Using Sound to Represent Uncertainty in UKCP09 Data with Google Maps API

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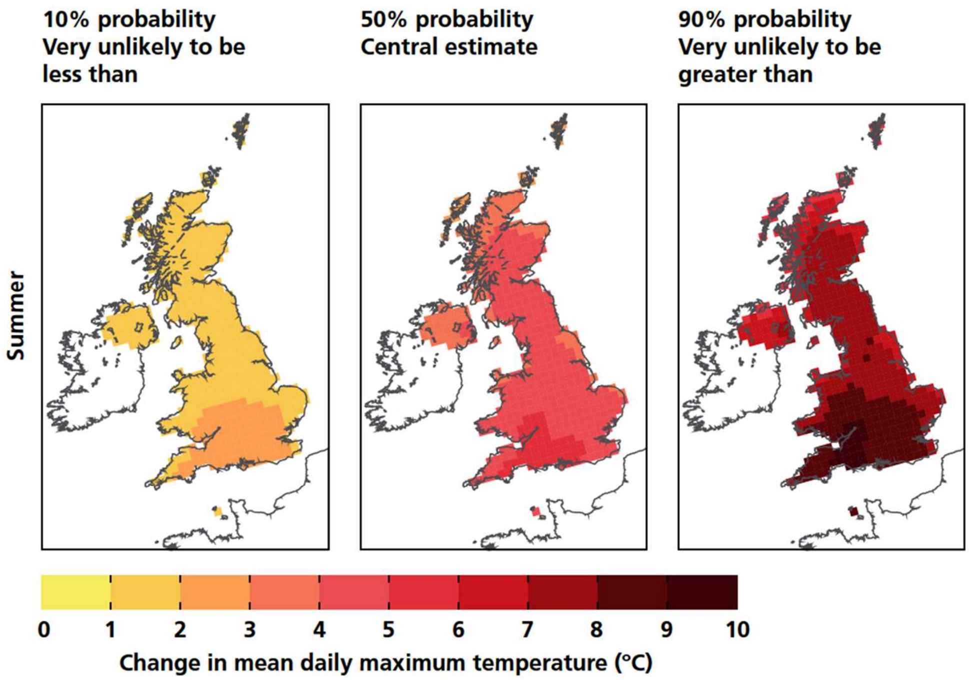

Three maps showing the 10%, 50% and 90% probability levels for the UKCP09 data for summer (in the 2080s, under the medium emissions scenario) from the UKCP09 supporting documentation (Murphy et al. 2009, fig.4.7).
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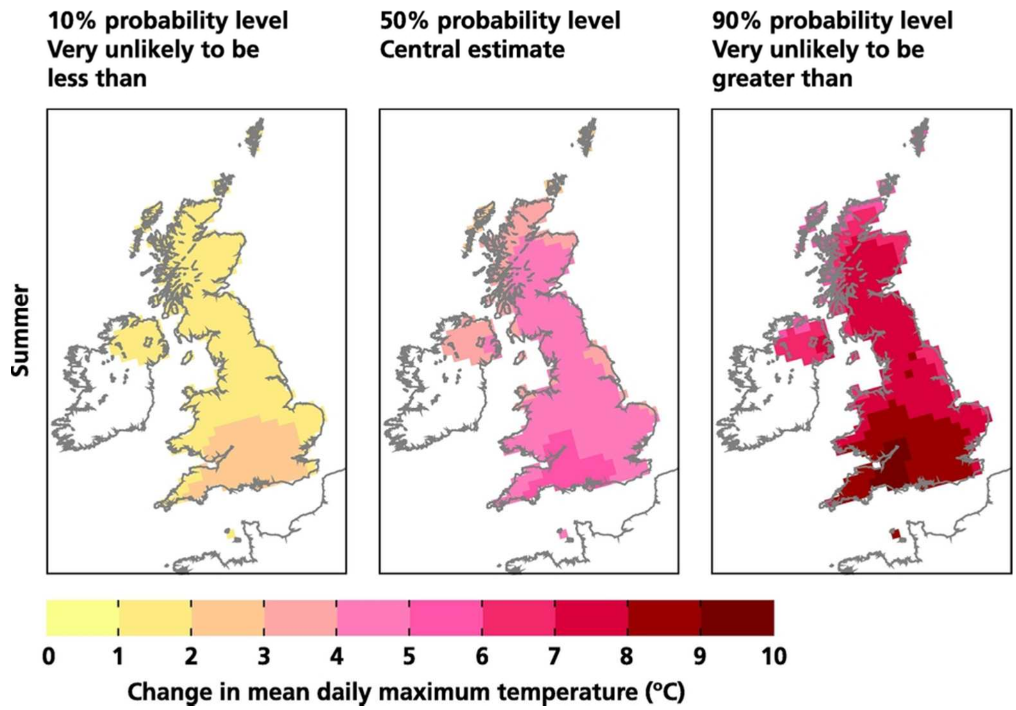

Three maps showing the 10%, 50% and 90% probability levels for the UKCP09 data for summer (in the 2080s, under the medium emissions scenario) from the UKCP09 supporting documentation (Murphy et al. 2009, fig.4.7).
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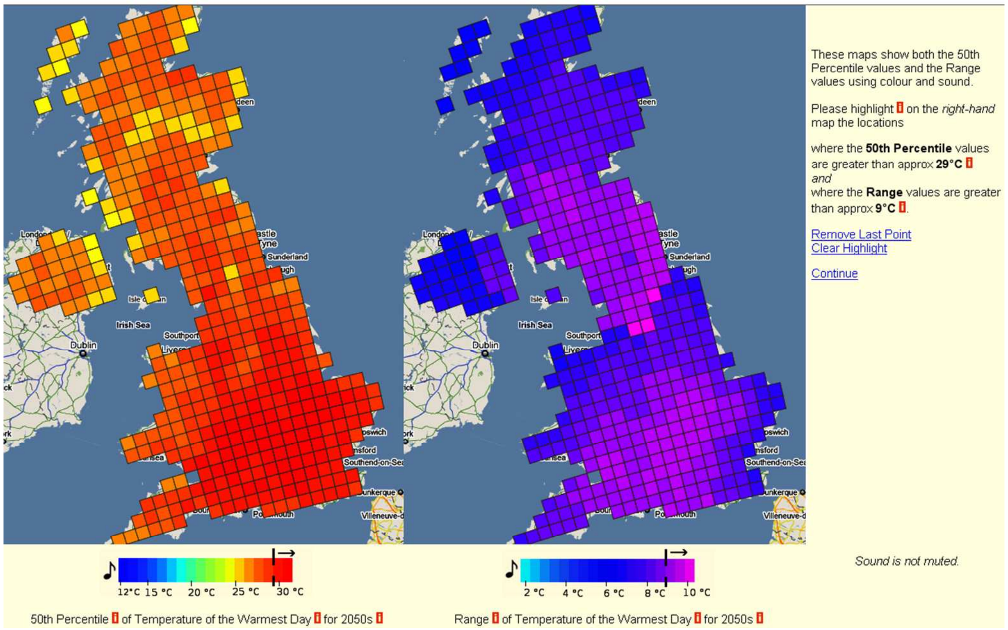
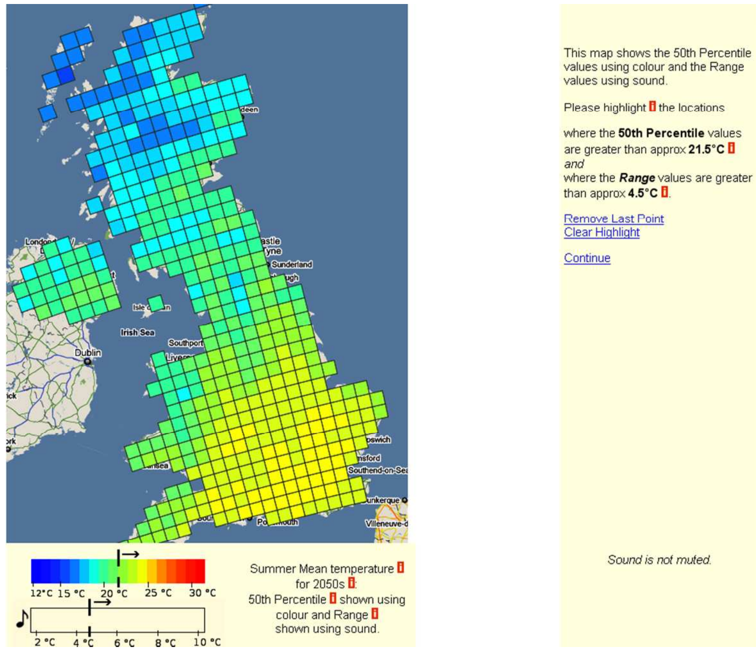
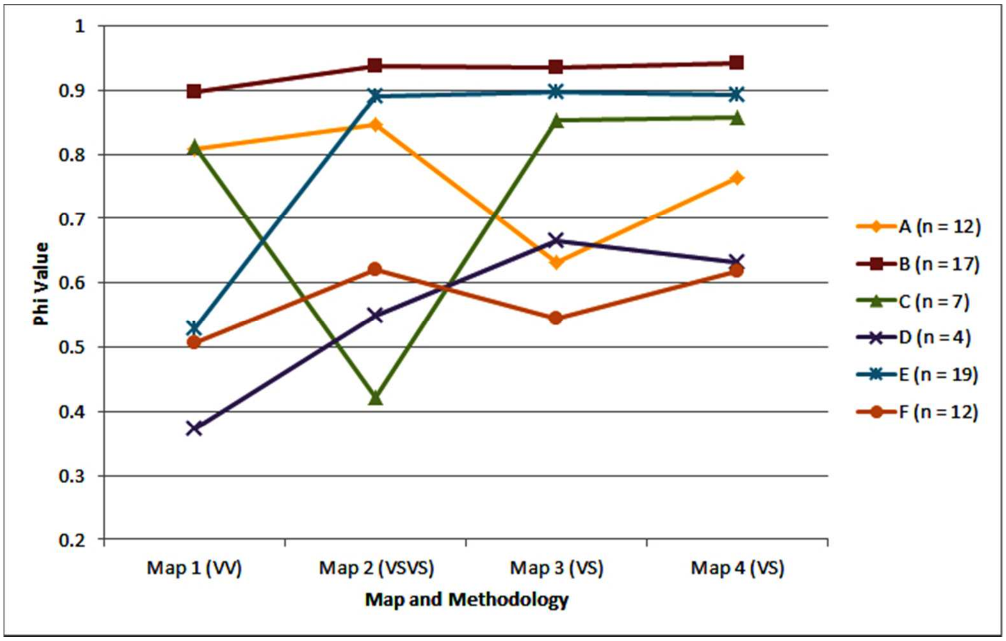


An example of Map 2 (VSVS) where vision and sound were used to represent both central estimate (left-hand map) and range data (right-hand map). The video clip at http://vimeo.com/17029341 shows how the sonification aspect works, see also the supplementary documentation for more details. © 2011 Google.
328x213mm (96 x 96 DPI)



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 supplementary documentation for more details. © 2011 Google.
329x211mm (96 x 96 DPI)



The six clusters (A-F) of the 71 participants Phi values for each map stage.
184x116mm (96 x 96 DPI)

$$\varphi = \frac{ad - bc}{\sqrt{efgh}}$$

Formula used to calculate the Phi value for each map. Values a, b, c and d relate to the table above and φ is the Phi value.
43x23mm (96 x 96 DPI)

Using Sound to Represent Uncertainty in UKCP09 Data with Google Maps API

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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 (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 data set 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 data set as an example, sonification methods are compared to 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 (circa. 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 recognised 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 data set provides a wide range of future climate projections for the UK up to 2100 (Jenkins et al. 2009, Sexton et al. 2011) and is the first future climate projections data set 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. & 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 25km x 25km 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.

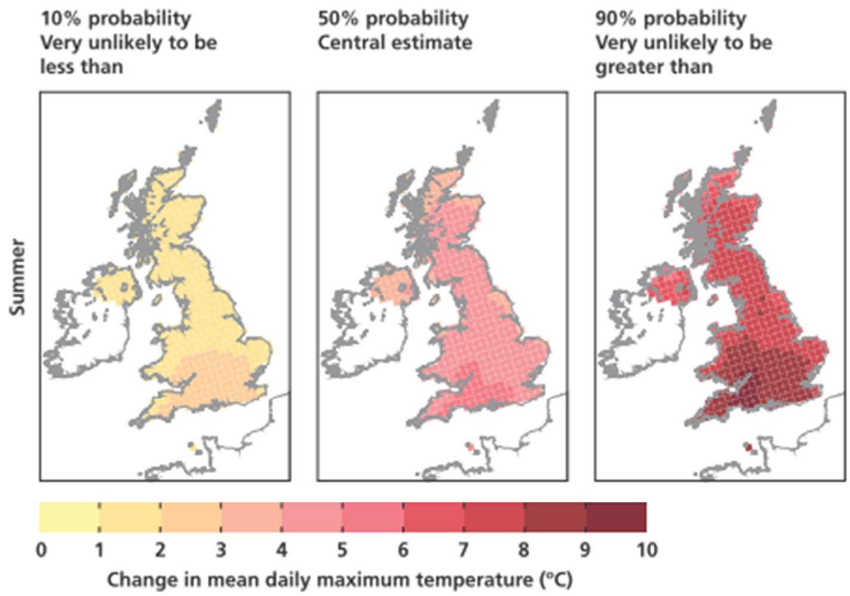

Figure 1. Three maps showing the 10%, 50% and 90% probability levels for the UKCP09 data for summer (in the 2080s, under the medium emissions scenario) from the UKCP09 supporting documentation (Murphy et al. 2009, fig.4.7).

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 hours 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 data set and preferred learning style to assess which factors influenced the ability to interpret the sonification effectively. The evaluation was run in small groups (2-8 participants) with each participant completing the evaluation individually on a computer. This was then followed by a recorded semi-structured interview session (~20 minutes) 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 supplementary documentation on the ASL website[1].

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 data set; 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 & sound) whereas the evaluation maps (Maps 1-4) showed both central estimate and range data[1]. For the evaluation itself the data were represented in three different ways as shown in Table 1 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.

Table 1. Data shown for each map and information on how the data were shown to the user. Figure 2 shows an example of Map 2 (VSVS) showing both data sets on two maps and Figure 3 shows an example of Map 3 (VS) showing both data sets on one map. Map 3 was repeated (as Map 4) to evaluate the potential learning effect with a different data set. 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.

[1] More details available in the supplementary document available at *Weblink to ASL website*

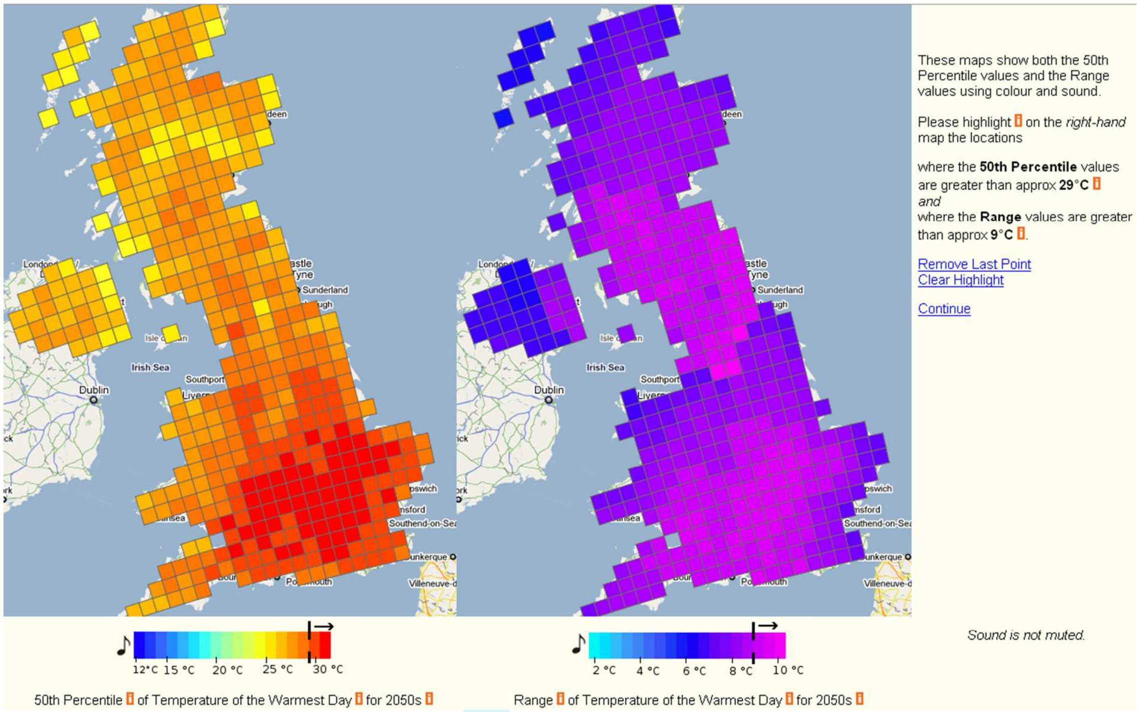

Figure 2. An example of Map 2 (VSVS) where vision and sound were used to represent both central estimate (left-hand map) and range data (right-hand map). The video clip at http://vimeo.com/17029341 shows how the sonification aspect works, see also the supplementary documentation for more details. *©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

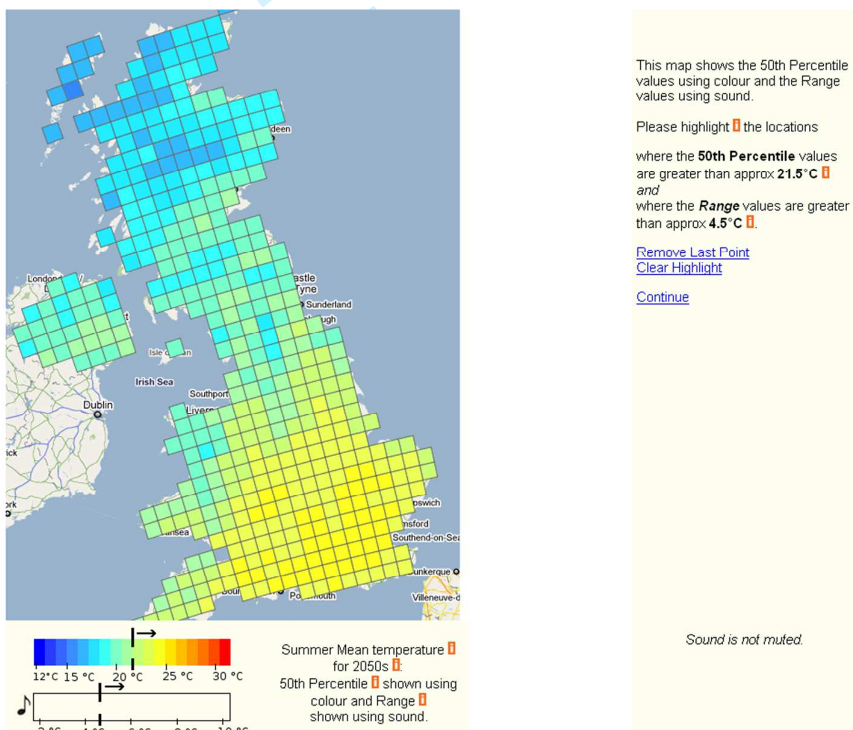

Figure 3. An example of Map 3 (VS) where the central estimate temperature data were represented visually and the range data were shown using sound. The video clip at http://vimeo.com/17029358 shows how the sonification aspect works, see also the supplementary documentation for more details. *© 2011 Google.*

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 summarised the participants' answers for each map and method combination into a single figure. The Phi score was calculated by creating a 2x2 matrix (Table 2) of the counts of the cells that were and were not selected (user highlighted) against the cells that should and should not have been chosen for that data combination (correct answer).

Table 2. Example matrix of the values used for the Phi equation.

$$\varphi = \frac{ad - bc}{\sqrt{efgh}}$$

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

The Phi 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 Phi 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 Phi value) in some circumstances (Table 3). 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 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 data set 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 Phi 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.

Table 3. Mean Phi values for each of the four maps (top row) and independent samples t-tests, comparing the means of Phi for the four maps. * = significant at the 0.01 level.

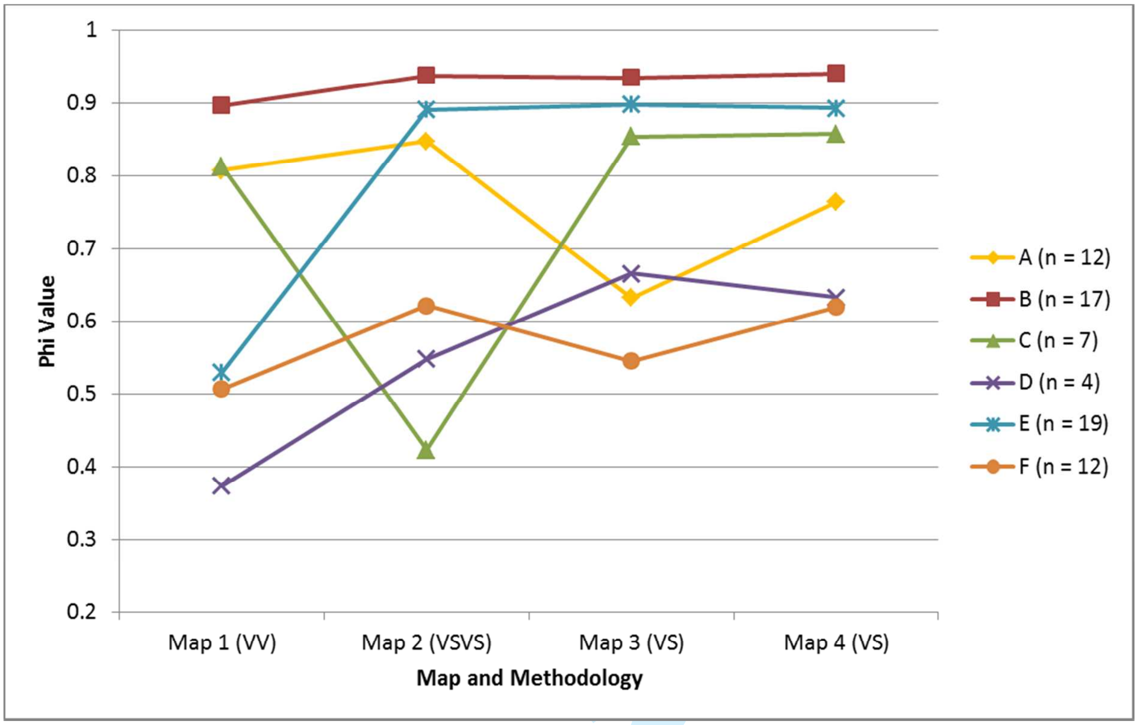

Figure 4. The six clusters (A-F) of the 71 participants Phi values for each map stage.

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 data set 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 & 4) was repeated. Ideally, the order the maps were shown would be randomised, and this was considered in the pilot stage, but found to be too complex for the participants. The problem with the randomisation 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.

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 & 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 data set 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 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[2] so the experiment could be repeated. The inclusion of uncertainty information in the UKCP09 data set 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 one 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.

Acknowledgements

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[2] At www.nickbearman.me.uk/go/bearman_et_al_2013_asl

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Map No	Code	Method & Data on Left-hand Map	Method & 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 & 4	VS	Visual (central estimate) Sound (range)	*Visual (none)* *Sound (none)*

Table 1. Data shown for each map and information on how the data were shown to the user. Figure 2 shows an example of Map 2 (VSVS) showing both data sets on two maps and Figure 3 shows an example of Map 3 (VS) showing both data sets on one map. Map 3 was repeated (as Map 4) to evaluate the potential learning effect with a different data set. 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.

		User Highlighted		
		0	1	Total
Correct Answer	0	a	b	e
	1	c	d	f
	Total	g	h	n

Table 2. Example matrix of the values used for the Phi equation.

Mean Phi 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	-

Table 3. Mean Phi values for each of the four maps (top row) and independent samples t-tests, comparing the means of Phi for the four maps. * = significant at the 0.01 level.

Supplementary Document

This document provides additional information on the evaluation design and method used in the research reported in Bearman *et al.* (2013) Using Sound to Represent Uncertainty in UKCP09 Data with Google Maps API, Atmospheric Science Letters. It should be read in conjunction with the paper.

1. Evaluation Design

1.1 Internet Surveys

Internet surveys are well established as a way of gathering data for academic research and benefits include wide (potentially global) reach, flexibility of design and ease of data processing (Evans and Mathur, 2005). However, representativeness of respondents can be a significant weakness (Peng, 2001) as can technical barriers (Evans and Mathur, 2005). Equally, different computer configurations may render the survey differently (Rivara et al., 2011) and many of the issues associated with traditional research methods still apply in the virtual arena (Madge and O'Connor, 2002).

Online surveys are often limited in the complexity of the questions that can be included, usually restricting the possibilities to multiple choice and free text answers. When spatial data input is required, these types of questions are often used to choose the nearest town/city, or to type in the user's postcode, with more complex or precise spatial information often difficult to elicit from users. Questions such as 'which route did you use to explore the beach?' (Coombes and Jones, 2010) or 'which area would you define as your neighbourhood?' (Minnery et al., 2009) are very pertinent examples. Asking respondents to draw on paper maps is one solution (Coombes and Jones, 2010), but data processing may be time-consuming and error-prone. Therefore an online method of collecting spatial data is of use in this situation.

1.2 Online Mapping APIs

There are many different online mapping services that could be used to capture spatial data in a questionnaire. The vast majority of online mapping services provide an API (Application Programming Interface), which allows third party websites to include their mapping services and, to varying degrees, customise the interface the user is shown. A number of different APIs were considered for this project, including Google Maps and Bing Maps. OpenLayers is an open source equivalent of these commercial mapping APIs, but it is not well known outside the core "open geo" community. It also is reasonably technical to use and would have taken much longer to learn and understand than the commercial APIs, so it was not considered for this case study. Another option that could be used is ArcGIS Server to provide the mapping back-end to the system, but this is not available at UEA because of licence costs and it would have been more technical to implement.

Out of the commercial mapping services, Google Maps is very much the dominant offering, with 17% of the whole travel market share (Hitwise, 2010). This is probably partly due to Google's seemingly unique balance between minimalism and usability, which they first applied to the search industry (Google, 2011). When this was transferred to the online mapping area, it took off and is now one of the (if not the) clearest exclusive online mapping service (O'Berine, 2010). Google Maps does not include mapping such as that from the Ordnance Survey, which is much more detailed, but possibly less appropriate for this application. Due to this dominance it was thought that the majority of users would be familiar with the Google Maps interface and Google Maps API (GMAPI) was chosen to implement this evaluation. Google also had very good tutorials and help files showing how to implement the API and a very good user support group to provide information that was not in the tutorials.

1.3 Use of Google Maps API

The GMAPI was used in this case study to show both the UKCP09 data set to the users (both visually and sonically) and to capture their responses. The UKCP09 data was overlaid on top of the Google Maps interface using the data in KML (Keyhole Markup Language) format (OGC, 2010) to show the data visually. The sound element was added by joining the API to a sound add-on and hard coding the data into the evaluation itself which was subsequently sonified. This is obviously not ideal, but was the best compromise available, because of limitations in the KML class of the Google Maps API. The participants' responses were extracted from the MySQL database and processed using a GIS at the analysis stage, as discussed in the paper.

1.4 Use of Sound

The sounds used in this evaluation were a scale of trumpet notes, with a low note representing a low value (50% probability or range as appropriate) and a high note representing a high value. There are many different sound variables that could have been used, but it was decided to use variation in pitch to represent the data. The three most commonly used variables in sonification are pitch, loudness and timbre (Neuhoff, 2011). Loudness (or volume) is another dimension that is frequently used, but it has limited success because it has a much lower resolution (i.e. number of discernible levels) than pitch, and memory for volume is extremely poor (Neuhoff, 2011). Timbre is a relatively easy concept to understand (often explained as the quality of the sound, or how we can tell a trumpet and a piano apart when they are played at the same frequency with the same loudness), but timbre is not suitable for an ordered scale, as it is meaningless to say a trumpet is more (or less) than a piano). Pitch does not have limitations of volume or timbre as described above, and it is a very easy concept to explain to the participants.

2. Evaluation Method

The evaluation consisted of three main parts, firstly the background questions including the participants use and knowledge of GIS, UKCP09 data and climate change. The second section was a computer-based session which included the evaluation maps and some quantitative questions on how participants felt they had performed. Thirdly there was a semi-structured interview session of around 20 minutes, where participants discussed the effectiveness of the sonification. A total of 72 participants took part and they were evaluated in small groups, usually between 3 and 6 people. Small groups were preferred because it enabled a more effective discussion and allowed all of the participants to take part (Hopkins, 2007).

To evaluate the effectiveness of the sonification the participants were asked to complete a series of map based tasks using the UKCP09 data sets. 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. The two training maps (T1 and T2) used the UKCP09 data for the Baseline period, either the mean daily summer temperature or the warmest day data (see Table 1). For the main evaluation itself, data were randomly selected from the four available remaining options (see Table 1).

<table>
<tr><th>Map No</th><th>Data Randomly Selected From:</th></tr>
<tr><td>T1</td><td rowspan="2">EITHER the mean daily summer temperature (summer mean) for baseline
OR temperature of the warmest day (warmest day) for baseline</td></tr>
<tr><td>T2</td></tr>
<tr><td>1</td><td rowspan="4">Summer mean for 2020s OR
Summer mean for 2050s OR
Warmest day for 2020s OR
Warmest day for 2050s</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
</table>

Table 1. The order that the data were shown to the user. The data for Maps T1 and T2 were randomly chosen from baseline summer mean or warmest day, and the data for Maps 1-4 were randomly chosen from the four remaining data sets.

In order to keep the training maps simple, they only showed one data set (the 50% probability) to the participants, using vision (V) for T1 and sound with vision (S) for T2. The main maps (Maps 1-4) showed both the 50% probability and range data using a variety of different visual and sonic representation methods (see Table 2). The type (summer mean / warmest day) and date (2020s / 2050s) of the data that were shown was randomly selected, as shown in Table 1.

Map No	Code	No. of Maps	Method & Data on First Map	Method & Data on Second Map
T1	V	One	Visual (50% probability)	*(none)*
T2	S	One	Visual & Sound (50% probability)	*(none)*
1	VV	Two	Visual (50% probability)	Visual (range)
2	VSVS	Two	Visual & Sound (50% probability)	Visual & Sound (range)
3	VS	One	Visual (50% probability) Sound (range)	*(none)*
4	VS	One	Visual (50% probability) Sound (range)	*(none)*

Table 2. Data shown for each map and information on how the data were shown to the user

This computer session was followed by the semi-structured interview with each group, as described in the main paper.

More details on the method of using Google API are available in Bearman and Appleton (2012) and more details on the evaluation are given in my PhD thesis (Bearman, 2013) available at http://www.nickbearman.me.uk/go/phd.

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