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Predictive GAM seabed maps can account for defined and fuzzy boundaries to improve accuracy in a scottish sea loch seascape

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ABSTRACT

Marine seabed mapping is an important element in marine spatial and conservation planning. Recent large scale mapping programmes have greatly increased our knowledge of the seafloor, yet at finer resolutions, large gaps remain. Loch Eriboll, Scotland, is an area of conservation interest with a diverse marine environment supporting habitats and species of conservation importance. Here we test and present strategies for a predictive seabed substrata map for Loch Eriboll using drop down Stereo Baited Remote Underwater Video (SBRUV) imagery collected as part of systematic underwater survey of the Loch. A total of 216 SBRUV deployments were made across the study site in depths of 3 m–117 m, with six seabed classes identified using an adaptation of the EUNIS (European Nature Information System) hierarchical habitat classification scheme. Four statistical learning approaches were tested, we found, Generalised Additive Models (GAMs) provided the optimal balance between over- and underfitted predictions. We demonstrate the creation of a predictive substratum habitat map covering 63 km^2 of seabed which predicts the probability of presence and relative proportion of substratum types. Our method enables naturally occurring edges between habitat patches to be described well, increasing the accuracy of mapping habitat boundaries when compared to categorical approaches. The predictions allow for both defined boundaries such as those between sand and rock and fuzzy boundaries seen among fine mixed sediments to exist in the same model structure. We demonstrate that SBRUV imagery can be used to generate cost effective, fine scale predictive substrata maps that can inform marine planning. The modelling procedure presented has the potential for a wide adoption by marine stakeholders and could be used to establish baselines for long term monitoring of benthic habitats and further research such as animal distribution and movement work which require detailed benthic maps.

1. Introduction

Global targets of protected area coverage for the ocean have increased following concerns that environmental benefits needed to meet objectives under the UN Sustainable Development Goals (SDGs) will not be delivered (O'Leary et al., 2016; Woodley et al., 2019). A minimum of 30% of the global ocean under effective protection by 2030 has been recommended under the Kunming-Montreal Post-2020 Global Biodiversity Framework (GBF) (CBD, 2022), even though the previous global target of protecting 10% of the ocean by 2020 (Aichi Target 11), was not met. Effective marine conservation planning to protect a representative suite of habitats and species requires sufficiently detailed and accurate seabed substratum and habitat maps (Diesing et al., 2014; Boswarva et al., 2018; Ware and Downie, 2020). A recent resurgence in the recognition of the importance of seafloor mapping, and subsequent launches of mapping initiatives, are providing much needed reliable bathymetric data to inform marine conservation and management (Wölfl et al., 2019). Currently, nearly 25% of the global ocean seafloor has been mapped with bathymetric data following the Nippon Foundation-GEBCO Seabed 2030 Project challenge to survey 100% of the ocean floor by 2030 (Mayer et al., 2018). In Europe, the European Marine Observation and Data Network (EMODNet) Seabed Habitats project has delivered a predictive seabed habitat map (EUSeaMap, 2021) with the 2019 iteration covering 87% of European sea regions

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(Vasquez et al., 2019). At its highest resolution, the EUSeaMap is a grid of approximately 4 km^2 squares. While such mapping programmes have greatly increased the amount of seafloor data available, higher resolution seabed maps are needed at local spatial scales to better support assessments of the status of the seabed, and to inform conservation and management (Diesing et al., 2014).

Systematic approaches to Marine Protected Area (MPA) designation, the monitoring and assessment of seabed impacts and the improvement our knowledge of seascape ecology, are reliant on accurate seabed substrate maps that aid identification of associated benthic habitats (Boswarva et al., 2018; Ware and Downie, 2020). To ensure consistency and comparisons across mapping initiatives, there also needs to be a common method of seabed habitat classification (Galparsoro et al., 2012; Boswarva et al., 2018). The EUNIS (European Nature Information System) hierarchical habitat classification system is the common framework across Europe that aims to improve consistency in habitat classification of terrestrial, freshwater and marine environments (Galparsoro et al., 2012; Boswarva et al., 2018; Ware and Downie, 2020). Many of the broad scale seabed habitats that underpin the UK MPA network are derived from EUNIS habitat classifications (Jones, 2012; Cunningham et al., 2015). However, recent assessments suggest that these high-level categories may not fully represent the suite of marine habitats and species present in UK waters (Cooper et al., 2019; Ware and Downie, 2020). Commonly occurring habitats and species may be over-represented within the UK MPA network, whereas those that occur less frequently or are not captured within the broad EUNIS classifications, for example, biogenic reefs formed by the polychaete *Lanice conchilega*, may be underrepresented and therefore under protected (Ware and Downie, 2020). Higher resolution data could allow the development of more meaningful habitat classification and mapping of underlying seabed substrata to better guide MPA designation, and improve monitoring by allowing habitat fragmentation and changes in the coverage of protected features to be detected.

Seafloor geology and topography, influences benthic community structure and ecological processes (Micallef et al., 2012; Boswarva et al., 2018). Topographic features shape seabed habitat diversity at multiple scales by influencing sediment type, hydrodynamic exposure and sedimentation rates (Danovaro et al., 2014; Mestdagh et al., 2020). Seabed habitat is also influenced by dynamic processes in the water column such as currents, chemical and biological patchiness, and stratification which effect benthic-pelagic coupling (Kavanaugh et al., 2016; O'Leary and Roberts, 2018). Therefore, developing high resolution seafloor habitat maps can enable us to study ecological relationships between seabed spatial environmental patterns, associated biological communities and ecological processes (Boswarva et al., 2018; Swanborn et al., 2022).

Traditional methods of collecting data to inform seabed mapping include: sediment grabs, scientific trawls and underwater video or photographic imagery. Acoustic methods, such as Multibeam Echo Sounders (MBES) in combination with ground truth sampling (seabed imagery and sediment grabs) have been increasingly employed in recent years for large scale seafloor mapping (Boswarva et al., 2018; Mestdagh et al., 2020). MBES backscatter is a valuable tool for providing information on the sea floor hardness and surficial sediment characteristics, where stronger backscatter signals indicate hard, consolidated substrates such as bedrock, boulder and cobble, and weak signals represent soft, muddy substrates (Lurton et al., 2015; Proudfoot et al., 2020). Acoustic techniques are largely appropriate for seabed substrata that are readily discernible from the resultant data (e.g. upstanding rock reef) but are limited in reliably mapping seabed types where the acoustic signature may overlap (e.g. coarse and mixed sediments) (Micallef et al., 2012; Ware and Downie, 2020). Seabed imagery (photographic/video) is therefore widely used to ground truth acoustic methods, but can also be used effectively as a primary source of data for seafloor maps (Hughes, 2014).

Spatial predictive mapping and distribution modelling approaches are increasingly applied in the marine environment to model and map habitats, species and biological assemblages across a seascape (Swanborn et al., 2022). These approaches can provide continuous probability and abundance data for features of interest to produce large spatial coverage maps of marine environments (Boswarva et al., 2018). Most distribution models and predicted maps are correlative and develop environmental relationships from survey data and are constructed using interpolative approaches such as kriging, statistical methods and machine learning. Beyond providing predicted maps, these modelling approaches can provide insight to the causal biological processes governing distributions and abundances (Burns et al., 2019). Predicted seabed maps, built from environmental point data offer a solution to rapidly generate cost effective maps over wide areas but must address challenges of robust ground-truthing and use of relevant and reliable spatial predictor data (Boswarva et al., 2018). Robust predicted seabed maps can provide useful variables, either as continuous probabilities of presence or categories to develop species distribution models for benthic and demersal species. Predicted seabed maps also offer an opportunity to study the effects of adjacent unsampled seabed types and local patch configuration on the distribution of species allowing seascape metrics to be more easily incorporated in distribution models (Swanbornet al. 2022).

Here, we apply these techniques to Loch Eriboll, on the North coast of Scotland (Fig. 1). The whole of Loch Eriboll is recognised as a non-statutory Marine Conservation Area (MCA) identifying the marine environment, bird and seal colonies as of particular conservation interest. Three Sites of Special Scientific Interest (SSSIs) have been designated in the immediate vicinity of the loch, for geological and botanical interests, while the island of Eilean Hoan in the outer loch is designated as an SSSI for breeding great black-backed gulls (*Larus marinus*) and non-breeding Greenland barnacle geese (*Branta leucopsis*) (Nature Scot, 2021). A recent review of historical data has also highlighted the likely presence of a number of Scottish Priority Marine

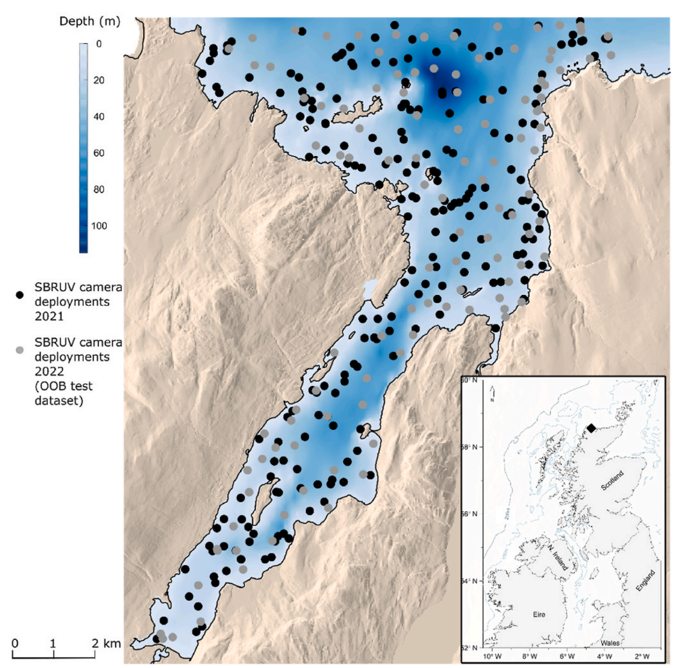

Fig. 1. Stereo Baited Remote Underwater Video (SBRUV) drop camera sample location map of the Loch Eriboll study area (British National Grid ESPG:27700 projection, hillshade illumination: azimuth = 100°, elevation = 55°). Black circles show the location of SBRUV camera deployments used to fit the models (In-Bag data) from 2021. Grey circles show the location of 2022 SBRUV camera deployments used to assess model predictive ability (Out-Of-Bag data). Inset: black diamond shows the location of Loch Eriboll on the North Coast of Scotland, United Kingdom. Contains OS data Crown copyright and database right 2020 and the GEBCO_2019 Grid, www.gebco.net.

Features (PMFs), species and habitats considered to be of marine nature conservation importance (Burns et al., 2020b). The remote nature of Loch Eriboll means it is particularly sparsely populated with limited human development. There are currently two active fin fish farms, a small scale fishery creeling for lobsters and crabs (Harries et al., 2018), and the loch is also used for military training exercises (Harries et al., 2018). The seaward, mouth of the loch is fished by mobile fishing gears which include otter trawls and dredges for scallops and mussels (International Council for the Exploration of the Sea (ICES), 2021a, 2021b) . The variety of substrata, exposed and sheltered shores, bathymetry, and salinity regimes make Loch Eriboll a potential area of high habitat and species diversity (Burns et al., 2020b).

2. Materials and methods

2.1. Study site

Loch Eriboll, on the north coast of Scotland (Fig. 1 - inset) is a sea loch which lies on the major fault line of the Moine Thrust. The bedrock of Loch Eriboll includes Durness limestone, Basal Quartzite and Pipe Rock, and Lewisian Gneiss (Searle et al., 2019) with this varied geology supporting a mosaic of marine habitats. The outer loch area is exposed to north and north-westerly winds and swell. Tidal motion from the middle to the head of the loch is generally between 0.5 knots to 1 knot (UK Hydrographic Office, 2017). The mean depth of the loch is 23.7 m (±21.0 s.d.). Maximum depths of 63 m are present in the inner loch and one deep basin at the outer loch descends to 117 m northeast of the island Eilean Hoan (Fig. 1).

2.2. Data collection

Drop down Stereo Baited Underwater Video (SBRUV) cameras were used to collect seabed imagery data. A depth stratified random sampling approach was used to select deployment locations. A total of 216 deployments were made across the study site in 2021. A set of 114 SBRUV deployments were collected as a true Out-Of-Bag (OOB) sample test set during the 2022 field season and used to assess the predictive accuracy of the models. SBRUVs were deployed from a small day boat during daylight hours. During each SBRUV deployment, the SBRUV was attached to a surface marker buoy and left on the seabed for a minimum of 50 min. GPS locations for each deployment were recorded. Video images (MP4 format) were captured using two GoPro Hero 9 cameras at 1080p resolution, mounted in underwater housings on each SBRUV frame, illuminated by underwater torches attached to the frame. The use of stereo camera systems allowed for back up footage to be captured on an overlapping area of seabed in the event of one camera failing or being obscured. Additionally, the collection of this large video dataset, in which biological habitat, benthic communities, and individual species can also be observed and analysed, promotes the ethos of “Collect once and use many times” (Boswarva et al., 2018).

2.3. Video processing and seabed identification

Still images were extracted from the video recordings to classify substrata and undertake substratum prediction modelling. To classify substratum type, each video clip was watched by two observers who identified all substratum types visible in the field of view. The left camera footage was always viewed when available. If the left camera was obscured footage from the right camera was viewed. Once collated, the results from both observers were compared. If recorded substrata differed between observers, the video clip was re-watched by both observers and an agreement reached to classify the substratum. Seabed classes were categorised by substratum type broadly equivalent to EUNIS level 2 (2022; Table 1). The seabed classes used in the present study were rock, cobble and boulder, gravel, sand, muddy sand and mud.

2.4. Predictive modelling

Four possible prediction methods were trialled including spatial interpolation using Ordinary Kriging (OK), machine learning using Random Forest (RF) and, statistical approaches using Generalised Linear Models (GLMs) and Generalised Additive Models (GAMs). To account for spatial autocorrelation, some studies advocate combining OK with RF, GLM and GA by kriging model residuals (e.g. Guo et al., 2015; Wu and Li, 2013). However, using residuals from one model as data in another model is ill-advised given that residuals are variables with unobserved values and, by using them as data we ignore uncertainty (Freckelton, 2002; McElreath, 2020). Therefore, to account for spatial autocorrelation we opted instead to include spatial covariates (latitude and longitude) directly in the RF models, GLMs and GAMs. The explanatory variables included in the OK, RF models and GAMs were latitude, longitude and depth. Depth and latitude only were included in the GLM to avoid co-variance between latitude and longitude. This was negated in the GAM by using a two-dimensional tensor product. Depth was fitted in the GAM with a thin plate regression spline. GLMs and GAMs were fitted as binomial models with logit links.

The OK models contained the same set of predictor variables as GLMs and GAMs. Each substratum category (mud, sandy mud, sand, gravel, cobble-boulder and rock) was modelled independently, with one probability of presence model, of each type (OK, RF, GLM and GAM) fitted for each substratum category. While RF models may be fitted as either classifiers or as binomial regressions, we opt here to use a classifier approach as the most likely approach to be adopted by users of RF. We therefore fitted the RF models with presence absence of the substratum defined as a categorical variable. All other models were fitted to binomial presence absence data. Five-fold Cross-Validation (CV) was used to compare the four model types. Random samples were used to generate the five folds in 100 iterations of the CV. The mean combined Root-Mean-Square Error (RMSE, eq. (1)) and standard deviation were used to evaluate model prediction accuracy for the four model types across all six substrata.

Table 1
EUNIS Criteria for defining benthic habitats at level 2. EUNIS Marine Habitat Classification (2022).

Zone		Substrate					
		Hard/firm		Soft			
		Rock[a]	Biogenic habitat[b]	Coarse	Mixed	Sand	Mud
Phytal gradient/hydrodynamic gradient	Littoral	MA1	MA2	MA3	MA4	MA5	MA6
	Infralittoral	MB1	MB2	MB3	MB4	MB5	MB6
	Circalittoral	MC1	MC2	MC3	MC4	MC5	MC6
Aphytal/hydodynamic gradient	Offshore circalittoral	MD1	MD2	MD3	MD4	MD5	MD6
	Upper bathyal	ME1	ME2	ME3	ME4	ME5	ME6
	Lower bathyal	MF1	MF2	MF3	MF4	MF5	MF6
	Abyssal	MG1	MG2	MG3	MG4	MG5	MG6

[a] Includes soft rock, clays, artificial hard substrata.
[b] Biogenic habitat formed by plants or animals that modify the nature of the underlying substratum.

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad \text{eq.1}$$

The GAM, OK and RF model predictions were assessed using an OOB test dataset. The 114 OOB videos were processed and seabed type identified in the same way as the 2021 training/test data. These OOB data were presented to the models across all range of possible values of probabilities (p) of substrata presence (0.0–1.0). Accuracy was assessed by comparing the model prediction with the truth from the OOB test dataset at each value of p creating a range over which prediction accuracy varied. At high probabilities (p) the prediction covers a wider area and is more likely to generate both true and false positives. Therefore, p provides a measure of precision to judge accuracies against and, here we apply 1-p as a more intuitive measure of precision. The models were compared using the maximum mean (across all substrata) prediction accuracy and the Area Under the Curve (AUC).

3. Results

3.1. Substrata classification from video imagery

A total of six seabed classes were identified from the 216 SBRUV camera deployments in Loch Eriboll. The seabed classes were identified visually based on sediment characteristics. The classes broadly align to the EUNIS level 2 (i.e. broad habitat) within the hierarchical classification scheme: Rock, Cobble and Boulder, Gravel, Sand, Muddy Sand, Mud (Fig. 2). From the SBRUV deployment locations we identified finer, mud dominated sediments mostly located in the southerly, inner loch with some gravel, boulder and cobble also present. Muddy sand mixtures were also found stretching north in the deeper portions of the mouth of the loch. Sandy sediments were mostly located to the northern portion of the loch and predominantly to the northwest. Hard, rocky substrata were prevalent round the littoral fringes of the loch with cobble and boulder being found mostly on the eastern side at the loch mouth. Up to three substratum types were visible in a single image with habitats composed of combinations such as gravel, sand and rock (Fig. 3.).

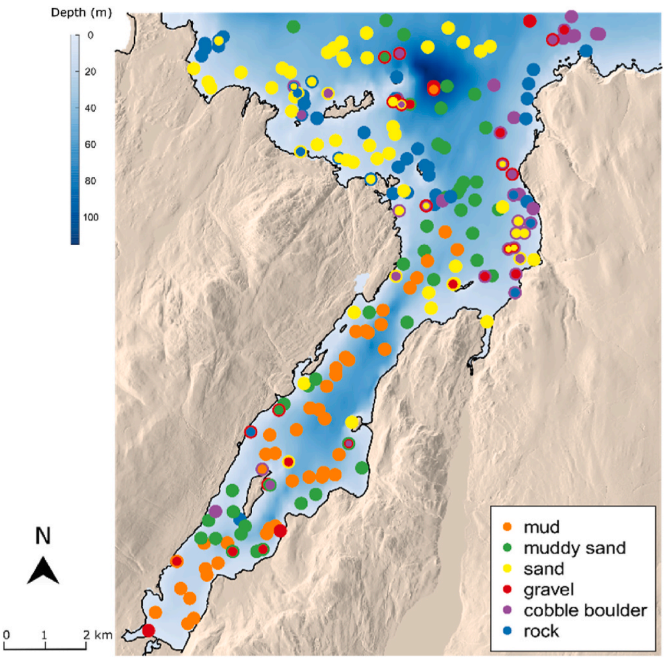

Fig. 3. Substratum category observed at each sample site from video collected in 2021. Coloured discs correspond to substrata classification(s) visible in the field of view of one stereo video camera. Where multiple substratum categories exist at one location up to three sizes of circles are used to indicate all substratum categories visible.

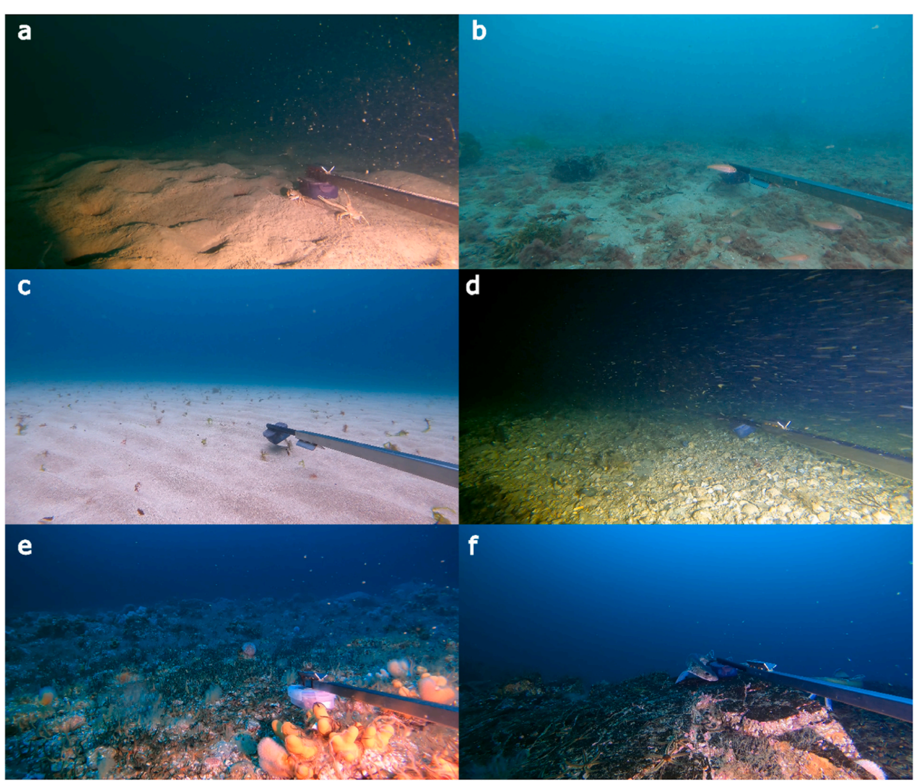

Fig. 2. Still images of example seabed classifications from video. Mud at sample station W62 (a), sandy mud at sample station W55 (b), sand at sample station W182 (c), gravel at samples station W173 (d), cobble-boulder at sample station W216 (e) and rock at sample station W193 (f).

3.2. Seabed model

The results from CV indicated the RF model had the lowest predictive error (Table 2). However, predicting on substratum as a categorical variable, as was the case with RF, presents an easier target for inference compared with the probability of presence reported by the other model types (i.e. only two categories rather than an infinite range of values). The RF model, therefore, shows inflated success compared with the other methods. The GLMs were the poorest performing models with reference to RMSE and were discounted from further consideration. While OK performed well for substratum types with high spatial autocorrelation such as mud (Supplementary material Figure S.1 a), unrealistic overfitted predictions were made for patchy substrata such as sand and gravel (Supplementary material f igure S1 c & d). This tendency for overfitting is evidenced by the poorer performance of both RF and OK when tested against the OOB test dataset (Table 2). Finally, after visualising the model predictions GAMs were considered the most appropriate balancing over- and underfitting to the available data. Predicted outputs from the OK and RF models are available in Supplementary.

The GAM captured the distribution of each substratum type well when compared to the presence-absence points (Fig. 4). From visual inspection of the GAM predictions the cobble-boulder category performed the poorest of the substrata categories (Fig. 4e). This is likely due to the way cobble-boulder was distributed in two distinct areas of the loch. To the east at the mouth of the loch the recorded presences of cobble-boulder were clustered. To the west and towards the head of the loch in the south, by contrast the distribution of cobble-boulder presence was patchier. Substrata which showed more uniform distribution, either clumped or spread more evenly, such as mud, muddy-sand and sand were better approximated by the GAM prediction (Fig. 4 a, b & c).

The GAM outputs presented here display continuous probability surfaces for each substratum with no defined boundary existing between two different habitat types. Here, we calculate the area coverage of each habitat type based on two cut-off probability values, ≥0.1 and ≥0.5 (Table 3). Probability values ≥ 0.1 represent all locations where there was any possibility of a particular substratum being present, often mixed with other substratum types. Values ≥ 0.5 were characteristic of locations where there was a high probability of finding that particular substratum. At the 0.1 probability cut-off mud covered the least area, while gravel substratum showed the largest area coverage. However, at ≥ 0.5 probability of the substrata being present gravel coverage was lowest and sand coverage is highest. These conflicting results are the result of adopting a probability of presence approach for each substratum. Substrata such as gravel, which were spread widely across the loch seabed and were commonly mixed with other substratum types tended not to be concentrated at one location. Therefore, the probability of presence was relatively high in all areas, but these substrata tended to be found mixed with other substratum types. Conversely, substrata showing little difference in area coverage at the two cut-off values, such as rock or mud were concentrated and localised in particular areas. Additionally, for rock and mud substrata little mixing with other seabed types was evident.

Combining the output predictions from the six substratum GAMs allows a detailed map of the relative position and arrangement of each substratum in the seascape to be generated (Fig. 5). Similar substratum types, such as cobble boulder and gravel commonly appear adjacent to each other in the modelled predictions as displayed to the northeast of the loch (Fig. 5). Similarly, finer sediments like mud, muddy sand and sand can be seen overlapping and adjacent in the southern portion of the loch. However, there are exceptions to this pattern particularly where rock (often exposed bedrock) and boulders are within and adjacent to patches of finer sediments such as mud and sand. Often these associations form district boundaries between habitat patches in contrast to the more overlapping and gradual transitions between substrata with similar grain sizes.

Table 2
Root-Mean-Square Error (RMSE) and Standard Deviation (SD) of Ordinary Kriging (OK), Random Forest (RF) Generalised Linear Model (GLM) and Generalised Additive Models (GAM) predictions. Mean and SD RMSE was calculated over 100 k-fold CV iterations of randomly sampled data splits across all six substrata of the 2021, In-Bag data. The Maximum mean accuracy and precision (1-probability of presence) was calculated using the OOB 2022, test dataset. The dashed line seliniates *RF was predicted as a categorical, presence absence so there was no range of probabilities AUC in this instance is a horizontal line with the same value as maximum mean accuracy. Similarly, precision was measured across the range of values.

	GLM	OK	RF	GAM
Mean RMSE (SD)	0.367 (0.063)	0.334 (0.059)	0.061 (0.051)	0.339 (0.087)
Maximum mean Accuracy (and precision)	–	0.585 (0.399)	0.593 (0–1*)	0.715 (0.97)
AUC	–	0.522	*	0.602

4. Discussion

Seabed imagery has been widely used in seabed mapping, both as a primary source of data and to ground truth other methods, for effective and non-destructive sampling of the seafloor (Hughes, 2014). Detailed, georeferenced in situ observations of the seafloor (e.g. substratum types and geology), the like of which can be provided by the use of Stereo Baited Remote Underwater Video (SBRUV)s, are extremely valuable (Swanborn et al., 2022). SBRUV systems have become more accessible in recent years and offer an efficient way to map areas at a resolution that is relevant to marine management or marine conservation applications. Here, we have combined high resolution seabed imagery from SBRUVs with predictive habitat mapping to generate a seabed map for Loch Eriboll, Scotland. The predictive habitat map identifies the presence of individual seabed substrata with high accuracy, correctly predicting over 70% of OOB test data at a high level of precision. The model accounts for both defined and undefined boundaries between substratum types and allows a full substratum, seabed map to be generated.

4.1. The predicted model of seabed substrata

Bedrock and rocky reef were clearly distinguishable from the seabed imagery collected in this study. Within the EUNIS marine habitat classification (2022), “Rock” is hard compact substrata that includes bedrock, boulders and cobbles (generally >64 mm in diameter). Here, we have used two separate categories: rock (bedrock) and boulder cobble as we are able to differentiate between them using video imagery. Sedimentary substrata are typically defined according to differences in the relative proportions of particle size fractions, usually derived from analysis of sediment samples from grab samples. Here, we were able to identify gravel, sand, muddy sand and mud as discrete sedimentary substrata.

The models developed in the current study output the probability of presence of each category of substrata. The model predictions can be used to define boundaries between different substratum types and compare the size and arrangement of these patches. A prominent difficulty in mapping soft-sediment, sand or gravel in benthic systems is that distinct boundaries are often uncommon and both gradual spatial gradients and ecotones exist in transitions between substratum types (Brown et al., 2011; Zajac et al., 2013). The fuzzy boundaries between substratum types that we describe acknowledge that seascapes are often characterised by transition zones rather than distinct boundaries (Lucieer and Lucieer, 2009; Lecours et al., 2015). The models described here can, not only define distinct boundaries, they are also capable of modelling overlap in substratum types and can better represent the “fuzzy,” ill-defined boundaries commonly seen in real world transitions between patches (Kågesten et al., 2019).

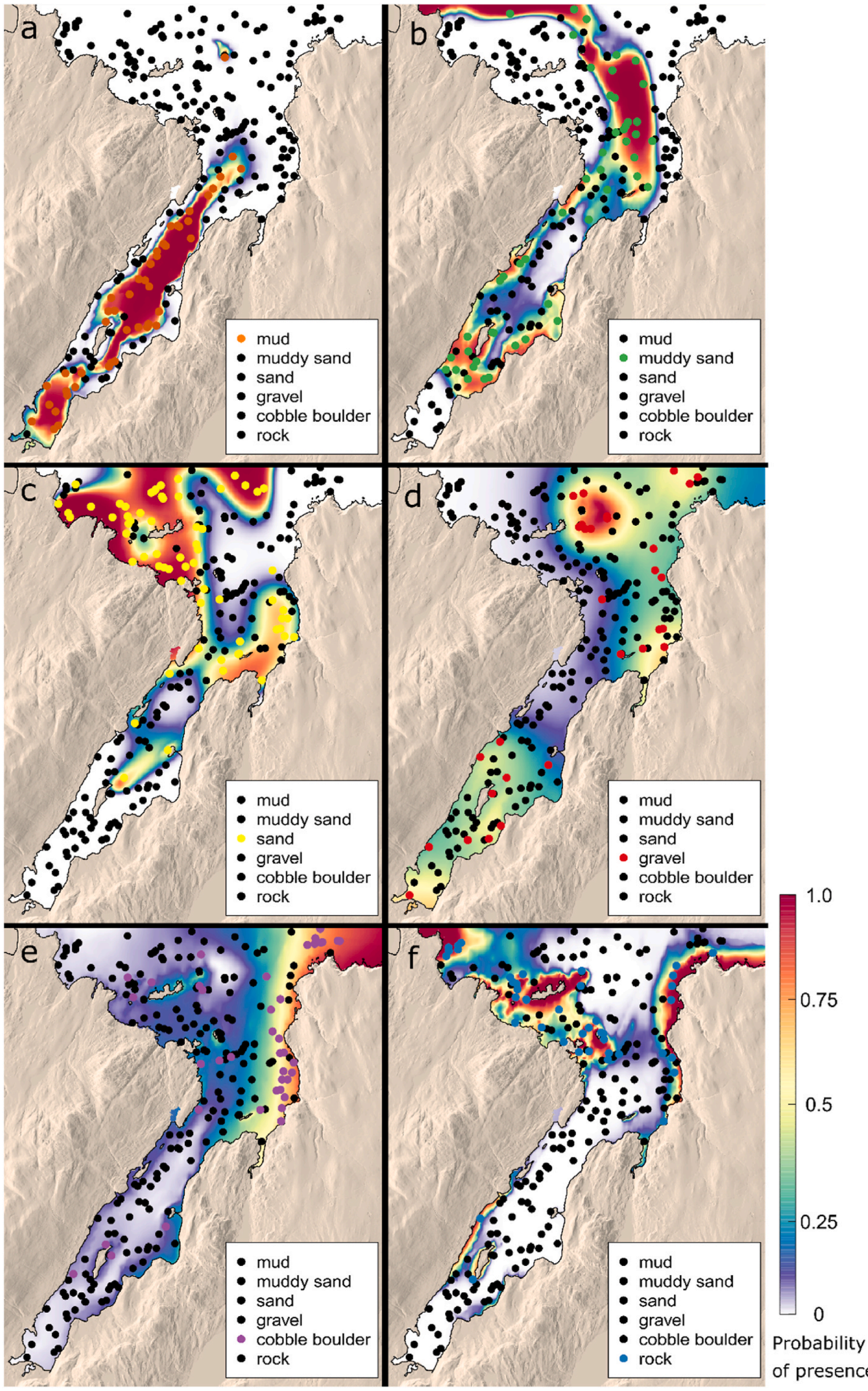

Fig. 4. Individual substratum GAM predictions display the probability of presence of each substratum category; mud (a), muddy sand (b), sand (c), gravel (d), cobble boulder (e) and rock (f). For each substrata coloured circles show detected presence from the In-Bag, 2021 stereo video camera footage Black circles show sample sites where the substratum type was not detected.

The continuous surface approach has been innovated in landscape ecology as an improvement on patch-based models and benefits seascapes in a similar way by applying continuously varying surfaces which do not require distinct patch boundaries (Wedding et al., 2011; Swanborn et al., 2022). Continuous surface models account for heterogenous within- and between-patch complexity and avoid arbitrary categorisations and the inflated accuracy common among classification approaches with small numbers of categories (McGarigal and Cushman, 2005; McGarigal et al., 2009; Burns et al., 2020a). Our use of readily available high-quality camera systems and the ability of our models to properly represent these different boundaries has enabled the creation of realistic detailed substrata maps. Our method recognises that ecological processes often operate at gradual, multiscale variations in spatial heterogeneity. Creating these maps is an important step forward in developing subsequent habitat models required for adopting a seascape approach to fisheries management (e.g. understanding essential fish habitat) and wider conservation applications.

Table 3
Substrata area coverage in Loch Eriboll. Areas in km^2 of each substratum calculated on $\geq$ 0.1 and $\geq$0.5 probability of presence derived from the GAMs. The relationship between the substrata categories defined in this paper and EUNIS habitat Level 2 codes (2022) are also displayed.

Substrata type	Prob. $\geq$ 0.1		Prob. $\geq$ 0.5		EUNIS Habitat description/category	
	Area (km^2)	Proportion of study area	Area (km^2)	Proportion of study area		
Mud	14.15	0.224	10.61	0.168	MB6	Infralittoral mud
					MC6	Circalittoral mud
					MD6	Offshore circalittoral mud
Muddy-sand	29.14	0.462	14.48	0.230	MB6	Infralittoral mud
					MB4	Infralittoral mixed sediment
					MC6	Circalittoral mud
					MC4	Circalittoral mixed sediment
					MD6	Offshore circalittoral mud
					MD4	Offshore circalittoral mixed sediment
Sand	34.99	0.555	17.84	0.283	MB5	Infralittoral sand
					MC5	Circalittoral sand
					MD5	Offshore circalittoral sand
Gravel	36.20	0.574	0.22	0.003	MB3	Infralittoral coarse sediment
					MB4	Infralittoral mixed sediment
					MC3	Circalittoral coarse sediment
					MC4	Circalittoral mixed sediment
					MD3	Offshore circalittoral coarse sediment
Cobble-boulder	34.10	0.541	8.47	0.134	MB1	Infralittoral rock
					MC1	Circalittoral rock
					MD1	Offshore circalittoral rock
Rock	22.49	0.357	12.92	0.205	MB1	Infralittoral rock
					MC1	Circalittoral rock
					MD1	Offshore circalittoral

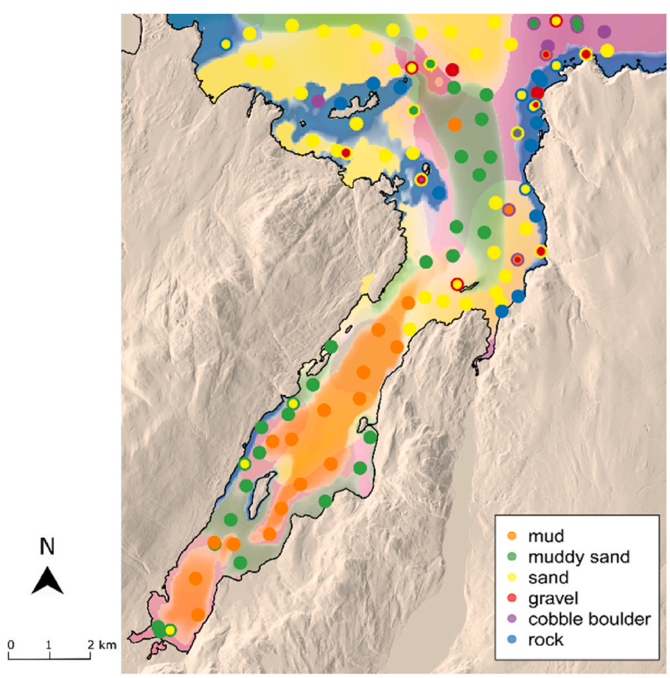

Fig. 5. Loch Eriboll seascape. Combined GAM predictions for the probability of presence of each of the six substratum categories overlayed to display the mosaic of substratum habitat patches. Thresholds for the six substrata displayed here defined to contain 90% of the probability density for each substratum. Coloured discs correspond to substrata classification(s) from the 2022 OOB data. Where multiple substratum categories exist at one location up to four sizes of circles are used to indicate all substratum categories visible.

4.2. *Habitat classification from seabed substrata*

The predictions from the substrata models developed here would be expected to support the habitats, biological communities and species reported by (Burns et al., 2020b). In our present study we have been able to clearly identify rock as a substratum, and rock reefs have been recognised as an important substrate providing a foundation on which many biological habitats are based (Ware and Downie, 2020). Sedimentary substrata also support a range of biological habitats. However, at the level of the EUNIS categories, sedimentary substrata are likely to have overlapping ranges or are present on a continuum (e.g. boulders/cobble with some gravel, to gravel with some cobbles) (Ware and Downie, 2020) as we have demonstrated here. Biological communities, habitats and species composition can therefore also subtly change along this gradient, making specific habitat classification difficult (Brown and Collier, 2008).

There is increasing evidence that benthic communities do not always conform to the hierarchical structure of the EUNIS marine habitat classification (Galparsoro et al., 2012). This is evident in rocky substrata, where the benthic community can include species that are characteristic of both rock and sediment habitats, and might not match well to the current biotope descriptions (Galparsoro et al., 2012). Differentiating between closely related sediments (e.g. EUNIS classifications MC3 Circalittoral coarse sediment and mixed sediments) using acoustic methods is challenging due to overlapping acoustic signatures (Ware and Downie, 2020). Video methods also have a limited power to discriminate habitat based on certain fine scale sediment characteristics, for example, it can be difficult to distinguish particle grain size or infauna community structure from video imagery. Yet, some studies have shown that quantifying finer scale differences, which can be provided by grab-sampling methods, can sometimes confuse broader scale habitat patterns (Brown and Collier, 2008; Cooper et al., 2019). A potential implication for habitat mapping from seabed substrata is that certain areas may need to be classified as sediment mosaics, where there are varying proportions of individual component sediment types (Ware and Downie, 2020). While biologically more accurate, this may present uncertainty in the context of MPA designation, monitoring and management. Management of sediment mosaics could be complex where the component sediments differ in their sensitivity to a specified activity (Ware and Downie, 2020). Advocates for whole site management would argue that implementing management measures based on the assumption of discrete "feature" boundaries, therefore, is unrealistic. Overall, it is recommended that even with the updated EUNIS habitat classifications for 2022, increased flexibility in classifications and innovative seabed mapping and monitoring technologies are needed to reflect gradients more accurately in habitat and seabed substrata (Ware and Downie, 2020).

4.3. Applications of a seabed map

Seabed maps that visually represent the arrangement and proportions of different substrata patches are a crucial tool in seascape ecology, enabling us to quantify seascape structure at multiple scales (Swanborn et al., 2022). Predictive habitat maps, as we have demonstrated here, can account for heterogeneity with multiple, potentially mixed substrata and poorly defined patch boundaries. This patchiness and gradient in substrate characteristics, or seascape structure, influences the distribution of species and habitats, and ecological processes (Bell and Furman, 2017). However, knowledge gaps remain about the effects of patch size, spacing and substrata composition influences on animal abundance, distribution and movements, and, in particular how small scale effects influence population and demographic range shifts. (Kaiser and Barnes, 2008; Burns et al., 2019; Pittman et al., 2021; Swanborn et al., 2022). Building a more accurate picture of the seafloor, at spatial scales relevant to movement patterns of individual species, will allow us to address some of these knowledge gaps and identify optimally connected seascapes (Pittman et al., 2011).

Adopting a seascape approach to management and conservation is increasingly recognised as important, yet practical implementation of seascape approaches has been slow (Pittman et al., 2021). The need to protect connected heterogeneous seascapes, rather than single isolated patches has been highlighted in recent studies (see Elliott et al., 2017; Rees et al., 2020). Creating seafloor maps can aid in defining where particular habitats exist, and help identify the mosaic of habitat patches that is likely to be important for species of conservation importance, such as those to be included in MPAs (Boswarva et al., 2018; Vassallo et al., 2018). Using seabed imagery to build habitat maps also provides us with a clear baseline against which future images can be compared for monitoring seafloor impacts (Boswarva et al., 2018). Having this clear baseline of benthic habitat status, we will be able to assess concepts such as "seafloor integrity", increasing our understanding of the spatial connectedness of habitats, and the degree to which connectedness aids resilience to perturbations.

5. Conclusion

The models we present here will support developing a seascape understanding of the Loch Eriboll study site and provide the basis for cost effective mapping using drop down camera footage in coastal waters. The predictive substrata map produced here is a first step towards developing a comprehensive and fine scale resolution habitat mapping method to allow the distribution of benthic communities to be predicted in the Loch Eriboll seascape. This knowledge will be useful to marine and conservation planners and support future work which require high resolution maps of marine habitat mosaics such as research into fish movement and habitat use.

CRediT authorship contribution statement

N.M. Burns: Writing – original draft, Visualization, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **D.M. Bailey:** Writing – review & editing, Conceptualization. **C.R. Hopkins:** Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors (Burns, Bailey and Hopkins) declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Financial support was provided by Scottish Government Rural and Environment Science and Analytical Services Division. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All code and data used to produce the current manuscript are currently available at https://github.com/NeilMBurns/Predictive_GAM_seabed_maps, DOI:https://zenodo.org/doi/10.5281/zenodo.6379933.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecss.2024.108939.

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