Norwegian Financial Mechanism and Republic of Lithuania

Coastal Research and Planning Institute, Klaipėda University

Project: A system for the sustainable management of Lithuanian marine resources using novel surveillance, modeling tools and ecosystem approach

Technical Report No. 5

PREDICTED HERRING (CLUPEA HARENGUS) SPAWNING GROUNDS IN THE LITHUANIAN COASTAL WATERS

Project indicator:
1. Documented model of spatial distribution of fish feeding and spawning grounds

Prepared by: Johan Näslund[1]

Contributors: Aleksej Šaškov[2]
Andrius Šiaulys[2]
Martynas Bučas[2]
Darius Daunys[2]
Tomas Didrikas[2]

[1]AquaBiota Water Research
[2] Coastal Research and Planning Institute, Klaipeda University

March 2011, Klaipėda

STOCKHOLM, MARCH 2011

Client:
Performed by AquaBiota Water Research within the EEA and Norwegian Financial Mechanism Programme project LT0047 “A system for the sustainable management of Lithuanian marine resources using novel surveillance, modelling tools and an ecosystem approach”

Contact information:
AquaBiota Water Research AB
Address: Svante Arrhenius väg 21 A, SE-114 18 Stockholm, Sweden
Phone: +46 8 16 12 28
Web page: www.aquabiota.se

Quality control/assurance:
Göran Sundblad (goran.sundblad@aquabiota.se)

Distribution:
Free

AquaBiota Report 2011:01

ISBN: 978-91-85975-12-9
ISSN: 1654-7225

SUMMARY

Maps of species and habitats have become an important tool for managing the marine environment and detailed knowledge on the distribution of spawning grounds of commercially important fish species is a vital part of an ecosystem based approach to fisheries management. In this study, GIS layers of environmental variables such as depth, substrate, terrain roughness, aspect and wave exposure were prepared for the Lithuanian coast at two different levels of detail. By using a maximum-entropy modelling approach, using the program MaxEnt, the GIS layers of produced environmental variables were used to predict herring (*Clupea harengus*) spawning grounds on the Lithuanian coast (50 m resolution). Higher resolution data was available for a smaller sub-area of the coast, near Palanga, and was used separately to model herring spawning grounds at an elevated level of detail (25 m resolution). In the sub-area, the detailed bathymetry also allowed the construction of more accurate depth derived environmental layers, such as terrain roughness index. The sub-area modelling resulted in a more reliable prediction of potential herring spawning grounds which allowed a detailed assessment of which environmental characteristics that are important for herring spawning in the Lithuanian coast.

Although this study was constrained by a limited spatial distribution of the occurrence of herring spawning ground data and variable quality of the predictor variables, the results are expected to be ecologically sound and may hence provide valuable support for marine spatial planning.

INTRODUCTION

Knowledge on the spatial distribution of ecologically important features is a key tool in order to effectively manage marine resources and apply an integrated ecosystem based management. In this context geographic information systems (GIS) have been shown to be an important tool for both research and management as it provides the basis for modelling and displaying the distribution of species and habitats (Guisan and Zimmerman 2000). By relating species distributions to environmental conditions, researchers may infer both ecological conclusions as well as predict species and habitat distributions across seascapes (Elith and Leathwick 2009). Spatial distribution modelling using presence-only methods has proven highly useful for certain types of data (Elith et al 2006). One of the most used, and recommended, modelling tools for presence only data is the program MaxEnt.

The Baltic Sea herring (*Clupea harengus*) supports an economically and culturally important fishery and is a critical component of the Baltic Sea ecosystem. Baltic Sea herring is capable of restructuring lower trophic levels (Hansson et al. 1990; Arrhenius and Hansson 1993), thus influencing nutrient dynamics (Hjerne and Hansson 2002) Together with cod (*Gadus morhua*) and sprat (*Sprattus sprattus*), herring is an important component of the Baltic Sea off-shore food-web (Sparholt 1994; Köster and Möllmann 2000; Harvey et al. 2003).

In order to have a sustainable use of fish stocks, it is crucial to ensure a high level of recruitment. An essential factor for successful fish recruitment is that suitable spawning habitats are available (Mumby et al 2004). Although herring is an important fish species in the Baltic Sea, many aspects related to its spawning grounds are poorly known. Thus, by identifying important spawning habitats, their importance for population size can be assessed and possibly protected to ensure long-term recruitment success. The present study was carried out in order to produce a map of potential herring spawning grounds in Lithuanian coastal waters.

This study was carried out within the EEA and Norwegian Financial Mechanism Programme project LT0047 “A system for the sustainable management of Lithuanian marine resources using novel surveillance, modelling tools and an ecosystem approach”.

MATERIALS AND METHODS

Geographical area and data on herring spawning

The area of study was limited to the Lithuanian exclusive economic zone. Data on herring spawning was collected by the Coastal Research and Planning Institute, Klaipeda University, mainly during 2009 and 2010 using diving censuses. A total of 105 locations were visited (see Figure 1 and Table 1). At each visited location the depth, position and whether herring roe were observed or not were noted. Herring roe were observed at a total of 57 locations. Data collection was limited to the northern part of the coast as this is the region where herring spawning mainly have been observed previously.

Table 1. *Data on the diving censuses. N.a. - not available.*

	Start date	End date	Number of locations	Min depth (m)	Max depth (m)
Pre 2009	n.a.	n.a.	5	6	11
2009 season	7 April	29 April	59	4	14
2010 season	19 April	7 May	41	3	10

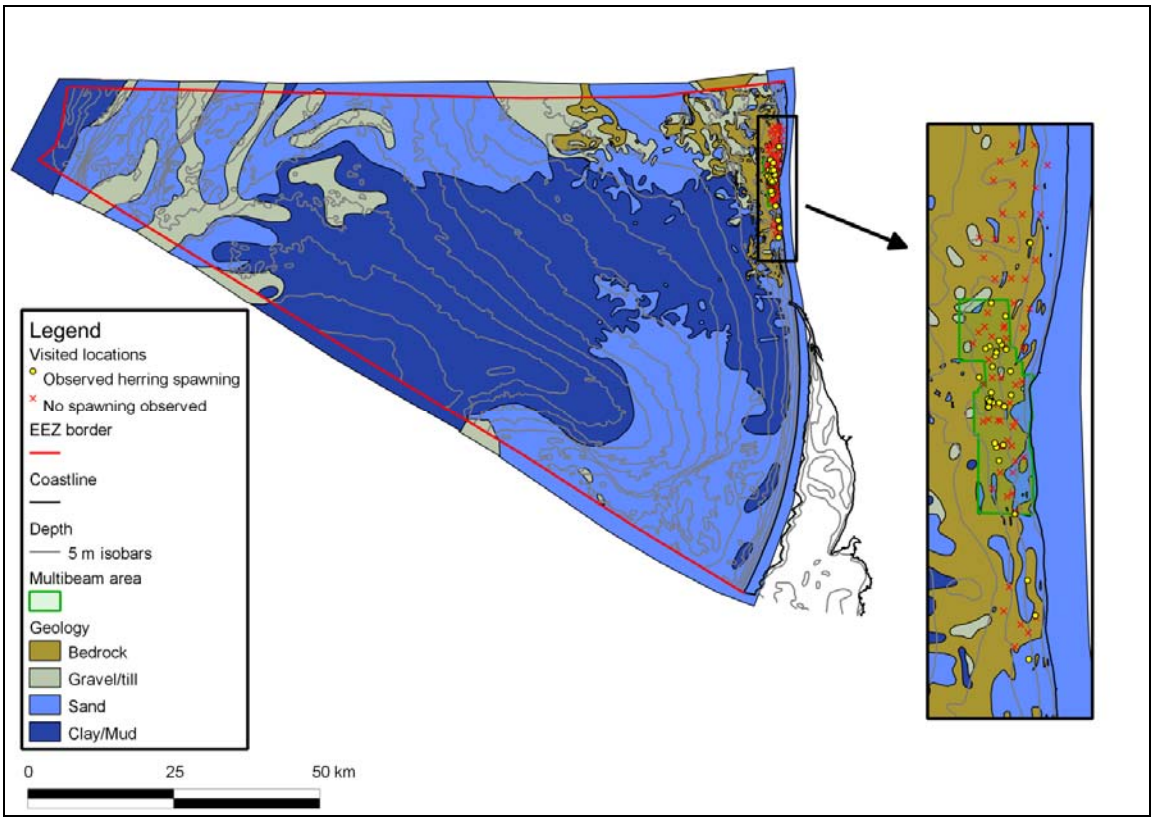


Figure 1*. Map over the Lithuanian coast showing the EEZ, sampled locations, 5 m depth isobars and geology. A sub-area with multibeam data is enclosed in green outline*

Development of GIS predictor variable layers

Open source software was used for the development of GIS layers: GRASS 6.4.0 (GRASS Development Team 2010) and SAGA API 2.0.6 (Conrad 2006). The projection WGS 84 / UTM zone 34N was used throughout the study.

Different sources of environmental data were used as input for the creation of GIS predictor variable layers. Grids with a spatial resolution of 50 m were created for the whole Lithuanian coast. More detailed bathymetry was available for a sub-area of the coast, where multibeam measurements have been performed (see Figure 1). For the multibeam sub-area, grids with a spatial resolution of 25 m were also created.

The distributions of all continuous environmental variables were plotted in R to see if they were normally distributed. Continuous variables that were non-normally distributed were transformed if it was possible to significantly improve their distribution towards normality.

Bathymetry was available for the whole Lithuanian EEZ in GIS layers as lines (isobars) with 5 m depth interval. In order to calculate a continuous grid with depth for the Lithuanian EEZ, the following procedure was used: (1) evenly distributed points were added to all lines containing the depth values from the isobars, utilizing the "Points from lines" module in SAGA 2.0.6. The distance between the points were chosen so that the smallest features of the isobars would be represented. (2) the final depth grid was interpolated from the created points using the SAGA "Triangulation module". The depth grid was not validated with independent data as none were available.

The developed depth grid was used as input for the SAGA "Standard terrain analysis" module in order to calculate curvature (planar and profile curvature), slope and aspect (later transformed to eastness [sin aspect] and northness [cos aspect] using the r.mapcalculator in GRASS). Two ruggedness measures were also calculated in SAGA using the modules "Terrain ruggedness index" (Riley, De Gloria et al. 1999) and "Vector ruggedness measure".
Data on the geology of the Lithuanian EEZ was available as polygons containing substrate classes. The polygons were converted into grids in GRASS using the v.to.rast function.

For a sub-area of the coast, near Palanga, data were also available from multibeam measurements as points with about 5-10 m interval. A continuous grid at 25 m resolution for the multibeam area was created using the SAGA "Triangulation module". The detailed bathymetry allowed the creation of more accurate topography related predictor layers at finer scale than was possible for the whole coastal area. The developed depth grid was used to calculate curvature (planar and profile), curvature index, eastness (sin aspect), northness (cos aspect), slope, terrain roughness index (75, 150 and 250 m window), vertical terrain roughness index and protection index using the SAGA modules "Standard terrain analysis", "Terrain ruggedness index" and "Vector ruggedness measure". The SAGA module Wind effect (Windward/Leeward index) was used to create a grid that described the degree of exposure/shelter to wave energy coming from west by using the depth grid as elevation input and a western wind direction. As wind effect is a somewhat confusing term for this predictor layer, the grid is called "Western wave energy exposure index" in this report.

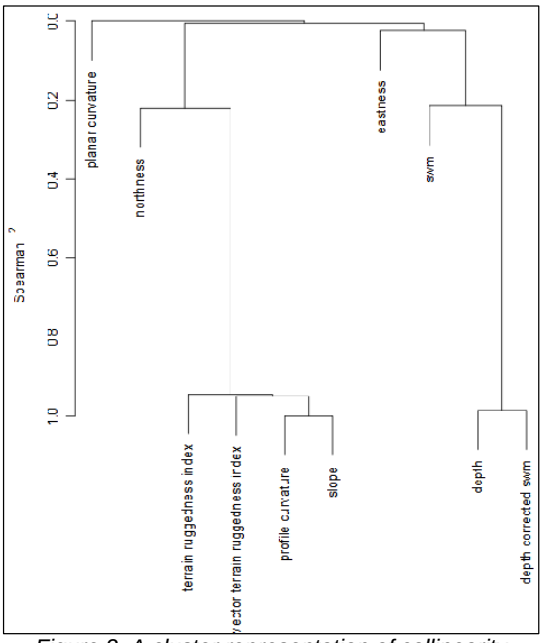


Figure 2. A cluster representation of collinearity between predictor layers for the whole coast model.

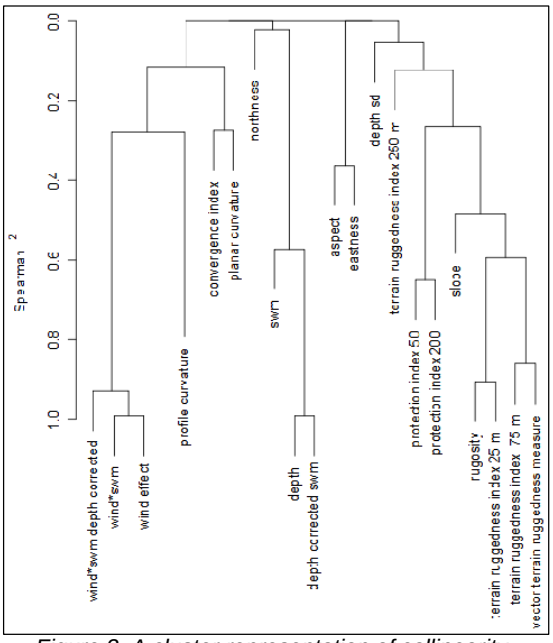


Figure 3. A cluster representation of collinearity between predictor layers for the Sub-area model.

Wave exposure at the sea surface had been previously calculated for Lithuanian waters with a resolution of 25 m (Wijkmark and M. 2010) by using the Simplified Wave Model method SWM (Isæus 2004). The SWM is calculated using wind data from land and fetch length (i.e. the distance of open water over which the wind can act and develop waves). The wave exposure at the sea floor was calculated in GRASS with r.mapcalc by using the formula $SWM \times \exp((((22 \times ((9.8^2)/SWM)^{\wedge}(1/3))^2)/9.8) \times (-depth))$

***Table 2**. Input data for the environmental predictor layers.*

	Variable	Type	Resolution (m)	Source
Whole coast	Substrate	Vector		Klaipeda
	Depth	Vector (isobars)	5 m interval	Klaipeda
	Wave exposure	Grid	25	AquaBiota
Sub-area	Substrate interpretation (multibeam backscatter)	Vector	< 10	Klaipeda
	Depth (multibeam point measurements)	Vector	< 10	Klaipeda

see Bekkby, Isachsen et al. (2008) for more details. A summary of the environmental data that were used as input for the predictor layers is presented in Table 2.

Predictor variable selection

To test for correlations among environmental predictor variables we used R version 2.12.1 (R development core team 2011) and the Hmisc package to plot a cluster representation of the degree of collinearity (Figure 2 and 3).

Environmental variables that are highly correlated may be used in the same model but is problematic as it may result in model building bias as well as difficulties in interpreting the results. Therefore, smaller subsets of non-correlated variables were used as potential predictor layers for the modelling. For correlated variables, selection was based on ecological importance. Additionally, predictor variables that only contributed to a very small degree, based on jack-knife importance, were also removed, whereupon the model was re-run. See Table 3 (page 9) for a summary of the layers used in the final model.

Modelling and probability predictions

The program MaxEnt, version 3.3.3e, was used to create probability maps of potential herring spawning habitats (Phillips, Anderson et al. 2006; Elith et al. 2011). All observations on herring spawning locations (presences) from the data were used as input for a GIS vector layer containing the coordinates for all points. The points were converted into raster layers (one with 25 m resolution and one with 50 m resolution) by using r.stats and r.out.ascii in GRASS, and thereafter edited with a text editor for input into MaxEnt. Some presence points were located in the same grid cell, leading to a final number of 39 presence localities for the whole coast model and 36 for the sub-area model.

Table 3. The predictor layers used in the final models.

	Variable	Type	Resolution (m)	Produced in
Whole coast	Depth corrected SWM	Continuous	50	WaveImpact & GRASS
	Substrate	Categorical	50	GRASS
	Terrain Roughness index	Continuous	50	SAGA
Sub-area	Terrain roughness index (250 m calculation window)	Continuous	25	SAGA
	Western wave energy exposure index	Continuous	25	SAGA
	Depth	Continuous	25	GRASS
	SWM	Continuous	25	WaveImpact
	Compass direction (N, E, S, W)	Categorical	25	GRASS
	Substrate (multibeam interpretation)	Categorical	25	GRASS

The model for the whole coast was reduced in size to the part of the coast where herring spawning is known to occur. The boundary for the whole coast model was N, 6213795; S, 6175445; W, 498551; E, 505751 (in WGS84 long 20°58’36” – 21°5’29”, lat 56°4’9” - 55°43’28”). The restriction of the model to this area was made in order to not inflate the model performance (due to including large areas with very low probability for presence) (VanDerWal, Shoo et al. 2009). The sub-area model was restricted to the area where multibeam measurements had been made. MaxEnt was run with the default settings with

the exceptions that 10 replicate bootstrap runs (random selection of test data with replacement) were performed using 30 % of the data for model testing in each bootstrap run.

The correlation between the two models was compared in the overlapping area using the r.covar function in GRASS. The correlation between the two models was 0.30. From this it was clear that the whole coast model greatly overpredicted the probability for herring spawning habitats, compared to the more detailed sub-area model (approximately 4.74 times higher). Therefore, the difference in prediction for the two models (4.74) was used to correct the predictions for the whole coast model to give comparable probability predictions between the two models..

The 3D image of the sub-area model was created in GRASS using the nviz tool and the depth layer derived from multibeam measurements and the predicted distribution map from MaxEnt.

Analyses of stratification in the sampled points

In order to analyse potential bias due to stratification in the collection of samples the following procedure was used: (1) the vector layer containing all visited locations was updated by sampling all predictor layers used in the models with the v.what.rast function in GRASS. (2) The attribute table was exported to Microsoft excel and the environmental variables were plotted in graphs. (3) Corresponding statistics for the whole predictor layer was calculated using the r.univar function in GRASS.

Boxplots were used for continuous variables and bars for categorical variables. The distribution of environmental variables at sampled locations compared to the whole area is shown in fig 4 for the large scale

Figure 4. *Distribution of environmental variables at sampled locations compared to the whole area for the whole coast model. Black points denote median, boxes 1st and 3rd quantile and error bars maximum and minimum.*

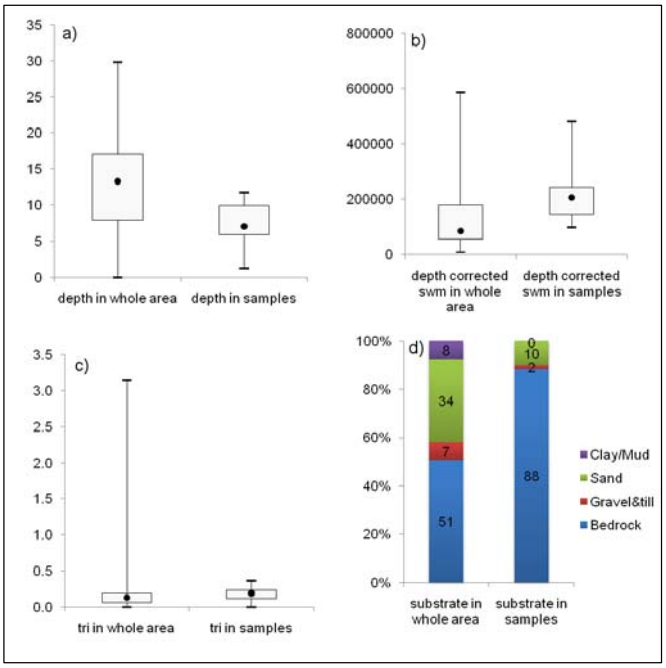
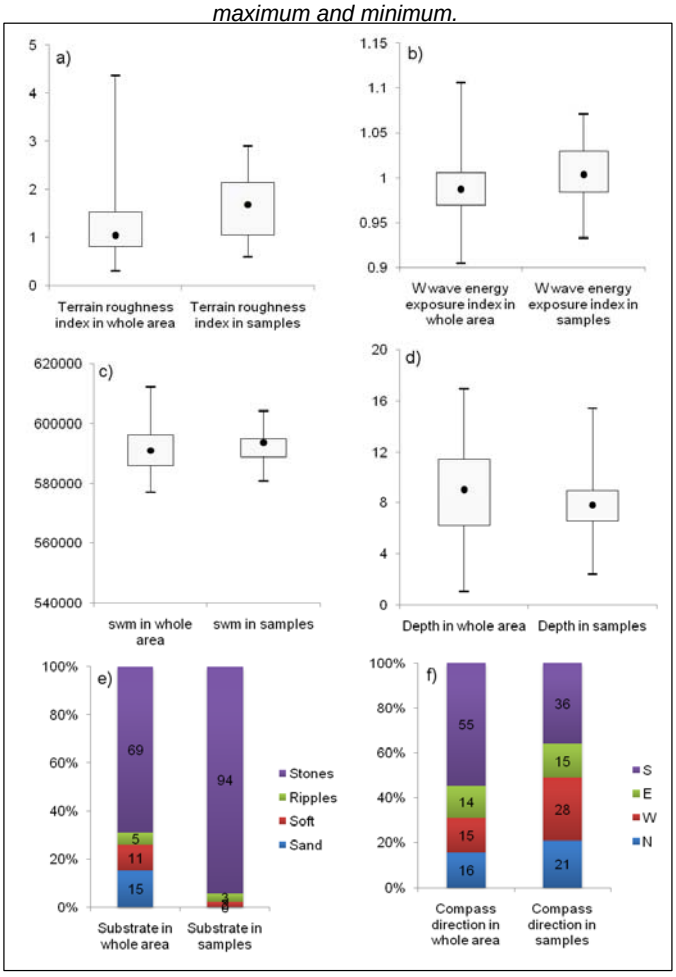


Figure 5. *Distribution of environmental variables at sampled locations compared to the whole area of the sub-model. Black points denote median, boxes 1st and 3rd quantile and error bars maximum and minimum.*



model and in Figure 5 for the sub-area model.

The distribution of environmental variables at the sampled locations for the whole coast model shows that samples at relatively deep (Figure 4a), low depth corrected wave exposure (Figure 4b) and with a low or high terrain ruggedness index (Figure 4c) are slightly under-representatively sampled. However, bedrock is considerably over-representatively sampled for the whole coast area with 88 % of the sampling effort, compared to its extent of 51 % in the modelling area.

The distribution of environmental variables at the sampled locations for the sub-area shows that samples with a low or very high terrain ruggedness index (Figure 5a) and Western wave energy exposure index are slightly under-representatively sampled. However, the substrate “stones” is over-representatively sampled for the sub-area with 94 % of the sampling effort, compared to its extent of 69 % in the modelling area (Figure 5e).

RESULTS

The distribution of potential herring spawning habitats for the whole coast model was best explained by a model including depth corrected SWM, substrate and terrain ruggedness index (see Table 4). The model was stable, with an average training AUC of 0.944 with a standard deviation of 0.01 and an average test AUC of 0.942 with a standard deviation of 0.01. The AUC in MaxEnt is calculated from created pseudo-absences. The predicted map for the whole coast model is shown in Figure 6.

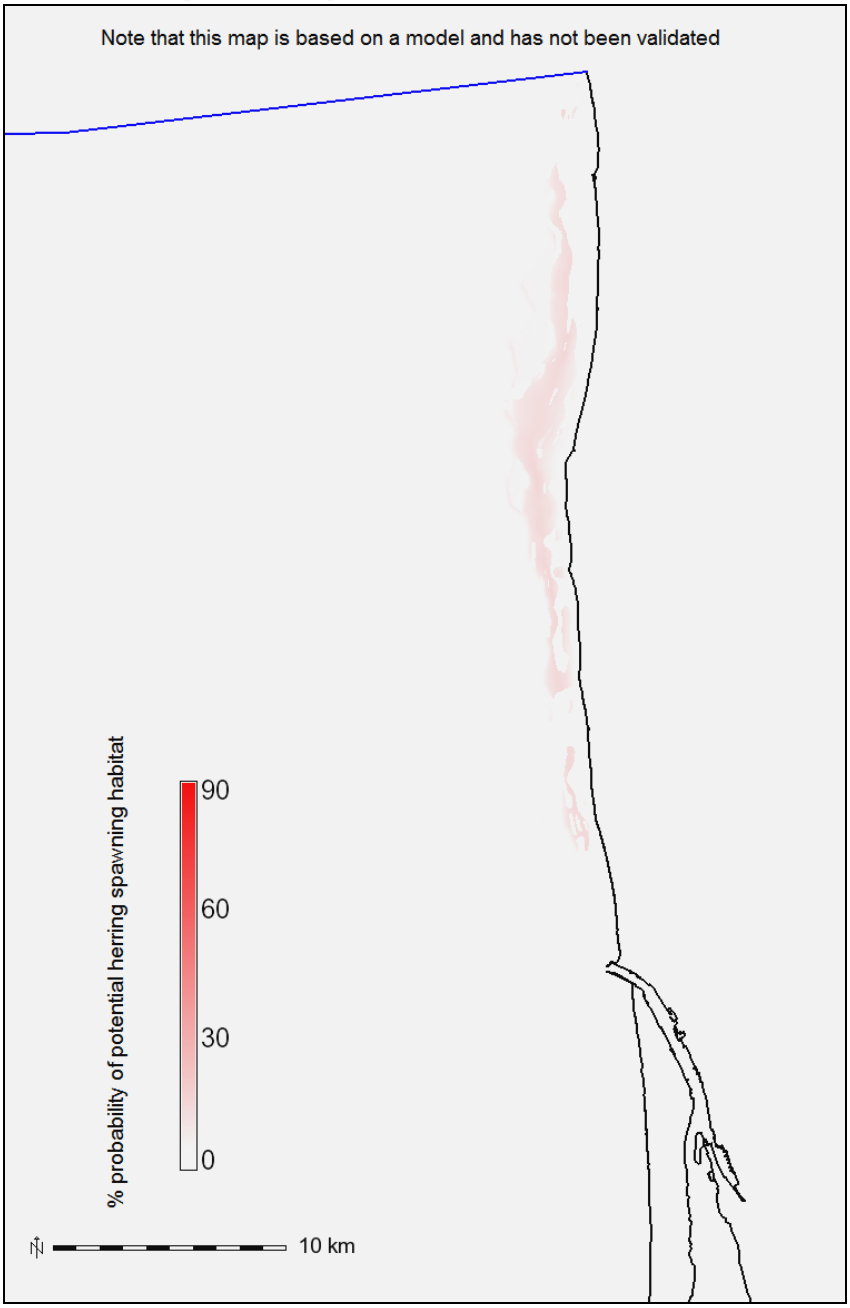


Figure 6. *The modelled probability for presence of Herring spawning habitat on the Northern part of the Lithuanian coast.*

The distribution of potential herring spawning habitats in the sub-area model was best explained by a model including terrain roughness index, western wave energy exposure index, depth, SWM, compass direction and substrate (see Table 5). Based on bootstrap-runs the model was stable, with an average

training AUC of 0.954 with a standard deviation of 0.01 and an average test AUC of 0.934 with a standard deviation of 0.03. The map with predicted herring spawning habitats in the sub-area model is shown in Figure 7. This map but including plotted presence and absence points is shown in the appendix (Figure 10) and may serve as an additional tool for the evaluation of model performance and reliability. The same prediction of potential herring spawning grounds visualized in 3D, utilizing the available detailed bathymetry is shown in Fig 8.

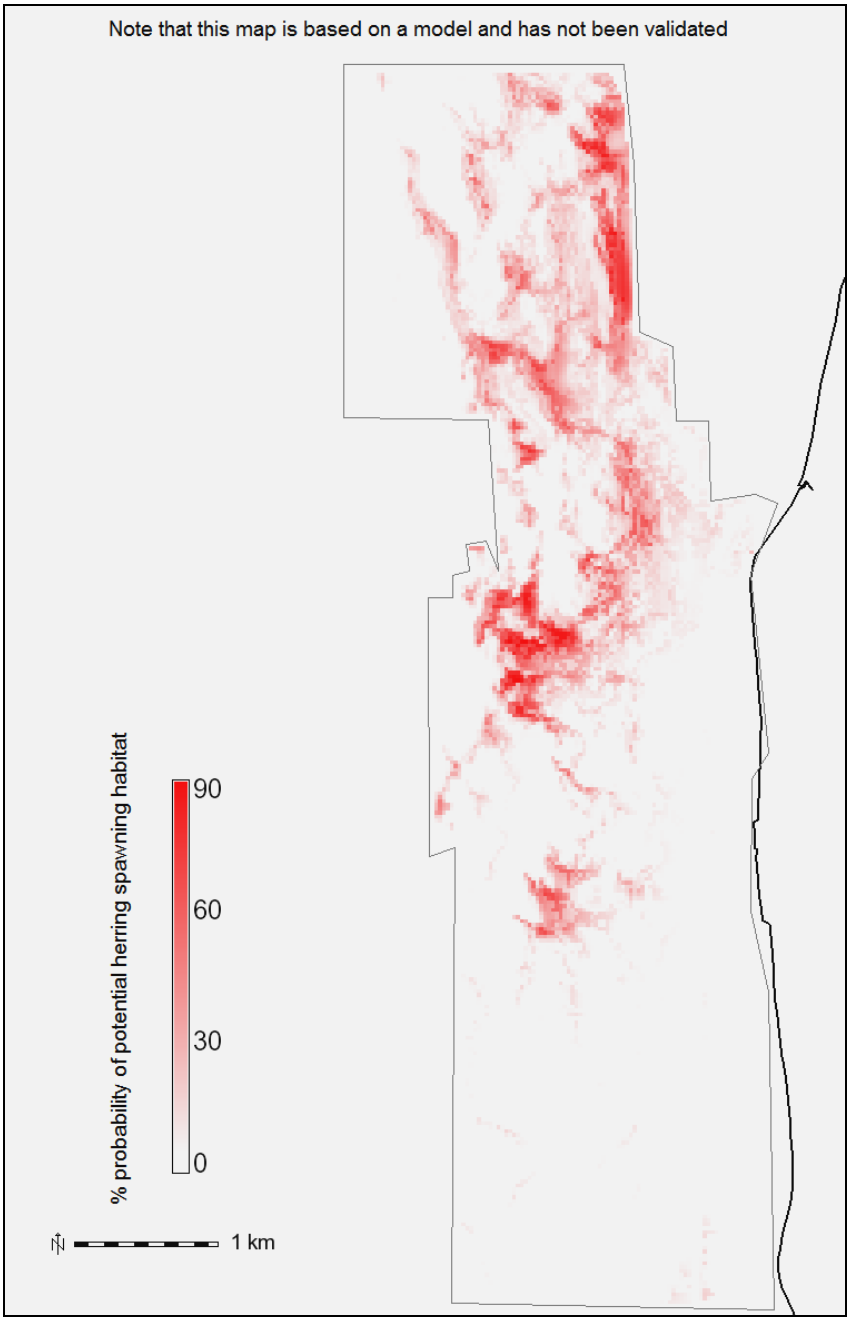


Figure 7. *The modelled probability for presence of Herring spawning habitat in the sub-area.*

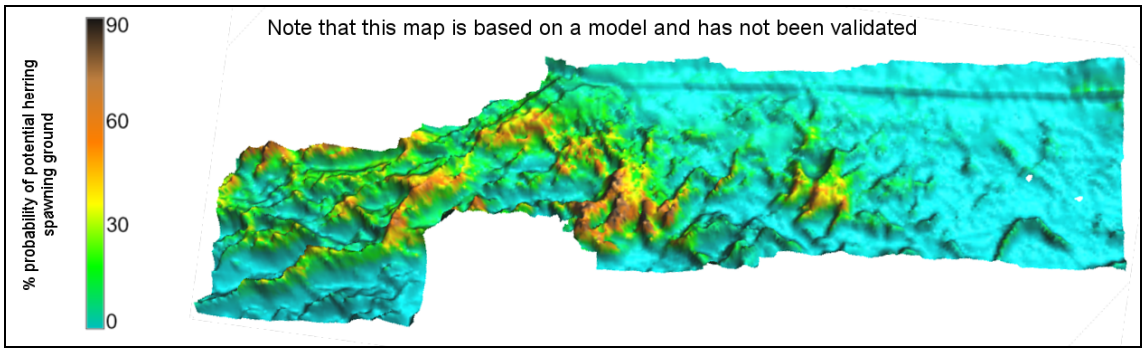


Figure 8. *3D visualization of the modelled probability for presence of Herring spawning habitat in the sub-area, made by draping the predicted map on a digital terrain model derived from the depth predictor layer. The importance of terrain features is clearly visible, with high predicted probability of herring spawning grounds in rugged terrain.*

Table 4. *The contribution (importance) of the environmental variables in the whole coast model.*

Variable	Contribution (%)
Depth corrected SWM	66.2
Substrate	28.0
Terrain ruggedness index	5.8

Table 5. *The contribution (importance) of the environmental variables in the sub-area model.*

Variable	Contribution (%)
Terrain ruggedness index	34.8
Western wave energy exposure index	18.9
Depth	16.2
SWM	15.0
Compass direction	9.2
Substrate	5.8

The contributions (importance) of the environmental variables to the models are shown in Table 4 for the whole coast model and in Table 5 for the sub-area model. Response curves for the two models are shown in Figure 9 and 10, respectively.

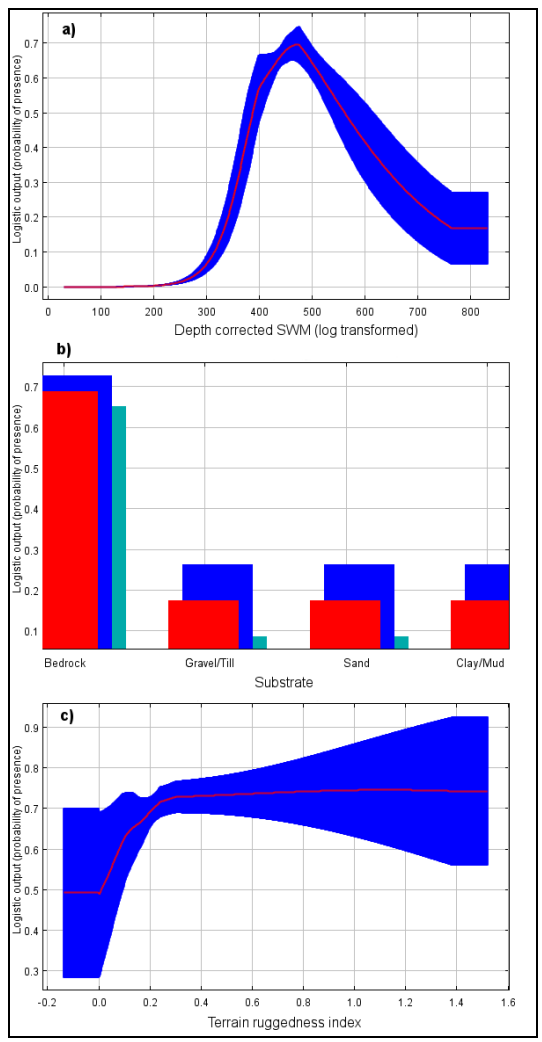


Figure 9. *Average response curves for the whole coast model is shown in red. a) depth corrected SWM, b) substrate c) terrain ruggedness index. Standard*

deviation based on the 10 bootstrap runs is denoted in blue.

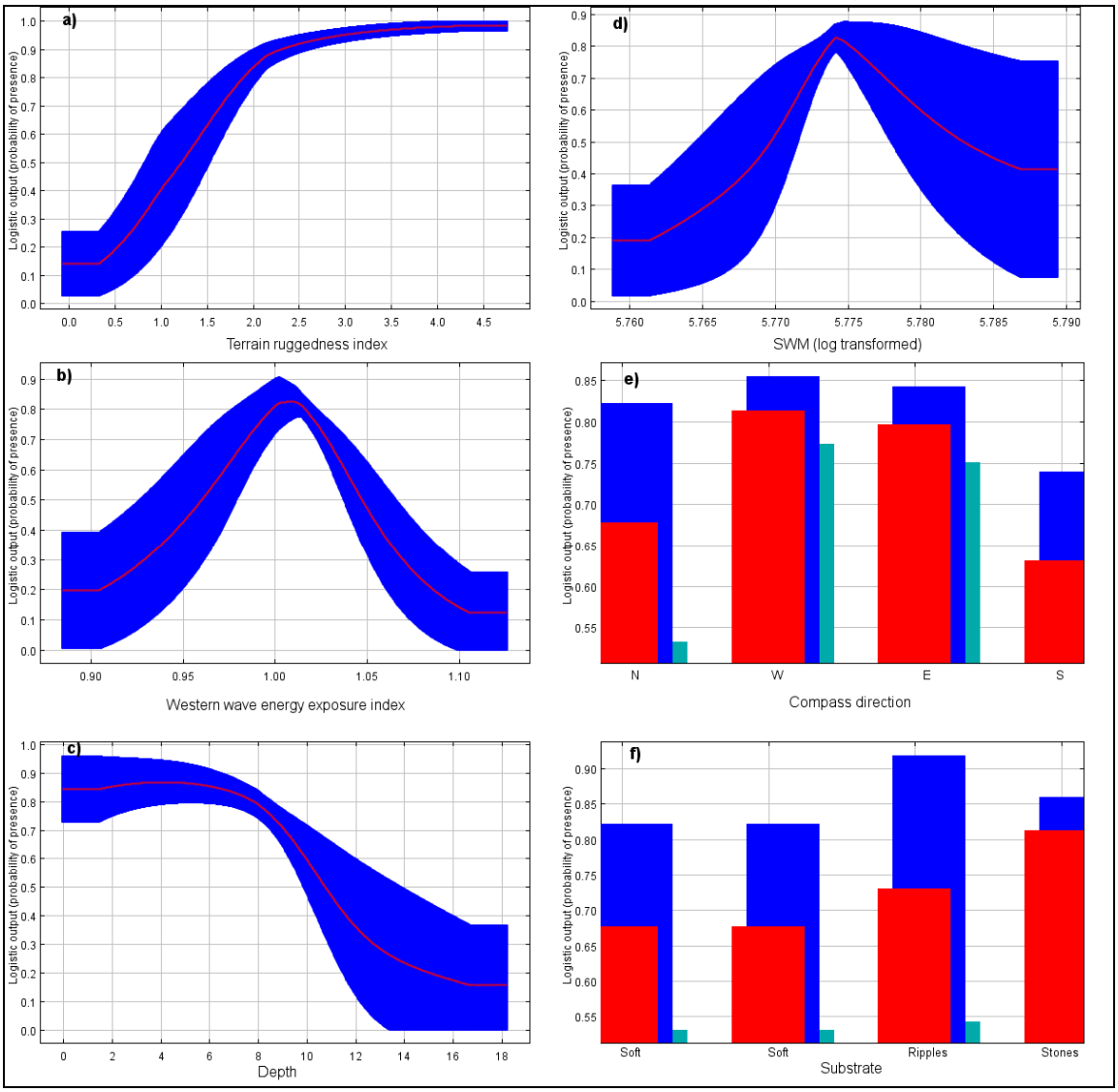


Figure 9. *Average response curves for the whole coast model are shown in red. a) terrain ruggedness index, b) western wave energy exposure index c) depth d) SWM (log transformed) e) compass direction f) substrate. Standard deviation is denoted in blue.*

DISCUSSION

Due to the fact that no independent validation data was available for the study, the maps of predicted potential herring spawning habitat should be interpreted with caution. However, these spatial predictions of potential herring spawning grounds are ecologically sound in general and the model was stable, with relatively low variance among the bootstrap runs. They are useful as a guide for further studies of potential distribution of important herring recruitment areas in Lithuanian waters. However, it is important that the models are evaluated further in the future by using independent control data.

The models of potential herring spawning grounds are based on data collected by divers and where they have observed herring roe directly. As some locations were visited during consecutive years and, in some cases, herring roe was observed in one of the years but not the other, not only spatial but also temporal variation is important. Additionally, spawning at some suitable spawning sites may also occur later than when they were visited by divers, since herring spawning at this latitude have been observed between March-June (Aneer 1989; Fey 2001; Krasovskaya 2002), longer than the sampling period of the diving census study (Table 1). Thus, the predicted probability maps give the relative probability for a diver of finding roe at a specific location given the conditions at the time of original sampling. The high temporal variation and the fact that it may be difficult to find herring roe while diving, suggest that a model which uses presence only data would be most suitable (Elith at al 2011). Presence-absence type models normally perform better than presence only models as more data may be used, but are sensitive to the presence of false absences, which are likely to have occurred in our dataset.

The whole coast model has a relatively low resolution, due to the lack of appropriate environmental variables that may function as suitable predictor layers. Despite this, the predicted map for the whole coast may give a broad overview on where suitable herring spawning grounds can be found. The response curves from the model (Figure 9) further indicate that herring spawning grounds are mainly occurring with an intermediate wave exposure, on hard substrate (bedrock) and in rugged terrain (Table 4 and Figure 9). These results are in agreement with Rajasilta et al. (1993) and Aneer's (1989) studies in Finnish and Swedish archipelagos respectively, where herring spawning mostly occurs on hard substrate and/or vegetation shallower than 10 m. The importance of intermediate wave exposure for the model may have been affected by potential erosion of herring roe from sites with relatively high exposure, which are also shallower. Even if this would be the case, i.e. herring spawning do occur at locations with a high degree of exposure but is quickly eroded away; these sites would still be comprised of locations without herring roe – which is needed for successful hatching of larvae. The whole coast model has a relatively coarse resolution in the environmental predictor layers and predicts spatial patterns on a relatively coarse and large scale, compared to the sub-area model.

The sub-area model had a higher level of detail but was, naturally, limited to a much smaller area than the whole coast model. Despite this, the high level of detail in the bathymetry provided a way to investigate which terrain features that are related to herring spawning grounds. The response curves in the sub-area model indicate that the environmental characteristics related to suitable herring spawning grounds are: (1) Rugged terrain (2) an intermediate wave exposure and degree of shelter to West (3) locations not deeper than 10-14 m (4) a slope facing either West or East (5) hard substrate. Considering depth and substrate, these results are in agreement with Rajasilta et al. (1993) and Aneer's (1989) studies in Finnish and Swedish archipelagos respectively, similar to the whole coast model results. The other environmental characteristics related to modelled spawning grounds (terrain ruggedness, slope and wave exposure) could potentially be explained by erosion of roe from exposed locations (potentially accumulating at sheltered sites) or that herring mainly spawn at somewhat sheltered locations in Lithuanian coastal waters.

The high relative importance of topography related environmental variables in the sub-area model, where a detailed bathymetry was available, clearly shows the importance of access to high quality bathymetric data for marine spatial predictive modelling (compare Table 4 and 5). The importance of topography related environmental variables in order to predict where herring spawning occur is further highlighted by a high correlation (0.91) between the two different depth grids used in the models. This correlation indicates that solely differences in depth cannot explain the large discrepancy between the two models. Thus, it is more likely the poor spatial resolution of the bathymetry for the whole coast model, which does not allow calculations of topographic features at a finer scale, which has caused the low level of detail in the whole coast model.

The analysis of potential stratification in the diving censuses (Fig 4 and 5) indicate that the models should be interpreted with caution. On the other hand, this mainly seems to be an issue for the substrate variable. The lack of samples from soft substrate locations makes it difficult to draw a conclusion from the models that herring spawning almost exclusively occur at hard substrates. However, the analysis of potential stratification in sampled substrates was made by sampling the environmental layers which are estimations of the reality and not always correct. The notes from the diving censuses (which include visual substrate classifications) show that the substrate predictor layer does not reflect the heterogeneity in substrate present in some grid cells (meaning that patches of sand were present in some cells classed as hard substrate). Furthermore, in the studies by Aneer (1989) and Rajasilta et al. (1993) herring spawning was found to be mainly related to hard substrates and it is plausible that herring spawning does not occur on soft substrate in Lithuanian waters.

The two models in this study complement each other and may be used and interpreted in different ways. The whole coast model may provide more useful from a spatial planning perspective, and gives indications on a larger scale where important herring spawning grounds are located in Lithuania. The sub-area model on the other hand, shows that various terrain related features, at a level of detail not available for the whole Lithuanian coast, are important for herring spawning and may provide more accurate indication on which environmental characteristics that are associated with spawning site selection.

ACKNOWLEDGEMENTS

We gratefully acknowledge the funding from the EEA and Norwegian financial mechanism programme. Sincere thanks to the project leader Dr. Darius Daunys, Klaipeda University and Dr. Martin Isæus, AquaBiota Water Research for making this project possible and to Göran Sundblad, AquaBiota Water Research, for helpful discussions and comments on the report.

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APPENDIX:

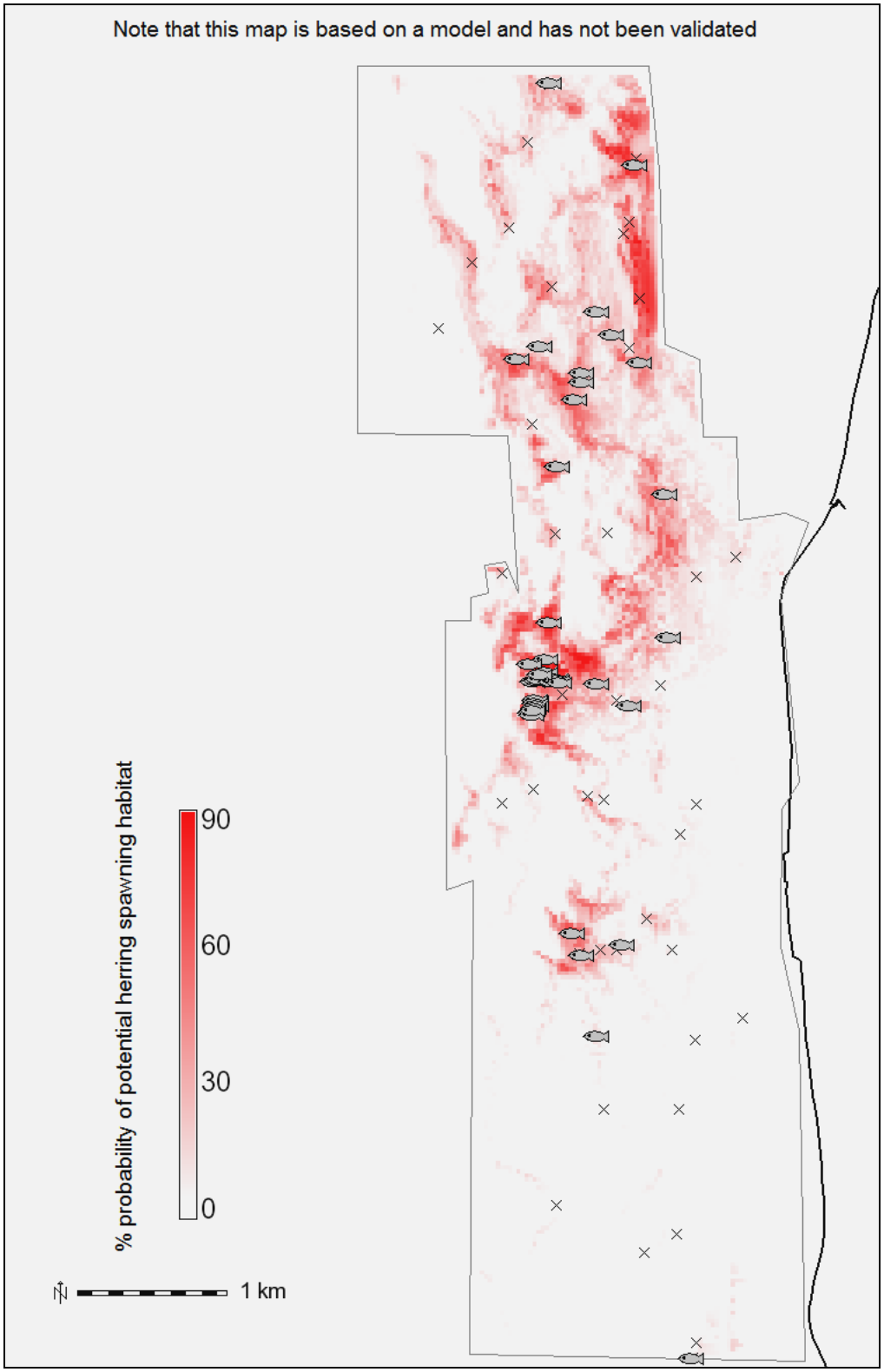

***Figure 10**. Fishes denote locations with observed herring spawning grounds. Crosses denote visited locations where no spawning was observed (note that the absence locations have not been used to build the model).*