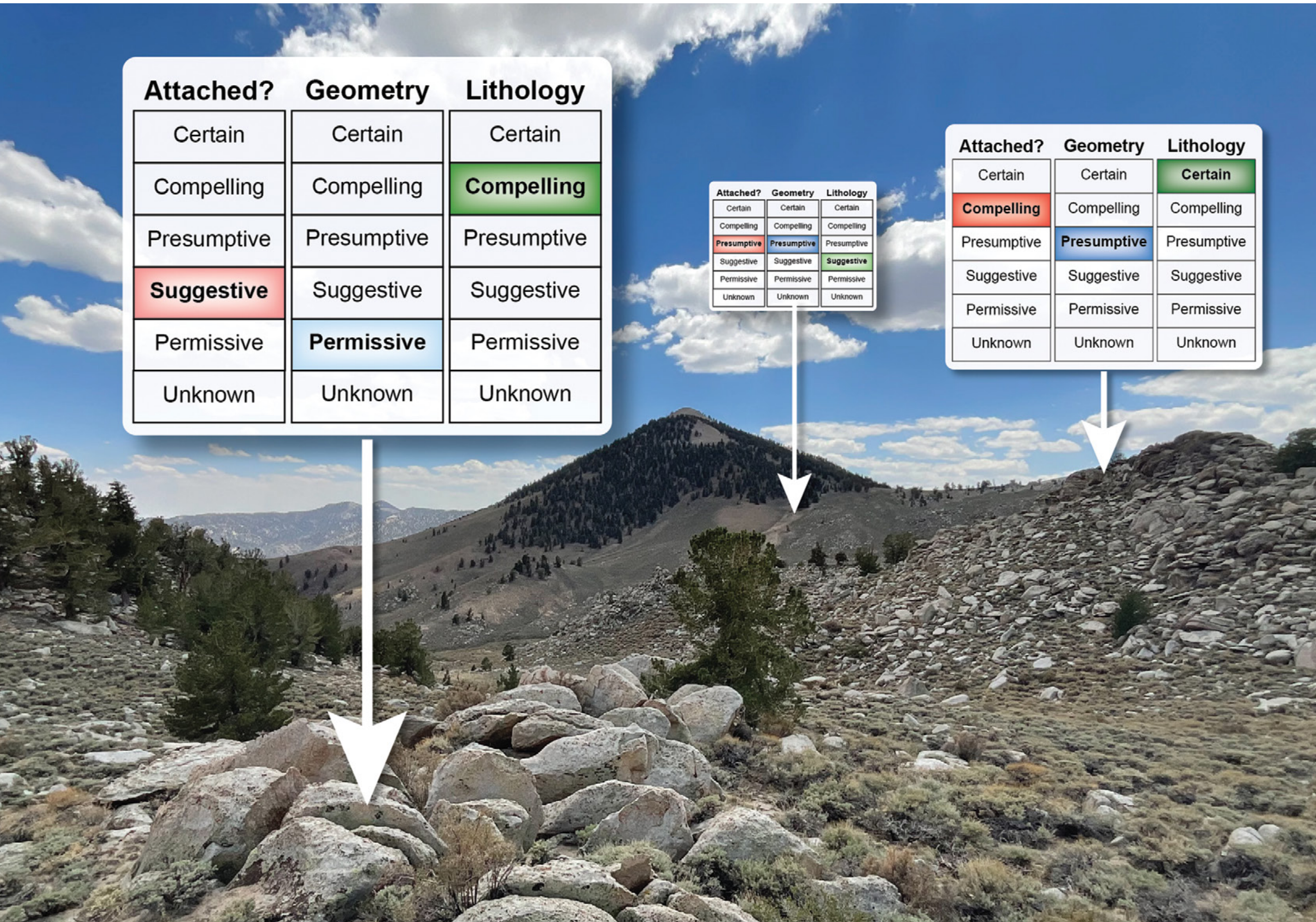
Member Recognition Issue

GSA TODAY

THE GEOLOGICAL SOCIETY OF AMERICA®

VOL. 33, NO. 7 | JULY 2023

Improving the Practice of Geology through Explicit Inclusion of Scientific Uncertainty for Data and Models



Improving the Practice of Geology through Explicit Inclusion of Scientific Uncertainty for Data and Models

Basil Tikoff*, *Department of Geoscience, University of Wisconsin–Madison, Madison, Wisconsin 53706, USA;* **T.F. Shipley,** *Department of Psychology, Temple University, Philadelphia, Pennsylvania 19122, USA;* **E.M. Nelson, R.T. Williams,** *Department of Geoscience, University of Wisconsin–Madison, Madison, Wisconsin 53706, USA;* **N. Barshi,** *Capital High School, Madison Metropolitan School District, 1045 E Dayton Street, Madison, Wisconsin 53703, USA;* **C. Wilson,** *Collaborative Robotics and Intelligent Systems Institute, Oregon State University, Corvallis, Oregon 97331, USA*

ABSTRACT

The field of geology is poised to make a fundamental transition in the quality, character, and types of science that are possible for practitioners. Geologists are developing data systems—consistent with their workflow—to digitally collect, store, and share data. Separately, geologists and cognitive scientists have been working together to develop tools that can characterize the level of uncertainty of both data and models. The transformational change comes from the simultaneous combination of these two approaches: digital data systems designed to capture and convey scientific uncertainty. This approach promotes better data collection practice, improves reproducibility, and increases trust in community-based digital data. We applied these methods—attending to uncertainty and its incorporation into digital repositories—to the Sage Hen Flat pluton in eastern California, USA, where two published maps provide different interpretations. Incorporating uncertainty into our workflow, from field data collection to publication, allows us to move beyond binary choices (e.g., is this data/model right or wrong?) to a more nuanced view (e.g., what is my level of uncertainty about the data/model?) that is shareable with the larger community.

INTRODUCTION

G.K. Gilbert's 1886 article, "The Inculcation of the Scientific Method by Example," introduced the protocol of using multiple working hypotheses when conducting geological fieldwork. Gilbert recognized the need for an explicit statement and consideration of alternative models in order to mitigate biases that arise from human reasoning. Humans infer causes to explain their observations about the world. Once a sufficient (or even convenient) explanation is available, that explanation tends to be favored over others; subsequent, inconsistent observations are frequently disregarded. This tendency is referred to as "confirmation bias," and it is one of many cognitive biases that affect human judgment. Gilbert's fundamental contribution was in recognizing—nearly 100 years before the formal study of decision biases—that scientific observation was vulnerable to the same reasoning pitfalls. In short, he realized that doing better science requires not only taking advantage of the mind's strengths but also supporting its weaknesses. If one accepts that the mind plays a role in both data collection and interpretation, then it follows that knowing something about how the mind operates will result in better science.

Cognitive science has addressed the mind's struggle with multiple competing hypotheses and the human tendency to filter data at both conscious and unconscious levels. One of the most effective methods developed to reduce bias is to structure the environment of inquiry to "nudge" people toward more nuanced conclusions. For example, a particularly powerful workflow was demonstrated within geoscience practice wherein all reasonable interpretations are explicitly articulated prior to deciding which is the most reasonable (Bond et al., 2008; Alcalde et al., 2017). This approach is a recent example of utilizing Gilbert's multiple working hypothesis methodology. But, as a community, we can move beyond the need to de-bias our approaches and develop workflows that support nuanced data collection and model articulation. A workflow to enhance field-based geologic practice, built from cognitive science principles and designed to support the mind, has become possible with an unexpected ally: digital database systems.

Digital database systems are now available for field-based geology (e.g., StraboSpot; Walker et al., 2019). Access to basic digital database systems enables researchers to record nuance-rich and contextual information regarding individual outcrops, with the added benefit of improved data sharing with the larger community. These systems are integral to designing new workflows that take advantage of strengths and support areas of weakness in the human mind.

This article highlights how the simultaneous use of cognitive science principles and digital data systems allow us to fundamentally improve field geology through the characterization and capturing of the uncertainty of both data and models. Geologists already know that uncertainty information is useful, which is why digital systems for seismic interpretation have worked to incorporate uncertainty judgments (Leahy and Skorstad, 2013) and why geologists already capture this information for some features (e.g., dotted versus dashed versus solid contacts on maps). We introduce a system for capturing uncertainty across a broad range of geological features. Then we show how these rankings can be incorporated and used in a digital data system. Finally, we demonstrate the utility of this approach by applying it to geological mapping in the Sage Hen Flat pluton in eastern California, where two published

GSA Today, v. 33, https://doi.org/10.1130/GSATG560A.1.

*basil@geology.wisc.edu

maps provide different interpretations of the same geology. We show that mapping with the explicit use of uncertainty rankings allows the community to more directly evaluate published data and models with nuanced interpretation.

CHARACTERIZING UNCERTAINTY

As noted by R. Allmendinger (pers. commun., 2013): "Geophysicists collect data then filter; Geologists must filter reality, then collect data." Considering the case of field-based geology, the filtering is both perceptual (and likely to be unconscious) and cognitive (and therefore more likely to be conscious and strategic). Unconscious filtering is seen, for example, in the diagrams labeled "what a geologist sees" in S. Marshak's physical geology textbook (Marshak, 2009), where extraneous vegetation and cover are ignored. Experience allows experts to disembed key features and thereby visually focus attention on subtle geological patterns (Hanawalt, 1942; Kastens and Ishikawa, 2006; Reynolds, 2012). Conscious filtering is more complex. Geologists continuously make a series of decisions in the field: What data do I collect, where should I collect it, and is it worth collecting? All these decisions are susceptible to bias. Thus, much of the field data in publications is heavily filtered before being made available to peer-reviewers and readers.

What geologists call "data" or an observation is not, strictly speaking, a property of the world that is visible to everyone. Rather, field data are the accumulated balance of evidence for a claim about a property of the world. Although geologists might object to this characterization, the geologist authors of this article have been convinced by our cognitive scientist colleagues that it is true. For example, consider a geologist who wonders whether to record a measurement because that person is uncertain if a rock is fully attached to the underlying bedrock. In such a situation, the geologist must decide based on the balance of evidence for or against this rock's "attachedness." In the discipline's current working approach, a geologist will either take and report the measurement or not: It is a binary choice. The quality of the evidence is lost, as is all the potentially valuable data that was overlooked because the quality was under the threshold to collect and/or report. When we talk about data uncertainty, these are the types of issues that we are considering.

In the system we propose, there is a six-point scale to characterize uncertainty in data (recorded observations) (Fig. 1). The scale ranges from **no evidence** to **certain,** with four broad categories in between, from low to high: **permissive, suggestive, presumptive, compelling.** These terms are chosen to reflect the judged likelihood that an observation reflects the true state of the world (respectively, less than 25% chance, 25%–50%, 50%–75%, and greater than 75%). For data, it is possible to be completely uncertain (**no evidence**) or to have such compelling evidence that the data is essentially **certain.** The scale is designed to leverage humans' strengths in making stable judgments about mental states when using a consistent scale with a limited set of categories (Preston and Colman, 2000).

Data quality is a combination of the variability in the world (e.g., local heterogeneity in a surface orientation or diagenetic changes to minerals) and variability due to the mind (e.g., visual skill in identifying the "representative" plane of a feature to record). The two sources of variability are inherently intertwined, as one's confidence in recording a feature accurately will be inversely proportional to the observed variability of the feature in the locale. Humans can reliably estimate their relative uncertainty and thus accuracy of decisions (Maniscalco and Lau, 2012). In present practice, some of these quality judgments are recorded, such as in a field notebook, but not as part of the community record. Consequently, most quality judgments are lost, including those where no data were recorded at all, as when a geologist bypasses an outcrop looking for a better-quality one.

Models are necessarily uncertain, and the same ranking system is applicable to them (**permissive, suggestive, presumptive, compelling**; Fig. 1). As an end member, models can be *incorrect* if there is evidence to refute a model (e.g., flat Earth model) or *unsupported* if there is no data to support a model. Likewise, no scientifically interesting models ever attain the status of *certain*. All models are uncertain because they: (1) contain untested or contested assumptions; (2) have many parts for which each part may introduce some type of uncertainty; (3) contain parts that have nonlinear effects on inferred consequences from observations; and (4) cannot incorporate data that are yet to be obtained. Because of these limitations, models are generally less certain than the relevant data for which they account.

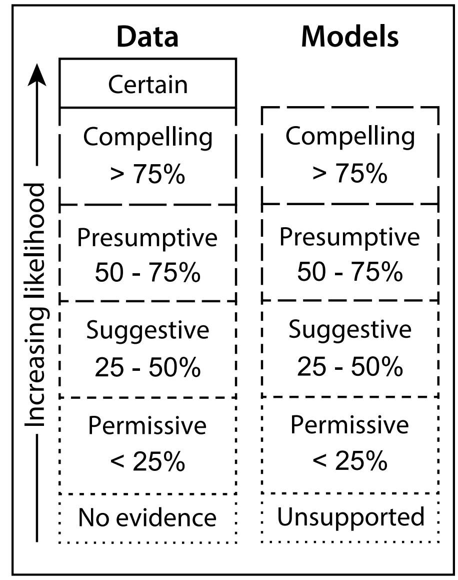


Figure 1. The uncertainty scale for geological data and models. The categories are linked to estimates of statistical likelihood, from low to high, of *permissive* (less than 25% chance), *suggestive* (25%–50%), *presumptive* (50%–75%), *compelling* (75%–99%), and *certain* (100%). Data can be categorized as *no evidence* or *certain*. In contrast, it is not possible for a model to be *certain*. Further, models can be *unsupported*. It is possible for both data and models to be *incorrect.*

UNCERTAINTY AND BEDROCK MAPPING

To characterize and store data uncertainty information, it is necessary to clearly specify the different aspects of the data that could be uncertain. First and foremost, this characterization must be streamlined into field protocols. Because field time is valuable and limited, uncertainty information will not be collected unless it requires minimal time expenditure. Second, the specific observations, to which uncertainty is assigned, depend on the map type. Bedrock mapping, for example, requires the determination of whether the rock at Earth's surface is directly connected to, and thus is representative of, the rocks below the surface at that location (*attachedness*). For comparison, attachedness for surficial mapping is less critical; attachedness has no relevance for a landslide deposit. Thus, while the identical scale (no evidence, permissive, suggestive, presumptive, compelling, certain) is useable for all maps, the observations to which they pertain may vary.

In this contribution, we concentrate on bedrock mapping. We introduce four basic observations that geologists are likely to encounter at an individual outcrop: (1) attachedness, (2) lithological correlation, (3) 3D geometry, and (4) kinematics. As noted, each of these observations requires an inference, and the inference improves with experience. *Attachedness* is discussed above. *Lithological correlation* is the determination of whether a particular rock belongs to a larger group of rocks (e.g., a named formation). We expect the majority of uncertainty will be due to challenges inherent in evaluating nuances in rock properties to correlate to a known unit and explicitly recognize that a professional geologist will be able to determine rock type at any outcrop (e.g., granitoid), although ambiguities in rock type (e.g., tonalite vs. granodiorite) can also be reflected in this category. *Three-dimensional geometry* describes how accurately one can quantify the internal spatial features of an outcrop. An example of 3D geometry is the determination of strike and dip of bedding, which is measurable to approximately ±3° for both measurements given the natural variability of rock. However, there are multiple cases where one is not certain of the 3D geometry, such as non-planar bedding measurements (e.g., cross bedding). *Kinematics* is an interpretation of movement associated with the rock. Kinematics could include primary (e.g., paleocurrents) or secondary (e.g., fault offset) features.

We identified these four aspects of an outcrop to retain potentially valuable information in one aspect (e.g., lithology) that might have been lost due to uncertainty in some other feature (e.g., attachedness). The features are not completely independent. For example, a low certainty ranking for attachedness would necessarily indicate that the geometry is unlikely to reflect the orientation of the underlying rocks. However, some features are more independent. For example, lithology can be accessed independent of attachedness or geometry, and conversely geometry and kinematics can be observed compellingly in some cases even when the lithologic unit is uncertain.

AN EXAMPLE OF BETTER GEOLOGY ENABLED: SAGE HEN FLAT PLUTON, CALIFORNIA

Background

We provide an example of the use of uncertainty scales from the Sage Hen Flat pluton in the White-Inyo mountains of eastern California. The plutonic bodies of the White-Inyo range intrude into a nearly continuous section of exposed Late Precambrian–Paleozoic strata that are weakly metamorphosed and deformed by multiple generations of Paleozoic folding (e.g., Stevens et al., 1997). However, the Late Jurassic Sage Hen Flat pluton is unique among these intrusions because its emplacement does not disrupt any of the regional structural trends (Morgan et al., 2000).

The relevance of the Sage Hen Flat pluton for our study is that there are two geological maps—both done by professional geologists with significant mapping experience—that disagree in both map pattern and cross section (Figs. 2 and 3). The Ernst and Hall (1987; afterward E&H) map was part of a regional map of the White Mountains. The Bilodeau and Nelson (1993; afterward B&N) map focused solely on the Sage Hen Flat pluton. For our purposes, the geological maps are models based on data. There are places where the data are clearly distinguished from inferences: the strike-and-dip symbols, solid contacts between units, etc. The cross sections are models and are necessarily more speculative than the geological maps because of the lack of sub-surface information.

The difference between the geological maps is most prominent in the northwestern corner of the pluton, which is highlighted in Figure 3. The E&H map interprets the local geology as recording a fault contact between

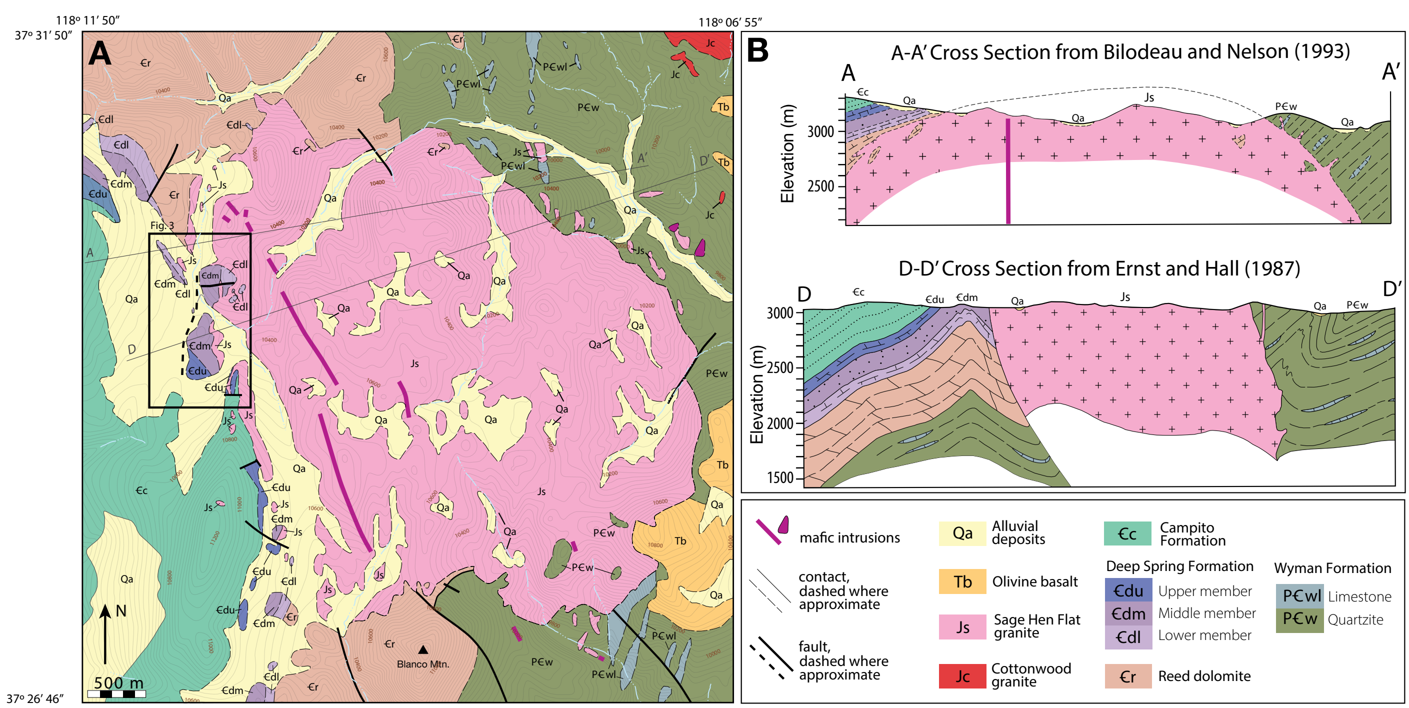


Figure 2. (A) Geological map (modified from Bilodeau and Nelson, 1993) and two different cross sections depicting different models for the regional geology. The Bilodeau and Nelson (1993) cross section (B, line A–A') indicates an intrusive contact for the Sage Hen Flat pluton. The Ernst and Hall (1987) cross section (B, line D–D') depicts the western edge of the Sage Hen Flat pluton as a faulted contact. The box on the geological map (A) shows the location of Figure 3. Both cross sections lines (A–A' and D-D') cross the area shown in Figure 3.

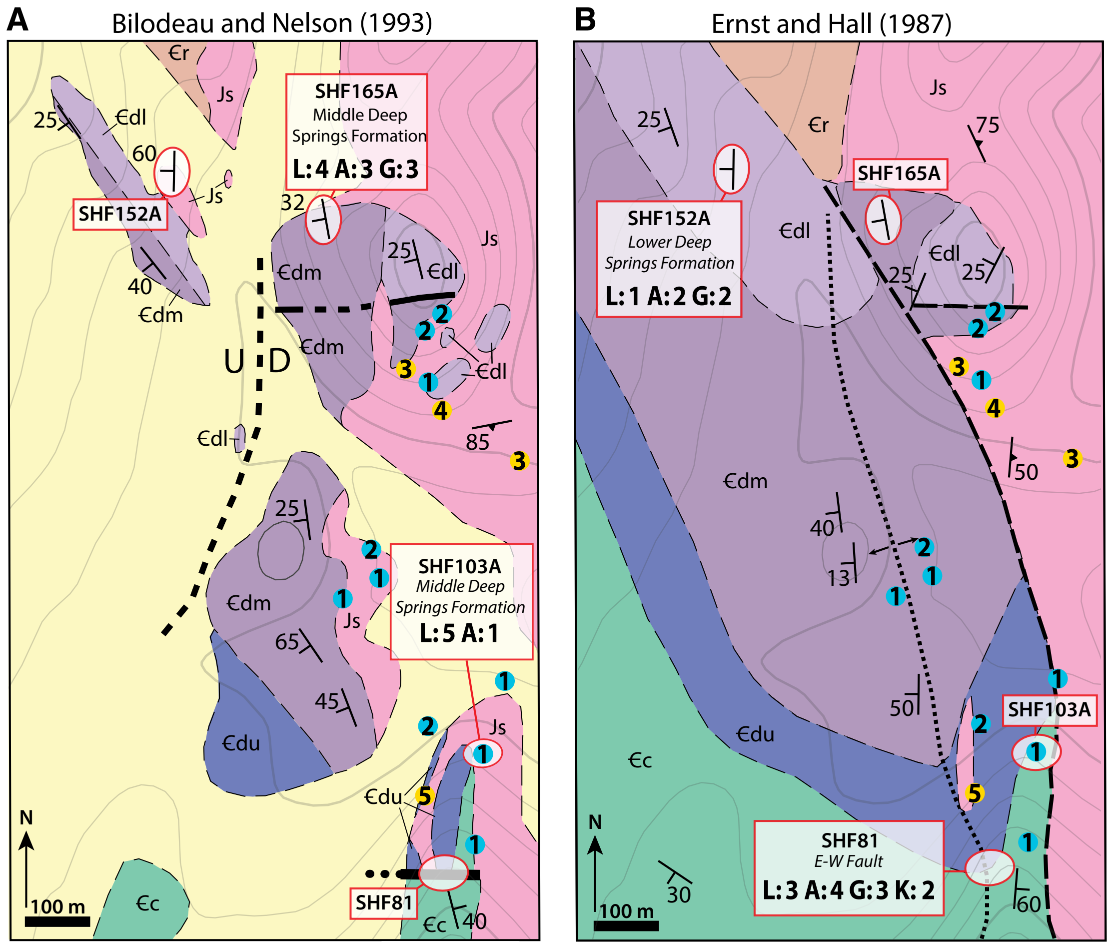


Figure 3. Geological maps of the northwest corner of the Sage Hen Flat pluton extracted from the geological map of (A) Bilodeau and Nelson (1993) and (B) Ernst and Hall (1987). The circled numbers show the location and attachedness values (blue = 1, 2; yellow = 3–5) for granitic outcrops discussed in the text. These data are part of the public "Sage_Hen_Flat_ Tikoffetal" project on StraboSpot.org. L—lithology; A—attachedness; G—geometry; K—kinematics. See Figure 2 for legend.

Sage Hen Flat granite and country rock on the western margin of the pluton. The B&N map indicates that the plutonic contact on the western margin is intrusive. We focused our efforts in this location to investigate the interplay of data and model uncertainty, reasoning that the likely cause of the model uncertainty—as indicated by their disagreement—was data uncertainty.

Application of the Uncertainty Scales

The existence of two differing models for the geometry and origin of some features is not unique in geology, but it is particularly well illustrated in the case of the Sage Hen Flat pluton. We remapped the pluton in the summers of 2019 and 2021 in order to construct and then utilize uncertainty scales that are applicable to field geology. The data were recorded in the StraboSpot system with the uncertainty values noted. The publicly available full data set contains 461 stations with notes on the geological features, associated uncertainty, and photographs ("Sage_Hen_Flat_Tikoffetal" project on StraboSpot.org). Uncertainty for attachedness and lithology were collected on the 0–5 scale outlined above. Geometry information was collected in those cases in which: (1) attachedness was 2/5 or higher, and (2) a bedding or foliation was possible to measure. Kinematics were only noted in a few locations where kinematic features, in this case fault traces, were present.

Our intention is not to find that one mapping team is wrong and one is right. Rather, our objectives are to (1) understand what data drove the previous interpretations; and (2) demonstrate that showing uncertainty allows geologists to make an informed judgment.

Station SHF165A (Fig. 3) shows a location for which there is agreement between B&N, E&H, and our data. We are explicit in our evaluation of attachedness, lithology, and geometry: A practitioner can determine how much to trust our data. In contrast, we interpret that if B&N or E&H took a measurement, they likely did so only in cases for which attachedness was presumptive (3/5) or higher.

For Station SHF152 (Fig. 3), the B&N and E&H maps are in conflict. Our data suggest that B&N is incorrect in mapping it as a granite: The outcrop is a carbonate, although it is bleached, potentially by fluids expelled from the nearby Sage Hen Flat pluton. The E&H map indicates that the outcrop is the Reed (dolomite) Formation. We are less certain, because of the metasomatic alteration, but assign this outcrop to the Deep Springs Formation (1/5). If the B&N *data* are incorrect, does it alter their *model* for the margin of the pluton? In our opinion, the answer is no. It is relatively uncritical if this outcrop consists of granite or carbonate with respect to their model of an intrusive contact.

The more interesting case are the outcrops of Sage Hen Flat granite (Fig. 3): Blue circles show location of outcrops with low attachedness rankings (1/5 or 2/5), whereas yellow circles distinguish outcrops with high-attachedness rankings (3/5 or higher). Note that both maps are consistent with our high attachedness ranking outcrops. The difference is that there are numerous low-attachedness ranking outcrops that are consistent with the B&N map but not the E&H map (Fig. 3). Outcrop 103A (Fig. 3) shows one such example; although attachedness is low, most geologists would likely interpret that these rocks are nearly in place, as there is no reasonable process that could have moved them from elsewhere. We now ask the critical question of the E&H map: Do the incorrect *data* alter their *model* for the margin of the pluton? The answer, for us, is yes. The existence of abundant granite outcrops west of their interpreted fault—where no granites should outcrop—suggests that the model has more uncertainty than that of B&N.

At Station SFH081 (Fig. 3), the Lower Deep Springs Formation strikes into the Campito Formation, and both units display similar bedding orientations. A fault is shown on the B&N map but not on the E&H map. We judge the presence of this fault to be compelling (4/5). In this case, we can also investigate the kinematics. There is not an exposed fault surface with slickensides, and the movement cannot be resolved by stratigraphic offset. Geometrically, the fault movement could be N-side-down, dextral, or some combination. We rank the kinematics as suggestive (2/5) and, similar to B&N, would not indicate fault movement using a symbol on the map.

DISCUSSION

Data Uncertainty

Our uncertainty evaluations at the northwestern corner of the Sage Hen Flat pluton provide more robust field data than previously available. Geologists are already making these types of evaluations, but they are not doing it systematically, using a shared vocabulary, or storing the evaluations in a format that other geologists can access.

In our opinion, the data we present are more useful than the data that B&N and E&H provided, largely because our data collection system includes uncertainty. The advantages of our approach are (1) we have created methods to record the data that are accessible, so the community—including geologists who have not physically been there—can evaluate it and offer alternative geological inferences; (2) the collected data are nuanced, which allows all interested members of the community to consider how much to rely on a specific measurement; (3) we collected more data because we had a digital system that allowed us to collect it quickly; (4) the data are less filtered, as we were willing to collect low-certainty data because we could identify it as such; and (5) the need to explicitly evaluate uncertainty at every station motivated us to evaluate each outcrop independently, which reduces bias by reducing the influence of preconceptions (about the adjacent outcrops, regional geology, existing models, etc.).

Model Uncertainty

Our approach allows us to make better models through (1) the use of shared language to characterize the quality of the *model*; (2) the use of more robust field *data* (more data, stored in an accessible way, with quality evaluations); and (3) the ability to more closely link the quality of the *data* to the quality of the *model*. We apply these concepts to the two models for the western margin of the Sage Hen Flat pluton: (1) a faulted contact (E&H; Fig. 2B), and (2) an intrusive contact (B&N; Fig. 2B).

Prior to spending time in the field, we evaluated both the E&H and B&N models as "suggestive." Having collected data in this area, we promote the B&N model to "presumptive" and keep the E&H model as "suggestive." The data that we collected that are not consistent with the B&N model (e.g., SHF152A; Fig. 3) are nevertheless consistent with the processes interpreted in their cross section. In contrast, some of our data do not support the E&H model; the granitic outcrops with low attachedness rankings in the southern part of the area shown in Figure 3 are inconsistent with a faulted contact. Thus, although the E&H model remains suggestive (in the 25%–50% likely category), it is less likely than the B&N model. We note that in any field area, a compelling or even presumptive model may not exist, because the nature of the outcrop quality or the complexity of the region does not allow the true relationships to be discerned.

Our assessment applies only to a small area (Fig. 3) of the E&H and B&N maps, but illustrates a structured way to engage in assessments of model certainty. In particular, it addresses where models are uncertain and the level of that uncertainty. A critical point is that we are not trying to determine which model is correct: Our evaluation is more nuanced than one model is right and the other one is wrong. In large part, both models are well supported by high-certainty field data. It is unclear that additional geological mapping, by itself, would further adjudicate between the existing models.

Data Uncertainty and Model Uncertainty Interaction

Data uncertainties interact with the model uncertainties in a variety of different ways. The influence of data uncertainty on model generation is clear. All scientists likely recognize that one's interpretation can only be as good as one's data. For a sparse data set from an area where exposures are limited, model uncertainty is closely tied to the underlying data uncertainty. Thus, compelling models are made with consistent, compelling data. In contrast, permissive models are made with either consistent permissive data or a mix of inconsistent suggestive, presumptive, and compelling data. As data sets get larger, these relationships change. For example, a large number of consistent, permissive data could support a suggestive (or more certain) model. These relations can be developed statistically in the future as the community develops its facility with digital methods.

Most geologists engage in model comparison, but they are not doing it explicitly or consistently when collecting data. Model uncertainty guides data collection in areas where data can distinguish between different models. For this reason, we focused our work on the northwestern corner of the Sage Hen Flat pluton, where there was a clear need to collect unbiased data in order to evaluate competing models. Note the similarity of our approach to that of Gilbert (1886). The use of model uncertainty produces the same cognitive advantages as Gilbert's idea of multiple working hypotheses, particularly in debiasing of data collection.

We argue that we can make a fundamental improvement to the approach of Gilbert by focusing on data rather than models. This approach is facilitated by the use of digital data systems coupled with a workflow informed by cognitive science. In the absence of digital tools, people reason using models because there is no effective way for the mind to keep track of *all* of the data and its attendant uncertainties. Digital data systems offload this cognitive burden, which in turn can improve estimates of relative model certainty. This process encourages data collection—particularly of unexpected features and/or low-certainty data—that can provide new model insights and transform practice. Marginal data in bulk can provide better estimators than sparse data to refine spatial and non-spatial interpretations. Data analytics developed for field-collected data uncertainty could prove to be a key for developing robust quality control and quality assurance for digital data systems.

Recording geologists' uncertainty allows transparent connections between uncertainty in data and the uncertainty in models. One can produce better models because one can evaluate the quality of the data upon which the model is built. Critically, the geologists who have used the uncertainty scales in the field do not find them cumbersome or overly time consuming. The use of uncertainty simultaneously could increase a scientist's trust of data types outside of their expertise as they could rely on the evaluation of uncertainty by others. Communicating the uncertainty in data and models may reduce the barriers to model revision or replacement and speed the advance of science.

Future Work

The presented workflow provides one possible approach for geologists to capture and communicate uncertainty in data and models. Although it is not meant to be prescriptive, it exhibits important attributes for gathering uncertainty information for field practitioners: (1) it does not interfere with workflow, (2) it facilitates transparent data collection, (3) it captures uncertainty about a manageable number of categories, and (4) the results are replicable and psychologically meaningful. These guidelines may be useful to other communities using field-based data that adopt the collection of uncertainty data to support their research needs.

This contribution aims to improve the quality of field-based geologic information through the explicit communication of uncertainty and the manner in which that uncertainty is communicated. There are, however, other discussions that need to be held at a community level. For example, practitioners in bedrock mapping may want to develop new conventions for visually communicating uncertainty. It may be time—with cognitive scientists involved in the process—to update how we record, represent, and communicate geologic information.

CONCLUSIONS

It is generally recognized that science and society are undergoing a digital revolution. The geological community has the opportunity to adapt best practices of the past to the emerging new workflows that result from the ability to operate digitally. We propose the systematic use of uncertainty scales when collecting digital field data and developing models, which are easily recorded by digital technologies, as better science practice.

We applied the use of uncertainty scales to bedrock mapping at the Sage Hen Flat pluton in eastern California, where different data resulted in different models for the regional geology. New data was collected in the area of most divergence between the two geological maps. The purpose of our evaluation was to show how data that contain uncertainty estimates provide a fundamentally better record of geological field data, can adjudicate between different models, and can guide future research. The language associated with the data and model uncertainties can also allow nuanced (e.g., non-binary) decisions and facilitate productive communication between researchers.

ACKNOWLEDGMENTS

Robert Dott provided a version of an "evidence meter," which he modified from an earlier effort by Preston Cloud. S. Morgan, M. St. Blanquat, R. Law, A. Glazner, and J. Bartley all provided data and/or information about the Sage Hen Flat pluton. J. Newman and J.D. Walker are thanked for multiple conversations about how to incorporate uncertainty into StraboSpot. The concept for the map comparison in Figure 3 came from an informal student presentation by L.D. Wilson, J.D. Higdon, and J.A. Davidson (from A. Glazner, pers. commun., 2022). Reviews by Steve Reynolds and two anonymous reviewers helped us improve the manuscript. This work was supported by the National Science Foundation under Grant NSF DUE 1839705 (TS) and 1839730 (BT), and NSF EarthCube 192973 (BT).

REFERENCES CITED

Alcalde, J., Bond, C.E., Johnson, G., Butler, R.W.H., Cooper, M.A., and Ellis, J.F., 2017, The importance of structural model availability on seismic interpretation: Journal of Structural Geology, v. 97, p. 161–171, https://doi.org/10.1016/j.jsg.2017.03.003.

Bilodeau, B.J., and Nelson, C.A., 1993, Geology of the Sage Hen Flat Pluton, White Mountains, California: Geological Society of America Map and Chart Series MCH077, scale 1:24,000, 1 sheet, 18 p.

Bond, C.E., Shipton, Z.K., Gibbs, A.D., and Jones, S., 2008, Structural models: Optimizing risk analysis by understanding conceptual uncertainty: First Break, v. 26, https://doi.org/10.3997/1365-2397.2008006.

Ernst, W.G., and Hall, C.A., 1987, Geology of the Mount Barcroft–Blanco Mountain Area, Eastern California: Geological Society of America Map and Chart Series MCH066, scale 1:24,000, 1 sheet.

Gilbert, G.K., 1886, The Inculcation of the Scientific Method by Example, with an Illustration Drawn from the Quaternary Geology of Utah: American Journal of Science, v. 31, p. 284–299, https://doi.org/10.2475/ajs.s3-31.184.284.

Hanawalt, N.G., 1942, The effect of practice upon the perception of simple designs masked by more complex designs: Journal of Experimental Psychology, v. 31, p. 134–148, https://doi.org/10.1037/h0061522.

Kastens, K.A., and Ishikawa, T., 2006, Spatial thinking in the geosciences and cognitive sciences: A cross-disciplinary look at the intersection of the two fields, *in* Manduca, C.A., and Mogk, D.W., eds., Earth and Mind: How Geologists Think and Learn about the Earth: Geological Society of America Special Paper 413, p. 53–76, https://doi.org/10.1130/2006.2413(05).

Leahy, G.M., and Skorstad, A., 2013, Uncertainty in subsurface interpretation: A new workflow: First Break, v. 31, https://doi.org/10.3997/1365-2397.31.9.71079.

Maniscalco, B., and Lau, H., 2012, A signal detection theoretic approach for estimating metacognitive sensitivity from confidence ratings: Consciousness and Cognition, v. 21, p. 422–430, https://doi.org/10.1016/j.concog.2011.09.021.

Marshak, S., 2009, Essentials of Geology, third edition: New York, W.W. Norton and Company, 628 p.

Morgan, S.S., Law, R.D., and Blanquat, M. de S., 2000, Papoose Flat, Eureka Valley–Joshua Flat–Beer Creek, and Sage Hen Flat plutons: Examples of rising, sinking, and cookie-cutter plutons in the central White–Inyo Range, eastern California, *in* Lageson, D.R., Peters, S.G., and Lahren, M.M., eds., Great Basin and Sierra Nevada: Geological Society of America Field Guide 2, p. 189–204, https://doi.org/10.1130/0-8137-0002-7.189.

Preston, C.C., and Colman, A.M., 2000, Optimal number of response categories in rating scales: Reliability, validity, discriminating power, and respondent preferences: Acta Psychologica, v. 104, p. 1–15, https://doi.org/10.1016/S0001-6918(99)00050-5.

Reynolds, S.J., 2012, Some important aspects of spatial cognition in field geology, *in* Manduca, C.A., and Mogk, D.W., eds., Earth & Mind II: Synthesis of Research on Thinking and Learning in the Geosciences: Geological Society of America Special Paper 486, p. 75–78, https://doi.org/10.1130/2012.2486(12).

Stevens, C.H., Stone, P., Dunne, G.C., Greene, D.C., Walker, J.D., Swanson, B.J., Ernst, W.G., and Skinner, B.J., 1997, Paleozoic and Mesozoic evolution of east-central California: International Geology Review, v. 39, p. 788–829, https://doi.org/10.1080/00206819709465303.

Walker, J.D., Tikoff, B., Newman, J., Clark, R., Ash, J., Good, J., Bunse, E.G., Moeller, A., Kahn, M., Williams, R., Michels, Z., and Rufledt, C., 2019, StraboSpot data system for structural geology: Geosphere, v. 15, p. 533–547, https://doi.org/10.1130/GES02039.1.

Manuscript received 23 December 2022
Revised manuscript received 29 March 2023
Manuscript accepted 1 April 2023