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Evaluation of a eukaryote phylogenetic microarray for environmental monitoring of marine sediments

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ABSTRACT

Increased exploitation of resources in sensitive marine ecosystems emphasizes the importance of knowledge regarding ecological impacts. However, current bio-monitoring practices are limited in terms of target-organisms and temporal resolution. Hence, developing new technologies is vital for enhanced ecosystem understanding. In this study, we have applied a prototype version of a phylogenetic microarray to assess the eukaryote community structures of marine sediments from an area with ongoing oil and gas drilling activity. The results were compared with data from both sequencing (metabarcoding) and morphology-based monitoring to evaluate whether microarrays were capable of detecting ecosystem disturbances. A significant correlation between microarray data and chemical pollution indicators, as well as sequencing-based results, was demonstrated, and several potential indicator organisms for pollution-associated parameters were identified, among them a large fraction of microorganisms not covered by traditional morphology-based monitoring. This suggests that microarrays have a potential in future environmental monitoring.

1. Introduction

The ocean provides valuable resources such as food, energy and materials. Harvesting these resources can substantially impact marine ecosystems. Current knowledge regarding the bioecological effects of anthropogenic activities, such as oil extraction, trawling and deep-sea mining is limited. Marine ecosystems contain a complex network of interacting organisms (Arrigo, 2005), yet it is only larger, visible organisms that are commonly considered in monitoring programs, despite evidence that microorganisms play key roles in maintaining ecosystem functions (Bik et al., 2012). Therefore, to better understand anthropogenic impacts on an ecosystem, a more complete diversity of organisms needs to be considered.

To investigate the effects of petroleum exploitation, microscopy-based monitoring programs with taxonomic classification of macro- and to some extent meiofauna are conducted on benthic samples (Diaz et al., 2004; Gray, 2000; Miljødirektoratet, 2015). This is time-consuming and does not allow frequent assessments of samples (Baird and Hajibabaei, 2012; Brodin et al., 2012; Hajibabaei et al., 2011). Because of this, sampling schedules are often conducted with long temporal intervals, e.g. every third year (OSPAR, 2007), limiting the capacity to distinguish between anthropogenic short and long term effects (e.g. of oil drilling and climate change) and natural factors. It is therefore of interest to develop new, more efficient methods to generate ecosystem data in environmental samples, such as marine sediments (Baird and Hajibabaei, 2012; Chariton et al., 2010; Leray and Knowlton, 2015).

Previous studies have suggested that the implementation of molecular high throughput methods could improve biological monitoring (Aggelen et al., 2010; Baird and Hajibabaei, 2012; Brodin et al., 2012; Gescher et al., 2008; Hajibabaei et al., 2011; Lallias et al., 2015; Lanzén et al., 2016; Leray and Knowlton, 2015; Thomsen and Willerslev, 2015). The use of DNA based methods makes it possible to include

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microorganisms in the assessments (Lallias et al., 2015) and allows us to obtain information on taxa affiliated with several trophic levels in a biological system (Lanzén et al., 2016). This enables more complete assessment of anthropogenic impacts on the ecosystem and provides insight into impacts on ecosystem structure, beyond binary ("affected"/"not affected"). Molecular high throughput assays, using sequencing or microarray hybridization of phylogenetic marker genes, can provide more objective analyses when samples from many locations are compared and when conducting environmental monitoring over long periods of time (Baird and Hajibabaei, 2012), since these methods are less subjective to errors from morphometric assessments by individual taxonomists (Mann et al., 2010). They can also increase the rate and cost-effectiveness of sample processing (Ansorge, 2009; Wetterstrand, 2012). Metagenomic sequencing does indeed provide more information and is able to obtain a deeper characterization of genomes and microbial communities compared to microarrays. However, when optimized, microarrays may serve as an attractive tool for routine, more targeted monitoring of a high number of samples, with both costs and time benefits (Thissen et al., 2019). Microarrays also have the potential for implementation as part of automatic remote sensing pipelines such as an Environmental Sample Processor (ESP), where samples can be collected and processed in situ, with direct data transfer to land for analysis (Jones et al., 2008; Preston et al., 2009). This would be advantageous in routine monitoring of remote areas with limited infrastructure, e.g. deep-sea habitats and areas covered with ice. Automatization may also be beneficial from an economical perspective, since it can reduce boat time and therefore significant costs during these monitoring programs. These benefits can allow for increased temporal resolution, potentially allowing detection of early warning signals, preceding state changes in ecosystems associated with negative and often permanent alterations in ecosystem functioning (Scheffer et al., 2012).

Several studies have tested the potential of high throughput molecular methods, sequencing in particular, for monitoring environments and ecosystem health (Caldwell Eldridge et al., 2017; Carew et al., 2013; Hajibabaei et al., 2011; Kisand et al., 2012; Lanzén et al., 2016; Lejzerowicz et al., 2015). Further, microarrays targeting algae that cause toxic blooms have been tested and integrated in environmental monitoring (Diercks et al., 2008; Dittami et al., 2013a; Dittami et al., 2013b; Edvardsen et al., 2013; Galluzzi et al., 2011). Also, microarrays targeting a broader diversity have been designed for the 16S small subunit (SSU) ribosomal RNA (rRNA) gene and tested on environmental samples (DeSantis et al., 2007; Dubinsky et al., 2012; Nemir et al., 2010; Wang et al., 2017; Yergeau et al., 2009; Zhao et al., 2017). However there are several challenges related to using microarrays for assessing environmental samples (Avarre et al., 2007; Zhou and Thompson, 2002). High sample complexity has been demonstrated to decrease hybridization specificity (Koltai and Weingarten-Baror, 2008) and quantification problems arise because of PCR biases (Palmer et al., 2006; Taberlet et al., 2012).

In this study, a previously developed microarray design (Lekang et al., 2018) was tested on sediment samples from an ongoing environmental monitoring program on the Norwegian continental shelf, to evaluate the impact on targeted taxa by several environmental and discharge parameters. The results were compared to data obtained by metabarcoding (Lanzén et al., 2016) and morphology-based monitoring (DNV, 2011). The main objective was to evaluate the potential of integrating phylogenetic microarrays in routine monitoring using this prototype version of a phylogenetic microarray.

2. Methods

2.1. Samples

Sediment grab samples were collected by Det Norske Veritas (DNV) and Molab as part of an environmental monitoring program in the North Sea, Region III in May 2010 (DNV, 2011), using a van Veen grabb. Aliquots of 50–100 g of sediment were transferred to 250 ml plastic containers (Kautex Textron) and fixed using 96% ethanol, to a final concentration of 70–80%. Samples were stored at −20 °C until further processing. Sediment properties, such as geographical position, grain size and content of chemical compounds were assessed and reported by DNV and Molab (DNV, 2011). In total, 30 samples were included in this study. The fields included were Oseberg C (OSEC); station 05, 06, 08–10 and 15–18, Oseberg D (OSED); station 01, 03–05 and 08, and Veslefrikk (VFR); station 01–11, 20–21, K1–K3 (Fig. S1). These were selected based on chemical and physical properties of the samples, which established gradients optimal for such an assessment. Physical parameters (depth and distance from platform), sediment characteristics (grain size, composition; sand, silt/clay and gravel) and chemical parameters (Total Organic Material (TOM), Total Hydrocarbons (THC), Polycyclic Aromatic Hydrocarbons (PAH), Napthtalene Phenantren and Dibenzothiophene (NPD), Barium (Ba), Cadmium (Cd), Chromium (Cr), Copper (Cu), Mercury (Hg), Lead (Pb), Zinc (Zn)) are listed in Table S1. The same samples were also studied by metabarcoding (Lanzén et al., 2016) and by traditional morpho-taxonomic techniques (DNV, 2011).

2.2. Sample preparation for microarray analysis

To assess whether we could obtain biological data relevant to environmental monitoring using microarray analyses, genomic DNA extracted from sediments sampled from the 30 samples are described in the previous section (Table S1). In this study, we used the same genomic DNA extracted for the sequencing analysis (Lanzén et al., 2016). Briefly, genomic DNA was extracted in 10 replicates of 0.5 g sediment from each sample using the PowerSoil® DNA extraction kits (MO BIO Laboratories Inc., Carlsbad CA) (Lekang et al., 2015). The replicate genomic DNA extracts were pooled prior to quantification and PCR. Genomic DNA extracts were quantified using a Qubit® 2.0 Fluorometer (Invitrogen). PCR amplification targeting 18S SSU rRNA was carried out using 25 µl Hot Start Taq Master Mix (Qiagen) and 1 µg/µl of Bovine Serum Albumin (BSA, Thermo Scientific). To each PCR reaction, 2.5 µl of the template was added. To each reaction, 0.5 µM of each of the primers, F-566 and R-1200 (Hadziavdic et al., 2014) with a T7-promotor attached to the reverse-primer (R-1200-T7) were used. PCR amplification was carried out in a thermal cycler (C1000TM Thermal Cycler, BioRad) using the following program: 95 °C for 15 min, 35 cycles consisting of 95 °C for 45 s, 60 °C for 45 s, 72 °C for 1 min, and a final extension step of 72 °C for 10 min. Ten replicate PCR reactions were run per sample. Amplification was verified with gel electrophoresis. Positive PCR products were pooled and purified using Agencourt AMPure XP (Beckman Coulter Inc).

From each sample, 500 ng of the PCR product was used as template in the RNA transcription reaction using the MEGAscript T7 kit (Ambion) following the manufacturer's protocol, with the exception that 5-(3-Aminoallyl)-UTPs (InvitrogenTM) was included in a 1:1 ratio to UTP. Five replicate transcriptions for each sample were conducted. The reactions were incubated at 37 °C for 4 h. RNA transcripts were pooled and purified in two replicates with MEGAclearTM Transcription Clean-Up Kit (Ambion), -precipitation with 5 M Aluminum Acetate and eluted in 25 µl nuclease free water. Replicates for each of the samples were pooled and the final samples quantified by Qubit.

The RNA was labeled with Cy3 Mono-Reactive Dye Pack (Amersham), following manufacturer's recommendations. To each labeling reaction, 10 µg RNA was added to a tube of Cy3 dye. The labeling reaction was stopped using 8 µl of 1 M Tris-EDTA, pH 8 (Sigma). Labeled RNA was further purified using MEGAclearTM Transcription Clean-Up Kit (Ambion) to eliminate excess Cy3-molecules. Both staining and purification were conducted in an ozone-free environment, and the Cy3-labeled RNA was quantified using NanoDrop® ND-1000 Spectrophotometer. Labeled RNA was split in aliquots of 4 replicates, stored at −80 °C and further fragmented and hybridized within 5 days.

2.3. Microarray experiment

The labeled RNA was hybridized using a previously designed and optimized microarray (V.1.2) (Lekang et al., 2018). In this specific microarray, the probes were designed to target 208 OTUs obtained from a metabarcoding assessment (Lanzén et al., 2016), of the sediment samples included in this study. This strategy, where the probes target OTUs rather than taxonomic group, makes it possible to also detect undescribed organisms. This is an advantage since such organisms represent a substantial fraction of the benthic biodiversity. Each OTU was targeted by several unique probes to reduce the risk of false positives. The process of designing probes has been described in detail, in a previous study (Lekang et al., 2018).

The samples were hybridized in replicates of four. The replicates were randomly distributed among the microarrays. For each sample replicate, 50 ng RNA was used for hybridization. Labeled RNA was eluted to a final volume of 19 μl using nuclease free water, according to the protocol from the manufacturer (Agilent technologies). Then, 5 μl of 10× blocking agent (Agilent) and 1 μl of 25× fragmentation buffer (Agilent) were added to each reaction and incubated at 60 °C for 30 min. The fragmentation reaction was stopped by placing the samples on ice for 1 min. Before hybridizations, 25 μl of 2× GE hybridization buffer HI-RPM (Agilent) was added to each reaction and centrifuged 1 min at 13000 rpm. Finally, 40 μl of the hybridization mixture was loaded onto gasket slide wells and the microarray slides were placed on top with probes facing down. The arrays were hybridized at 61 °C in a rotating oven for 17 h. After hybridization, slides were washed using a Gene expression wash buffer kit (Agilent) following manufacturer's recommendations. Scanning was performed immediately after washing using an Agilent G2505B (Agilent Technologies). Fragmentation, hybridization, wash and scanning of slides were conducted in an ozone free environment.

2.4. Data analysis

Data was extracted from microarray images using Feature Extraction v. 10.7.3.1 (Agilent Technologies) and imported to the Software J-Express 2012 build 119 (Dysvik and Jonassen, 2001). Several filters were applied in J-Express to remove spots flagged by the feature extraction software due to pixel variation (glsFeatNonUnifOL and glsBGNonUnifOL), outlier status compared to replicate probes (glsFeatPopnOL and glsBGPopnOL), background noise (lsWellAboveBG) or saturated spots (glsSaturated) as calculated in the feature extraction step. Median values were calculated for replicate probes on each array and the 4 replicates of each sample were quantile normalized. The data was stored in CSV format. To filter the data we used a six-step filtration pipeline (Lekang et al., 2018) in order to decrease false positives caused by cross-hybridization. Briefly described, the filtration removed OTUs that did not obtain a satisfactory signal in a certain number of probes, and further normalized over-estimated intensity values of probes due to cross-hybridization. We filtered all data with both average filtration (all replicas together) and individual filtration (individual replicas) as previously described (Lekang et al., 2018).

Statistical analysis was conducted using the R software (R_Development_Core_Team, 2008). Technical variation between hybridization replicates was calculated and compared with sample variation from each of the tree fields. A heatmap was generated using log-transformed data from the 30 sediment samples from VFR, OSEC and OSED using the R-packages vegan (Oksanen et al., 2013) and gplots (Warnes et al., 2015). The information regarding OTU taxonomy was obtained from the previously published metabarcoding study (Lanzén et al., 2016) (Table S2).

Microarray data from the sediment samples at VFR, OSEC and OSED were compared to previously published data from microscopy and metabarcoding (DNV, 2011; Lanzén et al., 2016). Initially, Spearman correlation coefficients were calculated to compare relative abundances of sequences obtained by metabarcoding and corresponding hybridization intensity signals. In this analysis, all OTUs targeted in the microarray and further detected by metabarcoding were included. Hellinger transformation was then conducted on the microarray data and on relative abundance data from microscopy and metabarcoding. Bray-Curtis dissimilarity matrices were calculated based on the transformed values, and the matrices were used to perform multivariate statistics tests, conducted using the vegan-package in R (Oksanen et al., 2013). Specifically, non-metric multidimensional scaling (NMDS; function *metaMDS*), permutational ANOVA (PERMANOVA; function a*donis*), Mantel and partial Mantel-tests were performed. Correlations of environmental parameters to the NMDS coordinates were investigated using the function *envfit*. PERMANOVA was carried out by only including parameters significantly correlated to NMDS coordinates ($p < 0.05$). Parameters were added sequentially, starting with the one with highest correlation to the NMDS coordinates and subsequently removed from the model unless found to be significant by PERMANOVA. To assess the effect of environmental parameters and diversity profiles, Mantel and Partial Mantel tests were performed for all sediments collectively and for each field (VFR, OSEC and OSED) separately. In both the PERMANOVA and Mantel tests, a separation was made between parameters such as sediment characteristic and depth and parameters associated with contamination.

To identify possible indicator-OTUs from the microarray dataset, Spearman rank correlations between hybridization intensity signals and environmental parameters were determined. A *p*-value cut-off of 0.05 after Bonferroni correction was applied. Variation between replicate hybridizations from the sample was compared to variation between replicate hybridizations of different samples, by non-parametric comparison of distribution of Bray-Curtis dissimilarities (Wilcoxon Rank Sum Test).

3. Results

3.1. Evaluation of microarray hybridization and metabarcoding

There was low variation between replicate hybridizations of the 30 samples from Oseberg C, Oseberg D, and Veslefrikk, and the variation between separate samples was demonstrated as higher than replicate variation for individual samples ($p < 3E\text{-}16$; Fig. 1).

A Mantel-test was performed to compare biodiversity-profiles obtained by microarrays and metabarcoding, and demonstrated significant correlation between the two methods ($r = 0.47$, $p = 0.001$). The quantitative estimates obtained by microarray and metabarcoding were compared, including only OTUs targeted by the microarray, by calculating Spearman rank correlation coefficients across all 30 samples, as well as for the three individual fields (Table 1). Relative abundance estimates obtained by the two methods were also correlated, resulting in coefficients ranging from 0.40–0.63.

In total 208 OTUs were included on the microarray tested in this study. When comparing the hybridization data to sequencing data, using only these 208 OTUs, the microarray detected 37–100% (80% on average) of the OTUs detected by metabarcoding (Table S3). The OTUs detected by metabarcoding (Lanzén et al., 2016), but not by microarray had a relatively low relative mean abundance (5×10^{-4}) according to the sequencing results. Among these, 44% were singletons in their respective sample. The OTUs detected by both metabarcoding, and the microarray, had a higher mean relative abundance (4×10^{-3}) according to the sequencing results. The number of OTUs not detected by metabarcoding, but detected by the microarray, ranged from 26 in OSEC-06 to 80 in OSEC-08.

3.2. Correlation to environmental parameters

NMDS was performed based on hybridization intensity signals from samples collected at all three fields, along with metabarcoding from the

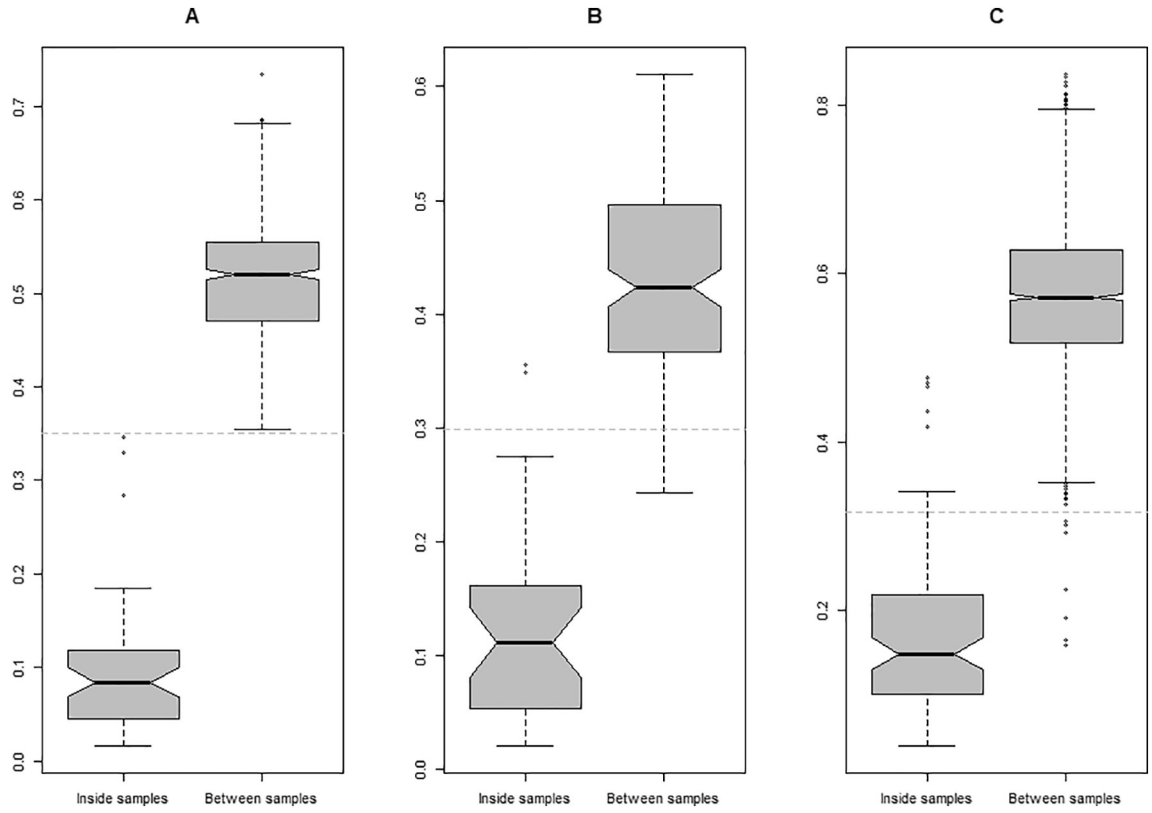

Fig. 1. Boxplot presenting the variation among hybridization replicates and between distinct samples from the tree locations; a) Oseberg C, b) Oseberg D and c) Veslefrikk.

Table 1
Spearman correlation (r) and significance (*** ≤ 0.001) between relative abundance of sequences and hybridization intensity signals for OTUs targeted by probes and additionally detected by sequencing.

Samples	Spearman correlation
All samples	$r = 0.56^{***}$
Veslefrikk	$r = 0.63^{***}$
Oseberg C	$r = 0.57^{***}$
Oseberg D	$r = 0.40^{***}$

previous study (Lanzén et al., 2016) and morpho-taxonomy results (DNV, 2011) from the same sample stations (Fig. 2). Among the samples from VFR, three samples representing the least contaminated sites within this field (VFR-02, VFR-08 and VFR-11; see Table S1) appear closely together and distinct from other, more contaminated VFR samples (Fig. 2a).

Based on NMDS, microarray-based community results were more strongly correlated to most of the environmental parameters (included Barium), compared to what was observed for the metabarcoding-results (Table 2). However, grain size and depth correlated more strongly with morpho-taxonomy based results. NMDS correlations were consistent with PERMANOVA, indicating a significant impact of Barium ($p < 0.001$) and depth ($p < 0.001$) on community structure. When controlling for depth, a significant impact was still indicated for Barium ($p < 0.001$).

According to Mantel-tests, microarray-based community data correlated more strongly to physical, non-contamination related parameters (depth, sand and grain size; $r = 0.33$, $p < 0.001$) than to contaminants ($r = 0.15$, $p < 0.05$; see Table 3). Mantel-tests performed individually on VFR results generated results that were consistent with this ($r = 0.42$ and, $p = 0.002$ for physical parameters vs. $r = 0.30$ and $p < 0.05$ for contaminant-related). A partial mantel test discounting influences of depth, sand, and grain size did not confirm a significant influence on community composition of contamination alone when performed on samples from all three fields. Nevertheless, partial Mantel-tests on samples from VFR did indicate a significant influence of contamination ($r = 0.5$, $p < 0.05$), as opposed to results of OSEC or OSED.

3.3. Biodiversity and indicator analysis

Hybridization intensity signals for all OTUs detected in the sediment samples are presented in a heatmap with OTUs affiliated to taxonomic groups and a dendrogram presenting the results of a hierarchical clustering analysis based on Bray-Curtis dissimilarities (Fig. 3). Six of the samples from VFR (03, 20, 05, 04, K3 and K1), representing the most contaminated (in terms of Ba and THC) formed a cluster in the dendrogram presented above the heatmap. Finally, all samples from OSED, grouped together according to the hierarchical clustering.

Several OTUs were present in most samples and did not seem to decrease in abundance with a high level of contamination (Fig. 3). However, some OTUs and taxa were more abundant in certain samples; e.g. OTUs from the class Cnidaria had high hybridization intensity signals in several samples from OSEC. This was also the case for a cluster of OTUs assigned to Annelida, more specifically, the family Canalipalpata. These OTUs were detected in some VFR samples, but were not correlated to contamination. Several OTUs from Arthropoda and a cluster of OTUs assigned to Ciliophora (Alveolata) were less abundant in samples from VFR, which had high levels of Ba and THC. There were also some OTUs that appeared more abundant in samples from VFR with a high level of Barium and hydrocarbons: OTU16294, assigned to Peridiniales (Dinophyceae, Alveolata) and two OTUs assigned to Ascomycota (Fungi). The two latter OTUs were detected in OSEC-08 and 09, two of the most Ba-rich samples in this field (Table

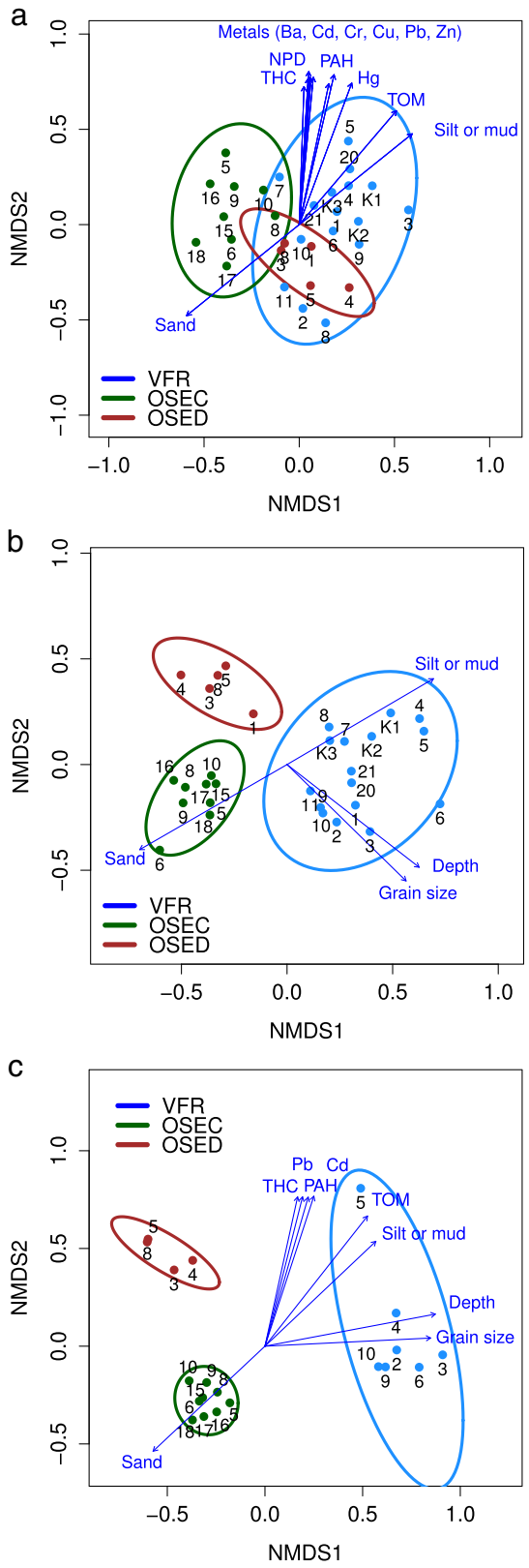

Fig. 2. NMDS based on Bray-Curtis dissimilarities of community composition from a) microarray, b) metabarcoding using data presented in (Lanzén et al., 2016) and c) microscopy using data presented in (DNV, 2011). Hybridization intensities and relative abundances of sequence-reads were Hellinger-transformed and significant environmental parameters marked with blue vectors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Correlation of environmental parameters to NMDS clustering patterns. R^2 values for linear correlation of parameter vectors with maximal correlation to NMDS space resulting from Bray-Curtis distance of Hellinger transformed hybridization intensity signals are displayed together with significance (* ≤ 0.05, ** ≤ 0.01, *** ≤ 0.001) as determined by *envfit* in the R package vegan.

Parameter	Microarray	Sequencing	Microscopy
Depth	***r* = 0.77***	***r* = 0.87***	***r* = 0.88***
Distance from drilling site	*r* = 0.22	*r* = 0.55	*r* = 0.76
Grain size	*r* = 0.64	***r* = 0.86***	***r* = 0.96***
Silt/mud	***r* = 0.86***	***r* = 0.89***	***r* = 0.91****
Sand	***r* = 0.86***	***r* = 0.89***	***r* = 0.92****
Gravel	*r* = 0.03	*r* = 0.05	*r* = 0.03
Total Organic Material (TOM)	***r* = 0.91***	*r* = 0.05	***r* = 0.97*****
Total Hydrocarbons (THC)	***r* = 0.78****	*r* = 0.33	***r* = 0.86***
Polcyclic Aromatic Hydrocarbons (PAH)	***r* = 0.81***	*r* = 0.38	***r* = 0.89***
Naphthalene PhA Dibenzothiophene (NPD)	***r* = 0.88****	*r* = 0.41	***r* = 0.94***
Barium (Ba)	***r* = 0.96*****	*r* = 0.49	***r* = 0.88***
Cadmium (Cd)	***r* = 0.84****	*r* = 0.43	***r* = 0.91***
Chromium (Cr)	***r* = 0.97****	*r* = 0.51	***r* = 0.97*****
Copper (Cu)	***r* = 0.89*****	*r* = 0.43	***r* = 0.95***
Mercury (Hg)	***r* = 0.93***	*r* = 0.59	***r* = 0.95***
Lead (Pb)	***r* = 0.87*****	*r* = 0.40	***r* = 0.93***
Zinc (Zn)	***r* = 0.89*****	*r* = 0.43	***r* = 0.95***

Significant values are highlighted in bold.

S1).

Several potential indicator OTUs were identified based on correlations of hybridization intensity signals with environmental parameters (Table S4). These OTUs were taxonomically assigned to Metazoa (5 OTUs), Alveolata (4 OTUs) and Fungi (2 OTUs). Of the metazoan OTUs, four were assigned to Arthropoda and one to Gastrotricha. Two of the OTUs from Alveolata were assigned to Dinophyceae and the other two OTUs to Ciliophora. Both of the fungal OTUs were affiliated with Ascomycota. Three OTUs correlated with parameters describing depth or sediment characteristics (OTU20507; Gastrotricha, OTU21201; Ciliophora, OTU8414; Ciliophora). Most of the correlations to environmental parameters were negative. However, both fungal taxa were positively correlated with Ba, whereas both Dinophyceae taxa were positively correlated with THC, Ba and Hg. Additionally, three OTUs that could not be taxonomically classified (OTU20507, OTU21201 and OTU8414), had a positive correlation with sand.

4. Discussion

In this study, an 18S rRNA microarray (Lekang et al., 2018) was used to evaluate phylogenetic microarrays as a method for environmental monitoring of marine sediments. This method was applied to a set of samples also analyzed using microscopy (DNV, 2011) and metabarcoding (Lanzén et al., 2016), and the resulting data were compared. Furthermore, biological aspects, such as distribution of taxonomic groups in the benthos and possible indicator OTUs for oil and gas drilling contamination, were assessed.

4.1. Evaluation of the microarray assessment

Comparisons between microarray datasets and results obtained by sequencing have demonstrated correlations between the two methods (Brodie et al., 2006; Tottey et al., 2013; Yergeau et al., 2009), in agreement with our results. Several OTUs, not present in the metabarcoding dataset, were detected only by the microarray (Table S3). These might either represent true diversity in the samples, not detected by sequencing, or false positives. Several studies comparing microarrays and metabarcoding have indicated significant correlations when using higher taxonomical levels, such as phyla and class (Claesson et al., 2009; van den Bogert et al., 2011; Yergeau et al., 2009). However,

Table 3
Mantel test statistics. Permutation-based Mantel tests were used to evaluate the correlation between two dissimilarity matrices ("explanatory" and "dependent" variables below). Bray-Curtis dissimilarity was used to derive community dissimilarities, and log-transformation for environmental parameters.

Explanatory variables	Dependent variables	R statistic	Significance
All environmental variables	Community dissimilarity all samples	0.15	$p < 0.05$
Depth, sand, grain size	Community dissimilarity all samples	0.33	$p < 0.001$
Contamination (THC, Ba, Cd, Cr, Cu, Hg, Pb, Zn)	Community dissimilarity all samples	0.15	$P < 0.05$
Depth, sand, grain size	Community dissimilarity Veslefrikk	0.42	$p < 0.05$
Contamination (THC, Ba, Cd, Cr, Cu, Hg, Pb, Zn)	Community dissimilarity Veslefrikk	0.30	$p = 0.02$
THC and Ba	Community dissimilarity Veslefrikk	0.37	$p < 0.05$
Depth, sand, grain size	Community dissimilarity Oseberg C	−0.11	$p = 0.68$
Contamination (THC, Ba, Cd, Cr, Cu, Hg, Pb, Zn)	Community dissimilarity Oseberg C	−0.26	$p = 0.92$
THC and Ba	Community dissimilarity Oseberg C	−0.24	$p = 0.92$
Depth, sand, grain size	Community dissimilarity Oseberg D	−0.48	$p = 0.89$
Contamination (THC, Ba, Cd, Cr, Cu, Hg, Pb, Zn)	Community dissimilarity Oseberg D	−0.22	$p = 0.70$
THC and Ba	Community dissimilarity Oseberg D	−0.12	$p = 0.62$

correlation typically decreases with more resolved taxonomic levels (e.g. family or genus) (Claesson et al., 2009; van den Bogert et al., 2011), indicating cross-hybridization between closely related taxa. Here we used a more taxonomy-independent approach, instead based on probes chosen from individual OTUs defined by de novo clustering of metabarcoding data. Nonetheless, using the same microarray design but from a previous study, we demonstrated that several false positive hybridizations correspond to OTUs with high sequence similarity to true positive OTUs, and that some OTUs were classified within the same genus as true positive OTUs (Lekang et al., 2018). This suggests that many false positives may be explained by cross-hybridization to closely related species or strains. Thus, the microarray biodiversity profiles provide meaningful biological information because changes in biodiversity patterns will be reflected in the microarray results, although the presence of specific strains may be challenging without further optimization of the microarray.

Reproducibility is critically important for biodiversity studies since data are compared spatially and temporally, and large variation within samples will generate noise that limits this comparison. Microscopy-based investigations of environmental samples depend on manual evaluations of morphological features by individual taxonomists. The data might therefore vary depending on the person conducting the survey (Archibald, 1984; Mann et al., 2010; Morales et al., 2001) especially at higher taxonomic resolution. Variation in quality might therefore impact conclusions on long time-series. Molecular methods based on phylogenetic marker genes are considered to be more objective, because taxonomical identification is done by comparing nucleic acid sequences (Zimmerman et al., 2014). Still, it is important to assess variation between replicate samples as well as the reproducibility of molecular methods. In this study, four technical hybridization replicates were included for each sample. The VFR, OSEC and OSED samples exhibited low variation between replicates (Fig. 1), and variation between hybridization replicates was significantly lower than variation between different samples. These results demonstrate that the microarray is able to distinguish biodiversity signals between separate samples.

4.2. Correlation to environmental parameters

Microarray technology has previously been proposed as a tool with good potential for environmental monitoring (Rich et al., 2011; Rivas et al., 2011; Wang et al., 2017). Here we aimed to assess this by comparing microarray-based results to morpho-taxonomy and metabarcoding results from the same samples. A fully developed microarray or metabarcoding approach may potentially provide information on all taxonomic groups, including microorganisms. This is an advantage because smaller organisms quickly respond to changes in the environment due to their small size and rapid generation time (Santos et al., 2010). Furthermore, metabarcoding is more universal in the sense that it can cover all organisms targeted by the primers used, whereas microarrays are restricted to specific taxa targeted by the probes. Compared to morpho-taxonomy techniques, however, molecular methods are not directly quantitative, but rather semi-quantitative, because quantitative abundances can primarily be assessed between samples or over time of the same taxa but not strictly between taxa in one sample (D'Amore et al., 2016). However, changes in biological composition relative to environmental parameters are arguably more important than the number of individuals from each taxonomic group.

In this study, both metabarcoding and morphology data yielded better separation of sites as compared to the microarray data. The microarray-based diversity profiles obtained in this study correlated equally well to most environmental parameters tested, particularly to those associated with contamination or disturbance, such as Barium (Table 2). The metabarcoding results did not correlate as strongly with these parameters. However, higher correlation has been demonstrated by splitting the sequence dataset into metazoan and non-metazoan sequences in a previous study based on the same metabarcoding dataset (Lanzén et al., 2016) (data not shown here). Sample VFR05 was indicated to be most affected by contaminants according to both morphology and microarray results (Fig. 2). Indeed, VFR05 was also the most contaminated sample in reference to chemical data (Table S1). This suggested that results from microarray and microscopy yielded similar conclusions based on correlations between community composition and contaminants.

Even though a positive correlation was demonstrated between all contaminants and the community structure profiles obtained by the microarray, this was likely an effect of autocorrelation between contaminant levels rather than suggesting a biological effect from all contaminants. Out of the measured disturbance indicators, Barium was indicated as the most strongly correlated to community structure, according to PERMANOVA, which agrees well with practices and experiences of current monitoring. Barium is a heavy metal, often used as

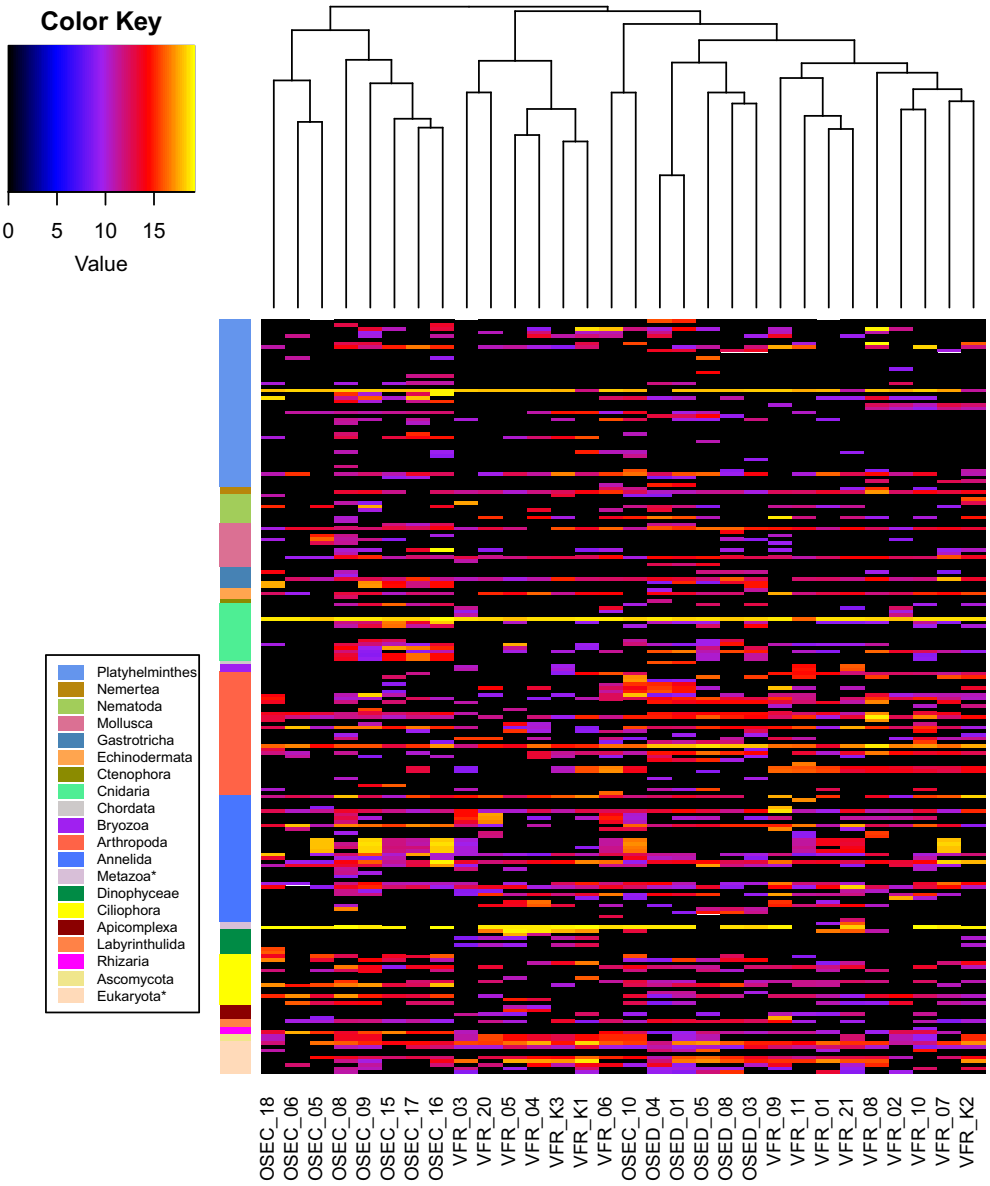

Fig. 3. Heatmap of log-transformed hybridization intensity signals from Veslefrikk, OsebergC and OsebergD sediment samples. Color gradients are from black to yellow, representing low to high intensity, respectively. The color on the left axis indicates taxonomic group as coded in the accompanying legend. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

an indicator of drilling activity because it is a component of barite (BaSO4), which is present in drilling mud (Breuer et al., 2004), drill fluids, and other fluids used in offshore petroleum activities (Neff et al., 1987).

Based on the microarray results, depth, sand and grain size appeared to affect community structure stronger than the chemical parameters. However, this seems to vary among the oil fields because the effects of contaminants were suggested to be more significant for VFR compared to OSEC and OSED (Table 3).

4.3. Indicator organisms

Environmental parameters correlated significantly with the abundance of several taxa, thus potentially useful of indicator organisms in routine monitoring (Table S4). This included four OTUs assigned to Copepoda, negatively correlated to several contaminants, including Ba and Pb. Copepoda has previously been demonstrated to be highly sensitive to petroleum contamination (Bonsdorff, 1981; Frithsen et al., 1985). Two OTUs assigned to Macrodasyida and Euplotida (Hypotrichia) were also negatively correlated to depth and Cd. These two taxa were also sensitive to these environmental parameters in the metabarcoding study (Lanzén et al., 2016). Interestingly, a positive correlation to sand content (%) was also demonstrated with both microarray and sequencing for both of these taxa. Several organisms are known to respond positively to pollution (Frithsen et al., 1985). In this study, two OTUs assigned to Microascales (Fungi), correlated positively with Ba, which was also supported in the metabarcoding study (Lanzén et al., 2016). Microascales has been suggested to degrade aromatic hydrocarbons, such as toluene (Prenafeta-Boldu´ et al., 2006). Organisms within Dinophyceae have previously been suggested to ingest hydrocarbons (Cooper, 1968) and this has been demonstrated for Dinophyceae; *Noctiluca scintillans* and *Gyrodinium spirale* (Almeda et al., 2014). After a large oil spill in the Bay of Biscay in 1967 (Torrey Canyon), dinoflagellate blooms were linked with the elimination of crude oil (Cooper, 1968). In this study, two OTUs assigned to Dinophyceae (Alveolata) were demonstrated to correlate positively with THC, Ba and Hg.

An important advantage of methods based on phylogenetic markers,

such as 18S rRNA genes, is that we can obtain information from a broader spectrum of organisms in an ecosystem than classical microscopy methods, which mainly focus on macro- and meiofauna. Several studies have previously suggested that stressor-effects on microorganisms differ from larger organisms (Danovaro et al., 1995; Lanzén et al., 2016; Santos et al., 2010). In our study, most organisms included on the microarray were multicellular organisms (metazoans, > 80%). Nonetheless, > 50% of the potential indicator OTUs identified were microorganisms, indicating that these are valuable in environmental monitoring and that changes in their abundance should be considered and included in monitoring programs.

5. Conclusions

This study demonstrates that our previously developed phylogenetic microarray design is capable of profiling eukaryotic community structure with an accuracy similar to metabarcoding and morpho-taxonomy approaches. Specifically, obtained results were significantly correlated with environmental parameters, including contaminants from offshore oil and gas activities. In combination with high throughput sequencing, microarrays have the potential to increase the temporal and spatial resolution of environmental monitoring by contributing to a more complete ecosystem understanding of anthropogenic activity effects.

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CRediT authorship contribution statement

Katrine Lekang:Conceptualization, Methodology, Data curation, Formal analysis, Writing - original draft, Writing - review & editing.**Anders Lanzén**:Conceptualization, Data curation, Formal analysis, Writing - review & editing.**Inge Jonassen**:Conceptualization, Writing - review & editing.**Eric Thompson**:Conceptualization, Funding acquisition, Writing - review & editing.**Christofer Troedsson**:Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Aggelen, G.V., Ankley, G.T., Baldwin, W.S., Bearden, D.W., Benson, W.H., Chipmann, J.K., Collette, T.W., Craft, J.A., Denslow, N.D., Embry, M.R., Falciani, F., George, S.G., Helbing, C.C., Hoekstra, P.F., Iguchi, T., Kagami, Y., Katsiadaki, I., Kille, P., Liu, L., Lord, P.G., McIntyre, T., O'Neill, A., Osachoff, H., Perkins, E.J., Santos, E.M., Skirrow, R.C., Snape, J.R., Tyler, C.R., Versteeg, D., Viant, M.R., Volz, D.C., Williams, T.D., Yu, L., 2010. Integrating omic technologies into aquatic ecological risk assessment and environmental monitoring: hurdles, achievements, and future outlook. Environ. Health Perspect. 118, 1–5.

Almeda, R., Connelly, T.L., Buskey, E.J., 2014. Novel insight into the role of heterotrophic dinoflagellates in the fate of crude oil in the sea. Sci. Rep. 9 (pp).

Ansorge, W.J., 2009. Next-generation DNA sequencing techniques. New Biotechnol. 25, 195–203.

Archibald, R.E.M., 1984. Diatom illustrations—an appeal. Bacillaria 7, 173–178.

Arrigo, K.R., 2005. Marine microorganisms and global nutrient cycles. Nature 437, 349–355.

Avarre, J.-C., de Lajudie, P., Béna, G., 2007. Hybridization of genomic DNA to microarrays: a challenge for the analysis of environmental samples. J. Microbiol. Methods 69, 242–248.

Baird, D.J., Hajibabaei, M., 2012. Biomonitoring 2.0: a new paradigm in ecosystem assessment made possible by next-generation DNA sequencing. Mol. Ecol. 21, 2039–2044.

Bik, H., Porazinska, D.L., Creer, S., Caporaso, J.G., Knight, J.R., Thomas, W.K., 2012. Sequencing our way towards understanding global eukaryotic biodiversity. Trends Ecol. Evol. 27, 233–243.

Bonsdorff, E., 1981. The Antonio Gramsci oil spill impact on the littoral and benthic ecosystems. Mar. Pollut. Bull. 12, 301–305.

Breuer, E., Stevenson, A.G., Howe, J.A., Carroll, J., Shimmield, G.B., 2004. Drill cutting accumulations in the Northern and Central North Sea: a review of environmental interactions and chemical fate. Mar. Pollut. Bull. 32, 727–733.

Brodie, E.L., DeSantis, T.Z., Joyner, D.C., Baek, S.M., Larsen, J.T., Andersen, G.L., Hazen, T.C., Richardson, P.M., Herman, D.J., Tokunaga, T.C., Wan, J.M., Firestone, M.K., 2006. Application of a high-density oligonucleotide microarray approach to study bacterial population dynamics during uranium reduction and Reoxidation. Appl. Environ. Microbiol. 72, 6288–6298.

Brodin, Y., Ejdung, G., Strandberg, J., Lyrholm, T., 2012. Improving environmental and biodiversity monitoring in the Baltic Sea using DNA barcoding of Chironomidae (Diptera). Mol. Ecol. Resour. 13, 996–1004.

Caldwell Eldridge, S.L., Driscoll, C., Dreher, T.W., 2017. Using High-Throughput DNA Sequencing, Genetic Fingerprinting, and Quantitative PCR as Tools for Monitoring Bloom-Forming and Toxigenic Cyanobacteria in Upper Klamath Lake, Oregon, 2013 and 2014. Scientific Investigations Report (Reston, VA).

Carew, M.E., Pettigrove, V.J., Metzling, L., Hoffmann, A.A., 2013. Environmental monitoring using next generation sequencing: rapid identification of macroinvertebrate bioindicator species. Front. Zool. 10, 1–15.

Chariton, A.A., Batley, G.E., Hardy, C.M., 2010. Improving aquatic ecological assessments. Integr. Environ. Assess. Manag. 6, 187–188.

Claesson, M.J., O'Sullivan, O., Wang, Q., NikkilÃ¤, J., Marchesi, J.R., Smidt, H., de Vos, W.M., Ross, R.P., O'Toole, P.W., 2009. Comparative analysis of pyrosequencing and a phylogenetic microarray for exploring microbial community structures in the human distal intestine. PLoS One e6669.

Cooper, L.H.N., 1968. Scientific consequences of the wreck of the 'Torrey canyon'. Helgoländer Meeresun. 17, 340–355.

D'Amore, R., Ijaz, U.Z., Schirmer, M., Kenny, J.G., Gregory, R., Darby, A.C., Shakya, M., Podar, M., Quince, C., Hall, N., 2016. A comprehensive benchmarking study of protocols and sequencing platforms for 16S rRNA community profiling. BMC Genomics 17. https://doi.org/10.1186/s12864-015-2194-9.

Danovaro, R., Fabiano, M., Vincx, M., 1995. Meifauna response to the Agip Abruzzo oil spill in subtidal sediments of the Ligurian Sea. Mar. Pollut. Bull. 30, 133–145.

DeSantis, T.Z., Brodie, E.L., Moberg, J.P., Zubieta, I.X., Piceno, Y.M., Andersen, G.L., 2007. High-density universal 16S rRNA microarray analysis reveals broader diversity than typical clone library when sampling the environment. Microb. Ecol. 53, 371–383.

Diaz, R.J., Solan, M., Valente, R.M., 2004. A review of approaches for classifying benthic habitats and evaluating habitat quality. J. Environ. Manag. 73, 165–181.

Diercks, S., Metfies, K., Medlin, L.K., 2008. Development and adaptation of a multiprobe biosensor for the use in a semi-automated device for the detection of toxic algae. Biosens. Bioelectron. 23, 1527–1533.

Dittami, S.M., Hostyeva, V., Egge, E.S., Kegel, J.U., Eikrem, W., Edvardsen, B., 2013a. Seasonal dynamics of harmful algae in outer Oslofjorden monitored by microarray, qPCR, and microscopy. Environ. Sci. Pollut. Res. 20, 6719–6732.

Dittami, S.M., Pazos, Y., Laspra, M., Medlin, L., 2013b. Microarray testing for the presence of toxic algae monitoring programme in Galicia (NW Spain). Environ. Sci. Pollut. Res. 20, 6778–6793.

DNV, 2011. Miljøovervåkning Region III 2010 Det Norske Veritas. pp. 286.

Dubinsky, E.A., Esmaili, L., Hulls, J.R., Cao, Y., Griffith, J.F., Andersen, G.L., 2012. Application of phylogenetic microarray analysis to discriminate sources of fecal pollution. Environ. Sci. Technol. 46, 4340–4347.

Dysvik, B., Jonassen, I., 2001. J-express: exploring gene expression data using Java. Bioinformatics 17, 369–370.

Edvardsen, B., Dittami, S.M., Groben, R., Brubak, S., Escalera, L., F., R., Reguera, B., Chen, J., Medlin, L., 2013. Molecular probes and microarrays for the detection of toxic algae in the genera Dinophysis and Phalacroma (Dinophyta). Environ. Sci. Pollut. Res. 20, 6733–6750.

Frithsen, J.B., Elmgren, R., Rudnick, D.T., 1985. Responses of benthic meiofauna to long-term, low-level additions of no. 2 fuel oil. Mar. Ecol. Prog. Ser. 23, 1–14.

Galluzzi, L., Cegna, A., Casabianca, S., Penna, A., Saunders, N., Magnani, M., 2011. Development of an oligonucleotide microarray for the detection and monitoring of marine dinoflagellates. J. Microbiol. Methods 84, 234–242.

Gescher, C., Metfies, K., Frickenhaus, S., Knefelkamp, B., Wiltshire, K.H., Medlin, L.K., 2008. Feasibility of assessing the community composition of prasinophytes at the helgoland roads sampling site with a DNA microarray. Appl. Environ. Microbiol. 74,

5305–5316.
Gray, J.S., 2000. The measurement of marine species diversity, with an application to the benthic fauna of the Norwegian continental shelf. J. Exp. Mar. Biol. Ecol. 250, 23–49.
Hadziavdic, K., Lekang, K., Lanzén, A., Jonassen, I., Thompson, E.M., Troedsson, C., 2014. Characterization of the 18S rRNA gene for designing universal eukaryote specific primers. PLoS One 9, e87624.
Hajibabaei, M., Shokralla, S., Zhou, X., Singer, G.A.C., Baird, D.J., 2011. Environmental barcoding: a next-generation sequencing approach for biomonitoring applications using river benthos. PLoS One 6, e17497.
Jones, W.J., Preston, C.N., Marin III, R., Scholin, C.A., Vrijenhoek, R.C., 2008. A robotic molecular method for in situ detection of marine invertebrate larvae. Mol. Ecol. Resour. 8, 540–550.
Kisand, V., Valente, A., Lahm, A., Tanet, G., Lettieri, T., 2012. Phylogenetic and functional metagenomic profiling for assessing microbial biodiversity in environmental monitoring. PLoS One 7, e43630.
Koltai, H., Weingarten-Baror, C., 2008. Specificity of DNA microarray hybridization: characterization, effectors and approaches for data correction. Nucleic Acids Res. 36, 2395–2405.
Lallias, D., Hiddink, J.G., Fonseca, V.G., Gaspar, J.M., Sung, W., Neill, S.P., Barnes, N., Ferrero, T., Hall, N., Lambshead, J.D., Packer, M., Thomas, W.K., Creer, S., 2015. Environmental metabarcoding reveals heterogeneous drivers of microbial eukaryote diversity in contrasting estuarine ecosystems. ISME J 9, 1208–1221.
Lanzén, A., Lekang, K., Jonassen, I., Thompson, E.M., Troedsson, C., 2016. High-throughput metabarcoding of eukaryotic diversity for environmental monitoring of offshore oil drilling activities. Mol. Ecol. https://doi.org/10.1111/mec.13761.
Lejzerowicz, F., Esling, P., Pillet, L., Wilding, T., Black, K.D., Pawlowski, J., 2015. High-throughput sequencing and morphology perform equally well for benthic monitoring of marine ecosystems. Sci. Rep. 10p.
Lekang, K., Thompson, E.M., Troedsson, C., 2015. A comparison of DNA extraction methods for biodiversity studies of eukaryotes in marine sediments. Aquat. Microb. Ecol. 75, 15–25.
Lekang, K., Hadziavdic, K., Sandned Skaar, K., Jonassen, I., Thompson, E.M., Troedsson, C., 2018. Development and testing of an 18S rRNA phylogenetic microarray for marine sediments. J. Microbiol. Methods 154, 95–106.
Leray, M., Knowlton, N., 2015. DNA barcoding and metabarcoding of standardized samples reveal patterns of marine benthic diversity. Proc. Natl. Acad. Sci. U. S. A. 112, 2076–2081.
Mann, D., Sato, S., Trobajo, R., Vanormelingen, P., Souffreau, C., 2010. DNA barcoding for species identification and discovery in diatoms. Cryptogam. Algol. 31, 557–577.
Miljødirektoratet, 2015. Environmental Monitoring of Petroleum Activities on the Norwegian Continental Shelf. Norwegian Environment Agency.
Morales, E.A., Siver, P.A., Trainor, F.R., 2001. Identification of diatoms (Bacillariophyceae) during ecological assessments: comparison between light microscopy and scanning electron microscopy techniques. Proc. Acad. Natl. Sci. Phila. 151, 95–103.
Neff, J.M., Rabalais, N.N., Boesch, D.F., 1987. Offshore oil and gas development activities potentially causing long-term environmental effects. In: Boesch, D.F., Rabalais, N.N. (Eds.), Long-Term Environmental Effects of Offshore Oil and Gas Development. Elsevier Applied Science, London, pp. 149–174.
Nemir, A., David, M.M., Perrussel, R., Sapkota, A., Simonet, P., Monier, J.-M., Vogel, T.M., 2010. Comparative phylogenetic microarray analysis of microbial communities in TCE-contaminated soils. Chemosphere 80, 600–607.
Oksanen, J., Blanchet, F.G., Kindt, R., Legendre, P., Minchin, P.R., O'Hara, R.B., Simpson, G.L., Solymos, P., Stevens, M.H.H., Wagner, H., 2013. vegan: Community Ecology Package.
OSPAR, 2007. Assessment of the Impact on the Marine Environment of Offshore Oil and Gas Activity - an Overview of Monitoring Results in the United Kingdom, the Netherlands and Norway. OSPAR Commission, London, UK, pp. 1–7.
Palmer, C., Bik, E.M., Eisen, M.B., Eckburg, P.B., Sana, T.R., Wolber, P.K., Relman, D.A., Brown, P.O., 2006. Rapid quantitative profiling of complex microbial populations. Nucleic Acids Res. 34, e5.
Prenafeta-Boldu´, F.X., Summerbell, R., de Hoog, G.S., 2006. Fungigrowing onaromatic hydrocarbons: biotechnology's unexpected encounterwith biohazard? FEMS Microbiol. Rev. 30, 109–130.
Preston, C.M., Marin III, R., Jensen, S.D., Feldman, J., Birch, J.M., Massion, E.I., DeLong, E.F., Suzuki, M., Wheeler, K., Scholin, C.A., 2009. Near real-time, autonomous detection of marine bacterioplankton on a coastal mooring in Monterey Bay, California, using rRNA-targeted DNA probes. Environ. Microbiol. 11, 1168–1180.
R_Development_Core_Team, 2008. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
Rich, V.I., Pham, V.D., Eppley, J., Shi, Y., DeLong, F., 2011. Time-series analyses of Monterey Bay coastal microbial picoplankton using a 'genome proxy' microarray. Environ. Microbiol. 13, 116–134.
Rivas, L.A., Aguirre, J., Blanco, Y., González-Toril, E., Parro, V., 2011. Graph-based deconvolution analysis of multiplex sandwich microarray immunoassays: applications for environmental monitoring. Environ. Microbiol. 13, 1421–1432.
Santos, H.F., Cury, J.C., Carmo, F.L., Rosando, A.S., Peixoto, R.S., 2010. 18S rDNA sequences from microeukaryotes reveal oil indicators in mangrove sediment. PLoS One 5, e12437.
Scheffer, M., Carpenter, S.R., Lenton, T.M., Bascompte, J., Brock, W., Dakos, V., van de Koppel, J., van de Leemput, I.A., Levin, S.A., van Nes, E.H., Pascual, M., Vandermeer, J., 2012. Anticipating critical transitions. Science 338, 344–348.
Taberlet, P., Coissac, E., Pompanon, F., Brochmann, C., Willerslev, E., 2012. Towards next-geneartion biodiversity assessment using DNA metabarcoding. Mol. Ecol. 21, 2045–2050.
Thissen, J.B., Be, N.A., McLoughlin, K., Gardner, S., Rack, P.G., Shapero, M.H., Rowland, R.R.R., Slezak, T., Jaing, C.J., 2019. Axiom microbiome array, the next generation microarray for high-throughput pathogen and microbiome analysis. PLoS One 14, e0212045.
Thomsen, P.F., Willerslev, E., 2015. Environmental DNA – an emerging tool in conservation for monitoring past and present biodiversity. Biol. Conserv. 183, 4–18.
Tottey, W., Denonfoux, J., Jaziri, F., Parisot, N., Missaoui, M., Hill, D., Borrel, G., Peyretaillade, E., Alric, M., Harris, H.M.B., Jeffrey, I.B., Claesson, M.J., O'Toole, P.W., Peyret, P., Brugere, J.-F., 2013. The human gut chip "HuGChip", an explorative phylogenetic microarray for determining gut microbiome diversity at family level. PLoS One e62544.
van den Bogert, B., De Vos, W.M., Zoetendal, E.G., Kleerebezem, M., 2011. Microarray analysis and barcoded of pyrosequencing provide consistent microbial profiles depending on the source human intestinal samples. Appl. Environ. Microbiol. 77, 2071–2080.
Wang, J., Zhao, W., Liang, Y., Han, Y., Wang, X., Zhang, X., Ma, X., Zhang, D., Huang, Z., 2017. Development of a prototype 16S rRNA gene-based microarray for monitoring planktonic actinobacteria in shrimp ponds. Int. Aquat. Res. 9, 71–80.
Warnes, G.S., Bolker, b., Bonebakker, l., Gentleman, R., Liaw, W.H.A., Lumley, T., Maechler, M., Magnusson, A., Moeller, S., Schwartz, M., Venables, B., 2015. Package 'Gplots': Various R Programming Tools for Plotting Data.
Wetterstrand, K., 2012. DNA Sequencing Costs. Data from the NHGRI Genome Sequencing Program (GSP).
Yergeau, E., Schoondermark-Stolk, S.A., Brodie, E.L., Dejean, S., DeSantis, T.Z., Goncalves, O., Piceno, Y.M., Andersen, G.L., Kowalchuk, G.A., 2009. Environmental microarray analyses of Antarctic soil microbial communities. ISME J 3, 340–351.
Zhao, W., Wang, J., Liang, Y., Huang, Z., 2017. Development of a 16S rRNA gene-based microarray for the detection of marine bacterioplankton community. Acta Oceanol. Sin. 36, 106–114.
Zhou, J., Thompson, D.K., 2002. Challenges in applying microarrays to environmental studies. Curr. Opin. Biotechnol. 13, 204–207.
Zimmerman, J., Glõckner, G., Jahn, R., Enke, N., Gemeinholzer, B., 2014. Metabarcoding vs. morphological identification to assess diatom diversity in environmental studies. Mol. Ecol. Resour. 15, 526–542.