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Effect of Geospatial Uncertainty Borderization on Users' Heuristic Reasoning

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Abstract: A set of mental strategies called "heuristics" – logical shortcuts that we use to make decisions under uncertainty – has become the subject of a growing number of studies. However, the process of heuristic reasoning about uncertain geospatial data remains relatively under-researched. With this study, we explored the relation between heuristics-driven decision-making and the visualization of geospatial data in states of uncertainty, with a specific focus on the visualization of borders, here termed "borderization". Therefore, we tested a set of cartographic techniques to visualize the boundaries of two types of natural hazards across a series of maps through a user survey. Respondents were asked to assess the safety and desirability of several housing locations potentially affected by air pollution or avalanches. Maps in the survey varied by "borderization" method, background color and type of information about uncertain data (e.g., extrinsic vs. intrinsic). Survey results, analyzed using a mixed quantitative-qualitative approach, confirmed previous suggestions that heuristics play a significant role in affecting users' map experience, and subsequent decision-making.

Keywords: uncertainty visualization, heuristics, borderization, cognitive science

1. Introduction

Extensive research in uncertainty visualization has provided evidence of the key role of uncertainty in information communication and comprehension. Starting from the early categorization of MacEachren (1992) several authors (e.g., MacEachren et al. 2005; Griethe & Schumann, 2006; or Senaratne & Geharz, 2007) have proposed different taxonomizations and guidelines on how to choose best visual variables to show uncertainty based on the data type and data quality issue. Different variables have also been tested and ranked according to their intuitiveness for users (MacEachren et al., 2012). Kinkeldey et al. (2014) later reviewed and condensed these findings into the *uncertainty visualization cube*, classifying uncertainty visualization techniques according to the three dichotomies of *intrinsic/extrinsic*, *coincident/adjacent*, and *static/dynamic*.

The choice of visualization techniques also influences users' perception and decisions, as it can support accurate judgement by mitigating cognitive biases and, on the other hand, potentially generate a faulty interpretation of the data (Zuk et al., 2006). Users tend to perceive realistic (Smallman & St. John, 2005) or high-quality visualizations (McCabe & Castel, 2008) to be more accurate and trustworthy. Perceptually salient visualizations can increase decision accuracy (Fabrikant et al., 2010) but also turn users' attention away from other information that might be equally relevant for the task to be solved (Stone et al., 1997). Furthermore, visual variables are often associated with certain intuitive meanings and can cause systematic errors in judgements when used counterintuitively in visualizations (Tversky et al., 2011). The choice of visual variables is thus crucial to produce cartographic outputs that feel intuitive and easy to understand for users (MacEachren et al., 2012).

In this context, MacEachren (2015) stated that the research on *heuristics* is crucial for understanding how uncertainty visualization techniques affect map perception. First introduced by Tversky & Kahneman (1974), *heuristics* are a set of logical strategies that humans commonly employ to navigate through uncertain environments. These strategies allow us to save time and mental effort by ignoring unneeded information and subsequently help us form judgements and decisions that are effective in most contexts. Tversky & Kahneman originally proposed three types of heuristics:

- *Representativeness*: the belief that an event may be more likely to happen if it fits the mental stereotype we associate with that event;
- *Availability*: the tendency to assess the probability of an event based on how easily we can remember instances of similar events;
- *Adjustment to an anchor*: the tendency to make decisions by only considering the first piece of information we have received.

The role of heuristics in human reasoning has been explored in several knowledge domains. However, the relation between uncertainty visualization and human reasoning remains underexplored, particularly in a geospatial context (Kinkeldey et al., 2017). Several scholars (e.g., Zuk & Carpendale, 2007; Chuprikova et al., 2018) have made calls for a more in-depth investigation on how cognitive biases impact users' reasoning under geospatial uncertainty.

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2. Related work

In a study by Hope & Hunter (2007), users were asked to choose between different land areas with several suitability levels and associated data uncertainty to decide where to build an airport. Their response patterns showed a tendency for *loss aversion*, echoing previous findings from Tversky & Kahneman (1979), which argued that humans tend to minimize losses rather than avoiding risk per se. Other studies have noted that visualization techniques can trigger *visuospatial biases* by convoying users' attention on certain map elements; these biases may or may not improve final decisions' accuracy (Padilla et al., 2018). Kübler et al. (2019) have acknowledged that the effects of uncertainty visualizations on decision outcomes might often be unpredictable as they depend on the users' personal background and other situational factors.

Relevant cases for our study are the *containment* and the *distance heuristic*, i.e., the tendency to view two points inside and outside a bordered area as thematically distinct (Padilla et al., 2018), with the misperception increasing at increasing distance from the border itself (Padilla et al., 2018). Discrete boundaries in a map are intuitively associated with a change in semantic meaning, regardless of what the border actually represents (Fabrikant & Skupin, 2005). In a study about users' interpretation of positional uncertainty of a point, McKenzie et al. (2016) found that the containment heuristic is more likely to be triggered when the probability distribution of the point location is visualized with a crisp border rather than a "fuzzy" one. Cox et al. (2013) have analyzed users' response to the so-called *cone of uncertainty*, used by the American National Hurricane Center to map storm track predictions across the US. The cone's borders only show the area where 2/3 of storm tracks are likely to fall into; however, the authors of the study found that map-readers consistently misinterpret the visualization by wrongly judging points outside the borders as completely safe. This is consistent with the concept of *deterministic construal error* as outlined by Padilla et al. (2018). Ruginski et al. (2016) tested several alternative views of the cone of the uncertainty, concluding that ensemble views and fuzzy borders are likely to mitigate the containment heuristic compared to the original visualization.

3. Methods

3.1 Concept and general design

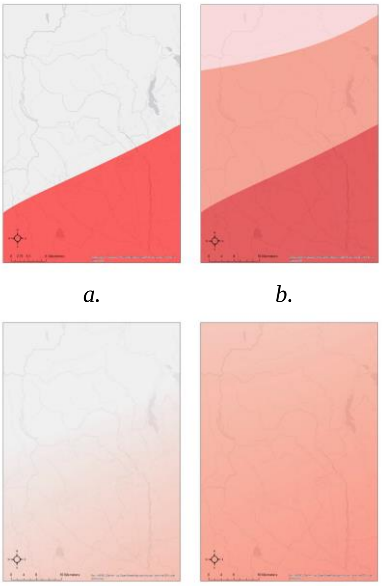
This study aims to investigate how map-readers use heuristics to reason upon geospatial data under uncertainty, with a specific focus on the issue of "borderization" – the visualization of borders – in the context of natural hazard maps.

The first challenge is to identify objective criteria to detect heuristics use: due to their abstract and subjective nature, a structured methodological framework to study heuristics has yet to be fully established (Gigerenzer & Gaissmaier, 2011). Therefore, we first use an initial tentative list of assumptions as detection criteria. We then select two types of natural hazards suitable for the study: levels of PM10 (an air pollutant) and risk of avalanches. Both hazards are usually known by the general public, and the question of how to visualize their borders is not trivial due to the physical characteristics of these phenomena.

The design concept for the study aims to create several visualizations of PM10 and avalanche risks across a certain section of space, with several housing locations overlaid on the map at varying levels of risk. The maps also include information about areas with high data uncertainty. We then developed an online survey in which we asked users to rate the desirability and safety of each housing location, along with their levels of confidence in their choices. Users also provided free statements to further explain the motives behind their ratings. Results are analysed using a mixed qualitative-quantitative approach.

3.2 Case studies

For the PM10 maps, we use point data of average daily PM10 concentrations in 2017 from urban background stations as provided by the European Environmental Agency. These data cover more than 2,000 locations across Europe. Due to the uneven geographic distribution of the points, they also offer a certain degree of uncertainty useful for this research. We selected a section of North-western Italy as the study area, as it shows large variations in PM10 levels within a relatively narrow space. To build the maps, we perform a Kriging interpolation on ArcMap 10.8, using the in-built function for Empirical Bayesian Kriging. This method is advantageous for this study as it provides the error estimate, i.e., the likelihood of the interpolation to be correct in any given point. The results of Kriging interpolation are then visualized using four different "borderizations" (see Fig. 1):



a. b.

c. d.

Figure 1: The four PM10 "borderizations". a: single crisp border, b: layered crisp border, c: limited fuzzy border, d: total fuzzy border.

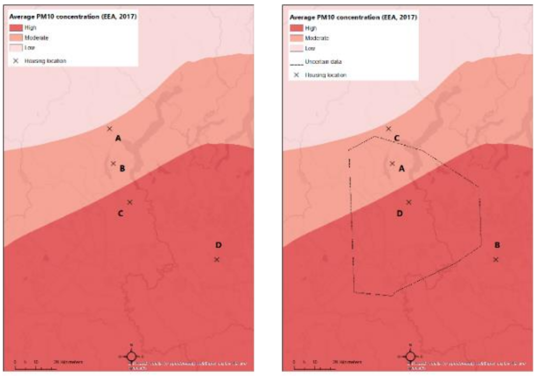
- <u>single crisp border</u>: a visualization showing an area with high PM10 concentration (defined as an area where yearly PM10 averages exceed the level of 20 μg/m3, which has been deemed as safe for human health by the WHO), colored in bright red and delimited by a single line as a discrete border. The space in this "borderization" is therefore dichotomic, as values outside the high-risk area have no assigned class;

- layered crisp border: a visualization where the study area is divided into three classes of risk, from high (more than 20 μg/m3) to moderate (between 10 and 20 μg/m3) to low, each delimited by a single line and colored with progressively lighter shades from red to pink;

- limited fuzzy border: a "borderization" where the border of the high-risk area, instead of one single line as in "single crisp border", is visualized through a fuzzy gradient transitioning from red to white;

- total fuzzy border: a "borderization" that merges "layered crisp" and "limited fuzzy border" by extending the red-to-white gradient across the whole area from high- to low-risk.

As previously described, we then added four housing locations (labelled from A to D) with varying levels of risk to the maps. The location distribution was linked to the position of the borders and the colors on the maps, with one location falling within the high-risk area and the area of data uncertainty, two falling within either one of the areas, and one outside both. (see Fig. 2)



a. *b.*

Figure 2: Example of a PM10 map (layered crisp border) with extrinsic uncertainty (b) and without (a).

In the second case study (avalanche risk maps), we selected a section of the small mountain valley of Saas Grund, Switzerland, using data from the *Naturgefahren-Hinweiskarten* (eng. "Indicative maps for natural hazards") as provided by the Swiss Environmental Office.

In contrast to the usual *Naturgefahrenkarten* ("Natural hazard maps"), *Hinweiskarten* only provide an overview of natural hazard risks across large areas, with a relatively low degree of detail and spatial accuracy, and usually do not include information about the intensity of natural hazards themselves. The avalanche risk is categorized into three levels, from high to low. We selected the high-risk area, Saas Grund, which comes in very close proximity to human buildings. As the original metadata do not provide any information on the positional error relative to the high-risk area border, we arbitrarily assign it an uncertainty buffer of 100 m in both directions.

Somewhat similarly to the PM10 maps, the high-risk area is visualized with three "borderizations":

-a "fuzzy" border with a 100-m-wide gradient transitioning from the colored high-risk to the white non-high-risk area;

-two "crisp" borders with a superimposed extrinsic 100-m-wide layer to represent the uncertainty buffer. This layer was visualized using two different techniques: a textured area, as already experimented by Hegarty et al. (2010) in a similar context, and an opaque grey band to simulate a "foggy" layer as proposed by MacEachren (1992).

Each map had two versions, with the high-risk area being alternatively colored in red or green, to investigate whether users would react differently to a high-risk area represented with a counterintuitive color such as green.

Finally, we added five housing locations (labelled from A to E) to the maps, with one location lying fully inside the high-risk area, one fully outside, one still outside but close to the buffer, and two on the uncertainty buffer but inside and outside the high-risk area respectively. (see Fig. 3)

Figure 3: "Fuzzy red" and "fuzzy green" avalanche risk maps.

3.3 User test

Sixty-one users (of which thirty-three females) with diverse ages and personal backgrounds took part in the study, designed as a public and fully anonymous survey on the platform SoSciSurvey provided by the Technical University of Munich. Firstly, we collected some background information about the respondents, such as age, gender, education, and expertise level with maps and natural hazard data. Each user is randomly assigned to one of two groups and presented with seven maps, four from the first case study and three from the second, so that the survey does not become excessively long but each user is still able to view every "borderization" once. Survey respondents were asked to rate the safety and desirability of all housing locations on each map, as well as the level of confidence in their rating choices, using a 10-point Likert-type scale whose results were coded as numbers from one (lowest safety or desirability) to ten. We then performed statistical testing to analyse variations in average ratings across different maps using the Wilcoxon-Mann-Whitney test, which we deemed best suited for our case as we were comparing the averages of several pairs of non-normal distributions.

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Additionally, we asked users to add brief explanations of the main motives behind their ratings under each map. We used these statements to look for certain keywords that might suggest using heuristics (e.g., words related to "contain") and checked whether their usage would match previous statistical results. To come up with a keyword count that is as objective as possible, we counted only the keywords in longer and more meaningful sentences that obviously hinted at the presence of heuristics – e.g., "C and D are located *within* the high concentration zone". Respondents were also presented with four pairwise map comparisons and asked which one is better suited to represent natural hazard risks. Finally, we asked users to rank several color shades according to their association with an intuitive idea of "risk". This had the goal to control for the potential presence of color-blind respondents, whose answers could alter survey results unexpectedly.

4. Results and discussion

4.1 Effects of "borderizations" on heuristics

The point labels on both case studies are here reported with a fixed order from A (safest point) to D/E (least safe point), even though they were randomized in the survey.

4.1.1. PM10 maps

Users consistently ranked points from A to D with decreasing levels of desirability across all borderizations. In "single crisp border" without extrinsic uncertainty, where A and B were outside the high-risk area, A had a higher desirability rating than B and C higher than D. This suggested a distance heuristic being at play, as A and B, like C and D, were located inside the same risk category and users had no parameters other than distance from the border to tell apart their risk levels. Apparently, users perceived B as less safe than A because it was closer to the border of the high-risk area. The opposite was true for C with respect to D. Additionally, in the maps without extrinsic uncertainty, ratings for A decreased from "single crisp border" to the other visualizations. In contrast, those of B decreased from "single crisp border" to "limited fuzzy border". Conversely, the ratings of C and D increased from "single crisp border" to other "fuzzy borderizations". This suggests the presence of a containment heuristic: in fact, "fuzzy" borders seemed to reduce the perceived safety for "safe" points and increase it for the "unsafe" ones.

This effect was also evident in the maps with extrinsic uncertainty. Ratings for A decreased in the two "crisp border" visualizations after introducing extrinsic uncertainty, even though A was located outside the uncertain area. This further indicates a distance heuristic, as A was closer to the border of the uncertain area than to the border of the high-risk area. Additionally, ratings for B decreased across all borderizations with extrinsic uncertainty compared to those without, while ratings for C showed an increase in "layered crisp border". It seems that due to a containment heuristic the ratings for B and C decreased and increased respectively after the introduction of the uncertain area, as they were both located inside it. However, the effect was stronger in the "crisp border" maps than in the "fuzzy border" ones, which might suggest that with a "fuzzy" border, users tended to rely more on the colors of the map rather than on the heuristics.

Interestingly, in the visualizations with extrinsic uncertainty, ratings for A did not decrease from the "crisp border" maps to the "fuzzy border" ones, unlike in the maps without extrinsic uncertainty. Additionally, the standard deviation of the ratings for A remarkably increased in the "crisp border" maps after the introduction of extrinsic uncertainty. This seems to indicate that not only the extrinsic uncertainty layer increased the perceived risk in "safe" points such as A, but it also made rating choices less straightforward and increased variations in judgement among users. While users could easily assess risk levels of A using the containment and distance heuristics in the "crisp border" maps without extrinsic uncertainty, the same was no longer valid with extrinsic uncertainty. Similarly, ratings for B in the maps without extrinsic uncertainty decreased from "crisp border" to "fuzzy border". Still, they did not show the same decrease in the maps with extrinsic uncertainty. As previously mentioned, ratings for B decreased across all "borderizations" with extrinsic uncertainty compared to the same ones without. This further shows that uncertainty reduced not only the overall perceived safety for B, but also the effect of the containment heuristic that had made assessments relatively easy for B in the "crisp border" maps without uncertainty. (Fig. 4)

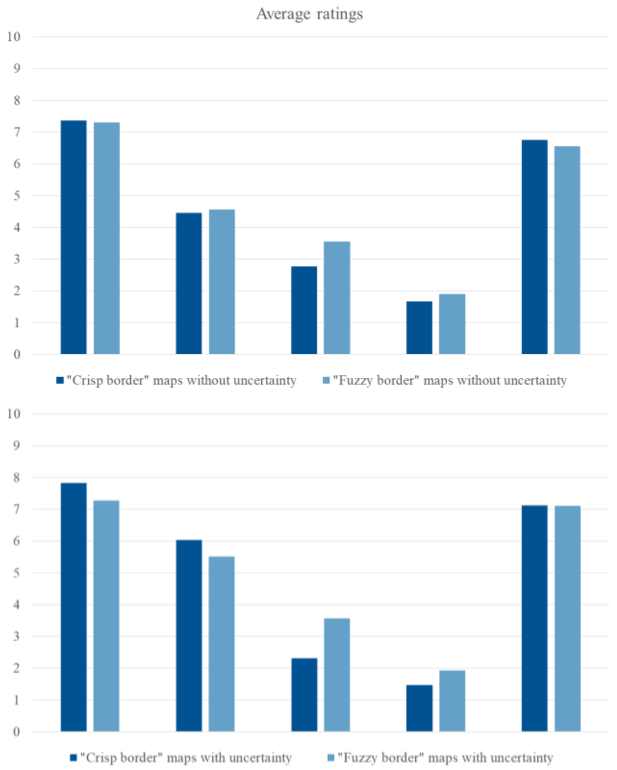

Figure 4: Average ratings in "crisp" and "fuzzy border" maps before (top chart) and after introducing extrinsic uncertainty.

Conversely, the introduction of uncertainty did not cause any significant decrease in C and D ratings, and the ratings for C increased significantly from "crisp border" to "fuzzy border" even if C was located in the uncertain area. This

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suggests a pattern of *loss aversion*. C's potential gains after the introduction of uncertainty, meaning that C could potentially fall outside the high-risk category, outweighed the risks that uncertainty itself posed around C. Simultaneously, the introduction of extrinsic uncertainty only had a net negative effect for B, which was safely outside the high-risk area before.

	A	B	C	D	Conf.
Single crisp	8,28	6,00	1,94	1,38	7,47
with unc.	*7,59*	*4,16*	*2,34*	*1,75*	*7,16*
Layered crisp	7,31	6,07	2,72	1,55	6,72
with unc.	*7,38*	*4,93*	*3,34*	*1,62*	*6,55*
Limited fuzzy	7,31	5,00	3,09	1,66	7,34
with unc.	*7,63*	*4,19*	*2,94*	*1,56*	*7,00*
Total fuzzy	7,24	6,07	4,10	2,21	6,86
with unc.	*7,21*	*5,14*	*4,34*	*2,34*	*6,28*

Table 1: average ratings and confidence by borderization type.[1]

	Rating		Value	p
Before/after unc.				
Single crisp	6,00	4,18	386,5	<0,01
Layered crisp	6,07	4,93	184,0	<0,01
Limited fuzzy	5,00	4,19	316,0	<0,01
Total fuzzy	6,07	5,14	190,5	<0,01
Without unc.				
Single vs. limited	6,00	5,00	197,0	0,021
Layered vs. total	6,07	6,07	90,5	0,839
With unc.				
Single vs. limited	4,16	4,19	124,0	0,946
Layered vs. total	4,93	5,14	68,0	0,433

Table 2: results of significance testing for point B.[1]

4.1.2. Avalanche maps

In stark contrast to the PM10 maps, the avalanche maps showed relatively few significant patterns, mostly due to differences between the two groups of users rather than between different maps presented to the same sample.

However, the distance heuristic was present in all maps, as ratings for points inside the same risk category (such as A and B) showed significant differences. A had a higher rating than B, which lied closer to the high-risk area; the same was true for D in respect to E. Even more tellingly, D and E had the same differences in ratings even in the "fuzzy border" and "crisp border" maps, despite D and E having the same background color in the "fuzzy border" maps. This further suggests that users intuitively felt safer in D than E, with no information to base their ratings on other than distance from the border of the high-risk area.

Ratings for A and C did not show any differences between maps, while ratings for B only decreased in "Green with texture" compared to "Green with fog". As this effect only occurred in these two maps, it is hard to detect any significant heuristic being at play behind it. D was the point with the most considerable variations, showing a substantial increase in "green with texture" compared to "green with fog" and "fuzzy green", as well as in "red with fog" compared to "fuzzy red" although not between "red with fog" and "red with texture". Interestingly, ratings for E also increased significantly in "green with texture" compared to "green with fog". As both maps' ratings came from the same group of users, such difference cannot be attributed to structural differences between groups. Therefore, we hypothesized that the use of a textured layer to visualize uncertainty might have increased the perceived safety in "unsafe" points (D and E) when the high-risk area was shown in green. A similar effect can be seen for D in the maps in red, but only for "red with fog". This may suggest that, in the case of E, the strong effect of the red color used to visualize the background could have outweighed a possible counter-effect of increased perceived safety from the textured uncertainty layer. However, ratings for E in "green with texture" also showed a higher standard deviation than in the other maps; this may indicate that the modest effect of rating increase for E could have simply been due to a few uncharacteristic results skewing the average.

However, the decrease mentioned above in ratings for B – located outside the high-risk area but inside the uncertain area – in "green with texture" compared to the other maps might suggest a modest effect of the containment heuristic, with an unsafe point (D) increasing and a safer one (B) decreasing in ratings.

4.2 User confidence and personal characteristics

Users reported significantly higher confidence for their ratings in the PM10 maps without extrinsic uncertainty than in the maps with extrinsic uncertainty. However, in the detailed breakdown by "borderization", the decrease in confidence was only significant in "single crisp border" and "total fuzzy" border.

Interestingly, these were the "borderizations" with the highest and lowest reported confidence respectively. We hypothesized two different reasons for this behavior. In the case of "single crisp border", the decrease in confidence might have been because the map without uncertainty was completely dichotomic, therefore containment and distance heuristics made it easy to assess risk levels across the map by only using one border as a reference. The inclusion of the uncertainty layer introduced an element of doubt and complexity, disrupting the original heuristics-driven perceptions. For "total fuzzy border", users may have already been confused by the subtle gradient encompassing the whole map, and the introduction of the new border of the uncertainty layer made it even more challenging to gauge risk levels. Users did not have any border to use as a reference to begin with, and the new

[1] Limited examples due to space constraints. For further data, please contact the authors or visit cartographymaster.eu/wp-content/theses/2020_Libertini_Thesis.pdf

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uncertainty layer also made it hard to base one's judgements on the background color.

Once again, confidence in the avalanche maps did not show any significant patterns, apart from a decrease from "fuzzy green" to "red with fog". As the two maps appeared one after the other in the survey and point ratings between the two did not change, we believe it could have been the result of a small adjustment-to-an-anchor effect, with users applying in the second map the same ratings as in the first map but with less confidence.

Among users' characteristics, we found that users with low levels of cartographic expertise also had lower confidence levels. Somewhat surprisingly, females reported lower levels of confidence than males and appeared to be more conservative in their ratings for all points across all maps. However, their rating patterns showed the same structure of their male counterparts regarding the use of heuristics and the differences between points.

4.3 Open statements and pairwise comparisons

Response patterns from open statements mostly seemed to confirm numerical findings. Keyword usage was most common in "single crisp border", with twenty-one occurrences in the maps without uncertainty and thirteen in those with uncertainty. Conversely, we could only find three and four occurrences in "total fuzzy border" before and after the introduction of uncertainty, respectively. Interestingly, keyword usage decreased with uncertainty in the "crisp border" maps, while the opposite happened in the "fuzzy border" ones. This suggests that while complicating the use of heuristics in the "crisp border" maps, the uncertainty layer introduced an element of simplification in the "fuzzy border" ones. However, in "total fuzzy border" the keyword usage was always low in both maps. (Fig. 5)

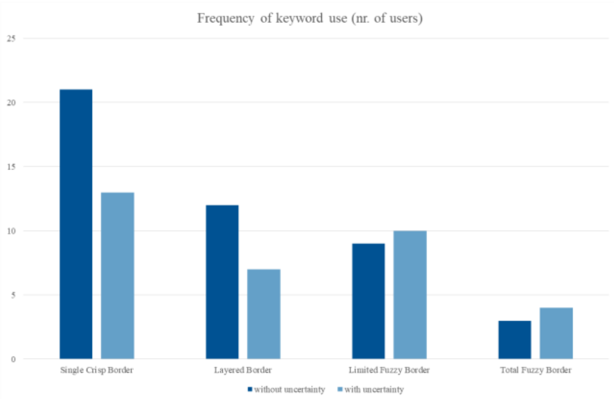

Figure 5: Frequency of keyword usage by "borderization".

A more in-depth analysis of the statements supports the hypothesis that "total fuzzy border" did, in fact, only increase confusion. A user wrote that "the subtle gradient makes it difficult to work out the differences", while another one reported that it was "hard to distinct [sic] the points quickly". Additionally, some users felt that the colored gradient covering the entire map increased the overall perception of a threat, thus triggering risk avoidant behaviors even in places that previously seemed safe. This might hint at the affect heuristic being at play. Conversely, users seemed to feel more comfortable with "limited fuzzy border": one claimed that this was the "best visualization for this topic, it shows the uncertainty", while another one wrote that "a more graduated scale gives [sic] more accurate information". Compared to "single crisp border", users also reported that "limited fuzzy border" seemed more intuitive to represent this particular type of natural hazard due to the physical nature of its boundaries.

Open statements under the avalanche risk maps did not show significant patterns in keyword usage frequency; this was also aligned with numerical findings. However, users did consistently report that the green color felt somewhat inappropriate to represent a high-risk area: one user wrote "the color scheme associates with a positive event not a disaster thus it creates biases in my mind. But I was attentive to the legend". Extrinsic uncertainty produced more conflicting results: while users felt that the two types of extrinsic visualizations seemed less intuitive than a fuzzy gradient, they also helped decision-making by triggering distance and containment heuristics.

At the same time, statements under the maps with extrinsic uncertainty seemed to hint at a risk aversion pattern, unlike the loss aversion seen in the PM10 maps. Users claimed that points lying on the uncertainty buffer "seemed" to become more at risk after introducing the extrinsic layer. Therefore, it seems that the introduction of extrinsic uncertainty increased the perception of a threat both in high-risk areas and in non-high-risk areas lying close to the border of the high-risk ones. However, numerical findings did not support these claims and average ratings hardly showed any detectable patterns in the avalanche maps.

In the four pairwise comparisons, many users felt that "fuzzy red" was more intuitive than "fuzzy green" to map natural hazard risk. "Fuzzy red" was preferred over "red with texture" and "limited fuzzy border" over "single crisp border" for the same goal; this seems to confirm that a gradient is more effective than an abrupt border to communicate spatial information about natural hazard risks. However, two-thirds of users selected "layered crisp border" as more useful than "total fuzzy border". This might mean that, while a gradient may be the best option overall, users still need some sort of border to gauge risk levels accurately. (Fig. 6)

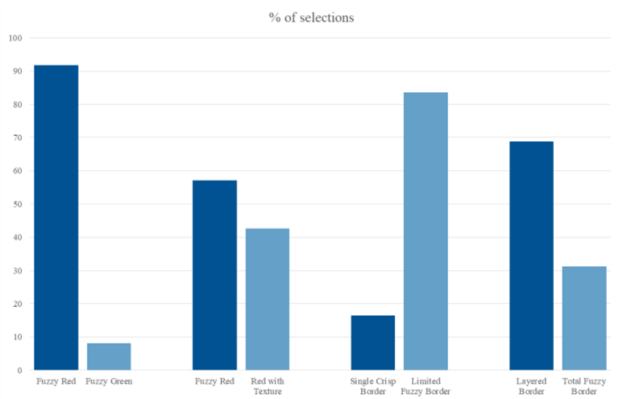

Figure 6: Results from the four pairwise comparisons.

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Finally, results from the color shades ranking once again showed that most users indeed associated red or darker shades with "higher risk" and green or lighter shades with "lower risk". A few users displayed completely atypical patterns, which might suggest that they were color blind. However, the average ratings remained mostly unchanged even after removing these uncharacteristic results.

4.4 Summary of findings

Survey findings showed evidence of a containment heuristic behind users' choices. Respondents assessed risk levels in the "crisp border" maps by treating the space dichotomically and clearly distinguishing points outside the high-risk area from those outside. "Fuzzy" borders appeared to introduce an element of nuance and doubt which seemingly made it harder to rely on this heuristic.

Use of the distance heuristic was equally evident, as respondents seemed to rely on distance from a border area to evaluate different locations in terms of risk, in the absence of any other piece of information. However, the exact border used as reference was not always the same across all maps.

Among the three original heuristics, availability did not play any meaningful role in users' choices. We did find evidence of the representativeness heuristic: map stimuli perceived as representative from the users, such as a red color or a fuzzy border, had a clear impact on the rating distribution. However, some non-representative elements were preferred over more representative ones that were not equally helpful to support judgement. Finally, the relative lack of significant results from the avalanche maps might have been due to the adjustment-to-an-anchor heuristic. In fact, users may have applied similar ratings as before simply because these maps were presented later than the others in the survey, and also because users might have become more aware of the study subject by then.

When it comes to the effect of different "borderizations" on heuristics, we found that a "fuzzy" border could help reduce the use of simple heuristics compared to a "crisp" border by supporting complexity in judgements.

The extrinsic uncertainty layer had somewhat ambiguous effects. While it seemed to aid decision-making in the "crisp border" PM10 maps, it mostly appeared to increase confusion in the "fuzzy" ones. In the avalanche maps, the extrinsic layers did not affect ratings significantly.

Additionally, we found evidence from the open-ended statements and the shade ranking that certain colors felt more intuitive to represent natural hazard risk, therefore that their manipulation could help reduce heuristic use.

Somewhat surprisingly, we also observed that female users appeared to be more conservative and less confident than males in their ratings. Further research on this issue could determine whether this behavior has any structural basis.

Finally, the anonymous online survey proved to be an effective tool to carry out the study and uncover patterns in heuristics use, as respondents could provide genuine answers without any external pressure. We also found the simple and highly consistent survey structure ensured high answer comparability and was effective in maintaining users' focus for the whole duration of the survey. Randomization of point locations helped provide more truthful answers; however, the study could have benefitted from randomization of the map order.

5. Conclusion

With this study, we confirmed previous findings by demonstrating that map readers use several simple heuristics to guide their behaviors. Namely, we found that containment and distance heuristics were commonly used to assess the level of natural hazard risk across different points in space; this usage was more frequent with certain visualizations, such as "crisp" borders, than "fuzzy" borders. Additionally, our work contributed to the research of geospatial reasoning with further insights into how extrinsic uncertainty can affect map judgement by either triggering or mitigating heuristics. We also found solid evidence that the choice of background color can impact map perception and map-related judgements significantly. Overall, this study can serve as a reference to design heuristics-aware visualizations of boundaries and natural hazards, thus better support users in decision-making.

Future research in the field may benefit from a more structured theoretical framework for objective criteria to detect heuristics use, as well as from increased interdisciplinary collaboration with cognitive science to explore new ways and techniques to facilitate the understanding of users' map-related reasoning processes.

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