How Do Texture and Color Communicate Uncertainty in Climate Change Map Displays?

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Abstract

We report on an empirical study with over hundred online participants where we investigated how texture and color value, two popular visual variables used to convey uncertainty in maps, are understood by non-domain-experts. Participants intuit denser dot textures to mean greater attribute certainty; irrespective of whether the dot pattern is labeled certain or uncertain. With this additional empirical evidence, we hope to further improve our understanding of how non-domain experts interpret uncertainty information depicted in map displays. This in turn will allow us to more clearly and legibly communicate uncertainty information in climate change maps, so that these displays can be unmistakably understood by decision-makers and the general public.

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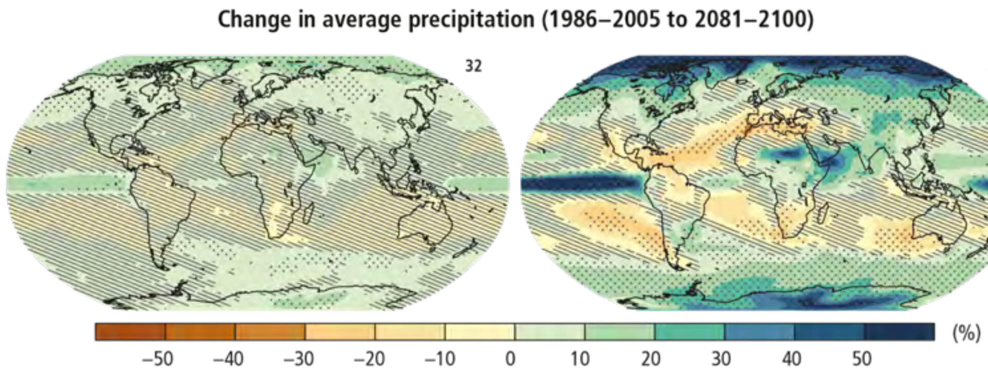


Figure 1 Thematic map conveying climate change predictions using color value combined with color hue to communicate average changes in precipitation. The visual variable texture, including stippling (black dots) and hatching (diagonal lines) visualizes prediction uncertainties (Source: [5]: Figure SPM.7).

1 Introduction

Maps are a popular means to inform decision-makers and the general public about climate change. For example, well-known and highly cited reports produced by the Intergovernmental Panel on Climate Change [5], the European Environment Agency (EEA 2017), and the US National Climate Assessment (e.g., [14]) contain on average at least one thematic map every dozen pages to make climate change visible and tangible to everyone (Figure 1). Important decisions on climate change mitigation and adaptation are often made with the help of such maps [15]. Climate change predictions contain various sources and types of uncertainties. This information is also visualized in the earlier mentioned climate change reports, as to alert decision-makers and the public of the inherent prediction uncertainties (Figure 1). For instance, the numbers printed in the upper right corner above the two maps in Figure 1 describe the number of model outcomes used to compute the depicted average change in precipitation over the depicted period. The stippling texture (dot pattern) in these maps indicate regions where the projected change is large compared to natural internal variability (i.e., greater than two standard deviations of internal variability in the 20-year averages), and where 90% of the models agree on the sign of change. The hatching texture (diagonal line pattern) in Figure 1 shows regions where the projected change is less than one standard deviation of the natural internal variability in the 20-year averages (WGI Figure SPM.8, 3Figure 1.20, Box 12.1). The visualization of complex and difficult to interpret climate change statistics, including the inherently difficult to comprehend concept of uncertainty can lead to uninformed (at worst, wrong) decisions and respective harmful consequences. It is therefore critically important that climate change maps clearly and legibly communicate the information, so that these displays can be unmistakably understood by the decision-makers.

2 Background

The visualization of uncertainty has been empirically studied by a diverse visualization community for over 20 years [13]. GIScientists, for instance, have investigated the suitability of various visual variables for the communication of uncertainty in maps [8]. Particular attention has been paid, for instance, to how color value ([12, 16]) and texture [10, 9] might intuitively communicate uncertainty information in thematic maps. Empirical study results

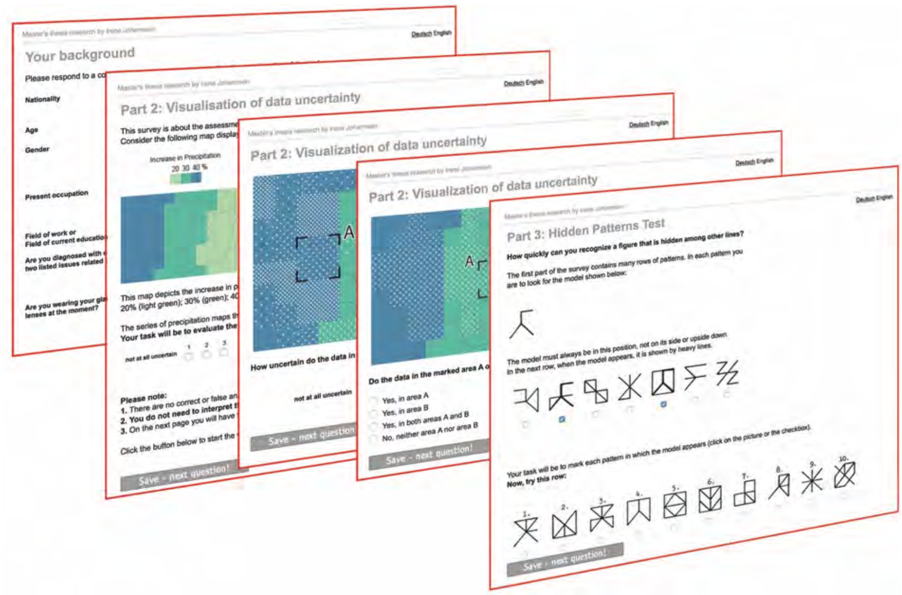
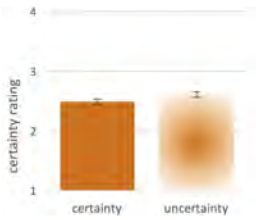


Figure 2 Entire procedure of the online study, and respective sequence and style of test stimuli (administered in English and in German), showing both black and white textures, two question types, and the response box.

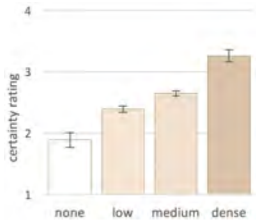
to date suggest that the graphic variable color value is particularly intuitively understood and associated with uncertainty [12]. This research also provides empirical evidence that the graphic variable texture, as shown in Figure 1, is particularly easy to read [11, 10, 16]. However, empirical findings are contradictory on how color value and texture intuitively communicate uncertainty, when the concept is labeled differently, i.e., uncertainty or certainty [10, 12], herein labeled un|certainty. In the following, we report on an empirical, online study that aims to narrowing mentioned research gaps.

3 Empirical Study

We systematically examine how the visual variables color value and texture [1] are intuitively understood by non-domain-expert map readers to convey un|certainty information in climate change maps. We also wish to further develop GIScience theory, focusing on the widely known, but little empirically evaluated cartographic principles "darker-is-more" and "denser-is-more", typically used to convey increasing data magnitudes, and how these principles apply to the intuitive understanding of the visualization of un|certainty. For this, we specifically developed a new uncertainty visualization method which simulates color value by means of regularly spaced white and black dot textures of varying dot densities. This method not only combines the intuitively understood properties of the graphic variable color value to convey uncertainty [12], but it is also directly based on the graphic variable texture, which previous empirical uncertainty visualization research suggests to be highly legible [12, 16]. We were inspired by the halftone technique, a classic reprographic method to simulate continuous tone by means of a dot pattern, varying either in dot size or in dot spacing [17]. We thus employed black and white dot patterns of various densities to lighten or darken areas in the classed, univariate precipitation change maps used as stimuli in our study (Figure 2). Our developed map stimuli were directly inspired by the maps



(a) un|certainty concept.



(b) density of dot texture (black or white).

Figure 3 Main Effects: un|certainty concept (a) and visual variable texture density (b).

available in the IPCC Report 2014, as shown in Figure 1. To control for potential perceptual confounds, we carefully checked map stimuli against color deficient viewing simulations [7] and by running biologically inspired vision models [6] to assure consistent center-surround contrasts across all stimuli. The online study had three sections (Figure 2); comprising of a background questionnaire (Part 1), two types of map-based questions (Part 2), and the Hidden Patterns Test (Part 3), a standardized spatial abilities test [4], deployed via an online survey (i.e., onlineumfragen.com). We collected data during July 14-27, 2017, targeting various international GIScience/cartography, geography and geomatics lists. Participants could choose to complete the test either in German or in English. We retained 104 participants for data analysis (52 females and males), because they completed the entire test (Total N=799, completion rate of 13%). Based on the background questionnaire, our participants have mostly a geography, cartography, and geomatics background (approx. 40% of the total sample), but are considered non-climate-domain experts. After completing the background questionnaire and a warm up trial, participants were then asked to rate on a 4-step response scale matching the four depicted dot densities (within subject factor: density) how un|certain (between-subject factor: question type) the labeled zones highlighted on a series of maps, looked to them. In the second map-based portion of the study, participants were also asked to compare two precipitation maps that differed in dot color black|white (within-subject factor: color) of the newly developed uncertainty visualization method. Finally, participants completed the Hidden Patterns test to assess their visuo-spatial abilities.

4 Results

To compare ratings across the un|certainty conditions, we assigned “not at all un|certain” to rating 1 and “very” un|certain to rating 4. We then linked the word pairs “very uncertain” with “not at all certain” to compare the ratings across un|certainty conditions. We ran mixed ANOVAs on the ratings, and where data assumptions were violated, we relied on the Aligned Rank Transform (ART) [18]. Interestingly, textures that are labeled uncertain (Figure 3a), on average, receive significantly higher certainty ratings, compared to those that are labeled certain ($F(1,102) = 8.877$, $p < .01$, partial $\eta^2 = .08$).

Participants associated the increased density of the dot textures (Figure 3b) with increased certainty ($F(3,306) = 40.026$, $p < .001$, partial $\eta^2 = .28$). All textured zones are rated more certain compared to the non-textured zones ($\bar{x} = 2.39$, $F(1,102) = 49.13$, $p < .001$, partial $\eta^2 = .33$). The differences between the increasing texture densities are all significant ($p < .001$). There were no significant differences comparing the color of the dot texture (white vs. black dots). We also did not find any significant differences between participants’ expertise with climate change mapping and their spatial abilities relating to the Hidden Patterns test.

5 Discussion

In contrast to our hypotheses, based on above cited uncertainty visualization research, the response pattern shown in Figure 3b is the same, whether participants rate uncertainty or certainty. In other words, we find empirical support for the basic cartographic principle the more (denser) the (dot) texture, the more participants associate this with more certainty in precipitation change maps. In doing so, we replicate similar studies using different types of textures (hatching, dot size, dot arrangement, and color) to convey uncertainty [12, 3, 16]. This is somewhat in contradiction with the cartographic principle "the darker-is-more", assumed with color value. The denser (more certainty) a white (dot) texture on the dark map background, the lighter it appears. However, [12] found that the progression from a light color shade or from light appearing fuzziness (i.e., more uncertainty) to a dark or solid color shade (i.e., more certainty) was amongst the top three most intuitively understood visual variables to convey uncertainty. To our surprise, the color of the dots (white vs. black) did not make a significant difference in our collected certainty ratings. One explanation for this unexpected result is that the developed dot textures possibly appeared too coarse as to produce distinguishable (just noticeable) differences in color value across the white and the black dot conditions. Looking into participants' open responses in the comments response box, it seems that a significant portion of them interpreted the dots in the textures to mean precipitation measurement locations. With an increase of the precipitation sampling locations within a zone, a plausible conclusion could thus mean an increase in data certainty.

6 Conclusion and Outlook

We set out to empirically assess whether the well-known cartographic principles "darker-is-more" and "denser-is-more" also applied to the intuitively understood visualization of data un|certainty. Our empirical findings suggest that the increase of regularly spaced dot textures in precipitation change maps are indeed associated with perceived increase in data certainty. This association pattern is stable whether or not the term uncertainty or certainty are used to label the textures in the map displays. However, certainty ratings increase significantly when the term uncertainty is used in the maps, compared to when the texture is labeled certainty. Unexpectedly, the color of the dot texture has no significant influence on un|certainty ratings in our study. While we varied the spacing of the regular dot textures, others have also varied the arrangement of textures (e.g., [2, 8]). This invites like-minded researchers to further systematically investigate dot arrangements in future empirical studies. In closing, we hope to have shed further light on how the popular visual variables texture and color value might be employed to clearly and legibly communicate uncertainty information in climate change maps, so that these displays can be unmistakably understood by decision-makers and the general public.

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