

Beyond classified geological maps: the case for AI-enabled mapping of geological properties

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Traditional geological maps represent our knowledge of Earth's geology and are constructed by classifying the ground into discrete units (polygons in 2D, volumes in 3D) based on changes in properties such as age, composition, and texture. These traditional classified maps offer a summary of regional geology, but – in addition to being unable to represent gradational changes – the classified nature of these maps poses a problem for their verification, because the most appropriate class label for any location cannot be objectively measured, only subjectively asserted.

It is therefore inevitable that different geologists will draw different class boundaries in different locations according to their differing judgement, even if hypothetically they may agree entirely on the physical and chemical properties of the ground itself – which are objectively measurable. This conflation of objectively measurable properties with subjectively interpreted classes makes it impossible to definitively assess whether one classified map is closer to reality than another, and therefore also whether proposed updates genuinely improve accuracy, or just better match the proposer's interpretation. This situation makes progress difficult and continues to cause issues with inconsistency across map-tile and political boundaries where different geologist's interpretations meet.

We propose a simple but fundamental shift in approach to separate the objectively measurable from the subjectively inferred, and therefore avoid their conflation. We propose that geological mapping should be conducted as a two-stage process:

1) Model and map predictively, as continuous spatial fields, the objectively measurable properties on which our traditional classifications are based, as well as any other properties of interest (e.g. mechanical properties, critical metal concentrations, geothermal heat flow, presence of fossils etc). These maps of objectively measurable properties, which AI-techniques can be designed to produce, can be objectively verified by comparing their predictions to real measurements of these properties. Better maps will close the gap between predictions and observations in held-out test data. 2) For any given predictive map of objectively measurable properties, proceed if necessary to segment and classify this map output into different units, e.g. of lithology, lithostratigraphy, biostratigraphy, chronostratigraphy etc. We note that A) this discretisation step will inherently result in loss of information to quantisation error, unless an infinite number of classes are used (so it is important to retain the underlying property maps). B) this loss of information may be beneficial to aid communication – it is easier to talk about maps composed of named units than continuous but anonymous maps of geological properties. C) the class or unit we choose to assign a location to does not change the objectively measurable geological properties at that location.



Figure 1- Left of diagonal: Bayesian deep-learned predictive map of geological properties, in this case chemical composition with a ternary colour scheme (K - red, Fe - green, Ca - blue). Posterior predictive distributions can be obtained for any location. From <https://geoscientist.online/sections/features/geological-mapping-in-the-age-of-artificial-intelligence/>
Right of diagonal: Traditional classified geological map, in this case British Geological Survey Bedrock Geology. From <https://geologyviewer.bgs.ac.uk>