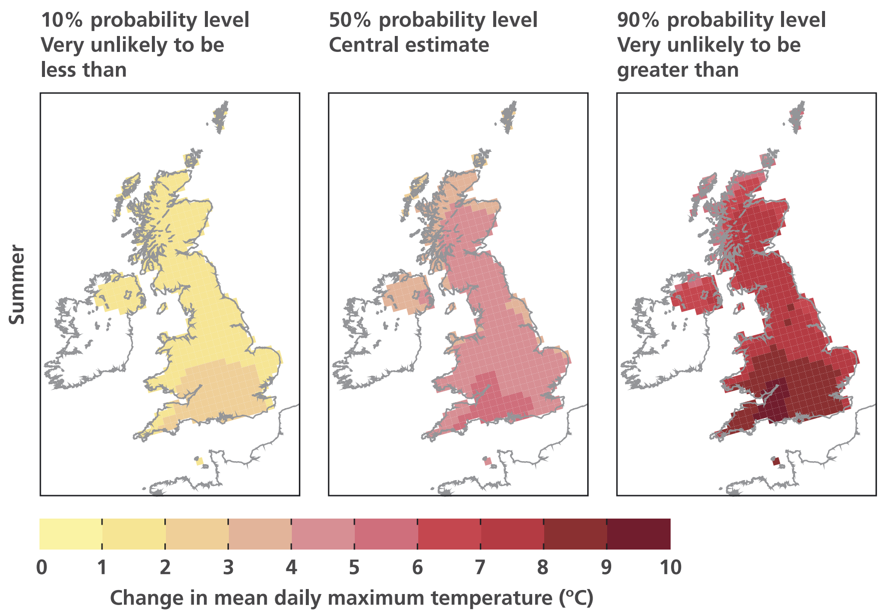

Figure 1. Three maps showing the 10, 50 and 90% probability levels for the UKCP09 data for summer (in the 2080s, under the medium emissions scenario) from the UKCP09 supporting documentation (fig.4.7 from Murphy *et al.*, 2009).

assess which factors influenced the ability to interpret the sonification effectively. The evaluation was run in small groups (two to eight participants) with each participant completing the evaluation individually on a computer. This was then followed by a recorded semi-structured interview session (20 min) where the participants discussed the effectiveness of the sonification. Small groups were preferred because it enabled a more effective discussion and allowed all of the participants to take part (Hopkins, 2007). For more details on the evaluation structure and process, see the Supporting information.

The existing framework of Google Maps was used to create the evaluation (allowing the spatial data to be displayed) and the sonification and survey components were added to the interface using the API (Application Programming Interface). Google Maps is one of the market leaders in mapping for an online audience and is familiar to a wide variety of Internet users. There are a number of tutorials available on the Google website which provided a starting point for this research (Google, 2007). The main coding was completed in JavaScript and PHP, controlling the map and questionnaire presentation, with data stored in a MySQL database and a Flash add-on was used for the sound element. More details on the methodology are available in Bearman and Appleton (2012).

As discussed earlier, there were two different elements to each dataset; the central estimate (the projected temperatures) and the range (the uncertainty). For each map, participants were asked to highlight areas that exceeded a specific threshold for the central estimate data and a specific threshold for the range data (e.g. ‘Please highlight the area where the central estimate exceeds 29°C and where the range exceeds 9°C’). During the pilot testing phase, it became clear that the sonification technique had to be explained to the users before the main evaluation took place. Therefore, two training maps were included to allow the users to become familiar with the interface and sonification techniques before starting on the main evaluation. These only showed the central estimate data (with one training map using vision and the other using vision and sound), whereas the evaluation maps (Maps 1–4) showed both central estimate and range data (more details available in the Supporting information). For the evaluation itself the data were represented in three different ways as shown in Table I and Figures 2 and 3. The data shown for each map was randomly selected from either mean daily summer temperature or temperature of the warmest day for either 2020s or 2050s.

The highlighted areas were recorded in a MySQL database as a series of geographic points and then read into a point shape file. This was processed using a point-in-polygon analysis to calculate which UKCP09 grid cells were highlighted by the user for each map. Each result was compared against the ‘correct’ answer (i.e. the areas exceeding the specified thresholds) using Pearson’s Phi measure of agreement for binary data (Equation 1). This coefficient summarized the participants’ answers for each map and method combination into a single figure. The ϕ score was calculated by creating a 2×2 matrix (Table II) of the counts of the cells that were selected and were not selected (user highlighted) against the cells that should and should not have been chosen for that data combination (correct answer).

$$\varphi = \frac{ad - bc}{\sqrt{efgh}} \qquad (1)$$

Equation (1) is the formula used to calculate the ϕ value for each map. Values *a, b, c* and *d* relate to the table above and ϕ is the ϕ value (Field 2000, p. 695).

The ϕ value can range between $+1$ and -1, with a value of $+1$ representing that exactly the correct areas were selected and a value of -1 meaning that all of the incorrect areas were selected. Values for this evaluation were between $+1.0$ and $+0.2$. The ϕ value for one map from one participant was much lower than the rest (-0.3) so this participants’ results were excluded from the analysis.

5. Results

Using sound to represent the uncertainty in UKCP09 did improve performance (as measured by the ϕ value) in some circumstances (Table III). When sound was used to reinforce information shown visually, performance was significantly better ($p = 0.005$). When sound was used to show range data and vision to show the central estimate, the improvement was less clear cut. Performance was still significantly better than

Table I. Data shown for each map and information on how the data were shown to the user.

Map No	Code	Method and data on left-hand map	Method and data on right-hand map
1	VV	Visual (central estimate) Sound (none)	Visual (range) Sound (none)
2	VSVS	Visual (central estimate) Sound (central estimate)	Visual (range) Sound (range)
3 and 4	VS	Visual (central estimate) Sound (range)	Visual (none) Sound (none)

Figure 2 shows an example of Map 2 (VSVS) showing both datasets on two maps and Figure 3 shows an example of Map 3 (VS) showing both datasets on one map. Map 3 was repeated (as Map 4) to evaluate the potential learning effect with a different dataset. When sound was used to represent the data, a trumpet note was used with lower notes representing lower values and higher notes representing higher values.

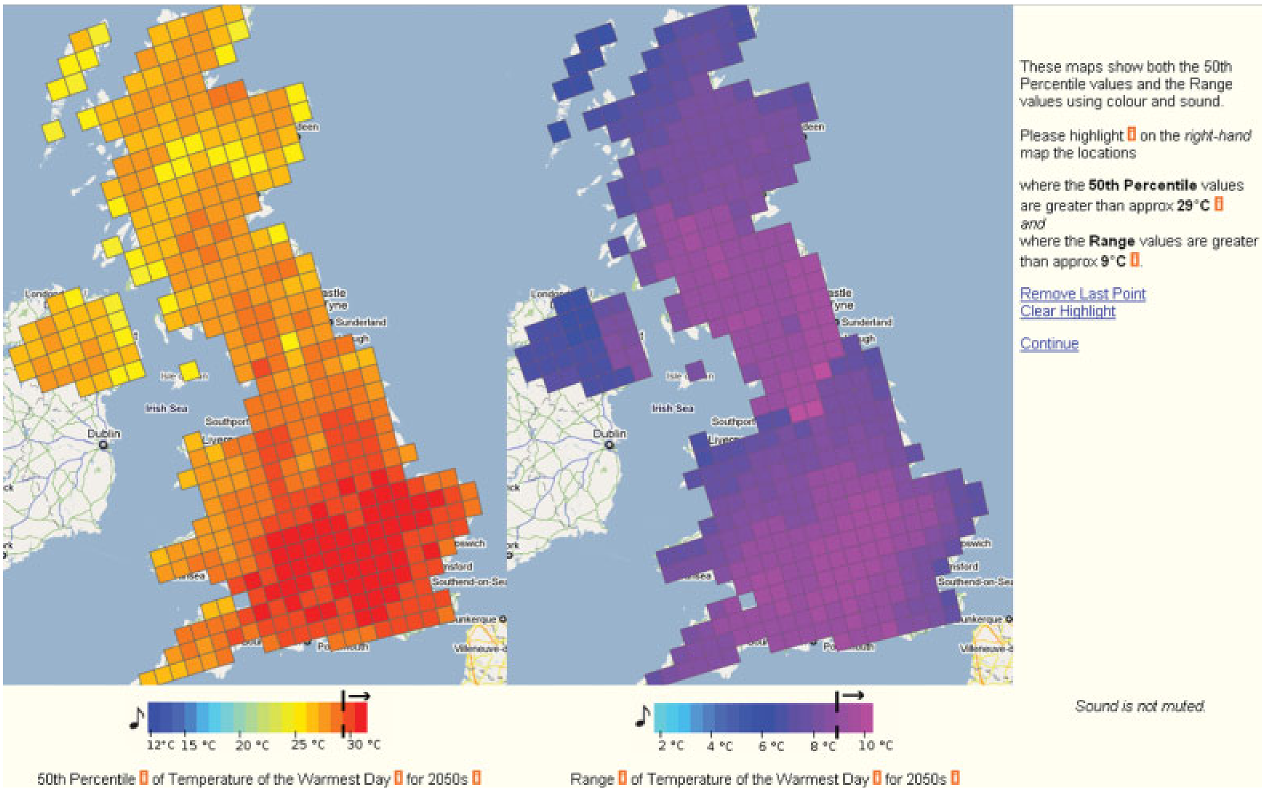

Figure 2. An example of Map 2 (VSVS) where vision and sound were used to represent both central estimate (left-hand map) and range data (right-hand map). The video clip at http://vimeo.com/17029341 shows how the sonification aspect works, see also the Supporting information for more details. © 2011 Google.

when the data were shown just visually ($p = 0.004$) but the participants took significantly longer to complete the exercise (data not shown). Participants who were aware of the UKCP09 dataset showed a significant improvement over those who did not (mean $\phi = 0.856$, compared to 0.747, $p < 0.001$), but general levels of GIS knowledge and climate change did not make a significant difference. Results from the discussion session showed that some participants found the sounds beneficial, whereas others found them distracting. This was also apparent in the ϕ scores, but the reasons for this difference were not obvious. When looking at the results for all individuals, it was clear that there were groups of participants with different patterns of results. A clustering exercise was undertaken to see whether groups of participants had different characteristics. A two-stage clustering exercise was undertaken, initially using hierarchical clustering to discover the optimal number of clusters, and then K-means clustering to allocate the participants to the clusters (Everitt, 1980). Six different clusters could be seen in the hierarchical cluster analysis, and the K-means allocation is plotted in Figure 4.

Cluster B performed well throughout all stages, whereas clusters D and F performed relatively poorly. Clusters A and F show a slight (but not significant) learning effect for the VS method. Cluster E had much better performance when using sound in either form than vision alone, and cluster C performed well apart from VSVS. It proved difficult to identify any common factors that had a consistent influence on each cluster. Those participants who knew the dataset well performed more effectively (as discussed earlier), but this did not explain the difference between the clusters; neither did a number of other factors (including learning style and knowledge of climate change and GIS). More research into the differences between participants is required to fully understand why there is this divergence and which factors are representative of each cluster; this includes increasing the sample size as some of the clusters were small.

As shown in Figure 4, some of the clusters showed a learning effect where participants improved their score as they worked through the evaluation. However, it is difficult to separate any learning effect that might exist from the different methodologies, because the maps were always shown in the same order and only one of them (VS, Maps 3 and 4) was repeated. Ideally, the order the maps were shown would be randomized, and this was considered in the pilot stage, but found to be too complex for the participants. The problem with the randomization in the pilot study was that it had the potential to start with a relatively complex interface with very little introduction. This could be solved by a more explicit training session and/or demonstration, but would make the evaluation longer.

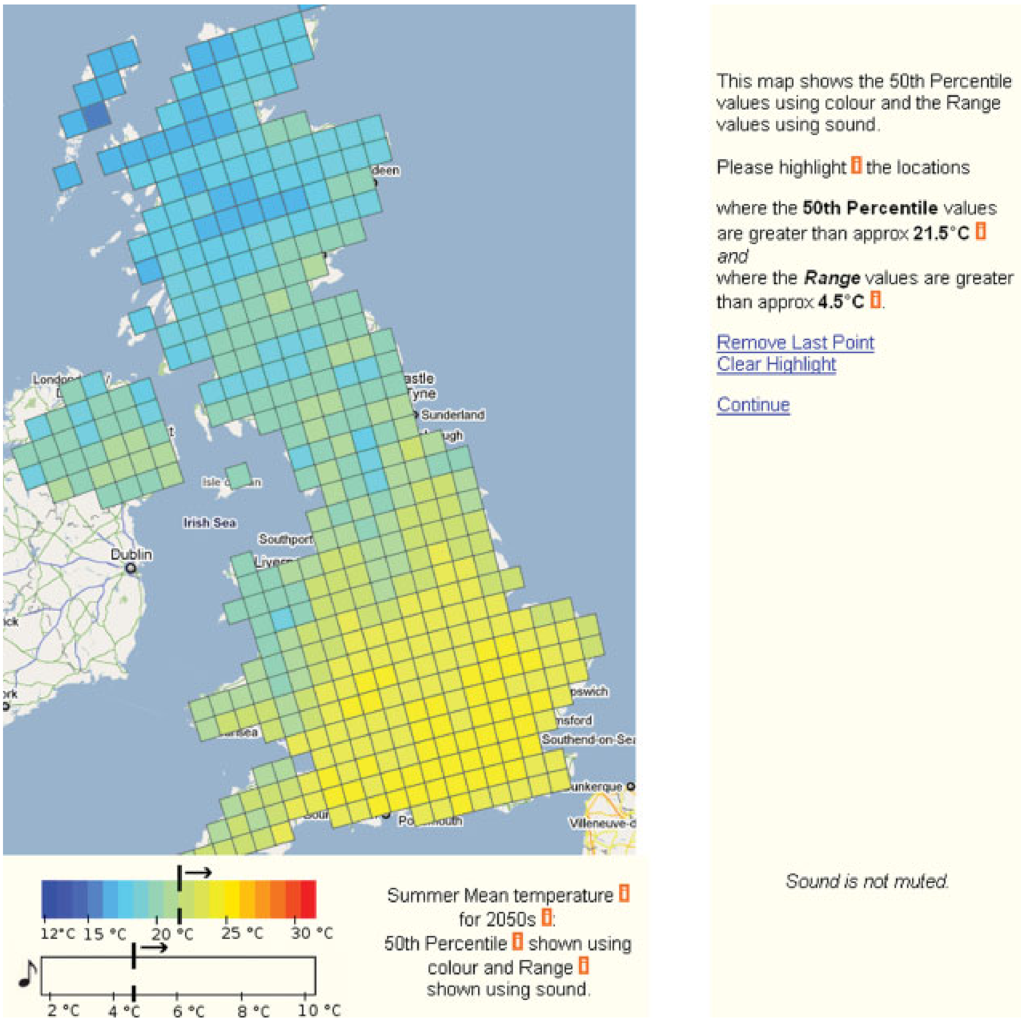

Figure 3. An example of Map 3 (VS) where the central estimate temperature data were represented visually and the range data were shown using sound. The video clip at http://vimeo.com/17029358 shows how the sonification aspect works, see also the Supporting information for more details. © 2011 Google.

Table II. Example matrix of the values used for the ϕ equation.

		User highlighted		
		0	1	Total
Correct answer	0	a	b	e
	1	c	d	f
	Total	g	h	n

Table III. Mean ϕ values for each of the four maps (top row) and independent samples *t*-tests, comparing the means of ϕ for the four maps.

Mean ϕ value	0.680	0.786	0.783	0.821
T-test Results	Map 1 (VV)	Map 2 (VSVS)	Map 3 (VS)	Map 4 (VS)
Map 1 (VV)	—	—	—	—
Map 2 (VSVS)	0.005*	—	—	—
Map 3 (VS)	0.004*	0.968	—	—
Map 4 (VS)	<0.001*	0.198	0.159	—

* Significant at the 0.01 level.

6. Discussion and Conclusion

Using sound to supplement the visual interface resulted in significantly better performance from the participants than the visual interface alone. Two different ways of using sound were evaluated, with both being more effective than vision alone. However, when using sound to show additional information (VS, Maps 3 and 4) participants took significantly longer to answer than when using sound to reinforce information shown visually (VSVS, Map 2). While these differences are significant across the whole user group, some participants found the sound much more helpful and performed better than others. Familiarity with the dataset being sonified was important and appears to be a significant factor in being able to use the sonification. There are other factors that influence the usefulness of the sonification as highlighted by the clustering of the results, but further research is required to establish what these factors are.

The Google Maps interface provided a suitable approach to represent the UKCP09 data in an easy to access way, as well as allowing the sonification element of the evaluation to be included. Changes

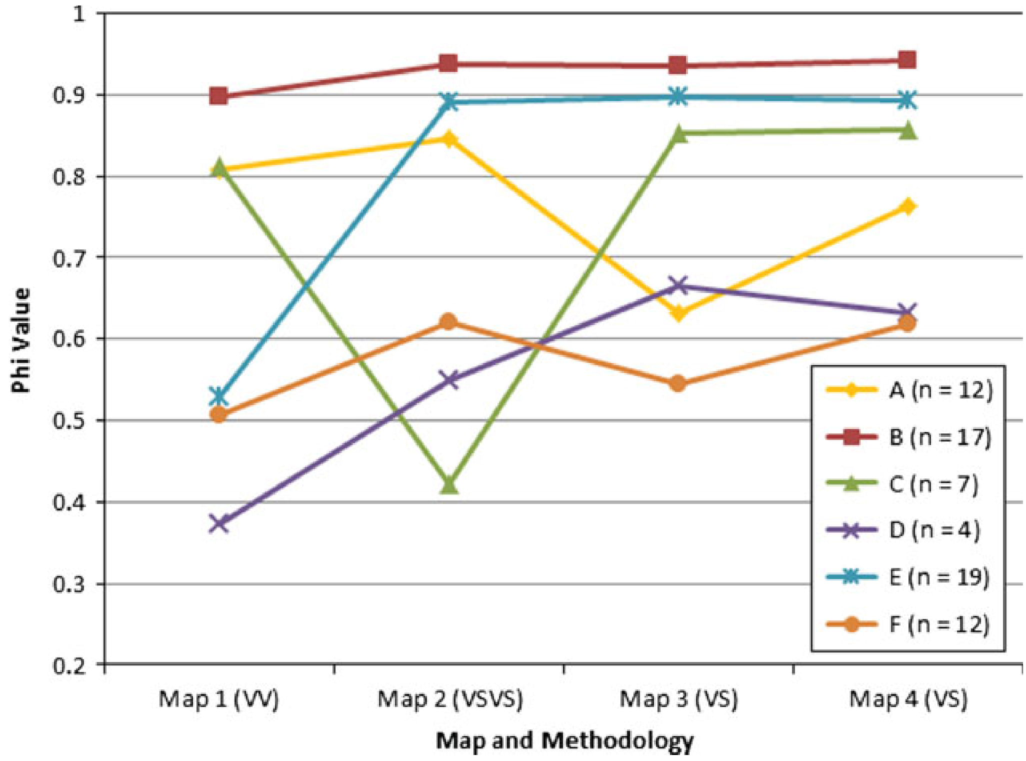

Figure 4. The six clusters (A–F) of the 71 participants ϕ values for each map stage.

to the Google Maps API are made every three months so the interface for the evaluation used during the data collection no longer works. However, videos of the implementation and supporting flowcharts and commented code are available (www.nickbearman.me.uk/go/bearman_et_al_2013_asl2). so the experiment could be repeated. The inclusion of uncertainty information in the UKCP09 dataset is a great opportunity for users of the data to include a much more comprehensive understanding of uncertainty in their work; however, there is a significant learning curve to progress from using single value predictions to multiple value projections. Training sessions run by UKCIP helped with this, but were only run for 1 year after the release of the projections. This research shows that sonification can be used to represent additional data, and future research could increase the amount of sonified data using techniques such as an auditory box plot of the temperature data over each grid cell (Hermann *et al.*, 2011).

Sonification can be very useful in some situations, and this research demonstrates that it can result in significantly improved performance when used to reinforce information shown visually. Findings in the literature show that combining sound and vision together or sound, vision and haptic together in interfaces can improve user performance (Jeong and Gluck, 2003); however, the details of the impact of sound specifically are unclear (Constantinescu and Schultz, 2011). It is likely that this variation is due to a non-sound factor in the experiment, such as the nature of the data being sonified or the background of the participants, which is reflected in this research. Additionally, there has been very little testing of the sonification techniques used to represent spatial data, so more research is required in the theoretical side of sonification as well as the user evaluation side to enable a more effective understanding of the cognitive processes involved.

Supporting information

The following supporting information is available:

Appendix S1: This document provides additional information on the evaluation design and method used in the research reported in this paper.

Table S1. The order that the data were shown to the user.

Table S2. Data shown for each map and information on how the data were shown to the user.

Acknowledgements

This research was conducted as part of ESRC/NERC PhD Studentship No. ES/F012454/1 with additional financial support from Ordnance Survey, completed when NB was at UEA. The authors would like to thank all the volunteers who took part in the evaluation, the staff at UEA who helped with the pilot testing and the reviewers for their input into the manuscript. NB is now an Associate Research Fellow at the European Centre for Environment and Human Health (University of Exeter Medical School) which is part financed by the European Regional Development Fund Programme 2007 to 2013 and European Social Fund Convergence Programme for Cornwall and the Isles of Scilly.

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