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Terms and Abbreviations

BSH	Broad Scale Habitat
Cefas	Centre for Environment, Fisheries and Aquaculture Science
DCO	Development Consent Order
EIA	Environmental Impact Assessment
EMODnet	The European Marine Observation and Data Network
EUNIS	European Nature Information System
ES	Environmental Statement
MBES	Multi Beam Echo Sounder
MLC	Maximum Likelihood Classification
MNCR	Marine Nature Conservation Review
NSIP	Nationally Significant Infrastructure Project
OEL	Ocean Ecology Ltd
OWF	Offshore Windfarm
PCA	Principal Component Analysis
PEIR	Preliminary Environmental Information Report
PSD	Particle Size Distribution
SSS	Side Scan Sonar
TCE	The Crown Estate
TRI	Terrain Ruggedness Index
WTGs	Wind Turbine Generators

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1. Introduction

1.1. Rampion 2

Rampion Extension Development Limited (hereafter referred to as 'RED') (the Applicant) applied to The Crown Estate (TCE) for an extension to the Rampion Offshore Wind Farm (Rampion 1) in 2018 and, following approval under the plan-led Habitats Regulations Assessment (HRA), was awarded development rights for the Rampion Extension Site in 2019. The proposed Rampion 2 Offshore Wind Farm Project (Rampion 2) is located adjacent to Rampion 1 in the English Channel, off the Sussex coast. Rampion 2 is designated as a Nationally Significant Infrastructure Project (NSIP) under Section 15(3) of the Planning Act 2008, thus requiring a Development Consent Order (DCO) accompanied by and Environmental Statement (ES) in accordance with the Environmental Impact Assessment (EIA) Regulations 2017. Rampion 2 is defined as a Schedule 2 project under EIA Regulations 2017.

RED is developing the Rampion 2 Offshore Wind Farm Project (Rampion 2) located adjacent to the existing Rampion Offshore Wind Farm Project ('Rampion 1') in the English Channel.

Rampion 2 will be located between 13km and 26km from the Sussex Coast in the English Channel and the offshore array area will occupy an area of approximately 160km2.

The key offshore elements of the Proposed Development will be as follows:

- up to 90 offshore wind turbine generators (WTGs) and associated foundations;
- blade tip of the WTGs will be up to 325m above Lowest Astronomical Tide (LAT) and will have a 22m minimum air gap above Mean High Water Springs (MHWS);
- inter-array cables connecting the WTGs to up to three offshore substations;
- up to two offshore interconnector export cables between the offshore substations;
- up to four offshore export cables each in its own trench, will be buried under the seabed within the final cable corridor; and
- the export cable circuits will be High Voltage Alternating Current (HVAC), with a voltage of up to 275kV.

The key onshore elements of the Proposed Development will be as follows:

- a single landfall site near Climping, Arun District, connecting offshore and onshore cables using Horizontal Directional Drilling (HDD) installation techniques;
- buried onshore cables in a single corridor for the maximum route length of up to 38.8km using:
  - trenching and backfilling installation techniques; and
  - trenchless and open cut crossings.

- a new onshore substation, proposed near Cowfold, Horsham District, which will connect to an extension to the existing National Grid Bolney substation, Mid Sussex, via buried onshore cables; and
- extension to and additional infrastructure at the existing National Grid Bolney substation, Mid Sussex District to connect Rampion 2 to the national grid electrical network.

A full description of the Proposed Development is provided in **Chapter 4: The Proposed Development, Volume 2** (Document Reference: 6.2.4).

1.2. Aims and Objectives

Ocean Ecology Limited (OEL) was contracted by GoBe / Rampion Extension Development (RED)to conduct a benthic characterisation of the Rampion 2 survey area to characterise the habitats present within the subtidal zone of the proposed project boundary. Following delays to the subtidal survey due to sustained periods of unsuitable weather, OEL were requested to conduct a predictive modelling exercise using the newly acquired site specific acoustic data and wealth of existing ground-truthing data available to provide full coverage mapping for the survey area. This interim deliverable was used to inform the project Preliminary Environmental Information Report (PEIR), when Rampion 2 site-specific data were incomplete. However, the results of the site-specific benthic surveys were subsequently fed into the model to produce a final high confidence EUNIS map, which was available for inclusion into the ES.

1.3. Predictive Habitat Mapping

Predictive habitat mapping is a widely used, automated process of classifying benthic habitat (Degraer et al. 2008, McGonigle et al. 2009, Brown et al. 2011, Stephens & Diesing 2014, Calvert et al. 2015, Boswarva et al. 2018). It utilises a variety of high-resolution physical variables identified as proxies for habitat and the composition of species and communities of species associated with particular habitats (Brown et al. 2011). Thus, promoting wide-scale, relatively fast and cost-effective methods of mapping large areas of the seabed to high degrees of accuracy (Andersen et al. 2018). Predictive maps can also act as a baseline in which to develop further comprehensive investigations, further maximising survey time and effort (Wynn et al. 2012).

There are an abundance of methods available for producing predictive habitat maps from acoustic and ground truthed data. The most common utilise either unsupervised (data clustering and pattern recognition) or supervised (classifying known signatures to train unknown areas) (Brown et al. 2011, Calvert et al.2015).

The Maximum Likelihood Classification (MLC) is one widely applied, pixel based, supervised classification technique (Brown et al. 2005, Ierodiaconou et al. 2011, Calvert et al. 2015, Boswarva et al. 2018). It utilises acoustic data and their derivatives to produce class signatures, applying ground-truth data (known also as sea-truth data) to identify or “train” similar regions in acoustic data where no sea-truthing data exists (Calvert et al. 2015). The MLC method uses a neighbourhood approach based on the theory that neighbouring cells are more likely to be of the same classification type. It is suited for manipulation of geophysical data layers within Global Information System (GIS) thus producing full coverage and cost-effective predictive habitat maps utilising the ESRI ArcGIS platforms (Che Hasan et al. 2014, Calvert et al. 2015, Boswarva et al. 2018). A disadvantage of using MLC is that it assumes a Gaussian distribution when assigning classes to pixels (Ierodiaconou. 2011), whilst habitat distributions are likely to be multimodal.

Surfaces derived from bathymetric data can be used to develop a broader picture of the topographic complexity and biological relevant units of the seabed (Brown et al. 2011, Costa & Battista 2013). Derivatives such as aspect, slope, and rugosity can be used to describe the seabed in terms of exposure to wave current, energy sediment accretion, and seabed complexity respectively (Rattray et al. 2013), whilst topographic roughness is known to influence habitat and colonisation (Wilson et al. 2007).

Seabed classification point data typically obtained from grab sampling and seabed imagery is utilised for the purpose of training (ground-truthing) and validating predictive habitat maps. The collation of all available, historical seabed classification data is beneficial to identify potential knowledge gaps, reducing the timely costs of repeat sampling whilst informing the focussed collection of additional seabed information from otherwise unknown locations (Calvert et al. 2015, Boswarva et al. 2018). A wide breadth of historical point data can be collated from online data repositories (eg.EMODnet). However careful consideration should be taken into the validity of historical data in respect to the age of the data obtained from dynamic and changeable seabed environments which have the potential to display significant short-term changes in seabed composition (Boswarva et al. 2018).

The selection of data used to validate the accuracy of the predictive maps is important for ensuring that all classifications are represented whilst not inflicting bias. The ratio of training to validation points varies, however a 70:30 or 80:20 ratio of training to validation points is typical (Calvert et al. 2015, Boswarva et al. 2018, Boswarva. 2021 (unpublished). Further, the application of a random stratified sampling strategy ensures that all classifications are accounted for in both the training and validation.

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2. Methods

All modelling and modelling processes were conducted in ESRI ArcGIS utilising the Spatial Analyst Extension within a combination of ESRI ArcMap version 10.7 and ESRI ArcPro Version 2.7.

2.1. Ground-truthing

EUNIS classification point data were obtained and collated from various sources, utilising a wide breadth of all available, historical seabed information within the Rampion 2 survey area:

- Cefas OneBenthic Database (https://openscience.cefas.co.uk/matool_mhtest/)
- EMODnet – EUNIS habitat point observations (https://www.emodnet-seabedhabitats.eu)
- Rampion 2 Particle Size Distribution (PSD) analysis data (OEL, 2021)
- Rampion 1 Offshore Windfarm (OWF) benthic ecology baseline characterisation (EMU, 2011)
- Rampion 1 OWF pre-construction benthic survey report (Natural Power, 2016)

2.1.1. Cefas OneBenthic Database

Using the OneBenthic Database, 203 sediment samples from the South Coast Regional Seabed Monitoring Plan (RSMP) collected between 1998-2015 from within the Rampion 2 scoping boundary were extracted. To ensure sample data was not truncated prior to analysis, the data was split into 10 subgroups based on the size classification used for the sediment analysis and individually run through Gradistat grain size distribution and statistics package version 9.1 to determine the EUNIS Broadscale Habitat type (BSH).

2.1.2. EMODnet EUNIS habitat point observations

A total of 76 EUNIS classifications were extracted from the EMODnet Seabed Habitats Portal. These records obtained from sublittoral surveys conducted by Sussex Seasearch were collected between 1982 and 2016.

2.1.3. Rampion 2 PSD Analysis

Broadscale EUNIS classifications were obtained from 11 grab samples collected by OEL in 2021 as part of the ongoing Rampion 2 benthic survey. The data was run through Gradistat grain size distribution and statistics package version 9.1 to determine the EUNIS BSH type. Note that due to timescales the corresponding macrobenthic data was not available to allow for EUNIS biotope classification.

2.1.4. Rampion 1 OWF

A total of 197 habitat classifications from grab samples and seabed still images collected during two Rampion 1 offshore windfarm surveys were obtained from GoBe.

Classifications were first converted from Marine Habitat Classifications for Britain and Ireland (MNCR) format to the EUNIS classification.

2.2. Training and validation

The ground-truth data was divided into four datasets containing EUNIS BSH, Level 4 and Level 5 and All EUNIS classifications combined. A random stratified sampling technique was conducted on each EUNIS classification to ensure sampling incorporated all available classes. Seventy % of the data from each classification was selected for model training whilst thirty % was retained for model validation (**Table 1** and **Appendix C**). A sense check was conducted on all data, in which data collected from duplicate coordinates were removed.

Table 1 Total data points used to train and validate each predictive map.

EUNIS Level	Training	Validation
All	354	92
BSH	330	128
Level 4	131	48
Level 5	108	46

2.2.1. Confusion matrix

Confusion matrices are calculated to measure map accuracy by highlighting the percentage of pixels classified correctly. They are produced in ArcMap by combining the outputs of each predictive map with its corresponding validation dataset. The resulting integer values are converted to percentages using the expression NT(([values]/[Total]) * 100+0.5.

2.2.2. Cohen's kappa

Cohen's Kappa is a widely applied discrete multivariate technique for assessing the accuracy of habitat mapping predictions. It measures the degree of agreement between variables above that expected by chance alone (Lucieer et al. 2013). The value is interpreted further to identify the level of agreement and percentage of reliable data (**Table 2**).

It is calculated from the confusion matrix

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}$$

Where Pr(a) represents the actual observed agreement and Pr(e) represents an agreement by chance.

Table 2 Interpretation of Cohen's Kappa adapted from (Altman 1991, McHugh 2012, Lucieer et al. 2013).

Value of Kappa	Level of agreement	Agreement *	% data that are reliable
0-.20	None	Poor	0-4%
.20-39	Minimal	Fair	4-15%
.40-.59	Weak	Moderate	15-35%
.60-.79	Moderate	Good	35-63%
.80-.90	Strong	Very good	64-81%
Above .90	Almost Perfect	Very good	82-100%

2.3. Physical variables

Acoustic data in the form of Multibeam Eco Sounder (MBES) bathymetry and backscatter were obtained from GoBe in a series of .xyz formatted data files. These files were transformed and mosaiced into two rasters displayed at 1 m resolution. A Side Scan Sonar (SSS) raster in .tiff format was obtained from GoBe at 0.1 metre resolution. The backscatter raster (available in **Appendix A-** Physical Variables) was omitted from the final maps due to strong differences in acoustic signatures between the nearshore and offshore areas, which had the potential to significantly influence the final model predictions.

2.3.1. Bathymetric derivatives

Six derivatives were calculated from the bathymetric raster, these were: Slope, Aspect as Eastness and Northness (in radians), Terrain Ruggedness Index (TRI), Curvature, and Profile Curvature. Each physical variable is displayed in **Appendix A-** Physical Variables.

2.4. Environmental variables

All environmental variables were downloaded from the EMODnet data portal (https://www.emodnet-seabedhabitats.eu/access-data/download-data/) in .tiff format. This included: kinetic energy at the seabed due to wave energy, light at the seabed, and fraction of light at the seabed. Due to their limited variability across the site the environmental variables were omitted from the final models. An example of each data layer is displayed in **Appendix B-Environmental** Variables.

2.5. Data transformation

Only the bathymetry, SSS and bathymetric derivatives were selected for the final predictive mapping process. A "Standardise" and "Stretch" function was applied to each variable using the "Transformation" function within the Geomorphometry and Gradient

Metrics toolbox (https://evansmurphy.wixsite.com/evansspatial/arcgis-gradient-metrics-toolbox) extension in ArcPRO.

2.6. Principal Components

Principal Component Analysis (PCA) transforms a number of different, but potentially correlated, variables into a smaller number of uncorrelated principal components (Amiri-Simkooei et al. 2011). In doing so, it condenses all information into the first few bands, removing highly correlated information and thus reducing dimensionality without losing data (Costa & Battista 2013). PCA was conducted on the transformed variables. The resulting outputs produced a series of multiband rasters containing the first three principal components and a statistical text file containing the covariance matrix, correlation matrix, eigenvalues and the percent of accumulated eigenvalues.

2.7. Signature files

Signature files were created in ArcPro from each EUNIS classification dataset and the resulting multiband PCA raster. A signature file is a subset of cells which represent a class or cluster. Signatures incorporate small buffers around sea-truth points, and in doing so assume that the associated habitat within a buffer is the same as the classified data entry (Brown et al. 2005).

2.8. Maximum Likelihood Classification

MLC is a widely applied pixel based predictive mapping approach (Brown et al. 2005, Ierodiaconou et al. 2011, Calvert et al. 2015, Boswarva et al. 2018) that calculates the probability a given pixel belongs to a specific class, thereby producing a grid of classes in the form of a raster thematic map (Lerodiaconou et al. 2011, Micallef et al. 2012). MLC was conducted here by combining the variables selected within the multi-band PCA rasters with signature files containing EUNIS classification data. The resulting predictive habitat maps are displayed in **Figure 1** to **Figure 4**.

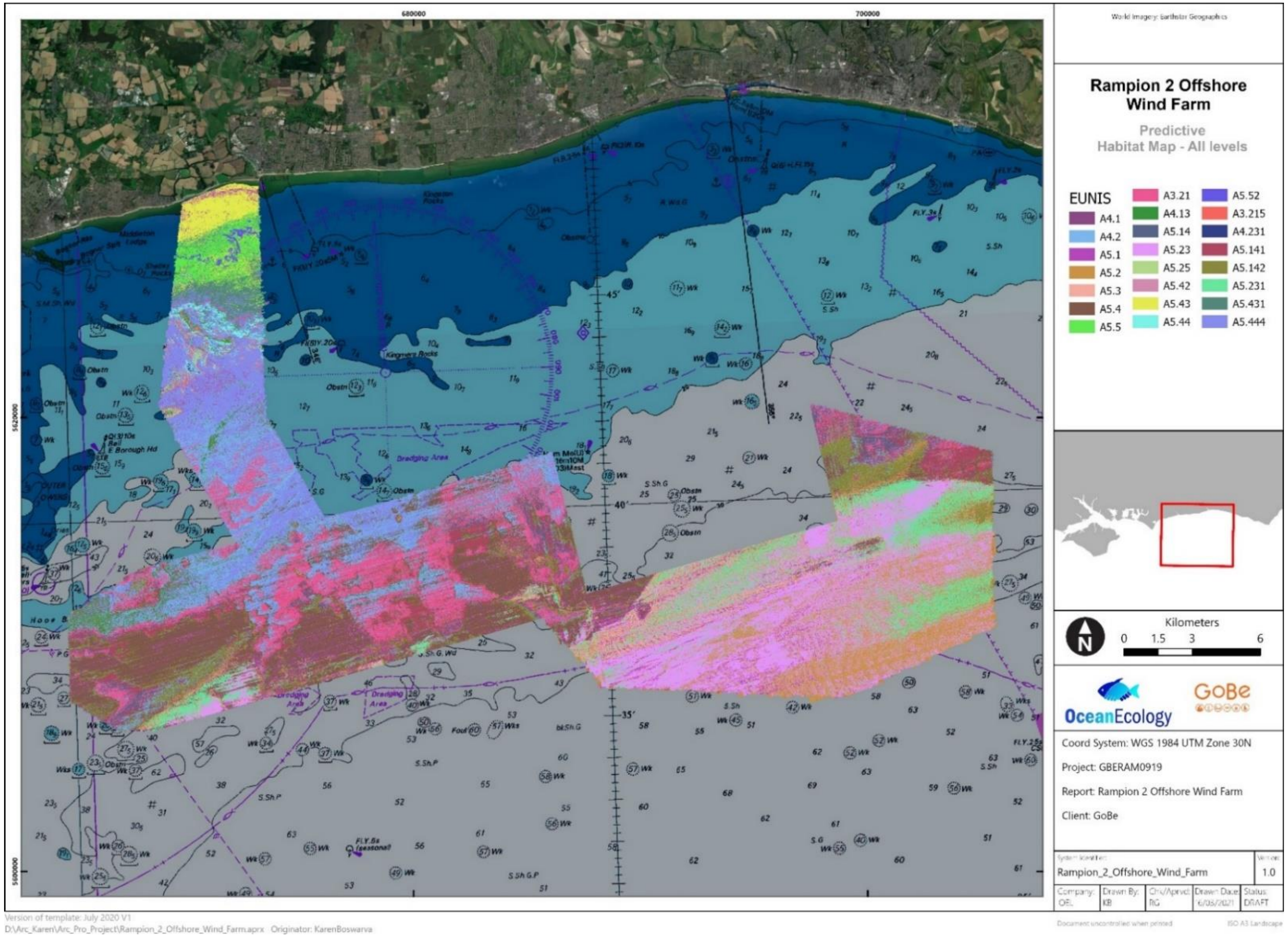

Figure 1 A composite predictive habitat map of the Rampion 2 OWF area combining BSH, Level 4, and Level 5 EUNIS classifications.

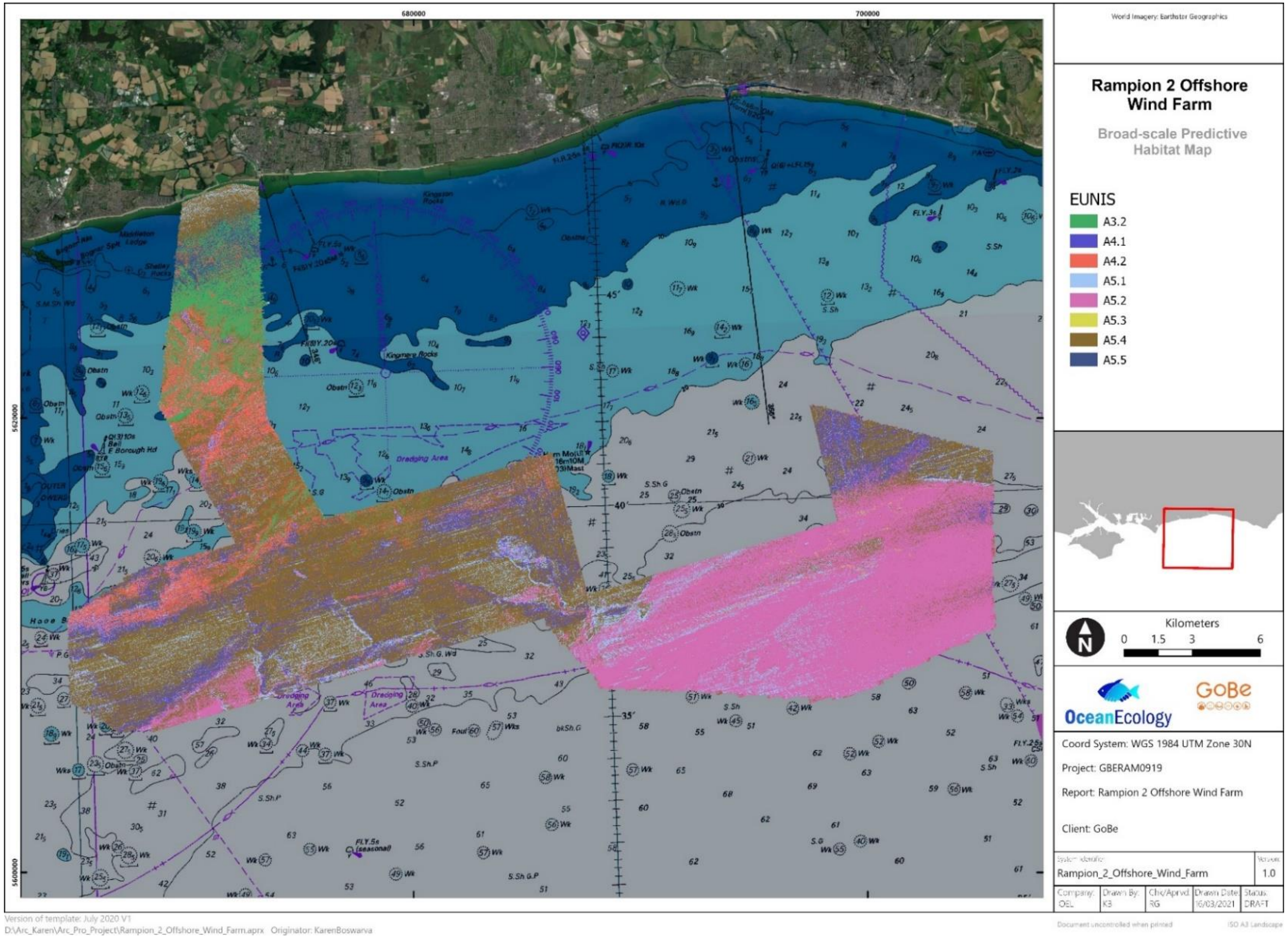

Figure 2 Broadscale predictive habitat map of the Rampion 2 OWF area.

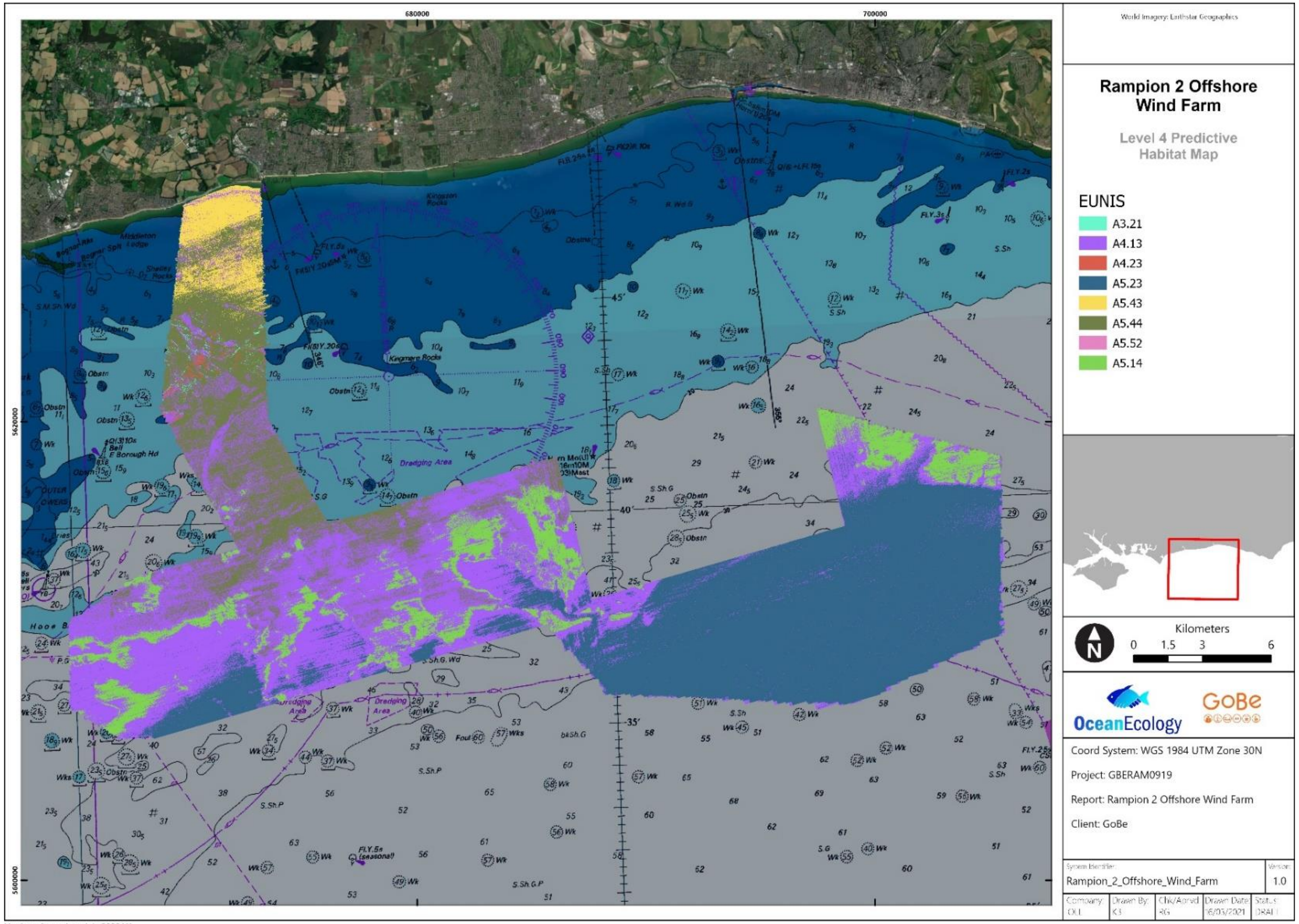

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Figure 3 Level 4 predictive habitat map of the Rampion 2 OWF area.

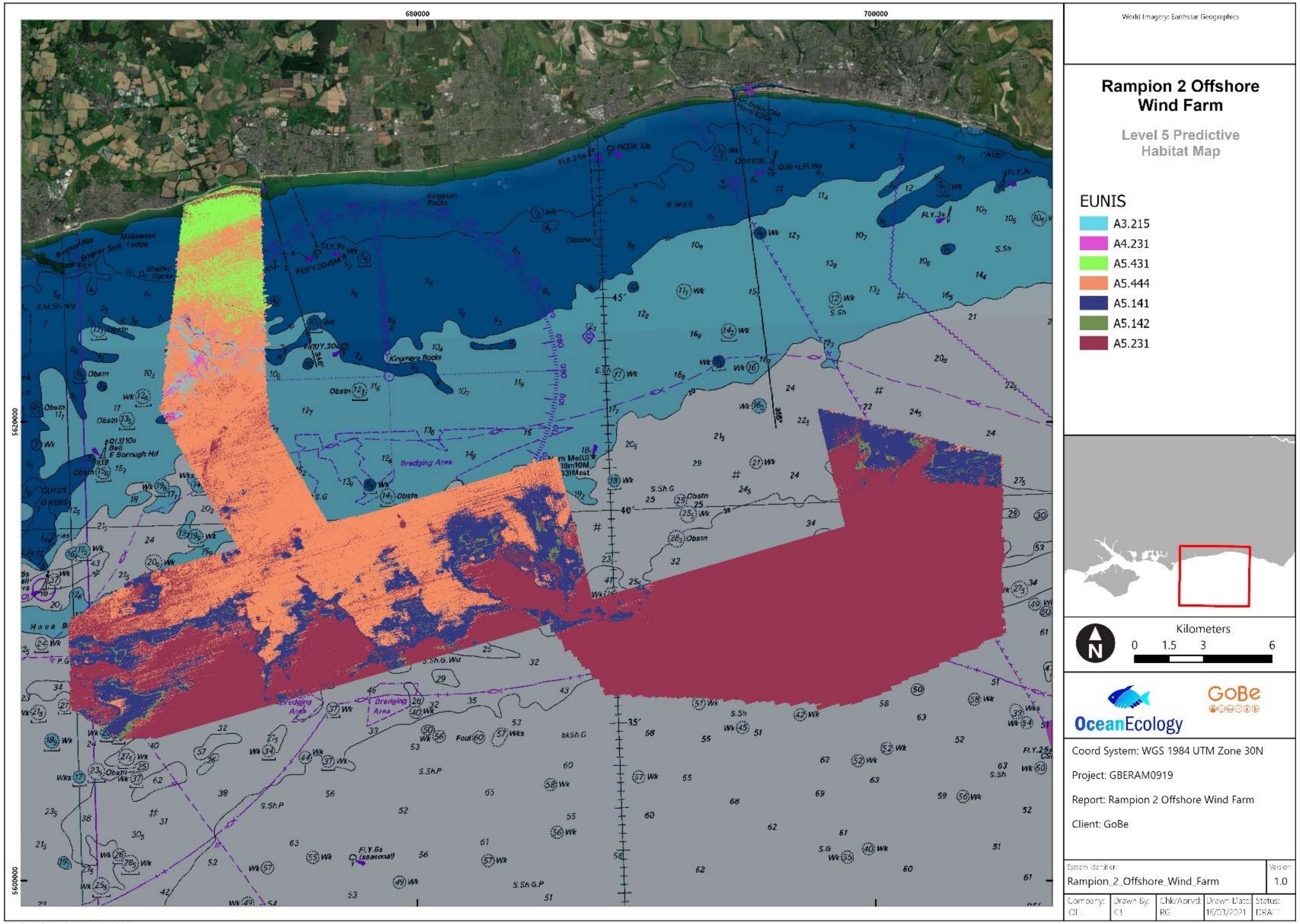

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Figure 4 Level 5 predictive habitat map of the Rampion 2 OWF area.

3. Results

3.1. Predictive habitat/biotope maps

The following tables, Table 3 to **Table 6** indicate the percentage cover of each EUNIS habitat predicted across the Rampion 2 survey area. The predictive map containing all classifications predominantly comprised of Sublittoral mixed sediments (A5.4) and Infralittoral fine sand (A5.23), this is mirrored in the dominance of A5.4 and Sublittoral sand (A5.2) in the EUNIS BSH predictive map. The Level 4 predictive map was dominated again by A5.23 and also Mixed faunal turf communities on circalittoral rock (A4.13). Whilst the Level 5 predictive map was dominated by Infralittoral mobile clean sand with sparse fauna (A5.231).

Table 3 The number and percentage of pixels classified per EUNIS classification.

EUNIS	Pixels	Percentage
A5.1	4742032	5.3
A5.25	90884	0.1
A3.215	291887	0.3
A4.2	9384946	10.4
A5.4	12471648	13.8
A4.231	22653	0.0
A5.44	576257	0.6
A5.5	1332005	1.5
A5.431	1361360	1.5
A5.2	8553162	9.5
A5.52	188862	0.2
A5.42	52131	0.1
A4.13	2274892	2.5
A5.444	7220945	8.0
A5.43	1558810	1.7
A3.21	9220683	10.2
A5.3	3576479	4.0
A5.142	3631076	4.0
A5.14	1939491	2.2
A5.23	12140803	13.5
A5.231	6213811	6.9
A5.141	3239935	3.6

Table 4 The number and percentage of pixels classified per broad scale habitat EUNIS code.

EUNIS	Pixels	Percentage
A3.2	4446032	4.9
A4.1	8135910	9.0
A4.2	6406370	7.1
A5.1	8499124	9.4
A5.2	27375931	30.4
A5.3	143450	0.2
A5.4	33928940	37.7
A5.3	1148995	1.3

Table 5 The number and percentage of pixels classified per Level 4 EUNIS code.

EUNIS	Pixels	Percentage
A3.21	130345	0.1
A4.13	31805413	35.3
A4.23	170530	0.2
A5.23	32996090	36.6
A5.43	2686030	3.0
A5.44	13507665	15.0
A5.52	35902	0.04

Table 6 The number and percentage of pixels classified per Level 5 EUNIS biotope code.

EUNIS	Pixels	Percentage
A3.215	460188	0.5
A4.231	222063	0.2
A5.431	2741621	3.0
A5.444	25679147	28.5
A5.141	12291105	13.6
A5.142	909288	1.0
A5.231	47781340	53.0

3.2. Model Validation

Model validation is displayed as a series of confusion matrices (**Table 7** to **Table 10**) indicating the percentage of pixels classified correctly and highlighting the miss-classified EUNIS codes, and a Cohen's Kappa score of agreement per predictive map (**Table 11**). Overall, the greatest percentage of correctly classified pixels occurred within sublittoral coarse sediment (A5.1) with 81.5% of pixels classified correctly. The greatest percentage of miss-classifications occurred within the map displaying all levels, miss-classification was largely reduced in all single level maps. The Cohen's

Kappa scores ranged from non/poor level of agreement (all EUNIS levels) to moderate/good (Level 4 and level 5).

3.2.1. Confusion matrix

Table 7 Confusion matrix for all EUNIS classification levels.

	A5.444	A5.1	A5.4	A5.2	A4.7	A5.141	A4.13	A4.72	A5.3	A5.231
A5.1	9.50	81.50	9.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
A4.2	0.50	83.50	8.50	8.50	0.50	0.50	0.50	0.50	0.50	0.50
A5.4	0.50	53.50	38.50	0.50	7.50	0.50	0.50	0.50	0.50	0.50
A5.2	0.50	33.50	0.50	66.50	0.50	0.50	0.50	0.50	0.50	0.50
A4.13	0.50	100.50	0.50	0.50	0.50 h	0.50	0.50	0.50	0.50	0.50
A5.444	16.50	66.50	16.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
A3.21	0.50	100.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
A5.3	0.50	64.50	0.50	23.50	5.50	0.50	0.50	0.50	0.50	5.50
A5.142	0.50	50.50	50.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
A5.14	0.50	33.50	0.50	0.50	0.50	33.50	33.50	0.50	0.50	0.50
A5.23	0.50	33.50	16.50	33.50	0.50	0.50	0.50	0.50	16.50	0.50
A5.231	0.50	57.50	0.50	14.50	0.50	0.50	0.50	14.50	0.50	14.50
A5.141	0.50	60.50	40.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50

Table 8 Confusion matrix for the EUNIS BSH predictive map.

	A5.4	A5.2	A4.1	A5.1	A4.7	A5.3
A3.2	0.5	0.5	0.5	100.5	0.5	0.5
A4.1	7.5	30.5	15.5	46.5	0.5	0.5
A4.2	37.5	12.5	0.5	50.5	0.5	0.5
A5.1	3.5	11.5	3.5	81.5	0.5	0.5
A5.2	2.5	68.5	0.5	22.5	4.5	2.5
A5.4	27.5	12.5	3.5	57.5	0.5	0.5
A5.5	100.5	0.5	0.5	0.5	0.5	0.5

Table 9 Confusion matrix for the EUNIS Level 4 predictive map.

	A5.43	A5.44	A3.21	A5.14	A4.13	A5.23	A4.72
A4.13	0.5	0.5	33.5	0.5	66.5	0.5	0.5
A5.23	0.5	0.5	0.5	3.5	0.5	89.5	6.5
A5.44	20.5	60.5	0.5	0.5	20.5	0.5	0.5
A5.14	0.5	0.5	0.5	80.5	20.5	0.5	0.5

Table 10 Confusion matrix for the EUNIS Level 5 predictive map.

	A4.139	A5.431	A5.444	A5.141	A5.142	A5.231	A4.721
A5.444	20.5	20.5	60.5	0.5	0.5	0.5	0.5
A5.141	0.5	0.5	0.5	85.5	14.5	0.5	0.5
A5.142	0.5	0.5	0.5	66.5	33.5	0.5	0.5
A5.231	0.5	0.5	0.5	0.5	0.5	96.5	3.5

3.2.2. Cohen's Kappa

Table 11 Results of the Cohen's Kappa

Predictive Model Type	Cohen's Kappa score
All	0.12
Broad scale	0.26
Level 4	0.69
Level 5	0.63

4. Discussion

In general, the resulting maps are all good predictive indicators as to the true characteristics of the seabed. The benefits of producing predictive maps such as these promote wide-scale mapping of the seabed in areas which are relatively data poor when compared with inshore coastal waters. They can act as a baseline for seabed characterisation in which to build a more in-depth picture and assist in selecting appropriate survey designs targeting key areas of interest highlighted by the results. It is expected that further ground truthing information collected as part of the Rampion 2 subtidal benthic survey campaign will, once added into the model, will improve the predictive power of all the maps and increase overall map agreement.

Potential reef habitat is identified from the predictive model as occurring in low density throughout the composite and broad scale maps, particularly in the northwest of the survey area. The SSS backscatter and TRI (**Appendix A-** Physical Variables) display acoustic signatures indicative of harder sediments such as reef. However, within the Level 4 model, rock classifications are identified as over representative, which is likely a misclassification of mixed and coarse classifications.

The series of models did not predict the presence of species of conservation importance. The A5.431 biotope containing a species of prolific, non-native mollusc *Crepidula fornicata* was identified from within the Level 5 model as dominating the nearshore infralittoral.

The disparity between the confusion matrices and corresponding Cohen's Kappa scores is likely a result of the combined effect of a low abundance and high diversity of validation points over a vast area resulting in low percentages of agreement per EUNIS classification rather than a result of poor predictive power. This is evident in the high percentage of correctly classified validation points generally seen throughout all single level maps.

Seven biotopes were identified as occurring throughout the survey area. It is inherently challenging to assign biological features to physical proxies as they often do not display physical signatures that would differentiate them from higher order classifications. Further, biotopes, (Level 5 classifications) may be localised and species specific. Therefore, care should be taken when analysing the occurrence of biotope information as the extent of biotopes may either be over or underestimated. For example, the biotopes within these predictive maps include; *Flustra foliacea* and *Hydrallmania falcata* on tide-swept circalittoral mixed sediment (A5.444), *Pomatoceros triqueter* with barnacles and bryozoan crusts on unstable circalittoral cobbles and pebbles (A5.141), *Mediomastus fragilis*, *Lumbrineris* spp. and venerid bivalves in circalittoral coarse sand or gravel (A5.142), Infralittoral mobile clean sand with sparse fauna (A5.231), Sponges and anemones on vertical circalittoral bedrock (A4.139), and *Crepidula fornicata* with ascidians and anemones on infralittoral coarse mixed sediment (A5.431). Further only biotopes identified from existing ground truth data will be present in the resulting map therefore potentially creating an oversimplification of biotopes throughout the survey area. Despite the random stratified sampling of all ground truth data, disparity occurs when biotopes are both over and underrepresented. For example, the majority of biotope data consisted of A5.231 (72 out of 108 training points) whilst only a single data point of A4.139 was available in which to classify further unknown areas. Further delineation of habitat features is advised in order to increase the quantity of biotope classified data and therefore improve the predictive maps. This is particularly important for identifying further the extent of the prolific non-native species *C. fornicata*. The physical variables utilised in these predictive maps were selected to best describe the physical features which influence species and communities of species, including depth, slope, aspect, seabed roughness, and seabed profile. There is an exhaustive amount of physical and environmental variables that could also be included in the analyses, in particular Bathymetric Position Index and Vector Ruggedness Measure (both additional derivatives of bathymetry in relation rugosity), and these could be explored further to identify if they can improve the final outputs. Backscatter is a valuable predictive mapping tool and is used widely as a proxy for habitat type as changes in sediment type and their boundaries are often associated with changes in acoustic intensity, with softer sediments displayed as low reflectivity and harder sediments displayed as high reflectivity. Side scan sonar (SSS) offers a similar sediment/habitat proxy as backscatter, however there are inherent flaws which can influence the visual appearance and therefore the interpretation of the resulting acoustic data. SSS often displays varying degrees of shadow as it passes over a 3-dimentional seabed environment, this is particularly apparent in complex rocky environments. In predictive mapping, shadows displaying lower reflectivity than surrounding area have the potential to be classified as a separate feature. The track lines of SSS caused by the equipment's nadir tend to be more visible in SSS and require additional processing to reduce their influence in the predictive mapping process. These nadir marks were visible and caused some influence within the outputs of these maps, however their influence did not over-shadow true features visible in the bathymetry and SSS.

Backscatter was omitted from the final iterations of predictive maps due to the quality of the mosaic having an impact on model outputs. Notably, a sharp decrease in sonar intensity between the nearshore and offshore sections of the data (**Appendix A-** Physical Variables). This is an anomaly of mosaicking sonar data from multiple sources (i.e. the nearshore and offshore tranches) in ArcPro and could potentially be rectified by either mosaicking and editing xyz data initially in geoprocessing software and exporting as a single data layer, or by producing two predictive maps, one of the nearshore and one of the offshore. The latter has its own limitations as it would require further splitting of ground truth data, resulting in a potential loss of predictive power within either area.

Environmental variables (**Appendix B-Environmental** Variables) were tested within early models runs; however no environmental layers feature in the final model outputs.

This was due to an overall lack of variation in each variable on a survey scale causing a reduction in the resolution of the corresponding PCA. The limited features of each environmental variable were felt to be captured by the combined influence of the physical variables, notably bathymetry.

It should also be noted that the age of the data used in the training and validation of the model has the potential to influence the output predicted habitats and therefore the overall reliability of the maps; particularly in high energy and dynamic environments that are subject to significant short-term changes in habitat composition (Boswarva et al. 2018). Typically, however these changes will be less likely to occur in BSHs than community level classifications/biotopes. Therefore, part of the data collation and QC should include research into the general environmental conditions of the site and a review of any significantly observed changes in seabed classification data. A targeted sampling plan could then be designed for the purpose of verifying the output model predictions. This sampling plan could then be further used to improve the predictive mapping outputs.

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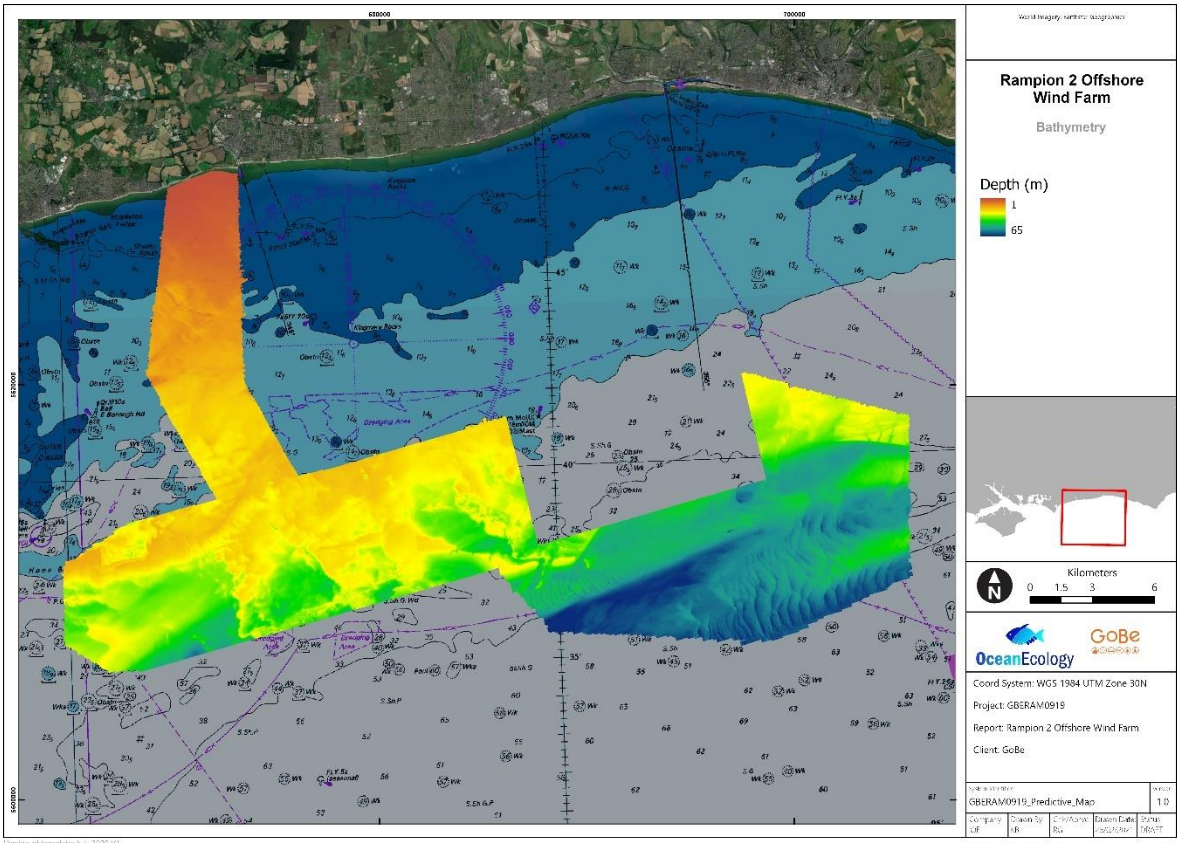
Appendix A- Physical Variables



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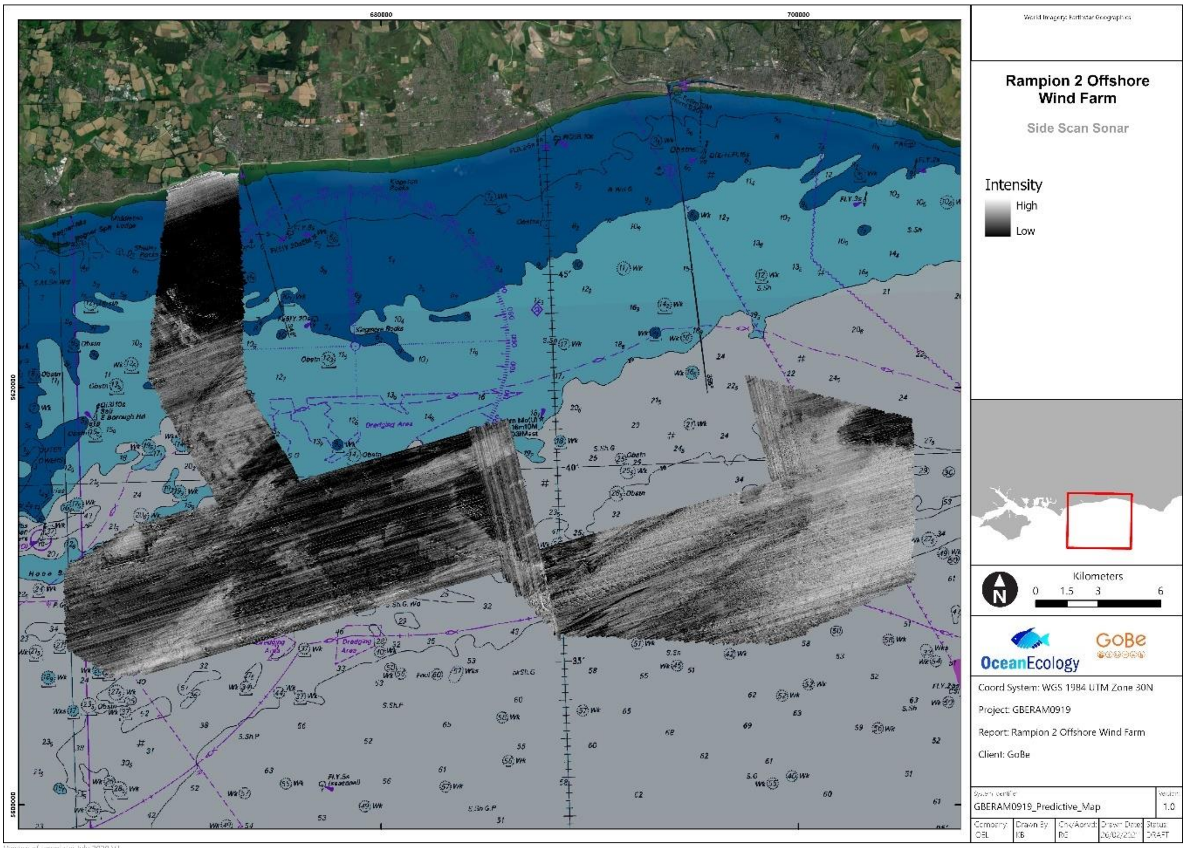

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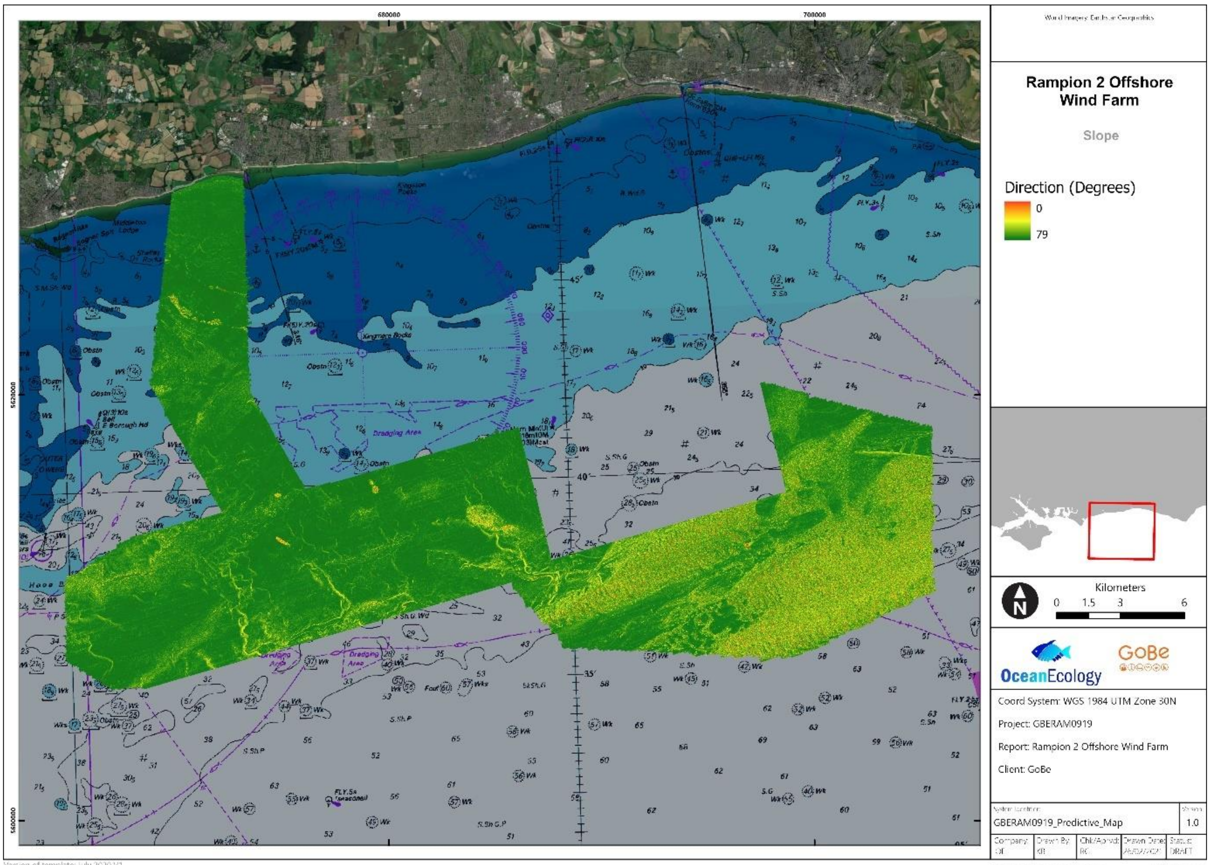

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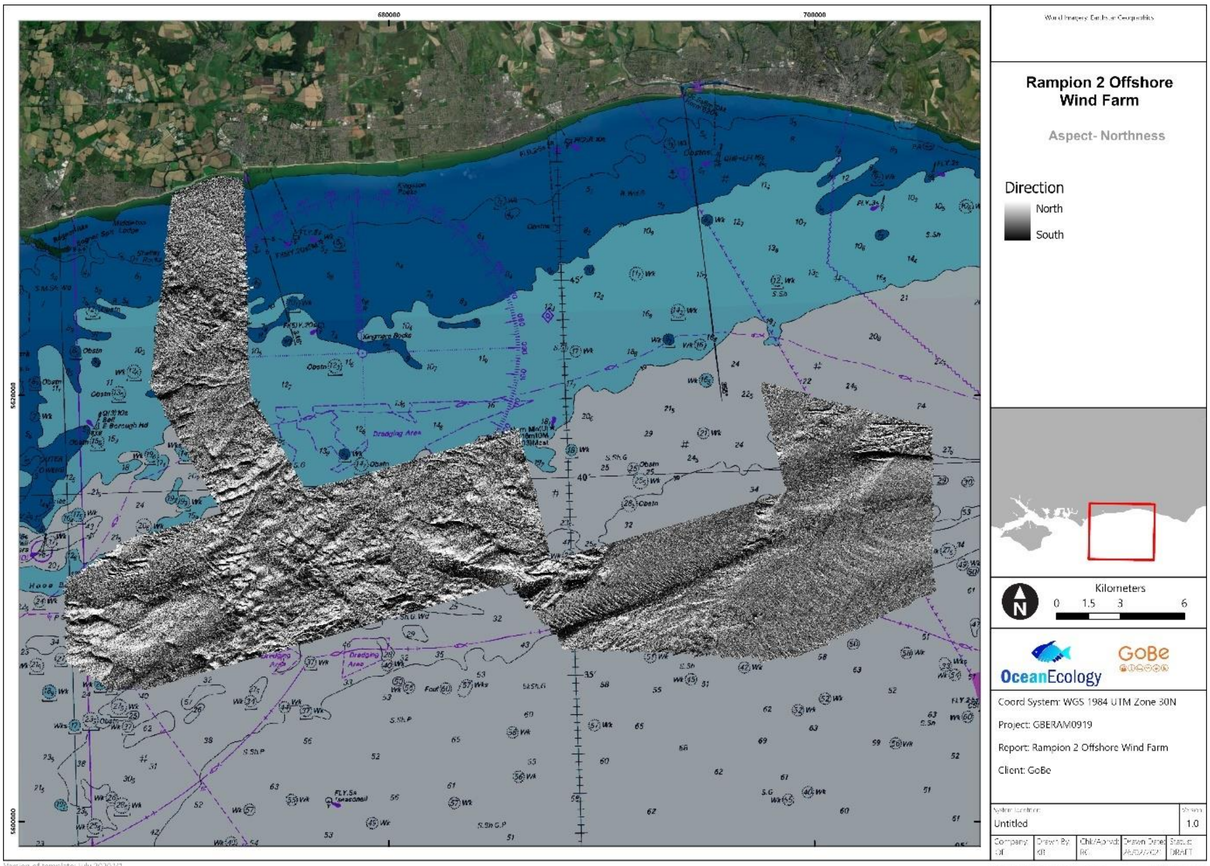

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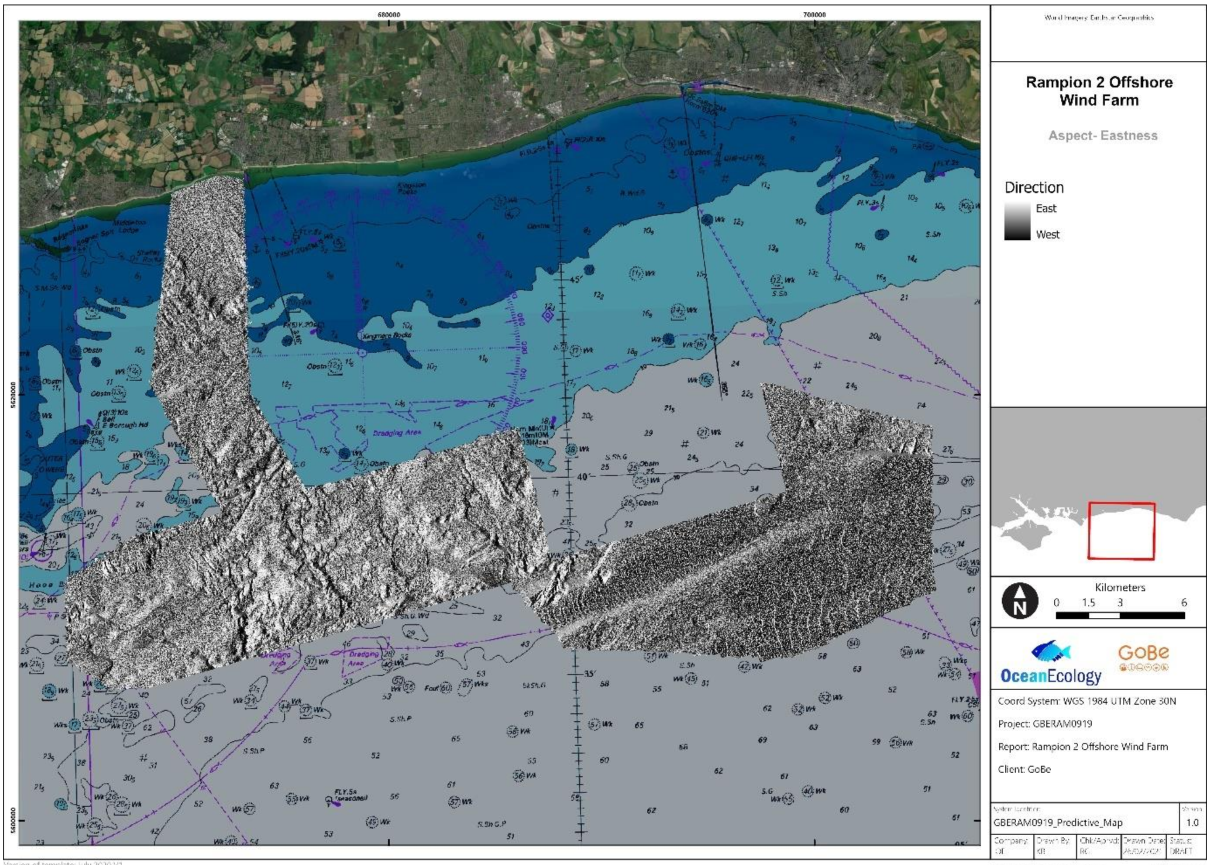
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Aspect- Eastness
Direction
East
West
Kilometers
0 1.5 3 6
OceanEcology
GoBe
Coord System: WGS 1984 UTM Zone 30N
Project: GBERAM0919
Report: Rampion 2 Offshore Wind Farm
Client: GoBe
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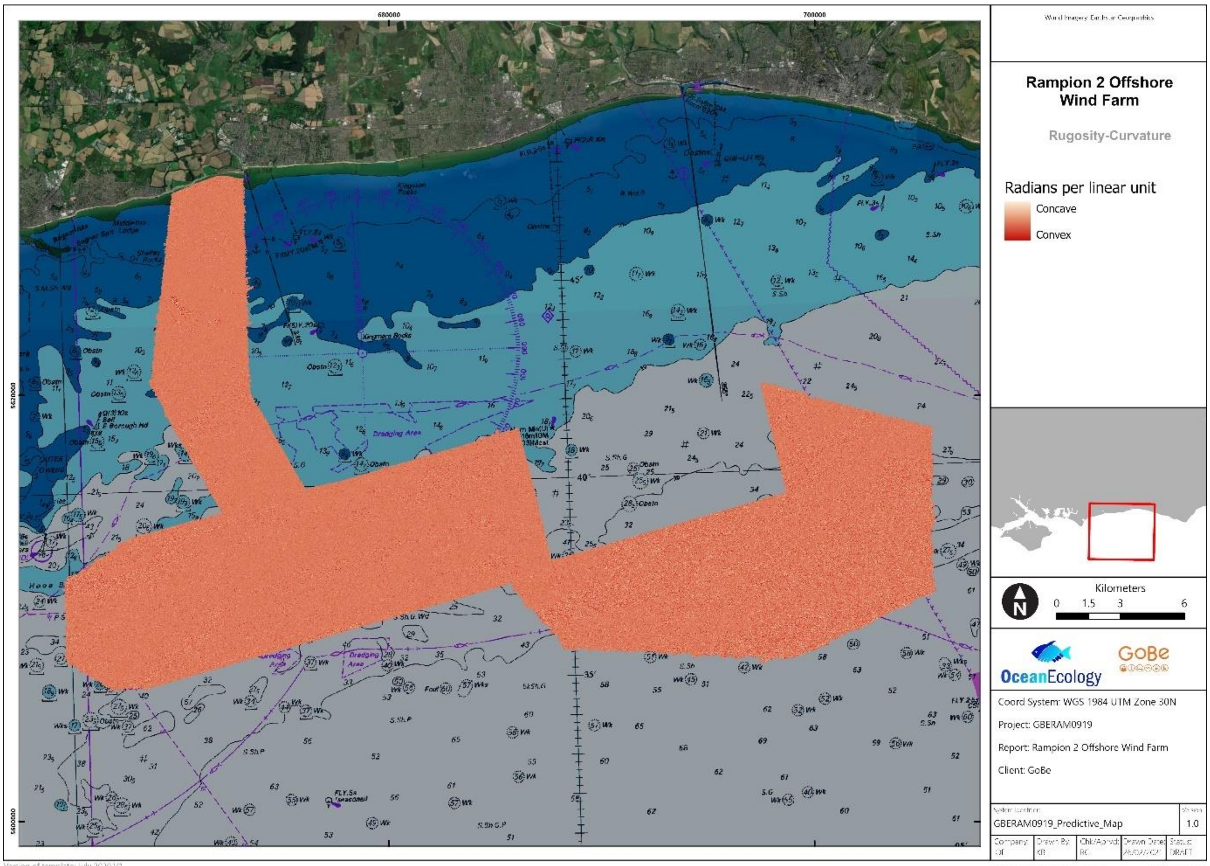
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Rugosity-Curvature
Radians per linear unit
Concave
Convex
Kilometers
0 1.5 3 6
OceanEcology
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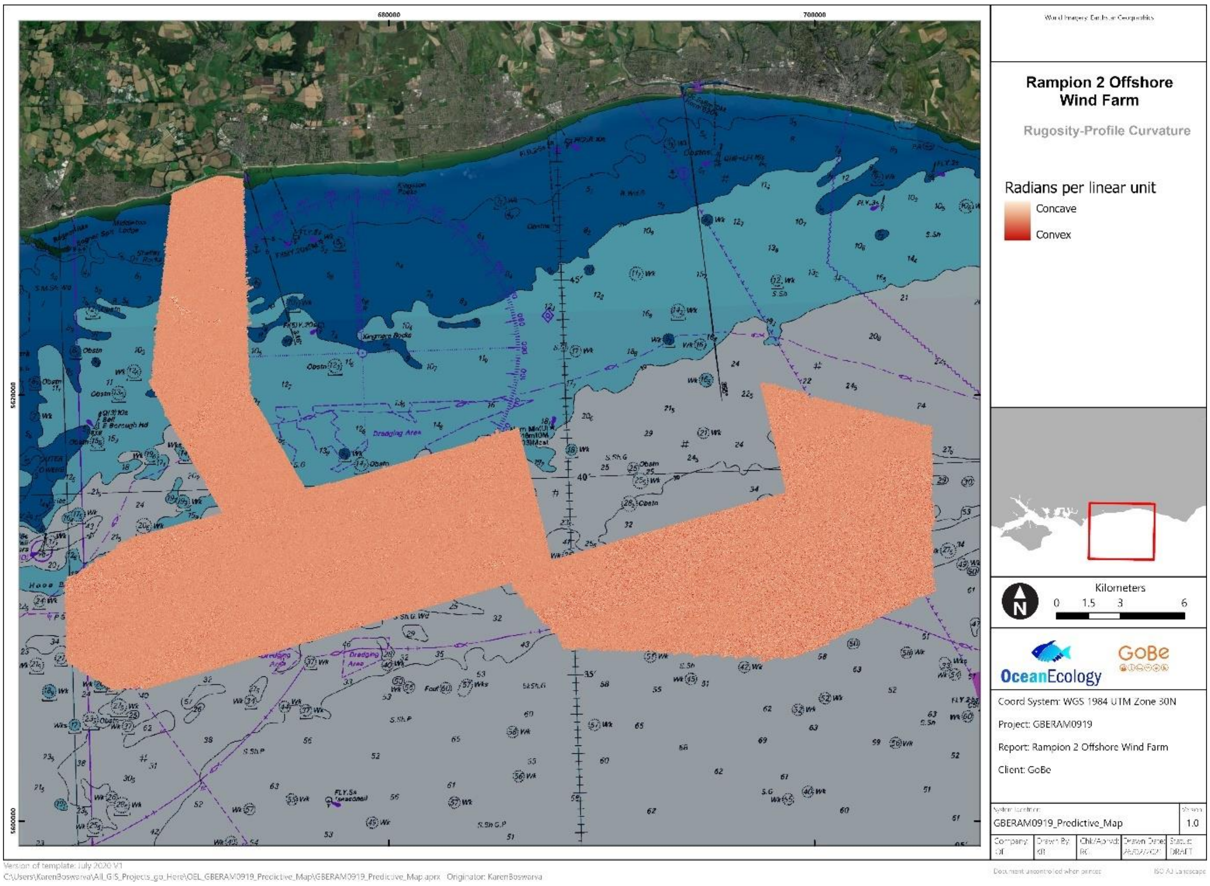

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Rugosity-Profile Curvature
Radians per linear unit
Concave
Convex
Kilometers
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OceanEcology
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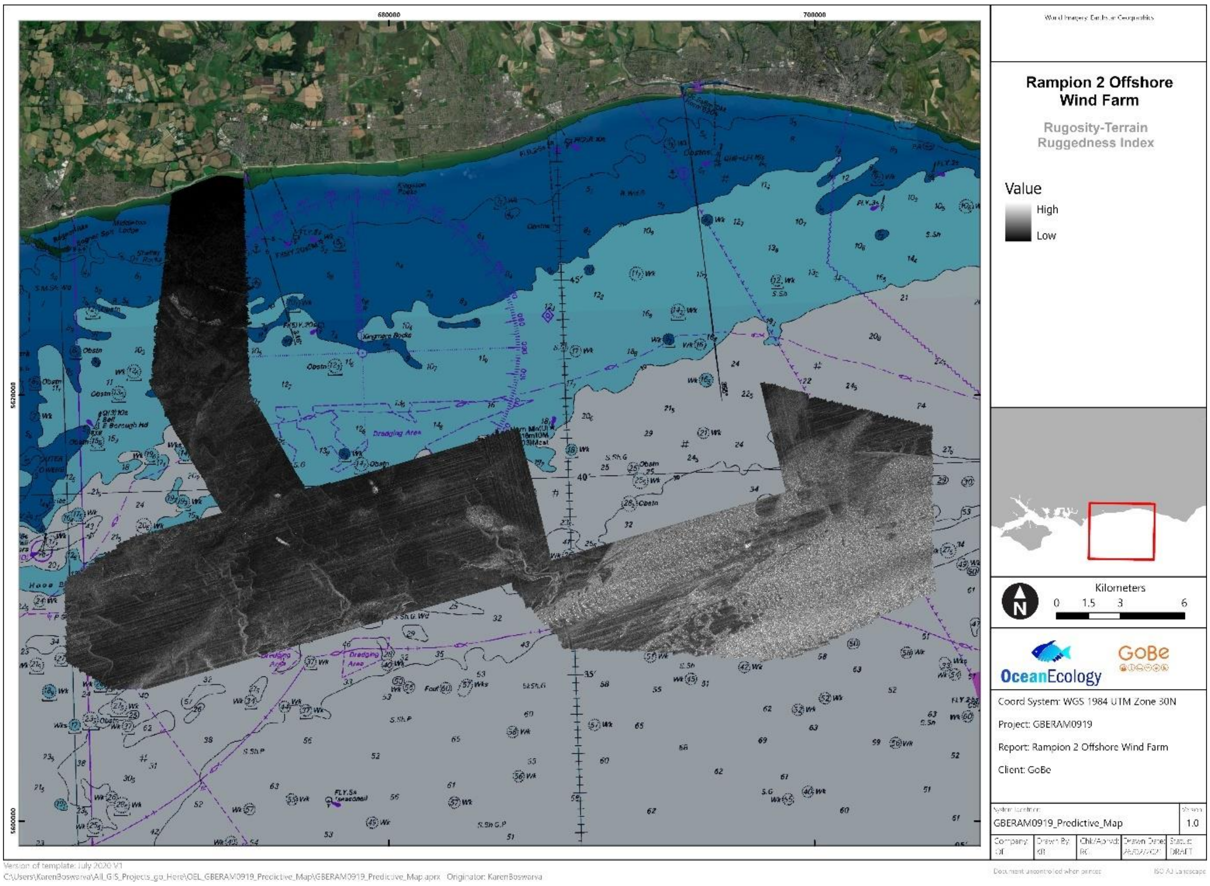

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Rugosity-Terrain Ruggedness Index
Value
High
Low
Kilometers
0 1.5 3 6
OceanEcology
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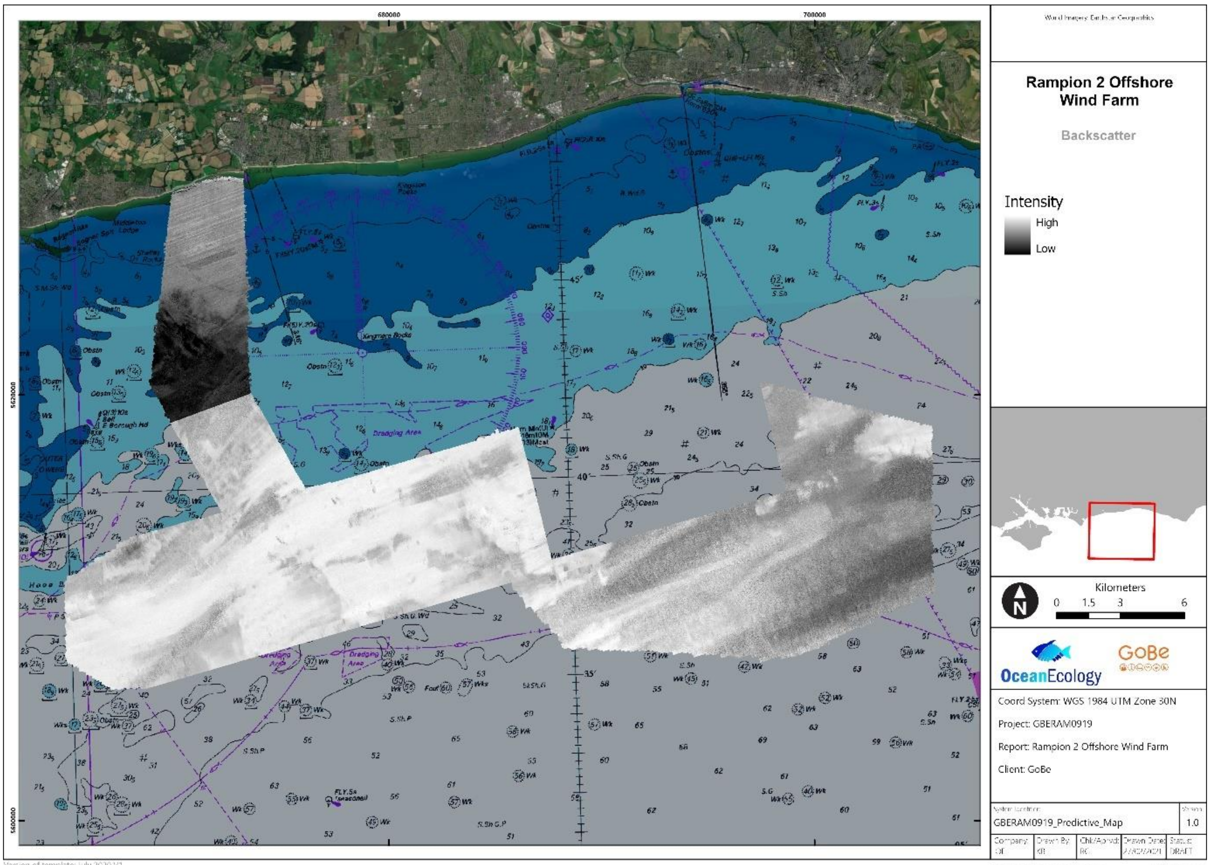

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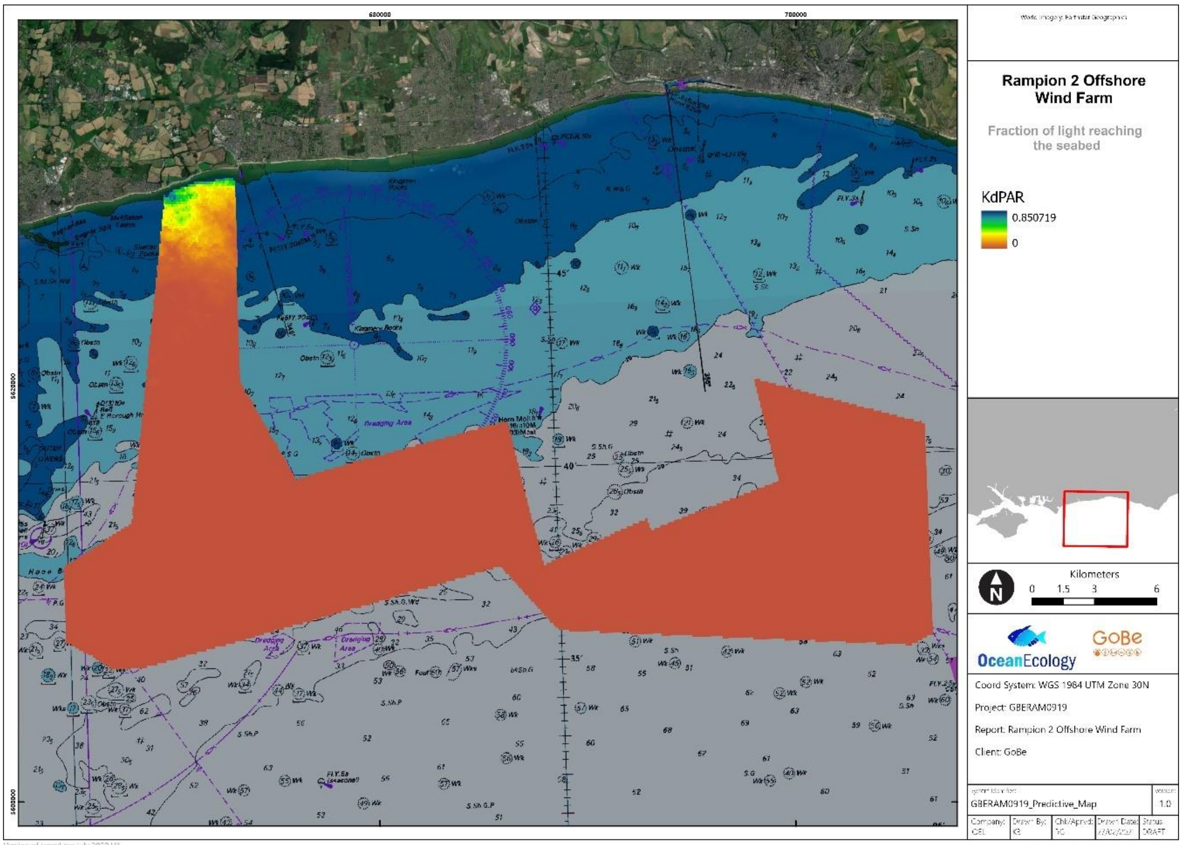
Appendix B-Environmental Variables



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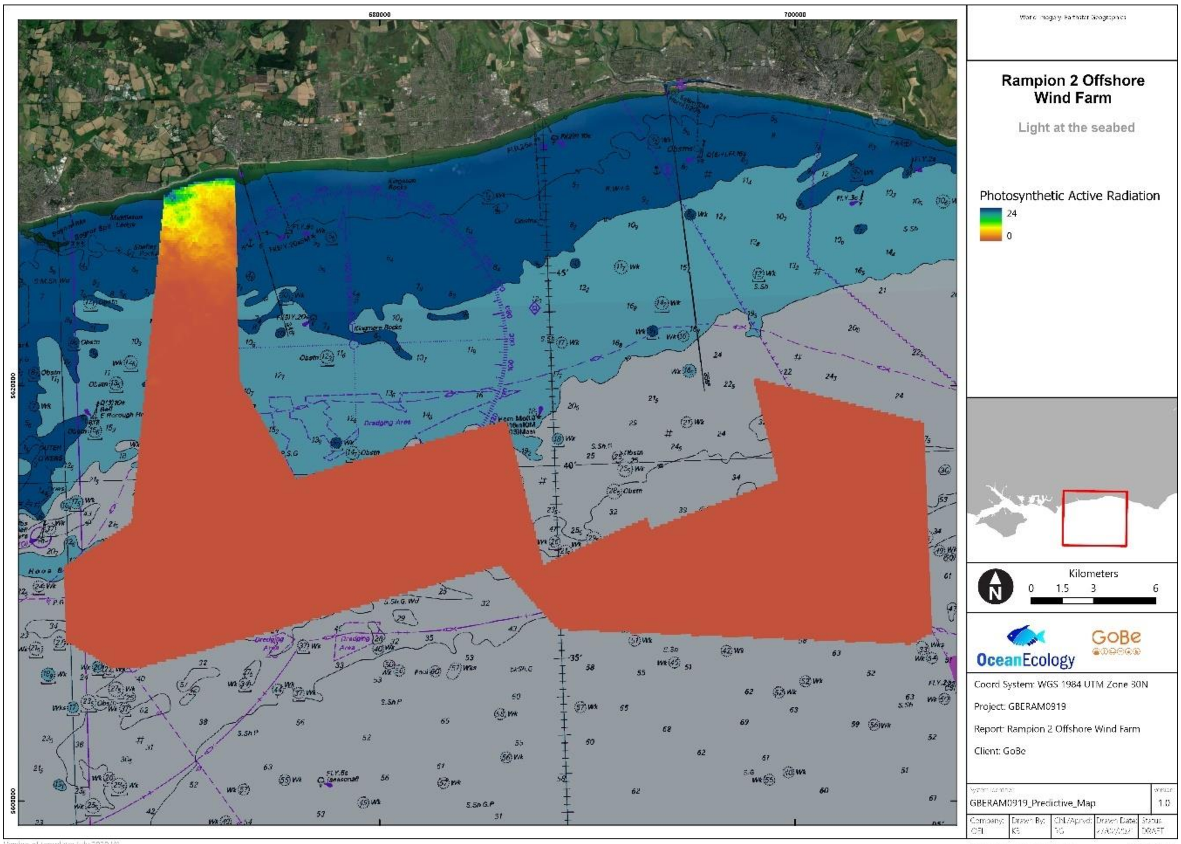

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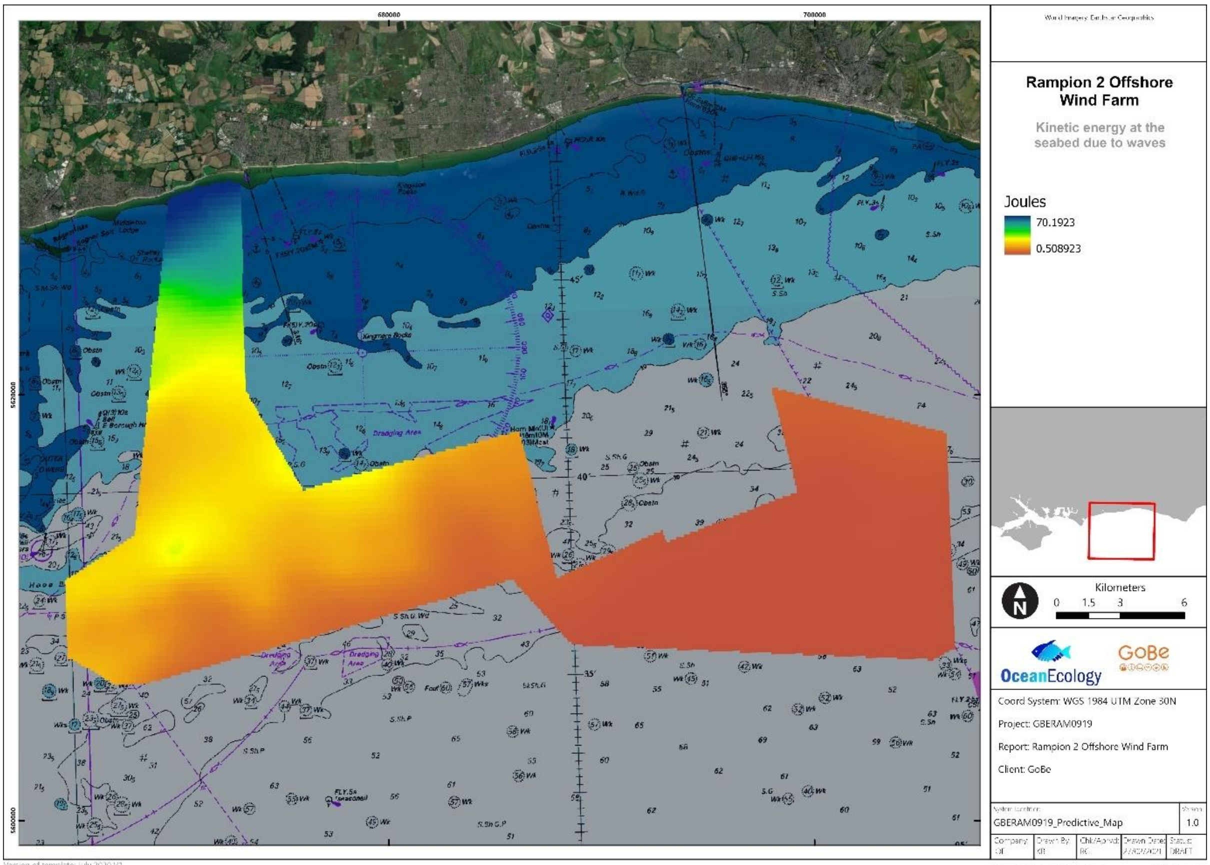

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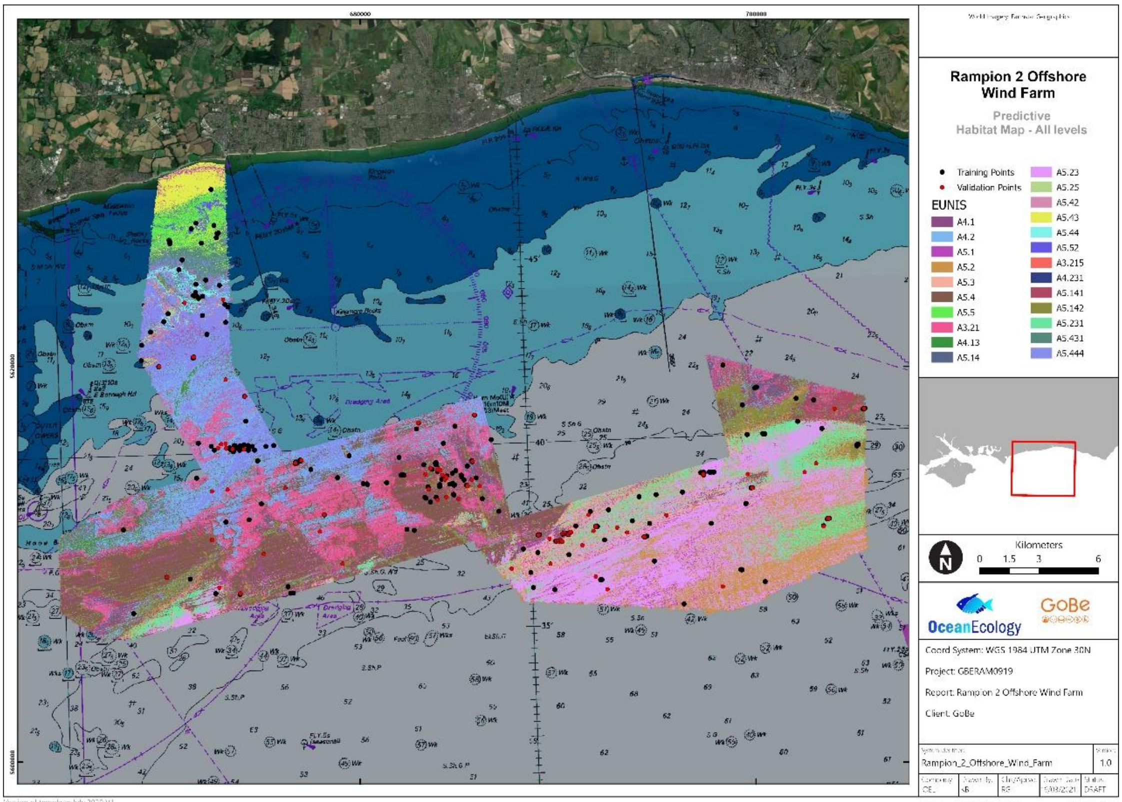
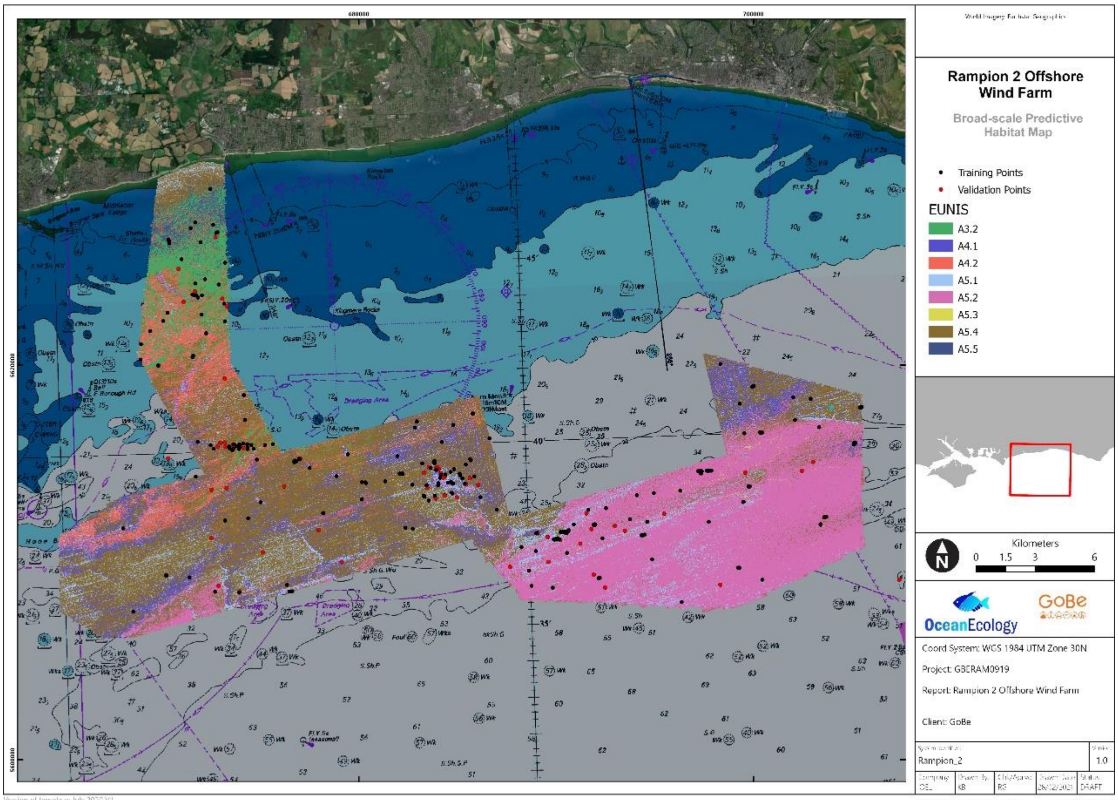
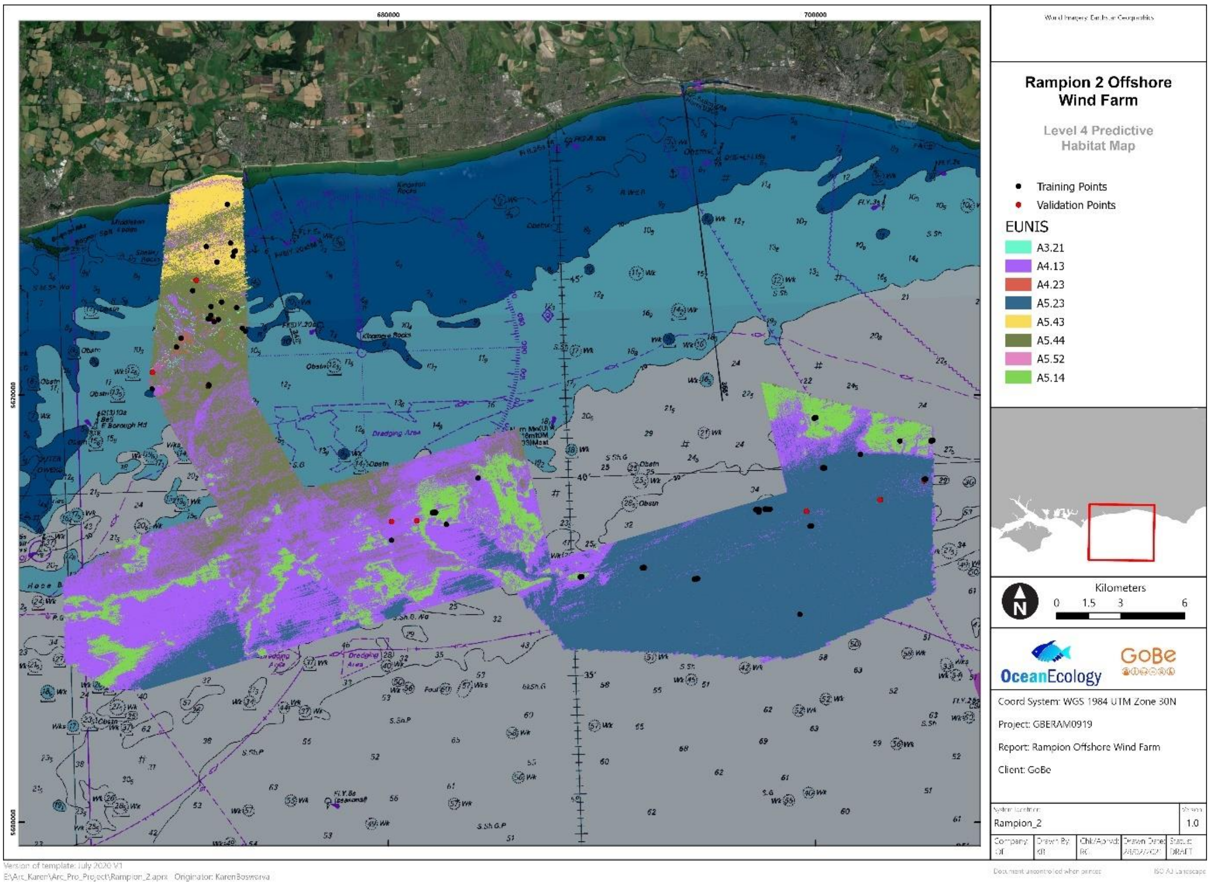
Appendix C- Predictive habitat maps displaying training and validation data points



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Training Points
Validation Points
EUNIS
A3.21
A4.13
A4.23
A5.23
A5.43
A5.44
A5.52
A5.14
Kilometers
0 1.5 3 6
OceanEcology
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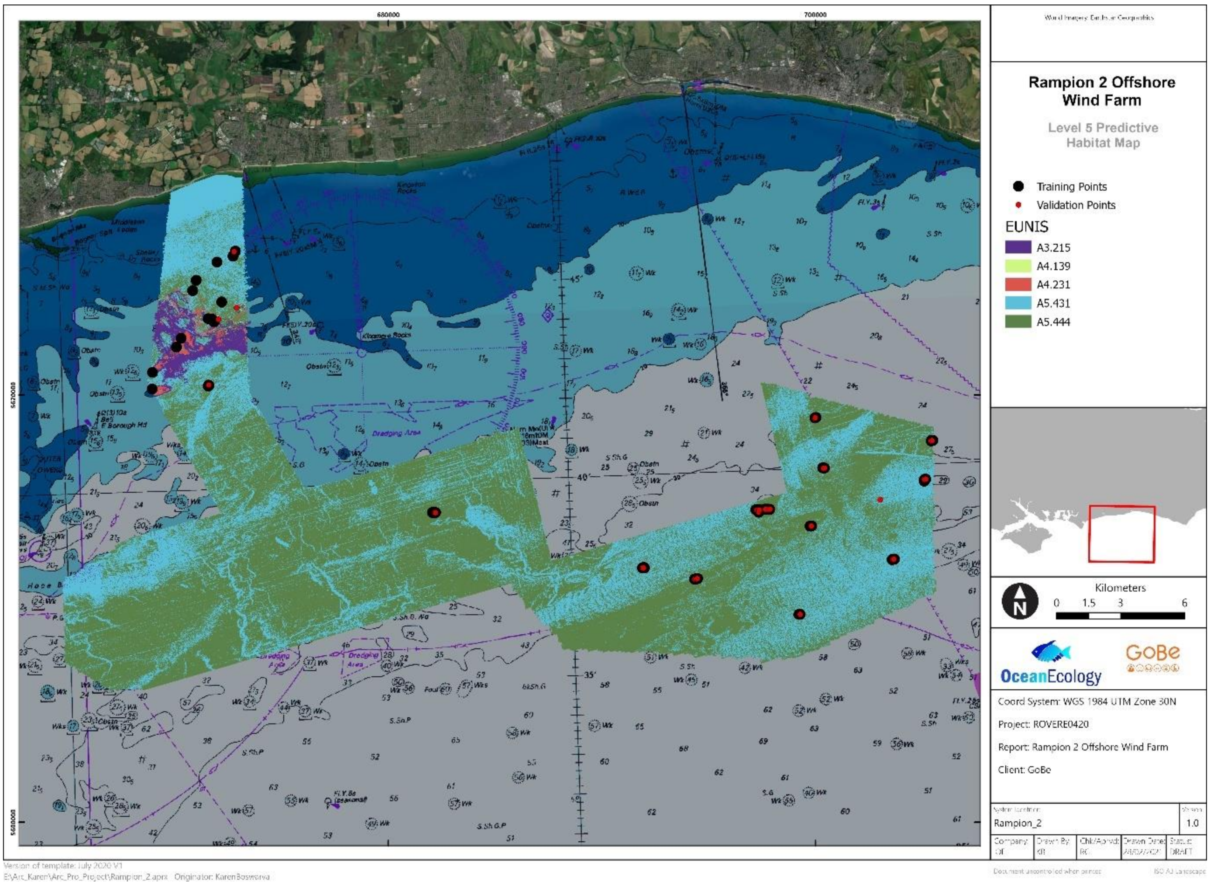
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Level 5 Predictive Habitat Map
Training Points
Validation Points
EUNIS
A3.215
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A4.231
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Kilometers
0 1.5 3 6
OceanEcology
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Project: ROVERE0420
Report: Rampion 2 Offshore Wind Farm
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Appendix D - EUNIS Descriptions

EUNIS Level 5 Biotopes:-

A3.215: [Sabellaria spinulosa] with kelp and red seaweeds on sand-influenced infralittoral rock
A4.231: Piddocks with a sparse associated fauna in sublittoral very soft chalk or clay
A5.141: [Pomatoceros triqueter] with barnacles and bryozoan crusts on unstable circalittoral cobbles and pebbles
A5.142: [Mediomastus fragilis], [Lumbrineris] spp. and venerid bivalves in circalittoral coarse sand or gravel
A5.231: Infralittoral mobile clean sand with sparse fauna
A5.431: Crepidula fornicata with ascidians and anenomes on infralittoral coarse mixed sediment
A5.444: [Flustra foliacea] and [Hydrallmania falcata] on tide-swept circalittoral mixed sediment

EUNIS Level 4 Biotope Complexes

A3.21: Kelp and red seaweeds (moderate energy infralittoral rock)
A4.13: Mixed faunal turf communities on circalittoral rock
A4.23: Communities on soft circalittoral rock
A5.14: Circalittoral coarse sediment
A5.43: Infralittoral mixed sediments
A5.44: Circalittoral mixed sediments
A5.52: Kelp and seaweed communities on sublittoral sediment

EUNIS Broadscale Habitats

A3.2: Atlantic and Mediterranean moderate energy infralittoral rock
A4.1: Atlantic and Mediterranean high energy circalittoral rock
A4.2: Atlantic and Mediterranean moderate energy circalittoral rock
A5.1: Sublittoral coarse sediment
A5.2: Sublittoral sand
A5.3: Sublittoral mud
A5.4: Sublittoral mixed sediments
A5.5: Sublittoral macrophyte-dominated sediment

Rampion 2
WIND FARM