

Interactive comment on “How can geologic decision making under uncertainty be improved?” by Cristina G. Wilson et al.

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Section 4 did not convince me. I still followed the arguments in Sections 4.1 and 4.2, describing why it is more successful to work on changing the environment, rather than teaching the decision maker new skills. But I found it hard to truly understand how the two case studies in Section 4.2 truly connect with the biases outlined in the earlier sessions. In particular, Case 2, which focuses on sub-surface geology had so many details related to sub-surface geology that I found it generally hard to follow. Both cases seemed to be examples that show that one should provide the user with as much useful information and software support as possible. Obviously, it's always useful to provide as much reliable, comprehensive information as possible to a decision maker, and such information will

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improve the decision process, and the software should be as transparent as possible. What am I missing here? Maybe the new point is that the biases are to be detected and software is to be designed specifically to overcome these specific biases. Is that the key point? But how do you identify all these holes and biases? How do you design software to fill these holes? How do you make sure the software solution is reliable in all cases and does not "nudge" the expert into the wrong correction?

To address reviewer comments about the case studies, we have shortened the geologic descriptions (removing sub-discipline jargon) and improved the connection between the case study section and the preceding bias review section. Details of these changes are discussed in comments below.

Regarding the identification of biases by AI – this is something we cover in the conclusion when discussing nudge design and the importance of “explainability”.

In terms of style, the first 3 sections are a pleasure to read, but include some repetitions, e.g., many statements are made in Section 1 and then repeated in more detail in later sections. So I suggest to look for redundant statements and shorten those sections a bit.

Redundancies were checked for and removed, specifically repetitious references to IT/AI solutions to debiasing.

For Section 4 my main suggestions would be to 1) work hard on clarity in the case studies of how exactly they connect to the biases discussed earlier; 2) spell out the way forward, i.e. how could the lessons learned here be generalized to other applications. In fact, I might even suggest to drastically shorten + de-emphasize the case studies to be only 1-2 paragraphs each, and maybe moving the rest to an appendix, then to focus on the main message of the paper in terms of fighting general biases and how to do that instead. I don't know, however, whether the remaining material warrants publication in this venue.

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For case study 1, we have improved the connection to the preceding bias review section by explicitly detailing how automated flights can address susceptibility to anchoring bias in field decisions about where to fly. The title of case study 1 was changed to: “Optimizing field data collection with UAVs to minimize anchoring bias”. We have also removed many extra details about UAVs not directly pertinent to the case study. Most of the changes were to the first three paragraphs:

“In this case study, we describe how automated UAV navigation could be used to nudge geoscientists to be more efficient when making decisions regarding reconnaissance and mapping and mitigate against anchoring bias. The advent of better mobile robot platforms has allowed for the deployment of robots by ground, sea, and air to collect field data at a high spatial and temporal resolution. Here, we focus on the use of aerial robots (semi-autonomous or autonomous UAVs) for data collection, but the conclusions we draw are likely applicable to other mobile robot platforms (i.e., underwater autonomous vehicles, ground robots).

Currently, the majority of geoscience research with UAVs is non-autonomous, i.e., user-controlled. Efforts have been made to automate interpretation of geological data from UAV imagery or 3D reconstruction with some success (Thiele et al., 2017; Vasuki, Holden, Kovesi, Micklethwaite, 2014; Vasuki, Holden, Kovesi, Micklethwaite, 2017), and the application of image analysis and machine learning techniques continue to be developed (Zhang, Wang, Li, Han, 2018). In reconnaissance and geologic mapping, the decision of where to go and how to fly there is made by the expert – either the expert fly’s the UAV and makes navigation decisions in-situ or they pre-set a flight path for the UAV to follow semi-autonomously (cf. Koparan et al., 2018; Ore, Elbaum, Burgin, Detweiler, 2015). However, a UAV that is capable of attending to measurements in real time and reacting to local features of measurement data could navigate autonomously to collect observations where they are most needed. Such autonomous workflows should increase the efficiency of data collection, and could be designed to mitigate against potential biases. Here, we consider how an automated UAV navigation nudge

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could reduce the tendency to anchor field exploration based on existing models and hypotheses.

In our hypothetical example, a UAV surveys a large bedding surface with the aim of identifying fracture orientations. The bedding surface exposure is large, but split into difficult to access exposure, e.g., due to cliff-sections or vegetation (see Column A, Figure 4). A birds-eye view afforded by the UAV improves the ability to observe fractures, which would otherwise require time-costly on-foot reconnaissance to different outcrops of the bedding surface. Note that in our hypothetical example we assume that fracture information is obtained only when the flight path crosses fractures (e.g., Column B, blue flight path), thereby representing a high level reconnaissance rather than a flight path in which overlapping imagery is collected. When the UAV flight path is user-controlled, the decision of where and how to fly is unlikely to be optimal: users could be distracted by irrelevant information in UAV view, and are likely biased towards exploring certain features and ignoring others (see Andrews et al., 2019). For example fractures may only be sampled where fracture data is dense, or in an orientation that maximizes sample size but not the range in orientation (see Watkins, Bond, Healy, Butler, 2015), or when it fits with a hypothesis (e.g. tensional fractures parallel to the axial trace of a fold). These strategies are all informed by expectations, leaving the geoscientist vulnerable to anchoring her sampling behavior to align with initial interpretations and hypotheses. This anchoring bias is visualized in Column B (blue flight path), where the user detects two unique fracture orientations (a, b) on the first exposure visited, but then spends needless time (T1 to T2) at exposure that offers no new information, before finally visiting exposure that features the previously identified orientations (a, b) and a novel N-S fracture orientation. This novel orientation is not detected in the user's flight path – the accompanying certainty plot in Column B shows that time spent at uninformative exposure (T1 to T2) results in increased certainty that all orientations have been sampled, when in fact they have not (i.e., the threshold of confidence is reached before sampling the N-S orientation). This is reflected in the rose diagrams in Column B, which show the orientation of fractures and the relative number of fractures

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sampled in each orientation; even at time T3 the three fracture sets (as shown in the rose diagram in Column A) are not represented.”

For case study 2, we have improved the connection to preceding bias review section by explicitly detailing how seismic interpretation aids (built into software) can address susceptibility to availability bias during interpretation. The title of case study 2 was changed to: “Fault interpretations in 3D seismic image data to minimize availability bias”. We also removed details about the technique of automated horizon tracking (including the accompanying Figure 5) which are not directly pertinent to the case study. Most of the changes were to the first three paragraphs:

“In this case study, we consider how software interpretations of seismic image data, and the information derived from them, could be used to nudge geoscientists to consider alternative models and minimize availability bias. Understanding of the geometries of sub-surface geology is dominated by interpretations of seismic image data, and these interpretations serve a critical role in important tasks like resource exploration and geohazard assessment. 3D seismic image volumes are analyzed as sequences of 2D slices. Manual interpretation involves visually analyzing a 2D image, identifying important patterns (e.g., faulted horizons, salt domes, gas chimneys) and labeling those patterns with distinct marks or colors; then, keeping this information in mind while generating expectations about the contents of the next 2D image. Given the magnitude and complexity of this task, there has been a strong and continued interest in developing semi-autonomous and autonomous digital tools to make seismic interpretation more efficient and accurate (e.g., Araya-Polo et al., 2017; Di, 2018; Farrokhnia, Kahoo, Soleimani, 2018).

Here, we consider how 3D information could be used with digital nudge technology to inform fault interpretations in a 3D seismic image volume. Simple normal fault patterns show a bull’s-eye pattern of greatest displacement in the center of an isolated fault, decreasing towards the fault-tip (see Image A, Figure 6). Consider interpreting 2D seismic image lines across the fault starting at in-line A (Image A) and working

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towards in-line F: with each subsequent line the displacement of horizons across the fault should increase and then decrease, although this pattern will not be known until the interpretation is completed. Holding this information on displacements for individual faults between in-line interpretations in complicated seismic image data (e.g. with multiple faults per seismic section, Image B, Figure 6) is incredibly challenging even for the well-practiced expert. We imagine a digital nudge that alerts users to discrepancies in fault displacement patterns, and prompts consideration of alternative fault patterns, thereby relieving some of the cognitive burden of 3D interpretation from the expert and guarding them against availability bias by encouraging consideration of models beyond what is most readily accessible to the mind.

In our hypothetical example, a geoscientist analyzes a 3D seismic volume, interpreting in a series of 2D in-line images faults and horizon off-sets. As subsequent in-lines (A-F) are interpreted, fault displacement patterns are co-visualized, so inconsistencies from normal fault displacement can be clearly seen. Fault 1 (Image B) conforms to a simple fault-displacement pattern (see Fault 1 displacement-distance plot). Fault 2 appears to conform to a similar pattern until in-line D when the interpreted displacement decreases; on interpretation of in-line E, the displacement on Fault 2 increases again, further highlighting the displacement anomaly on in-line D. Reduced displacement in itself does not highlight an issue, but consideration of the displacement-distance plot for Fault 1 suggests that if the interpreted displacement for Fault 2 is correct then the two faults are behaving differently. In our imagined digital tool, this discrepancy in displacement between nearby faults would be flagged for further consideration by the user, and potential alternative models could be highlighted. You can see the hypothetical conclusion certainty plots for the interpreter for the two faults (Fault 1 = green line, Fault 2 = pale blue line) during the interpretation process. Note the decrease in certainty of the interpreter for Fault 2, as they interpret in-lines D and E, in comparison to the increasing certainty for Fault 1 as consecutive interpreted in-lines conform to a simple normal fault displacement pattern. At in-line E the co-visualized displacement-distance plot nudges the interpreter to consider a new interpretation for Fault 2 at in-line D. Certainty

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in this new interpretation (displayed as dark blue dashed line on certainty plot), now increases as subsequent in-line interpretations conform to expected displacements.”

P. 5, Line 16-17: Mentions the three types of biases for the 3rd time. Too much repetition.

This is only the second time the bias types are mentioned (besides the abstract). We feel the repetition in this instance is warranted.

No changes to manuscript

P. 5, Line 30. There's something missing here. "Over ??? have found ... "

Formatting error, missing " $\frac{2}{3}$ "

Changed to "two-thirds"

P. 11. There is a Section 4.1.1, but no 4.1.2. P. 14,

We intend section 4.1.1 to be included as an appendix or be contained within some box that distinguishes it from the main text.

No changes to manuscript

Line 24. "of of"

Changed to "of"

Interactive comment on Solid Earth Discuss., <https://doi.org/10.5194/se-2019-70>, 2019.

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