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Semi-automated mapping of rock in the Irish Sea, Minches, western Scotland and Scottish continental shelf

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Summary

This report describes the results from a semi-automated approach to the mapping of bedrock outcropping at the seabed, applied to Charting Progress 2 (CP2) regions 5 (Irish Sea), 6 (Minches and Western Scotland) and 7 (Scottish Continental Shelf). It represents the third phase of this work, following development and initial application of the approach in the Eastern Channel (CP2 region 3) and Western Channel and Celtic Sea (CP2 region 4) (Diesing *et al* 2015), Southern North Sea and Northern North Sea (Downie *et al* 2016).

The method consisted of two elements, namely: 1) the automated spatial prediction of the presence and absence of rock at the seabed using a random forest ensemble model, and; 2) manual editing of the model outputs based on ancillary geological data and expert knowledge.

The random forest prediction yielded satisfying results with an overall accuracy of 79% and a kappa of 0.49 based on a test set of samples not involved in model building.

The combined approach represented a significant update to previous mapping of rock at the surface and rock with thin sediment in these regions. The model was highly successful in predicting rock at outcrop around the Outer Hebrides. Predictions in deeper water areas of the outer continental shelf and coastal regions were reviewed and edited using expert judgement, based on more localised, higher resolution data sources.

The confidence in the developed rock layer was also assessed according to the method first used by Diesing *et al* (2015), based on the type (quality) of bathymetric data, probability of rock presence based on the random forest ensemble and agreement between predictions and observations in a spatially explicit way.

The final output gives a significantly improved representation of the presence of bedrock at the seabed in CP2 regions 5, 6 and 7, and, in combination with the outputs of Diesing *et al* (2015) and Downie *et al* (2016), gives a complete representation for the UK continental shelf.

Contents

1 Background

In preparation for the first stage of the Marine Conservation Zones (MCZ) project, the Department for Environment, Food and Rural Affairs (Defra) commissioned contract MB0103 to produce a UK-wide data layer showing areas of rock and hard substrate at or near the seabed surface (Gafeira *et al* 2010). The British Geological Survey (BGS) carried out this work as a subcontractor of ABPmer. The outputs were:

1. Rock and hard substrate polygon layer.
2. Rock and cobbles point layer.
3. Confidence layer.
4. Layer showing areas in which multibeam bathymetry data has been collected.

In 2011, BGS updated the polygon dataset and named it DigHardSubstrate250, which is provided alongside version 3 of DigSBS250.

The Joint Nature Conservation Committee (JNCC) has a responsibility for reporting on the status of the UK's reefs, which is a habitat defined under Annex I of the Habitats Directive[4]. Reefs are made up of three sub-types: bedrock, stony and biogenic. DigHardSubstrate250 is a useful product for JNCC in that it indicates the potential location and extent of bedrock reef. The layer would benefit from being updated as new data becomes available and methods for spatial prediction are developed.

In 2015, JNCC partially funded BGS and Cefas to carry out a semi-automated mapping of rock at the seabed surface in Charting Progress 2 (CP2) regions 3 and 4 (adjusted for the new EEZ boundary). The aim was to demonstrate a method that maximises the benefits of both automated mapping approaches and in-depth geological knowledge which could subsequently be applied to other sea areas around the UK. The methods and results can be found in Diesing *et al* (2015). In 2016 the work was extended to include CP2 region 2 and an extended region 1 (Downie *et al* 2016). Outputs from phases one and two are illustrated in Figure 1.

[4] Council Directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora. Official Journal of the European Communities No L 206/7.

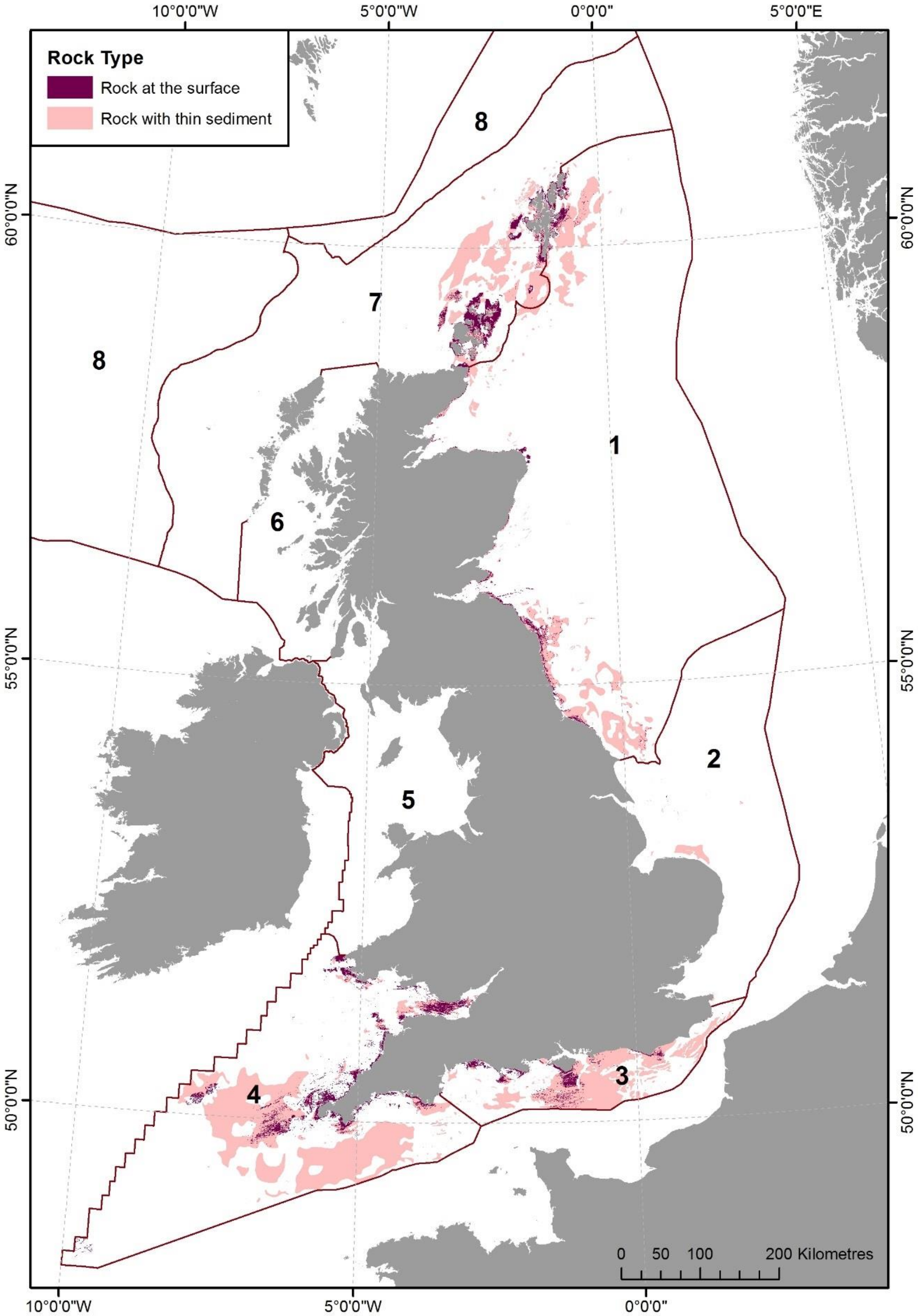

Figure 1. Final rock prediction outputs from phase 1 (Diesing *et al* 2015) and phase 2 (Downie *et al* 2016). The numbers indicate the CP2 regions.

2 Aims and Objectives

2.1 Project Aims

This report describes the third phase of this work, where the aim was to extend the coverage of the mapping completed by Diesing *et al* (2015) and Downie *et al* (2016) to produce a standard interpretation of rock distribution for Charting Progress 2 (CP2) regions 5, 6 and 7 (Irish Sea, Minches and Western Scotland and Scottish Continental Shelf).

2.2 Objectives

1. Develop a vector-based geospatial data product showing the potential extent of rock at, or near, the sea floor for subtidal areas of regions 5-7 shown in Figure 2 at a spatial scale equivalent to 1:250,000.

2. Identify sub-types as follows: rock at the surface, rock with thin sediment (up to 0.5m), according to the following definitions:

    a. **Rock at the surface**: Rock present at outcrop. This suggests a habitat dominated by exposed bedrock. Whilst it is unlikely that large areas of exposed rock will exist with zero sediment present, this classification should capture areas of negligible or highly mobile, patchy sediments where the veneer is minimal.
    b. **Rock with thin sediment**: These are essentially subcrops of bedrock, i.e. areas where bedrock rises to the seabed surface, but remains largely covered by a thin veneer of sediment. This will be derived by subtracting areas predicted as 'rock at the surface' from previously mapped rock areas (DigHardSubstrate250).

3. Keep a record of manual edits made to allow for efficient updates in future.

4. Carry out a 3-step confidence assessment for each polygon and include scores in the output data product.

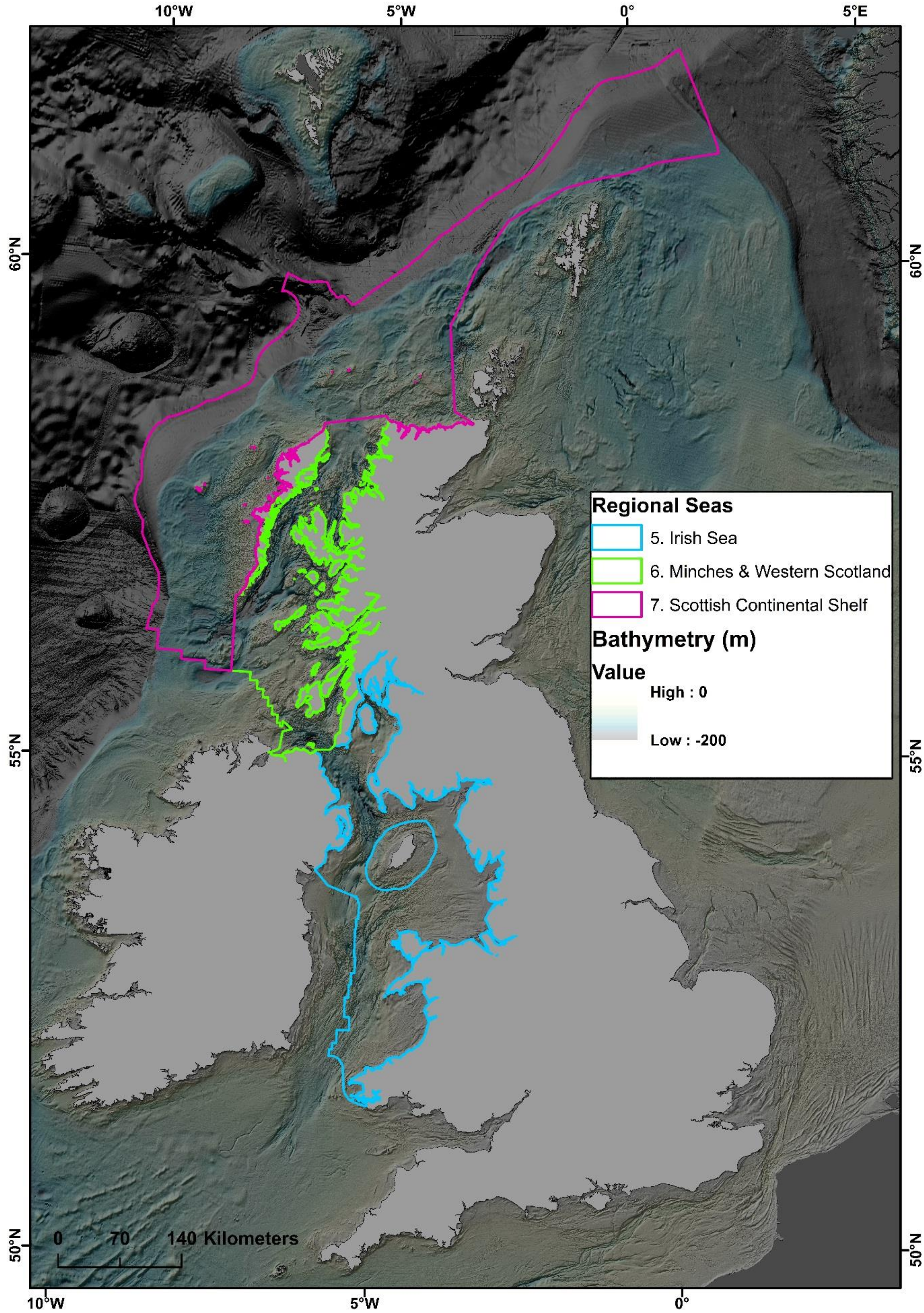

Figure 2. Bathymetry and CP2 regional sea boundaries. This study addresses regions 5, 6 and 7. Note that region 7 is adjusted to remove the area already included in the Downie *et al* (2016) study. General bathymetry from EMODnet Digital Terrain Model for European Seas (www.emodnet-bathymetry.eu).

3 Materials and Methods

3.1 Study Site

The study site comprises CP2 regions 5 (Irish Sea), 6 (Minches and Western Scotland) and most of 7 (Scottish Continental Shelf), excluding the part covered by phase 2 (Figure 2).

3.2 Data

3.2.1 Substrate observations

The input dataset contained 21,787 substrate observations within the study area (Figure 3). These were obtained from the Defra marine vector dataset (JNCC 2011). These data have been successfully used in previous studies involving the mapping of rocky substrates (Stephens *et al* 2014; Diesing *et al* 2015; Downie *et al* 2016). Of these data, 15,120 (69.4%) were recorded as indicating the unambiguous absence of rock. 5,525 (25.4%) were recorded as indicating the unambiguous presence of rock, i.e. rock and no other substrate type was recorded. In 889 (4.1%) cases rock occurred together with other substrate types. No information on substrate type was recorded in 253 (1.2%) cases. For further analysis, ‘no data’ and ambiguous records were removed. This decision was based on previous experience which indicated that excluding ambiguous samples would give the most accurate predictions (Diesing *et al* 2015). This meant that 20,645 observations were retained for further analysis (Figure 3).

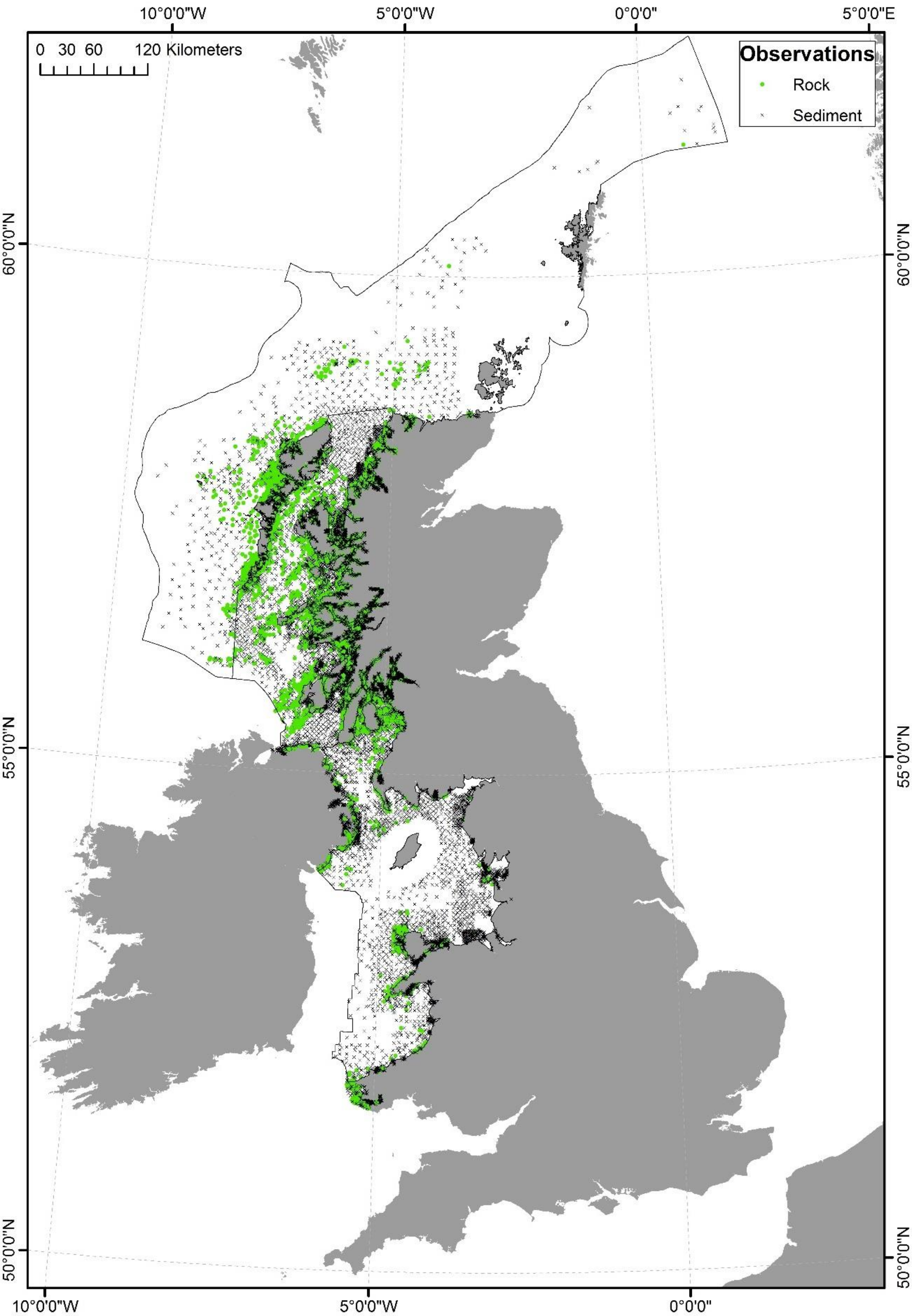

Figure 3. Presence and absence of rock extracted from Defra Marine Vector data. Note that inconclusive cases (i.e. those observations that included both rock and sediment) were ignored.

3.2.2 Predictor features

In order to predict rock presence at unobserved locations, the substrate observations had to be related to auxiliary variables (referred to as features) that have continuous coverage across the study area. These predictor features are comprised of a bathymetry digital elevation model (DEM), topographic characteristics derived from the bathymetry (such as slope and roughness), outputs from hydrodynamic modelling and polygon layers indicating properties of the seabed. Detailed descriptions of all features are given in Table 1.

Table 1. Predictor features utilised in this study.

Feature	Description	Unit	Reference
Bathymetry	Bathymetry (water depth) projected to UTM 30 North at a resolution of 25m.	m	(Astrium Oceanwise 2011)
Roughness	Derived from bathymetry; the difference between minimum and maximum of cell and its 8 neighbours.	m	(Wilson *et al* 2007)
Slope	Derived from bathymetry, the maximum slope gradient.	degree	(Wilson *et al* 2007)
Aspect	Derived from bathymetry, direction of steepest slope, expressed as Eastness (sine of aspect) and Northness (cosine of aspect).		(Wilson *et al* 2007)
Curvature	Derived from bathymetry, rate of change of slope. Profile curvature is measured parallel to maximum slope; plan curvature is measured perpendicular to slope.		(Wilson *et al* 2007)
Bathymetric Position Index (BPI)	Derived from bathymetry, vertical position of cell relative to neighbourhood (identifies topographic peaks and troughs). Radii of 3, 5, 10, 20, 30, 40 and 50 pixels were used.	m	(Lundblad *et al* 2006)
BGS Hard Substrate	DigHardSubstrate250 data product. Delineates areas of rock at outcrop, or overlain by thin (<0.5m) sediment based on bathymetric data, the BGS legacy sample database and expert interpretation.		(Gafeira *et al* 2010)
Indicators of Mobile Sediments	Seabed morphologies characteristic of mobile sediments were delineated using hillshade, slope and rugosity data.		(Westhead *et al* 2014)
Quaternary Thickness	Data layer detailing thickness of Quaternary cover on the UK Continental Shelf categorised into three classes: 0-5m; 5-50m; >50m.		(Westhead *et al* 2014)
Relative Resistance	Representation of the relative resistivity of bedrock on the UK Continental Shelf based on age and lithology. Derived utilising BGS DigRock250[5] following the method described by Clayton and Shamoon, (1998).		(Clayton & Shamoon 1998)
Distance to Coast	Euclidean distance to nearest coastline.	m	

[5] http://www.bgs.ac.uk/downloads/start.cfm?id=2892

Current Velocity	Mean M2 tidal current velocity averaged across water column calculated using a Telemac model with an unstructured grid of variable resolution.	ms^{-1}	Cefas in-house product. Not yet published.
Peak Wave Orbital Velocity	Peak wave orbital velocity at seabed. Surface wave parameters (wave height and period) were output from a POLCOM model for the years 2000 to 2008. The original resolution of the data is 12km. Bottom orbital velocities were calculated from these and the 1 arcsec Defra DEM. Maximum, mean and standard deviation of peak orbital velocity were calculated.	ms^{-1}	(Holt & James 2001; Aldridge *et al* 2015; Bricheno *et al* 2015)

3.3 Methods

3.3.1 Pre-processing of observations

The first step was to extract the values of each predictor feature at the location of each substrate observation. Not all predictor features had the same spatial extent or resolution. This meant that for some predictor features there were gaps, mainly around the coast or far offshore, resulting in some observation locations having no data values (NA) for some or all features. Any observations that contained NA values for at least one predictor feature were discarded. Of the 20,645 observations (see Section 3.2.1: ‘Substrate observations’) 18,061 intersected all predictor layers and were retained in the dataset. Of the 18,061 observations, 5,330 (29.5%) observations indicated ‘presence’ (P) of bedrock and 12,731 (70.5%) were ‘absence’ (A).

The quality and reliability of the bathymetry data is not consistent across the study area. The dataset is a collation of available data, mostly collected since the 1980s using varying techniques to acquire and process the data. This means that, although the grid resolution is constant at 25m across the study area, the underlying data are of varying quality and this will also affect the topographic variables derived from the bathymetry. Table 2 shows the number of observations in each category of bathymetry quality.

Table 2. Observations by bathymetry quality class. Ordered by reliability, increasing from left to right.

Type	Chart	Singlebeam echosounder	Multibeam echosounder	Total
Number of observations	5,892	4,467	7,702	18,061
Percent of observations	33 %	25 %	43 %	

To test the model predictions, the data were split randomly into training (70% of observations) and test datasets (30%). The ratio of presence to absence records were kept equal in both the training and test datasets (Table 3).

Table 3. Training and test datasets.

	Training	Test	Total
P	3,731	1,599	5,330 (29.5 %)
A	8,912	3,819	12,731 (70.5 %)
Total	**12,643**	**5,418**	**18,061 (100 %)**

3.3.2 Model training

Probability of rock was modelled using a random forest (RF) model (Breiman 2001). RF has become one of the most widely used and successful statistical learning models for classification and regression, showing good performance in a large number of domains (Pal 2005; Prasad *et al* 2006; Cutler *et al* 2007; Chan & Paelinckx 2008; Chapman *et al* 2010; Che Hasan *et al* 2012, 2014; Huang *et al* 2012, 2014; Oliveira *et al* 2012; Lucieer *et al* 2013; Stephens & Diesing 2014, 2015; Diesing *et al* 2014). RF is an ensemble technique, which aggregates the results of many classification trees, each built using a random subset of the training data and a trialling random subset of predictor variables at each node split. The result is a 'forest' of tree models, with the number of splits determined either by achieving pure end nodes (default) or a number of end nodes determined by the user. RF is a non-parametric technique, i.e. no assumptions regarding the shape of distributions of the response or predictor variables are made (Cutler *et al* 2007). It can handle complex, non-linear relationships between predictor and response variables. As well as using the test set to validate the model, RF implicitly generates a cross-validated measure of model accuracy. RF also provides a relative estimate of predictor feature importance. This is a measure of the variability explained by each feature, averaged across every tree in the RF.

The model was built in the free statistical computing software R (R Development Core Team 2011) using the 'randomForest' package (Liaw & Wiener 2002). In this case, the 'forest' included 2,500 classification trees. The number of observations in each random subset was set at 300 presences and absences each. Other settings were kept at their defaults. Predictions were made for the probability of encountering rock at each raster cell. Probability predictions by RF are derived based on the fraction of votes given for a specified class by the ensemble of trees.

Prior to training the model, a feature selection step was implemented to test the statistical significance of the predictor features for the presence/absence prediction of rock. The Boruta algorithm (Kursa & Rudnicki 2010) is a feature selection wrapper (Guyon & Elisseeff 2003) based on the RF model. The algorithm uses the feature importance score generated by RF to test each of the predictor features against the effect of random noise. Only features with Boruta scores significantly higher than random were retained for use in the final model. A further feature selection step removed correlated variables from the set of predictors used in the final model. Out of any two variables with a correlation coefficient above 0.7, only the variable with the higher Boruta score was retained in the final set of predictors.

To evaluate the predictive performance of the model, four validation statistics were calculated, including the Area Under the Curve (AUC), Sensitivity[6], Specificity[7] and Kappa (Cohen 1960) statistics. The AUC statistic is a threshold-independent goodness measure between 0 and 1, where a value of 0.5 signifies a model that is no better than random, whilst a value of 1 corresponds to perfect discrimination. As a general guideline, AUC values over 0.9 indicate excellent, 0.8 - 0.9 very good, 0.7 - 0.8 satisfactory and below 0.7 poor discriminative ability (Hosmer & Lemeshow 2000). The AUC statistic is, however, sensitive to the prevalence of rock presence observations in the test data (Lobo *et al* 2008) and it is good practice to combine it with other validation measures. Sensitivity, Specificity and Kappa are all calculated from dichotomised, presence/absence predictions. The threshold used to convert probabilities to presence and absence, and consequently to calculate Sensitivity, Specificity and Kappa, affects the overall accuracy and the likelihood of false negatives and false positives. The objectives of mapping will define which threshold is appropriate. Where the cost associated with false negatives (i.e. not predicting rock where it occurs) is high, a

[6] Sensitivity: the amount of true presence predictions as a proportion of the total number of presence observations.
[7] Specificity: the amount of true absence predictions as a proportion of the total number of absence observations.

threshold which places more weight on sensitivity would be more appropriate. Conversely, where false positives (i.e. predicting rock in places where it does not occur) have a high cost, the threshold should place more weight on specificity. Using equal sensitivity and specificity, i.e. the threshold where positive observations are just as likely to be wrong as negative observations, gives the most unbiased prediction, whilst optimising the sum of specificity and sensitivity gives the highest overall accuracy (Manel *et al* 2001).

The output probability prediction was initially split into five classes to encompass the range of probabilities. Class boundaries were set as follows:

1) High confidence in predicted absence of rock: threshold was set to yield 0.99 sensitivity; almost all rock presence observations in the test dataset occur above this cut-off.
2) Absences and presences with lower confidence: threshold was set to maximise the sum of sensitivity and specificity, with absences below and presences above threshold.
3) Maintaining the prevalence of rock: threshold was set to maintain the fraction of rock presences observed in training data in the predictions across raster cells.
4) High confidence in predicted presence of rock: threshold was set to yield 0.99 specificity; almost all rock absences are below this cut-off.

3.3.3 Knowledge-based enhancements

The output of the RF predictions was reviewed manually by a mapping geologist, in order to assess its validity in terms of the established geology of the area and additional data not incorporated in the model. The first stage of the process involved conversion of the modelled output into a readily editable ESRI shape file. This procedure was first defined in Diesing *et al* (2015), and in accordance with the project requirement. The steps detailed below were followed:

- Conversion of the RF output to 20m raster in order to perform generalisation.
- Each cell was replaced with a majority of eight neighbouring cells. This essentially reduces smaller areas and increases a large (majority) area.
- Boundary cleaning; smoothing of the boundaries between zones by buffering and debuffering. This results in smaller areas being engulfed into larger ones, according to boundary length. Large areas have a higher priority to expand into smaller ones.
- Conversion of raster back to polygons.
- Elimination of polygons smaller than 0.015625km^2 (based on a minimum mappable unit feature with a diameter of 125m for 1:250K mapping).
- Aggregate polygons with less than 125m distance between features, then removal of holes.

Following the generalisation process, the modelled output was reviewed against available multibeam bathymetry data, published mapping and sample data, and polygons were deleted or re-attributed in accordance with the geological understanding of the region. Based on these data additional polygons were also added where appropriate. In addition, published seabed substrate maps previously published by BGS were incorporated where appropriate.

A number of small, irregular polygons were removed on the basis that they represented artefacts from the bathymetric data.

3.3.4 Confidence assessment

The confidence assessment method follows that used in Diesing *et al* (2015), which is based on the three-step confidence assessment framework of Lillis (2016). The assessment was performed on a per-polygon basis due to the possible heterogeneity of inputs into the model across the output area. The method requires the assessor to follow a flow diagram and score the polygon appropriately at each stage (Figure 4).

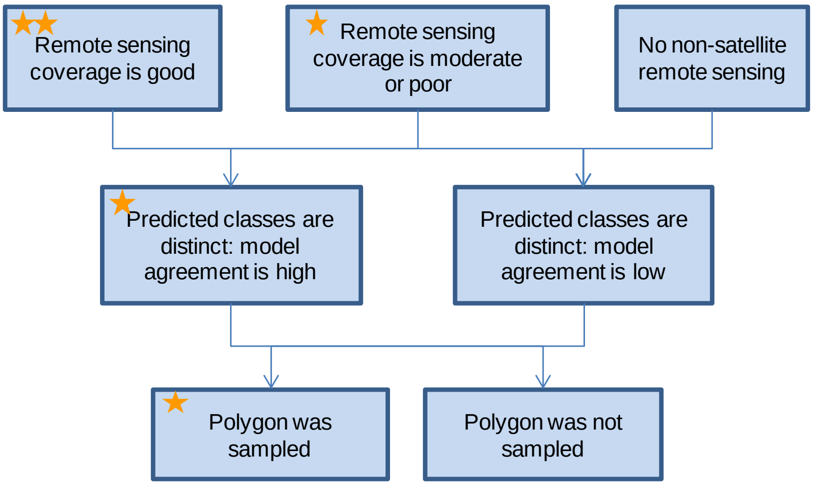

Figure 4. Three-step confidence decision tree; the assessor starts at the top and follows the arrows. Stars/points are awarded according to the answers given and the final score is the sum of the stars/points.

From this method, a maximum qualitative score of 4 can be achieved by a polygon (Table 4). The final score should not be taken as a quantitative probability of the habitat's likelihood in extent or presence, the measurement is a qualitative score based on the data inputs and level of agreement between the predictive models.

Application for polygons identified as rock at outcrop

The remote sensing coverage confidence was assessed based on the type of acoustic data that were available: A score of two was given where multibeam echosounder data were present, a score of one for singlebeam echosounder data and a score of zero for all other data types. Beyond the multibeam data that were built into the compiled bathymetry grid used in the automated process, additional data from the Maritime and Coastguard Agency's Civil Hydrography Programme and Defra's Marine Conservation Zone mapping programme were also included as part of the knowledge-based review. As such, a value of two was scored for these areas.

The distinctness of class boundaries criterion was scored in two stages:

1. Initially the agreement of the RF ensemble outputs was used: A score of one was attained where the value was above an agreement threshold set to yield a sensitivity of 0.99 (indicating high probability of presence of rock) or where the value was below an agreement threshold set to yield a specificity of 0.99 (indicating high probability of absence of rock). Intermediate values were given a score of zero.

2. Following the knowledge-based enhancements, where expert judgement led to modification or addition of a polygon, the initial score was overwritten with a score of one. This indicates higher confidence associated with validation of the presence of an area of rock outcrop by more detailed study or assessment by a geologist.

In the case of the amount of sampling criterion, a score of one was given if a polygon was sampled and the majority of samples agreed with the prediction. Both the sample database used in the automated process, as well as the BGS core database that was used as part of the knowledge-based review were included. A score of zero was attained if a polygon was not sampled or the majority of samples within the polygon disagree with the prediction.

Application for polygons identified as rock with thin sediment

The BGS DigHardSubstrate250 dataset includes an assessment of confidence based on data density. However, for production of the shapefile in this project a standard value of zero was applied for Remote Sensing Coverage as limited bathymetry data were available to produce this shapefile. A value of one for the Agreement confidence criteria was also applied to reflect the influence of human judgement.

Table 4. All possible combinations of scores under the three-step scheme. Polygons with equal scores are therefore assumed to have roughly similar levels of confidence, regardless of the route through the decision tree.

Score	Remote sensing coverage	Distinctness of class boundaries	Amount of sampling
4	★★	★	★
3	★★		★
	★★	★	
	★	★	★
2	★★		
	★		★
	★	★	
		★	★
1	★		
		★	
			★
0			

4 Results

4.1 Random forest predictions

The feature selection process indicated that all potential predictor variables contributed significantly to the presence/absence predictions except the Mobile Sediments layer. Mobile sediments performed less well than the random variables created by the Boruta and was removed at this stage of the variable selection. Eleven variables were deemed important by the Boruta. Subsequent removal of correlated variables reduced the number of variables to nine. The final selected variables were: Hard Substrate; Distance to coastline; BPI10; Bathymetry; Mean Peak Orbital Velocity; Current Velocity; Roughness; Relative Resistance and Quaternary Thickness. Table 5 gives the permutation importance scores for all tried variables and indicates the variables that were selected for the model based on the removal of correlated features.

Table 5. Permutation importance scores for potential predictor variables derived from the Boruta algorithm.

Predictor variable	Boruta permutation importance	Predictor Importance	Selected Predictor variables
Hard Substrate	78.51263	Important	Selected
Distance to Coastline	32.78059	Important	Selected
BPI10	31.7228	Important	Selected
BPI20	30.68438	Tentative	
Bathymetry (m)	30.49339	Important	Selected
Curvature - Planar	30.47821	Important	
BPI30	30.472	Tentative	
BPI3	29.69261	Tentative	
BPI5	29.39213	Tentative	
Peak Orbital Velocity - mean	29.29792	Important	Selected
Curvature	28.88138	Tentative	
Current Velocity	28.66958	Important	Selected
Peak Orbital Velocity – Standard deviation	28.24919	Tentative	
Peak Orbital Velocity - Max	28.20342	Tentative	
Curvature - Profile	26.90288	Tentative	
BPI50	24.95622	Tentative	
Roughness	24.14258	Important	Selected
BPI40	23.3583	Tentative	
Slope	23.02846	Tentative	
Relative Resistance	19.24999	Important	Selected
Aspect - Northness	13.95219	Important	
Quaternary Thickness	13.00908	Important	Selected
Aspect - Eastness	6.065795	Tentative	
Mobile Sediments	1.571773	Unimportant	Removed

The threshold-independent AUC score for the model was 0.83, which indicates a well performing model. Accuracy statistics calculated using the four selected thresholds are given in Table 6. In the final output map, high sensitivity and high specificity thresholds of 0.99 were used to indicate high confidence in absences and presences of rock.

Setting a high sensitivity of 0.99 yielded a probability threshold of 0.13 (Table 6 and Figure 5a). Almost all rock presences in the test dataset occur above this cut-off (Figure 5b). Likewise, setting specificity at 0.99 yielded a probability threshold of 0.86 (Table 6 and Figure 5a) and almost all rock absences are found below this cut-off (Figure 5b). The overall cut-off between rock presence/absence was set at the threshold which ensured that prevalence of rock in the predicted output remained the same as in the input data. The selected threshold avoids over-prediction, assuming the model input data is an unbiased estimate of the prevalence of rock in the area. It was also found to give the highest overall accuracy, at 79% of all observations in the test dataset correctly classified, as well as the highest Kappa value at 0.49.

Table 6. Accuracy statistics for each threshold used to convert probability of presence to presence/absence classes. The threshold used in the final map is highlighted. PCC = Percent Correctly Classified.

Threshold Method	Threshold	PCC	Sensitivity	Specificity	Kappa
Maximising confidence in predicted absence of rock, i.e. High Sensitivity	0.13	44%	0.99	0.20	0.13
Maximising overall accuracy, i.e. Maximum of Sensitivity + Specificity	0.46	75%	0.79	0.73	0.46
Maintaining the prevalence of rock, i.e. Predicted Prevalence= Observed Prevalence	0.61	79%	0.64	0.85	0.49
Maximising confidence in predicted presence of rock, i.e. High Specificity	0.86	75%	0.16	0.99	0.20

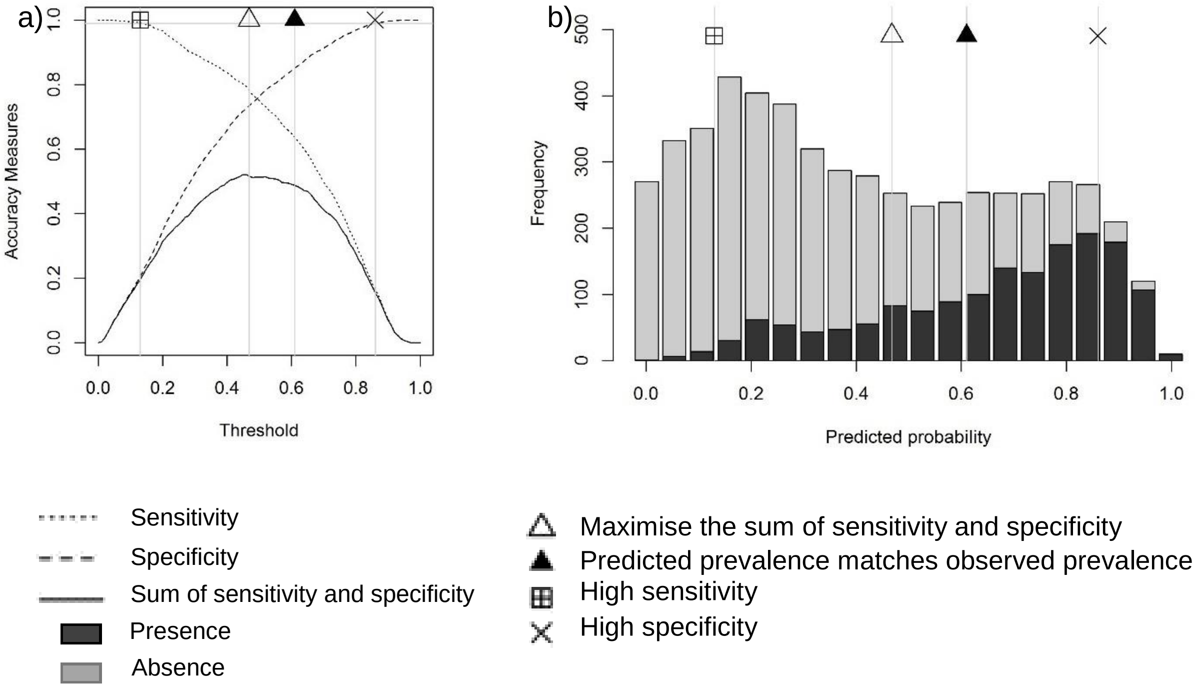

Figure 5. a) Selected thresholds for converting probability of presence to presence and absence plotted against sensitivity and specificity and b) the frequency of observed presences and absences.

The resulting spatial predictions of rock presence and absence with high and low confidence are shown in Figure 6.

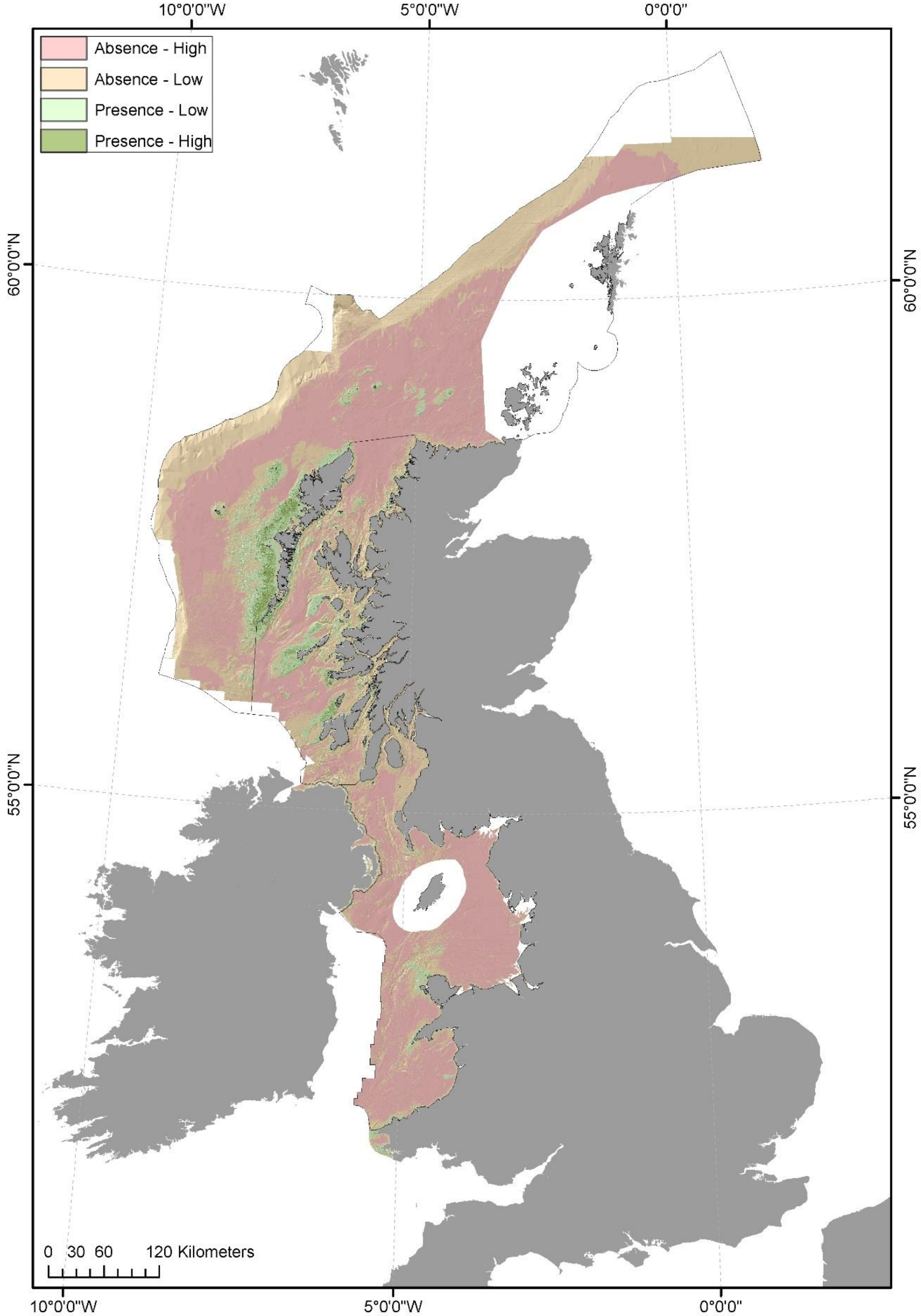

Figure 6. Resulting predictions of rock presence/absence and associated confidence. The boundary between 'Absence – High' and 'Absence – Low' confidence occurs at a probability value of 0.13 (high sensitivity). The boundary between 'Absence – Low' and 'Presence – Low' occurs at a probability value of 0.61 (maintaining prevalence). The boundary between 'Presence – High' and 'Presence –

Low' confidence occurs at a probability value of 0.86 (high specificity). General bathymetry from EMODnet Digital Terrain Model for European Seas (*www.emodnet-bathymetry.eu*).

Figure 7 shows partial dependence plots of the nine selected predictors: Rock outcropping at the seabed is more likely at distances to the coast >100km, positive BPI10, shallow water depths, increased peak orbital velocities and current velocities (>1.5ms^{-1}), increased seabed roughness (>10m), high and low relative resistance of bedrock to erosion, and in areas where hard substrate is mapped at or near the seabed.

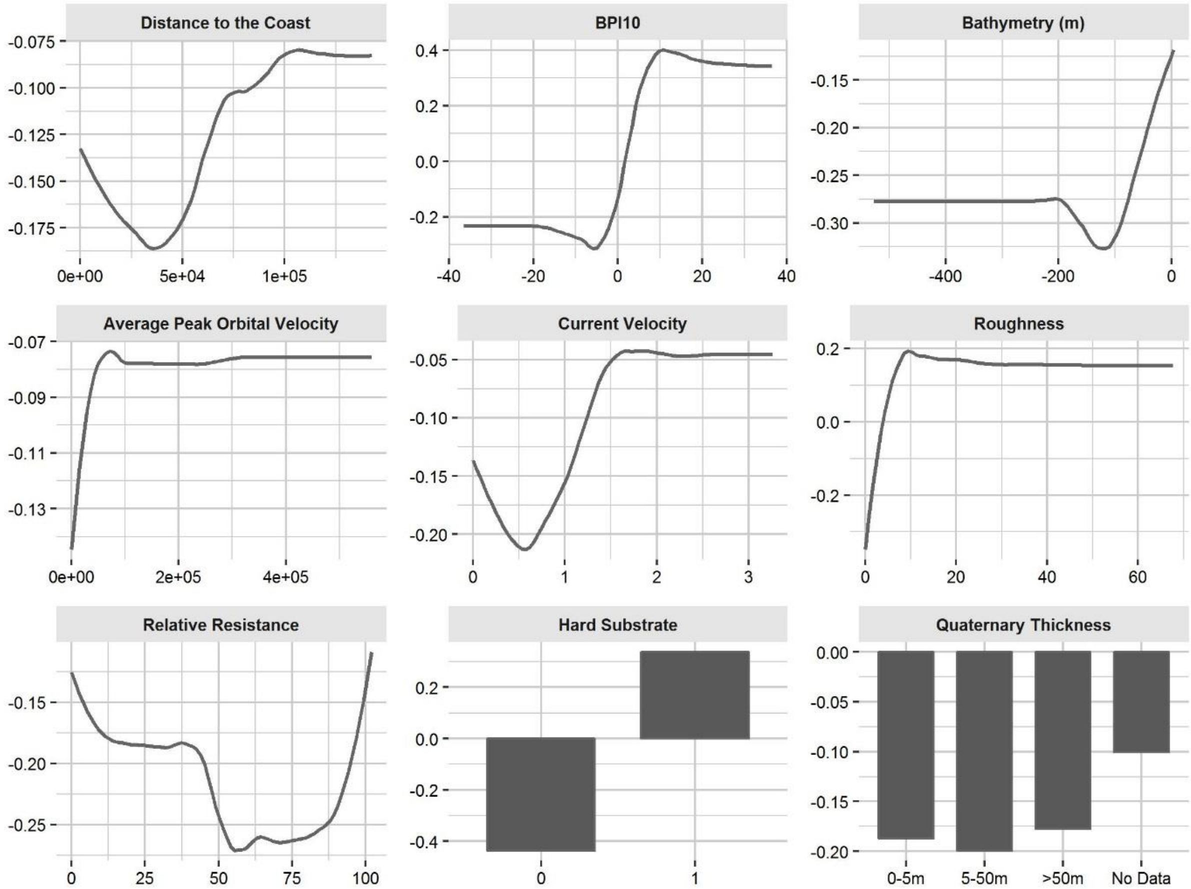

Figure 7. Partial dependence plots showing the response to chosen predictor variables: Distance to the Coast, BPI10, Bathymetry (m), Average Peak Orbital Velocity, Current Velocity, Roughness, Relative Resistance, Hard Substrate and Quaternary Thickness.

4.2 Knowledge-based enhancements

The rock prediction dataset was reviewed against available multibeam bathymetry and sample data, as well as previously published maps (Table 7). This validation process was conducted in accordance with the geological understanding of each region. Where available, the high-resolution multibeam bathymetry data (2-12m resolution) were particularly useful for this exercise. The multibeam data employed (as they account for the largest datasets) were acquired by the MCA's Civil Hydrography Programme (CHP).

Table 7. Published data and mapping used to support expert interpretation.

Feature	Description	Reference
Bathymetry	EMODnet – medium resolution bathymetry compilation (~150m resolution). High resolution (~2-12m resolution) swath bathymetry acquired by MCA's Civil Hydrography Programme (CHP).	**EMODnet**: www.emodnet-bathymetry.eu MCA's CHP: https://www.gov.uk/guidance/the-civil-hydrography-programme
BGS Seabed Sediments	DigSBS250 V3; 1:250 000 scale seabed sediments mapping for the UKCS.	Cooper *et al* (2010a)
BGS Seabed Sediments	1:50 000 scale seabed sediments mapping for the UKCS[8].	British Geological Survey
BGS Hard Substrate	DigHardSubstrate250 data product. 1:250 000 scale. Delineates areas of rock at outcrop, or overlain by thin (<0.5m) sediment based on bathymetric data, the BGS legacy sample database and expert interpretation.	Gafeira *et al* (2010); Cooper *et al* (2010b)
BGS Indicators of Mobile Sediments	Seabed morphologies characteristic of mobile sediments were delineated using hillshade, slope and rugosity data. 1:250 000 scale.	Westhead *et al* (2014)
BGS Quaternary Thickness	Data layer detailing thickness of Quaternary cover on the UK Continental Shelf categorised into three classes: 0-5m; 5-50m; >50m.	Westhead *et al* (2014)
BGS Quaternary Deposits	1:1M scale mapping of the UKCS, compiled digitally from analysis of information displayed on BGS 1:250,000 scale paper maps across the UKCS, supplemented by expert interpretation.	Holmes *et al* (1993)
BGS Bedrock Geology	DiGROCK250 1:250k scale bedrock mapping of the UKCS.	Westhead *et al* (2013)
OSEA3 Hard substrates and non-rock hard substrates	Hard substrates and indicators of non-rock hard substrates – Multiple maps and supporting datasets.	Dove *et al* (in press)
OSEA 3 Geology and Surficial Processes	Characterization of coastal and seabed geology – Multiple maps and supporting datasets.	Dove *et al* (in press)

[8] Available on www.maremap.ac.uk and the BGS GeoIndex Offshore (http://mapapps2.bgs.ac.uk/geoindex_offshore/home.html)

ABPmer - Seabed Geological and Geomorphologial features	Compilation of previously mapped geological and geomorphological features.	ABPmer (2009)

In this study area, the predicted rock polygons were validated or deleted following the integrated review. In addition, polygons were added based on new interpretation of the data, as well as from previously published mapping, as detailed in Table 7. The primary reasons for deleting polygons were as follows:

- A number of small, irregular polygons were removed on the basis that they represented artefacts from the bathymetric data;
- Elevated features incorrectly predicted as rock are in fact sedimentary bedforms. These features include mobile sediment bedforms (e.g. sediment waves and banks) and glacial bedforms (e.g. moraines). Although these moraines may be considered a hard substrate, they are not included in this assessment due to lack of ground truthing data. Where glacial landforms comprise moulded bedrock, these have been validated.

As noted in other areas, the automated approach is less effective at discriminating rock pavements, relatively flat areas of bedrock present within the coastal zone. Updates to mapping in the coastal zones were therefore required, and largely carried out using higher resolution multibeam echosounder data.

The model was particularly effective at discriminating areas of rock at the surface and rock with thin sediment within the rock platforms around the Outer Hebrides, where the outcrop is relatively rugged in character (Figure 8). Within the deep-water areas, located on the outer continental shelf and adjacent continental slopes, large areas were incorrectly predicted as rock and were subsequently deleted during the knowledge-based review. This was largely due to the low resolution of the available bathymetry data and the areas of rock were predominantly artefacts within the bathymetry dataset.

As with the previous assessments (Diesing *et al* 2015; Downie *et al* 2016), the second category, ‘Rock with thin sediment’ was derived by subtracting the ‘Rock at outcrop’ and ‘Rock with thin sediment’ polygons generated by the prediction (following expert assessment) from the BGS DigHardSubstrate250 mapping, and this was combined with the re-assessed rock polygons above to derived the final output layer (Figure 9). As there was a significant amount of high quality bathymetry available from the CHP MCA surveys within this area, it was also possible to modify these polygons and add additional features in some areas, in order to improve their accuracy (Figure 10).

In addition to the rock outputs, a ‘changes’ shapefile was also generated in order to document the modifications to the modelled output. This will allow the same expert-driven modifications to be quickly applied to future reruns of the model.

4.3 Confidence assessment

The confidence assessment recorded results between zero and four (Figure 11). Polygons scoring zero values are largely in coastal areas and are therefore in areas not covered by remotely sensed data, with lower sample frequencies. Zero values were recorded for approximately 14% of the polygons.

Polygons based on model predictions scored between zero and four depending on sample and multibeam bathymetry coverage. Fewer than 1% of the polygons received a confidence score of four, with 45% achieving the intermediate values of two or three and the remaining 40% recording values of one.

This is partially accounted for by the large number of polygons derived from the BGS DigHardSubstrate250 layer and classified as ‘rock with thin sediment’, which received lower confidence scores as a value of zero was assigned to the remote sensing data that underpinned the original analysis (Gafeira *et al* 2010).

4.4 Project outputs

The outputs of this work are available under the Open Government Licence and are available to download in Shapefile format as an annex to this report:

C20171116_RockMapping_IrishSeaWScotland (ZIP file, 43.1mb).

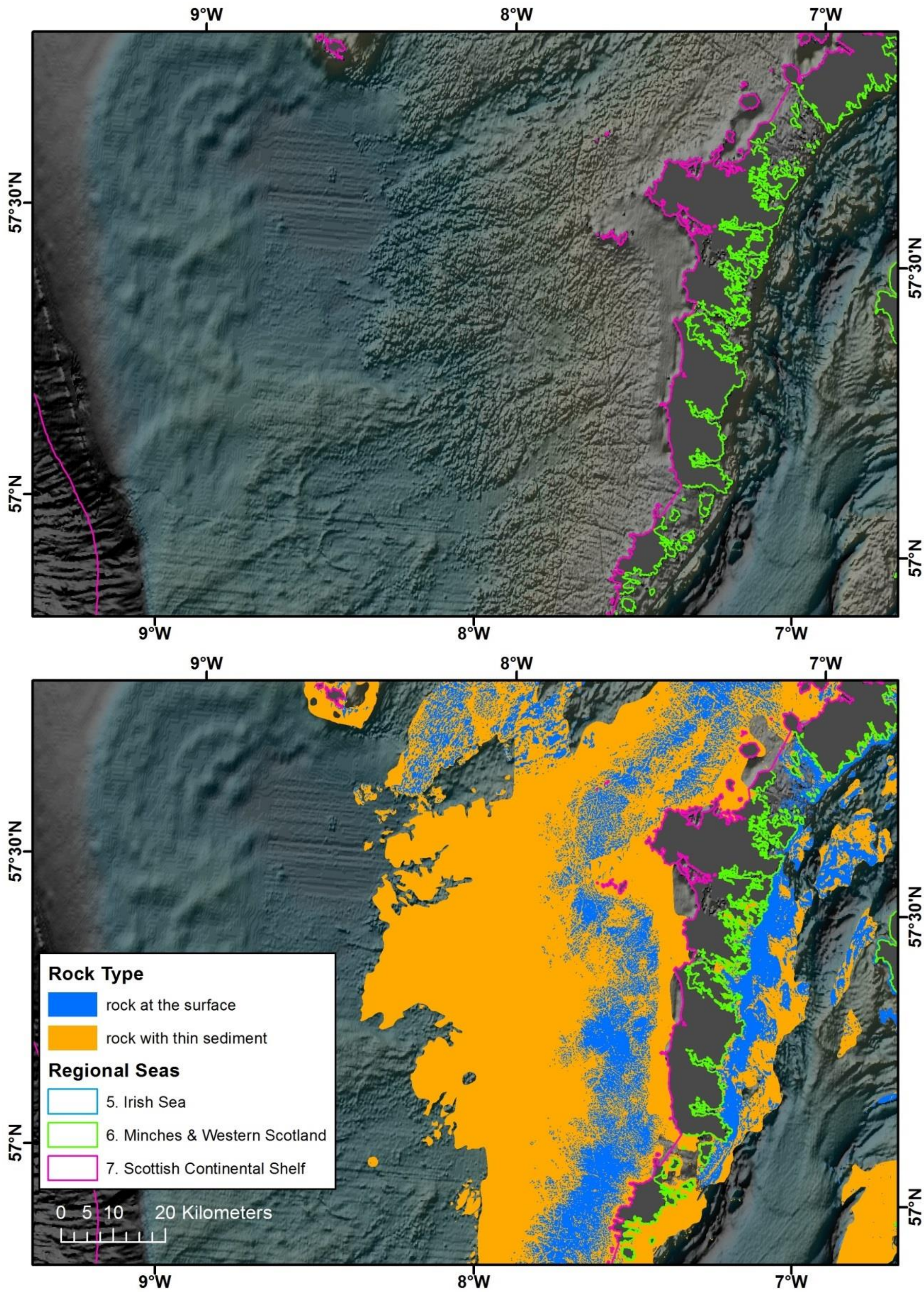

Figure 8. Example of the accurate prediction of 'rock at the surface' and 'rock with thin sediment' for an area west of the Outer Hebrides. General bathymetry from EMODnet Digital Terrain Model for European Seas (www.emodnet-bathymetry.eu).

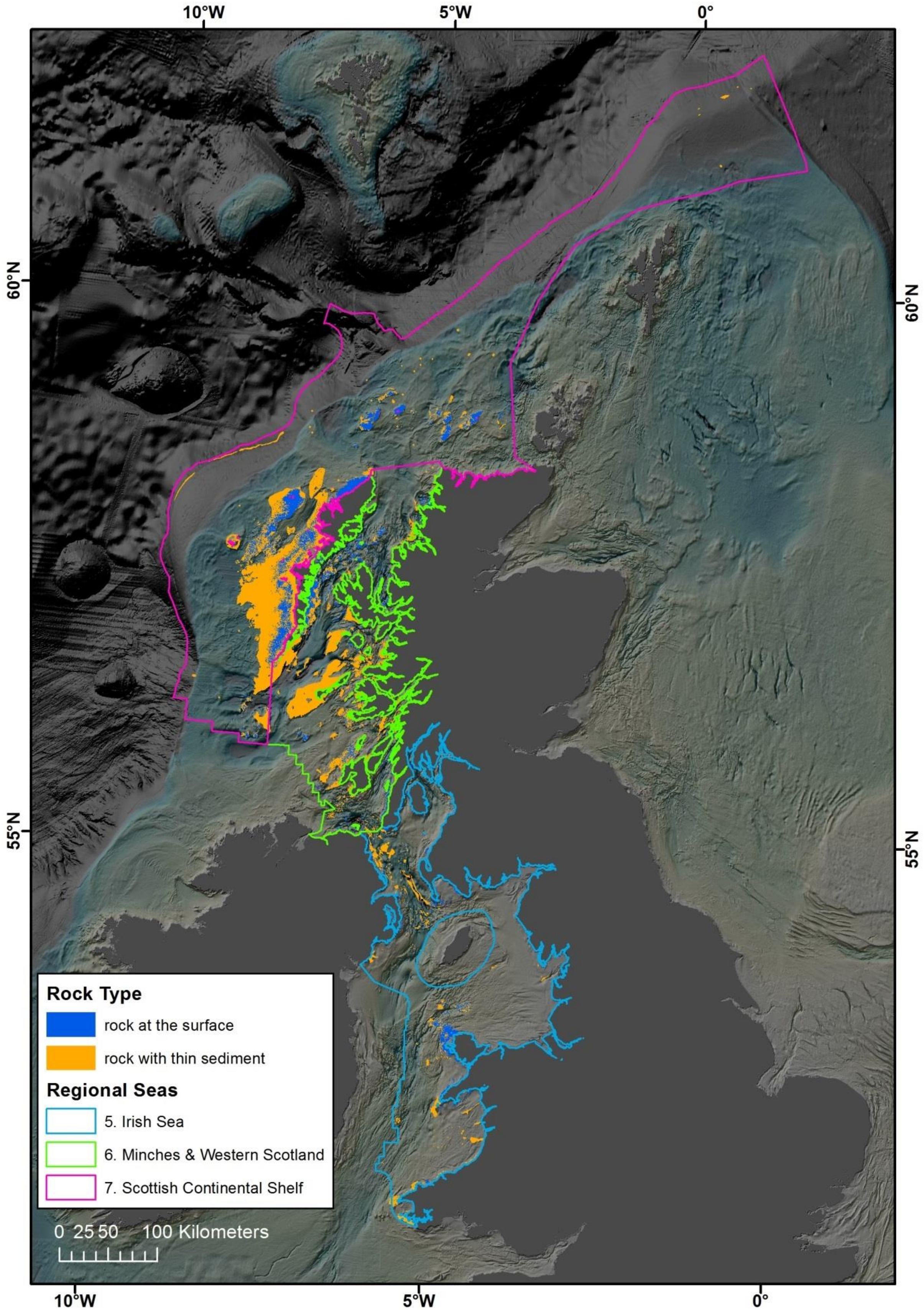

Figure 9. Distribution of rock at the seabed surface and rock covered with thin sediment (<0.5m) within the study area. General bathymetry from EMODnet Digital Terrain Model for European Seas (*www.emodnet-bathymetry.eu*).

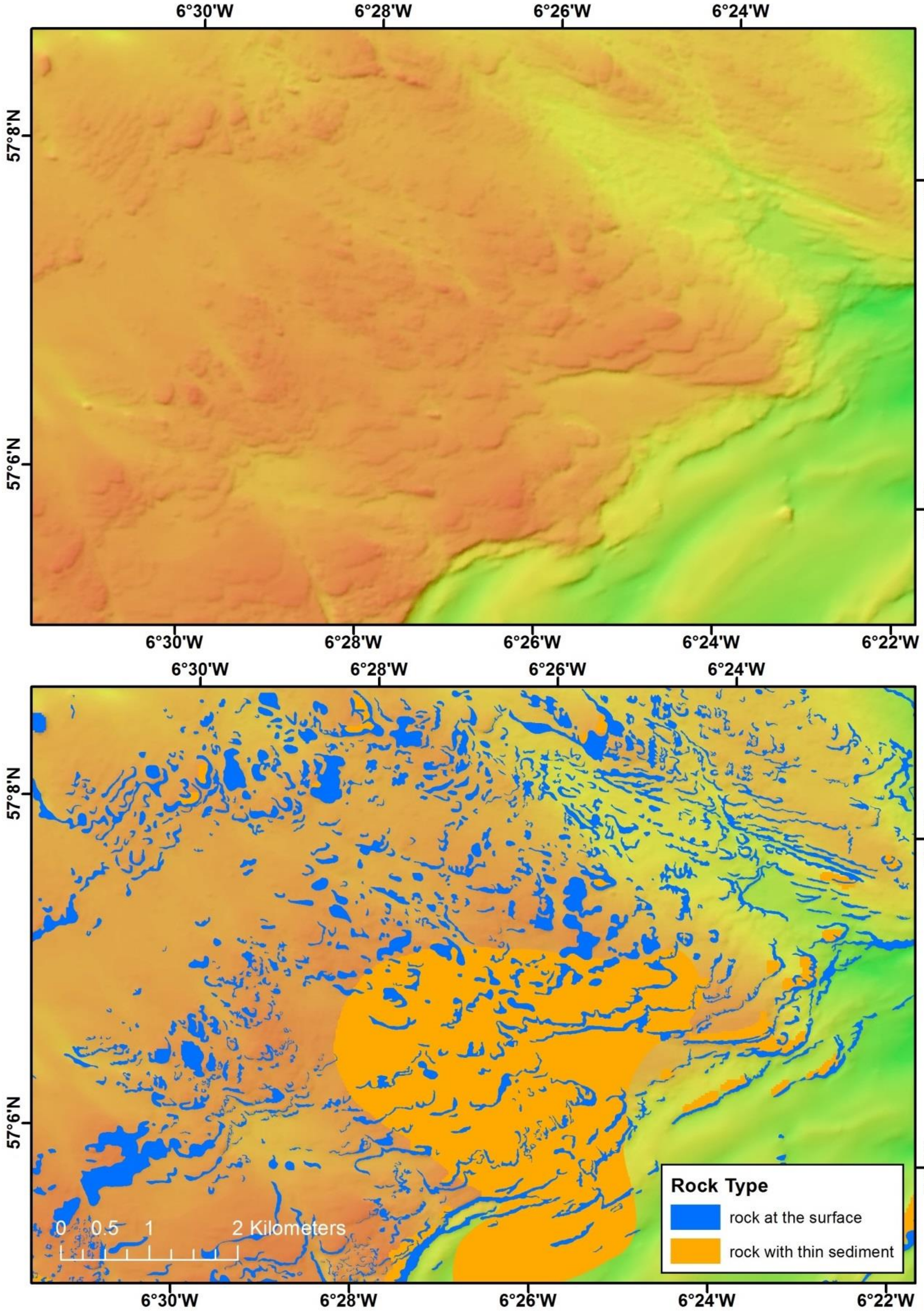

Figure 10. Example where additional 'Rock at the surface' features were added based on BGS sea-bed sediment 1:50 000 mapping using CHP MCA multibeam echosounder data. Bathymetry from Marine and Coastguard Agency (MCA) multibeam echosounder data acquired as part of the MCA Civil Hydrography Programme © Crown Copyright

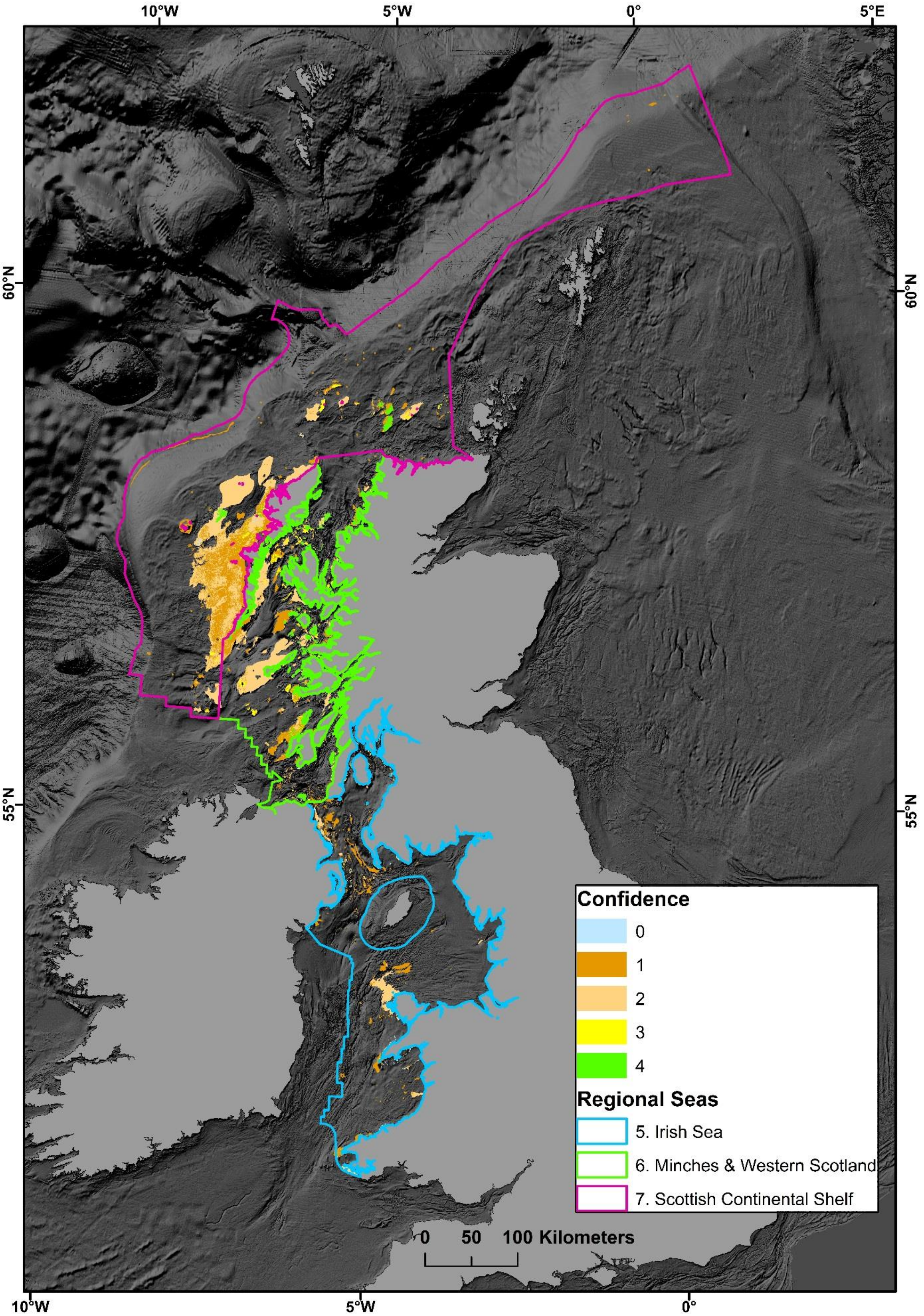

Figure 11. Confidence assessment of the updated map output. Values between zero and four where four indicates maximum confidence.

5 Discussion

This study has derived a new data layer of rock in 5, 6 and 7 (Irish Sea, Minches and Western Scotland and Scottish Continental Shelf), representing the third phase of roll-out of the method developed by Diesing *et al* (2015). The derived data layer has a nominal scale of 1:250,000 and as such gives a sufficiently detailed indication of the distribution of rock at or near the seabed at a regional scale. Whilst the data layer was derived by using the best-available data sources and methods, it should be noted that the derived results are unlikely to be sufficient for detailed monitoring of change in reef extent, due to the inherent and unavoidable inaccuracies in data and methods.

We have demonstrated how automated approaches to seabed mapping and in-depth geological knowledge can be combined to derive an improved representation of bedrock at and near the sea bed, this means that the applied method could be described as semi-automated.

With incomplete knowledge and data, the best option to derive meaningful predictions is a combined approach as demonstrated in this report. It is noteworthy that we have made an effort to include as much knowledge as possible at the automated prediction stage by including predictor variables that are known or expected to influence the presence of rock at the seabed. Likewise, it should be noted that tools like variable importance plots are useful in understanding which variables are suitable predictors. In this area BGS hard substrate and Distance to shore were among the three most important features, along with terrain features (e.g. BPI). This differs from previous regions, indicating heterogeneity between study areas.

The insights gained from the variable importance plot and the manual reclassification of seemingly misclassified objects could be fed back to the automated classification stage and it could be expected that such an iterative process will improve automated prediction results and reduce the amount of expert intervention required. Future work could therefore focus on improving existing features and finding new one that lead to improved predictions. Such an iterative approach could be repeated until no further improvements in classification accuracy are achieved. Additionally, new or improved data become available over time (e.g. improvements to the Defra DEM reflecting new hydrographic survey data). It would therefore be desirable to regularly update the predictions in order to reflect improvements in data, methods and knowledge. The general method that was set up as part of the project lends itself to such a task as processes of automated prediction and knowledge-based enhancements have been formalised.

The shapefiles produced by this approach represent a significant update to our previous understanding of the distribution of rock at, or near the seabed CP2 regions 5, 6 and 7 (Irish Sea, Minches and Western Scotland and Scottish Continental Shelf). Combined with the two previous study areas (Diesing *et al* 2015; Downie *et al* 2016), mapping produced using this semi-automated approach now covers the entire UKCS (Figure 12). This mapping can be used to inform a significant update to the BGS map series and also contribute to updates on a regional scale, for example, EUSeaMap and EMODnet outputs.

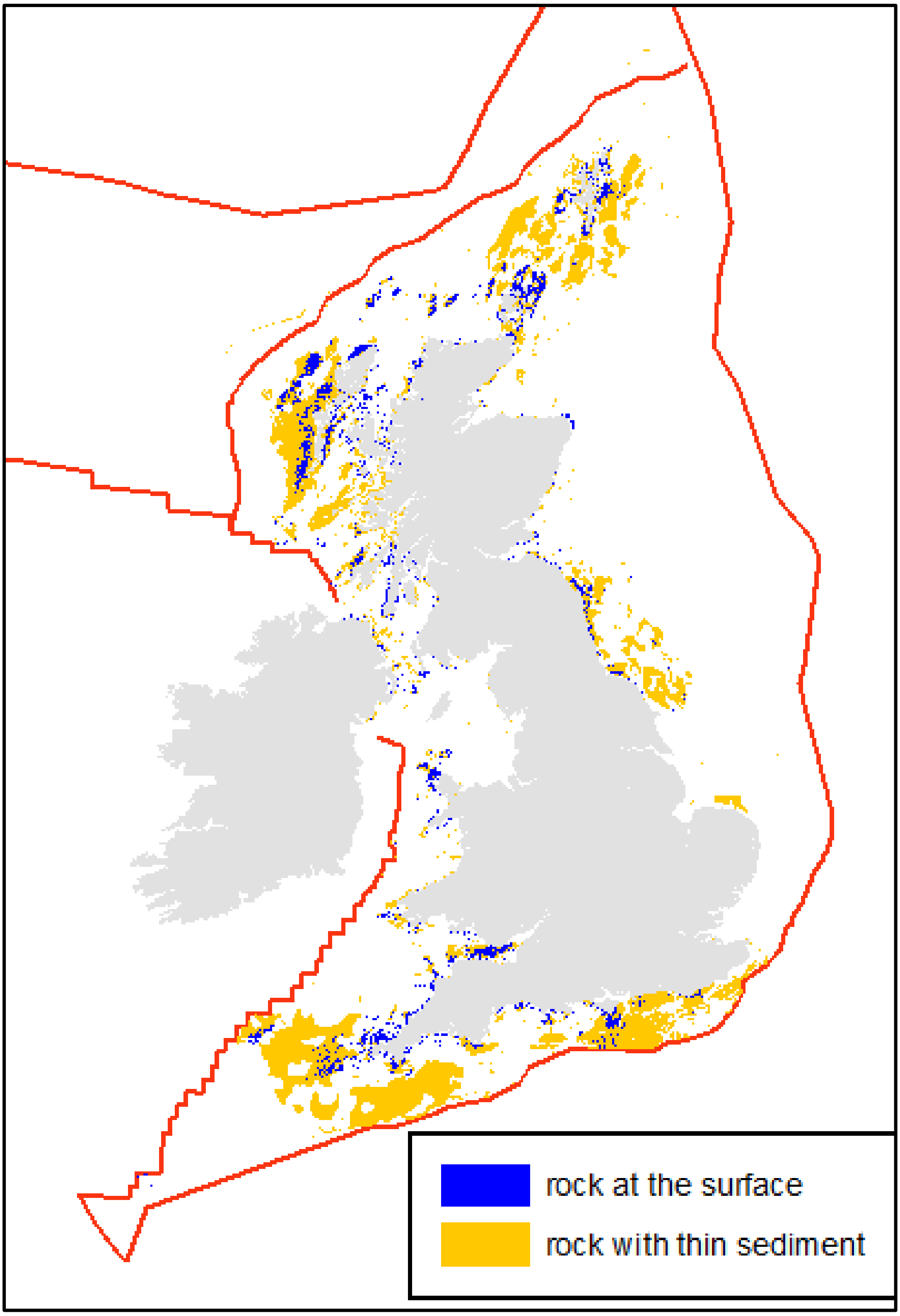

Figure 12. The combined outputs of this study, Diesing *et al* (2015) and Downie *et al* (2016).

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