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Clare E. Bond

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Uncertainty in Structural Interpretation: lessons to be learnt

Clare E. Bond, Department of Geology and Petroleum Geology, School of Geosciences, University of Aberdeen, Meston Building, Kings College, Aberdeen, AB24 3UE

clare.bond@abdn.ac.uk

Uncertainty, interpretation, structure, models

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Abstract

Uncertainty in the interpretation of geological data is an inherent element of geology. Datasets from different sources: remotely sensed seismic imagery, field data and borehole data, are often combined and interpreted to create a geological model of the sub-surface. The data have limited resolution and spatial distribution that results in uncertainty in the interpretation of the data and in the subsequent geological model(s) created. Methods to determine the extent of interpretational uncertainty of a dataset, how to capture and express that uncertainty, and consideration of uncertainties in terms of risk have been investigated. Here I review the work that has taken place and discuss best practice in accounting for uncertainties in structural interpretation workflows. Barriers to best practice are reflected on, including the use of software packages for interpretation. Experimental evidence suggests that minimising interpretation error through the use of geological reasoning and rules can help decrease interpretation uncertainty; through identification of inadmissible interpretations and in highlighting areas of uncertainty. Understanding expert thought processes and reasoning, including the use of visuospatial skills, during interpretation may aid in the identification of uncertainties, and in the education of new geoscientists.

1. Introduction – uncertainty in science

Over the last decade uncertainty has become increasingly analysed. Scientific uncertainty is common vernacular within scientific studies and a familiar topic in popular science journalism (e.g. Uncertain Science… Uncertain World (Pollack, 2005), The Blind Spot: Science and the Crisis of Uncertainty (Byers, 2011)). Much of the media focus on scientific uncertainty has concentrated on climate change, aided by political heavyweights taking up the fight against anthropogenically induced climate change sceptics, e.g. Gore (2006). The fact that uncertainty in science has become central to the climate change debate, has led to an increase in the profile of uncertainty in science more broadly (Figure 1). In Earth Science this growing interest in uncertainty is exemplified by recent conferences e.g. *Capturing uncertainty in geomodels: best practices and pitfalls* Geological Society of London conference, December 2013, and text books on the topic e.g. *Modelling Uncertainty in the Earth Sciences* (Caers, 2011). In some sectors of the discipline the interest is driven by economics, as Earth resources are explored for and produced in increasingly challenging and expensive environments. In other areas the desire to predict future responses of environmental systems to present day actions is the driver, particularly for waste storage, e.g. CO_2 and radioactive waste, and geothermal energy projects (e.g. Vasco et al., 2000; Sifuentes et al. 2009).

Geology is an inherently uncertain science. Uncertainty in geology has been recognised outwith the discipline by the philosopher and science historian Robert Frodeman. Frodeman (1995) recognises geology as a science in which: 1) Uncertainty is the norm rather than a special case, and 2) geological reasoning is seen as a 'unique' and desirable skill that will aid solutions to 21st century problems. This external recognition of geological uncertainty, coupled with the increasing acknowledgement of geological uncertainty within the discipline (as indicated by citation metrics, Figure 1); and the public and industrial desire to better understand uncertainties makes it timely to review current understanding of geological uncertainty. The discipline-underpinning skills of geological interpretation and reasoning, identified by Frodeman (1995) as unique and desirable, are important methodologies employed by geologists to enable analysis of data and the creation and testing of hypotheses within a large uncertainty space. Here I explore recent research on geological uncertainty, interpretation and reasoning skills, with specific reference to structural geology. Many of the examples and references are given from a petroleum industry perspective, but are equally applicable to other industrial geology sectors such as mining, carbon capture and storage, and radioactive waste disposal.

1.1 Uncertainty

The term uncertainty, encompasses known errors or variability, as well as those that we are unable to predict or have no knowledge of (e.g. Donald Rumsfeld's "unknown, unknowns" – as made famous by his 2002 US, Department of Defence briefing (Rumsfeld, 2002)). It encompasses aleatoric uncertainty (these are known, or expected and are irreducible) as well as epistemic (those we could know in practice, and are reducible). Aleatoric uncertainty is most often described through the concept of rolling a dice and comes from the Latin *alea*, to roll a dice. The probability of rolling a six for each roll is 1 in 6 and, unless the dice is biased, and therefore the uncertainty cannot be reduced. In a geological context it may be thought of as the known uncertainty in a measurement, for example: the geological age of a fossil, or the precision of a radiometric date. Epistemic uncertainty is an uncertainty that may be reduced if more knowledge or data is obtained e.g. if more structural data is collected to characterise a fold. The word epistemic derived from the Greek *episteme*, knowledge. A useful overview of aleatory and epistemic uncertainty is given by Der Kiureghian and Ditlevsen (2007).

The range in possible uncertainties in any given subject area, or scenario, are many and complex. Taxonomic approaches have been proposed to classify uncertainties in environmental systems (e.g. Walker et al., 2003; Refsgaard et al., 2007). These papers (e.g. Refsgaard et al., 2007) offer taxonomies and classifications of uncertainties as a method to identify, quantify and integrate different types of uncertainty within a system, with positive impacts for communication and management of the overall uncertainty. These papers also highlight the complexities in communicating uncertainties between disciplines, due to different terminology usage and conceptualisations of different 'types' of uncertainty (e.g. Janssen et al., 2005).

For discipline-specific geological uncertainty there are potentially fewer categorisations, but the concept of multiple types and levels of interacting uncertainty should not be ignored. Figure 2 shows a simple tree based classification of uncertainty; at the first branch uncertainty is divided into subjective and objective uncertainties. Walker et al. (2003) argues that explicitly separating subjective and objective uncertainty, through labelling, should aid the identification of uncertainties that we may potentially otherwise miss. In the example in figure 2 a seismic reflection image is used to represent the different types of uncertainty: e.g. subjectivity in fault placement, or existence; versus the objective (error bound) position of a seismic reflection amplitude. Within this simple taxonomy there are further levels and categorisations, but it serves as an example of how uncertainties may be broken down and considered in a geological context.

2. Geological Uncertainty

Traditionally geological uncertainties have been thought of in a 'classical' science context with a focus on objective uncertainty, such as the errors on a reading or measurement. Many of these types of geological errors, for example the error in reading a strike and dip measurement of a bedding surface in the field, are small compared to the natural variability in the data itself; and are sensibly ignored given a big enough sample (Bond et al., 2007a). Technological improvements are constantly improving analytical precision in measurements of many natural phenomena to the extent that other assumptions or simplifications introduce more significant errors than the errors of the data measurements (Figure 3). This is particularly significant in geology where we extrapolate observations over significant distances and our uncertainty space is much greater than that constrained by data.

In terms of subjective uncertainties, geoscience has generally been quite poor in both acknowledging and providing methods to communicate these types of uncertainty. This would seem a negative statement, but working within a context of large subjective uncertainty is actually the core strength of a geologist, as recognised by Frodeman (1995); in that a geologist has a skill set that allows construction of an interpretation when faced with a high level of uncertainty. It also stems from the culture of the discipline, in which subjective uncertainty is an implicit element of the data collection and interpretation process. In geology decisions and hypotheses are made at each step in this process, creating an evolving 'working model'. To some degree a culture of iterative hypothesis creation and testing starts in the first basic training programs of any degree program (see section 2.1 – the working model) and is a continuous feature for most professional geoscientists (e.g. undertaking seismic interpretation, or constructing geological models). But human biases, including anchoring to an initial model (see section 2.3 – cognitive biases) have the potential to limit this process.

2.1 The Working Model

Conceptual or mental models are used commonly, for example in the association of causal relationships such as the burning of fossil fuels and climate change (Sloman and Fernbach, 2011;

Newell et al., 2014). Mental models are based on prior experience and beliefs, and can change or be updated as more experience or knowledge is acquired. Such mental models and their evolution are fundamental to geological interpretation and are described here in the context of a working model. The working model is best exemplified by a geological mapping exercise in which a geology student makes observations, collects data (recorded in a notebook and/or on a map) and then decides where to walk next (i.e. what data they will next collect to inform their working model). The strategy taken will be informed by the task and the geology, but will likely, for a trained geoscientist, be a variation of the following: walk across strike to locate the next unit, continue this process to build a picture of the rock units in the area (lithologies, initial geometrical relationship, thickness etc. – create an initial cross section 'the working model'), followed by mapping boundaries of these units away from the transect line (updating the cross-section and 3D geometrical understanding – revising the working model).

Studies using GPS tracking technology have demonstrated the impact of geological training and experience on decisions made to complete a geological map in the field (e.g. Baker and Libarkin, 2007; Riggs et al., 2009), these geological specific findings chime with earlier work on spatial choice in large scale environments (Gärling et al., 1997) and the use of analogues and experience to inform conceptual models (Bond et al., 2008; Newell et al., 2014). The more experienced geologist makes conscious predictable decisions about their field routing (sampling the geology to complete the map most efficiently), whilst those with less experience (mapping without a working model, or reasoning for their route choice) produce a chaotic route track.

Imagine trying to complete the geological boundaries on a map containing only outcrop information. The geologist can evoke rules and reasoning (e.g. V-ing into valleys) but without contour information many of these fall down; it is a bit like trying to complete an un-numbered dot-dot puzzle. Visuospatial skills to conceptualise how geological boundaries will interact with topography are a key skill for the geological mapper. In work by Hambrick et al. (2012) individuals with good visuospatial skills but little geological knowledge were shown to out-perform those with similar, low, levels of geological experience in a geological mapping exercise. These findings are echoed by Liben (2014) who used childrens' scores in a well-known test of space conception to demonstrate a link between these and spatial reasoning using a map. The employment of a working model, that relies on visuospatial reasoning skills, during data collection in the field allows the geologist to construct a sensible narrative for the data collected. This model will be refined as new data is collected, or even thrown away completely when the original working model falls-down or a more elegant solution appears; but it allows the geologist to build an interpretation. This methodology ensures the practiced geologist is never left with un-interpreted outcrop locations as their geological map at the end of the day (an unnumbered dot-dot puzzle). For an experienced field geologist even the simplest observations at an initial outcrop, such as the bedding-cleavage relationship, should allow a working cross section to be built (Figure 4a), with additional data collected along a transect enabling refinement of the predictions.

2.2 Multiple working hypotheses and scientific culture

Working models are generally non-unique and more than one working model or hypothesis can be run in parallel (Figure 4b), with models refined, or disposed of, as new data is collected. The ability to work with multiple working hypotheses, has long been recognised as having a positive effect on interpretation, minimising the potential for the interpreter to favour an initial model (Chamberlin, 1965)[1]. In practice however this is rarely done; partly because the possibility of conceptual uncertainty (or multiple potential models) is rarely recognised, compounded by other psychological barriers to the employment of multiple models. Chamberlin himself recognised several issues in pursuing multiple working hypotheses: 1) the human brain has a limited capacity to deal with and express more than one model at a time, 2) a favour towards single model solutions, they are simpler to deal with and their uniqueness has an elegance, 3) the 'danger of vacillation', or preference for one model. Although, further studies have shown that vacillation, or uncertainty over which model to choose is uncommon with early anchoring to a single model being the norm (e.g. Rankey and Mitchell, 2003).

Multiple conceptual models are not employed frequently in professional geoscience. One reason for this is scientific culture, which is dominated by the scientific publication process in which scientists generally advocate a single model or idea that is peer-reviewed. Promoting multiple possible solutions does not sit easily in this style of review system where advocating and defending a hypothesis is the norm. It also conforms to our psychological bias, as described by Chamberlin, to preferably converge on a single model or solution. Chamberlin was writing about what is now the established psychological field of cognitive bias, particularly with respect to judgement and decision making under uncertainty.

2.3 Cognitive biases

[1] Chamberlin was a geologist and his paper on multiple working hypothesis was originally published in 1896 in the Journal of Geology, which he founded.

The leading paper of Tversky and Khaneman (1974), and their other contributions in the area of cognitive bias, judgement and decision making under uncertainty (e.g. Tversky and Khaneman, 1973; Khaneman et al., 1982)) was recognised by a Nobel prize for Khaneman in 2002. In their Science paper *Judgement Under Uncertainty: Heuristics and Biases* (Tversky and Khaneman, 1974) they used a simple set of experiments to demonstrate for the first time the effect of *anchoring* on judgements. Development of these and other cognitive bias theories have since evolved, but application to, and assessment of, their impact on geological uncertainty and decision-making has been limited. Table 1. provides a summary of classic cognitive biases, that affect geologists undertaking interpretation of geological data.

Early work on cognitive bias in geology was undertaken by (Chadwick, 1975) who showed that geologists see what they think they should see in the rocks rather than what is actually there. He demonstrated that geologists see more antiforms than synforms and tend to recall fold cleavage fans with text book geometries rather than as they actually are. Discussion and identification of cognitive biases affecting geological interpretation are discussed by Baddley et al. (2004) in the introduction to the Geological Society Special Publication on Geological Prior Information (Curtis and Wood, 2004). This volume contains reference to geological uncertainty from a perspective of prior knowledge. Other geological papers that discuss the subject of cognitive bias and the implications for uncertainty and risk in geology from an oil industry perspective include Rankey and Mitchell (2003), Bond et al. (2007b, 2008; 2012), Polson and Curtis (2010), Rowbotham (2010) and a general overview by Curtis (2012). Key outcomes of the papers are discussed below.

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Rankey and Mitchell (2003) undertook the first experiment to investigate the interpretations of multiple geologists to the same dataset. In their experiment six geoscientists interpreted seismic and well data for a carbonate reef system. The authors identified evidence of model uncertainty, particularly in net- gross predictions, and evidence of *anchoring* after the interpreters were provided with additional data part way through the experiment. Their experiment was followed by the work by Bond et al. (2007b) who published the first demonstration of geological conceptual uncertainty at a 'whole' geological model scale, with a significant number of interpreters. The work of Bond et al. (2007b) gathered interpretations to a single synthetic seismic dataset from 412 geoscientists. The participants evoked a range of structural and sedimentary styles returning interpretations spanning coral reefs and sequence stratigraphy through to extension and compression tectonic styles and salt or shale based tectonism. The synthetic seismic image had been created from a forward model so the authors were able to appraise the interpretations against the initial model, which was an inverted normal growth fault. Only 21% of the interpreters applied the 'correct' inversion concept to the model (Bond et al., 2007b), highlighting the potential conceptual uncertainty for a dataset and the potential risks in using single deterministic models.

As well as showing the range of conceptual uncertainty to a single synthetic seismic image and evidence of availability bias, Bond et al. (2007b) showed evidence of interpreter desire to use *confirmation* bias through provision of an initial model to aid their interpretation. In the experiment the participant interpreters were stripped of their normal working practices: they had no regional context, including no regional seismic data, and no well data. The unannotated seismic image shown in figure 5b was all the knowledge the interpreters had. This proved a challenge both in terms of data collection - people do not like to be taken out of their comfort zone, but also for the interpreters who did not have a contextual basis from which to start their interpretation. During the data collection process many participants asked *"Where in the World is it?"* and/or wrote on their interpretation ideas of locations e.g. *"Gulf of Mexico?"* (Bond et al., 2007b). The participants were not only trying to retain their normal working practice comfort zones, but were attempting to evoke their prior knowledge of an area to aid them in their interpretation. The use of prior knowledge in this way can impart elements of *confirmation* and *initial model* bias on the interpretation.

If interpreters use geographical locations to inform interpretational style, you might expect this process to be reversible. i.e. an interpreter could complete an interpretation and then give an indication of the likely global location. At the Geological Society of London Tectonic Studies Group meeting in 2006, this theory was tested with a 'Where in the World?' poster. Participants interpreted the Bond et al. (2007b) seismic image (figure 5b) and then placed a sticky dot on a World map to indicate the approximate location of the seismic image globally (figure 5a). The numbers on the dots in figure 5b indicate the order starting at 1 in which the dots were placed on the map. There is some evidence of spatial clustering or *herding*, but the global spread is significant.

The concept of *herding* is discussed in a geological context by Baddley et al. (2004), and demonstrated in the elicitation experiment of Polson and Curtis (2010). In the latter the authors tracked the decisions of experts as they made probability judgements on the existence of key features in a geological reservoir and discussed their own judgements with others, revising their initial probabilities during the elicitation process. In many ways the concept of *herding* around an influential individual, is similar to a conceptual bandwagon to which scientists' anchor their ideas or opinions. In geology we may think about the concepts of listric faulting or inversion in the UK North Sea that dominated thinking in the 1980s and 1990s, or the change in understanding of salt tectonics through improved seismic imaging and new conceptual models (e.g. Jackson, 1995).

The types of cognitive biases discussed: confirmation, initial model, herding, availability have a tendency to restrict or slow-down the progress of scientific discovery. Interpreters are safe in their interpretations favouring the accepted dogma over a new or radical idea. In essence application of existing models and hypotheses are a form of heuristic (or rules of thumb), as referred to by Tversky and Khaneman (1974). Heuristics allow us to make complex decisions quickly and play an important role in decision making in all aspects of life. Heuristics are often used when the brain is over-loaded with multiple complex pieces of information, or information that cannot be processed quickly enough. e.g. when assessing if we have enough time to cross a road before the next car comes. Heuristics can be used as a time saving device, allowing complex tasks to be completed efficiently, and can be an effective decision making tool, see Gigerenzer and Gaissmaier (2011) for a review of current research understanding of heuristic use.

As Munier et al. (2003), Bond et al. (2008) and Rowbotham et al. (2010) suggest garnering multiple hypotheses or solutions can help explore the interpretational space for a model supporting the suggestion of Curtis (2012) that this may then lead to new ideas. As Thomas Khun describes in *'The structure of scientific revolutions'* (Khun, 1962), science generally progresses in simple small sequential steps that build on existing research. Rarely are new concepts or ideas generated and when they do they are often a mistake (penicillin – discovered in a petri dish) or from the coming together of data or thoughts from other disciplines.

In summary, humans are very good at applying conceptual analogues to data, and if our analogues do not fit the data our brains will try and fit what is there to our concepts (preconceptions and notions). Simply we will try to find the best analogue from our knowledge base. This may sound unscientific but it is the basis for heuristics and the building of concepts, scientific knowledge and understanding. In geology, as in other areas, our analogue database works a lot of the time, but given the large uncertainty space in which geologists work there is scope to look beyond and make better predictions that span a broader range of possibilities. Both Rowbotham et al. (2010) and Curtis (2012) discuss the implications of uncertainty and subjectivity in interpretation highlighting the need to embrace this subjectivity. Curtis (2012) advocates that by striving to recognise and quantify uncertainties potential outcomes are maximised. Indeed Curtis (2012) suggests that recognizing subjectivity explicitly may lead to novel hypotheses. In recognizing subjective uncertainty, as long as we conform to the disciplines rule's, we have the potential to better recognise uncertainties and decrease risk in geological models.

2.4 Geological Reasoning and Rules

Frodeman's (1995) paper entitled *Geological reasoning: geology as an interpretative and historical science* focused on the employment of reasoning and rules. This is not a process that is entirely unique to geology, but geological interpretation is heavily reliant on it. Some of the rules employed by geologists are based on mathematical or topological/geometric rules e.g. how surfaces intersect, and the lines and patterns geological boundaries make at their intersection with topography, such as V's in valleys. Other physical rules include time, such as superposition and cross-cutting relationships (e.g. Hutton, 1788; Chiaruttini et al., 1998); conservation of volume, area and line length when thinking about balancing and restoring sections (Chamberlin, 1910; Dhalstrom, 1969). These rules, or reasonings, are fundamental to a geologist's skill set, allowing creation of models that both honour data points, but that are also 'valid' geometrically and philosophically, conforming to the 'rules' of nature.

Working models and geological reasoning go hand-in-hand. The two examples in figure 4, both rely on geological knowledge and reasoning for model construction. Figure 4a, requires knowledge of cleavage-bedding relationships in folded strata to predict the presence of folds, and facing relationships to predict antiform or synform fold closure. The multiple hypothesis example in Figure 4b, requires knowledge of possible geological concepts (e.g. faulting and folding) that would allow the same strata to be seen at a lower level on one side of an escarpment than the other. Both the single 'working model' solution (figure 4a) and the multiple hypotheses (figure 4b), provide a basis for further exploration and testing of the model, to recognise the uncertainties in the solution (or solutions) that will be presented as the final model. Specific discussion on rules and reasoning to test models with reference to structural geology are covered in section 4.

3. Structural Uncertainty

A geological framework model represents the large-scale architecture of the sub-surface, and as such combines structural and stratigraphic information into an overall framework. It is essentially a 3D representation of the key geological geometries in a given rock volume. Here I consider structural uncertainty in the context of the creation of a geological framework model. There are of course other structural uncertainties, many at a finer scale, but focusing on the uncertainties in structural model creation also highlights the extent to which populating the large scale framework with other structural features (e.g. fractures) is confounded by uncertainties in the framework model. In the discussion of structural uncertainty that follows I focus on geological framework models created from sub-surface data mainly from a petroleum context, but the points made and associated discussion are equally applicable to other geological sectors e.g. mining.

3.1 Data

To create most 3D models of the geology of the subsurface, multiple datasets are used as a basis for the interpretation. These consist of reasonably constrained elements such as borehole data, and less constrained data such as seismic images. Data can also be collected in different geographical coordinate systems and some remotely sensed geophysical data (such as seismic imagery) has a time-based vertical scale, as compared to depth-based borehole data. Conversion of co-ordinate systems and time-depth relationships add, generally uncommunicated, uncertainties to stratigraphic horizon correlations between datasets.

There are inherent uncertainties in each data type, from the original data collection strategies, to the processing of the data collected. At each stage assumptions and simplifications are made, documentation of these assumptions are generally not passed along the data collection-processing workflow to the interpreter who creates the geological framework model. For example, the processing of seismic data to create seismic images requires the geophysicist to stack the seismic data, and in doing so makes assumptions. For geological framework models created using seismic imagery, understanding the geophysical processing of seismic data can be critical to the seismic interpretation strategy. This is particularly the case for areas in which the dips of beds are steep, because reflection seismic imaging best images horizontal beds and is often processed on the basis that most beds will be horizontal to sub-horizontal and continuous. Zones of steeply-dipping beds tend to be in areas of structural complexity, therefore understanding the processing assumptions of the geophysicist when interpreting structures is critical. The example presented by Kostenko et al. (2008) of a single fold-thrust structure in the Niger Delta highlights the issue of interpreting seismic data in areas of steeply dipping beds. Kostenko et al. (2008) document the changes in conceptual model for the fold-thrust, the original model was based on data from a single well and seismic imagery. Data from an off-shoot drilled from the well changed the model and the predicted hydrocarbon reserves.

Each dataset used will have uncertainty, as will the methods by which they are integrated, so even with 'hard' data uncertainties exist before a model is constructed.

3.2 Fault and horizon interpretation

In creating a geological framework model often very little interpretation is actually completed in 3D. The volume representation is created from 2D geological map and cross-section interpretations, based on surface mapping, correlation between boreholes, and seismic surveys.

This information is then used to create surfaces. e.g. top surfaces of formations and faults, which together form the 3D model. For structural geology the uncertainties in field data collection, seismic data, or borehole logs, are generally small compared with the interpretational space across which this 'hard' data is then extrapolated to create a 3D model. Various software programmes are available to fill the space between cross-sections to create surfaces within a volume, and a 3D model. The model is hence created from a mixture of subjective interpretation and mathematical interpolation (Tacher et al. 2006). 3D modelling software packages span a range from interpretation driven through to fully automated model construction techniques, see Jessell et al., (2014). Increasingly the availability of 3D seismic surveys; allows for pseudo-3D interpretation. Interpreters working with 3D seismic data often utilise a gridding system effectively allowing interpretation of a closely spaced 2D mesh, working between 2D and 3D visualisations.

Seismic reflections around faults are perturbed by distributed damage associated with faulting (Sibson, 1977), making seismic imaging difficult (Iacopini and Butler, 2011). For all types of seismically imaged faults, tying the interpreted adjacent horizons to the fault, requires assumptions to be made by the interpreter. These assumptions may include: fault drag and/or rollover, multiple fault strands, over-turned beds etc. Each assumption will have implications for the final model, as the fault off-set will vary with each assumption. It is easiest to think about the implications in terms of an Allan, or fault cut-off, diagram (Allan, 1989) that depicts, horizon offsets across a fault. Figure 7 shows two alternative interpretation scenarios for a normal fault, and the associated Allan diagrams. If it is assumed that sand-sand juxtaposition across a fault could provide a fluid-flow pathway, the uncertainty in the interpretation results in very different risks for across fault flow. Different modelling software packages, permit different methods for tying horizons to faults, many will simply project the line or horizon at the same dip angle onto the fault unless the interpreter manually defines the tie.

The use of software for seismic interpretation restricts the interpreter's view and workflow. The workflows inherent in the software do not allow for example easy transition between horizon and fault picking, which if interpreting on paper would perhaps be normal. In seismic interpretation software most interpreters will work with vertically exaggerated data. Understanding the true dip and geometry of faults in a vertically exaggerated workspace is not simple. Stewart (2011) provides evidence of the extent of vertically exaggerated seismic imagery in publications between 2006 and 2010, and plots the true dip of interpreted faults to illustrate the potential interpretation issues of working in a vertically exaggerated framework including mis-interpreting fault dip and geometry. In a further paper Stewart (2012) considers the implications of validating vertically exaggerated sections concluding that the aspect ratios of 1:1 are required for section validation by restoration.

Interpretation of fault geometries and linkages in 3D space add a further dimension of uncertainty to fault interpretation. Figure 8 shows two hypothetical sub-surface top horizon maps in which the interpretations of fault linkage provide very different pictures of the connectivity of the fault system, with impacts for reservoir connectivity, potential sediment distribution etc. Because the horizon offsets at the linkage points may be below seismic resolution, it may not be possible to distinguish between linked and non-linked faults in a seismic image. These examples of interpretational uncertainty in fault linkage allows for multiple concepts as well as positions for horizons or faults to be chosen. i.e. there is interpretational uncertainty.

3.3 Uncertainties and Risks

The terms uncertainty and risk are often expressed together, with uncertainty in a geological model creating a source of potential risk to the final user of that model. Determining risk requires an understanding of how a model will be used and how the uncertainties in that model will impact on the answers to questions asked of the model (e.g. will a fault seal?). Figure 9 summarises some elements of structural uncertainty and their potential impact when 'risking' a structural interpretation and model. Note that some uncertainties do not matter if they do not impact on the question asked of the model.

Geological framework models are based on cumulative uncertainties, from the original data collection and processing through to final interpretation. Static geological framework models are often used to predict other properties, for example fracture attributes, from forward modelling strain, or mapping curvature (e.g. Fischer and Wilkerson, 2000; Hennings et al., 2000), or monte carlo simulations of fluid flow. This is often done without considering the uncertainties in the original model. Although, it is often time consuming to consider multiple models they can be used to help define the uncertainty space and allow predictions to be made based on a range of uncertainty. If these uncertainties are then translated into risk it is easier to determine what uncertainties cause the greatest risk for the decision maker, enabling improved decisions for new data acquisition strategies and focused understanding of remaining uncertainties.

4 Rules and Reasoning to test models.

Rules and reasoning may be used to test or risk geological models. Such tests can highlight where interpretational uncertainty has resulted in the creation of a model that does not conform to geological reasoning, and hence is unlikely or high risk. Some key techniques for model testing and their efficacy are discussed for the testing of different structural features.

4.1 Balancing and restoration

For much structural geology it is perhaps fair to say that *"it's all about geometry"*. Indeed in creating a static structural model 'that works' geometry is of utmost importance. Understanding geometrical relationships in 2D and 3D is critical to achieving a valid model. Model validation in structural geology is based on the concepts of restoration and structural balance: see Groshong et al. (2012) for a recent review, and Butler (2013) for examples. These concepts evoke assumptions of preservation of line length and/or area (Bally, 1996). Essentially when a geological framework model or cross section is restored sequentially to show the original stratigraphic relationships there should be no gaps or overlaps of material and the restored section should balance, in terms of line length or area, or in the case of a 3D model volume. Validating a cross-section through restoration or forward modelling is one method to test if a model 'works' geometrically.

The assumption of volume preservation in balancing models is in the broadest sense valid. i.e. it provides a good initial test of model validity. The geomechanical properties of the rocks and their dynamic evolution are generally not considered, although many kinematic back-stripping and restoration software packages use algorithms to account for burial compaction. As geomechanical rock properties are not taken into account the assumptions of line, area or volume balance must be applied with care. In some instances they may not be valid, i.e. Butler and Paton (2010), suggest that lateral compaction accounts for area balance mis-matches in the deep-water fold-thrust belt of the off shore Orange Basin. In this way structural balance can be used to evaluate the extent of other processes (e.g. strain or compaction) highlighting factors that may be of importance. See Woodward (2012) for a discussion on using balanced cross-sections to analyse interpretations. Judge and Allmendinger (2011) have taken the concept further and investigate methods to assess uncertainties in the balancing of cross-sections.

Geomechanical models have the potential to provide constraints on properties and improve understanding of, for example, fracture distributions in rock volumes, but also have their limitations and assumptions. Despite a vision that geomechanical models are on the brink of replacing geometrically-based kinematic models (Fletcher and Pollard, 1999), this has not yet happened. This is mainly because of the difficulties in creating geomechanical models and the high level of computing power required to run such models. Perhaps it is also because geometry is an important element of a framework model and provides a test that is relevant to the scale of the problem and the certainty of the data used to create the model.

4.2 Seismic stratigraphy and the concept of regional

In the experimental work of Bond et al. (2007b) several rules could be applied to the seismic image dataset that would have provided the interpreter with clues of the overall structure. The first would be the use of seismic stratigraphy matching that allows seismically imaged horizons to be correlated across the image. In the paper exercise version of Bond et al. (2007b) this could be easily achieved by bending the paper round on itself (figure 10), in software packages there are tools that allow the interpreter to 'grab' a selection and drag it around the screen for direct comparison of the 'seismic signature' with other parts of the seismic image. By correlating the horizons on either side of the deformed zone this allows the interpreter to define the pre-deformation level of the strata, and the 'regional' (Williams et al, 1989). In the Bond et al. (2007b) seismic image areas where strata is both below (implying extension) and above (implying compression) its corresponding regional can be identified (figure 10, dark green line). Applying the concept of regional allows easy identification of both extension and compression in the deformed region indicating that the structure must have inverted.

4.3 Fault Geometries and Damage

To test normal fault interpretations other rules can be invoked such as displacement distance characteristics (Chapman and Williams, 1983), in which assumptions are made about the mechanics of faulting. These assumptions have been bench marked against outcrop studies (e.g. Peacock and Sanderson, 1991; Peacock, 1991), and in different lithologies (Kim and Sanderson, 2005). A methodology for the use of normal fault displacement patterns to check interpretations of faults in 3D and their linkage has been outlined by Freeman et al. (1990) and employed by Needham et al. (1996) and others. Essentially this is an extension of an Allan diagram technique where fault cut-off patterns can be used to determine throw. For an isolated normal fault maximum displacement is expect in the centre of the fault (figure 11), for more complicated faults, with linked fault systems, displacement patterns will be more complex (figure 11). Further work in this area has evoked the use of empirical rules to determine strain in the wall rocks adjacent to faults from displacement offset patterns (Freeman et al. 2010). The idea being that a combination of displacement patterns and realistic fault rock strains can aid in the interpretation of faults and help determine fault linkages in seismic datasets.

Displacement-distance characterisation of faults has focused almost purely on normal faults, with poorer constraint for strike-slip, and thrust faults (Kim & Sanderson, 2005). The bow and arrow rule of Elliot (1976), in which the strike length of a thrust fault is shown to have an approximately linear relationship with fault displacement is an exception, and provides a good benchmark for understanding thrust displacement length relationships for isolated thrust faults. Wilkerson (1992) suggests that the bow and arrow relationship is limited to individual, non-metamorphic thrust sheets, with a bulk shear angle of 35-40 degrees. Most fold-thrust belts are however more complex. A range of theoretical models: e.g. fault-bend fold (Suppe, 1983) and its variants; trishear (Erslev, 1991) allow fold-thrust belts to be forward modelled creating pseudo-realistic geometries (Jamieson, 1987) and predictions of strain (e.g. Allmendinger, 1998). But the complexities of fold-thrust structures observed in the field (e.g. Teixell and Koyi, 2003) and seismic imagery (Iacopini and Butler, 2011), and the mis-match between the existing conceptual models and actual data (Torvela and Bond, 2011) is great. Recent work by Cardozo and Brandenburg (2014) show how trishear based algorithms can be used to create some of the complex geometries seen in natural examples imaged by seismic data offshore Venezula and in the Niger Delta, but not how to predict these geometries. Further research is needed to determine if displacements can be determined from thrust-fault lengths in fold-thrust belts.

Strike slip fault – geometries, also have complex patterns (Woodcock and Fisher, 1986) and although faults like the San Andreas, are well studied seismically (e.g. Huang and Turcotte, 1990). Predictive models of 3D geometries of strike slip faults based on field analogues are few; see Kim and Sanderson (2005) for a review of fault displacement-distance characteristics for strike-slip faults and Stirling et al. (1996) for a global overview of the characteristics of strike-slip faults.

Various authors have also attempted to correlate the spatial extent of off-fault damage to fault displacement (e.g. Beach et al., 1999; Shipton and Cowie, 2001; Shipton and Cowie, 2003; Childs et al. 2009). In a similar manner to displacement-distance characterisation fault damage studies have focused almost entirely on normal fault systems and have been dominated by a fault core-damage zone model (Caine et al., 1996), for high porosity sandstones; notably based on outcrop descriptions from the Navajo sandstone in Utah, although not exclusively. Well exposed sandstone outcrops provide a good opportunity to characterise field relationships, but these observations also come with a bias warning. Much of the data collected is for a single rock type and the observations made have been undertaken in the best exposed areas. Sampling bias is clearly a potential issue, and understanding of other systems, i.e. faults and damage in carbonates is more limited (Billi et al. 2003). Shipton et al. (2006) do summarise relationships in other rock types, and there are studies in other tectonic regimes, e.g. strike-slip (Kim et al. 2003), but analogue models are dominated by images of normal faults and damage zones in porous sandstones.

In summary, geometrical relationships can be used to test the geometric validity of cross-sections, or 3D models, through restoration and forward modelling. But the risking of 3D geological framework models of faulted and deformed systems through the systematic application of relationships such as fault displacement-distance, or off-fault damage in tectonic settings other than in normal fault settings in porous sandstone are as yet untested.

5 Quantification and Communication Strategies

Methods and techniques for both quantifying and visualising uncertainties in structural models are limited, although a series of recent papers have focused on this topic. In the following sections published techniques for quantifying and visualising uncertainty in 2D and 3D geological interpretations are reviewed.

5.1 Quantification of Uncertainty

Uncertainties in structural models can be represented in 2D on cross-sections and maps, or in the form of probability distribution functions (PDFs). For 3D geological models work has focused on *probabilistic* methods (e.g. Tacher et al. 2006), *geological inversion* (Wellmann et al., 2010), and *geological ranges* based on likely values (e.g. Lindsay et al., 2012).

The *probabilistic* method of Tacher et al. (2006) is based on an initial best guess model and a variability model that is defined using observations and geological constraints. The variability of each surface in the model is then expressed as a probability, the result being a set of 3D probability fields for each rock type. The work of Wellmann et al. (2010) takes a different approach by utilising *geological inversion* in which probability distributions of data position and orientation, for simulated datasets are used to construct multiple model realisations. Their examples show that interaction of uncertainties is important, indicating that the uncertainty is not simply an aggregate of individual elements within the 3D model.

Lindsay et al. (2012) investigate uncertainties in 3D geological models through application of *geological ranges*. Here, the focus is on orientation data (strike and dip), which is varied within a 10 degree range to create multiple final models. The uncertainty is quantified as two values: L the number of possible stratigraphic units at a given point, and a P value that represents the percentage of models in the suite that have the same stratigraphic unit at a given point. The values can be used in combination or alone to assess model uncertainty. In a more poorly constrained and complex example Bistachi et al. (2006) use geological rules to extend surface dip data to depth in a folded and faulted area of the Alps in combination with a predictor of certainty with depth. Bistachi et al. (2006) highlight the difference in predicting geological structure at depth from surface data, as compared to interpolating between data points within a domain; acknowledging that a deterministic or conceptual model must be made to extrapolate away from data points, and arguing that statistical based analysis of uncertainties for extrapolated surfaces (e.g. Tacher et al. 2006) do not make sense. Instead Bistachi et al. (2006) predict angular uncertainties for features with associated predicted uncertainties at depth. The authors acknowledge that for some geological bodies (e.g. pluton topology) systematic predictions are not possible and resort to creating a buffer zone to represent the potential uncertainty space based on knowledge and common-sense.

Expert elicitation has also been used to quantify uncertainty. Polson and Curtis (2010) used expert elicitation to predict the probability of the existence of key elements in a structural model (e.g. a fault). In contrast the approach of Lark et al. (2013), utilising expert elicitation, is based on a statistical assessment of the placement of surfaces in a 3D geological framework model by five geological interpreters, who were each given a geological map, digital elevation model and a unique set of boreholes (the authors withheld some boreholes to use as validation tests). In more recent work (Lark et al., 2014) the confidence of experts in surface positions within a 3D model has also been investigated, combining a statistical analysis of local geological variability around boreholes with structured elicitation of expert opinion on the reliability of the data inputs. This work is similar to that of Lelliott et al. (2009) who used an initial analysis of the uncertainties in input parameters to a model to create a quality index for each borehole. The reliability of borehole elevations, data density and geological complexity were assessed and a single index for the quality of information for the borehole was created. A learning algorithm was then used to predict expert score at validation sites.

Although not widely applied the use of *Bayesian* based methodologies in combination with expert elicitation of opinion (e.g. Polson and Curtis, 2010; Lark et al. 2013) is being used to provide constraints on geological models. A good review of Bayesian methods for geological systems is given by Wood and Curtis (2004). In a further paper Curtis and Wood (2004) demonstrate the use of the theory to utilise expert opinion to create a relative likelihood for 9 possible 3D geological models.

5.2 The Final Model - Communication and Visualisation of Uncertainty

In areas of scientific uncertainty or complexity scientists evoke models to predict and to simplify the scenario of interest. A sub-surface geological model is a geologist’s summary of the data and their interpretation of it, a hypothesis of the sub-surface reality. Models are fundamental to geological sciences, whether they are the creation of a geological map or cross section, or a model for thermal re-equilibration; they form a central facet of all geological disciplines. Some models (e.g. those based on experimental data) are easier to determine errors for, whilst others e.g. the location, or even existence, of a fault in an un-sampled sub-surface, are often essentially unconstrained. A model defines the extent of our interpretation and provides a method for both data collection and hypothesis testing (section 2.1) and a communication tool for hypotheses. But models often hide the extent and nature of uncertainties in the data, the interpretation process and the final model itself.

The methods by which geologists' present and communicate models, or geological interpretations, are influenced by scientific culture (see section 2.2), but also by the methods with which scientists communicate more broadly. These are controlled by the medium used for communication: paper maps and sections, power point presentations, and software: including full 3D visualisations of geological models. In all these examples the communication is of the final model – a 'best' interpretation based on the data available. Few of these methods labour on, or often show, the data on which a models is built. Traditional working practices, making fair copy maps from field slips which show only the final interpretation and not the data on which it is based (figure 6), have set a precedent for how ideas and models are communicated. Does the end-user of geological maps fully appreciate that a geological map is a model based on data? Not data itself. Perhaps now as much as anytime, the use of computer realisations of 3D models project a sense of reality to the virtual reality of the model and hence a perception of certainty.

Various methods have been trialled to represent and communicate uncertainty, creating visualisations from 1D-4D. Uncertainties in 2D cross-sections have been visualised using overlaid interpretations with the frequency of overlap highlighted by a colour-scale (Bond et al. 2015). Lark et al. (2013) represent uncertainty in cross-sections created from borehole data, as a series of statistical plots. On geological field maps the certainty of geological boundary placement is represented by different line strokes, and data (outcrop) is often marked by a green outline and/or heavier shading, however these annotations are generally lost in fair copy maps in which the final model is simply represented (see figure 6).

In the 3D work of Wellmann et al. (2010), uncertainties can be visualised in different dimensions – 1D borehole histograms, and 2D and 3D colour maps of surfaces. For 3D models Wellmann and Regenauer-Lieb (2012) develop uncertainty colour mapping of 3D models using *entropy* to define the uncertainty at points on the model. The entropy is defined for each point across the model as a value that represents the predictability of the location of the surface at that point. This workflow allows new data to be added to the model and for entropy to be recalculated allowing direct comparison of individual points from models created from different datasets, and for overall model certainty to be quantified, as well as visualised. In comparison to creating a colour map based on probabilistic determinations the use of entropy allows multiple elements of the model to be integrated into a single entropy value. Utilising similar methods the work of Lark et al. (2014) combines expert confidence in data with predictions of local variability to create colour maps. The work of Lindsay et al. (2012) also allows for coloured voxels and maps to be generated using single attributes, or a combination.

Other suggestions to represent uncertainty include: fuzziness (Bond et al. 2007a), focus and texture change (MacEachren, 1992, 1994) and pseudo-colouring (Hagen et al. 1992). Pang et al.

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(1997) provide a detailed overview of uncertainty representation in images including the use of sound and animation, and MacEachren et al. (2005) and Bond et al. (2007a) give overviews of uncertainty visualisation strategies for geological data. However, in almost all 2D and 3D cases uncertainty in geological models is represented by colour mapping (or grey scales) (figure 12), and in 1D graphically by plots and histograms.

Colour maps work well for quantitative uncertainties e.g. statistically generated, but the use of colour maps needs to be carefully considered when used to represent combined statistical and value-based judgements, or in representing a situation where a surface in a model may be thought to be in one of two positions, but not in the middle. i.e. consideration needs to be given for how non-linear uncertainties are aggregated, to create a single representative value, or how expert judgement is combined with probabilistic determinations.

Visualisation is one method by which uncertainties may be communicated, and standard 3D geological modelling software packages now allow the user to assign certainty parameters to their interpretations, that can be visualised on screen. Cognitive and Earth scientists are also beginning to consider how Earth science visualisation is best made (Rapp and Uttal, 2006). Other software packages have initiated the use of text notes that allow the interpreter to provide some reasoning for their choice of interpretation. In an interpretation context the reasoning behind interpretation choice generally remains in the interpreters head and methods to elicit this information so it can be utilised for uncertainty analysis and quantification is important. Future strategies may include pod-cast or video diary style animated context that highlight the uncertainties and choice points associated with interpretations. Rather, than the current strategies of flying-through perfectly rendered models that give no impression of uncertainty in the model.

6. Improving Interpretations

6.1 Interpretation and Model Building Workflows

Few studies examine interpretation and model building workflows. This may in part be because in industrial geology the constraints are not purely about science, but include commercial pressures such as time and economics. There are perhaps even fewer published examples from which we can learn where geological uncertainty and model building workflows have resulted in commercial failure In academia there have been few studies that analyse geological interpretations or interpretational practice with large numbers of participants. There does however seem to be recognition that 1) ideas generation and the creation and use of multiple models early in an interpretation workflow might help mitigate risk and improve interpretations, and 2) that rules and reasoning can be employed to distinguish between valid and invalid models and risk different model concepts.

In industry geological interpretation and model building is undertaken using software packages, the user interface of which constrains the interpreter (e.g. Stewart, 2011 and 2012). The work of Bond et al. (2008) suggests that throwing away the constraints of software when creating and exploring model space can be an important and easy mechanism that facilitates creation of multiple interpretations and ideas for the same dataset. The idea of creative space is further investigated by Bond et al. (2015) who investigate the difference in interpretation of the same synthetic model but with the interpreter either given seismic image data or borehole data; they

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conclude that the white space between boreholes may create a freedom in interpretation space that seismic imagery does not. Staged release of data may therefore allow more conceptual models to be generated initially. Bond et al. (2008) suggest that bringing together geologists with different backgrounds and with recent exposure to different concepts, in combination with the removal of context (e.g. regional and tectonic) will also result in greater number of ideas generated. In industry both software and workflows (e.g. Leahy and Skorstad, 2013) are now being generated to include multiple deterministic models higher into workflow practices, to better capture the uncertainty space and risks associated with using single deterministic models

Rowbotham et al. (2010) support the use of multiple conceptual models that may then be put into geostatistical simulations for stochastic modelling to risk outcomes. The models are generated based on an understanding of which factors will influence the final outcome when the model is queried (e.g. sand connectivity). With this approach knowledge of both the final use of the model and what factors will influence the decision making (the outcome) need to be known. Identifying the main areas of risk will require some initial interpretation to take place and the issues of interpreter bias (e.g. anchoring to an initial model) may affect the alternative models generated. In reality geological models are often created for more than one purpose and are used to satisfy a range of queries, for example as the exploration or development of a hydrocarbon field progresses a model will be used to address different questions.

The use of geological reasoning through validation techniques is highlighted by (Bond et al. 2007b, 2012, and Macrae, 2013) as an important tool to distinguish interpretations that work geometrically and through time. In the work by Macrae (2013) a causal link was established between thoughts about the geological evolution of an interpretation and better interpretation. Geometric and kinematic validity is an important consideration for any structural model and can be used to test models. Further, rules such as displacement-distance relationships for faults maybe used in some settings to risk valid models prior to stochastic modelling.

6.2 Educating Improvement

The first geological models created by geology students are normally in the form of cross-sections based on data from a geological map. As a student's university career progresses they will be exposed to different data types: field data, borehole data and seismic imagery from which they will construct geological models. Initially most of this work will be completed on paper without the constraints, or imposed workflows of software. But what makes an individual good at interpretation and geological model building? And perhaps more critically can we teach better interpretation?

Interdisciplinary work crossing the fields of psychology, cognition and education is robust in its findings that those with better visuospatial reasoning skills make better geological maps, and 3D interpretations (e.g. Humphreys et al., 1993; Wai et al., 2009, Lubinski, 2010; Hambrick et al., 2012; Liben, 2014), see also Manduca and Mogk (2006) and Kastens and Manduca (2012) and references therein for papers summarising current understanding in this field. There is still debate however, as to the extent that 3D thinking skills can be taught and nurtured (Libarkin and Brick, 2002; Black, 2005; Titus and Horseman, 2009; Uttal et al., 2013). Although (Liben and Titus,

2012) argue that teaching spatial reasoning skills and practical use of these skills should improve geological interpretation performance.

A question-posed by Bond et al. (2011) asked how differently experienced cohorts, coped with there not being a right answer. In a seismic interpretation exercise the student cohorts with least experience appeared less confident and able to deal with the uncertainty than professionals. Bond et al. (2011) suggested that this maybe the result of current teaching and learning practices in which students are taught and examined in the context of 'correct' answers. Teaching methods that challenge the idea of a "correct answer" may therefore be important to develop confidence and skills to deal with geological uncertainty.

Finally, the work of Bond et al. (2012) and Macrae (2013) suggests that teaching specific skills and reasoning techniques can improve interpretation outcome significantly, more so than education or experience; although there is statistical evidence that those with higher education experience do better than those without. The latter presumably relating to the number of conceptual models and hence knowledge available to an individual to apply to an interpretation problem. So providing multiple analogues or concepts for students to employ in combination with clear testing and reasoning rules will provide both knowledge and skills to improve interpretation ability.

7 Discussion and Conclusions

In recent years interest in uncertainty in geological models, as well as in science generally has increased. This interest in geological model uncertainty is in-part driven by economics, as Earth

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resources are exploited from increasingly challenging environments. But public awareness of global environmental issues particularly those linking energy demand with environmental system impacts is also a key driver, particularly for waste storage, e.g. CO_2 and radioactive waste, geothermal energy projects; and currently unconventional resource extraction. On the back of this efforts have been made to determine the range of uncertainty in geological interpretation (Bond et al. 2007b) and to investigate the role of bias (Rankey and Mitchell, 2003, Polson and Curtis (2010). These examples have mainly focused on the interpretation of seismic imagery and associated data, with a focus on petroleum industry problems. The petroleum industry, and petroleum focused academic endeavours, maybe leading the way in geological uncertainty analysis but there are mining focused examples (e.g. Lindsay et al., 2012), and many of the petroleum focused examples given here are equally applicable to gravity or magnetic data which is used more commonly in the minerals sector.

How uncertainties are communicated in geological models is important from a social and economic perspective, as the public are increasingly empowered to take part in decision-making processes involving scientific understanding. Engaging the public and communicating Earth Science, so that the risks and geological uncertainties are clearly presented, is crucial for effective policies, regulation and public acceptance (if appropriate) to be achieved. In an industrial setting the same is true for communicating uncertainties transparently in geological models with an economic or social impact, so that sites may be compared and effective decisions made.

Companies that design software for interpretation and geological model construction have taken on the uncertainty challenge, designing workflows that allow uncertainty judgements to be included during interpretation (e.g. Leahy and Skorstad, 2013), and in model creation (e.g. Wellman et al., 2010). These workflows are constrained by the computing environment. At the interpretation stage this generally 'forces' workers to interpret in a vertically exaggerated (e.g. Stewart, 2011 and 2012) and limited spatial view. Interpretations are constrained by mouse precision and the interpretation process by the user interface (i.e. difficulties in swapping between fault and horizon interpretation). Interpretation on paper is a much freer process and has been advocated as a method to generate multiple initial interpretations to a dataset (Bond et al. 2008). Technological advances (i.e. the increased power of touch screens) may allow a digital interpretation process to be similar to a paper based exercise, providing the interpreter with much greater freedom and fewer visual constraints.

Statistically significant analysis of seismic interpretation experiments on paper (Bond et al. 2012 and Macrae, 2013) suggest that interpretation ability, and hence by inference geological model creation, can be improved by training and the use of prompts to ensure the interpreter uses specific validation techniques, such as considering geological evolution. The classic structural geology techniques of section balancing and forward modelling, which formally consider geological evolution, and other reasoning techniques (e.g. displacement-distance characteristics) are key to check interpretational validity, and hence inform understanding of structural uncertainties.

Efforts have been made by several authors to use stochastic methods to create multiple 3D geological models to better represent the structural uncertainties in model creation. In some case these have been combined with subjective or conceptual models created by experts. The contrast between the two approaches is significant and the two are not easily married, but efforts to combine subjectivity into more quantitative approaches may provide fruitful, especially in combining expert elicitation with Bayesian theory (e.g. Curtis and Wood, 2004). These techniques may also be employed to consider specific risks associated with uncertainties in structural models. Methods to visualise these quantitative and subjective approaches have generally focused on colour mapping, with more novel ideas suggested, but not adopted.

The barriers to improve interpretation and model creation include the constraints of time and computing systems, but also in the way in which science is conducted, through the generation and advocacy of a single model, and in the way education focuses on ‘correct’ answers rather than solutions to problems. Educational studies suggest that 3D visualisation and thinking can be improved through education and exposure to 3D problems. Understanding how experts tackle problems with uncertainty at an early stage in geoscientists’ career may help the development of practices and ideas. As Curtis (2012) suggests embracing subjectivity in interpretation and the uncertainties structural models that this subjectivity creates, provides an opportunity to improve our understanding of the sub-surface.

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Figure Captions

Figure 1.

Paper publications track the change in usage of the words uncertainty and climate change in academic literature. The graph shows the number of articles published per year (left-hand vertical axis) between 1995-2013 (horizontal axis) that contain the word ‘Climate Change’ (purple line) and ‘Uncertainty’ (blue line) in the article title, abstract or key words, using a Scopus Search (www.scopus.com August 2014). The green line tracks the increase in use of the word ‘Uncertainty’ in the article title, abstract or key words in the Journal Earth and Planetary Science, as the number of articles published per year (left-hand vertical axis). The orange line represents the use of the word ‘Uncertainty’ in the article title, abstract or key words in the Journal of Structural Geology as a percentage of the papers published each year (right-hand vertical axis), although relatively few articles are published and the line shows significant fluctuations the overall trend is of an increase in usage.

Figure 2.

A tree diagram used to define different classifications of uncertainty, after Tannert et al. (2007). Uncertainty is divided into objective and subjective components. Objective uncertainties may be dealt with through the use of error bounds. For example in the seismic image a chosen velocity model could be used for depth conversion, an assessment of the possible range of velocity models could be employed to assigned errors or uncertainties to the depth of different horizons. Decisions can be made in a quasi-rational knowledge guided way and the uncertainties assessed. For subjective uncertainty the different interpretations of the seimsic image represent the subjective uncertainty in geological interpretation – creating error bounds is not so easy when different conceptual models are applied in an interpretation e.g. for fault placement and connectivity. Subjective uncertainties may be through of as intution or rule guided. Seimsic imagery from the Virtual Seismic Atlas (www.seismicatlas.org), interpretations by Rob Butler and Clare Bond.

Figure 3.

Graph of fault throw versus distance along a single fault from three studies (from Bond et al., 2007a). Krantz (1988) measured the height of a single bedding plane on either side of a fault scarp using traditional mapping techniques, Cowie and Shipton (1998) measured the heights of three bedding planes using a total station, and Maerten et al. (2001) used a differential GPS. Predicting fault throw with distance along the fault requires projection of the data collected on either side of the fault scarp onto a predicted fault surface – assumptions are made about both the fault plane and how the beds interact with the fault (i.e. straight along dip projection, assumes no bend-in of bedding planes towards the fault). A simple estimate of the errors involved in

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propagating bedding readings along dip, suggests that the errors in assumptions are greater than the improvements in technology.

Figure 4.

Making observations and predictions to construct and test model(s). A) Simple field observations, such as bedding cleavage relationships can be used to make predictions of what you would expect to see walking across strike. The scale and geometry of the folds, and other complications (e.g. faults) can be determined by further observation, but a reasonable prediction of the overall structural model can be made from the initial observation. B) A set of initial data or observations allows multiple models to be created that fit the data, there is not a unique solution.

Figure 5.

An un-interpreted seismic image and global ‘guesstimates’ of its location. A) World Map with sequentially numbered orange dots representing the global locations where individual geoscientists thought the seismic image (B) had come from.

There is an associated movie *.mov file of Figure 5A.

Figure 6.

Geological maps from the 1880s. A) Field slip of the Inchnadamph area showing the location of outcrop observations in stream sections. B) the final fair copy map which does not distinguish outcrop observations from interpretation. Reproduced with the permission of the British Geological Survey ©NERC. All rights Reserved.

Figure 7.

Hypothetical models for fault off-sets and their associated Allan diagrams, with implications for fluid flow in an off-set sandstone layers. A) Hypothetical model one is a single fault strand (red) that offsets the sandstone layer (orange) such that in the centre of the fault the sandstone layer is not juxtaposed on either side of the fault (as shown in the associated Allan diagram). If the fault forms a seal due to shale smear fluids will not be able to flow in the sandstone across the fault. B) The second model is of distributed faulting, and the sandstone remains juxtaposed across the fault zone despite the cumulative offset across the zone being the same as for the single fault in A). There will therefore be no shale smear and assuming no other fault seal processes fluids will be able to flow in the sandstone layer across the fault.

Figure 8.

Fault maps showing different interpretations of the same dataset. Assuming a limited amount of either field or seismic data faults may be linked differently by different interpreters. A) The fault interpretation map shows a high degree of linkage between fault strands. B) Fault interpretation of the same dataset shows minimal fault linkage. The different implications of the two interpretations A) and B) for sediment distribution, and reservoir connectivity in a hydrocarbon context would be significant.

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Figure 9.

Schematic block diagram of a hypothetical geology. The text in black highlights areas of potential structural uncertainty in the geological model, text in red gives indications of risks that may be associated with these uncertainties. Note that several uncertainties will impact, or contribute to a range of risks.

Figure 10.

Seismic image used for the interpretation exercise in Bond et al. (2007b). The dark green line denotes the 'regional', the top of the pre-deformation strata at the level it was at before deformation. Two seismically imaged horizons, at the top of the pre-deformation statigraphy are outlined in pink and blue at different positions across the image. Note that they can be observed to be both below and above the dark green regional line. This indicates that there has been both extension and compression within the central area of the seismic image. Outline boxes A and B at either end of the seismic image and their expanded interpretations to the right, show how seismic stratigraphy matching outside the deformation zone can be used to interpret a seismic stratigraphy and identify the regional. In the paper version the stratigraphy at either side of the section could be matched by folding the paper round on itself.

Figure 11.

Displacement – distance graph for hypothetical faults. The turquoise line depicts fault

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displacement with distance along a fault for a single isolated normal fault. The orange line depicts a scenario in which two initially isolated normal faults have linked to create a single fault. Fault lengths can be used to predict displacements, but linked faults do not conform to simple central displacement maxima. In-turn fault displacement patterns can be used to make predictions of fault linkage and fault linkage timing.

Figure 12.

Examples of commonly used methods to highlight uncertainty on 3D surfaces. A) colour mapping, B) contouring, C) combined colour map and contour. This is a hypothetical example, but the colours and contours could represent for example: uncertainty in horizon top height or facies type. The scale bar is common to all models. Examples created in Move software.

Tables

Bias	*Description*
Availability bias	The decision, model, or interpretation that is most readily 'available' in the mind or most dominant (e.g. as seen in textbooks).
Confirmation bias	To seek out opinions and facts that support 'confirm' ones own beliefs or hypotheses.
Anchoring bias	Failure to adjust from experts' beliefs, dominant approaches or initial

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	ideas. For example having come up with an idea of the geology to then change this view.
Optimistic bias	It won’t happen to me mentality, or there is definitely oil in this prospect, where the interpretation puts a positive spin on the desired outcome.
Positive outcome bias	Wanting things to turn out for the best, the interpretation maximizes positive outcomes (similar to optimistic bias).
Hypothesis testing bias	Starting with an initial hypothesis and trying to fit the data to it (similar to confirmation bias).

Table 1. A summary of common biases described in cognitive science literature that may affect the interpretation of geological data. The descriptions are based on those given in Krueger and Funder (2004), after Bond et al., (2008)

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Figure 1

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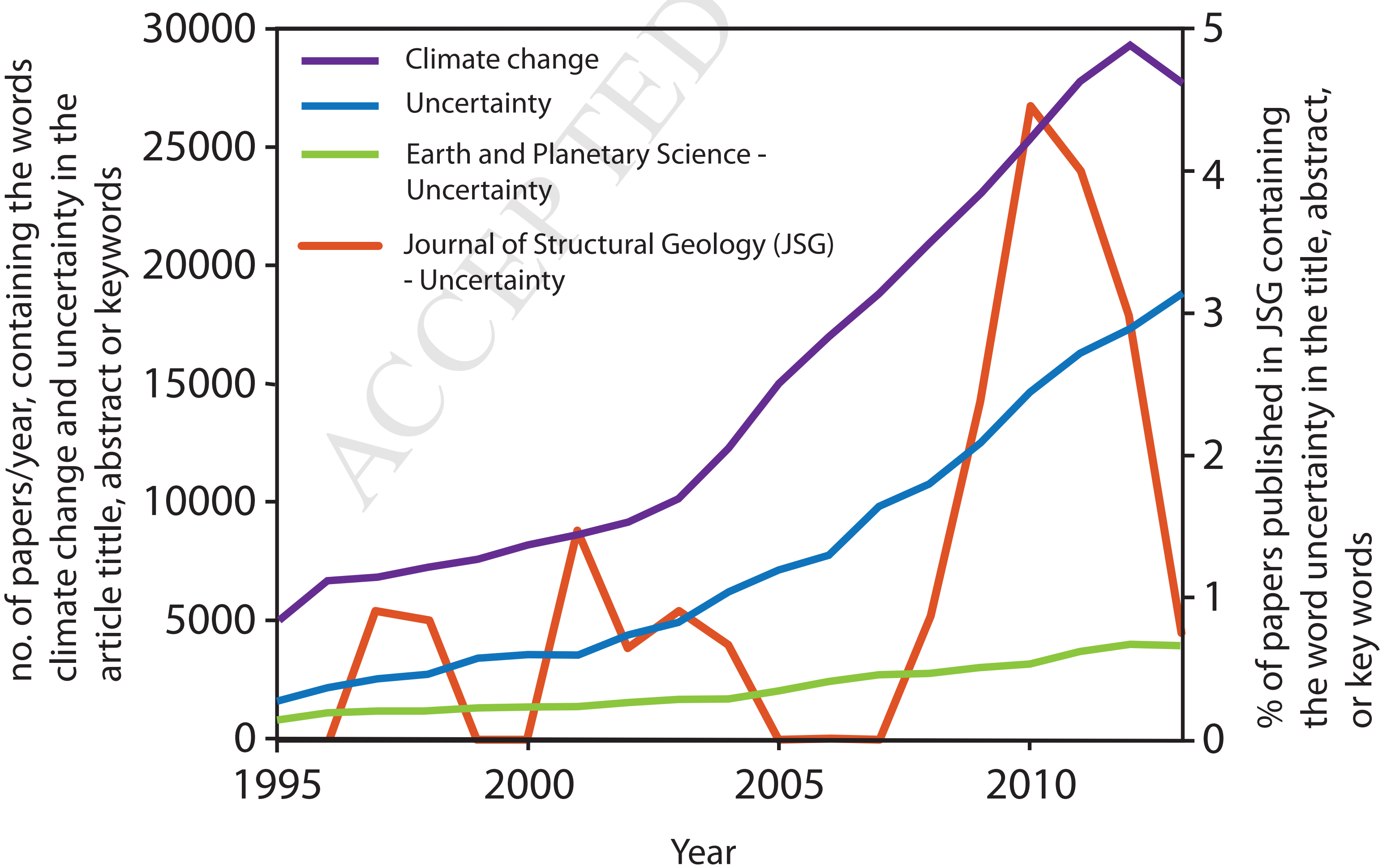

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Figure 2

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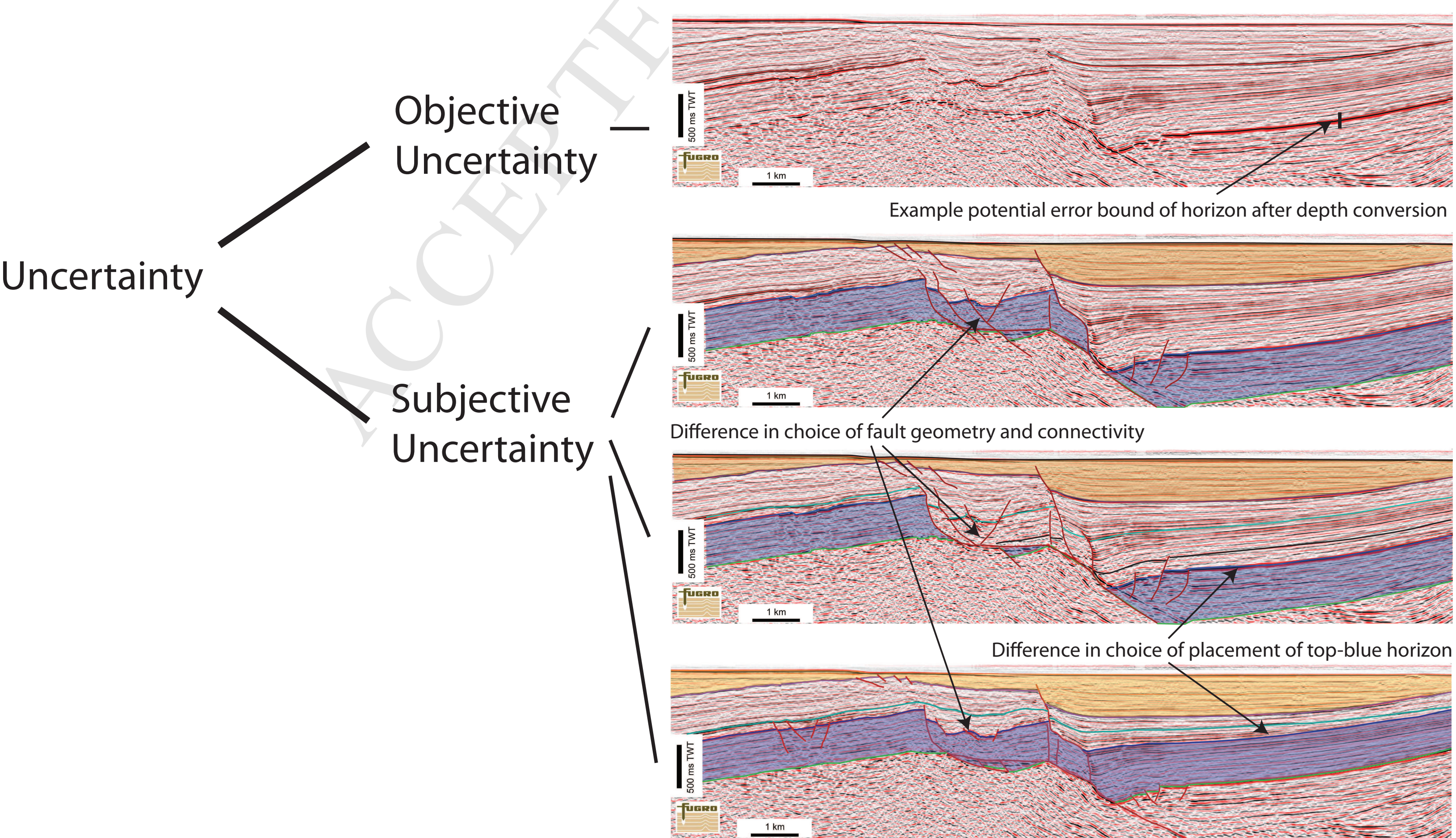

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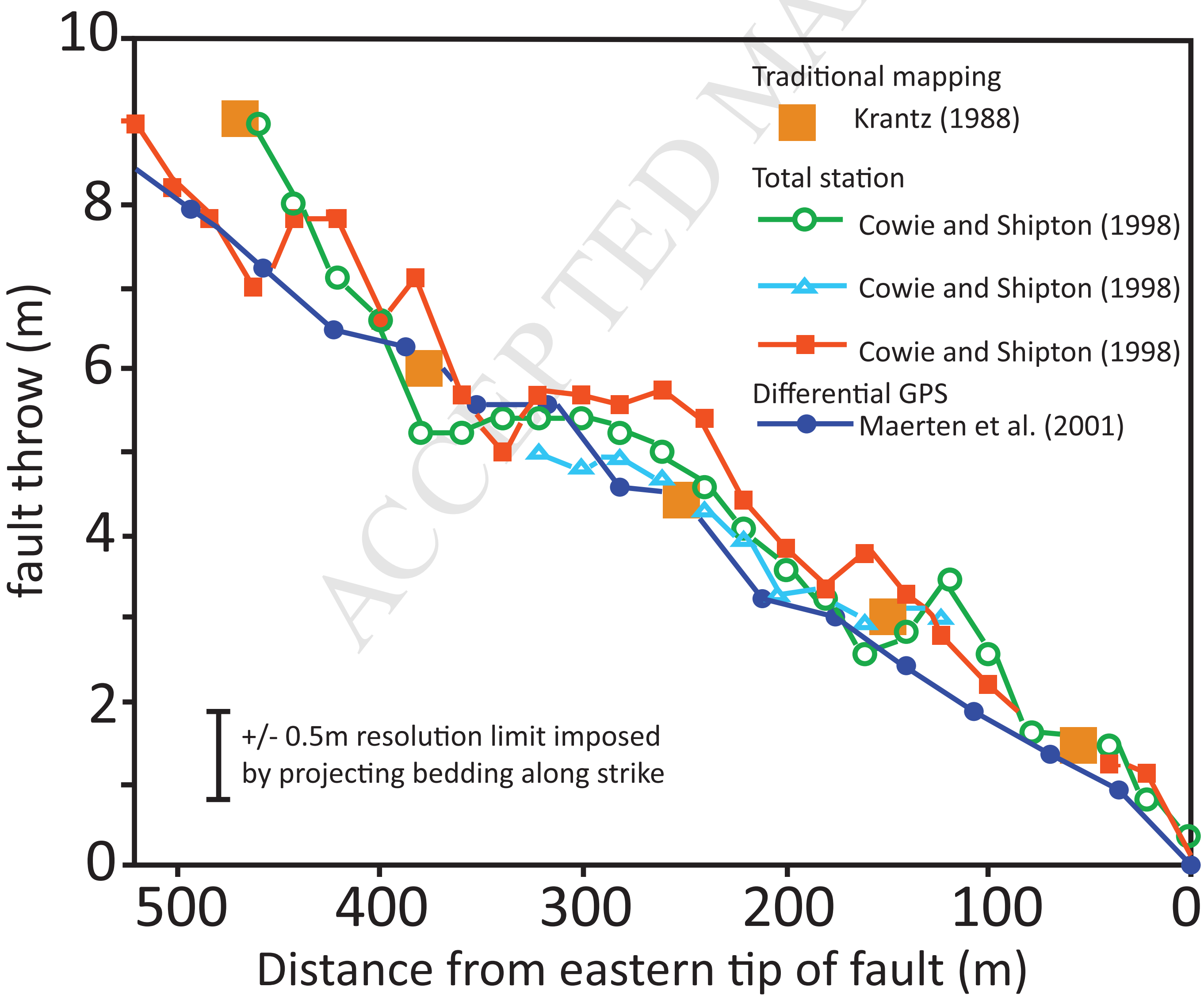

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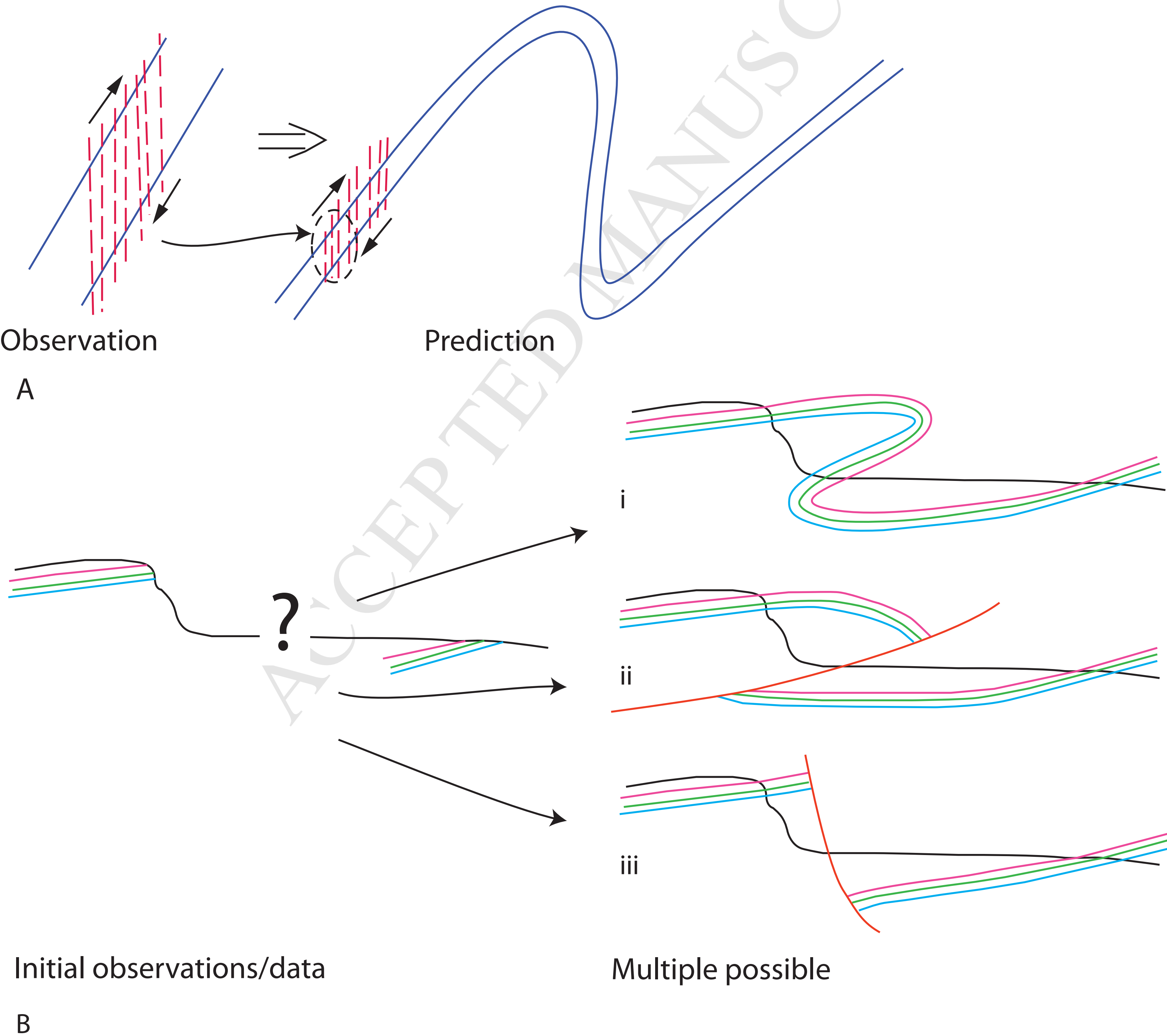

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Figure 5

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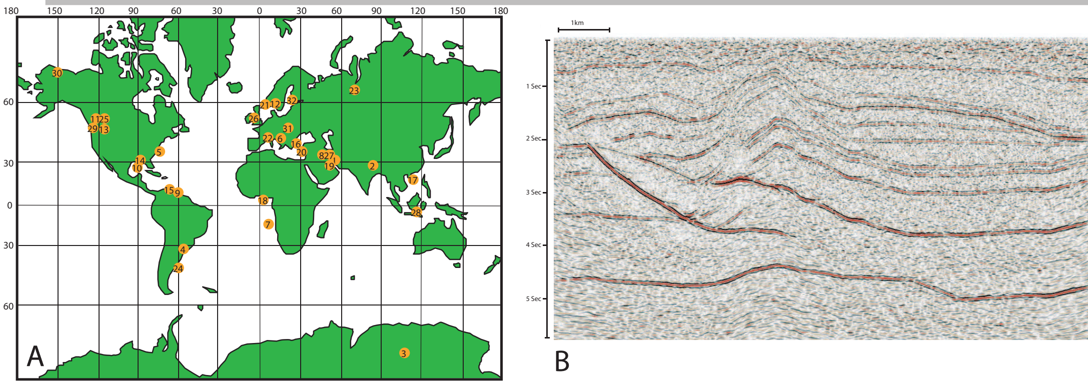

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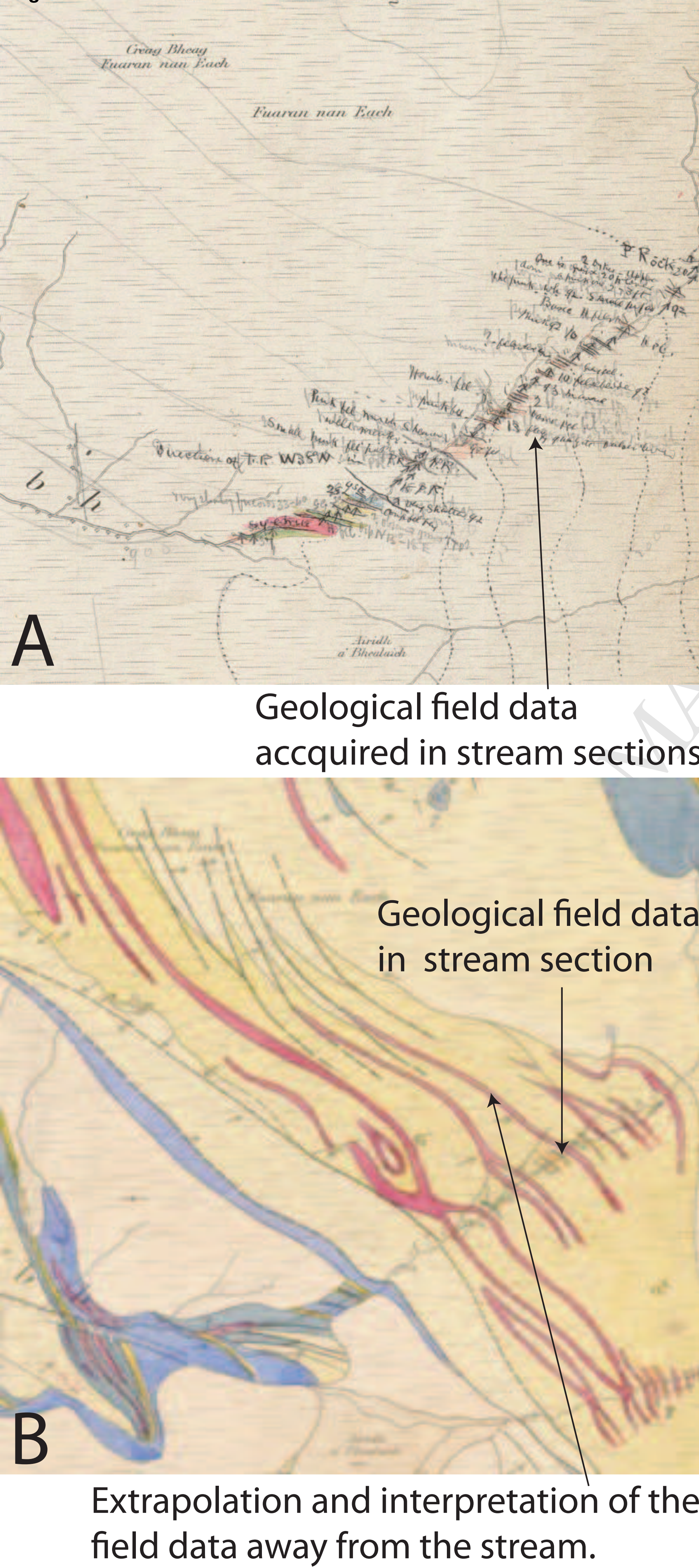

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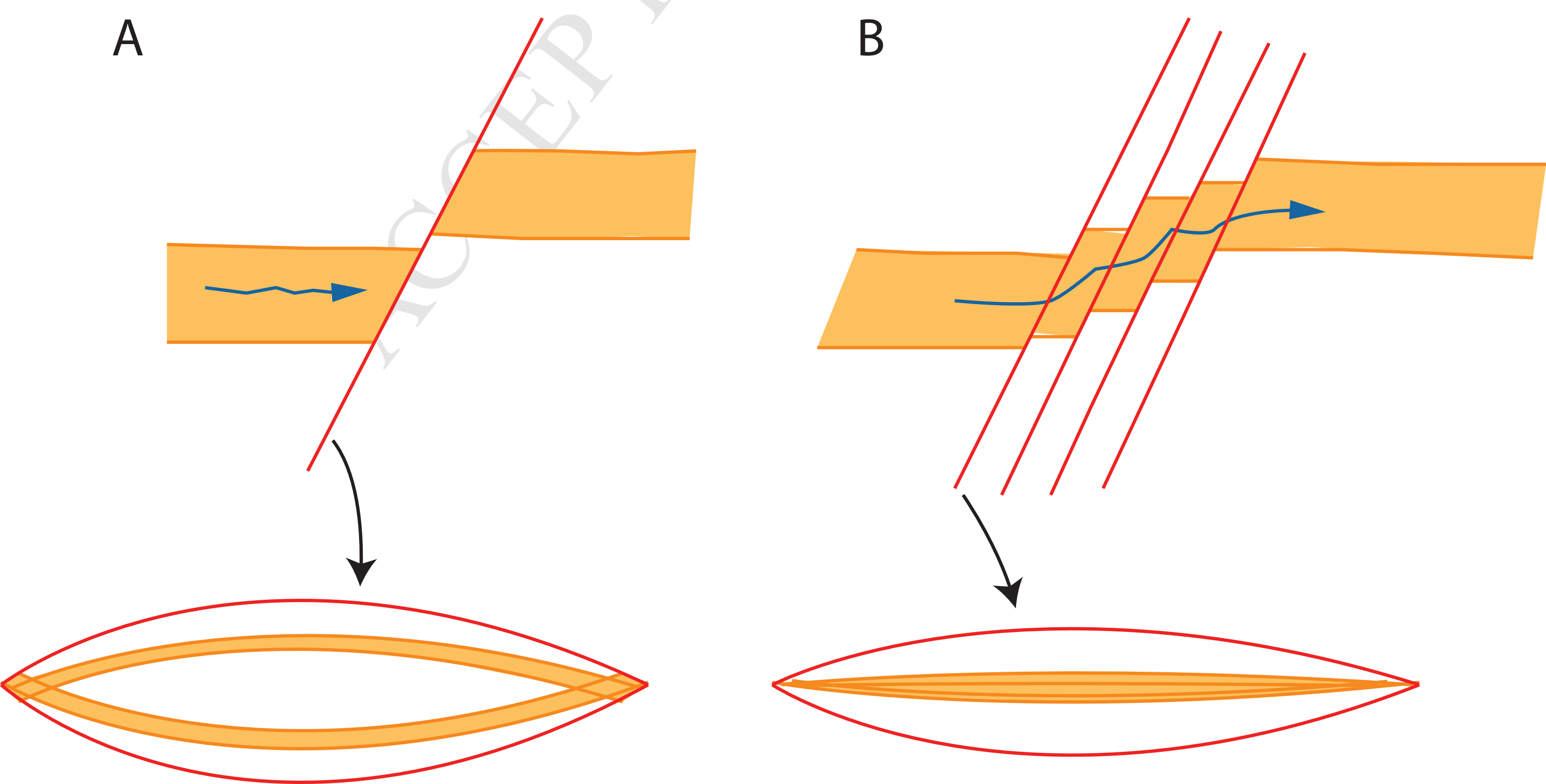

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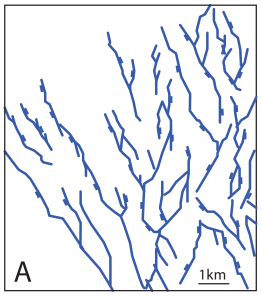

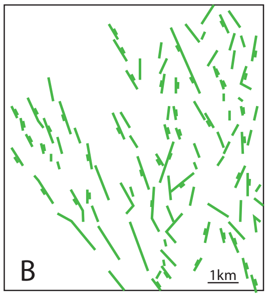

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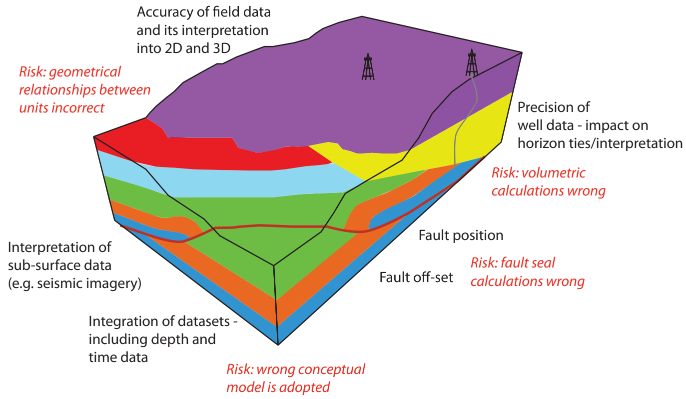

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Figure 10

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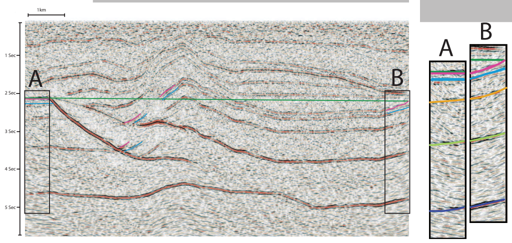

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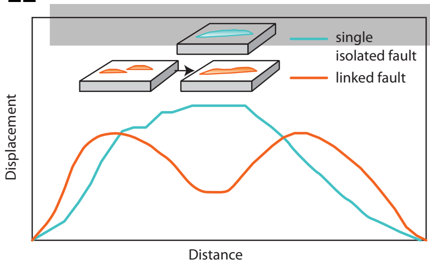

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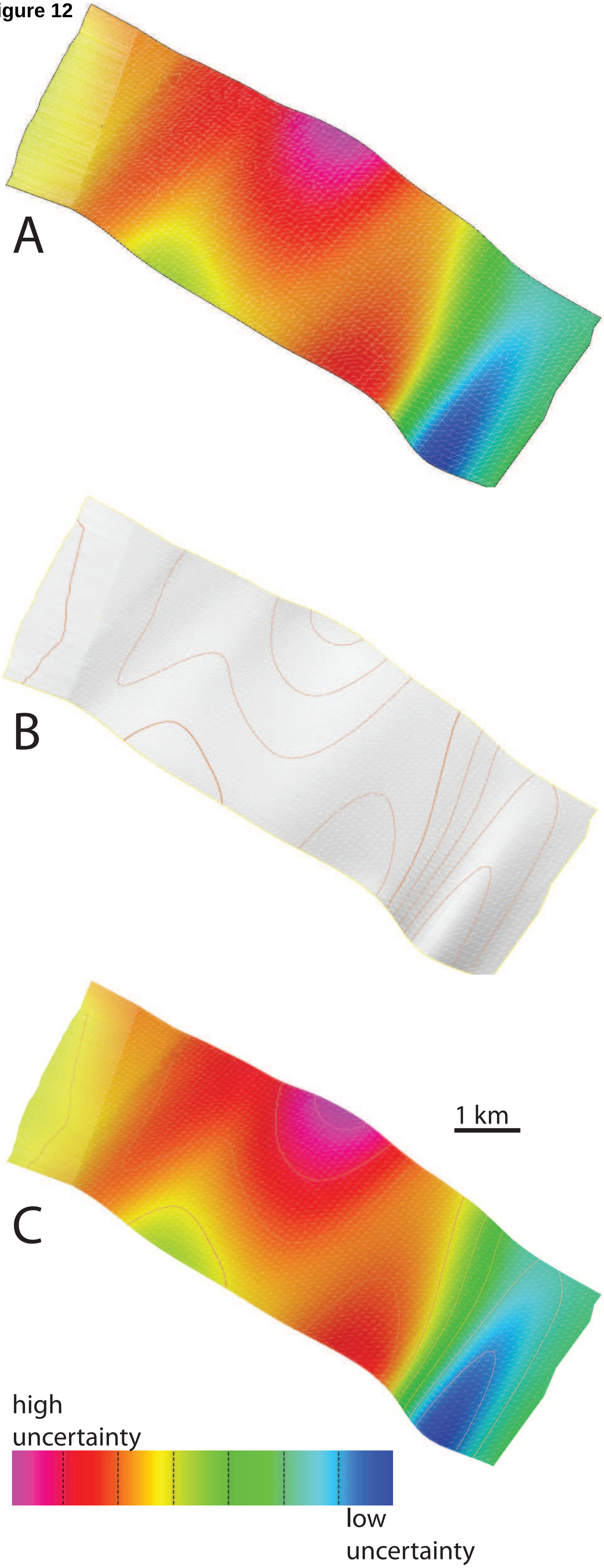
Figure 12



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