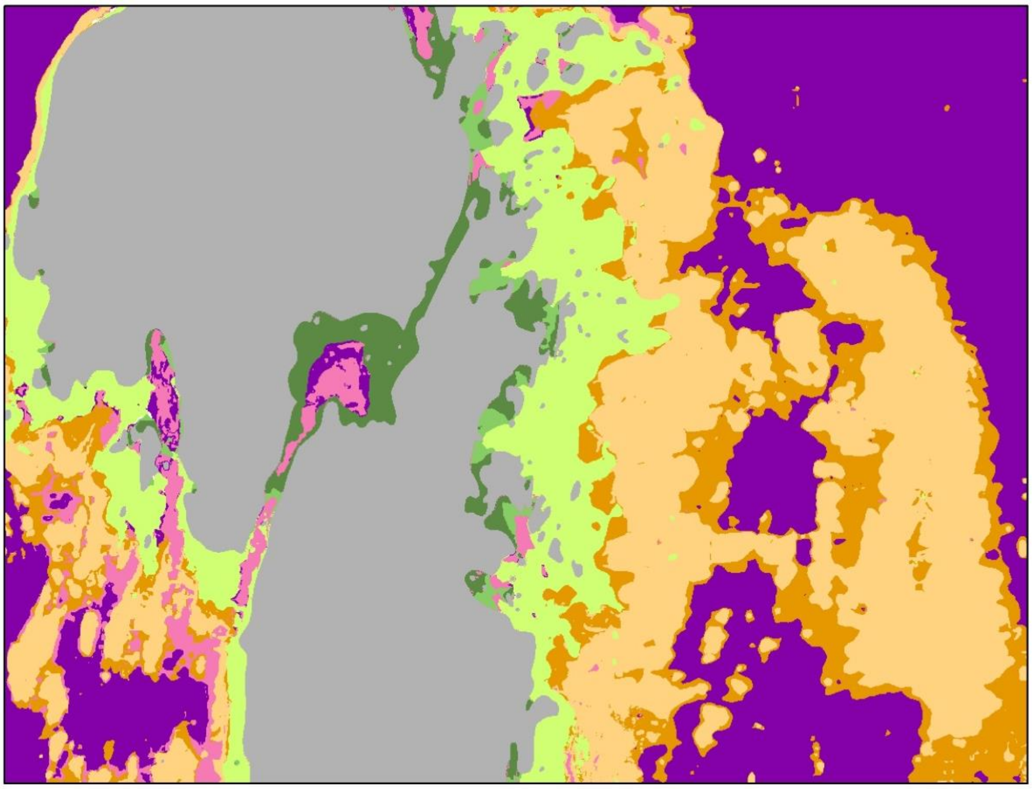
Underwater biotopes and anthropogenic pressures in Holmöarna



Författare: Antonia Nyström Sandman & Sofia A Wikström

AquaBiota Water Research April 2014

STOCKHOLM, APRIL 2014

Client:
Performed by AquaBiota Water Research for Forststyrelsen, Österbottens Naturtjänster.

Authors:
Antonia Nyström Sandman (antonia.sandman@aquabiota.se) and Sofia A Wikström

Contact information:
AquaBiota Water Research AB
Adress: Löjtnantsgatan 25, 115 50 Stockholm
Tel: +46 8 522 302 40
www.aquabiota.se

Quality control/assurance:
Sofia Wikström (sofia.wikstrom@aquabiota.se)

Distribution:
Free

Internet version:
Downloadable at www.aquabiota.se

Cite as:
Nyström Sandman A & Wikström S A. 2014. Underwater biotopes and anthropogenic pressures in Holmöarna. AquaBiota Note 2014:01. 19 pp.

CONTENTS

SUMMARY

We have here modelled the distribution of biotopes for Holmöarna according to the classification system *HELCOM Underwater Biotope and habitat classification* (HUB), which has been developed to create a common understanding of Baltic Sea biotopes, habitats and communities (HELCOM 2013). In addition, we have tested the influence of substrate information on model performance, using substrate from both field data and classified Lidar information.

Human activities influence the distribution of marine organisms. We have produced pressure maps for the area, grouped according to the MSFD, based on information on anthropogenic activities in the surrounding area.

1. INTRODUCTION

Planning, management and development of marine and coastal areas require extensive and reliable data describing the marine system, including its functions and values. In order to be included efficiently in the planning process, the data have to be collated in a way that makes them easy to use for planning authorities that may lack expertise in marine biology and geology.

SUPERB (Standardiserad Utveckling av Planering och Ekologiska Redskap för Bottenviken) is an Interreg IV project aiming to develop methods for mapping of biological values in shallow areas in the Gulf of Bothnia. The objective has been to develop standardized methods for production of the decision support that is required for planning and management. The current note is an addition to the report "Distribution of biotopes, habitats and biological values at Holmöarna and in the Kvarken Archipelago" (Wikström et al 2013). We have here modelled the distribution of HELCOM Underwater Biotopes for the Holmö area according to the recently finalised classification system (HELCOM 2013), and also produced maps of anthropogenic pressure for the area.

The system *HELCOM Underwater Biotope and habitat classification* has been developed to create a common understanding of Baltic Sea biotopes, habitats and communities. The biotope classification was developed by a group of experts from most countries boarding the Baltic Sea. Based on field data covering a large part of the Baltic, biotopes were defined based on community structure along different environmental gradients. It is an adaptation of the European habitat classification system EUNIS to the special environment of the Baltic Sea and shares with the EUNIS system a hierarchical structure where the upper levels describe the physical habitat (e.g. depth zone and seabed substratum) and the lower levels describe the biotope based on dominating vegetation and/or fauna. The system defines 328 underwater biotopes and ten biotope complexes. The first task was to model the distribution of underwater biotopes in Holmöarna using available environmental information. For a smaller sub-area substrate data classified from Lidar survey data as well as substrate from field data was used in the models, to evaluate the contribution of substrate information for habitat models.

Human activities influence the distribution of marine organisms. This influence or pressure is difficult to measure and even harder to map. Lately, attempts to quantify and map various aspects of anthropogenic pressure have been made within several projects (e.g. HELCOM 2010, MARMONI, MMSS (Nyström Sandman et al 2013 a&b), MMVN (Florén et al 2012)). We produced pressure maps for Holmöarna based on information on anthropogenic activities. The activities were grouped according to pressures listed in the MSFD.

2. MODELLING OF HELCOM UNDERWATER BIOTOPES

Field data from drop video, diving transects, snorkeling data and grab sampling were classified into HELCOM Underwater Biotopes (levels 5-6). For data selection and details on sampling methods see Wikström et al (2013). For simplicity, we did not consider the upper levels (2-3) in the modelling. This means that biotopes characterised by the same species but occurring on different substrates, for instance submerged rooted plants on muddy sediment, coarse sediment and sand, are modelled as one biotope. Only biotopes that are prevalent enough are possible to model. If there are too few occurrences in the data, the variation in the environmental variables cannot be properly captured. Also, ideally there is enough data to externally validate the models. Therefore the biotopes where modelled in two steps. First we aggregated all data into level 5 (table 1), where data was sufficient to produce externally validated models of good quality. Secondly, we modelled two level 6 classes, which were added to the map only in areas where the corresponding level 5 was predicted. The data used for the level 6 models were also included in the level 5 models, as level 6 is a subset of level 5. The level 6 predictions were not externally validated. The level 5 classes (J), *characterized by epibenthic sponges*, and (T), *characterized by sparse macrocommunity,* did not contain enough data to be modelled separately, and were therefore merged with (U), *characterized by no macrocommunity*. The modelled biotopes are given in table 1.

Table 1. Modelled biotopes according to the HUB system

level 5/6	Biotope
B	Characterized by submerged rooted plants
B4	Dominated by charales
C	Characterized by perennial algae
C5	Dominated by perennial filamentous algae
S	Characterized by annual algae
UJ	Characterized by no macrocommunity + epibenthic sponges
UT	Characterized by no + sparse epibenthic macrocommunity

The environmental variables used for the modelling were depth, wave exposure, slope, curvature and topographic position (table 2). All layers besides curvature have been described in Wikström et al 2012. Curvature describes how the depth in each point of the map is related to the average depth within a 300 m radius, which gives a measure of relative heights and depressions. Attempts were made to also include salinity based on CTD-data, but the salinity variations in the area were of too small a magnitude to be useful in the modelling.

Table 2. Environmental layers used for the modelling

Variable	Abbreviation	Description
Depth	depth	Interpolated from batyhymetric data from the Swedish Maritime administration and the lidar survey performed in SUPERB. Spatial resolution 10 m.
Wave exposure	swm_log	SWM (Simplified Wave Model). Spatial resolution 25 m. [Log transformation]
Slope	Slope	Calculated from the DEM. Spatial resolution 10 m.
Curvature	Curvature	Calculated from the DEM. Spatial resolution 10 m.
Topographic position	TPI250	Calculated from the a DEM with 100 x 100 m grid size with 250 m radius. Spatial resolution 10 m.
Morphometric index	MPI250	Calculated from the a DEM with 100 x 100 m grid size with 250 m radius. Spatial resolution 10 m.
Substrate	substrate	Substrate from field data or Lidar in six classes (see table 4)

We initially fitted a full model, i.e. using all environmental predictors, and model selection then consisted of trying to reduce the full model by removing the least important predictor until no further improvement could be made. Included also was an automated procedure that involves a penalizing function trying to limit each relationship to a horizontal line (i.e. reducing the complexity and potentially removing the variable completely; Wood & Augustin 2002). For all cases a binomial response has been used, i.e. the presence or absence of the response. Model performance was evaluated based on proportion deviance explained (how well the model fits the data) and the area under curve value (AUC) of receiver operating characteristic plots (Fielding and Bell, 1997). AUC values range between 0.5 and 1 and are independent of any cut off for the probabilities. AUC is a measure of the discriminatory ability of the model, i.e. how well presences are separated from the absences. Models that performs no better than guessing has an AUC value of 0.5, while a model that perfectly discriminates between presence and absence has a value of 1. Values above 0.8 can be considered excellent (Hosmer and Lemeshow, 2000). In other words, a value of 0.8 means that a randomly selected presence will have a higher predicted probability than a randomly selected absence in 80 % of the cases. Variable importance (how important each predictor is in relation to the other included predictors) was ranked according to the associated chi^2 value from the model (table 3).

Table 3. Model performance. The environmental variables are ranked according to their contribution to the model. Level 5: n=210, Level 6: n=310. AUCmap is calculated from the external validation data in relation to the resulting map.

HUB class	Variable importance				explained deviance	AUCmap
	Curvature	Slope	depth	swm_log		
B	3		2	1	0.433	0.814
B4			2	1	0.248	
C	2	5	1	4	0.413	0.907
C5	4	2	1	3	0.396	
S			2	1	0.302	0.818
UJ	1		3	2	0.337	0.771
UT	2	3	4	1	0.349	0.833

The biotopes were modelled in two steps, where the models of HUB level 5 have been externally validated, while the level 6 models are to be considered as more uncertain. The level 5 models are based on all level 5 data, including those biotopes modelled as level 6. The resulting predictions were added together in a process where the HUB class with the highest probability was chosen. In cases where the probability of two or more classes were equal, the predictions were added so that B > C > S > UJ > UT, corresponding to the priority order of the HUB classification system. The level 6 biotopes were only added to areas already classified as the corresponding level 5 (figure 1).

The class UJ, *characterized by no macrocommunity* (U) + *characterized by epibenthic sponges* (J) covers most of the deeper parts of the area. As there were no data on infauna in the dataset used for the modelling, the class U *no macrocommunity* in the present prediction also includes areas of deeper soft bottoms characterized by zoobenthos. Class J, *epibenthic sponges,* was quite rare in the data (only six precenses), and was thus modelled with class U. However, epibenthic sponges only occur on hard substrates and are therefore only found occasionally in the area predicted as UJ (figure 1).

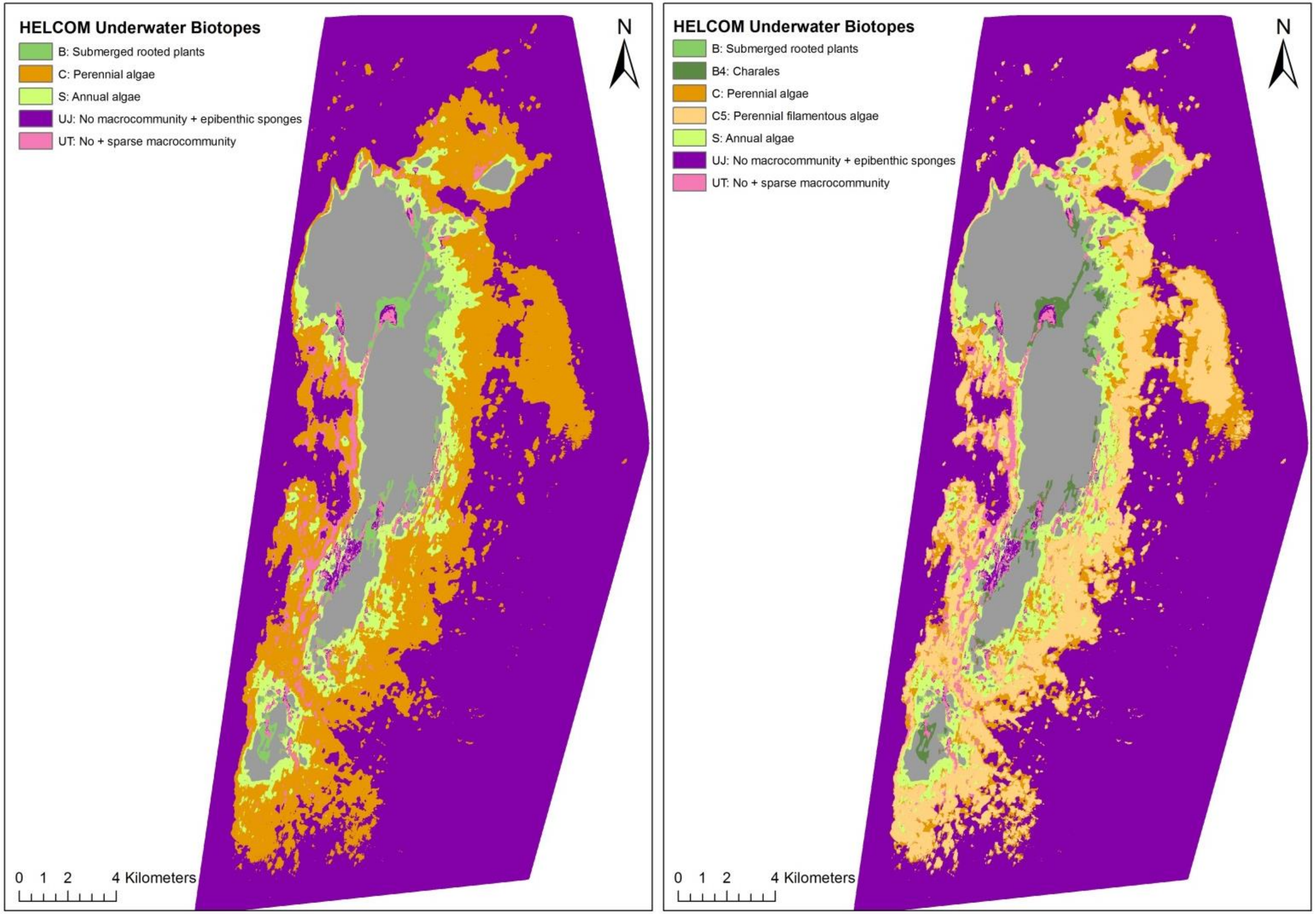


Figure 1. *Prediction of HELCOM Underwater Biotopes in Holmöarna. Left panel: Level 5 biotopes. Right panel: Level 5 and 6 biotopes, where the level 6 biotopes are predicted from unvalidated models.*

2.1. Models including substrate data from Lidar

Seabed substrate is an important predictor variable for the distribution of marine species and biotopes, but we often lack covering maps of substrate at a relevant level of detail. It has been shown in the SUPERB project that it is possible to derive a coarse classification of seabed substrate from Lidar data and here we evaluate to what extent substrate data derived from Lidar can improve the distribution maps of biotopes.

The substrate classification was based on Lidar data from a survey with the HawkEye II system in 2011, and data were analysed on a 10 m by 10 m grid (see Tulldahl 2013 for details). Each Lidar point was classified into one of five subclasses. The subclasses were then generalised into two classes (Hard, Soft). The cover for a class was calculated as the ratio between the number of Lidar points for that class in the 10 m x 10 m grid square, and the total number of Lidar data points in the same grid square, and then grouped into six classes (table 4).

Table 4. Substrate classes in the Lidar data. HB = hard substrates, MB = soft substrates.

Class	Description
1	=> 90% HB
2	70% <= HB < 90%
3	50% <= HB < 70%
4	50% <= MB < 70%
5	70% <= MB < 90%
6	=> 90% MB

For the analyses, we classified the field data into the same substrate classes, based on the substrate information from the inventory. A comparison between the substrate classes in the field data and the according substrate classes in the Lidar data gave quite a good correspondence for soft substrates (classes 4-6), but less so for hard substrates (table 5). This may be due to misclassification of the Lidar data, but likely also to positioning errors in the field data. Since hard substrate often occur scattered on soft substrate, small positioning errors in the field data is likely to cause confusion between these two classes.

Table 5. Comparison between substrate in field data and Lidar data

			Lidar class					
			Hard			Soft		
			1	**2**	**3**	**4**	**5**	**6**
field data class	Hard	**1**		4	18	14	5	3
		2		2	4	5	3	6
		3	1	2	4	3	7	8
	Soft	**4**						1
		5		1	2	1	2	2
		6			2	8	8	27

In order not to introduce this confusion into the biotope distribution models, we based the models on substrate data from the field survey. However, for comparison we also run comparable models based on substrate data from the Lidar classification. We also compared with models without any substrate information. For these models we used a subset of the original field data, which matched the area where Lidar data was available. The models are <u>not</u> externally validated since we had too little data available in the area covered by Lidar.

When using substrate data from the field data, substrate was included in all models except for class UT (table 6). The inclusion of substrate data substantially increased model performance for classes B, B4 and C5 compared to the model without substrate information (table 7). When using substrate data classified from Lidar, substrate was only included in the models of classes B, B4, C5 and S (table 6). In this case, only the model for class B4 (Charales) was substantially improved by inclusion of the substrate data (table 7).

These results show that substrate data on the level of detail that can be derived from Lidar has the potential to improve biotope distribution maps in the Kvarken area. It is however important to acknowledge that if there are classification errors in the substrate map they will be transferred to the biotope maps. We have not done a full evaluation of the accuracy of the Lidar substrate map and since we were not able to run an external validation of the biotope maps, we cannot say if this is a problem in the present study. In any case, due to the difficulties in accurate positioning of underwater field data we recommend that the models are built on substrate data from the field recording as far as possible.

Table 6. Comparison between models including substrate from field data, models without substrate data and models including substrate from Lidar data. n=143 for all models. AUCint is the internal AUC of the model.

	HUB class	Variable importance							explained deviance	AUCint
		TPI250	MPI250	Curvature	Slope	depth	swm_log	substrate		
Substrate from field data	B					2		1	0.434	0.903
	B4					2		1	0.249	0.867
	C			3		1	2	4	0.550	0.941
	C5		3			1	4	2	0.576	0.945
	S					1	2	3	0.356	0.886
	UJ			2		4	1	3	0.362	0.879
No substrate	B	2				3	1		0.345	0.876
	B4						1		0.085	0.740
	C			2		1	3		0.529	0.929
	C5		4	2		1	3		0.434	0.907
	S					2	1		0.338	0.883
	UJ			2		3	1		0.323	0.855
Substrate from Lidar	B	2				3	1	4	0.355	0.881
	B4						1	2	0.311	0.903
	C			2		1	3			
	C5			3		1	2	4	0.430	0.904
	S					2	1	3	0.345	0.884
	UJ			2		3	1			

Table 7. Difference in explained deviance and AUC values for models including substrate vs. models not including substrate.

	HUB class	explained deviance	AUCint
substrate from field data vs. no substrate	B	0.089	0.027
	B4	0.164	0.127
	C	0.021	0.012
	C5	0.142	0.039
	S	0.018	0.004
	UJ	0.039	0.024
substrate from Lidar data vs. no substrate	B	0.010	0.005
	B4	0.226	0.163
	C		
	C5	-0.004	-0.003
	S	0.007	0.001
	UJ		

3. ANTHROPOGENIC PRESSURES

The pressures were derived from 18 layers of anthropogenic activities and grouped according to the Annex III of the Marine Strategy Framework Directive (MSFD) (EC 2008). The pressure groups used were physical loss/physical damage, other physical disturbance, contamination by hazardous substances and nutrient and organic matter enrichment. The activities were in the form of point or polygon layers, and were transformed to continuous rasters through various GIS operations.

For **physical loss/damage**, the point layers marine establishments, guest harbours, jetty points were considered to have mainly local impact, and were therefore given a buffer zone corresponding to an approximate size of the establishment. Harbours were supplied as polygons and therefore assumed to only affect the actual area. Ferry lines, commercial traffic and waterways were given a maximum distance for erosion damage of 500-1000 m (based on Granath 2013, where 500 m was used due to historical reasons, but the author concluded that modern shipping caused erosion at larger distances). The development indicator was used so that all pixels with a value >1 were included in the analysis (table 8).

Other physical disturbance is underwater noise or marine litter. All layers included were given a maximum distance of 500-1000 m (table 8). For noise, the Swedish navy uses 1000 m radius as a safety distance for underwater detonations.

For **contamination by hazardous substances** and **nutrient and organic matter enrichment**, the point layers of potentially polluted areas, activities that require permits and environmentally hazardous activities were divided into activities that possibly contribute to nutrient and organic matter enrichment and other (table 9). From those layers, point density (points/km^2) was calculated. For hazardous substances, commercial traffic, harbours and classified waterways were given a maximum distance of 1000 m. For nutrient enrichment, guest harbours, commercial traffic (deep) and classified waterways were considered to have a potential impact, and were therefore given a maximum distance of 1000 m. Coastal nutrient data from CEMIR and farmland hotspots were analysed with a cost-distance method, where land was given a high cost.

The distance and cost-distance layers were transformed through the function $f=1/(x+1)$, to retrieve values between 0 and 1 for all layers (table 8). The buffer layers will have discrete values of 0 or 1, while the distance and point density layers have a range of values between 0 and 1. The different layers where then added according to table 8, to achieve pressure maps (figures 2-5). The maximum value is dependent on the number of layers included in the analysis. As the number of available layers differs between the pressure groups, the maximum value will differ as well.

Table 8. Anthropogenic activities grouped by pressure, including GIS operations and transformation functions.

Establishment/activity	Layer name	Physical loss/damage	function	Other physical disturbance	function	Contamination by hazardous substances	function	Nutrient and organic matter enrichment	function
Permit requireing activities	Tillståndspliktig verksamhet					Point density		Point density	
Potentially polluted areas	Potentiellt förorenade områden					Point density		Point density	
Environmentally hazardous activities	Miljöfarliga verksamheter					Point density		Point density	
Marine establishments, points	Marina etableringar, punkter	Buffer, 200m		Distance (max 500m)	1/(x+1)				
Coastal nutrient data from CEMIR	Kust_CEMIR_Näring							cost-distance	1/(x+1)
Guest harbours	Gästhamnar	Buffer, 200m		Distance (max 500m)	1/(x+1)			Distance (max 500m)	1/(x+1)
Jetty points	Bryggpunkter	Buffer, 20m		Distance (max 100m)	1/(x+1)				
Bathings	Badplatser	Buffer, 100m							
Maritime establishments, lines	Maritima etableringar, linjer	Buffer, 20m							
Ferry lines	Färjelinje	Distance (max 500m)	1/(x+1)	Distance (max 1000m)	1/(x+1)				
Commercial traffic, shallow	Yrkestrafik grundgående	Distance (max 500m)	1/(x+1)	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)		
Commercial traffic, deep	Yrkestrafik djupgående	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)
Farmland hotspot	Jorbruk hotspot							cost-distance	1/(x+1)
Harbours	Hamnar	objekt+distance (max 1000m)	no, 1/(x+1)	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)		
Waterways, classified	Farleder klassade	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)
Waterways	Farleder	Distance (max 1000m)	1/(x+1)	Distance (max 1000m)	1/(x+1)				
Development indicator	Exploateringsindikator	all >1						average/ha	

Table 9. Activities that possibly contribute to nutrient and organic matter enrichment

Classes with eutrophication effect	Branschklasser med eutrofieringspåverkan	Permit requireing activities	Potentially polluted areas	Environmentally hazardous activities
Sewage treatment	Avloppsreningsverk/rening av avloppsvatten	x	x	x
Animal ingredients	Animaliska råvaror			x
Biological treatment	Biologisk behandling	x		x
Animal retention	Djurhållning	x		x
Aquaculture	Fiskodling	x		x
Fodder	Foder	x		x
Pulp, paper and paper products	Massa, papper och pappersvaror	x		x
Milk, oils, fats etc.	Mjölk, oljor, fetter mm	x		x
Vegetable raw products	Vegetabiliska råvaror			x

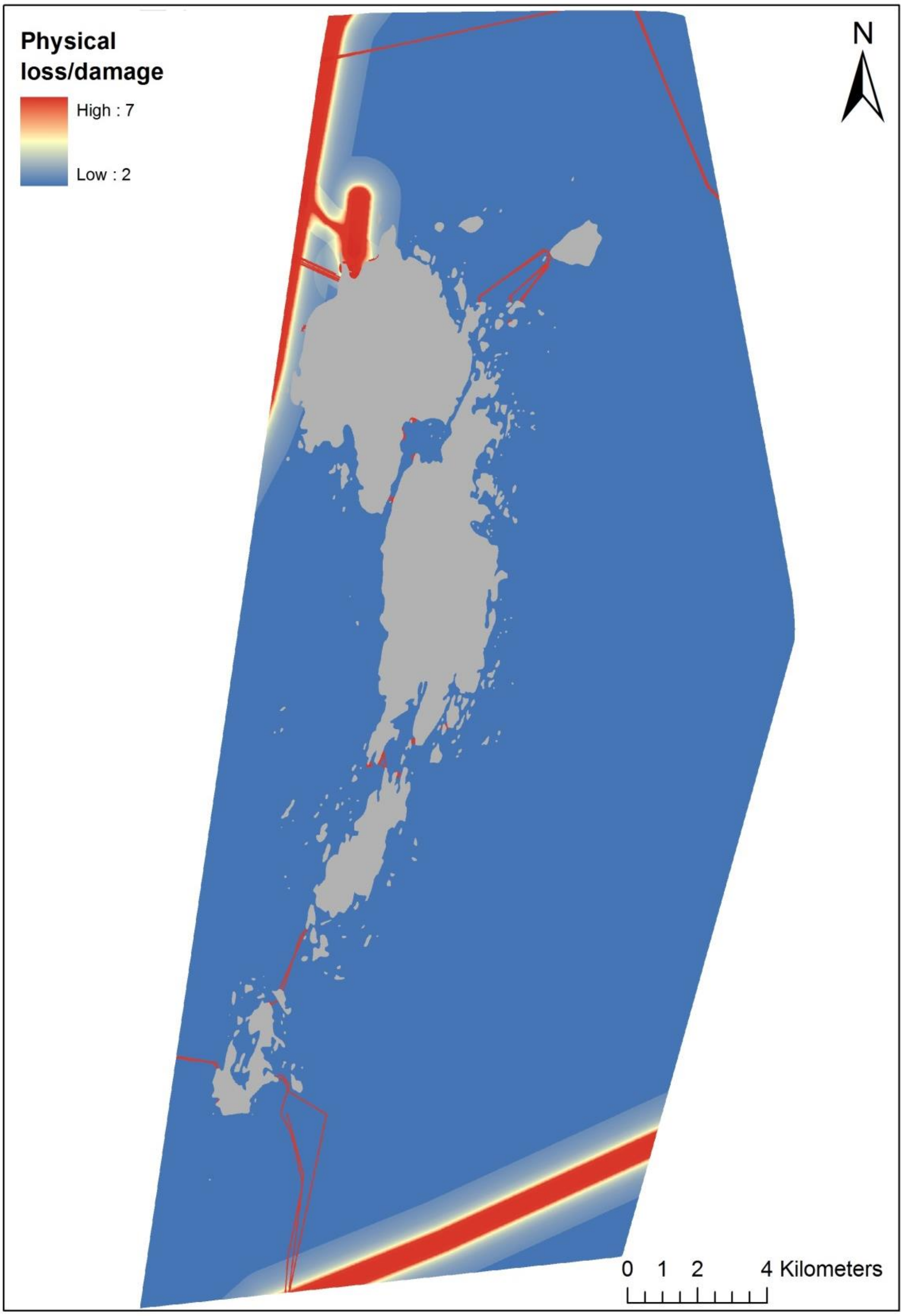


Figure 2. Physical loss/damage

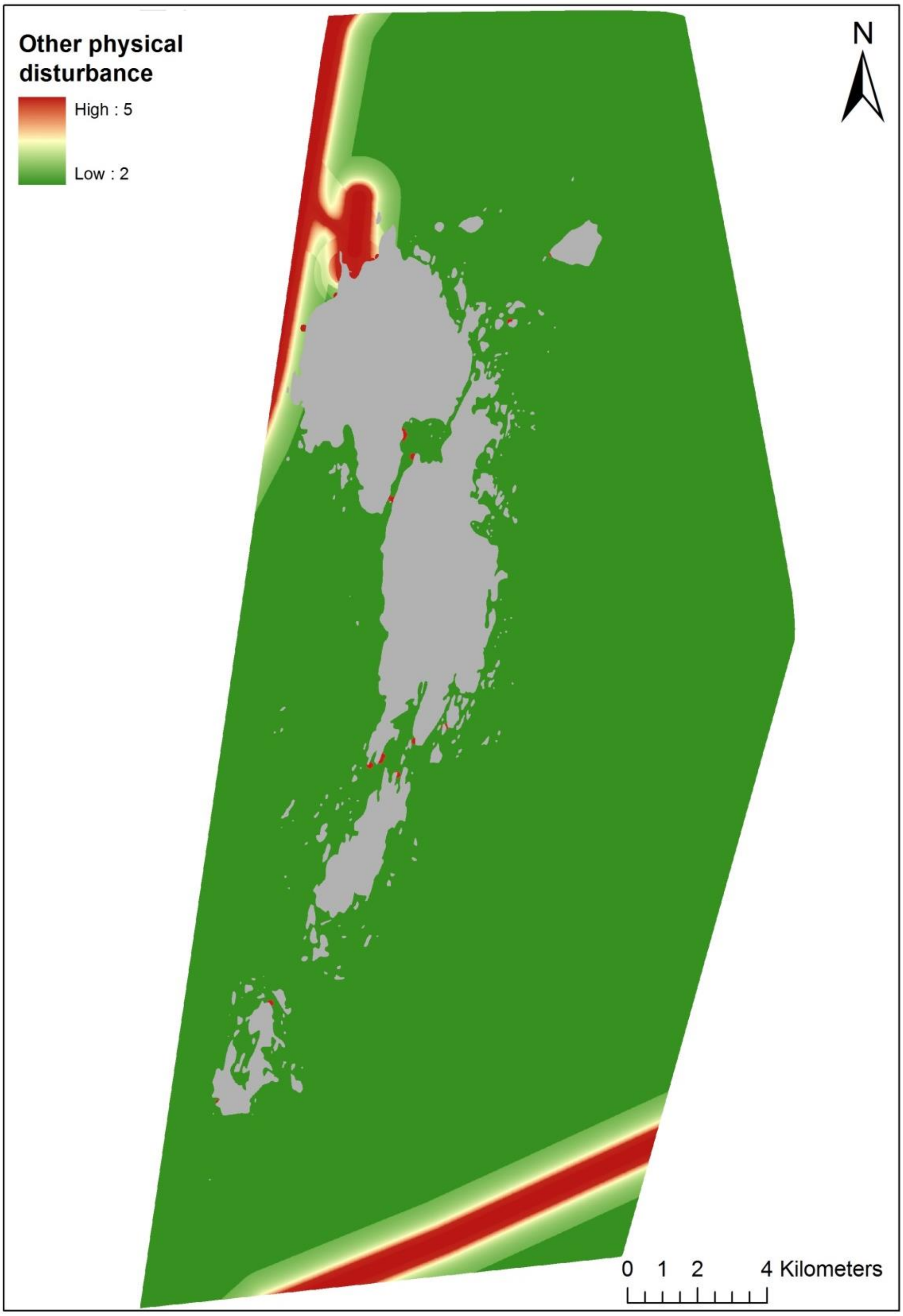


Figure 3. Other physical disturbance

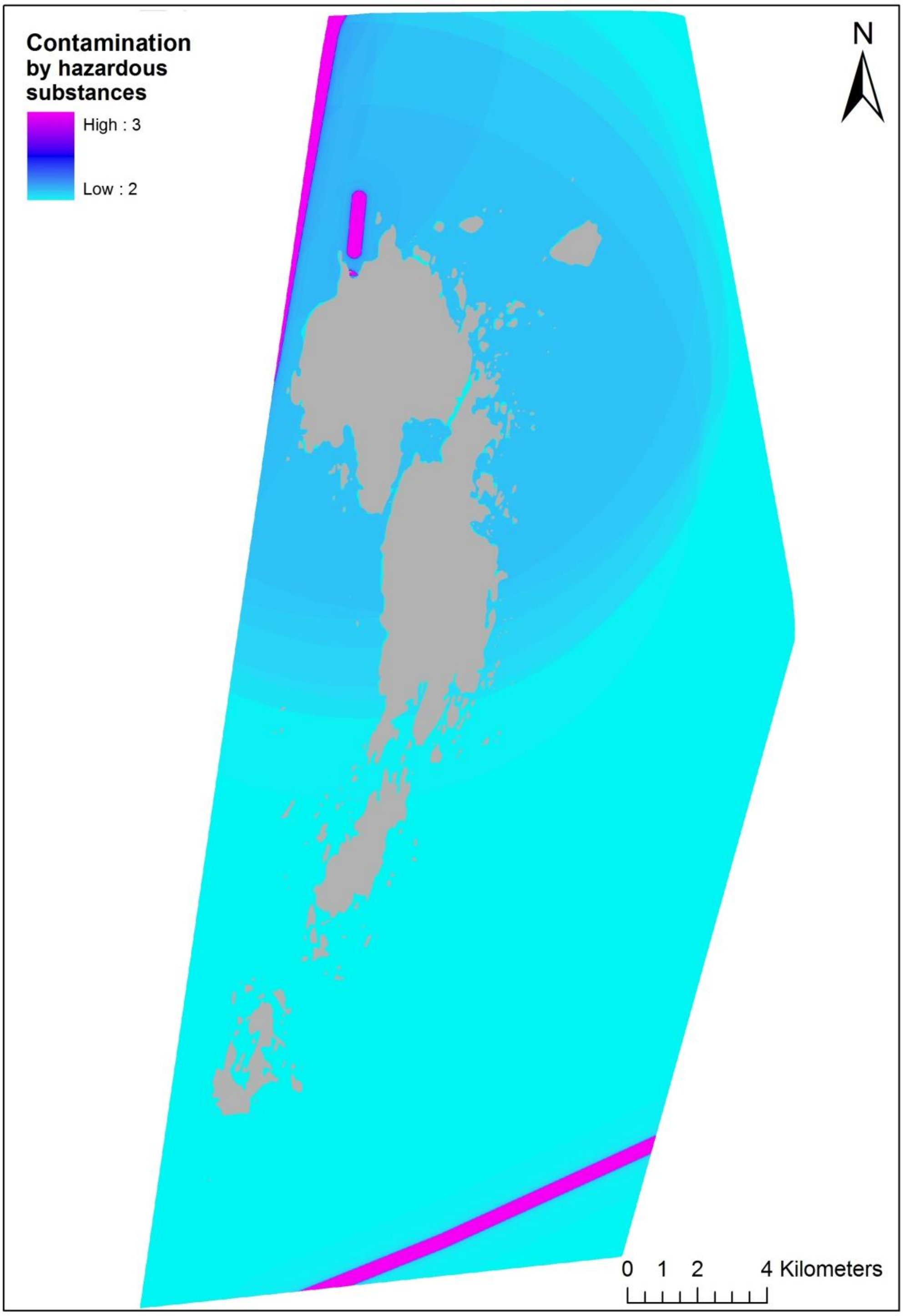


Figure 4. Contamination by hazardous substances

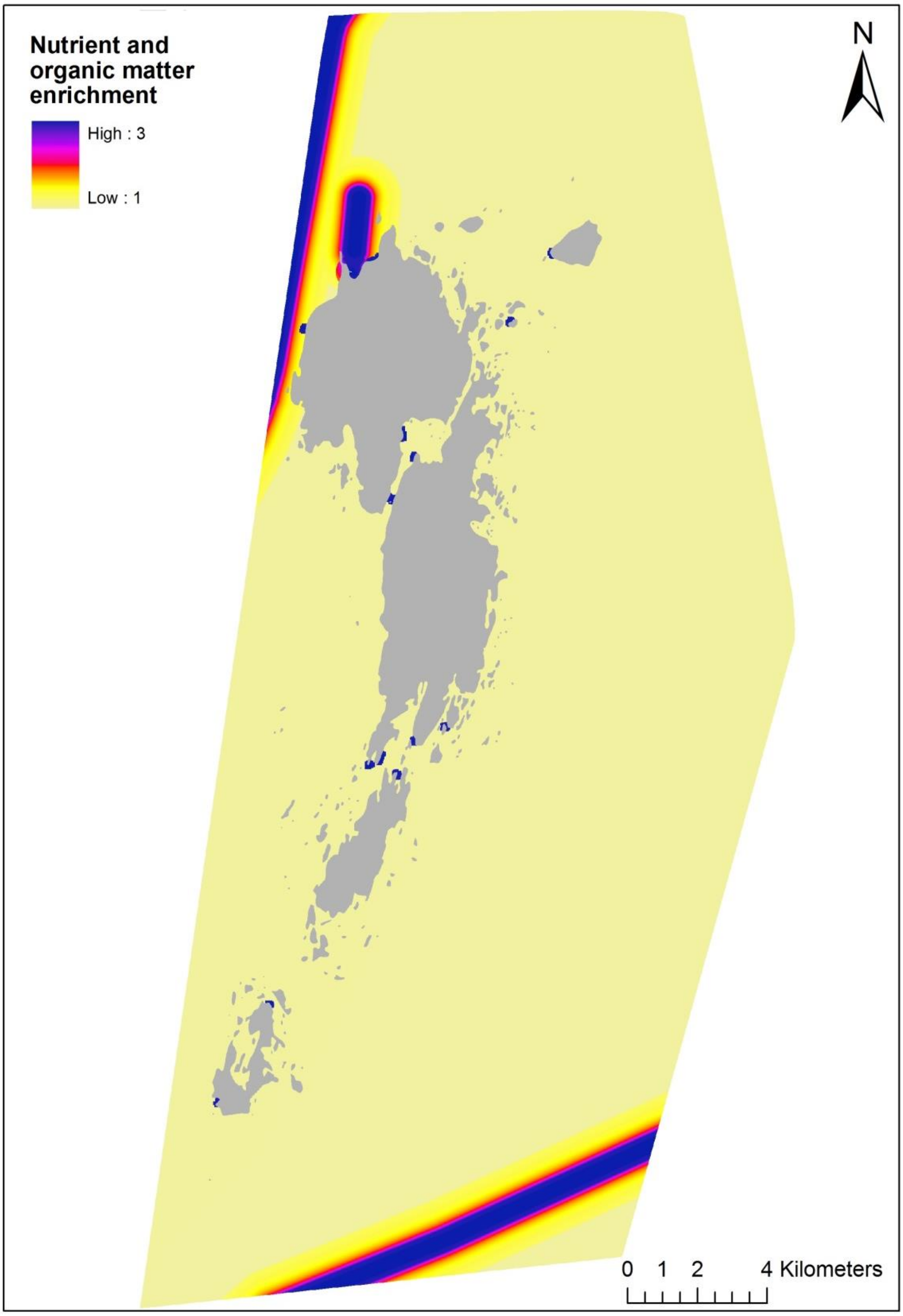


Figure 5. Nutrient and organic matter enrichment

REFERENCES

HELCOM 2010: Ecosystem Health of the Baltic Sea. HELCOM Initial Holistic Assessment. Baltic Sea Environmental Proceedings No. 122.

HELCOM 2013: Red List of Baltic Sea underwater biotopes, habitats and biotope complexes. Baltic Sea Environmental Proceedings No. 138.

EC (European Commission), 2008: Directive 2008/56/EC of the European Parliament and of the council of 17 June 2008 establishing a frameworkfor community action in the field of marine environmental policy (Marine Strategy Framework Directive). Official Journal of the European Union. For pressure list, see:
http://ec.europa.eu/environment/marine/pdf/SEC_2011_1255_F_DTS.pdf p92f.

Florén, K., Nikolopoulos, A., Fyhr, F., Nygård, L., Hammersland, J., Lindblad, C., Wiberg, P., Näslund J. & Isæus M. 2012: Modellering av Västernorrlands marina habitat och naturvärden. Länsstyrelsen Västernorrland Rapport 2012:03. 107 sid.

Granath L 2013: Erosionsskador i Furusundsleden 2000-2013. Utredning om utveckling, orsaker och möjliga åtgärder. Hydrographica 2013.

Hosmer D.W. & Lemeshow S. 2000: Applied Logistic Regression, 2nd Edition. A Wiley-Interscience Publication, John Wiley & Sons Inc., New York, NY, 2000, 373 sid.

MARMONI http://marmoni.balticseaportal.net

Nyström Sandman A., Didrikas T., Enhus C., Florén K., Isaeus M., Nordemar I., Nikolopoulos A., Sundblad G., Svanberg K. & Wijkmark N., 2013: Marin Modellering i Stockholms län, AquaBiota Report 2013:10.

Nyström Sandman A., Didrikas T., Enhus C., Florén K., Isaeus M., Nordemar I., Nikolopoulos A., Sundblad G., Svanberg K., Wijkmark N., 2013: Marin Modellering i Södermanlands län, AquaBiota Report 2013:09.

Tulldahl M. 2013: Holmöarna classification and mapping using lidar and field data in the SUPERB-project. FOI 2013-02-28.

Wikström S. A., Enhus C., Fyhr F., Näslund J. & Sundblad G. 2013: Distribution of biotopes, habitats and biological values at Holmöarna and in the Kvarken Archipelago. AquaBiota Report 2013:06

Wood, S.N. & Augustin, N.H. 2002: GAMs with integrated model selection using penalized regression splines and applications to environmental modelling. Ecological Modelling, 157: 157-177.