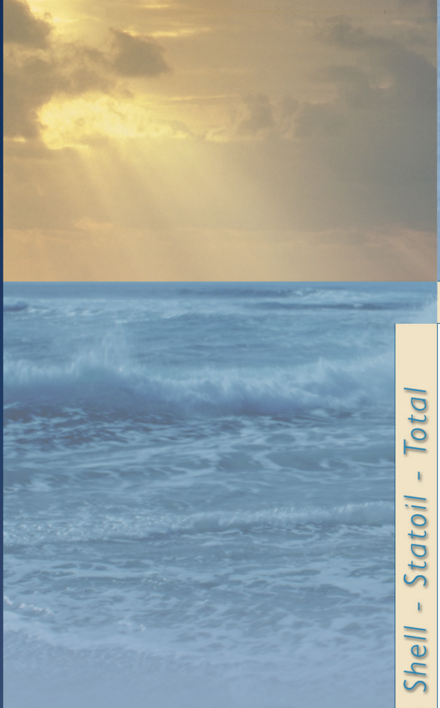

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NOEC Field validation part II: the Mowing Window Approach

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REPORT

TITLE

NOEC Field Validation part II;-
the Mowing Window Approach

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Summary

Field data has been analyzed to find estimates of pure NOEC (No observed Effect Concentrations) values. The data has been extracted from the Norwegian MOD (Miljø Overvåking Databasen), and includes the grain size (as µm), the level of petrogene chemicals in sediments (ppm or ppb) and the benthic fauna. By the selected strategy “Mowing Window Analysis” and the multivariate classification method SIMCA we have been able to find ”pure” and individual NOEC of all chemicals except the less toxic Barium. The most accurate values are found for the trace metals, while the values for THC and decalines are less accurate as their weathering in the environment is relatively fast.

All field NOECs are highest at samples characterized by small grain size (< as e.g mud) and decreases with increasing grainsize upto roughly 110 µm. At grainsizes larger than 110 µm, the NOEC values seem to roughly have the same value as the one found in the interval 90-110 µm. As a consequence, the benthic fauna do have higher tolerance to petrogen chemicals at finer sediments (mud-silt) than at sediment with average grain size larger than 110 µm (fine sand-sand). This is the effect observed in the data useful for validation purposes. Although the reason for grain size dependency of the field NOECs may be several, there have not been any experiments in this study to sort out these.

The study has been run in parallell with another R&D project exploring the SSD (Species Sensitivity Distribution) approach. The SSD approach, yielding fPNECS, is reported separately, but the results of the two studies are briefly compared and discussed in this report.

There is an overall fair agreement between the field NOEC values (i.e. within an order of magnitude) as compared to the predicted PNECs (Equilibrium Partitioning Method) from literature. There is however a significant discrepancy between the Mercury and Chromium value reported from literature (seem to be far too high) and the ones that are observed in field data.

KEYWORDS	ENGLISH	NORWEGIAN
GROUP 1	NOEC field values, validation	NOECverdier fra felt data, validering
GROUP 2	Mulitvariate Analysis, Mowing Window Analysis, SIMCA Classification	Multivariat Analyse, Vindu teknikker, SIMCA klassifikasjon

Content

Summary

The goal of this project (ERMS Task 5 Validation) has been to develop environmental effect concentrations of toxic stressors from field data. The project has been performed along two approaches; *i*) the Mowing Window Modeling (MWM) Approach where advanced multivariate statistics have been applied to the data revealing ”pure” No Observed Effect Concentrations (NOECs) and *ii*) the Species Sensitivity Distribution (SSD) on the same data revealing 5% risk fPNECS. The data includes a validated part of the data in the Norwegian database referred to as MOD (“Miljøovervåkingsdatabasen”).

This report gives the results from the MWM approach, aiming to:

1) validate predicted values from literature or laboratory, and
2) suggest NOECs to be used in the final ERMS modelling (Predicted Risk Assessments) for the Norwegian continental shelf.

To obtain the goal to deliver ”pure” NOECs for each toxic stressor, it is necessary to somehow sort out the problems that arise from the correlation between the different toxic stressors present (or else the most toxic stressors will influence and mask the less toxic stressor). Sorting out correlation includes either to resolve the problem of correlation among toxic stressors,or as a minimum, quantify and correct for the correlation among the stressors. Furthermore, the grain size should be taken into account, as shown as an outcome of the dataanalysis in part 1 of the validation.[1]

By the MWM approach we have succeed to identify “pure” and accurate NOECs for all trace metal elements except Barium (which seem to have a low toxicity). For each toxic stressor, the NOEC values vary with grain size. Note that the strong correlation between NOEC values for a specific chemical stressor and the grain size is not an assumption in this work, but an outcome from the data analysis. At average grain size less than roughly 110 µm, the NOEC value increase with decreasing average grain size. The interpretation is that the tolerance of the benthic fauna is higher the lower the grain size for grain sizes < 110 µm. For average grain sizes > 110 µm the NOEC value seem to be constant (i.e. equal to the one found at 110 µm). The paraffins as decalines and the paraffinic content included in the parameter THC are relatively rapid weathered. Thus the level of the paraffins at sampling time (the value recorded in the MOD) is probably too low as compared to the effect that is found in the benthic fauna at the time of sampling. We therefore believe that the NOECs determined for the paraffins are too low. This will be a general problem for all kind of data analytical methods applied to the MOD data. The problems of weathering is less for the aromatics as they are more resistant to weathering, but still we believe that these also may be somewhat too low (or conservative). The ”pure” field NOECs are given in the following table:

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[1] [1] Brakstad, Frode and Trannum, Hilde Cecilie (2005). Field validation 1. ERMS report no. 13

Chemical	Grain size 110 µm	90 µm	70 µm	50 µm	30 µm	10 µm
Ba	**690**	**532**	**597**	**921**	**2010**	**1520**
Cd	**0.020**	**0.020**	**0.021**	**0.043**	**0.057**	**0.106**
Cr	**5.43**	**5.57**	**5.70**	**9.04**	**23.90**	**33.80**
Cu	**1.17**	**1.60**	**2.24**	**3.80**	**7.25**	**11.06**
Hg	**0.010**	**0.010**	**0.013**	**0.014**	**0.02**	**0.05**
Pb	**6.47**	**7.80**	**6.00**	**12.90**	**18.30**	**21.50**
Zn	**6.80**	**9.77**	**11.82**	**17.94**	**44.40**	**67.90**
Decalins	**0.058**	**0.036**	**0.032**	**0.084**	**0.021**	**0.026**
NPD	**0.011**	**0.014**	**0.035**	**0.037**	**0.061**	**0.093**
PAH	**0.009**	**0.032**	**dnp**	**dnp**	**0.070**	**0.110**
THC	**8.00**	**8.11**	**9.40**	**9.73**	**8.87**	**21.40**

Table S1. The observed NOECs derived from the database MOD by the Moving Window approach (dnp: data not present). Note that the NOEC values for the decalina sand the THC is most probably far too low (see discussion in report).

The derivation method used to determine the field PNECs from the –SSD approach (UiO part of task 5 extended) will be presented in a separate report, although the results are briefly discussed in this report. The full comparison of the results from the 1) SSD approach and 2) the Moving Window approach will be presented in a separate memo.

Note that there is **no assumption** in this MWM work about grain sizes. The data analysis is unsupervised. We chose to perform individual analyses in the various grain size intervals because we expect the naturally occurring benthic fauna to be dependent upon the grain sizes. This information is present in the MOD, and to us it made sense to make use of it. It then turns out that the NOECs change as the grain sizes change. Again – this is not an assumption. This is an outcome of the analysis. It is furthermore interesting to observe that the NOEC dependency upon grain size is less severe as the grain size increases. Again, this is not an assumption.

We have followed the intention of the project; let the field data (not an a priori model) tell us about the tolerance of the benthic fauna to the different toxic stressors. This work is a pioneering work. We are probably the first research group in the world that has succeeded in separating the individual effects from several correlated chemical stressors in a natural system from each other. Thus, we believe that we have to live with the situation that the result it is not so strongly supported in the scientific community yet.

1. Introduction

Environmental monitoring of the effects of the oil related activity in the Norwegian sector is carried out by analyzing the benthic fauna found in samples taken from the sea bed. In addition to the biological data, there exists a set of chemical analyses that characterize the state of the fields with regards to the concentration of various metals and organic compounds in the sediment samples. These two types of data are related, as the environmental disturbance is expected to be more severe in a region with higher concentrations of the toxic stressors. Thus, establishing safety limits for the levels of various metals and organic compounds is of great interest.

There are many difficulties associated with modeling the biological effect of increasing concentrations of a toxic stressor. The grain size of the particles varies widely between stations, and different species thrive in different environments with regards to grain size. As the grain size of the sediment decreases, so does the toxicity of a chemical. It is therefore not possible to establish one single concentration that describes a safe level for the chemical independent of the grain size of the sediments.

Furthermore, any statistical analysis of the data is made more difficult due to correlations among the various chemicals present. Generally speaking, an increase in the level of one chemical is associated with the increase of other chemicals of the same type. Stations having a high concentration of given heavy metal, tend to contain high concentrations of other heavy metals as well. This makes it difficult to establish acceptable individual and independent concentration limits for the various toxic stressors.

The environmental effect of an increase in the level of a chemical is not immediate. The fauna must be given time to respond to the change in concentration. However, the chemical and biological analyses are performed on samples taken at the same time. Sites with high concentrations may therefore appear undisturbed if the increase in pollution is recent.

In a previous project, preliminary NOECs were established for a variety of metals and organic compounds based on a data from a small set of stations [1]. In the current project, the data material is vastly increased as the complete MOD data base is used. The reported NOECs in the present study are therefore better estimates of the field NOECs for the NCS.

2. Theory

Multivariate data analysis based on latent variables (LV) is used to determine the NOECs reported in this work. A latent variable is any linear combination of the original data. Thus a latent variable may be a factor from correspondence analysis, a PCA axis or a Partial Least Squares (PLS) component. The fundamental technique employed herein is Principal Component Analysis [2-6] for data exploration, and Soft Independent Modeling of Class Analogies (SIMCA) for classification [7-9]. A brief description of these methods is given in appendix 1.

Latent variables

Correlations among predictor variables always exist in historical data. Correlating variables contain, at least partly, the same information. Correlation is easily visualized in the common scatter plot. In the scatter plot displayed in Fig. 1, the two variables x1 and x2 are perfectly negatively correlated. High values for x1 are associated with low values for x2, and vice versa.

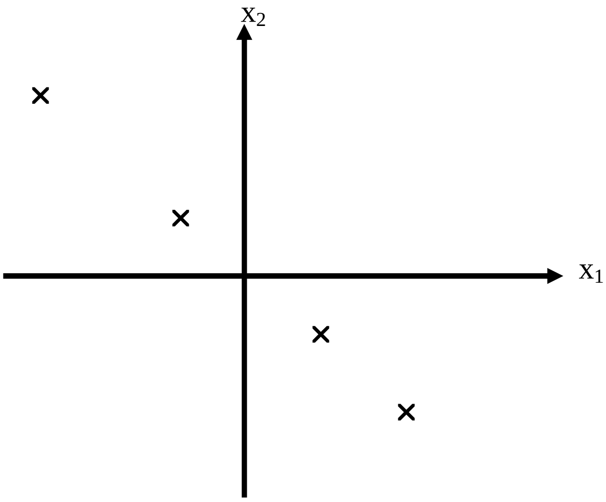

Fig 1. Scatter plot of two perfectly correlated variables.

The two measured variables in Fig. 1 can be combined into a single, mathematically constructed latent variable without loss of information. In Fig. 2, this is shown.

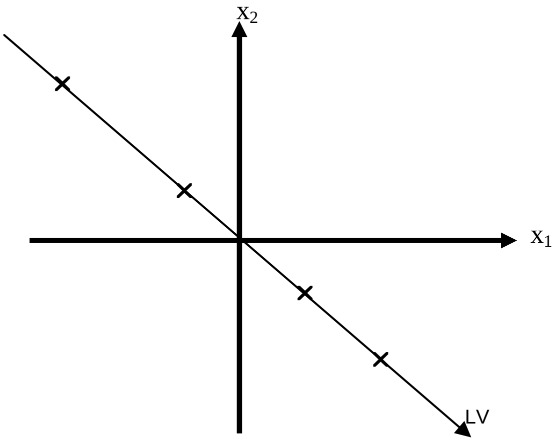

Fig 2.The latent variable (LV) constructed using two perfectly correlated variables.

The position of the four samples on the latent variable indicates their numerical value for this new value. This value is referred as the *score* of the object (or sample). The contribution from each of the variables to the latent variable is referred to as the variable's *loading*. The loading is related to the cosine of the angle between the latent variable and the variable in question. A high loading implies a large contribution from the variable to the latent variable. In Fig. 2, the two variables have approximately equal loadings, and thus contribute equally to the latent variable.

The relationship between the measured and the latent variables is expressed in eq. 1.

$$\mathbf{w} = p_1\,\mathbf{e}_1 + p_2\,\mathbf{e}_2 \quad (1)$$

Here, **w** designates the unit vector along the latent variable. p_1 and p_2 represents the loadings with regards to variable 1 and 2, respectively. $\mathbf{e}_1$ and $\mathbf{e}_2$ represents the unit vectors along the measured variables. Eq. 1 shows that the latent variable is a linear combination of the measured variable.

It is important to understand that replacement of the two measured variables x1 and x2 with the latent variable LV results in *absolutely no loss of data or information*. This is due to the perfect correlation between the two variables.

Exact correlations or no correlations are rarely seen in real data. Real data do however contain something inbetween, so called partial correlations.This makes latent variables immensely useful for data exploration, classification and modeling. In Fig. 3, the latent variable for two partly correlated variables is shown.

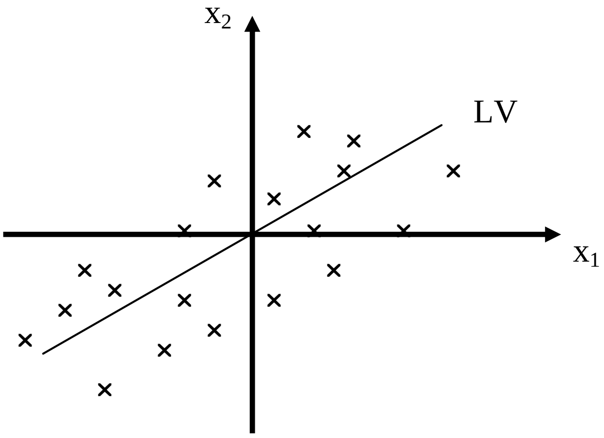

Fig 3. The latent variable for partly correlated variables

As opposed to the situation in Fig. 2, the samples do not lie on the latent variable. Rather, they are distributed around the latent variable. Fig. 4 illustrates how the scores of the objects can be found. For illustrative purposes only one object is shown in Fig. 4.

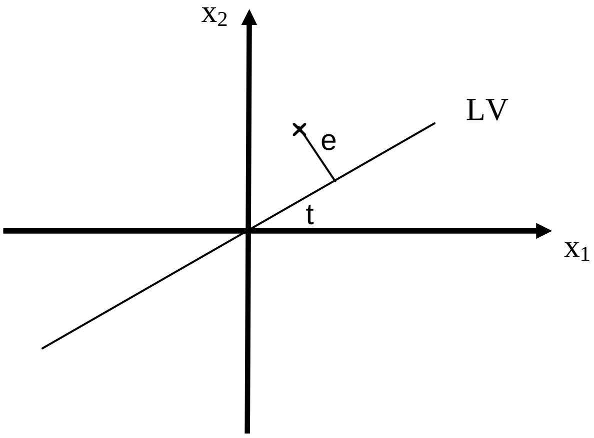

Fig. 4. Scores and residuals for partly correlated data.

The object's score (coordinate or value for the latent variable) is found by projecting the object onto the latent variable. In fig. 4, this is illustrated by the line going from the object down to the latent variable at a right angle. The score, *t*, is the distance from the origin to this point. The *residual* **e** is the distance from the object to the latent variable.

Mathematically, an object vector $\mathbf{x}_k$ can be written as

$$\mathbf{x}_k = t_k \mathbf{w} + \mathbf{e}_k \tag{2}$$

Referring to the latent variable as a model of the data, objects with small residuals are said to be well explained by the model.

A latent variable is simply a linear combination of the measured variables. Different criteria for calculating the linear combinations lead to different latent variables. An important latent variable is the *principal component* (PC), which is the latent variable that minimizes the squared sum of residuals $\mathbf{e}_k$ for the set of samples. Another way of saying this is that the PC is the line that best fits the data. This criterion makes principal components excellent for visualizing data, but they are also used for classification and regression modeling. Data analysis based on principal components is referred to as Principal Component Analysis (PCA).

Visualizing data using principal component analysis

The extraction of one principal component for a data set **X** can be written as

$$\mathbf{X} = \mathbf{t}_1\mathbf{p}_1^T + \mathbf{E} \tag{3}$$

$\mathbf{t}_1$ is a column vector containing the score of all objects with regards to the PC. $\mathbf{p}_1$ is a vector containing the loadings of all variables. Superscript ^{T} denotes the transpose of a vector (or a matrix). The matrix **E** contains the residuals – the part of the variation not explained by the PC. Thus, any data matrix can be written as the sum of the outer product of two vectors **t** and **p**, and a residual matrix.

It is possible to extract more than one PC. Scores and loadings exist for these PCs as well. Subsequent PCs are all orthogonal to each other. Using two principal components, eq. 3 becomes

$$\mathbf{X} = \mathbf{t}_1\mathbf{p}_1 + \mathbf{t}_2\mathbf{p}_2 + \mathbf{E} = \mathbf{T}\mathbf{P}^T + \mathbf{E} \tag{4}$$

The matrix **T** contains the score vectors as columns. The matrix **P** contains the loading vectors as columns.

The first two principal components are extremely useful, as they are the basis for the best two-dimensional scatter plot of any data matrix. Traditional scatter plots are obtained by plotting two variables against each other. Such plots are of course useful, but their inherent weakness is that the information displayed is only related to the two variables plotted. The use of principal components as axes, instead of picking two measured variables, create a two dimensional plot *where all variables contribute*. The advantage of this approach, as opposed to the traditional scatter plot, increases as the number of measured variables increases.

The PCA scatter plot displaying information about the objects (samples), is referred to as a score plot. Objects close to each other in the score plot, are similar objects. In addition to the distance criterion, the angle between object vectors in such a plot contains important information. Thus, groupings in such plots contain valuable information about the nature of the samples. Similar samples cluster in such a plot, while dissimilar samples are separated. Figure 5 displays a score plot based on two PCs. Clearly, two groups of samples can be seen.

In addition, this data set contains an atypical sample that is separated from the two major groupings.

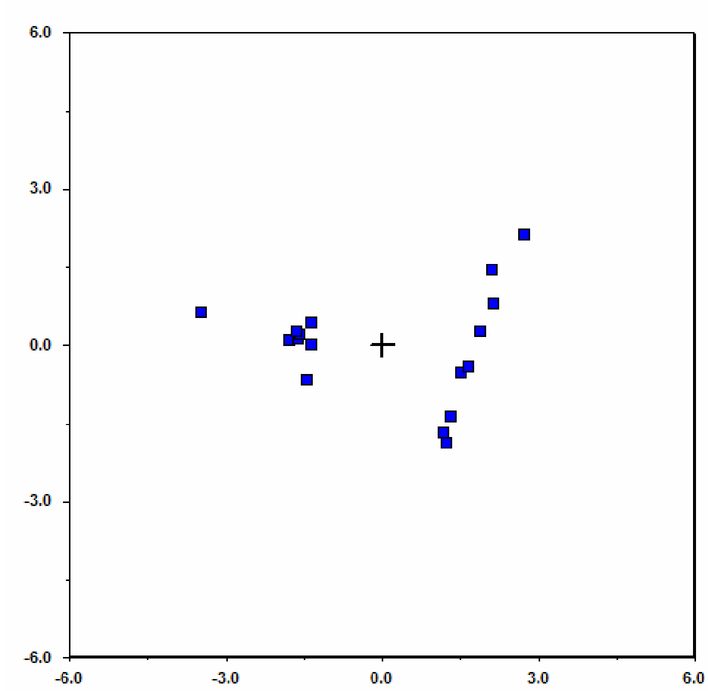

Fig. 5. Score plot using the first two principal components. Two main groups of samples are clearly seen. In addition, the data contains an outlying sample.

The score plot does not display any information about the correlation of the variables. To obtain this, a different scatter plot (also resulting from PCA) must be studied. The scatter plot displaying information about the correlation structure of the variables is referred to as the *loading plot*. Such a plot is shown in Fig. 6. Again, groupings in the plot indicate similarities.

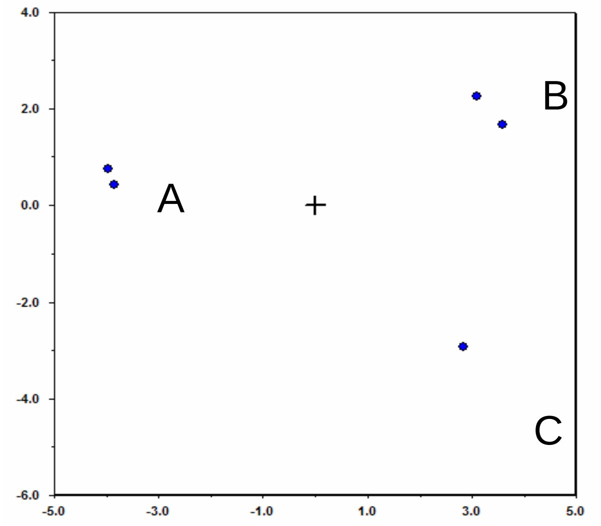

Fig. 6. Loading plot using the first two principal components. Three groups (A,B and C) of variables are observed.

Three main groups (A, B and C) of variables are observed. Inside each group, the variables are positively correlated. Groups C and A are positioned on opposite sides of the origin, at an angle of about 180° degrees relative to each other. This implies that the two variable groups are negatively correlated. Objects with a high value for the variables in group A tend to have small values for variable C, and vice versa. Group B lies at angle of about 90° to the other two groups. Thus, the variables in group B contain information that is not found in the other two groups. It is not possible to say anything about the values of the variables in group B based on the values of the variables in groups A and C.

It is possible to combine the score and loading plots into *biplots* [10].

To summarize, principal components represent an excellent tool for visualizing data. The reason is three-fold.

1) All variables and all objects contribute, albeit in a different manner, to the principal components.
2) The minimization criterion used when defining the PCs ensures that no two-dimensional plot is better suited for explaining the main trends in the data.
3) Interpretation of score and loadings plot is easy

As will be shown in the next section, the usefulness of principal components extends far beyond mere data exploration.

SIMCA - classification using principal components

Sample classification is important in a variety of fields. In the context of this project, it is important because one may perform a classification of the sampling sites according to the level of environmental disturbance. Numerous classification schemes exist, and most of these use distance (the definition of distance varies) as the classification criterion. Examples of such methods are dendrograms and the *K* nearest neighbor-technique.

In this work, the multivariate classification technique SIMCA (Soft Independent Modeling of Class Analogies) is used. In addition to Euclidean distance between samples, correlation structures are actively employed in the classification. This represents a major advantage over the purely distance based classification techniques, which invariable encounter problems once the data contains correlated variables.

SIMCA is a model based classification technique. Each predefined class is modeled separately and independently of the other classes. The modeling technique used in SIMCA is PCA, and the independent treatment of each class is extended to encompass the pretreatment procedures. The PCA model seeks to extract from the measured data **X** the part of the variation that is *shared* by the objects of the class. This common variation is described by the PCA model, while the residuals (see eq. 4) contains the variation connected with the individual differences within the class (unique sample variation) and experimental noise.

The residuals are not discarded or ignored. Quite the contrary - they are actively used in the classification procedure. After a PCA model of a class has been built, other objects are classified as belonging to the class (or not) depending on their residual distance to the class model. Larger residuals indicate a lower degree of class membership. Thus, the model boundaries are defined using the class residuals.

The residual standard deviation (RSD) for object k is calculated using eq. 5.

$$s_k^2 = \frac{\mathbf{e}_k^T \mathbf{e}_k}{M - A} \tag{5}$$

M is the number of variables measured. A is the number of principal components used in the model.

The RSD for each object is collected in a distance vector **s**, and the RSD for the class is calculated using eq. 6.

$$s_c^2 = \frac{\mathbf{s}^T \mathbf{s}}{N - A - 1} \tag{6}$$

N is the number of objects in the class.

While this establishes an average RSD based on the objects belonging to the class, the actual limit used when testing new objects is larger than this. The critical value s^2_{max} is found using an F-test using the proper degrees of freedom and α level.

$$s_{max}^2 = s_c^2 \cdot F_{kritisk} \tag{7}$$

Fig. 7 displays a set of objects, the PCA model and the boundaries found according to eqs. 5-7.

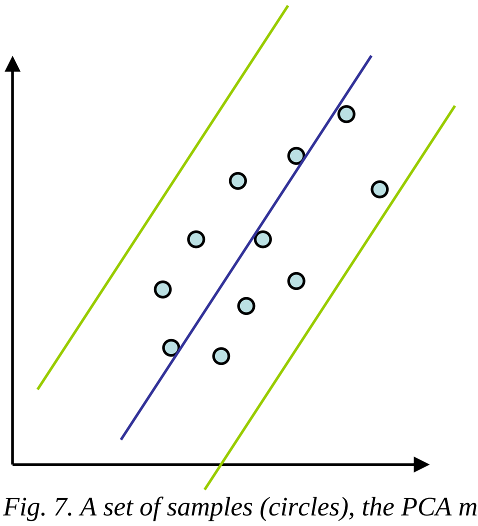

Fig. 7. A set of samples (circles), the PCA model (central line) and the boundaries found using the residuals (outer lines).

As can be seen from fig. 7, the model is now closed along the direction of the PC. What remains is to establish maximum and minimum allowed values for the scores of objects belonging to the class. This procedure can be found in the reference literature. The final SIMCA model is displayed in fig. 8. All samples falling outside the constructed sylinder will be classified as outliers.

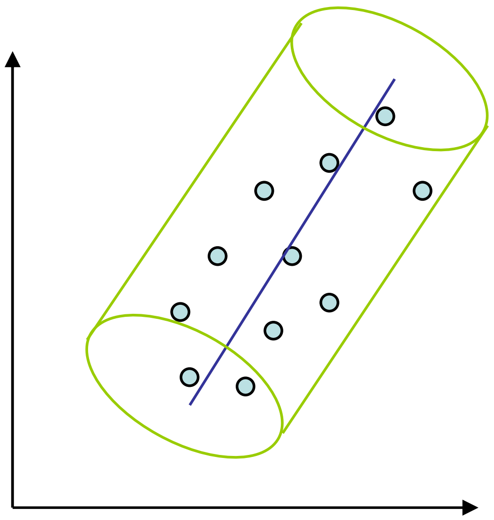

Fig 8. The final SIMCA model.

New objects are classified as belonging to the class if they are positioned inside the space spanned by the model. If they lie outside of the boundaries, they are rejected as members of the class. This is illustrated in fig. 9.

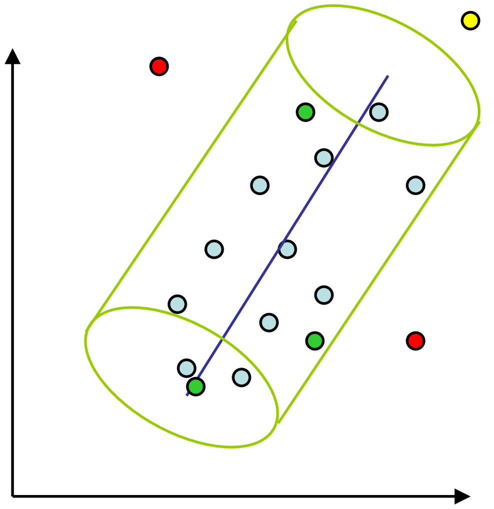

Fig. 9. Classification of new samples. The blue samples are used for building the model (the training set). The green samples are new samples shown to belong to the class. The red samples are rejected, as their residuals are too large. The yellow sample is rejected, as its score is too high.

In the illustrations above, a one component PCA model was used. In real cases, the number of PCs to use vary from 0 (a centre of gravity model) and upwards. The number of principal components to use increase as the number of underlying factors responsible for the variation in the data increases. Obtaining models of proper complexity is highly important, and several methods exist for this purpose.

Cross validating the number of principal components to use

The result of underestimating the number of PCs to use is an underfitted model. The residuals contain structural information, and the model both describes the class poorly and is of little use when classifying new objects. The simplest way of avoiding underfitting is of course to increase the number of PCs until most of the variance of the data is explained and modeled. This simple approach is extremely dangerous, as overfitted models are as unsuitable for classification as underfitted ones. An overfitted model fits the training set extremely well, but the artificially small residuals leads to most new samples been rejected. This includes samples that actually belong to the class.

One popular technique for model dimension estimation is cross validation [11, 12]. This is an internal validation technique, as the same samples are used both for model construction and for model validation. This may seem statistically unsound at first, but great care is taken to simulate the use of an external validation set.

Several cross validation methods exist. They all have in common that the data is divided into several groups. All objects are members of a group. In the following explanation, the number of groups is assumed to be four. This is just to simplify the discussion.

Firstly, a PCA model is built of the objects that do not belong to group 1. Next, the objects in group 1 are classified using a 1-component model of the rest of the data (groups 2, 3 and 4). The success rate of this classification is registered. Next, the same objects are classified using a 2-component model of groups 2, 3 and 4, and its success rate registered. This procedure is repeated up to a predefined number of components, e.g., 10. All the classification results are saved for later comparisons. Then, group 1 is reentered to the data matrix, and group 2 is deleted. The classification routine described above for group 1 is repeated for group 2. Next, group 3 is deleted, etc. Finally, the classification success rates for all the one component models of all groups are added. The same is done for all the two component models, three component models, etc. If e.g. the three component models show the best overall classification success rate, then a three component model is used when building the final model. Such a situation is depicted in fig. 10.

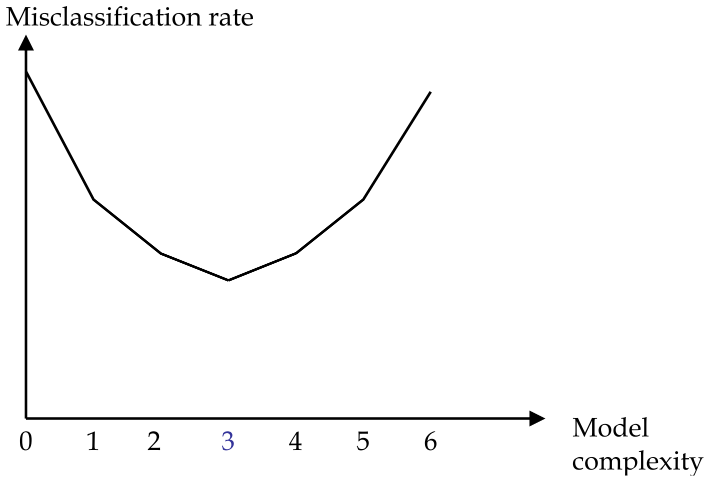

Fig 10. Evaluating the cross validation results. Overall, the best classification is obtained using a three component model. This is then the proper choice when constructing the final model.

The final model is of course built using all the groups – the complete training set.

Cross validation is often preferable using an external validation set. Using samples as external validation samples necessarily leads to fewer samples being used when constructing the final model. This is unfortunate if the total number of samples is limited, as the robustness of a model generally increases as the number of samples included increases.

Identifying the important variables – discriminating power

The discussion so far has revolved around building models for data containing one class. In real life situations one usually has more than one class of samples. In the environmental impact setting, one might divide the data into three possible groupings or classes: Disturbed sites, undisturbed sites, and a transition zone where the impact of pollution is only beginning to show or are nearly recovered. Ideally, one wants a test sample to be classified as a member of only one such group. For this to be the case, variables that are able to distinguish between different groups of samples are needed. These variables may not be important when building the models of individual classes, but they are crucial when it comes to discriminating between classes. This is illustrated in fig. 11.

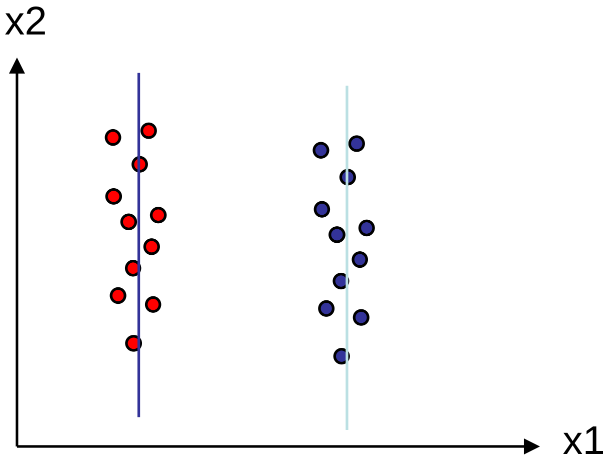

Fig 11. While x1 is of no importance for modeling the two classes of samples, it is invaluable when it comes to separating the two classes.

As can be seen in figure 11, variable x2 is the important variable when it comes to modelling the data. There is little internal variation in the level of variable x1 for the red class. The same can be said about the blue class. However, it is impossible to say whether a new sample belongs to the red or the blue class if not variable x1 is included in the analysis. Variable x1 has a huge *discrimination power,* while variable x2 has little or no such power.

In SIMCA, the discrimination power of a variable is calculated by first fitting the objects in the classes to their proper models. In fig. 11, this means fitting the red objects to the leftmost model and the blue objects to the rightmost model. The residual of the variable in question is calculated for both classes, and the values are added. Next, the objects are fitted to the *wrong* model. In fig. 11, the red objects are fitted to the rightmost model, and the blue objects to the leftmost model. Again the residuals of the variable in question are calculated for two fitting procedures, and the values added. The resulting number is divided by the total residual from the first fitting procedure. The higher this ratio, the better the discriminating power of the variable. The process is performed for each variable individually.

Variables with discriminating power above 3 are said to have a good discriminating ability.

The discriminating power of a variable is sensitive to such factors as size and shape of the models being compared. Therefore, it has been argued that a more robust measure of true discriminating ability is found by performing the test with zero component models (centre of gravity models). Thus all models will has spherical and similar form, and the discrimination powers will be more accurate. This is the approach used in this work.

Zero component models are typically found in multivariate classifications when only random (natural) variation is present. Thus, with only natural benthic variation present, with no systematic trends or strong differences in the benthic fauna due to external influences such as chemical stressors, a “zero component “ model is to be expected. Mathematically this means that all samples are distributed randomly around a point in the multivariate space. In three variable dimensions (e.g. stations defined by counts of three species), such a model would resemble a sphere. This type of model is often referred to as a centre of gravity model.
The new data entries are only classified toward the test model (no new PCA analysis is required). It is only important that the same parameters (species) are investigated

3. Data

The data analysis performed in this project is done on data from the MOD data base. In total, 2678 stations are included in the data base including chemical, sediment and biological data. Most of the analysis and modelleing work is done on the biological data. For 420 of the measured stations no biological analyses are registered in the data base. These stations were excluded from the data analysis.

The toxic effect of the metals and organic compounds varies with the grain size of the sediments. Therefore, the data set was divided into subsets depending on the grain size. Table 1 displays the grain size intervals used, and the number of stations found in each interval.

Grain size interval (μm)	Number of stations	Percentage of total (%)
0 – 20	241	11
20 – 40	212	9
40 – 60	122	5
60 – 80	301	13
80 – 100	783	35
> 100	599	27

Table 1. Grain size distribution of the MOD samples.

Each grain size interval was modeled separately.

To reduce the impact of heteroscedastic noise the biological data was square root transformed prior to analysis. All analyses were performed on mean centered and standardized data. Standardization is performed by dividing all occurrences of a variable with the variable’s standard deviation. The net effect is to downsize the importance of the more abundant species, and to allow less frequent species to influence the models.

In addition to grain size, the concentration of the following metals and organic compounds was measured for the samples: Barium, cadmium, chromium, copper, mercury, lead, zinc, decalins, NPD, PAH and THC.

Unfortunately, chemical analyses have not been carried out for all the samples where the biological analysis has been performed. Table 1 shows that biological data exists for 783 stations in the grain size interval 80 – 100 μm. Table 2 shows that chemical analyses are not carried out for all of these samples, and that the number of analyses varies among the chemicals.

Ideally, all chemicals should have been quantified for all samples. The NOECs are based on *observed* values, as the name implies. It is self-evident that NOEC estimates are more robust for the chemicals being measured more often. The number of analyses follow the guideline of the Norwegian Pollution Autorities, and is the explanation to why the number of analyses is less for the organics than the trace metals[2].

Chemical	**Number of analyses**
THC	688
Barium	683
Lead	683
Zinc	683
Cadmium	680
Copper	680
Mercury	423
NPD	204
Decalins	157
Chromium	139
PAH	36

Table 2. The number of chemical analyses performed for 783 samples in the grain size 80 – 100 μm interval.

Strategy and modeling

The fundamental assumption used in this work is that an increased concentration of a given chemical above a certain limit (the NOEC) results in the benthic fauna pattern undergoing changes, as illustrated in Figure 12.

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[2] Statens Forurensingstilsyn (Norwegian Pollution Authorities), 1999,, 99:01;Retningslinjer for Miljøovervåking av Petroleumsvirksomheten på norsk sokkel, DEL II Sedimentovervåking. ISBN no. 82-7655-164-5.

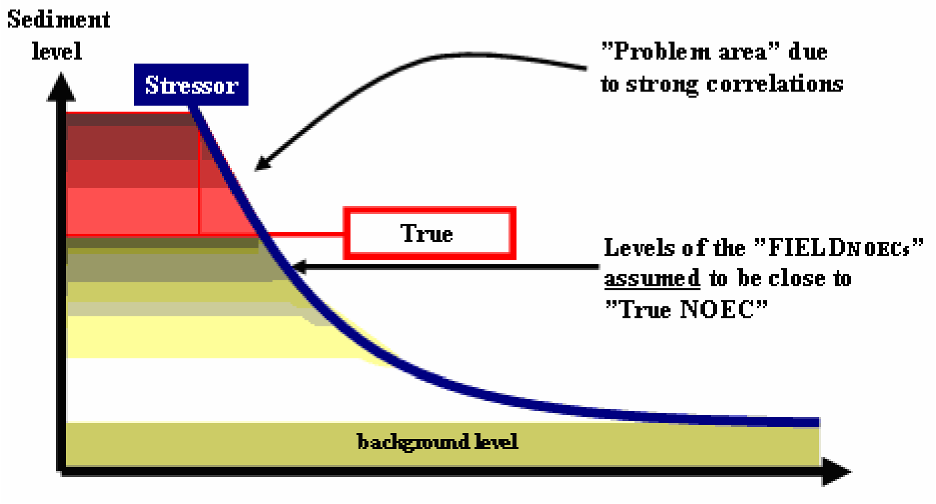

Figure 12. An illustration of the FIELD NOECs (No observed Effect Concentration) of a toxic stressor vs the true NOEC

Thus we assume that when the level of a chemical (potential toxic stressor) increases above the background level (or at a level where no effect on benthic fauna is observed), it will sooner or later result in an observed effect on the benthic fauna. The highest *observed* level of the stressor, before it reaches the level where an effect is seen, is the level we have defined to be the field NOEC level.

This makes it possible to search for patterns in the biological data, and to relate these patterns to variations in the chemical concentrations. It is important to understand that the modeling approach described below is performed *only on the biology data – not on the chemical concentrations.*

It is important to be aware that the methodology used in this approach is not based on any assumptions. The data analysis is a so called unsupervised method. Sometimes this is referred to as soft modelling, as no external information, model or assumption is applied to the data. We only describe what is in the data. In the MOD data there is a strong and clear correlation between decreasing NOEC values (i.e. increasing toxicity) as the grain size increase. Surely there may be numerous other significant environmental parameters that may explain toxicity, but we have to use those that are included in the MOD database. Grain size is included. We are aware that the benthic fauna differs from environment to environment, depending on both abiotic- (e.g. salinity, temperature, climate, depth, topography, grain size, currents etc.) and biotic factors (e.g. presence of predators, population density, biological preferences to physical factors etc.). However, we have tried to identify *the highest observed concentration of a specific chemical stressor present at a certain grain size interval where we at same time do not observe any response to the population of the benthic fauna*.

There is a consistency in all the results from this approach taking into account more than 2000 stations in the MOD from North to South in the North Sea (a distance close to the one from Oslo in Norway to Rome in Italy). But of course; the validation results have been found using the MOD, and ideally the results should be tested on data from other part of the world as suggested by the referees. This, however, has not been included in the project aim.

The preliminary NOEC were established in the previously mentioned report by Brakstad and Trannum (2005). It is important to be aware that these preliminary NOEC values were only starting values for the analysis. They were not in any way crucial to our work, as the proper level (i.e. the highest observed level where no effect on benthic fauna is evident) will be established by the method anyway.

Defining the training and test sets

Provided that the biology and chemistry data are related, the stations measured in the MOD data base may be categorized as belonging to one of three classes:

1) Undisturbed sites. The concentrations are at the background level, and no environmental effect is registered. These stations are modeled, and the resulting model describes the unpolluted state.
2) Disturbed sites. Here, the concentrations are so large that the benthic fauna clearly is disturbed. These sites are *not* used in the modeling, due to problems with correlating chemicals. It is not possible to identify the chemical responsible for the disturbance if several chemicals exceed the acceptable limit[3].
3) Transition sites. Sites belonging to this category have all concentrations, except one, below a predefined safe limit[4]. Any disturbances in the fauna for these stations can be assumed to originate from the increased concentration of said chemical. The true state (disturbed or undisturbed) of these stations is found by comparing them to the model of the undisturbed sites.

The separation of the stations into these three categories for each grain size interval is of the utmost importance for the analysis to produce reliable results. However, the biology responds slowly to an increase in concentration. Thus, a site classified as disturbed due to high concentrations of the chemicals may show no sign of disturbance if the pollution is recent. This does not represent a serious issue for this approach, as stations classified as disturbed (category 2) are excluded from the analysis. Situations where concentrations of toxic stressors are back to normal, but where the fauna still is affected may occur. In this situations the fauna will separate out as an distinct group in the analysis of the undisturbed sites. This is a rare and constructed situation, as it require al lthe trace elements to be back on background level and still effect on the benthic fauna. We have not seen this situation in the data.

In a previous project (Brakstad F, and H.C.Trannum, 2005), preliminary and initial NOECs were reported. These values were used to classify the stations as belonging to one of the three classes mentioned above. A station was said to be undisturbed if the concentrations of all metals and all organic compounds were below the initial NOECs. Transition sites were defined as stations having one concentration above the previously defined NOECs. Every chemical has a separate set of transition sites.

Within each grain size interval, the stations belonging to category 1 (undisturbed sites) constitute the *training set* for all chemicals. Stations were not included in the set of undisturbed sites unless the concentrations of at least six of the in total eleven chemicals were quantified[5]. The number of such sites for each grain size interval is shown in Table 3.

Grain size interval (μm)	Number of stations

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[3] Acceptable limit can be defines by e.g. statistical apppoach aa one-side t-test (above background level)

[4] Safe limit is the level of the toxic stressor where no obsevred effect is evident from e.g. benthic fauna

[5] By including sites with few chemical measurements in the undisturbed set, we run the risk of accidentally including polluted sites. To avoid this, we chose to only include stations where more than 50% of the measurements were performed. Still we test the relevance with the outcome from the PCA analysis on the macro fauna data towards the increase of the level of the toxic stressor.

0 – 20	20
20 – 40	38
40 – 60	14
60 – 80	17
80 – 100	84
> 100	49

Table 3. The number of training set samples for each grain size interval. For the training set samples at least six concentrations are measured, and none of these are above the previously reported NOECs.

The *test set* for a chemical in any given grain size interval consists of the samples that have a suspiciously high concentration of one chemical, while the remaining concentrations are either below the previously reported NOECs or not reported. The number of samples included in each test set varies widely, as can be seen in Table 4. Thus we used information from the biology space to confirm the chemistry space (within each interval) when the cause-effect relationship was established.

Relative size (no. of stations) of reference vs test set is of no importance, as long as the same parameters are included (here: same species).

All levels below the preliminary NOEC (definition; see above) were considered as candidates for the undisturbed sites. Thereafter this hypothesis was justified/corrected according to the statistical analysis.

The grain size intervals were found from the distribution of all samples in the MOD. Thereafter as many as possible intervals were decided, but the number of intervals was balanced with the number of samples (species and toxic stressors). Thus we ended up with the suggested six intervals.

	Grain size interval					
Chemical	**0 – 20**	**20 – 40**	**40 – 60**	**60 – 80**	**80 – 100**	**> 100**
Ba	0	0	0	0	0	0
Cd	0	11	12	12	3	36
Cr	0	20	0	0	23	20
Cu	4	48	0	16	2	0
Hg	9	5	7	19	42	27
Pb	5	5	6	0	11	11
Zn	9	39	0	12	17	17
Decalins	0	0	0	0	24	5
NPD	8	0	0	5	0	0
PAH	4	14	0	0	0	0
THC	8	0	13	19	32	3

Table 4. The number of samples in the test sets for the various grain size intervals.

Relative size (no. of stations) of reference vs test set is of no importance, as long as the same parameters are included (here: same species).
For each chemical, the test sets were sorted in ascending order with regards to the concentration of the chemical. The sorted test sets were used to validate the assumption that the biology and chemistry data are related. This was done by doing a PCA on the count data. The chemistry data was *not* used in the PCA, but the resulting score plots still display groupings according to the chemistry. This is demonstrated in figs. 13-15.

The number of stations used in each training sets is shown in Table 3. The number of species varies, but several hundred species were used in all calculations. The test sets, containing stations with one, and only one, chemical above the predefined safe level, contained the same number of variables (species). The number of stations included in each test set is shown in Table 4. The accuracy of the results is of course dependent upon the amount of data available. The smaller the number of samples in the test set, the larger is the risk of the NOEC deviating from the “true” value (see definitions). However, this is why this statistic is referred to as No *Observed* Effect Concentration. It is a statistic based upon actual observations. Without increasing the number of observations, there is no way one can increase the accuracy of the results. The number of observations is at present limited to the database of MOD. Furthermore – we single out the lowest concentration that corresponds to an environmental effect. This, however, is not the value we report. After sorting the test set samples in descending order (with regards to the concentration of the stressor in question), we report the concentration of the station *appearing after* the station just identified. The risk of reporting too high concentrations is therefore greatly reduced. The effect of having a larger test set is usually an increase of the NOEC.

In figure 13, a score plot from the biology data of the Hg test set for the grain size 80 – 100 μm is shown. A cluster of samples in the centre of the plot is clearly seen. A few samples separate from the main group. In the figure, the numbering of the samples is related to the Hg concentration (the higher the number, the higher the concentration.). The sample with the lowest Hg concentration is number 180. It is the samples that are removed from the main group are those with a lower mercury concentration. *This happens, even if the chemistry data is not used for constructing this plot – only the biology data is modeled*. The clear groupings in the score plot indicate that the fundamental assumption that the biology data contains information about chemical concentrations is valid.

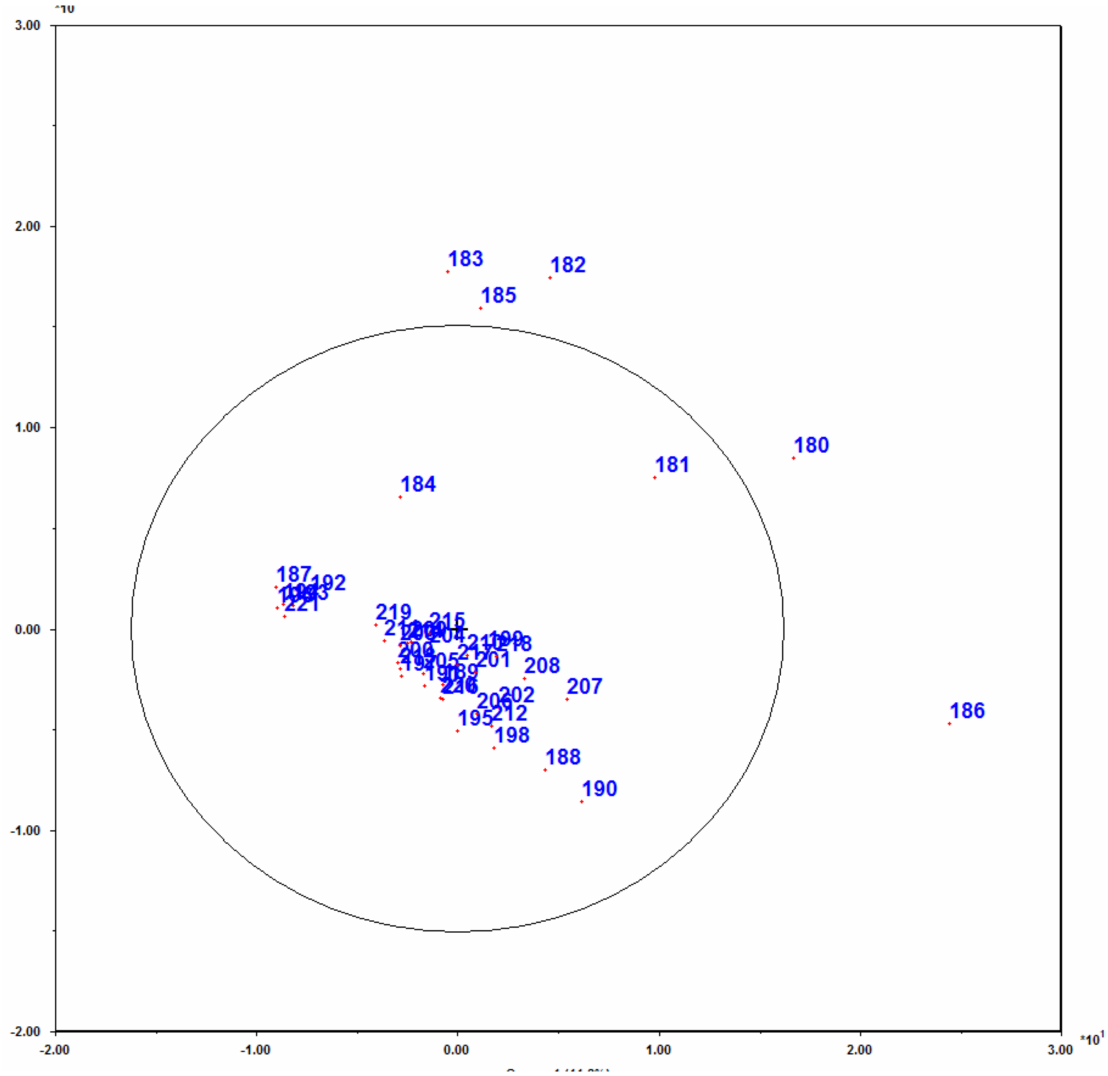

Fig. 13. A score plot of the Hg test set for the grain size interval 80 – 100 μm.

Fig. 14 displays the results from a similar analysis of the Cr test set for the same interval. Note that the analysis of the biology data groupings related to the (unused) chemistry data appears The same interpretation can be made for this test set, as the low concentration samples again appear as outliers in the plot.

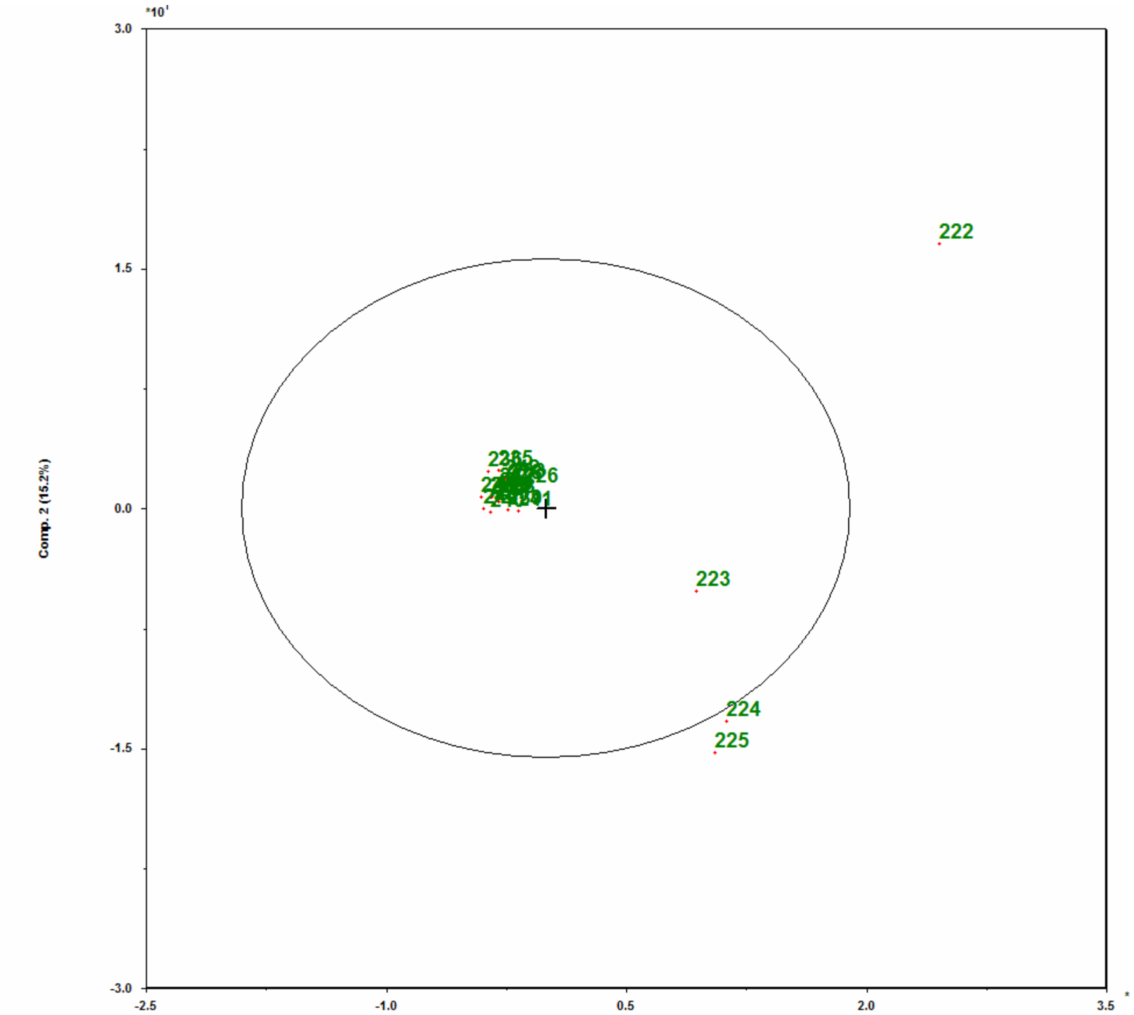

Fig. 14. A score plot of the Cr test set for the grain size interval 80 – 100 μm.

Finally, fig. 15 displays a similar analysis of the Zn test set for this grain size interval. Here, it is the sample with the highest concentration that appears as an outlying sample (the direction of a principal component is not important as compared to the important relative position of samples along the principal component) . Still, it shows that groupings related to the chemical composition of the samples can be observed in PCA score plots of biological data.

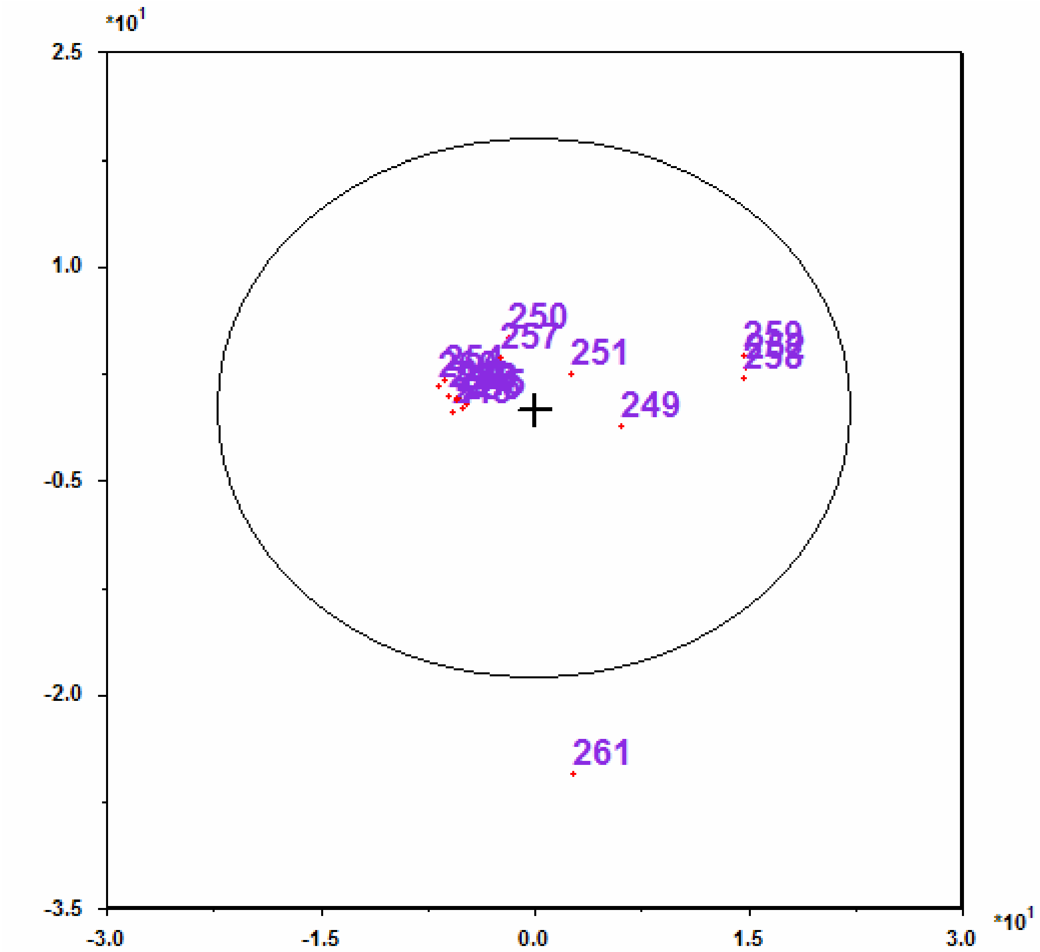

Fig. 15. A score plot of the Zn test set for the grain size interval 80 – 100 µm.

It is important to understand that while the score plots in figs. 13 – 15 clearly group samples according to the concentration of the samples, this simple analysis is not enough to obtain NOEC values. To achieve this, one has to *compare* the undisturbed situation (the training set) to the set of samples possibly showing a minor disturbance (the test set). SIMCA classification is used to perform this comparison.

Comparing the training and test sets

The undisturbed sites (the training sets) were modeled using cross validated SIMCA models. All test sets were also separately modeled using cross validated SIMCA models.

Within a grain size interval the following models now exist:

1) *One* training set model, based on counts of *all species* for those stations where all concentrations are below the previously reported NOECs.
2) *Several* test set models, one for each chemical. Each model is based on counts of *all species* for the stations where the chemical in question is the only one above the previously reported NOEC

The training set model (for each grain size interval) was compared to each of the test sets. The comparison was done to enable models with better possibility of separating truly undisturbed sites from sites showing minor disturbance. During the comparison, species with a particular ability of discerning undisturbed sites from sites being disturbed by a specific chemical were identified. The identification of species was done by studying the discriminating power of the species. Species having a discriminating power above 3.0, are traditionally seen as being able to discriminate between classes. After identifying the species that separate the undisturbed sites from sites showing, e.g. mercury disturbance, a new model of the *training set* was built. This new training set model is based solely on the species identified as having good discriminating power for the chemical in question (e.g., mercury). It is therefore well suited to identify stations where the chemical in question has caused a disturbance in the benthic fauna. It is, however, not useful for detecting other types of disturbance, as it is based only on the species that are characteristic for that specific type of disturbance (e.g., mercury). This means that one has to build many refined models of the training set within each grain size interval – one for each type of chemical disturbance.

Identification of the species to use when detecting cadmium induced disturbance for grain sizes above 100 μm is shown in Fig. 16.

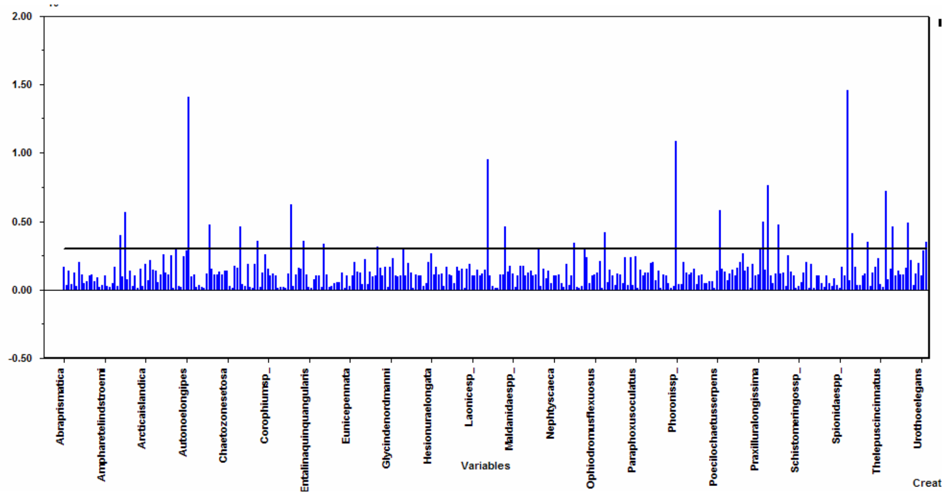

Fig. 16. Identification of species characteristic of a certain type of disturbance

Each bar represents the ability of a species to distinguish between the undisturbed situation and the mercury disturbed situation. The horizontal line represents a discriminating power of 3.0, and the training set is thus remodeled using only the species rising above this limit. The procedure is repeated for the other chemicals. Different species are used in the different cases.

SIMCA-based estimations of NOEC

The test sets were fitted to the appropriate models of the training sets. The residual standard deviations of the test set members were calculated, and compared to the acceptance criterion. We selected the acceptance criteria to correspond to a confidence level of 95%. Sites having an RSD lower than the limit (i.e. the 95% confidence level) were said to show no sign of disturbance. Sites having too large an RSD were said to be slightly disturbed. The concentration of the chemical in question was above the “true” field NOEC for those samples. The bars in Fig. 17 show the RSD values for the decalins training set for the grain size interval 80 – 100 μm. The decalin concentration increases moving from left to right in the figure.

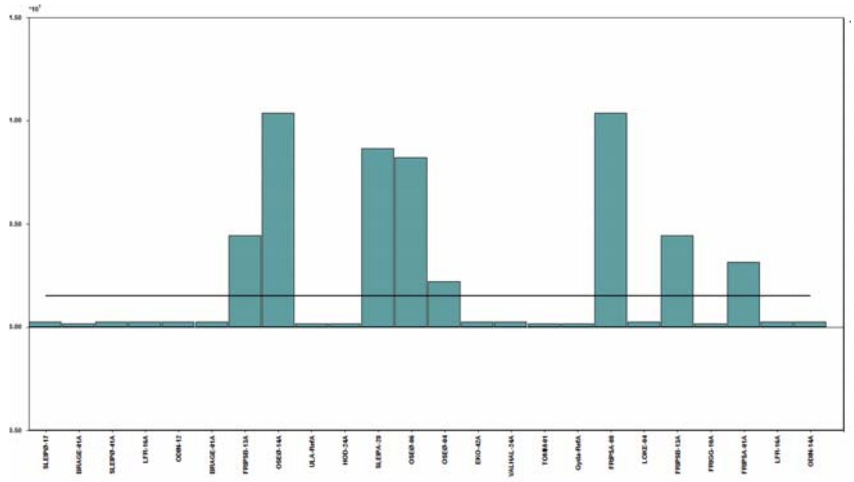

Fig. 17. RSD plot for decalins training set in the grain size interval 80 – 100 µm (line is 95% confidence interval)

The RSD of the first objects is well below the acceptance criterion. The seventh bar, however, is far higher than acceptable. The corresponding sample is disturbed due to the decalin concentration. Its concentration is the lowest concentration for which a disturbance effect has been observed. The NOEC, which refers to the highest concentration obtained without a discernible effect, is the decalin concentration of the *previous* sample (number 6).
The spatial and temporal variance are included in the multivariate model (SIMCA) based on F-statistics.

In the advent of all RSDs of the training set being above the limit, the NOEC from the previous work is kept[6].

To obtain robust estimates of the NOEC values, this procedure was not attempted for test sets with fewer than five samples. As can be seen in Table 4, several chemicals have such small test sets for some of the grain size intervals. In such cases, an attempt was made to expand the test set by increasing the allowed concentration of the *other* chemicals (not the one we are investigating) by a small amount. The estimated NOEC value from the previous grain size interval was used.(As an example, the previously reported NOECs for the 40 – 60 µm interval was used when defining test sets for the 60 – 80 µm interval.) This approach cannot guarantee that the correlation problem is completely avoided, but at the very least it minimizes the effect.

For barium and some of the organic compounds at some grain sizes, the test sets were still empty or too small to be of any use. In such cases, the highest concentration of the chemical in the *training set* was used as the NOEC, which is a conservative approach

Producing the final NOEC values
Estimates of the NOECs for various chemicals as a function of the grain size was obtained by fitting a second order polynomial to the observed NOECs. The resulting equations and NOECs are presented in the Results section.

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[6] The following NOECs were taken from the previous work: Ba: All values. Cd: None. Cr: 60-80, 40-60. <20. Cu: >100, 40-60. Hg: None. Pb: >100, 60-80. Zn: 40-60. Decalins: 60-80, 40-60, 20-40, <20. NPD: >100, 80-100, 40-60, 20-40. PAH: >100, 80-100. THC: 20-40.

Identifying marker species

The SIMCA model contains a statistic that quantifies the ability a given variable has for differentiating between different classes in a data set. This is referred to as the discriminating power of a variable. In this project, a species’ ability to discriminate between an undisturbed and a slightly disturbed site is of interest. Such species are *marker species* – their disappearance (or appearance) is an indication of environmental disturbance. The possible marker species with regards to a certain disturbance were identified by comparing the zero-component model of the training set to a zero component model of the appropriate test set. Variables with a discriminating power above 3 were identified as possible marker species. To ensure robustness, the SIMCA models compared were zero component models. The Results section contains a list of all the candidates for marker species.

Figure 18 shows the number of counts of the species *Glycera alba* for the stations without any discernible environmental disturbance (red bars), and for stations with too much mercury (blue bars). Bars shown in other colors refer to the stations with an increased concentration of another chemical (not mercury). All stations depicted in the figure are in the grain size interval 80 – 100 μm. Note that this species (G. alba) is not found in any of the mercury stations, except one. Thus, the species shows good discriminating power. Furthermore, the species presence in stations with, e.g., an increased chromium concentration (green bars) indicates the *Glycera alba* as a possible marker species for mercury pollution.

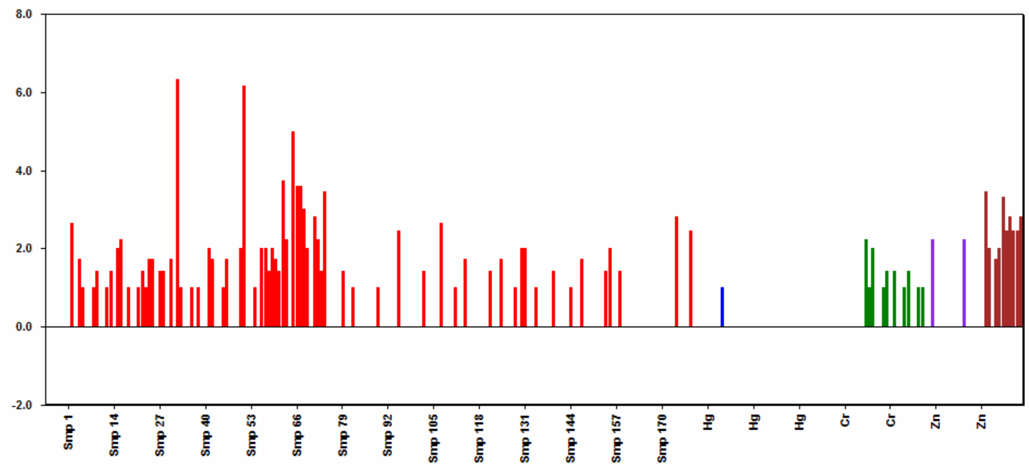


Fig. 18. The number of counts for the Glyecra alba species in the 80 – 100 μm interval. Red bars represent reference stations.

4. Results

Observed NOEC values

Table 5 contains the NOEC values for the various chemicals for the different grain size intervals.

Chemical	**Grain size** **110 µm**	**90 µm**	**70 µm**	**50 µm**	**30 µm**	**10 µm**
Ba	690	532	597	921	2010	1520
Cd	0.020	0.020	0.021	0.043	0.057	0.106
Cr	5.43	5.57	5.70	9.04	23.90	33.80
Cu	1.17	1.60	2.24	3.80	7.25	11.06
Hg	0.010	0.010	0.013	0.014	0.02	0.05
Pb	6.47	7.80	6.00	12.90	18.30	21.50
Zn	6.80	9.77	11.82	17.94	44.40	67.90
Decalins	0.058	0.036	0.032	0.084	0.021	0.026
NPD	0.011	0.014	0.035	0.037	0.061	0.093
PAH	0.009	0.032	dnp	dnp	0.070	0.110
THC	8.00	8.11	9.40	9.73	8.87	21.40

Table 5. Observed NOECs, ppm (dnp: data not present)

Grain sizes above 110 are included. However, we chose to collect all samples with a grain size above 100 µm in one interval. This is *strongly* supported by the shape of the NOEC curves – they level out (become more flat) as the grain sizes increase (see below)..

Final NOEC values

Figures 19– 29 show the experimentally observed NOECs, and the fitted second order polynomial that is used to predict the final NOECs for a given chemical as a function of the grain size. Note that the match of line to the data is expressed as the R^2 value (1.0 being perfect match, close to 0 being no match). Most of the values show a good match ($R^2 > 0,9$), while the low R^2 value of the paraffinics is due to their poor stability (se later discussion). The R^2 value will also vary for the trace elements due to experimental variation in the data (as e.g. sampling, work-up procedure, instrumental analysis).

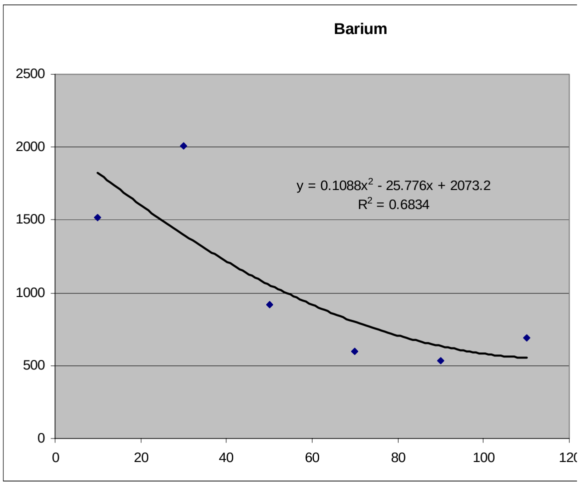


Fig. 19. Final NOEC for barium as a function of grain size.

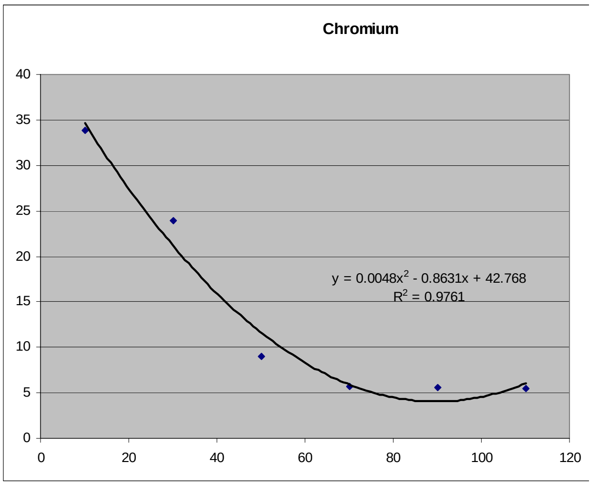


Fig. 20. Final NOEC for chromium as a function of grain size

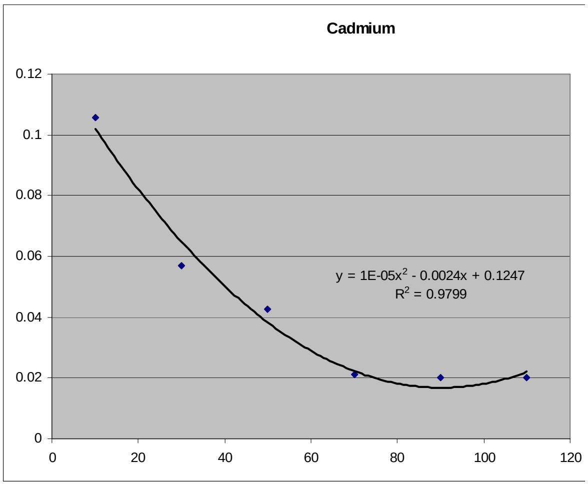


Fig. 21. Final NOEC for cadmium as a function of grain size

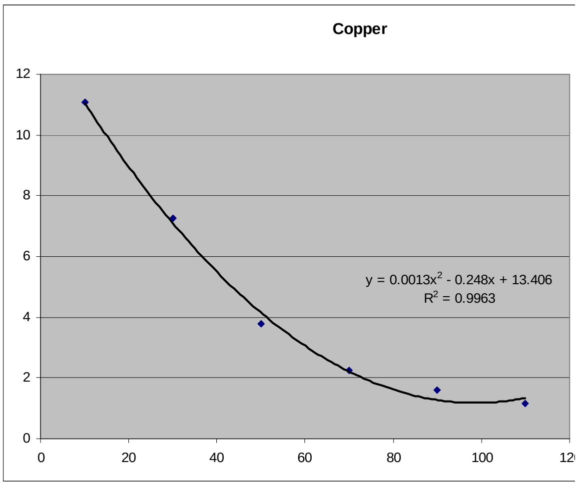


Fig. 22. Final NOEC for copper as a function of grain size

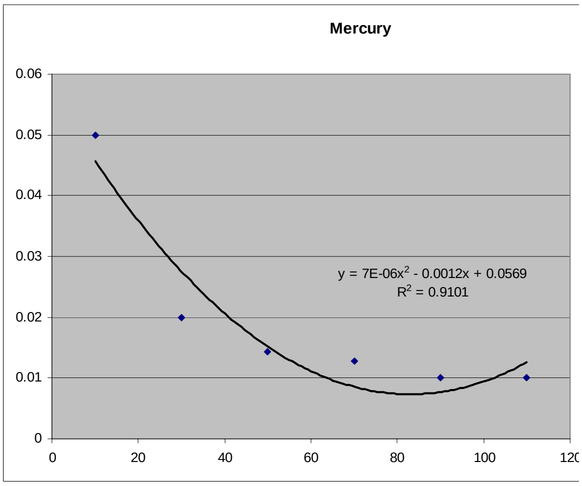


Fig. 23. Final NOEC for mercury as a function of grain size

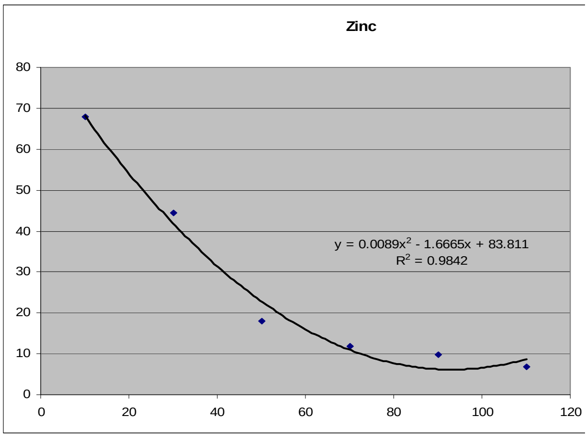


Fig. 24. Final NOEC for zinc as a function of grain size

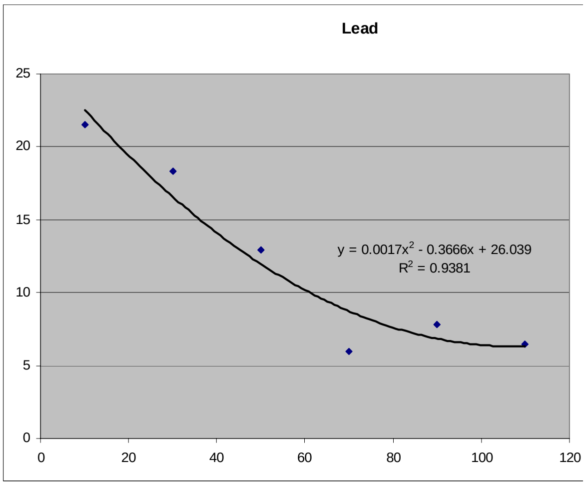


Fig. 25. Final NOEC for lead as a function of grain size

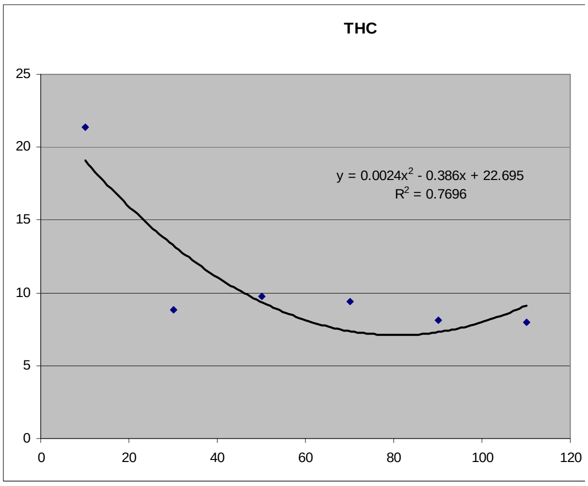


Fig. 26. NOEC for THC as a function of grain size

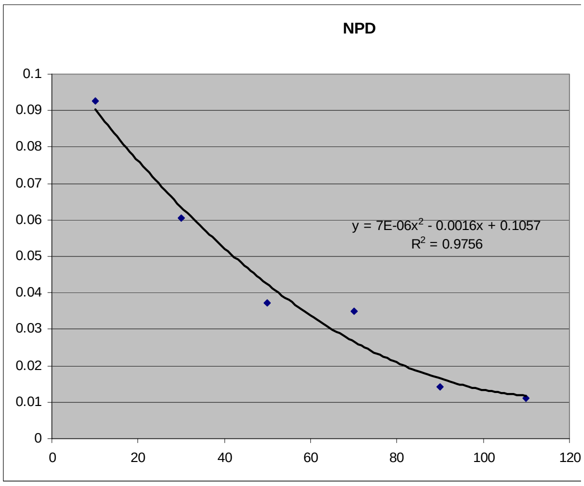


Fig. 27. Final NOEC for NPD as a function of grain size

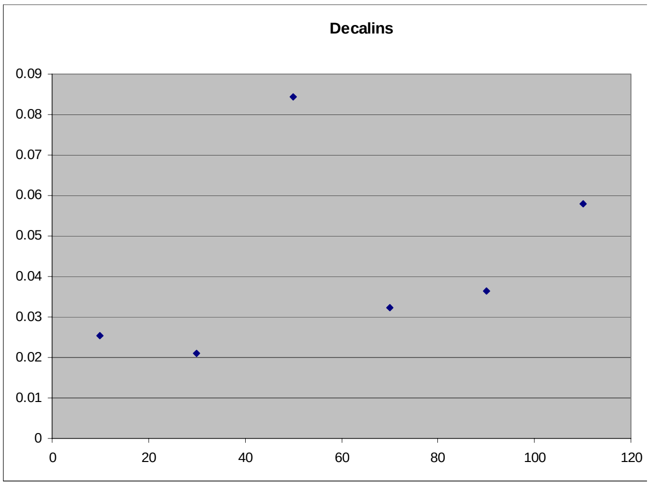


Fig. 28. NOEC for decalins as a function of grain size

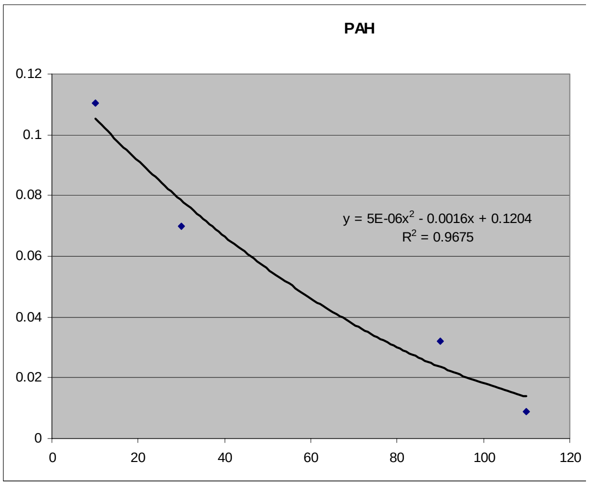


Fig. 29. Final NOEC for PAH as a function of grain size.

The second-order functions fitted to the experimentally observed NOECs are presented in Table 6. In table 6, ‘x’ refers to the grain size. ‘y’ is the final NOEC.

Chemical	**Function**
Barium	$y = 0.1088x^2 – 25.776x + 2073.2$
Chromium	$y = 0.0048x^2 – 0.8361x + 42.768$
Cadmium	$y = 0.00001x^2 – 0.0024x + 0.1247$
Copper	$y = 0.0013x^2 – 0.248x + 13.406$
Mercury	$y = 0.000007x^2 – 0.0012x + 0.05569$
Zinc	$y = 0.0089x^2 – 1.6665x + 83.811$
Lead	$y = 0.0017x^2 – 0.3666x + 26.039$
NPD	$y = 0.000007x^2 – 0.0016x + 0.1057$
PAH	$y = 0.000005x^2 – 0.0016x + 0.1204$

Table 6. Final NOECs for the chemicals as a function of the grain size. The function is valid from close to zero grain size and upto 80 µm. For grainsize larger than 80 µm the NOEC for grain size 80 should be used.

There seems to be a steady NOEC level until the grain size falls below a certain limit being around 100-110 µm average grain size (see discussion below). The NOEC then increases dramatically when average grainsize decreases from roughly 100 µm .For decalins and THC the functions are not presented. For decalins, the function is obviously of little use. For THC, the function fits the data poorly. A second-order function is therefore not suitable for THC. The problem with THC and decalines are their lack of stability toward natural weathering processes. This is illustrated in Figure 30 (below). The result is that all THC and decalin data in the MOD is probably far too low compared to the concentration when the effect was caused on the benthic fauna.

Discussion of problem with weathering of toxic stressors and the MOD

The organics are more or less rapidly weathered at the seafloor. Within some days as much as 90% of the THC may be weathered (e.g. Grahl-Nielsen and Brakstad, 1986). We refer to Figure 1 for the description of the problem that this generate into the validation part of the ERMS project.

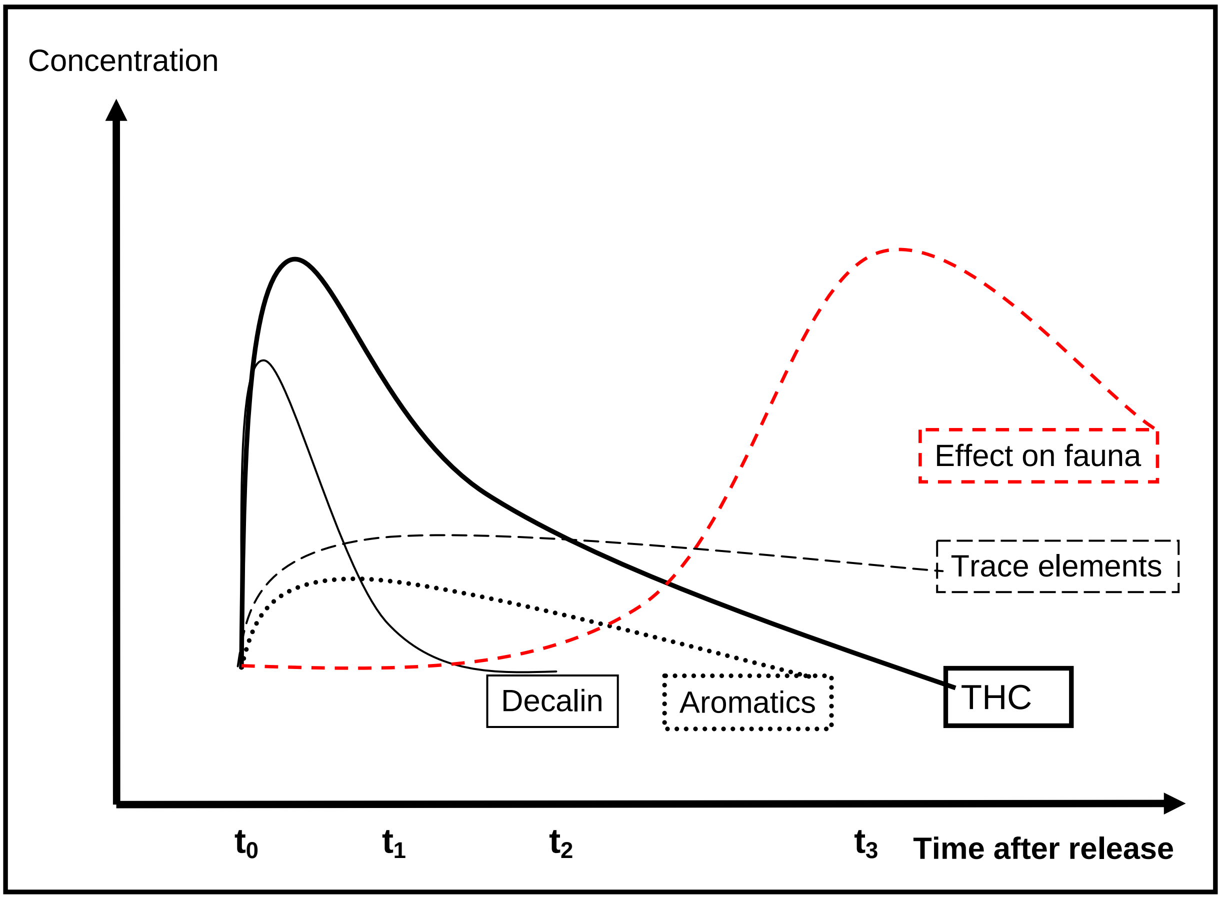


Figure 30 Illustrating the problem of relating an easily weathered parameters as THC and decaline to an observed effect in benthic fauna.

As illustrated in Figure 1 the initial concentration of toxic stressors will soon after the release be influence by various process of weathering. The result is that they disappear with time. The degree of disappearance will be dependent of type of toxic stressor. The effect on the benthic fauna will however not appear before after some time (1-2 months depending on degree of exposition). As an example, decalin may have a a relatively high concentration at the time of release (t_0), and thus initiate a change in the benthic community. However, the response in the benthic fauna (as evident from change in population) may not appear before after some time , e.g. as shown in Figure at t_0. In Figure 1 a small change in the benthic fauna is first evident after some time after the actual release (**t_2**). However, at sampling time, which at sampling a frequency every third year may be up to three year later, only a fraction of the decaline will be present while the benthic community still haven't recovered. This fraction is the data that are collected in the MOD.

The consequence is that for all organics the specific data column in MOD may be too low as compared to the actual toxic level (as. Eg NOEC or fPNEC). Both methods have their clear limitation as they tend to correlate the concentration level of a specific organic compound (decalins) or group or organic compounds (THC, NPD and PAH) *at sampling time to a certain level at exposure time*.

Discussion of the observed correlation between NOECs and grain size

The observation that the NOEC-value generally is inversely proportional with grain size, is probably related to the fact that a coarse sediment will increase the bioavailability of a metal. The proportion of free metal ions, which for most metals is the most bioavailable and toxic form, is generally inversely proportional with the amount of organic matter [13]. Thus coarse sediments, which naturally contain little organic matter, will increase the bioavailability of metals. Several studies have showed a direct relationship between metal concentration in the pore water and sediment toxicity (e.g.[14-16]). It has also been shown that both macrobenthos [17,18] and meiofauna [19, 20] have been less affected by metal contamination in mud than in sand.

Species with discriminating power

In tables 7 - 16, the species with discriminating power above 3.0 is presented for each chemical in each grain size interval. The species are listed in decreasing order with regards to their discriminating ability. In some cases, a discriminating power of 2.0 is used as criterion. Discriminating power of 2.0 was used in the following cases: THC: 80-100, 60-80, 40-60. PAH: 0-20, 20-40. Cd: 40-60. Cr 20-40. At these stations there were relatively few species with discrimination power > 3.0. Thus reducing the criteria to discrimination power from 3.0 to 2.0, we got more species and thus a more robust set of markers. This is indicated by an asterisk (*) for the cases where this applies.

Mercury, 0 – 20 µm	**Lead, 0 – 20 µm**	**Copper, 0 – 20 µm**	**PAH, 0 – 20 µm**
Euchone sp	Ampharetidae spp	*Clymenura borealis*	*Cerastoderma minimum*
Myriochele oculata	*Aonides paucibranchiata*	*Bathyarca pectunculoides*	*Kelliella miliaris*
Dodecaceria concharum	Diastylidae spp	*Onchnesoma steenstrupi*	*Glycera lapidum*
Clymenura borealis	Oligochaeta spp	*Myriochele oculata*	*Spiophanes kroyeri*
Levinsenia gracilis	*Polydora* sp	Fauvelopsidae spp	*Prionospio cirrifera*
Golfingia spp	*Eclysippe vanelli*	*Limopsis minuta*	*Eclysippe vanelli*
Timoclea ovata	*Chaetozone* sp	*Euclymene affinis*	*Yoldiella lucida*
	Yoldiella lucida	*Eriopisa elongata*	*Myriochele oculata*
	Heteroclymene robusta	*Myriochele* spp	*Harpinia pectinata*
	Spiophanes wigleyi	*Heteromastus filiformis*	*Ophelina norvegica*
	Euchone incolor	*Notomastus* sp	
	Chaetozone setosa		
	Capitellidae spp		
	Scutopus ventrolineatus		
	Ophelina norvegica		

Table 7. Species with discriminating power for Hg, Pb, Cu and PAH in the 0 - 20 μm interval.

Zinc, 0 – 20 µm	**NPD, 0 – 20 µm**	**THC, 0 – 20 µm**	**Cadmium, 0 – 20 µm**
Echinocucumis hispida	Ampharetidae spp	*Tharyx killariensis*	*Tmetonyx cicada*
Euchone incolor	Diastylidae spp	*Onchnesoma squamatum*	*Eclysippe vanelli*
Fauvelopsidae spp	*Thyasira croulinensis*	*Apistobranchus tenuis*	*Cossura longocirrata*
Spiophanes kroyeri	*Natatolana borealis*	*Lucinoma borealis*	*Tharyx killariensis*

Onchnesoma squamatum	*Onchnesoma squamatum*	*Ditrupa arietina*	*Neohela monstrosa*
Pectinaria auricoma	*Polydora* sp	*Notoproctus oculatus*	
Myriochele oculata	*Pectinaria auricoma*	*Chaetozone setosa*	
Paradiopatra quadricuspis	*Eclysippe vanelli*	*Lima tulagwyni*	
Onchnesoma steenstrupi	*Myriochele oculata*	*Pholoe inornata*	
		Bathyarca pectunculoides	

Table 8. Species with discriminating power for Zn, NPD, THC and Cd in the 0 - 20 μm interval.

Cadmium, 20 – 40 µm	**Chromium, 20 – 40 µm**	**Mercury, 20 – 40 µm**	**PAH, 20 – 40 µm**
Thyasira obsoleta	*Euchone* sp	*Tmetonyx similis*	*Euchone* sp
Jasmineira caudata	*Vargula norvegica*	*Thyasira eumyaria*	*Vargula norvegica*
Pherusa falcata	*Thyasira obsoleta*	*Thyasira obsoleta*	*Jasmineira candela*
Aricidea catherinae	*Branchiomma bombyx*	*Laetmatophilus tuberculatus*	*Thyasira obsoleta*
Augeneria tentaculata	*Macrochaeta polyonyx*	*Ophryotrocha* sp	
Scoloplos armiger	*Asychis biceps*	*Munna* spp	
Onchnesoma squamatum	*Limopsis minuta*	*Modiolula phaseolina*	
Hyalinoecia tubicola			
Onchnesoma steenstrupi			
Streblosoma intestinale			

Table 9. Species with discriminating power for Cd, Cr, Hg and PAH in the 20 - 40 μm interval.

THC, 40 – 60 µm (*)	**Cd, 40 – 60 µm (*)**	**Hg, 40 – 60 µm**	**Pb, 40 – 60 µm**
Kelliella miliaris	*Amythasides macroglossus*	*Thyasira equalis*	*Paradiopatra quadricuspis*
Abra sp	*Chone longocirrata*	*Onuphis* sp	*Myriochele oculata*
Euchone rubrocincta	*Astarte* sp	*Amythasides macroglossus*	*Eudorella emarginata*
Leptosynapta inhaerens	*Kelliella miliaris*	*Streblosoma intestinale*	*Entalina quinquangularis*
Polydora sp	*Levinsenia gracilis*	*Urothoe elegans*	*Thyasira ferruginea*
Yoldiella tomlini	Lysianassidae spp	*Chaetoderma nitidulum*	*Paramphinome jeffreysii*
Myriochele heeri	*Pista* sp	*Cerastoderma minimum*	*Prionospio cirrifera*
Polycirrus medusa	*Lumbriclymene* sp	*Harmothoe* sp	*Chaetozone setosa*
Harmothoe sp	*Dodecaceria concharum*	*Glycera lapidum*	*Tharyx* sp
Paradoneis sp		*Leptosynapta inhaerens*	*Euchone* sp
		Ampharete falcata	*Cerastoderma minimum*
		Pista sp	*Aricidea catherinae*
		Nemertea spp	*Laonice sarsi*
		Aricidea roberti	*Kelliella miliaris*
		Polycirrus sp	*Paradoneis lyra*
		Amphipholis squamata	*Octobranchus floriceps*
		Glycinde nordmanni	*Euclymene affinis*
		Phyllodoce groenlandica	*Amythasides macroglossus*
		Capitella capitata	*Yoldiella lucida*
			Terebellides stroemi
			Mugga wahrbergi
			Pholoe pallida
			Lumbriclymene spp
			Phylo norvegica
			Ascidiacea spp
			Nucula tumidula

Table 10. Species with discriminating power for THC, Cd, Hg and Pb in the 40 - 60 μm interval. For THC and Cd a discrimination power criterion of 2.0 is used.

Mercury, 60 – 80 µm	**Cadmium, 60 – 80 µm**	**THC, 60 – 80 µm (*)**
Cerastoderma minimum	*Harmothoe* sp	*Nothria hyperborea*
Exogone sp	*Ditrupa arietina*	*Capitella capitata*
Abra sp	*Myriochele danielsseni*	*Diastylis boecki*
Diastylidae spp	*Polydora* sp	*Ampelisca spinipes*
Diastylis sp	*Amythasides macroglossus*	*Polydora* sp
Phoronis sp	*Praxillella praetermissa*	*Apistobranchus* sp
Streblosoma intestinale	*Thyasira succisa*	*Myriochele fragilis*
Polycirrus sp	*Owenia fusiformis*	*Heteranomia squamula*
Amythasides macroglossus	*Scolelepis* sp	Amphilochidae spp
Parougia sp	*Onchnesoma steenstrupi*	*Exogone* sp
Asteroidea spp		*Kelliella miliaris*
Notomastus latericeus		*Synchelidium* sp
Aricidea laubieri		Scaphopoda spp
Retusa umbilicata		*Roxania utriculus*
Lysianassidae spp		*Aricidea* sp
Thyasira flexuosa		*Lumbrineris* sp
Aricidea wassi		
Ampharete lindstroemi		
Ophelina modesta		
Lumbrineris gracilis		
Pholoe pallida		
Ditrupa arietina		
Synchelidium sp		
Cirratulus cirratus		

Table 11. Species with discriminating power for Hg, Cd and THC in the 60 - 80 µm interval. For THC a discrimination power criterion of 2.0 is used.

Zinc, 60 – 80 µm	**Copper, 60 – 80 µm**	**NPD, 60 – 80 µm**
Onchnesoma steenstrupi	*Myriochele danielsseni*	*Thyasira succisa*
Octobranchus floriceps	*Thyasira succisa*	*Harpinia* sp
Harpinia sp	*Harpinia* sp	*Onchnesoma steenstrupi*
Maldanidae spp	*Onchnesoma steenstrupi*	*Octobranchus floriceps*
Abra longicallus	*Octobranchus floriceps*	*Owenia fusiformis*
Notomastus latericeus	*Owenia fusiformis*	*Myriochele fragilis*
Chaetoderma sp	*Notomastus latericeus*	*Notomastus latericeus*
Gnathia oxyurea	*Myriochele fragilis*	*Chaetoderma* sp
Leptophoxus falcatus	*Abra longicallus*	*Abra longicallus*
Pogonophora spp	*Scolelepis* sp	Maldanidae spp
Yoldiella tomlini	*Chaetoderma* sp	*Yoldiella tomlini*
Dodecaceria sp	Maldanidae spp	*Gnathia oxyurea*
Aricidea sp	*Ampelisca tenuicornis*	*Cuspidaria rostrata*
Nematoda spp	*Leptophoxus falcatus*	Pogonophora spp
Prionospio cirrifera	*Aricidea* sp	*Leptophoxus falcatus*
Cuspidaria rostrata	*Spiophane surceolata*	*Levinsenia gracilis*
Thyasira flexuosa	*Gnathia oxyurea*	*Parougia caeca*
Levinsenia gracilis	*Cirratulus caudatus*	*Polycirrus norvegicus*
Euclymeninae spp	*Lucinoma borealis*	*Ditrupa arietina*
Ampelisca tenuicornis	*Phaxas pellucidus*	
Falcidens crossotus	*Tharyx killariensis*	
Eclysippe vanelli	*Yoldiella tomlini*	
Thyasira croulinensis	*Polydora* sp	
Pulsellum lofotense	*Cuspidaria ostrata*	
Myriochele oculata	*Lumbrineris* sp	
Nicippe tumida	*Pectinaria auricoma*	
Scalibregma inflatum	*Dodecaceria* sp	
Eugyra arenosa	*Aricidea roberti*	
Eurydice pulchra	*Levinsenia gracilis*	
Ditrupa arietina	*Scolelepis korsuni*	
Phaxas pellucidus	*Pholoe baltica*	
	Westwoodilla caecula	
	Cirrophorus furcatus	
	Amphiura filiformis	
	Eclysippe vanelli	
	Caudofoveata spp	
	Myriochele oculata	

Table 12. Species with discriminating power for Zn, Cu and NPD in the 60 - 80 μm interval.

Hg, 80 – 100 µm	**Cr, 80 – 100 µm**	**Zn, 80 – 100 µm**	**THC, 80 – 100µm m (*)**
Corymorpha nutans	*Pholoe inornata*	*Nephtys cirrosa*	*Abyssoninoe hibernica*
Caudofoveata spp	*Harmothoe* sp	*Onchnesoma steenstrupi*	*Jasmineira candela*
Echinus sp	*Pectinaria koreni*	*Jasmineira* sp	*Falcidens crossotus*
Chone duneri	*Eugyra arenosa*	*Apistobranchus tullbergi*	*Diastylis boecki*
Ditrupa arietina	*Chaetozone setosa*	*Abyssoninoe hibernica*	*Byblis gaimardi*
Cnidaria spp	Nematoda spp	*Pectinaria koreni*	*Harpinia pectinata*
Clymenura borealis	*Tmetonyx cicada*	*Jasmineira candela*	*Praxillella* sp
Glycera tridactyla	*Ophiura affinis*	*Arcopagia balaustina*	*Nothria conchylega*
Falcidens crossotus	*Heteranomia squamula*	Caudofoveata spp	Lumbriclymeninae spp
Diastylis cornuta	*Nephtys cirrosa*	*Byblis gaimardi*	*Pectinaria* sp
Diastylis goodsiri		*Ampelisca gibba*	*Prionospio dubia*
Thyasira succisa		*Harmothoe glabra*	*Cochlodesma praetenue*
Euclymene sp		Lumbriclymeninae spp	*Goniada norvegica*
Ampelisca gibba		*Falcidens crossotus*	*Euclymene droebachiensis*
Ampharete falcata		*Nephtys hystricis*	*Thyasira pygmaea*
Euchone southerni			*Terebellides stroemi*
Heteranomia squamula			*Abra nitida*
Tharyx killariensis			Isaeidae spp
Cirratulus caudatus			Aphelochaeta sp
			Jasmineira sp
			Ampelisca gibba

Table 13. Species with discriminating power for Hg, Cr, Zn and THC in the 80 - 100 μm interval. For THC a discrimination power criterion of 2.0 is used.

Decalins, 80 – 100 µm	**Lead, 80 – 100 µm**	**Copper, 80 – 100 µm**	**Cadmium, 80 – 100 µm**
Ditrupa arietina	*Myriochele fragilis*	*Abyssoninoe hibernica*	*Abyssoninoe hibernica*
Natatolana borealis	*Owenia fusiformis*	*Jasmineira candela*	*Onchnesoma steenstrupi*
Exogone hebes	*Ophiura affinis*	*Ampelisca gibba*	*Apistobranchus tullbergi*
Nephtys cirrosa	*Ampharete* sp	*Falcidens crossotus*	*Ampelisca gibba*
Prionospio dubia	*Ampharete finmarchica*	*Nephtys hystricis*	*Jasmineira candela*
	Pectinaria koreni	*Byblis gaimardi*	*Chone collaris*
	Thyasira flexuosa	*Nothria conchylega*	*Scolelepis tridentata*
	Trichobranchus roseus	*Diastylis boecki*	*Natatolana borealis*
	Aphrodita aculeata	*Pholoe inornata*	*Ditrupa arietina*
	Paramphinome jeffreysii	*Apistobranchus* sp	*Nephtys hystricis*
	Harmothoe sp	*Thyasira pygmaea*	*Falcidens crossotus*
	Levinsenia gracilis	*Jasmineira* sp	*Octobranchus floriceps*
		Praxillella sp	*Byblis gaimardi*
		Lumbriclymeninae spp	*Sosanopsis wireni*
		Exogone sp	*Praxillella* sp
		Abra nitida	*Pseudopolydora paucibranchiata*
		Terebellides stroemi	*Cuspidaria costellata*
		Euchone sp	*Thyasira succisa*
		Orbinia armandi	*Goniada norvegica*
		Brissopsis lyrifera	Lumbriclymeninae spp
		Ostracoda spp	*Terebellides stroemi*
		Lumbrineris sp	*Thyasira pygmaea*
		Samytha sexcirrata	*Orbinia armandi*
		Paramphinome jeffreysii	*Cylichna alba*
		Rhodine loveni	*Leptophoxus falcatus*
		Pectinaria koreni	*Rhodine loveni*
		Goniada norvegica	*Synelmis klatti*
		Eclysippe vanelli	*Euchone* sp
		Laonice sarsi	*Abra nitida*
		Caudofoveata spp	*Hydroides norvegica*
		Pseudopolydora paucibranchiata	*Laonice sarsi*
			Nothria conchylega
			Apistobranchus sp
			Pectinaria koreni

Table 14. Species with discriminating power for decalins, Pb, Cu and Cd in the 80 - 100 μm interval.

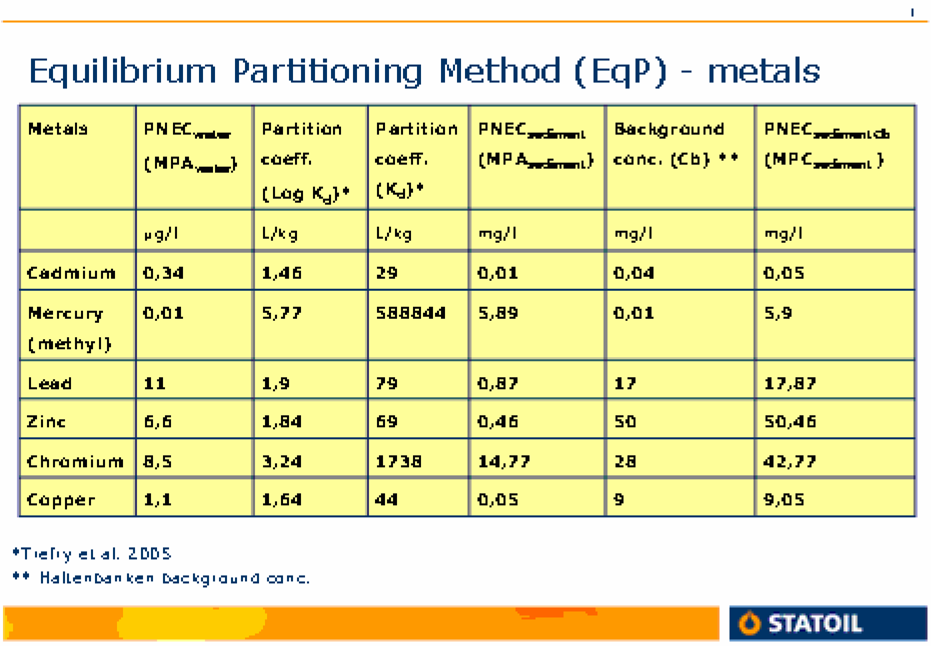
Cadmium, >100 µm	**Chromium, >100 µm**	**Mercury, >100 µm**	**Zinc, >100 µm**
Spiophanes sp	*Corymorpha nutans*	*Spiophanes* sp	*Protodorvillea kefersteini*
Limatula subauriculata	*Pisione remota*	*Clymenura* sp	*Limatula subauriculata*
Protodorvillea kefersteini	*Nothria conchylega*	*Diastyloides biplicata*	*Spiophanes* sp
Thracia phaseolina	*Spio mecznikowianus*	*Chone duneri*	*Bathyporeia* sp
Ditrupa arietina	*Gammaropsis* sp	*Cirrophorus furcatus*	*Samytha sexcirrata*
Poecilochaetus sp		*Spio* sp	*Harmothoe fragilis*
Anobothrus gracilis		*Limatula subauriculata*	*Spiophanes wigleyi*
Prionospio fallax		*Tharyx killariensis*	*Aricidea suecica*
Travisia forbesii		*Chone* sp	*Cirrophorus furcatus*
Pseudopolydora paucibranchiata		Capitellidae spp	*Yoldiella tomlini*
Capitellidae spp		*Protodorvillea kefersteini*	*Paraphoxus oculatus*
Lysianassidae spp			*Gnathia oxyurea*
Chone sp			*Opisthodonta pterochaeta*
Thyasira croulinensis			*Phoronis* sp
Opisthodonta pterochaeta			*Philine* sp
Spiophanes wigleyi			*Thyasira croulinensis*
Amphiura filiformis			*Ampelisca tenuicornis*
Clymenura sp			*Lumbrineris gracilis*
Edwardsia sp			*Pholoe synopthalmica*
Yoldiella tomlini			*Eteone flava*
Synchelidium sp			*Ampelisca typica*
Notomastus sp			
Euchone southerni			
Gari fervensis			
Astarte sulcata			
Mysella bidentata			

Table 15. Species with discriminating power for Cd, Cr, Hg and Zn when grain size is above 100 μm.

THC, >100 µm	**Decalins, >100 µm (*)**	**Lead, >100 µm (*)**
Nemertea spp	*Myriochele danielsseni*	*Owenia fusiformis*
Aricidea cerrutii	Ericthonius spp	*Lanice conchilega*
Cirratulus caudatus	*Aonides paucibranchiata*	*Notomastus latericeus*
Chaetozone sp	*Timoclea ovata*	*Antalis* sp
Labidoplax digitata	*Spio mecznikowianus*	*Spiophanes urceolata*
Ampharetidae spp	*Bathyporeia* sp	*Sthenelais limicola*
Spiophanes bombyx	*Polycirrus* sp	*Myriochele danielsseni*
Owenia fusiformis	*Phisidia aurea*	*Glycera lapidum*
Edwardsia sp	*Atylus vedlomensis*	Lysianassidae spp
Harmothoe antilopes	*Gnathia oxyurea*	*Chone* sp
Labidoplax buskii	*Themisto compressa*	*Cerianthus lloydii*
Unciola planipes	*Chone duneri*	*Timoclea ovata*
Goniada maculata	*Lumbrineris gracilis*	*Ophelia borealis*
Glycera alba	*Eumida ockelmanni*	*Aricidea wassi*
Myriochele oculata	*Tridonta montagui*	Mysella spp
	Nemertea spp	*Spiophanes kroyeri*
	Abra sp	*Spiophanes bombyx*
		Nematoda spp
		Ophryotrocha sp
		Aricidea simonae
		Amphiura filiformis
		Exogone verugera
		Philine sp

Table 16. Species with discriminating power for THC, decalins and Pb when the grain size is above 100 µm. For decalins and Pb a discrimination power criterion of 2.0 is used.

5. Comparison of field NOECs and PNECs from literature



Equilibrium Partitioning Method (EqP) - metals

Metals	PNEC$_{water}$ (MPA$_{water}$)	Partition coeff. (Log K$_d$)*	Partition coeff. (K$_d$)*	PNEC$_{sediment}$ (MPA$_{sediment}$)	Background conc. (Cb) **	PNEC$_{sediment,cb}$ (MPC$_{sediment}$)
	µg/l	L/kg	L/kg	mg/l	mg/l	mg/l
Cadmium	0,34	1,46	29	0,01	0,04	0,05
Mercury (methyl)	0,01	5,77	588844	5,89	0,01	5,9
Lead	11	1,9	79	0,87	17	17,87
Zinc	6,6	1,84	69	0,46	50	50,46
Chromium	8,5	3,24	1738	14,77	28	42,77
Copper	1,1	1,64	44	0,05	9	9,05

*Tiefry et al. 2005

** Haltenbanken background conc.

Table 17 PNEC estimated from EqP methods.. This is literature data included assessment factors dependent of the literature data available Table from Statoil

	Interval 1 < 63 µm (“mud - silt”)	***Interval 63 >< 94µm (“mud – fine sand”)***	***Interval 3 (“fine sand – sand”)> 94 µm***
Substances	***F-PNECx*** *(mg/kg)*	***F-PNECx*** *(mg/kg)*	***F-PNECx*** *(mg/kg)*
Ba	*2200*	*1931*	*1942*
Cd	*0.042*	*0.031*	*0.050*
Cr	*7.400*	*9.116*	*4.836*
Cu	*6.587*	*4.877*	*4.167*
Hg	*0.026*	*0.937*	*-*
Pb	*16.15*	*11.68*	*10.60*
Zn	*29.43*	*25.07*	*23.93*
THC	*41.95*	*99.62*	*72.82*
NPD	*0.231*	*0.144*	*0.343*
PAH	*0.146*	*-*	*0.134*
PAH*1	*0.196*	*0.108*	*0.097*
Decalins	*8.336*	*16.98*	*12.33*

Table 18 Field derived PNECs from the SSD approach. Table from University of Oslo

Table 17 and table 18 shows predicted toxic levels of stressors , so-called Predicted No Effect Concentrations (PNECs). Table 17 is derived from literature including assessment factors and table18 is the ones derived from data analysis of MOD (field PNECs derived by the SSD approach of UiO), respectively.
Comparing to the NOEC values from the Mowing Windows Modelling method (MWM method, see Table 5) may lead to the following conclusion:

1) *There is an overall fair agreement between the literature values and the field validation methods SSD and MWM (within an order of magnitude). There is however a significant discrepancy between the Mercury and Chromium values reported from literature and the ones that are observed in field data.*

2) *The MWM approach has succeeded in delivering ”pure” field NOEC values for specific schemical stressors, i.e. without any interference from other chemical stressors.*
   Until this pioneer work, there has not been reported any work in the literature who has been able to solve the problem of covariance among toxic stressors.

3) *The observed correlation between NOEC and grain size (Mowing Window Approach) has not been previously reported in literature, probably because (until now) there has been lack of data and methodology to cope with correlations among toxic stressors present at same time and place.*

4) *The observed correlation between NOEC and grain size (Moving window approach) has not been reproduced by the SSD approach, probably due to interference from correlation between chemical stressors.*

The results from the validation reports (MWM and SSD) will be discussed in a separate memo (Bjorgesæter, A. and Brakstad, F., 2005)

6 Definitions

NOEC; "No Observed Effect Concentration" of a chemical toxic stressor, i.e. the highest observed level of a toxic stressor that may be present without causing any observable effect on the organism under examination.

Field NOEC; **NOEC** applied to field data extracted from the MOD. Effect is the measured as change in the population of the benthic fauna. The more observations, the closer will the field NOEC be to the **true NOEC** value.

True NOEC; a theoretical value indicating the highest possible level of NOEC that may be found for a certain toxic stressor when a infinitely number of observation has been investigated. In practise the true NOEC value will never been found in field situation, as the toxic stressors are present as discrete numbers with a certain precision.

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8. Appendix 1 Validation of sensitive species according to the Moving Window Model.

In this appendix, a report written by Akvaplan-NIVA (Report APN-411.3191) on the marker species is included.

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Sammendrag / Summary

Species which show sensitivity, either by decreasing or increasing abundance, towards specific chemical stressors and at specific grain size intervals are identified through a multivariate statistical model (Moving Window Modelling, MWM). This report seeks a validation of the species identified as sensitive in terms of taxonomy. Distribution of taxa (or lowest possible taxa) both within specific grain size intervals and within grain size intervals at specific chemical stressors are tabulated.

Emneord:	Key words:
	ERMS Moving Window Modelling Grain size intervals Chemical stressors Sensitive species

Prosjektleder / Project manager	Kvalitetskontroll / Quality control
Sten-Richard Birkely	Salve Dahle

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Table of Content

1. Introduction

During this part of the ERMS-project (Environmental Risk Management System) a need for PNEC-values without correlation effect from all the toxic stressors (i.e chemicals) became visible. In this context it is later referred to as “pure field NOEC”. The aims of this subproject were to recognize organisms which displayed sensitivity to chemical changes in their habitats and at what level this occurs. In this present study a taxonomic validation of the sensitive species found is prepared.

2. Material and methods

Sensitivity of organisms is explored using a statistical multivariate model developed by Brakstad and Grung (*in prep.*). The model has built-in criteria for sensitivity of organisms to single chemical stressors and grain size intervals. Within here, the abundance of taxa present at various grain size intervals are investigated in order to find their possibility of being affected, positively or negatively, in presence of various toxic stressors (i.e. chemical substances). The model is constructed so that the effect of only one single chemical stressor is evaluated successively and is repeated for every grain size interval (0-20, 20-40, 40-60, 60-80, 80-100 and >100µm).

A total of 276 taxa were recorded as sensitive to an alteration in chemical status of their habitat.

3. Results and discussion

The distribution of taxa within the main taxonomic groups is given in Table 1 (partitioning into grain size intervals are here disregarded) and displays that a total of 276 taxa are found to be sensitive in presence of an alteration of chemical composition in their environment. The polychaetes comprise the most sensitive taxa and their potential to be affected are more than three times that of the molluscs and crustaceans. When exploring the taxonomic groups with the grain size intervals into account, the picture is approximately the same: there are highest proportions of polychaetes showing sensitivity to chemical stressors (Table 2). Alternative explanation for these findings could be that the polychaetes as a taxonomic group are well known to be present in high abundance and diversity at soft bottom habitats (Mannsvik et al. 2001).

Table 1. Distribution of taxa within the main taxonomic groups.

Main taxonomic groups	**Taxa**	
	Number	in %
Polychaeta	163	59
Mollusca	48	17
Crustacea	42	15
Echinodermata	10	4
Div. groups	13	5
Total	276	100

Table 2. Distribution of taxa (in number and %) at specific grain size intervals (in µm).

Grain size interval	Taxa							
0-20µm	No	in %	20-40µm	No	in %	40-60µm	No	in %
Annelida			Annelida			Annelida		
Cnidaria			Cnidaria			Cnidaria		
Coelenterata			Coelenterata			Coelenterata		
Crustacea	6	11	Crustacea	3	13	Crustacea	3	5
Echinodermata	1	2	Echinodermata			Echinodermata	2	4
Mollusca	10	19	Mollusca	4	17	Mollusca	12	21
Nematoda			Nematoda			Nematoda		
Nemertea			Nemertea			Nemertea	1	2
Oligochaeta	1	2	Oligochaeta			Oligochaeta		
Polychaeta	32	60	Polychaeta	14	61	Polychaeta	37	66
Sipuncula	3	6	Sipuncula	2	9	Sipuncula		
Tunicata			Tunicata			Tunicata	1	2
Total	53	100	Total	23	100	Total	56	100
60-80µm			80-100µm			>100µm		
Annelida	1	1	Annelida			Annelida		
Cnidaria			Cnidaria	1	1	Cnidaria		
Coelenterata			Coelenterata	1	1	Coelenterata	3	3
Crustacea	14	16	Crustacea	9	11	Crustacea	13	14
Echinodermata	2	2	Echinodermata	3	4	Echinodermata	3	3
Mollusca	18	21	Mollusca	12	14	Mollusca	13	14
Nematoda	1	1	Nematoda			Nematoda	1	1
Nemertea			Nemertea	1	1	Nemertea	1	1
Oligochaeta			Oligochaeta			Oligochaeta		
Polychaeta	46	54	Polychaeta	55	65	Polychaeta	56	62
Sipuncula	2	2	Sipuncula	1	1	Sipuncula		
Tunicata	1	1	Tunicata	1	1	Tunicata		
Total	85	100	Total	84	100	Total	90	100

If the ten most (or up to ten, in cases where the amount of sensitive taxa was lower) sensitive taxa are compared, and the data was pre-treated with partitioning both in grain size intervals and separated chemical stressors, the noteworthy feature was that hardly any taxa did occur at several grain size intervals (Table 3). Exceptions here were the sipunculid *Onchnesoma steenstrupi*, the polychaetes *Amythasides macroglossus*, *Chone duneri*, *Ditrupa arientina*, *Polydora* sp., *Streblosomea intestinale*, the mollusc *Cerastoderma minimum* and the crustacean *Gnathia oxyurea*. Hovever, when all the taxa showing sensitivity towards specific chemical stressors at specific grain size intervals were included, a variety of taxa occurred in more than one grain size interval (Appendix 1).

Table 3. Distribution of (up to) the ten most sensitive taxa at specific grain size intervals (gr.size, in µm) and specific chemical stressor. Abbreviations: Ann: annelids, Cni: cnidarians, Coel: coelenterate, Cru: crustaceans, Ech: echinoderms, Moll: molluscs, Nem: Nematoda, Nmt: nemerteans, Olig: oligochaets Pol: polychaets, Sip: sipunculids, Tun: tunicata.

Gr.size/ taxon.gr	**Chemical**				
	Cu		**Cd**		**Cr**
0-20	Taxa	**0-20**	Taxa	**20-40**	Taxa
Pol	*Clymenura borealis*	Cru	*Tmetonyx cicada*	Pol	*Euchone* sp
Moll	*Bathyarca pectunculoides*	Pol	*Eclysippe vanelli*	Cru	*Vargula norvegica*
Sip	*Onchnesoma steenstrupi*	Pol	*Cossura longocirrata*	Moll	*Thyasira obsoleta*
Pol	*Myriochele oculata*	Pol	*Tharyx killariensis*	Pol	*Branchiomma bombyx*
Pol	Fauvelopsidae spp	Cru	*Neohela monstrosa*	Pol	*Macrochaeta polyonyx*
Moll	*Limopsis minuta*	**20-40**		Pol	*Asychis biceps*
Pol	*Euclymene affinis*	Moll	*Thyasira obsoleta*	Moll	*Limopsis minuta*
Cru	*Eriopisa elongata*	Pol	*Jasmineira caudata*	**80-100**	
Pol	*Myriochele* spp	Pol	*Pherusa falcata*	Pol	*Pholoe inornata*
Pol	*Heteromastus filiformis*	Pol	*Aricidea catherinae*	Pol	*Harmothoe* sp
60-80		Pol	*Augeneria tentaculata*	Pol	*Pectinaria koreni*
Pol	*Myriochele danielsseni*	Pol	*Scoloplos armiger*	Tun	*Eugyra arenosa*
Moll	*Thyasira succisa*	Sip	*Onchnesoma squamatum*	Pol	*Chaetozone setosa*
Cru	*Harpinia* sp	Pol	*Hyalinoecia tubicola*	Nem	Nem spp
Sip	*Onchnesoma steenstrupi*	Sip	*Onchnesoma steenstrupi*	Cru	*Tmetonyx cicada*
Pol	*Octobranchus floriceps*	Pol	*Streblosoma intestinale*	Ech	*Ophiura affinis*
Pol	*Owenia fusiformis*	**40-60**		Pol	*Heteranomia squamula*
Pol	*Notomastus latericeus*	Pol	*Amythasides macroglossus*	Pol	*Nephtys cirrosa*
Pol	*Myriochele fragilis*	Pol	*Chone longocirrata*	**>100**	
Moll	*Abra longicallus*	Pol	*Dodecaceria concharum*	Coel	*Corymorpha nutans*
Pol	*Scolelepis* sp	Pol	*Levinsenia gracilis*	Cru	*Gammaropsis* sp
80-100		Pol	*Lumbriclymene* sp	Pol	*Nothria conchylega*
Pol	*Abyssoninoe hibernica*	Pol	*Pista* sp	Pol	*Pisione remota*
Pol	*Jasmineira candela*	Moll	*Astarte* sp	Pol	*Spio mecznikowianus*
Cru	*Ampelisca gibba*	Moll	*Kelliella miliaris*		
Moll	*Falcidens crossotus*	Cru	Lysianassidae spp		
Pol	*Nephtys hystricis*	**60-80**			
Cru	*Byblis gaimardi*	Pol	*Harmothoe* sp		
Pol	*Nothria conchylega*	Pol	*Ditrupa arietina*		
Cru	*Diastylis boecki*	Pol	*Myriochele danielsseni*		
Pol	*Pholoe inornata*	Pol	*Polydora* sp		
Pol	*Apistobranchus* sp	Pol	*Amythasides macroglossus*		
		Pol	*Praxillella praetermissa*		
		Moll	*Thyasira succisa*		
		Pol	*Owenia fusiformis*		
		Pol	*Scolelepis* sp		
		Sip	*Onchnesoma steenstrupi*		
		80-100			
		Pol	*Abyssoninoe hibernica*		
		Sip	*Onchnesoma steenstrupi*		
		Pol	*Apistobranchus tullbergi*		
		Cru	*Ampelisca gibba*		
		Pol	*Jasmineira candela*		
		Pol	*Chone collaris*		
		Pol	*Scolelepis tridentata*		
		Cru	*Natatolana borealis*		

		Pol	*Ditrupa arietina*		
		Pol	*Nephtys hystricis*		
		>100			
		Pol	*Spiophanes* sp		
		Moll	*Limatula subauriculata*		
		Pol	*Protodorvillea kefersteini*		
		Moll	*Thracia phaseolina*		
		Pol	*Ditrupa arietina*		
		Pol	*Poecilochaetus* sp		
		Pol	*Anobothrus gracilis*		
		Pol	*Prionospio fallax*		
		Pol	*Travisia forbesii*		
		Pol	*Pseudopolydora paucibranchiata*		

	Hg		**Pb**		**Zn**
0-20	Taxa	**0-20**	Taxa	**0-20**	Taxa
Pol	*Euchone* sp	Pol	Ampharetidae spp	Ech	*Echinocucumis hispida*
Pol	*Myriochele oculata*	Pol	*Aonides paucibranchiata*	Pol	*Euchone incolor*
Pol	*Dodecaceria concharum*	Cru	Diastylidae spp	Pol	Fauvelopsidae spp
Pol	*Clymenura borealis*	Olig	Oligochaeta spp	Pol	*Spiophanes kroyeri*
Pol	*Levinsenia gracilis*	Pol	*Polydora* sp	Sip	*Onchnesoma squamatum*
Sip	*Golfingia* spp	Pol	*Eclysippe vanelli*	Pol	*Pectinaria auricoma*
Moll	*Timoclea ovata*	Pol	*Chaetozone* sp	Pol	*Myriochele oculata*
20-40		Moll	*Yoldiella lucida*	Pol	*Paradiopatra quadricuspis*
Pol	*Tmetonyx similis*	Pol	*Heteroclymene robusta*	Sip	*Onchnesoma steenstrupi*
Moll	*Thyasira eumyaria*	Pol	*Spiophanes wigleyi*	**60-80**	
Moll	*Thyasira obsoleta*	**40-60**		Sip	*Onchnesoma steenstrupi*
Cru	*Laetmatophilus tuberculatus*	Pol	*Paradiopatra quadricuspis*	Pol	*Octobranchus floriceps*
Pol	*Ophryotrocha* sp	Pol	*Myriochele oculata*	Cru	*Harpinia* sp
Cru	*Munna* spp	Cru	*Eudorella emarginata*	Pol	Maldanidae spp
Moll	*Modiolula phaseolina*	Moll	*Entalina quinquangularis*	Moll	*Abra longicallus*
40-60		Moll	*Thyasira ferruginea*	Pol	*Notomastus latericeus*
Moll	*Thyasira equalis*	Pol	*Paramphinome jeffreysii*	Moll	*Chaetoderma* sp
Pol	*Onuphis* sp	Pol	*Prionospio cirrifera*	Cru	*Gnathia oxyurea*
Pol	*Amythasides macroglossus*	Moll	*Chaetozone setosa*	Cru	*Leptophoxus falcatus*
Pol	*Streblosoma intestinale*	Pol	*Tharyx* sp	Ann	Pogonophora spp
Cru	*Urothoe elegans*	Pol	*Euchone* sp	**80-100**	
Moll	*Chaetoderma nitidulum*	**80-100**		Pol	*Nephtys cirrosa*
Moll	*Cerastoderma minimum*	Pol	*Myriochele fragilis*	Sip	*Onchnesoma steenstrupi*
Pol	*Harmothoe* sp	Pol	*Owenia fusiformis*	Pol	*Jasmineira* sp
Pol	*Glycera lapidum*	Ech	*Ophiura affinis*	Pol	*Apistobranchus tullbergi*
Ech	*Leptosynapta inhaerens*	Pol	*Ampharete* sp	Pol	*Abyssoninoe hibernica*
60-80		Pol	*Ampharete finmarchica*	Pol	*Pectinaria koreni*
Moll	*Cerastoderma minimum*	Pol	*Pectinaria koreni*	Pol	*Jasmineira candela*
Pol	*Exogone* sp	Moll	*Thyasira flexuosa*	Moll	*Arcopagia balaustina*
Moll	*Abra* sp	Pol	*Trichobranchus roseus*	Moll	Caudofoveata spp
Cru	Diastylidae spp	Pol	*Aphrodita aculeata*	Cru	*Byblis gaimardi*
Cru	*Diastylis* sp	Pol	*Paramphinome jeffreysii*	**>100**	
Pol	*Phoronis* sp	**>100**		Cru	*Ampelisca tenuicornis*
Pol	*Streblosoma intestinale*	Ech	*Amphiura filiformis*	Cru	*Ampelisca typica*
Pol	*Polycirrus* sp	Moll	*Antalis* sp	Pol	*Aricidea suecica*
Pol	*Amythasides macroglossus*	Pol	*Aricidea simonae*	Cru	*Bathyporeia* sp
Pol	*Parougia* sp	Pol	*Aricidea wassi*	Pol	*Cirrophorus furcatus*
80-100		Coel	*Cerianthus lloydii*	Pol	*Eteone flava*

Coel	*Corymorpha nutans*
Moll	Caudofoveata spp
Ech	*Echinus* sp
Pol	*Chone duneri*
Pol	*Ditrupa arietina*
Cni	Cnidaria spp
Pol	*Clymenura borealis*
Pol	*Glycera tridactyla*
Moll	*Falcidens crossotus*
Moll	*Diastylis cornuta*
>100	
Pol	Capitellidae spp
Pol	*Chone duneri*
Pol	*Chone* sp
Pol	*Cirrophorus furcatus*
Pol	*Clymenura* sp
Cru	*Diastyloides biplicata*
Moll	*Limatula subauriculata*
Pol	*Protodorvillea kefersteini*
Pol	*Spio* sp
Pol	*Spiophanes* sp

Pol	*Chone* sp
Pol	*Exogone verugera*
Pol	*Glycera lapidum*
Pol	*Lanice conchilega*
Cru	Lysianassidae spp

Cru	*Gnathia oxyurea*
Pol	*Harmothoe fragilis*
Moll	*Limatula subauriculata*
Pol	*Lumbrineris gracilis*

	Decalins
80-100	Taxa
Pol	*Ditrupa arietina*
Cru	*Natatolana borealis*
Pol	*Exogone hebes*
Pol	*Nephtys cirrosa*
Pol	*Prionospio dubia*
>100	
Pol	*Myriochele danielsseni*
Cru	Ericthonius spp
Pol	*Aonides paucibranchiata*
Moll	*Timoclea ovata*
Pol	*Spio mecznikowianus*
Cru	*Bathyporeia* sp
Pol	*Polycirrus* sp
Pol	*Phisidia aurea*
Cru	*Atylus vedlomensis*
Cru	*Gnathia oxyurea*

	NPD
0-20	Taxa
Pol	Ampharetidae spp
Cru	Diastylidae spp
Moll	*Thyasira croulinensis*
Cru	*Natatolana borealis*
Sip	*Onchnesoma squamatum*
Pol	*Polydora* sp
Pol	*Pectinaria auricoma*
Pol	*Eclysippe vanelli*
Pol	*Myriochele oculata*
60-80	
Moll	*Thyasira succisa*
Cru	*Harpinia* sp
Sip	*Onchnesoma steenstrupi*
Pol	*Octobranchus floriceps*
Pol	*Owenia fusiformis*
Pol	*Myriochele fragilis*
Pol	*Notomastus latericeus*
Moll	*Chaetoderma* sp
Moll	*Abra longicallus*
Pol	Maldanidae spp

	THC
0-20	Taxa
Pol	*Tharyx killariensis*
Sip	*Onchnesoma squamatum*
Pol	*Apistobranchus tenuis*
Moll	*Lucinoma borealis*
Pol	*Ditrupa arietina*
Pol	*Notoproctus oculatus*
Pol	*Chaetozone setosa*
Moll	*Lima tulagwyni*
Pol	*Pholoe inornata*
Moll	*Bathyarca pectunculoides*
40-06	
Moll	*Kelliella miliaris*
Moll	*Abra* sp
Pol	*Euchone rubrocincta*
Ech	*Leptosynapta inhaerens*
Pol	*Polydora* sp
Moll	*Yoldiella tomlini*
Pol	*Myriochele heeri*
Pol	*Polycirrus medusa*
Pol	*Harmothoe* sp_
Pol	*Paradoneis* sp
60-80	
Pol	*Nothria hyperborea*
Pol	*Capitella capitata*
Cru	*Diastylis boecki*
Cru	*Ampelisca spinipes*
Pol	*Polydora* sp
Pol	*Apistobranchus* sp
Pol	*Myriochele fragilis*
Pol	*Heteranomia squamula*

Cru	Amphilochidae spp
Pol	*Exogone* sp
80-100	
Pol	*Abyssoninoe hibernica*
Pol	*Jasmineira candela*
Moll	*Falcidens crossotus*
Cru	*Diastylis boecki*
Cru	*Byblis gaimardi*
Cru	*Harpinia pectinata*
Pol	*Praxillella* sp
Pol	*Nothria conchylega*
Pol	Lumbriclymeninae spp
Pol	*Pectinaria* sp
>100	
Pol	Ampharetidae spp
Pol	*Aricidea cerrutii*
Pol	*Chaetozone* sp
Pol	*Cirratulus caudatus*
Coel	*Edwardsia* sp
Pol	*Glycera alba*
Pol	*Goniada maculata*
Pol	*Harmothoe antilopes*
Ech	*Labidoplax buskii*
Ech	*Labidoplax digitata*

	PAH
0-20	Taxa
Moll	*Cerastoderma minimum*
Moll	*Kelliella miliaris*
Pol	*Glycera lapidum*
Pol	*Spiophanes kroyeri*
Pol	*Prionospio cirrifera*
Pol	*Eclysippe vanelli*
Moll	*Yoldiella lucida*
Pol	*Myriochele oculata*
Cru	*Harpinia pectinata*
Pol	*Ophelina norvegica*
20-40	
Pol	*Euchone* sp
Cru	*Vargula norvegica*
Pol	*Jasmineira candela*
Moll	*Thyasira obsoleta*

Close investigations of the sensitivity in specific species when exposed to ”pure” chemical stressors have, to our knowledge, not been performed earlier. Using our method the correlation effect from having more than one chemical stressor present is removed, when analysing species abundance data. Additionally, the model support data partitioned into specific grain size intervals. Ultimately, information about specific taxa/species at selected grain size intervals displaying sensitivity when exposed to specific chemical stressors, can be obtained. In this manner additional information about specific taxa/species preferences towards grain size in their habitat can be pointed out.

4. References

Mannsvik, H-P, A. Pettersen, V. Lyngmo, F. Mikkola, K.L. Gabrielsen, 2001. Environmental monitoring survey of oil and gas fields in Region II, 2000. APN-report 411.1890.

5. Appendix

Appendix 1. Distribution of the most sensitive taxa at specific grain size intervals (gr.size in μm) and specific chemical stressor. Abbreviations: see Table 3.

gr.size/ taxonomic group	**Chemical**		**gr.size/ taxonomic group**	**Chemical**	
	Cu			**Cd**	
0-20	Taxa	Discr. Power	0-20	Taxa	Discr. Power
Pol	*Clymenura borealis*	5,003268	Cru	*Tmetonyx cicada*	4,945538
Moll	*Bathyarca pectunculoides*	4,612311	Pol	*Eclysippe vanelli*	4,093302
Sip	*Onchnesoma steenstrupi*	4,278846	Pol	*Cossura longocirrata*	4,018438
Pol	*Myriochele oculata*	4,01698	Pol	*Tharyx killariensis*	3,505455
Pol	Fauvelopsidae spp	3,806911	Cru	*Neohela monstrosa*	3,346224
Moll	*Limopsis minuta*	3,554729			
Pol	*Euclymene affinis*	3,511074	20-40	Taxa	Discr. Power
Cru	*Eriopisa elongata*	3,506131	Moll	*Thyasira obsoleta*	6,327158
Pol	*Myriochele* spp	3,47567	Pol	*Jasmineira caudata*	5,954488
Pol	*Heteromastus filiformis*	3,294544	Pol	*Pherusa falcata*	5,726713
Pol	*Notomastus* sp	3,238173	Pol	*Aricidea catherinae*	4,794903
			Pol	*Augeneria tentaculata*	3,812865
60-80	Taxa	Discr. Power	Pol	*Scoloplos armiger*	3,636282
Pol	*Myriochele danielsseni*	22,18708	Sip	*Onchnesoma squamatum*	3,602042
Moll	*Thyasira succisa*	13,42496	Pol	*Hyalinoecia tubicola*	3,512277
Cru	*Harpinia* sp	8,311364	Sip	*Onchnesoma steenstrupi*	3,378465
Sip	*Onchnesoma steenstrupi*	7,929089	Pol	*Streblosoma intestinale*	3,109482
Pol	*Octobranchus floriceps*	7,819224			
Pol	*Owenia fusiformis*	7,745275	40-60	Taxa	Discr. Power
Pol	*Notomastus latericeus*	6,891019	Pol	*Amythasides macroglossus*	5,659208
Pol	*Myriochele fragilis*	6,716559	Pol	*Chone longocirrata*	5,000054
Moll	*Abra longicallus*	6,536641	Moll	*Astarte* sp	3,413349
Pol	*Scolelepis* sp	6,128268	Moll	*Kelliella miliaris*	3,175252
Moll	*Chaetoderma* sp	5,824765	Pol	*Levinsenia gracilis*	2,459008
Pol	Maldanidae spp	5,685348	Cru	Lysianassidae spp	2,152263
Cru	*Ampelisca tenuicornis*	5,614306	Pol	*Pista* sp	2,114555
Cru	*Leptophoxus falcatus*	5,465201	Pol	*Lumbriclymene* sp	2,101358
Pol	*Aricidea* sp	5,409421	Pol	*Dodecaceria concharum*	2,066544
Pol	*Spiophane surceolata*	5,098379			
Cru	*Gnathia oxyurea*	5,030907	60-80	Taxa	Discr. Power
Pol	*Cirratulus caudatus*	4,962701	Pol	*Harmothoe* sp	5,152434
Moll	*Lucinoma borealis*	4,868146	Pol	*Ditrupa arietina*	4,849308
Moll	*Phaxas pellucidus*	4,831812	Pol	*Myriochele danielsseni*	4,230194
Pol	*Tharyx killariensis*	4,789083	Pol	*Polydora* sp	4,069929
Moll	*Yoldiella tomlini*	4,772001	Pol	*Amythasides macroglossus*	3,665944
Pol	*Polydora* sp	4,724812	Pol	*Praxillella praetermissa*	3,419912
Moll	*Cuspidaria ostrata*	4,365463	Moll	*Thyasira succisa*	3,196062
Pol	*Lumbrineris* sp	4,155856	Pol	*Owenia fusiformis*	3,174973
Pol	*Pectinaria auricoma*	4,089937	Pol	*Scolelepis* sp	3,028691
Pol	*Dodecaceria* sp	3,768536	Sip	*Onchnesoma steenstrupi*	3,003431
Pol	*Aricidea roberti*	3,610391			
Pol	*Levinsenia gracilis*	3,529645	80-100	Taxa	Discr. Power
Pol	*Scolelepis korsuni*	3,434747	Pol	*Abyssoninoe hibernica*	11,66323
Pol	*Pholoe baltica*	3,431411	Sip	*Onchnesoma steenstrupi*	8,684384

Cru	*Westwoodilla caecula*	3,369468
Pol	*Cirrophorus furcatus*	3,295871
Ech	*Amphiura filiformis*	3,175045
Pol	*Eclysippe vanelli*	3,155448
Moll	Caudofoveata spp	3,091685
Pol	*Myriochele oculata*	3,001396

80-100	Taxa	Discr. Power
Pol	*Abyssoninoe hibernica*	12,91062
Pol	*Jasmineira candela*	9,032858
Cru	*Ampelisca gibba*	7,639486
Moll	*Falcidens crossotus*	6,250767
Pol	*Nephtys hystricis*	6,209275
Cru	*Byblis gaimardi*	6,140516
Pol	*Nothria conchylega*	5,237448
Cru	*Diastylis boecki*	4,894814
Pol	*Pholoe inornata*	4,634649
Pol	*Apistobranchus* sp	4,210512
Moll	*Thyasira pygmaea*	4,149173
Pol	*Jasmineira* sp	4,139238
Pol	*Praxillella* sp	4,083238
Pol	Lumbriclymeninae spp	3,923486
Pol	*Exogone* sp	3,907349
Moll	*Abra nitida*	3,897631
Pol	*Terebellides stroemi*	3,853963
Pol	*Euchone* sp	3,721648
Pol	*Orbinia armandi*	3,600138
Ech	*Brissopsis lyrifera*	3,427137
Cru	Ostracoda spp	3,405008
Pol	*Lumbrineris* sp	3,37819
Pol	*Samytha sexcirrata*	3,325016
Pol	*Paramphinome jeffreysii*	3,207785
Pol	*Rhodine loveni*	3,205525
Pol	*Pectinaria koreni*	3,052524
Pol	*Goniada norvegica*	3,043745
Pol	*Eclysippe vanelli*	3,033194
Pol	*Laonice sarsi*	3,001929
Moll	Caudofoveata spp	3,000913
Pol	*Pseudopolydora paucibranchiata*	3,00082

	Cr	
20-40	Taxa	Discr. Power
Pol	*Euchone* sp	4,704525
Cru	*Vargula norvegica*	2,509505
Moll	*Thyasira obsoleta*	2,470599
Pol	*Branchiomma bombyx*	2,309621
Pol	*Macrochaeta polyonyx*	2,090349
Pol	*Asychis biceps*	2,054084
Moll	*Limopsis minuta*	2,053721
80-100	Taxa	Discr. Power
Pol	*Pholoe inornata*	4,741227
Pol	*Harmothoe* sp	4,532032

Pol	*Apistobranchus tullbergi*	7,524094
Cru	*Ampelisca gibba*	7,263782
Pol	*Jasmineira candela*	6,598246
Pol	*Chone collaris*	6,148372
Pol	*Scolelepis tridentata*	5,954846
Cru	*Natatolana borealis*	5,912909
Pol	*Ditrupa arietina*	5,730474
Pol	*Nephtys hystricis*	5,729621
Moll	*Falcidens crossotus*	5,72895
Pol	*Octobranchus floriceps*	4,659126
Cru	*Byblis gaimardi*	4,342209
Pol	*Sosanopsis wireni*	4,337181
Pol	*Praxillella* sp	4,290694
Pol	*Pseudopolydora paucibranchiata*	4,076955
Moll	*Cuspidaria costellata*	3,931916
Moll	*Thyasira succisa*	3,912193
Pol	*Goniada norvegica*	3,900481
Pol	Lumbriclymeninae spp	3,880317
Pol	*Terebellides stroemi*	3,598601
Moll	*Thyasira pygmaea*	3,59205
Pol	*Orbinia armandi*	3,366678
Moll	*Cylichna alba*	3,361206
Cru	*Leptophoxus falcatus*	3,361206
Pol	*Rhodine loveni*	3,359514
Pol	*Synelmis klatti*	3,359514
Pol	*Euchone* sp	3,357005
Moll	*Abra nitida*	3,257262
Pol	*Hydroides norvegica*	3,162282
Pol	*Laonice sarsi*	3,138245
Pol	*Nothria conchylega*	3,114992
Pol	*Apistobranchus* sp	3,077016
Pol	*Pectinaria koreni*	3,054512

>100	Taxa	Discr. Power
Pol	*Spiophanes* sp	
Moll	*Limatula subauriculata*	9,555223
Pol	*Protodorvillea kefersteini*	7,634731
Moll	*Thracia phaseolina*	7,248296
Pol	*Ditrupa arietina*	6,225585
Pol	*Poecilochaetus* sp	5,814672
Pol	*Anobothrus gracilis*	5,672343
Pol	*Prionospio fallax*	4,93781
Pol	*Travisia forbesii*	4,883564
Pol	*Pseudopolydora paucibranchiata*	4,745543
Pol	Capitellidae spp	4,72679
Cru	Lysianassidae spp	4,615292
Pol	*Chone* sp	4,614429
Moll	*Thyasira croulinensis*	4,594052
Pol	*Opisthodonta pterochaeta*	4,176662
Pol	*Spiophanes wigleyi*	4,163463
Ech	*Amphiura filiformis*	3,992958
Pol	*Clymenura* sp	3,590563
Coel	*Edwardsia* sp	3,53487

Pol	*Pectinaria koreni*	4,235805	
Tun	*Eugyra arenosa*	3,746741	
Pol	*Chaetozone setosa*	3,743017	
Nem	Nematoda spp	3,729394	?
Cru	*Tmetonyx cicada*	3,47948	
Ech	*Ophiura affinis*	3,260565	
Pol	*Heteranomia squamula*	3,027871	
Pol	*Nephtys cirrosa*		

>100	Taxa	Discr. Power
Coel	*Corymorpha nutans*	4,555463
Pol	*Pisione remota*	3,880468
Pol	*Nothria conchylega*	3,711901
Pol	*Spio mecznikowianus*	3,561625
Cru	*Gammaropsis* sp	3,387472

Hg

0-20	Taxa	Discr. Power
Pol	*Euchone* sp	5,873927
Pol	*Myriochele oculata*	3,551203
Pol	*Dodecaceria concharum*	3,084513
Pol	*Clymenura borealis*	3,076826
Pol	*Levinsenia gracilis*	3,060738
Sip	*Golfingia* spp	3,05567
Moll	*Timoclea ovata*	3,011461

20-40	Taxa	Discr. Power
Pol	*Tmetonyx similis*	6,702544
Moll	*Thyasira eumyaria*	4,617893
Moll	*Thyasira obsoleta*	4,576499
Cru	*Laetmatophilus tuberculatus*	3,454524
Pol	*Ophryotrocha* sp	3,425947
Cru	*Munna* spp	3,414779
Moll	*Modiolula phaseolina*	3,105439

40-60	Taxa	Discr. Power	
Moll	*Thyasira equalis*	7,820783	
Pol	*Onuphis* sp	7,37799	
Pol	*Amythasides macroglossus*	7,170755	
Pol	*Streblosoma intestinale*	7,01859	
Cru	*Urothoe elegans*	5,556212	
Moll	*Chaetoderma nitidulum*	5,344857	
Moll	*Cerastoderma minimum*	5,318232	
Pol	*Harmothoe* sp	3,90928	
Pol	*Glycera lapidum*	3,692973	
Ech	*Leptosynapta inhaerens*	3,672201	
Pol	*Ampharete falcata*	3,491395	
Pol	*Pista* sp	3,490288	
Nmt	Nemertea spp	3,402286	?
Pol	*Aricidea roberti*	3,393588	
Pol	*Polycirrus* sp	3,355789	
Ech	*Amphipholis squamata*	3,318821	
Pol	*Glycinde nordmanni*	3,318311	

Moll	*Yoldiella tomlini*	3,5227
Cru	*Synchelidium* sp	3,471807
Pol	*Notomastus* sp	3,396977
Pol	*Euchone southerni*	3,326564
Moll	*Gari fervensis*	3,130837
Moll	*Astarte sulcata*	3,068214
Moll	*Mysella bidentata*	3,040375

Pb

0-20	Taxa	Discr. Power
Pol	Ampharetidae spp	7,263939
Pol	*Aonides paucibranchiata*	5,223603
Cru	Diastylidae spp	5,0258
Olig	Oligochaeta spp	4,829782
Pol	*Polydora* sp	4,496211
Pol	*Eclysippe vanelli*	4,093302
Pol	*Chaetozone* sp	4,031633
Moll	*Yoldiella lucida*	3,572231
Pol	*Heteroclymene robusta*	3,55172
Pol	*Spiophanes wigleyi*	3,422088
Pol	*Euchone incolor*	3,400036
Pol	*Chaetozone setosa*	3,244886
Pol	Capitellidae spp	3,207818
Moll	*Scutopus ventrolineatus*	3,130567
Pol	*Ophelina norvegica*	3,097384

40-60	Taxa	Discr. Power
Pol	*Paradiopatra quadricuspis*	10,72497
Pol	*Myriochele oculata*	10,04358
Cru	*Eudorella emarginata*	8,66415
Moll	*Entalina quinquangularis*	7,001833
Moll	*Thyasira ferruginea*	5,860578
Pol	*Paramphinome jeffreysii*	5,809859
Pol	*Prionospio cirrifera*	5,797978
Moll	*Chaetozone setosa*	5,604077
Pol	*Tharyx* sp	5,42253
Pol	*Euchone* sp	5,36233
Moll	*Cerastoderma minimum*	5,162705
Pol	*Aricidea catherinae*	4,998672
Pol	*Laonice sarsi*	4,942362
Moll	*Kelliella miliaris*	4,636666
Pol	*Paradoneis lyra*	4,565732
Pol	*Octobranchus floriceps*	4,458491
Pol	*Euclymene affinis*	4,116926
Pol	*Amythasides macroglossus*	3,956127
Moll	*Yoldiella lucida*	3,878086
Pol	*Terebellides stroemi*	3,824872
Pol	*Mugga wahrbergi*	3,686234
Pol	*Pholoe pallida*	3,677792
Pol	Lumbriclymene spp	3,601256
Pol	*Phylo norvegica*	3,464161
Tun	Ascidiacea spp	3,343518

Pol	*Phyllodoce groenlandica*	3,109022
Pol	*Capitella capitata*	3,052878

60-80	Taxa	Discr. Power
Moll	*Cerastoderma minimum*	9,448618
Pol	*Exogone* sp	5,348273
Moll	*Abra* sp	4,893403
Cru	Diastylidae spp	4,887517
Cru	*Diastylis* sp	4,853146
Pol	*Phoronis* sp	4,794178
Pol	*Streblosoma intestinale*	4,70418
Pol	*Polycirrus* sp	4,481028
Pol	*Amythasides macroglossus*	4,254772
Pol	*Parougia* sp	3,926389
Ech	Asteroidea spp	3,632458
Pol	*Notomastus latericeus*	3,629781
Pol	*Aricidea laubieri*	3,59736
Moll	*Retusa umbilicata*	3,372866
Cru	Lysianassidae spp	3,371793
Moll	*Thyasira flexuosa*	3,370436
Pol	*Aricidea wassi*	3,167576
Pol	*Ampharete lindstroemi*	3,164838
Pol	*Ophelina modesta*	3,119938
Pol	*Lumbrineris gracilis*	3,111404
Pol	*Pholoe pallida*	3,073474
Pol	*Ditrupa arietina*	3,054671
Cru	*Synchelidium* sp	3,03415
Pol	*Cirratulus cirratus*	3,025309

80-100	Taxa	Discr. Power
Coel	*Corymorpha nutans*	7,841011
Moll	Caudofoveata spp	5,584032
Ech	*Echinus* sp	5,077346
Pol	*Chone duneri*	4,585238
Pol	*Ditrupa arietina*	4,585233
Cni	Cnidaria spp	4,473846
Pol	*Clymenura borealis*	4,043642
Pol	*Glycera tridactyla*	3,919954
Moll	*Falcidens crossotus*	3,689526
Moll	*Diastylis cornuta*	3,589269
Moll	*Diastylis goodsiri*	3,519481
Moll	*Thyasira succisa*	3,453652
Pol	*Euclymene* sp	3,449576
Moll	*Ampelisca gibba*	3,302516
Pol	*Ampharete falcata*	3,230049
Pol	*Euchone southerni*	3,224253
Pol	*Heteranomia squamula*	3,223625
Pol	*Tharyx killariensis*	3,167912
Pol	*Cirratulus caudatus*	3,109073

>100	Taxa	Discr. Power
Pol	*Spiophanes* sp	7,111158
Pol	*Clymenura* sp	5,840074
Cru	*Diastyloides biplicata*	5,437723

Moll	*Nucula tumidula*	3,260368

80-100	Taxa	Discr. Power
Pol	*Myriochele fragilis*	6,722714
Pol	*Owenia fusiformis*	5,62505
Ech	*Ophiura affinis*	5,293212
Pol	*Ampharete* sp	4,747067
Pol	*Ampharete finmarchica*	4,53929
Pol	*Pectinaria koreni*	3,873147
Moll	*Thyasira flexuosa*	3,792205
Pol	*Trichobranchus roseus*	3,455713
Pol	*Aphrodita aculeata*	3,299178
Pol	*Paramphinome jeffreysii*	3,29265
Pol	*Harmothoe* sp	3,155879
Pol	*Levinsenia gracilis*	3,103884

>100	Taxa	Discr. Power
Pol	*Owenia fusiformis*	5,055848
Pol	*Lanice conchilega*	4,016524
Pol	*Notomastus latericeus*	2,912966
Moll	*Antalis* sp	2,84651
Pol	*Spiophanes urceolata*	2,805353
Pol	*Sthenelais limicola*	2,803814
Pol	*Myriochele danielsseni*	2,792825
Pol	*Glycera lapidum*	2,623965
Cru	Lysianassidae spp	2,503602
Pol	*Chone* sp	2,503197
Coel	*Cerianthus lloydii*	2,493812
Moll	*Timoclea ovata*	2,381883
Pol	*Ophelia borealis*	2,29391
Pol	*Aricidea wassi*	2,267025
Moll	Mysella spp	2,226795
Pol	*Spiophanes kroyeri*	2,221827
Pol	*Spiophanes bombyx*	2,206058
Nem	Nematoda spp	2,127348
Pol	*Ophryotrocha* sp	2,103241
Pol	*Aricidea simonae*	2,051635
Ech	*Amphiura filiformis*	2,041248
Pol	*Exogone verugera*	2,024002
Moll	*Philine* sp	2,018152

Zn

0-20	Taxa	Discr. Power
Ech	*Echinocucumis hispida*	6,709069
Pol	*Euchone incolor*	4,904954
Pol	Fauvelopsidae spp	4,874652
Pol	*Spiophanes kroyeri*	4,449471
Sip	*Onchnesoma squamatum*	4,106073
Pol	*Pectinaria auricoma*	3,557794
Pol	*Myriochele oculata*	3,551203
Pol	*Paradiopatra quadricuspis*	3,144405
Sip	*Onchnesoma steenstrupi*	3,133645

60-80	Taxa	Discr. Power

Pol	*Chone duneri*	5,337407
Pol	*Cirrophorus furcatus*	5,187822
Pol	*Spio* sp	4,98809
Moll	*Limatula subauriculata*	4,677575
Pol	*Tharyx killariensis*	4,035884
Pol	*Chone* sp	3,984735
Pol	Capitellidae spp	3,464404
Pol	*Protodorvillea kefersteini*	3,036563

	Decalins	
80-100	Taxa	Discr. Power
Pol	*Ditrupa arietina*	3,799195
Cru	*Natatolana borealis*	3,774538
Pol	*Exogone hebes*	3,375001
Pol	*Nephtys cirrosa*	3,278534
Pol	*Prionospio dubia*	3,246078
>100	Taxa	Discr. Power
Pol	*Myriochele danielsseni*	3,110151
Cru	Ericthonius spp	3,104584
Pol	*Aonides paucibranchiata*	3,048224
Moll	*Timoclea ovata*	2,64245
Pol	*Spio mecznikowianus*	2,47436
Cru	*Bathyporeia* sp	2,39132
Pol	*Polycirrus* sp	2,274024
Pol	*Phisidia aurea*	2,257984
Cru	*Atylus vedlomensis*	2,212885
Cru	*Gnathia oxyurea*	2,204177
Cru	*Themisto compressa*	2,203773
Pol	*Chone duneri*	2,200186
Pol	*Lumbrineris gracilis*	2,200186
Pol	*Eumida ockelmanni*	2,091024
Moll	*Tridonta montagui*	2,080584
Nmt	Nemertea spp	2,063729
Moll	*Abra* sp	2,055967

	NPD	
0-20	Taxa	Discr. Power
Pol	Ampharetidae spp	7,352503
Cru	Diastylidae spp	5,525461
Moll	*Thyasira croulinensis*	4,327353
Cru	*Natatolana borealis*	4,018495
Sip	*Onchnesoma squamatum*	3,8863
Pol	*Polydora* sp	3,815098
Pol	*Pectinaria auricoma*	3,344882
Pol	*Eclysippe vanelli*	3,165974
Pol	*Myriochele oculata*	3,018177
60-80	Taxa	Discr. Power
Moll	*Thyasira succisa*	10,9007
Cru	*Harpinia* sp	7,835
Sip	*Onchnesoma steenstrupi*	6,859605
Pol	*Octobranchus floriceps*	6,239891
Pol	*Owenia fusiformis*	5,977357

Sip	*Onchnesoma steenstrupi*	9,295469
Pol	*Octobranchus floriceps*	8,951236
Cru	*Harpinia* sp	8,869392
Pol	Maldanidae spp	8,115242
Moll	*Abra longicallus*	7,230519
Pol	*Notomastus latericeus*	7,19801
Moll	*Chaetoderma* sp	6,353529
Cru	*Gnathia oxyurea*	6,015283
Cru	*Leptophoxus falcatus*	5,767752
Ann	Pogonophora spp	5,439845
Moll	*Yoldiella tomlini*	4,778203
Pol	*Dodecaceria* sp	4,719653
Pol	*Aricidea* sp	4,662438
Nem	Nematoda spp	4,577325
Pol	*Prionospio cirrifera*	4,576313
Moll	*Cuspidaria rostrata*	4,508568
Moll	*Thyasira flexuosa*	4,482567
Pol	*Levinsenia gracilis*	4,405638
Pol	Euclymeninae spp	4,112061
Cru	*Ampelisca tenuicornis*	3,406703
Moll	*Falcidens crossotus*	3,383909
Pol	*Eclysippe vanelli*	3,28926
Moll	*Thyasira croulinensis*	3,288842
Moll	*Pulsellum lofotense*	3,223805
Pol	*Myriochele oculata*	3,188185
Cru	*Nicippe tumida*	3,168784
Pol	*Scalibregma inflatum*	3,135554
Tun	*Eugyra arenosa*	3,120707
Cru	*Eurydice pulchra*	3,115693
Pol	*Ditrupa arietina*	3,077393
Moll	*Phaxas pellucidus*	3,007755
80-100	Taxa	Discr. Power
Pol	*Nephtys cirrosa*	6,823652
Sip	*Onchnesoma steenstrupi*	6,666541
Pol	*Jasmineira* sp	5,572777
Pol	*Apistobranchus tullbergi*	5,374726
Pol	*Abyssoninoe hibernica*	5,15575
Pol	*Pectinaria koreni*	4,817464
Pol	*Jasmineira candela*	4,584799
Moll	*Arcopagia balaustina*	3,94188
Moll	Caudofoveata spp	3,675514
Cru	*Byblis gaimardi*	3,649238
Cru	*Ampelisca gibba*	3,644492
Pol	*Harmothoe glabra*	3,383863
Pol	Lumbriclymeninae spp	3,328294
Moll	*Falcidens crossotus*	3,138806
Pol	*Nephtys hystricis*	3,103473
>100	Taxa	Discr. power
Pol	*Protodorvillea kefersteini*	9,118824
Moll	*Limatula subauriculata*	7,389348
Pol	*Spiophanes* sp	4,46852
Cru	*Bathyporeia* sp	4,345896

Pol	*Myriochele fragilis*	5,713728
Pol	*Notomastus latericeus*	5,332132
Moll	*Chaetoderma* sp	5,133722
Moll	*Abra longicallus*	4,798199
Pol	Maldanidae spp	4,629968
Moll	*Yoldiella tomlini*	4,136782
Cru	*Gnathia oxyurea*	3,847077
Moll	*Cuspidaria rostrata*	3,616798
Ann	Pogonophora spp	3,575503
Cru	*Leptophoxus falcatus*	3,381366
Pol	*Levinsenia gracilis*	3,158367
Pol	*Parougia caeca*	3,147506
Pol	*Polycirrus norvegicus*	3,136879
Pol	*Ditrupa arietina*	3,095465

Pol	*Samytha sexcirrata*	4,235233
Pol	*Harmothoe fragilis*	3,957857
Pol	*Spiophanes wigleyi*	3,852904
Pol	*Aricidea suecica*	3,778394
Pol	*Cirrophorus furcatus*	3,768706
Moll	*Yoldiella tomlini*	3,589396
Cru	*Paraphoxus oculatus*	3,58001
Cru	*Gnathia oxyurea*	3,48877
Pol	*Opisthodonta pterochaeta*	3,374767
Pol	*Phoronis* sp	3,303584
Moll	*Philine* sp	3,246238
Moll	*Thyasira croulinensis*	3,22447
Cru	*Ampelisca tenuicornis*	3,167683
Pol	*Lumbrineris gracilis*	3,160583
Pol	*Pholoe synopthalmica*	3,154559
Pol	*Eteone flava*	3,088329
Cru	*Ampelisca typica*	3,056986

	PAH	
0-20	Taxa	Discr. Power
Moll	*Cerastoderma minimum*	10,60996
Moll	*Kelliella miliaris*	4,785084
Pol	*Glycera lapidum*	3,61454
Pol	*Spiophanes kroyeri*	3,53675
Pol	*Prionospio cirrifera*	2,990211
Pol	*Eclysippe vanelli*	2,782115
Moll	*Yoldiella lucida*	2,666953
Pol	*Myriochele oculata*	2,535863
Cru	*Harpinia pectinata*	2,291685
Pol	*Ophelina norvegica*	2,039363
20-40	Taxa	Discr. Power
Pol	*Euchone* sp	4,009486
Cru	*Vargula norvegica*	2,353549
Pol	*Jasmineira candela*	2,245709
Moll	*Thyasira obsoleta*	2,060034

	THC	
0-20	Taxa	Discr. Power
Pol	*Tharyx killariensis*	6,364713
Sip	*Onchnesoma squamatum*	5,234209
Pol	*Apistobranchus tenuis*	5,075755
Moll	*Lucinoma borealis*	4,362557
Pol	*Ditrupa arietina*	4,278107
Pol	*Notoproctus oculatus*	3,978901
Pol	*Chaetozone setosa*	3,682913
Moll	*Lima tulagwyni*	3,215668
Pol	*Pholoe inornata*	3,162803
Moll	*Bathyarca pectunculoides*	3,048278
40-60	Taxa	Discr. Power
Moll	*Kelliella miliaris*	4,911002
Moll	*Abra* sp	2,658006
Pol	*Euchone rubrocincta*	2,589596
Ech	*Leptosynapta inhaerens*	2,487445
Pol	*Polydora* sp	2,288969
Moll	*Yoldiella tomlini*	2,288969

Pol	*Myriochele heeri*	2,229389
Pol	*Polycirrus medusa*	2,204729
Pol	*Harmothoe* sp	2,07277
Pol	*Paradoneis* sp	2,030536
60-80	Taxa	Discr. Power
Pol	*Nothria hyperborea*	4,870314
Pol	*Capitella capitata*	4,717545
Cru	*Diastylis boecki*	3,288317
Cru	*Ampelisca spinipes*	3,142838
Pol	*Polydora* sp	3,01036
Pol	*Apistobranchus* sp	2,743485
Pol	*Myriochele fragilis*	2,737228
Pol	*Heteranomia squamula*	2,584148
Cru	Amphilochidae spp	2,324931
Pol	*Exogone* sp	2,30946
Moll	*Kelliella miliaris*	2,301421
Cru	*Synchelidium* sp	2,17122
Moll	Scaphopoda spp	2,088037
Moll	*Roxania utriculus*	2,082105
Pol	*Aricidea* sp	2,021831
Pol	*Lumbrineris* sp	2,021365
80-100	Taxa	Discr. Power
Pol	*Abyssoninoe hibernica*	5,81054
Pol	*Jasmineira candela*	4,612712
Moll	*Falcidens crossotus*	3,522078
Cru	*Diastylis boecki*	2,987873
Cru	*Byblis gaimardi*	2,637746
Cru	*Harpinia pectinata*	2,637746
Pol	*Praxillella* sp	2,491669
Pol	*Nothria conchylega*	2,449236
Pol	Lumbriclymeninae spp	2,443871
Pol	*Pectinaria* sp	2,342676
Pol	*Prionospio dubia*	2,31297
Moll	*Cochlodesma praetenue*	2,301718
Pol	*Goniada norvegica*	2,240022
Pol	*Euclymene droebachiensis*	2,203142
Moll	*Thyasira pygmaea*	2,188574
Pol	*Terebellides stroemi*	2,154269
Moll	*Abra nitida*	2,146227
Cru	Isaeidae spp	2,1111
Pol	Aphelochaeta sp	2,030384
Pol	*Jasmineira* sp	2,005748
Cru	*Ampelisca gibba*	2,002807
>100	Taxa	Discr. Power
Nmt	Nemertea spp	5,031478
Pol	*Aricidea cerrutii*	4,760966
Pol	*Cirratulus caudatus*	4,682873
Pol	*Chaetozone* sp	4,165173
Ech	*Labidoplax digitata*	4,041452
Pol	Ampharetidae spp	4,022736
Pol	*Spiophanes bombyx*	3,893032

Pol	*Owenia fusiformis*	3,575343
Coel	*Edwardsia* sp	3,527443
Pol	*Harmothoe antilopes*	3,479275
Ech	*Labidoplax buskii*	3,388044
Cru	*Unciola planipes*	3,182432
Pol	*Goniada maculata*	3,158512
Pol	*Glycera alba*	3,150501
Pol	*Myriochele oculata*	3,085613