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Interpreting climate data visualisations to inform adaptation decisions

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ABSTRACT

The appropriate development of graphical visualisations to communicate climate data is fundamental to the provision of climate services to guide climate change adaptation decisions. However, at present there is a lack of empirical evidence, particularly in Africa, to help climate information providers determine how best to communicate and display climate data. To help address this issue, an online survey, primarily targeted at the African vulnerability, impacts and adaptation community, was designed and disseminated widely. The survey examines the interpretation of climate data as a function of the style and information content of graphical visualisations. It is shown that choices made when constructing the visualisations, such as presenting percentile information versus showing the range, significantly impact on interpretation. Results also show that respondents who interpret a higher likelihood of future changes to climate, based on the visualisation of climate model projections, express greater confidence in their interpretations. The findings have relevance to the climate risk community in Africa and elsewhere across the world, and imply that a naïve approach to visualising climate data risks misinterpretation and unjustified levels of trust, with the potential to misinform adaptation and policy decisions.

Introduction

Visualising climate data is a central component of communicating climate science research findings and climate model results. With a growing demand for climate information to guide climate change adaptation decisions (Hewitt et al., 2012) there is pressure on scientists to ensure that data visualisations are aesthetically attractive and tailored for specific user communities. However, this creates a tension as some visualisation approaches and techniques risk distorting the interpretation of the data; for example, Stauffer et al. (2014) discuss the use of different colour palettes in meteorological visualisations and highlight their potential to mislead. It is therefore crucial to have robust evidence to inform the appropriate design and dissemination of data visualisations to avoid misinterpretation. Yet in the field of climate science and climate change adaptation the current evidence base remains weak.

Issues in visualising data to inform decision making are not unique to climate science. In his seminal work on the graphical display of information, Edward Tufte provides a set of principles to guide the development of visualisations across disciplines. Tufte (1983) states that graphical displays should "avoid distorting what the data have to say" and "serve a

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reasonably clear purpose: description, exploration, tabulation or decoration''. The effectiveness of different visualisation approaches has since been well explored in the health (Hawley et al., 2008; Garcia-Retamero and Galesic, 2010; Galesic, 2011; Garcia-Retamero and Cokely, 2013), environmental hazards (Gahegan, 1999; Appleton et al., 2002; Bostrom et al., 2008; Martin et al., 2008; Pang, 2008) and computer science literatures (Robertson, 1990; Keller et al., 2006; Aigner et al., 2007; Vande Moere et al., 2012). Other studies routed in the psychological and cognitive science literatures describe common issues in communicating scientific data using visualisations. Carpenter and Shah (1998) discuss the multiple influencing factors that affect a user's ability to interpret visual displays of information, noting that interpretations are heavily influenced by the viewer's expectations about, or familiarity with, the graph's content. In a review of the recent literature, Glazer (2011) similarly reflects on the issue of familiarity but also stresses the importance of scientific literacy, highlighting the need for better education to help people interpret graphical information.

There is an increasing literature on the implications of different visualisations to communicate weather data and hazardous weather events (Haase et al., 2000; Broad et al., 2007; Demuth et al., 2012; Stephens et al., 2012; Cox et al., 2013; Radford et al., 2013; Ash et al., 2014), and in the last decade scientists have begun to investigate the use of visualisations to communicate climate change information (Nicholson-Cole, 2005; Johansson et al., 2010). Kaye et al. (2012) present different approaches to mapping climate data, paying particular attention to the complex issue of communicating uncertainties. However, despite the emergence of climate services (Visbeck, 2008), and the increasing use of online platforms to disseminate climate information (e.g. CIP, 2014; IPCC, 2014a; PCIC, 2014; World Bank, 2014), in examining the recent literature it is apparent that there is still limited empirical evidence of how different individuals and groups interpret different visualisations of climate data, especially in a developing country context.

Here we present results from an online survey designed to gather empirical data to investigate how the style and information content of visualisations affects interpretation of climate data. A distinction is therefore made between the visualisation *style*, denoting the type of graph and its aesthetic attributes, and the *information content* that depends on the choice of data being displayed (e.g. minimum to maximum versus 10th to 90th percentile range). We investigate how different groups and individuals interpret data when displayed in different ways and using different information content, focusing on accuracy of interpretation, confidence in the extraction of climate change messages and preferences for different types of communication.

In the latest assessment report from the Intergovernmental Panel on Climate Change (IPCC), developing countries in Africa are shown to be particularly vulnerable to climate stressors (IPCC, 2014b). Adaptation to climate change is a key development issue and there is an increasing effort amongst communities and sectors in African nations to reduce vulnerability to climate risks (Adger et al., 2003; Schipper et al., 2014; Wilby, 2014). The appropriate use and interpretation of climate information is one of the critical enablers of successful adaptation (Ziervogel and Zermoglio, 2009; Daron, 2014) and given the particular lack of studies investigating the interpretation of climate visualisations in Africa, the research is therefore aimed at the growing African vulnerability, impacts and adaptation (VIA) community.

Understanding how different visualisations of climate data affect interpretation is relevant for both conventional forms of printed media and for online data portals, which are becoming an increasingly important mode of communicating climate data. Advances in online data dissemination allow for increasing sophistication in the visualisation techniques used, often incorporating interactive platforms. However, this study is focused on relatively simple visualisations as there remains an insufficient empirical evidence to inform scientists and the user community about the diversity of interpretations for this class of climate data visualisations.

In Section ''Methods'', the method used in the study is described. Section ''Results'' presents the results of the online survey. First it is shown how the choice of information content in a visualisation affects interpretation of the data, and then the impact of different visualisation styles is explored. The conclusions of the study, and suggestions for future research priorities, are presented in Section ''Concluding remarks''.

Methods

Survey dissemination and structure

The empirical data analysed in this study was gathered using an online survey platform. The dissemination of the survey web page URL relied, largely, on an email advertisement sent to specific relevant email lists. Given our focus on the African VIA community, the primary email list utilised was the user community for the Climate Information Platform (CIP, 2014) hosted at the University of Cape Town. Additional email lists and websites targeting the VIA community in Africa, and elsewhere, were also used to advertise the survey (see Acknowledgements). The survey was distributed in September and October 2013 and it is estimated that approximately 2000 people received the link to the survey. In total, 272 people fully completed the survey, over half of whom focus their work on regions in Africa[1], and these respondents represent a diverse group of scientists, practitioners and policy makers (see Supplementary materials for respondent demographic information).

[1] Rather than asking respondents where they were based, or where they were originally from, the survey asked respondents to disclose their area of focus (if any) for their work. This is because the study seeks primarily to address the issues in interpretation for those who are using climate data for Africa, acknowledging that many people who work in the VIA community in Africa are mobile and work at institutions across Africa and the world.

At the beginning of the survey respondents were randomly divided into two *groups* of approximately equal size (hereafter Group 1 and Group 2) to enable comparisons between responses to different visualisations. Respondents in Group 1 ($n = 140$) received one set of visualisations while respondents in Group 2 ($n = 132$) received a different, though similar, set of visualisations. Each group was further randomly divided into two *streams*; respondents in Stream A were shown guidance information prior to completing the survey while those in Stream B were not (see Supplementary materials). This process resulted in four sub-samples of respondents: Group 1A, Group 1B, Group 2A and Group 2B. Analysis revealed very few significant differences between the responses across the two streams. Therefore, the results presented in Section "Results" show only the combined responses for the two main groups (i.e. Group 1 and Group 2), not accounting for the further sub-division into streams A and B. The impact of receiving the guidance information is, however, discussed where relevant.

Climate data

The choice of visualisation depends, in part, on the precise nature of the data. In this study the focus is on the interpretation of relatively simple climate datasets, typical of those being communicated to the VIA community. The data chosen for the survey consists of historical and future rainfall time series data at a single station location. The data was extracted from the Climate Information Platform (CIP, 2014) for Mombasa, Kenya; this location was chosen because it has two rainy seasons and the distribution of rainfall is similar to that of many regions across central, west and east Africa where high population densities are vulnerable to climate variability and climate change (IPCC, 2014b). To avoid biased responses, and prevent respondents from looking at other data to guide their answers, the geographical location of the data was not disclosed. Observations of monthly rainfall cover the period 1981–2010 and the future projections of the change in annual rainfall are taken from ten statistically downscaled global climate models (Hewitson and Crane, 2006) using the A2 SRES emissions scenario (IPCC, 2000) for the period 2041–2070, presented as anomalies using the same observational baseline period.

All visualisations showing the climate change projections were based on the same underlying data but this detail was not disclosed to respondents. This inevitably represents a key limitation of the study; answers provided to questions about visualisations shown later in the survey may have been influenced by a memory of answers provided to previous questions. However, it was determined that using different data for each visualisation would have further complicated the analysis and made cross-comparisons between different visualisations problematic.

Survey questions

For each visualisation, respondents were first asked two multiple choice questions which both had correct, objectively defined answers, to assess the accuracy of the respondents (results not shown); e.g. "How many models project an increase in average annual rainfall of more than 100 mm?" – the precise questions varied depending on the visualisations shown. Subsequent questions investigated the subjective interpretation of climate change messages from each visualisation. For these questions respondents were asked to estimate the likelihood of changing climate conditions, or to estimate the likelihood of exceeding thresholds, using a sliding bar across a continuous range (e.g. from "exceptionally unlikely" to "virtually certain"); the range was represented by a numerical scale from 0 to 100 for analysis purposes but the numbers were not shown to respondents when answering the questions. Finally, questions related to respondents' confidence in interpreting climate change messages and the clarity of the visualisations were asked; similarly a sliding bar with a continuous scale was used to answer these questions.

Towards the end of the survey there were additional questions investigating relative preferences for the visualisations shown, as well as some more general questions asking about respondents' preferred way of receiving climate information (i.e. through verbal, numerical or visual methods) and their level of trust in regional climate projections. A final set of questions were asked to gather additional demographic information (see Supplementary materials).

Results

Varying information content

In order to assess the impact of varying information content, two different graphs showing the same 30 years of observed monthly rainfall data were presented to the two groups. The graph shown to Group 1 (inset Fig. 1(a)) uses a common approach to plotting rainfall data; dark blue bars show observed mean monthly rainfall and light blue bars show the minimum to maximum range. The graph shown to Group 2 (inset Fig. 1(b)) uses the same visualisation style but here the light blue bars display the 10th to 90th percentile range.

Respondents were asked to assess the likelihood – across a continuous range from "exceptionally unlikely" (value of 0, Fig. 1) to "virtually certain" (value of 100, Fig. 1) – of exceeding a specific rainfall threshold. The responses (Fig. 1 frequency distributions) reveal the diversity in interpretations. While the majority of respondents in both groups answered that it was, to varying degrees, unlikely to exceed the threshold, some respondents expressed a much higher likelihood. These results provide evidence for substantial within-group differences revealing that people extract different messages from the same visualisation with the same quantitative data. The diversity of answers may be partly related to confusion about the question

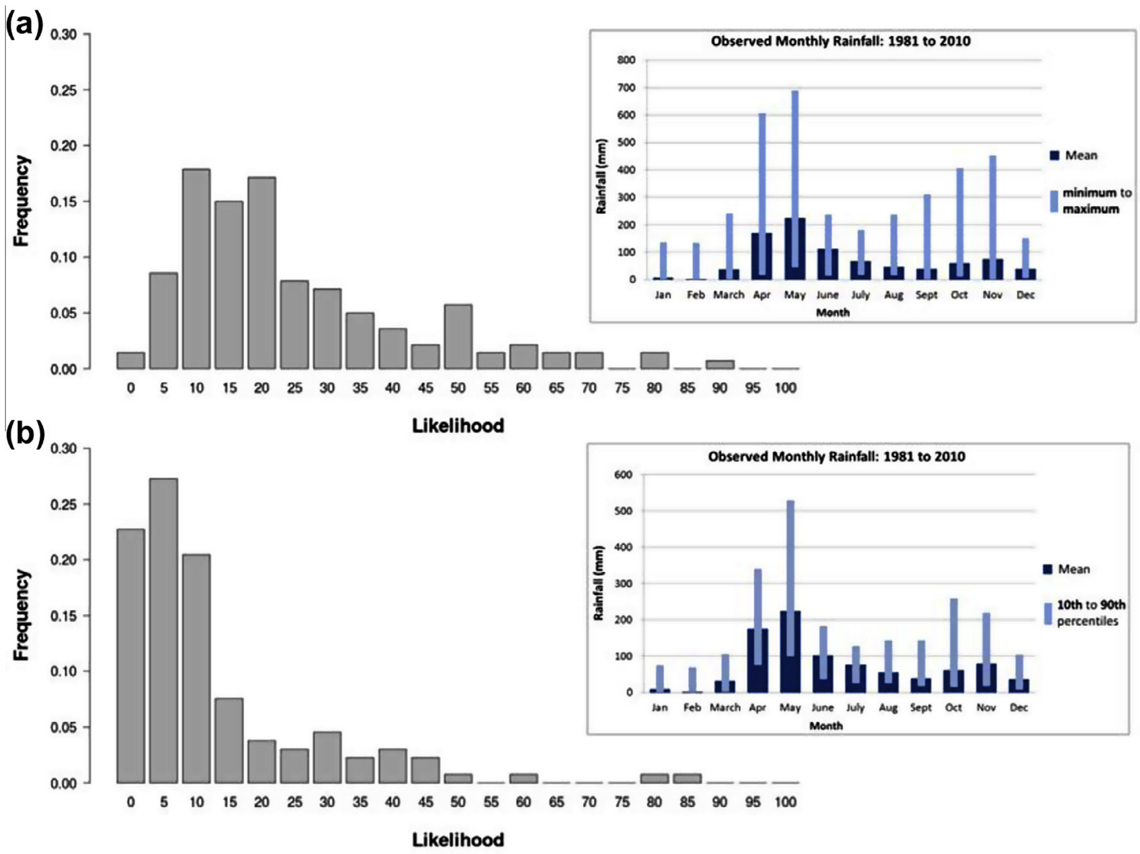

Fig. 1. Assessed likelihood of rainfall threshold exceedance. Normalised frequency distributions of responses to the question, "*how likely will it be for the rainfall in April 2014 to be more than 500mm?*", from respondents in Group 1 ($n = 140$) who were shown (a) mean, minimum and maximum observed rainfall information (inset top-right), and respondents in Group 2 ($n = 132$) who were shown (b) mean, 10th and 90th percentile observed rainfall information (inset bottom-right).

or the visualisation but the perceived clarity of the graphs were relatively high – mean clarity for Fig. 1(a) = 69.7 and Fig. 1(b) = 66.2 (on a scale where 0 corresponds to "strongly disagree" and 100 corresponds to "strongly agree" with the statement "the figure is clear and easy to interpret"). In addition, the responses show that there is a significant[2] between-group difference – mean likelihood for Group 1 = 24.9 and mean likelihood for Group 2 = 12.5 (p-value < 0.001) – showing that the assessment of exceeding rainfall thresholds is, in part, dependent on the choice of information displayed. There are no significant differences between the two Streams (A and B), meaning that the guidance information had little impact on the respondents' understanding of the visualisations.

Comparing different visualisation styles

A number of visualisations using different styles were developed (Fig. 2) to assess the impact of altering the visualisation style on the interpretation of climate data. In developing these visualisations the aim was not to generate optimal visualisations but rather to understand how different visualisations are interpreted. The four styles chosen represent different ways of communicating climate projection data. The first two styles (shown in Fig. 2(a) and (e) and Fig. 2(b) and (f)) are similar to those commonly found in existing climate information portals (e.g. CIP, 2014). The threshold visualisations (Fig. 2(c) and (g)) represent a novel infographic style and the bar-plots (Fig. 2(d) and (h)) represent a more conventional style which might be found in policy reports or printed media.

As explained in Section "Methods", each visualisation incorporates the same data showing the change (anomaly) in mean rainfall between a future period (2041–2070) and a reference period (1981–2010) for ten different climate model projections. Two of the four styles contain the same information content (Fig. 2(b), (d), (f) and (h)) while the other two styles contain different information content, albeit with the same underlying data; Fig. 2(a) and (e) show the minimum, maximum

[2] Differences between the means of distributions shown in this study are tested for significance using the non-parametric Mann–Whitney–Wilcoxon test; p-values are reported in the main text where relevant.

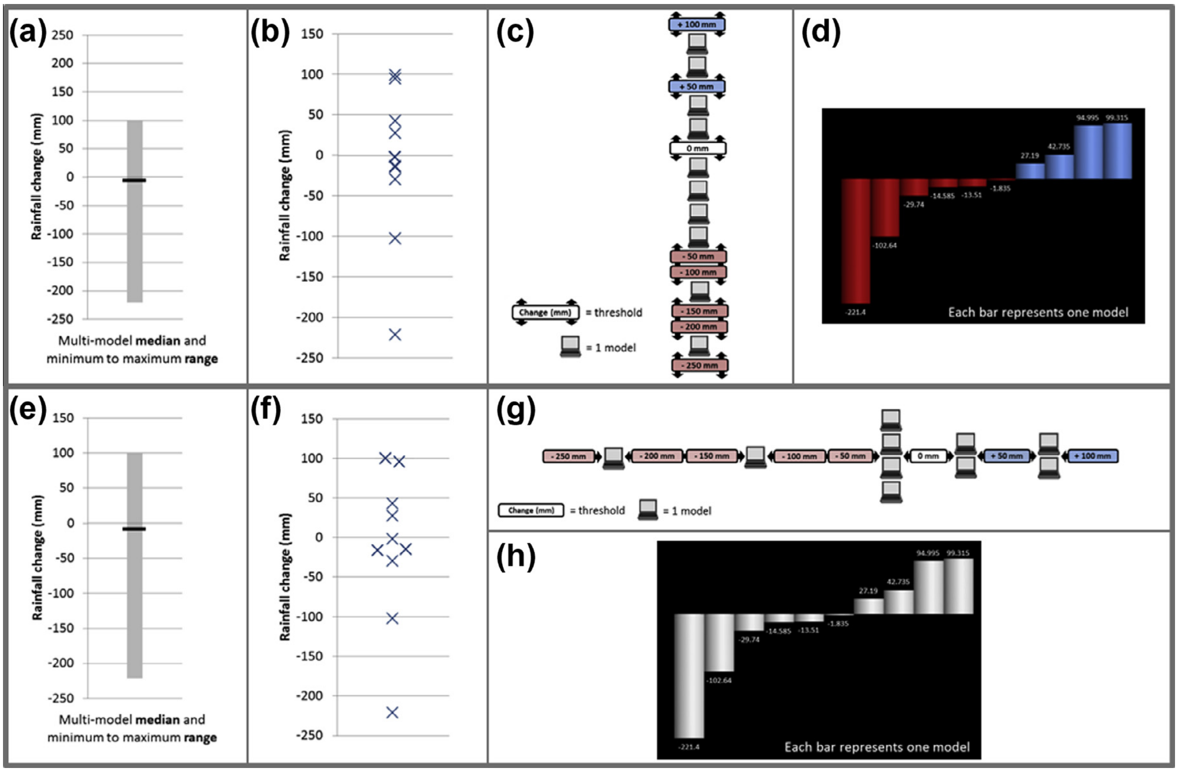

Fig. 2. Visualisations used in the survey for: (a–d) Group 1, (e–h) Group 2. Each visualisation had the title: "*Change in average annual rainfall from the past (1981–2010) to the future (2041–2070) for ten models*".

and multi-model median, and Fig. 2(c) and (g) show the number of models between specific intervals. Group 1 viewed Fig. 2(a–d) while Group 2 viewed Fig. 2(e) and (f); one style attribute of each visualisation was varied between the sets of visualisations (e.g. change in orientation between Fig. 2(c) and (g)).

The respondents were asked to assess the likelihood of future change in average annual rainfall. The frequency distributions of responses (Fig. 3) show how the visualisation affects the interpretation. Fig. 2(b) and (d) have the same information content but there is a significant difference (p-value < 0.001) in the mean response. In the equivalent figures for Group 2 (Fig. 2(f) and (h)) there is a similar shift in the distribution, though the difference is less significant (p-value = 0.06). This may be explained by the over-plotting at −14 mm in Fig. 2(b), which is accounted for by "jittering" in Fig. 2(f). However, other considerations, such as the lack of colour in Fig. 2(h), could also have influenced the interpretation. Indeed the use of colour in Fig. 2(d) appears to explain a greater tendency to interpret a decrease in rainfall, and though the difference in the mean response between Fig. 2(f) and (h) is not significant, the difference between Fig. 2(f) and (d) is significant (p-value < 0.01).

Self-assessed confidence

For each visualisation, respondents were asked to assess their confidence in their ability to answer the question about future rainfall change. The responses vary considerably for all visualisations, ranging along the scale from "not at all" to "extremely" confident, but there are some notable differences between the visualisations (Table 1 and Fig. 4). For example, the mean response from Group 1 respondents for Fig. 2(b) is significantly lower than the mean response for Fig. 2(d) (p-value = 0.02). This difference may arise because of the difficulty in distinguishing between the crosses in Fig. 2(b). It may also be related to the use of red and blue colour in Fig. 2(d) to denote models that show drying and wetting respectively; using intuitive colours is a common technique for communicating climate data, particularly to show precipitation and temperature changes. Another possible explanation is that confidence was higher for Fig. 2(d) because it was the last visualisation to be viewed. If respondents had become aware that the data for each visualisation was the same, they may have been more confident in their ability to answer later questions. However, Group 2 results are not entirely consistent, and the variability in responses remains high, implying that this factor (an artifact of the survey design) is likely to have had a limited influence.

Fig. 4 shows the relationship between confidence and expected change in rainfall revealing a consistent *Y-shaped* pattern. For all visualisations a significant positive relationship (Pearson correlations >0.3, p-values < 0.005) is found between

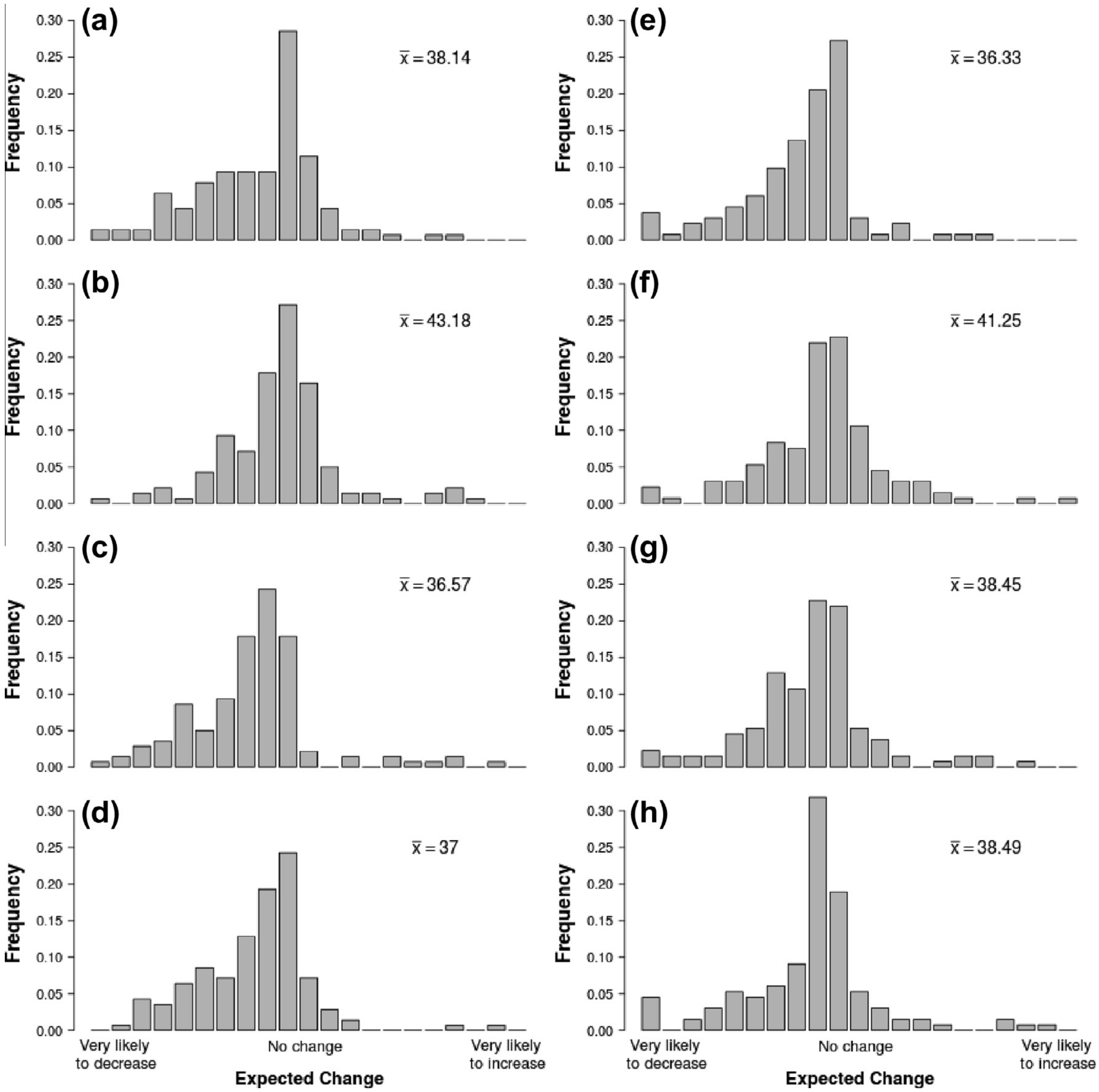

Fig. 3. Expected rainfall change in the future. Normalised frequency distributions of the responses to the question, "*How do you expect the average annual rainfall to change in the future?*" Each panel corresponds to the respective visualisation in Fig. 2: (a–d) Group 1 responses ($n = 140$), and (e–h) Group 2 responses ($n = 132$). $\bar{x}$ shows the mean response on a scale from 0 ("*very likely to decrease*") to 100 ("*very likely to increase*"), with 50 corresponding to "*no change*".

Table 1
Mean responses for each Group and visualisation regarding: *confidence* in answering the rainfall change question, on a scale where 0 corresponds to "*not at all confident*" and 100 corresponds to "*extremely confident*"; *clarity* – agreement with the statement that the visualisation is "*clear and easy to interpret*", on a scale where 0 corresponds to strongly disagree and 100 corresponds to strongly agree; and, *preference* – each visualisation was ranked in order of preference such that a mean response closer to one denotes a higher preference whilst a mean response closer to four denotes a lower preference.

Group 1				Group 2			
Visualisation	Confidence	Clarity	Preference	Visualisation	Confidence	Clarity	Preference
Fig. 2a	51.93	53.61	2.77	Fig. 2e	52.58	52.05	2.69
Fig. 2b	49.57	52.54	2.82	Fig. 2f	52.54	63.22	2.11
Fig. 2c	54.68	50.96	2.95	Fig. 2g	50.27	41.17	3.47
Fig. 2d	56.14	69.93	1.46	Fig. 2h	53.94	70.11	1.73

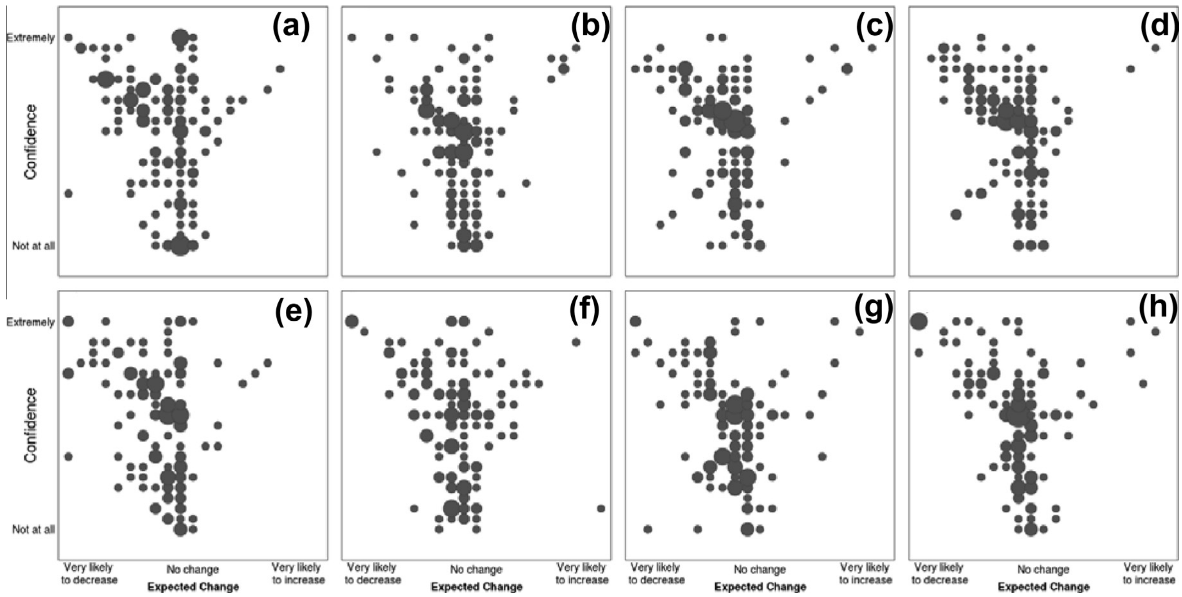

Fig. 4. Expected rainfall change versus confidence of respondents in their answers. Each panel corresponds to the visualisation in the same panel in Fig. 2: (a–d) Group 1 responses ($n = 140$); and (e–h) Group 2 responses ($n = 132$). The areas of the circles are proportional to the number of respondents.

confidence and the absolute difference of the expected change from the mean response. This means that those who interpret a high likelihood of a change in future rainfall, be that an increase or decrease, are more likely to express a high degree of confidence in their interpretation. As this relationship is found consistently for all visualisations, one can infer that confidence in interpreting climate change messages is influenced by factors other than the visualisation. Additional targeted research is required to explore this result further but some respondents commented that their low confidence resulted from a lack of knowledge about the reliability of the underlying climate model data. In addition, people may also have preconceived ideas of how rainfall might respond to climate change and may therefore interpret climate information in ways that align to their preconceptions.

Examining preferences

Respondents ranked each visualisation in order of preference (Table 1). The majority of respondents rank Fig. 2(d) (Group 1) and Fig. 2(h) (Group 2) highest (72% and 59% respectively). In Group 1 Fig. 2(a) and (c) were the least preferred visualisations (ranked last by 37% and 34% of respondents respectively), while Fig. 2(g) was the lowest ranked visualisation for the majority of respondents in Group 2 (61%). The difference in the percentage of people ranking Fig. 2(c) and (g) in lowest position suggests that seemingly small details, such as the horizontal or vertical alignment of the visualisation, may have a notable impact on preferences. In general, visualisations with more information content (i.e. more detail) are ranked higher and respondent comments suggest this is because more detailed figures enable a better understanding of the multi-model spread.

Preferences are also found to be related to the assessed clarity of the visualisation (Table 1). Assessed clarity is significantly lower (p-value < 0.001) for Fig. 2(b) (ranked by Group 1) than for Fig. 2(f) (ranked by Group 2) and this likely explains the lower preference ranking (Table 1). Furthermore, the highest mean preference rankings are given to Fig. 2(d) and (h), the two visualisations to which respondents express the highest level of confidence in interpreting climate change messages. This suggests that climate information providers need to be careful in developing visualisations. In addressing the demand for user friendly information, there is a need to preserve scientific robustness (Cash et al., 2002) and a sole focus on improving aesthetics, corresponding to preferences, may risk over-confidence in the interpretation of the underlying data (Nicholls, 1999; Spiegelhalter et al., 2011). Other factors that are likely to affect preferences include familiarity and cognitive ease (Kahneman, 2011), aspects particularly prevalent in an online survey; comments received on the survey suggest that familiarity was a key factor.

Sub-sampling by demographic and institutional factors

To date no studies have examined the interpretation of climate visualisations by the VIA community in Africa, and this was a primary motivation for targeting the study at African respondents. When comparing the answers of the respondents who focus their work on Africa to those who focus elsewhere (or have no regional focus) there were very few significant differences. In addition, when sub-sampling respondents based on the region of Africa in which they were focused (east, west, south, north and central) no clear differences emerged. This suggests that, in general, the variation in interpretations of people who focus their work on Africa, and utilise climate information developed to inform the African VIA community, are not dissimilar to the variation in interpretations of people who focus their work elsewhere.

However, there are some differences worth noting. For the climate change visualisations (Fig. 2), the African focused respondents expect, on average, a higher likelihood of decreasing rainfall than the non-African focused respondents (p-value < 0.05 for Fig. 2(e); African focused respondents stated rainfall was 4% more likely to decrease). This could be due to a greater sensitivity to drought risk amongst some African respondents, though additional research would be required to explore this result further. Also, the African focused respondents are generally more confident in their interpretations (p-value < 0.05 for Fig. 2(e); whole sample mean = 52.6% and African focused sample mean = 60.6%), and they rate the clarity of the visualisations higher than the non-African focused respondents (p-value < 0.01 for Fig. 2(b), (c) and (g), and p-value = 0.025 for Fig. 2(f)). The reasons behind these differences have not been investigated and therefore warrant further exploration.

More differences emerge by sub-sampling the respondents with respect to other demographic and institutional factors. For example, those who work in government planning are more likely to trust the underlying scientific data. Conversely, other demographic factors, such as age and gender, are found to have no significant impacts on interpretation across all visualisations.

While some of the different interpretations revealed in this study can be linked to demographic and institutional factors, most are the result of within-group (i.e. inter-individual) differences. People inherently differ in their interpretations and can therefore reach alternative conclusions, irrespective of gender, qualifications or discipline of focus. The VIA community is not homogenous and while it is important to ensure that methods of communication are tailored to specific audiences, all sectors of society consist of individuals with different backgrounds, capabilities and motivations. Any visualisation of climate data will be subject to different interpretations and this creates a challenge that must be acknowledged in guiding adaptation decisions.

Concluding remarks

It is critical to distinguish between visualisation approaches seeking to objectively communicate climate data and those seeking to convey specific messages about climate variability or climate change. In reality there is often a tension as climate information providers strive to remain impartial while attempting to translate data into information and aid users in extracting climate change messages from the data. Edward Tufte states "above all else show the data" (Tufte, 1983), but in using different visualisation styles, attributes and techniques tailored towards a specific user community, we are inherently adding a layer of interpretation.

Our primary focus is on the African VIA community where the existing empirical evidence base is particularly weak, but the results suggest that issues in interpreting climate data visualisations are common to respondents across the world. However, some differences do emerge when sub-sampling respondents working in the African VIA community, such as an apparent tendency to interpret a higher likelihood of drying in the future and higher confidence in interpreting messages from the visualisations; such findings may be explained by people attempting to confirm or disconfirm relationships based on prior expectations or beliefs, consistent with the well-established cognitive "confirmation bias" (Shah and Freedman, 2011). Yet overall there are much greater inter-individual differences and the wide diversity of interpretations is a finding that is common to all regions.

The study provides a basis for further research examining the interpretation of alternative and more complicated datasets and visualisation styles. In particular, increased attention should be given to how different audiences interpret visualisations of spatial data and large multi-model ensemble data, such as those being used to communicate climate data in the IPCC assessment reports. As noted by McInerny et al. (2014), producing visualisations from complicated, uncertain data requires expertise and knowledge from multiple disciplines. It is also critical that research to understand the effectiveness of different visualisations is situated in a multi-disciplinary context. Complementary research in the behavioral, computer, psychological and political sciences will help to unpack the role of visualisations in communicating climate data to different audiences.

The results from this study provide robust evidence that choices regarding information content, such as the use of percentile information as opposed to minimum and maximum information, can significantly impact how users interpret climate data. In addition, techniques commonly used to help convey messages, such as the use of red and blue colours to denote drying and wetting respectively, can influence how people interpret climate change signals. Choices about the visualisation style and information content form part of the interpretation process and climate data providers need to recognise the consequences of such choices in providing climate data and communicating climate change messages to a diverse user community. Given the increasing demand for climate services across the world, it has never been more important for climate scientists and climate service providers to make use of the available evidence to inform the display and communication of climate data.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.crm.2015.06.007.

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