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An index to represent lateral variation of the confidence of experts in a 3-D geological model

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ABSTRACT

A Confidence Index is proposed that expresses the confidence of experts in the quality of a 3-D model as a representation of the subsurface at particular locations. The Confidence Index is based on the notion that the variation of the height of a particular geological surface represents *general geological variability* and *local variability*. The general variability comprises simple trends which allow the modeller to project surface structure at locations remote from direct observations. The local variability limits the extent to which borehole observations constrain inferences which the modeller can make concerning local fluctuations around the broad trends. The general and local geological variability of particular contacts are modelled in terms of simple trend surfaces and variogram models. These are then used to extend measures of confidence that reflect expert opinion so as to assign a confidence value to any location where a particular contact is represented in a model. The index is illustrated with an example from the East Midlands region of the United Kingdom.

1. Introduction

Geologists understand the geology of a region in three dimensions, and recent technological developments allow them to represent this understanding in 3-D geological models. Geological information in the form of 3-D models, rather than traditional 2-D maps, is now the state of the art for planning and decision making (Mathers and Kessler, 2010; Royse et al., 2010).

All geological information is subject to uncertainty, since at most sites in a region information is inferred indirectly from observations at other locations, observations which may themselves be subject to error. As a result the final model has an inevitable uncertainty. This is of interest because the model may be interpreted as indicating the subsurface positions of particular features or the volumes of particular units over a specified region. Engineering decisions such as the route of a tunnel or the suitability of the subsurface for particular structures should be robust given the model errors that may be expected. Similarly, if the model is used in resource assessment or in hydrogeological modelling then the user requires some understanding of the model's uncertainty, and how this might vary in space. For this reason the problem of how to measure and represent model uncertainty is the subject of some considerable research interest.

Where 3-D structure is predicted from observations by purely geostatistical methods a measure of uncertainty is computed directly for individual predictions (Lark and Webster, 2006; Blanchin and Chilès, 1993). However, most models are not generated by a statistical algorithm but rather through expert interpretation; either expert 'manual' editing of surfaces produced by mechanical interpolation, or by interpolation from cross sections interpreted by the modeller, subject to constraints (e.g. 2-D coverages for particular units) imposed by the modeller as in the GSI3D software (Kessler et al., 2009; Mathers et al., 2011).

Lark et al. (2013) report a post hoc evaluation of uncertainty in a model produced in GSI3D by a designed experiment in which a team of modellers studied a common region. However, this approach is resource-intensive and not suitable for conditions where borehole data are sparse. It can be used to obtain benchmark statistics on model quality for particular geological terrains and settings, but is not suitable as a routine approach to quantify uncertainty in particular models.

Lelliott et al. (2009) propose a structured approach to represent the uncertainty in 3-D models. This was based on an initial analysis of factors that contribute to the uncertainty of a model in a specific geological setting produced with the GSI3D software. The factors identified include the reliability of the absolute elevations of the boreholes, the quality of the borehole logging, the drilling method,

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the geological complexity and the density of data. Any borehole may be given some index which reflects the quality of information it provides according to the above-listed constraints (e.g. under drilling method the quality of information was deemed best for cores obtained by sonic drilling and poorest for those obtained by cable percussion). The combination of information on the different sources of uncertainty into a single index was done by a machine-learning algorithm; this uses the various sources of information on model uncertainty as predictors of the expert score provided at a few calibration sites.

The present paper describes an index of confidence similar to that proposed by Lelliott et al. (2009). It differs from the previous measure in certain respects. It is designed specifically for models of subsurface structure inferred from subsurface observations (boreholes, seismic lines) rather than by projection from surface structure. We are concerned, therefore, with cases where the expert may make inferences about the height of a contact at some unobserved site by identifying a trend in the height of the same contact shown in boreholes or interpreted seismic data at other locations. We consider two general constraints on the model that the expert will form. The first is the *overall* geological complexity; this source of uncertainty will be small if there is strong evidence for relatively simple trends in surface heights, as may arise from a consistent dip or a dip with flexure. Lelliott et al. (2009) measure geological complexity by multiple fitting of a trend surface model to subsets of available data, which gives a measure of complexity in more general cases than ours but also risks confounding complexity as a source of uncertainty with data density since the multiple refitted surface will be more variable in areas where data are sparse, and less variable where the observations are strongly clustered in space. The second constraint on the model is *local* geological complexity which is, essentially, the variability of surface height about the overall trend. In our index the effect of this source of uncertainty depends on the proximity of local observations, such that the confidence in the model decays with distance from a borehole. By this simple partition of the sources of uncertainty in a model we are able to compute directly a simple Confidence Index which is interpretable in terms of a scale used to elicit information from geological experts and which varies in ways which are directly interpretable in terms of the distribution of borehole and other data and the distribution of faults. In this way the Confidence Index is entirely transparent.

In the remainder of this paper we describe the general form of our proposed Confidence Index, and the methods required to compute it. We then present a case study in which the index is computed for a model of some subsurface contacts in a part of the East Midlands of England.

2. The Confidence Index

2.1. General principles

The key idea implemented in the Confidence Index is that the confidence in the modelled surface is influenced by overall geological variability (the extent to which pronounced simple trends in the elevation of particular surfaces allow the modeller to project with some confidence beyond the range of data) and local geological complexity, which determines over what distance information in a borehole constrains the interpretation of local fluctuations around an overall trend. In order to implement the Confidence Index we use data on the elevation of the modelled surfaces of interest, either from boreholes or geophysical data. These data are then analyzed to partition the observed variation in elevation of each surface into a simple trend (a polynomial of degree 1 or 2 in the 2-D coordinates) and fluctuation about the trend. The latter is treated as a Gaussian random variable which may be spatially correlated, that is to say the observed deviations from the trend model at two locations are more likely to be similar if the locations are close together than if they are far apart. The correlation between the deviations from the trend at any two locations declines with the distance between them to zero, which is either reached or asymptotically approached at a distance called the range of autocorrelation. The autocorrelation is modelled as a function of distance by a suitable mathematical expression. As described in more detail below the proportion of the variation in observed heights which is described by the trend component of the model characterizes the overall complexity of the modelled surface, and the dependence of the autocorrelation function for the deviations from the trend characterizes the local geological variability. The rationale for this is that if the distance to the nearest borehole from some location, $\mathbf{x}$, is longer than the range of autocorrelation of the variations of a surface about the general trend, then that borehole provides no direct information on the local geological variability at $\mathbf{x}$.

Consider four contrasting locations in a modelled area.

A. The first is a location that coincides with a logged borehole used to produce the model. It is assumed that the borehole data are of good quality, and are reliably coded. At this location there is complete confidence in the model, because it is directly supported by an observation and the Confidence Index is allocated a maximum value, a_1. One might, however, identify among all the boreholes in a region subsets which command different degrees of confidence because of factors such as age, logging quality, drilling method, etc. In these circumstances one may elicit from geologists with local knowledge and experience, which includes experience of the borehole sets, values of the Confidence Index at sites that coincide with the different borehole subsets. These values may be denoted $a_2, a_3 \ldots$ all less than a_1.

B. The second location is one that coincides not with a borehole but with a point on a seismic line or some other geophysical measurement which provides information used in the model. Here the confidence in the model is enhanced by the extent to which the observation constrains the modelled surface, but it is likely that the value of the Confidence Index at such a location should be less than at a borehole location. That is because the depth of a contact at a location on a seismic line is inferred mathematically on the basis of assumptions about the seismic velocity of the units in the stack. This is an additional source of uncertainty. Once again it would be necessary to elicit from experts, with experience of geophysical measurement in the particular geological setting, a value for the Confidence Index relative to the maximum value a_1 for the best-quality borehole data. We denote this value by b, but recognize that it might be necessary to elicit more than one value for different subsets of geophysical data.

C. The third situation is a location some distance from any direct observation such that the observations only constrain the model at the location through any general trends in the height of the surfaces of interest that are identified in the data as a whole. The confidence in the model will be at a minimum at such a location, the question is what value should be ascribed to the Confidence Index in such circumstances. There are two general cases here.

   C.i In the first, the depth of the surface of interest shows no large-scale structure (dip or similar trend) across the modelled region, but is influenced by fine-scale fluctuations around a constant mean depth. Such variation is not readily predictable by the modeller.

   C.ii In the second, there is some long-range structure, such as a gentle dip across all or much of the region, which is not markedly affected by faulting. This broad-scale structure is predictable by the modeller, it represents the kinds of