

Spatial prediction of seabed sediment texture classes by cokriging from a legacy database of point observations



R.M. Lark ^{a,*}, D. Dove ^b, S.L. Green ^b, A.E. Richardson ^b, H. Stewart ^b, A. Stevenson ^b

^a British Geological Survey, Keyworth, Nottinghamshire NG12 5GG, UK

^b British Geological Survey, Murchison House, Edinburgh EH9 3LA, UK

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ABSTRACT

This paper illustrates the potential for statistical mapping of seabed sediment texture classes. It reports the analysis of legacy data on the composition of seabed sediment samples from the UK Continental Shelf with respect to three particle size classes (sand, mud, gravel). After appropriate transformation for compositional variables the spatial variation of the sediment particle size classes was modelled geostatistically using robust variogram estimators to produce a validated linear model of coregionalization. This was then used to predict the composition of seabed sediments at the nodes of a fine grid. The predictions were back-transformed to the original scales of measurement by a Monte Carlo integration over the prediction distribution on the transformed scale. This approach allowed the probability to be computed for each class in a classification of seabed sediment texture, at each node on the grid. The probability of each class, and derived information such as the class of maximum probability could therefore be mapped. Predictions were validated at a set of 2000 randomly sampled locations. The class of maximum probability corresponded to the observed class with a frequency of 0.7, and the uncertainty of this prediction was shown to depend on the absolute probability of the class of maximum probability. Other tests showed that this geostatistical approach gives reliable predictions with meaningful uncertainty measures. This provides a basis for rapid mapping of seabed sediment texture to classes with sound quantification of the uncertainty. Remapping to revised class definitions can also be done rapidly, which will be of particular value in habitat mapping where the seabed geology is an important factor in biotope modelling.

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1. Introduction

Seabed and habitat mapping is important for a range of activities in the marine environment, including fisheries, aquaculture, conservation, aggregate extraction, renewable energy, seabed infrastructure and the extraction of oil and gas. Conservation organisations, resource managers, marine spatial planners and policy-makers need to understand seabed habitats. As a result, benthic habitat mapping is a growing focus of activity for scientists, driven by scientific, economic and political factors (Harris and Baker, 2012). The composition of the substrate is recognised as an important property to map, not least because of its importance in determining the distribution of benthic marine organisms, and its value as a proxy variable in habitat mapping and the assessment of biotopes (Connor et al., 2006; Howell, 2010; Cameron and Askew, 2011). Geoscientists are therefore producing substrate maps to assist habitat mapping, and are using a variety of methods to do so. These include classical hand interpretation in which several geophysical and geotechnical data

sets are integrated; and the semi-automated interpretation of geophysical data sets.

The Marine Environmental Mapping Programme (MAREMAP) of the United Kingdom Natural Environment Research Council (NERC) is concerned with combined seabed and habitat mapping at national scale, integrating existing data sets and exploiting new technologies. Among the data sets available is the British Geological Survey's (BGS) database on seabed sediments and their particle size distribution, collected in a series of surveys from 1967 to 2009. Typically these sediment samples have been used in conjunction with geophysical data to produce regional seabed sediment and shallow geological maps and interpretations (Cameron et al., 1992; Gatliff et al., 1994). Such traditional geological mapping is valuable. However, since the legacy data are extensive, there is the potential to use statistical methods for spatial prediction to map seabed texture continuously or according to established classifications. This is potentially useful for three reasons. First, statistical mapping provides a quantitative account of the uncertainty in the predictions, which is inevitable given the spatial variability of the phenomena we are considering. Second, a statistical approach to mapping can be semi-automated, at least with respect to the generation of spatial predictions after the initial statistical modelling. This is useful because it means that maps can

* Corresponding author. Tel.: +44 115 9363026.

E-mail address: mlark@bgs.ac.uk (R.M. Lark).

be revised relatively easily. The classification schemes that best predict benthic habitats are regularly being refined and improved, and statistical mapping, as described in this paper, can be used to generate maps according to modified classifications in a relatively short time frame. Third, statistical mapping from the extensive data available allows us to generate maps rapidly. EU legislation, such as the Marine Strategy Framework Directive and the Habitats and Species Directive increases the requirement for broad-scale mapping, covering the UK Continental Shelf. Recent reviews suggest that just 10% of the UKCS habitat map coverage is derived from survey data (Department for Environment, Food and Rural Affairs, 2010). Because of this, it is extremely valuable to have semi-automated statistical mapping methods to underpin habitat prediction.

This paper is concerned with how a set of point observations can be used to map the spatial variations of seabed texture by geostatistical prediction. Geostatistical prediction by the method of kriging requires that we first model the spatially correlated variations of a set of variables and then to use this model to form predictions at unsampled sites (Webster and Oliver, 2007). The predictions have minimised error variance, conditional on the model, and this variance can be reported as a measure of the uncertainty of mapped values. This is a valuable feature of geostatistical prediction, because a rational and robust decision about habitat management at a particular location must be guided not only by the best prediction of the conditions at that location, but also by the uncertainty of those predictions, and the resulting probabilities that other conditions occur.

Geostatistical prediction by kriging is long-established (Matheron, 1963; Journel and Huijbregts, 1978; Webster and Oliver, 2007) and has been applied across the earth and environmental sciences including mining (Costa et al., 2000), hydrology (Zimmermann et al., 2008), soil survey (Burgess and Webster, 1980), regional geochemistry (Rawlins et al., 2003), agronomy (Bishop and Lark, 2007), entomology (Carbajo et al., 2006) and fisheries (Maravelias and Haralabous, 1995). One particular feature of particle size data, not generally encountered in geostatistics, is that they are compositional. That is to say, the percentages of sand, gravel and mud in a given sample sum to 100 by definition, and so these variables are not drawn from an unconstrained three-dimensional sample space but rather are drawn from the constrained simplex space which can be represented as a two-dimensional ternary diagram such as our Fig. 1. This has various implications for the statistical properties of the data, and so for their correct analysis (Aitchison, 1986), and this extends to geostatistical analysis and prediction (Pawłowsky-Glahn and Olea, 2004). Lark and Bishop (2007) demonstrated the geostatistical modelling and prediction of compositional data on particle size distributions in soil.

In this study our basic data are measurements of the percentages of mud, sand and gravel in the composition of the seabed sediment, but our predictions are of sediment classes. The primary set of classes on which we report here is simplified from the fifteen-class system of Folk (1954) into four broader classes as proposed by Long (2006). These simplified classes are commonly used as the substrate element for habitat mapping and inform at level 3 of the EUNIS classification system (Connor et al., 2006). These classes are shown, projected onto a ternary diagram, in Fig. 1. However, because the basic geostatistical modelling is done on the underlying data on the mud, sand and gravel percentages, it is relatively quick to re-map the data according to a modified classification, and we also demonstrate this here.

Our objective in geostatistical mapping according to a legend of classes is to calculate, for any unsampled site, the probability of observing each of the four textural classes there. This enables the data user not only to identify the most probable class at any location, but also to take account of the probability that other classes occur there. In this paper we use the BGS data set on seabed sediments to generate geostatistical predictions at a denser network of points where direct

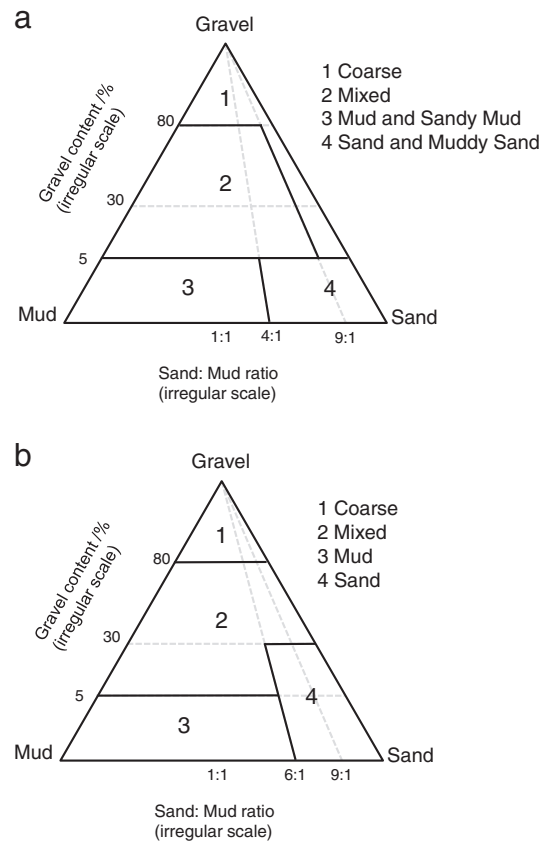


Fig. 1. (a). Ternary diagram showing the four simplified sediment classes that are often used in habitat mapping (Connor et al., 2006; Long, 2006). (b) An alternative classification proposed by James et al. (2010).

observations of sediment were not available. We use appropriate transformations of the data to deal with their compositional form, and use the results to compute the probability of occurrence of each of the four texture classes of Long (2006).

2. Methods

2.1. Data collection

The BGS conducted a systematic programme of regional geological surveys during the 1970s and 1980s (Fannin, 1989) which resulted in the production of a series of 1:250,000 scale maps covering the UK shelf, and a set of offshore regional reports e.g. Cameron et al. (1992). Particle-size data from more than 30,000 locations were accumulated during this programme and later project-driven surveys, the locations are shown in Fig. 2.

Sediment samples for particle size analysis were recovered from sediment grabs, corers, and dredges. The larger part of the samples was recovered with a Shipek Grab, but analysis was also routinely made on sub-samples from the tops of cores and dredged samples. If sufficient material was available the samples were separated into working and archive portions, where between 25 g and 150 g of sand (larger samples for more gravelly or muddy sediments) were required for analysis (Balson, 1983). Each sample was analyzed to determine the relative proportions of material in the gravel, sand, and mud particle size classes as defined on the logarithmic Wentworth scale (Wentworth, 1922). The material from each sample was separated into these particle-size classes by both wet and dry sieving on 2-mm and 63- μ m sieves. Gravel is classed as the portion which is retained at 2 mm, sand is the portion which passes through 2 mm

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