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Geostatistical modelling of surficial sediment composition in the North Sea and English Channel: using historical data to improve confidence in seabed habitat maps

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Abstract

This study aims to make the best use of historical data while addressing the need for a quantitative, repeatable procedure for the mapping of sediment composition over the UK areas of the North Sea and English Channel. The traditional approach has been qualitative, using expert interpretation to draw contours around point samples and so segment the sea bed into polygons representing different substrate types. The variability of sampling density of the observations and subsequent variability in confidence of the interpretation are usually not provided to the users of the resulting mapped layers, therefore they have no way of judging the confidence they should have in it; they just assume that 'the map is correct'. An additional hurdle is that the output map often has a classification system applied (e.g. the Folk classification of sediment types) and this may not be fit for purpose for all end users; a classification scheme that has use to a geologist may have little relevance to a biologist. Our objective was to use a database of historical samples obtained from the BGS (British Geological Survey) to model the spatial distribution of surficial sediment composition in a way that does not impose these constraints and permits the output of 'bespoke' maps, classified according to the needs of the end user. We achieved this using spatial prediction, specifically 'Kriging with external drift' (KED). Using a digital elevation model of the seabed as the 'external drift' significantly improves the outputs in comparison to ordinary Kriging (OK).

Keywords: Kriging, habitat mapping, surficial sediments, North Sea

1 Introduction

This study addresses a need for a quantitative, repeatable procedure for the mapping of sediment composition over large areas of the UK continental shelf. Traditionally, seabed sediment maps such as the series published by the British Geological Survey (eg. BGS, 1983) use expert interpretation to convert a spread of point-sample data into a classified sediment map. Analysis of sediment samples collected at each point allows them to be assigned to a sediment class, such as those in the Folk classification (Folk, 1954), and the expert then uses best professional judgement to draw contours around groups of points with the same class to produce a polygonised map showing the broadscale distribution of the various sediment types. Clearly the accuracy of the map varies according to the local density of the sampling points and is further compounded by the necessary interpolation that the expert has to make between points when selecting one of many possible contouring solutions.

These factors affect the confidence that can be placed in the map, and the end user is not usually aware that accuracy and confidence vary for different parts of the map; they tend to assume that 'the map is correct'. A further hurdle to using the map is that it has had a specific classification applied to it, in this case the Folk classification, and this may not be the most suitable classification for the purpose of the end user. For example they will not be able to determine from the Folk classification which areas of the map has sediment with > 5% mud content. Our objective is therefore to model the spatial distribution of surficial sediment composition in a way that does not impose these constraints and permits the output of 'bespoke' maps, classified according to the needs of the end user. The formal approach is by using spatial prediction.

Spatial prediction involves estimating the values of a target variable at unobserved locations. Geostatisitcal predictions use the spatial auto-correlation structure present in the data (i.e. points that are close together are likely to be more similar than those that are far apart) to make an estimation at an unobserved location (Gooverts, 2000). The technique called 'Kriging' is the most common form of such prediction and has become a synonym for geostatistical interpolation (Hengl, 2004). It has been shown that geostatistcal estimation usually out performs more mechanistic spatial prediction techniques such as inverse distance weighted interpolation (IDW). Both IDW and Kriging predictions use weighted averages of nearby observations to estimate values for unobserved points. IDW assigns weights based on the straight line distance from real observations, while Kriging fits a model to the spatial auto-correlation present in the data and uses this to determine weights based on statistical rather than 'real-world' distance. Kriging has many advantages; a well as predicting values for unobserved points it also provides an associated measure of the precision of those predictions (Kriging variance), and so gives an indication of 'confidence'. It also has the ability to include covariates that are more densely or exhaustively sampled throughout the study area in order to improve the prediction made (Gooverts, 2000).

Spatial prediction techniques that incorporate secondary information are sometimes referred to as 'Hybrid' techniques. They combine two approaches to make predictions; interpolation relying on weighted average of neighbouring observations (spatial predictions) and interpolation based on the relationship of the target variable with the covariate (regression). Incorporating secondary information will not usually be a replacement for making more observations, unless the relationship with the covariate is very strong, but it is a way of getting more out of existing data which in some cases, such as a Digital Elevation Model (DEM) of the seabed, may be cheaper to collect and can improve predictions significantly for little extra cost (Knotters, 1995). It is also worth mentioning that any prediction based solely on a relationship with a covariate has the limitation that it disregards any spatial auto-correlation that may be present in the data, which can itself improve estimates (Verfaillie et al., 2006).

Here we report on work undertaken in such a predictive modelling. The study area is limited to the UK sector of the Greater North Sea sub-region of the north-east Atlantic which comprises the North Sea and English Channel. Our aim was therefore to improve on the traditional seabed sediment type maps produced for this area by the British Geological Survey by developing a predictive model of seabed sediment composition for the UK parts of the North Sea and Channel. To do this we used a technique called Kriging with External Drift (KED), which incorporates a drift/trend model in the form of a digital elevation model of the seabed (i.e. a bathymetry layer). Performance of the KED model will be compared with Ordinary Kriging (OK) to assess the validity of using the more complex approach.

2 Methods

2.1 Data

The dataset contains 6769 sea bed sediment samples collected by the British Geological Survey between 1979 and 2008. This equates to approximately 1 sample per 24 km^2 throughout the study area, however the spatial distribution is not even with some areas being more densely sampled than others. This clustering is not enough to cause major problems with predictions; it can even be beneficial to have more samples at smaller distances as it can lead to a more accurate modelling of the spatial structure at small distances. The samples were collected using a Shipek grab. The sediment fractions recorded are %silt-clay, % sand and % gravel which respectively have particle sizes <63 µm, 63 µm to 2 mm, and >2 mm.

Two DEM bathymetry grids were used, a coarser 50 m resolution grid in the North Sea and a finer 25 m grid for the Channel (both from SeaZone Solutions Ltd). These were integrated into a 100 m grid for analysis (analysis at higher resolutions was prohibitive due to data processing considerations). The underlying data from which the DEM grids are derived is not consistent throughout the study area and there are some artefacts, particularly in the northern North Sea, which may affect the confidence of predictions in these areas.

It is preferable for the techniques used here that the dependant variables approximate a normal distribution (Isaaks and Shrivastava, 1989). Hengl (2004) recommends the use of the logit transformation to improve normality of percentage type variables; this has the benefit of constraining the back-transformed predictions within physical limits of 0 and 1.

ArcGIS 9.3 was used for the pre-processing of observations and handling the bathymetry DEM. The geostatistical analysis was performed in the statistical programming environment R 2.11.0 (R Development Core Team, 2011) using the gstat package (Pebesma, 2004).

2.2 Variogram modelling

Kriging predictions require a model of the spatial auto-correlation structure of data. Traditionally this is done fitting a mathematical function to a sample semi-variogram (Figure 1). The sample semi-variogram describes how the variability of the data (semivariance) changes with distance. Typically you expect to see smaller variability at shorter distances increasing to a sill, where spatial auto-correlation is no longer present. The distance at which the sill is reached is known as the range. The variogram model is used by the kriging algorithm to assign weights to the observations within the interpolation window. The interpolation window is the number of samples around the unobserved location which are to be used in the estimation, and it can be specified either by a number of samples or by a distance from the prediction location; a number of window sizes are tested to find the best solution.

2.3 OK and KED predictions

The kriging algorithm uses the variogram models to make OK and KED predictions. The process is the same for both but KED has the extra step of de-trending the data before the kriging predictions. The external drift is quantified as a linear function of the external variable (in this case bathymetry) within each interpolation window and the kriging prediction is made using the de-trended residuals.

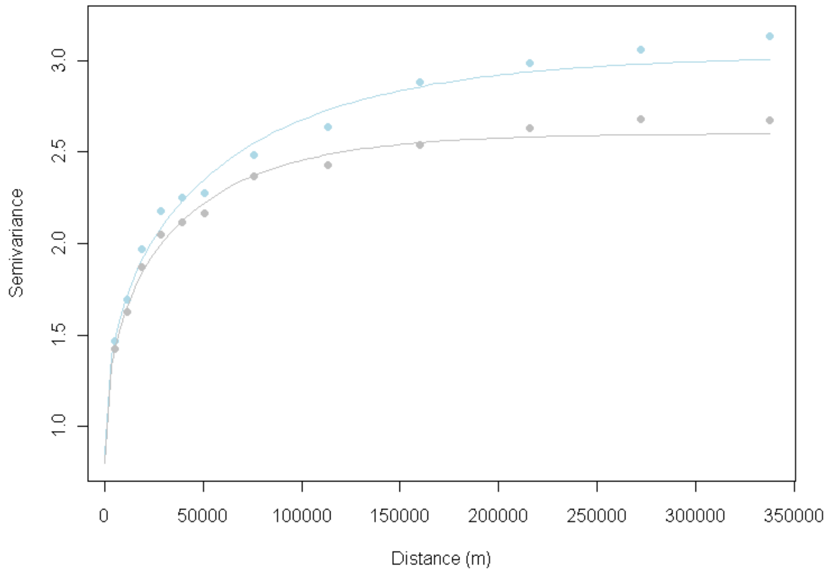

Figure 1: Sample variograms and fitted models for ordinary kriging (OK, blue) and kriging with external drift (KED, grey). The lower sill in the KED model indicates the variance explained by the trend model.

2.4 Cross-validation

A 100-fold cross validation procedure was used to test the performance of the models. This involves splitting the data set into 100 parts at random. Each part is taken in turn and predictions are made for this part using the rest of the data. The outcome results in observed and predicted values at each of our observations and measurements of model error can be made and models compared. This may not be as rigorous as an independent validation because all of the samples are used at the model specification stage; however in practice the cross validation will usually reflect the results of an independent validation. Several parameters are calculated to indicate the performance of models from the cross-validation.

3 Results and discussion

The results indicate that KED out performs OK, according to all of the error parameters calculated (Table 1). The calculated measurements of error include:

- *Mean error* which should be close to 0 and can indicate a bias estimator.
- *Mean squared error* which should be as low as possible and is useful in comparing models.
- *Root mean squared error* which is used to obtain the same units as the variable in question and

- *Pearson correlation coefficient* which measures the amount of (linear) correlation between observed and predicted values.

Table 1: Validation indices for 100-fold cross-validation, comparing OK and KED.

	%Silt-Clay		%Sand		%Gravel	
	OK	KED	OK	KED	OK	KED
ME: Mean error	-0.002	0.001	0.001	0	0.001	0.004
MSE: Mean squared error	1.273	1.219	1.952	1.923	3.921	3.864
RMSE: Root mean squared error	1.128	1.104	1.397	1.387	1.98	1.966
Pearson correlation coefficient (r)	0.75	0.762	0.756	0.76	0.8	0.803

It can also be beneficial to examine scatter-plots of observed *vs* predicted values in conjunction with the validation parameters. For examples, Figure 2 shows a good correlation between observed and expected values predicted for % silt-clay.

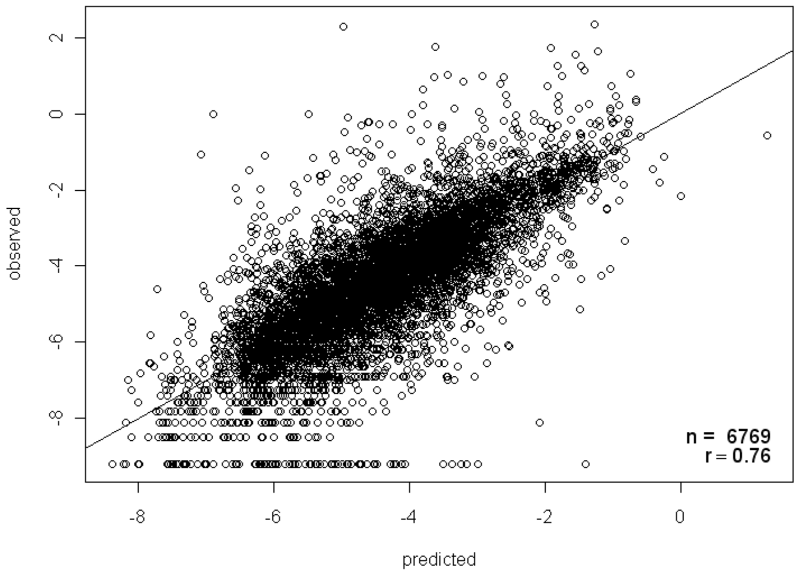

Figure2: % Silt-Clay (logit scale) predicted *vs* observed for 100-fold cross validation from the KED model.

The practical implications for using the bathymetry DEM as a trend model are that the bathymetric features are reflected in the sediment predictions resulting in a more accurate and realistic representation of the seabed (Figure 3). Along with the prediction surfaces are estimates of their reliability (kriging error). This is not an absolute measure of error but an indication of reliability (Gooverts, 2000) and generally corresponds to the underlying sampling density. It has potential applications when planning the best positions for future sampling.

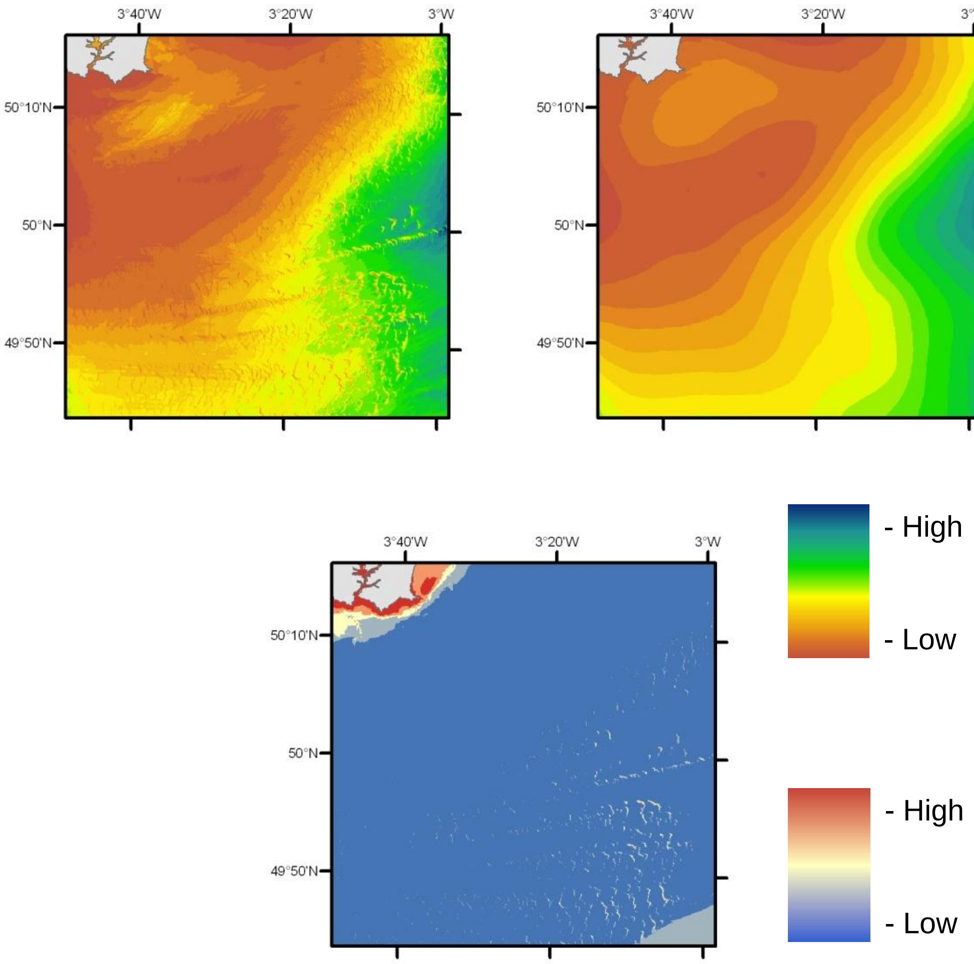

Figure 3: Detail comparison of %Gravel predictions from KED (top-left) and OK (top-right)
with KED variance (bottom, high variance = low confidence)

The final outputs (Figure 4) are high resolution prediction maps and associated confidence layers of surficial sediment composition across the North Sea and English Channel. Because there is a separate layer for each fraction (%Sand, % Gravel and % Silt-Clay) they provide versatility in that they can be interrogated and classified by whatever means are most useful to the end user.

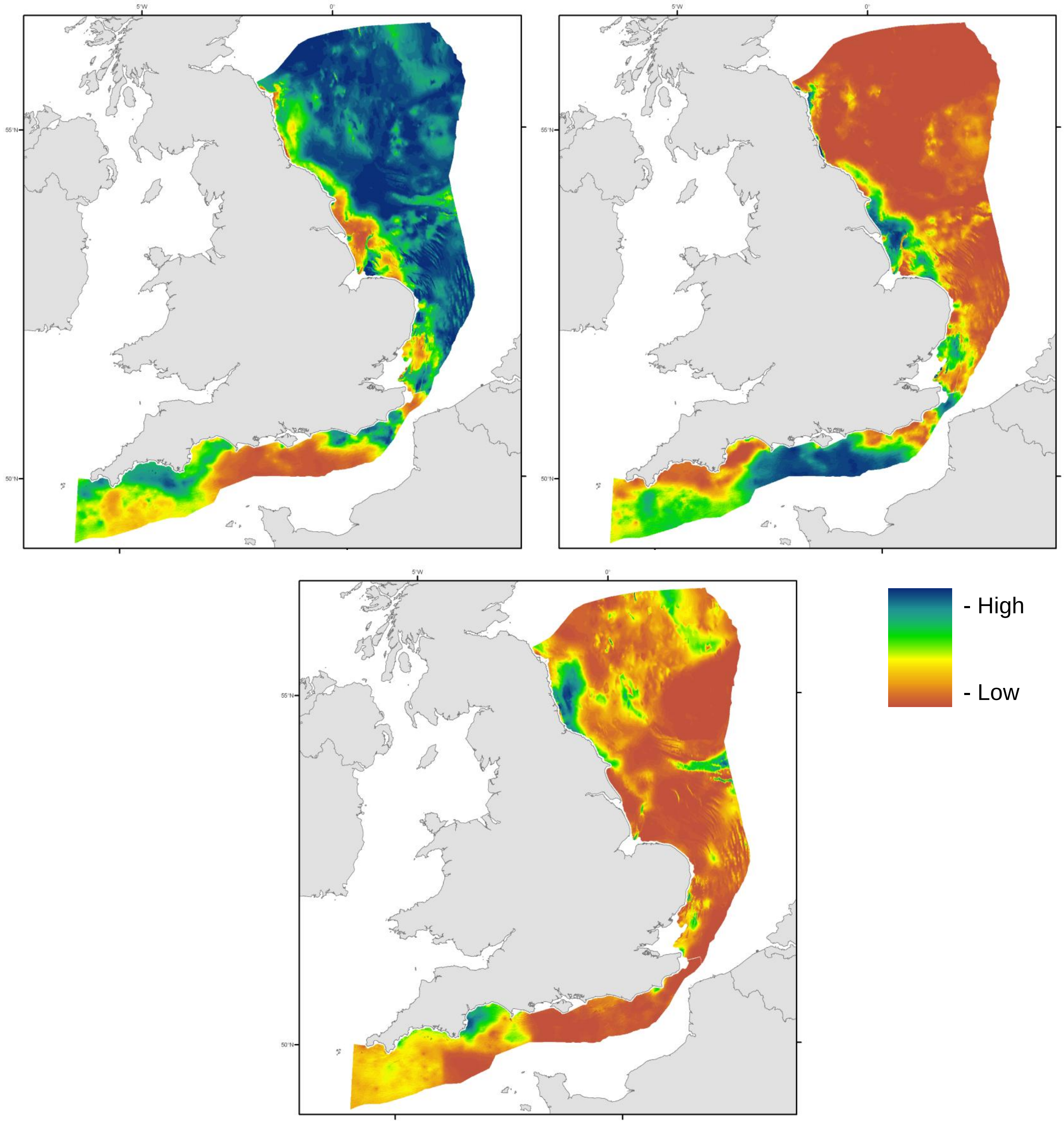

Figure4: Gridded predictions surficial sediment composition in the English North Sea and Channel
%Sand (top-left), %Gravel (top-right) and % Silt-Clay (bottom)

4 Conclusion

The initial aim of this study was to produce surficial sediment composition map layers by quantitative and repeatable methods. It was also important that the uncertainty associated with the estimates could be quantified and mapped alongside the predictions. Another requirement was that the outputs were versatile in that they could be used for a number of applications; being classified to the end users requirements. These aims have been achieved and it is envisaged that the outputs will be used to further model benthic habitats based on the EUNIS classification. With that said, there could also be scope to refine the predictions further at some time in the future. There are possibilities to do this in a number of ways. One is the improvement of underlying data. If more accurate bathymetry data was to become available then incorporating this would be beneficial. Applying more sophisticated modelling techniques would be another area of potential improvement; this applies to both modelling of the trend and geostatistical components.

Acknowledgements

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