

1 Advancing molecular macrobenthos biodiversity monitor-  
2 ing: a comparison between Nanopore and Illumina based  
3 metabarcoding and metagenomics.  
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29 **Abstract**

30 DNA-based methods and developments in sequencing technologies are integral  
31 to macrobenthos biodiversity studies, and their implementation as standardized

monitoring methods is imminent. Evaluating the efficacy and reliability of these technological developments is crucial for bulk macrobenthos biodiversity assessments.

In this study, we compared three DNA-based techniques for assessing the biodiversity of bulk macrobenthos samples from the Belgian North Sea. Specifically, we compared the results of Illumina MiSeq metabarcoding, Oxford Nanopore metabarcoding and Illumina NovaSeq metagenomic shotgun sequencing. The 303 bp COI Leray region served as the target region for the metabarcoding analysis.

Our results indicate that Nanopore and MiSeq metabarcoding performed comparable in terms of alpha and beta diversity, revealing highly similar location-specific community compositions. The NovaSeq metagenomics method resulted in lower alpha diversity and different community compositions compared to the metabarcoding approach. Despite these differences, location specific community compositions were maintained across all platforms.

Notably, read counts of the NovaSeq metagenomics showed the weakest correlation to morphological abundance and half of the species found using morphological identification were undetected with DNA based methods, primarily due to insufficient reference sequences.

Our findings underscore the critical importance of database completeness prior to implementing DNA-based techniques as standardized monitoring method. Nevertheless, our findings emphasize that Oxford Nanopore metabarcoding proves to be a viable alternative to the conventional Illumina MiSeq metabarcoding platform for macrobenthos biodiversity monitoring.

## Introduction

The European Union established the Marine Strategy Framework Directive (MSFD, 2008/56/EC), alongside the European Water Framework Directive (WFD, 2000/60/EC) and the European network for protected areas for conserving the most valuable North Sea species and habitats (Natura 2000 network, Habitat Directive). These directives form the basis of ecosystem management and use a variety of monitoring-based assessments (e.g., Borja et al., 2010) that aim to inform (non-)governmental decisions on marine environmental health. However, taxonomy-based monitoring practices rely on great taxonomic expertise, are time-consuming and limited in taxonomic resolution (Danovaro et al., 2016; Pawłowski et al., 2018), particularly when identifying understudied taxonomic groups and species at different life stages (Ammon et al., 2018; Gleason et al., 2023). Consequently, DNA-based technological developments have attracted particular interest in study of marine biodiversity (Bucklin et al., 2011; Cordier et al., 2019; Elbrecht et al., 2017; Lanzén et al., 2017; Leray & Knowlton, 2016). A reduction in labour time and the growing reference sequence libraries demonstrate DNA based methods to be a promising alternative for monitoring (Baird & Hajibabaei,

72 2012; DeSalle & Goldstein, 2019; Gostel & Kress, 2022; Leray & Knowlton,  
73 2015). Different DNA-based monitoring studies have demonstrated correspond-  
74 ence with morphological findings (Derycke et al., 2021; Mauffrey et al., 2021).  
75 As a result, DNA-based methods are repeatedly proposed as a suitable routine  
76 biodiversity assessment strategy to inform policy (Aylagas et al., 2020; Goodwin  
77 et al., 2017; Hering et al., 2018; Hinz et al., 2022; Pawlowski et al., 2018;  
78 Thalinger et al., 2019).

79 Generally, DNA-based biodiversity assessments are based on DNA metabarcod-  
80 ing, which allows for the identification of species from environmental samples  
81 based on a short DNA fragment that is amplified using universal primer pairs.  
82 This amplified DNA is then sequenced with next-generation sequencing plat-  
83 forms to identify the taxa found in samples (Taberlet et al., 2012). It is important  
84 to consider the biases that can be introduced at each stage (van der Loos &  
85 Nijland, 2021). This includes decisions on the sampling method and the appropri-  
86 ate use of preservation techniques (Gaither et al., 2011; Ransome et al., 2017),  
87 DNA extraction methods, using sufficient replicates (Van den Bulcke et al.,  
88 2021), and using appropriate primer pair(s) (Creer et al., 2016; Devloo-Delva et  
89 al., 2018; Leray & Knowlton, 2016). Bioinformatics pipelines are also crucial to  
90 take into consideration as the pipeline choice, and the processing settings greatly  
91 influence the output (Antich et al., 2021).

92 Current developments in DNA-based methods have resulted in the availability of  
93 several different third-generation sequencing platforms, such as Illumina, Ion Tor-  
94 rent, Oxford Nanopore sequencing and Pacific Biosciences (Hu et al., 2021).  
95 These platforms provide exciting opportunities to study the environment in con-  
96 venient ways that include obtaining abundance data (Klunder et al., 2022), epige-  
97 netic modifications (Zhao et al., 2023) and population genetics (Jahnke et al.,  
98 2022). For metabarcoding of gene fragments shorter than 500 bp, Illumina MiSeq  
99 is currently the standard platform because of its high accuracy (M. Meyer &  
100 Kircher, 2010). In comparison to Illumina MiSeq, the Oxford Nanopore sequenc-  
101 ing platform measures an electrical current that is produced when the nucleotides  
102 of a sequence pass through a transmembrane nanopore, allowing for real-time se-  
103 quencing and base calling (Bleidorn, 2016; Y. Wang et al., 2021). The advantages  
104 of Nanopore sequencing include lower costs, the sequencing of long fragments  
105 and its suitability for real-time in-field experiments (Krehenwinkel et al., 2019).  
106 However, the error rates of raw Nanopore sequences are currently higher (87-99%  
107 accuracy) compared to Illumina platforms, therefore different bioinformatics pro-  
108 cessing pipelines have been used to circumvent this problem (Baloğlu et al., 2021;  
109 Doorenspleet et al., 2023; Egeter et al., 2020). Short read Nanopore sequencing  
110 has been shown to have consensus with Illumina MiSeq in low-diversity samples  
111 (Egeter et al., 2020; van der Reis et al., 2023). However, comparisons of the se-  
112 quencing platforms also showed the lack of several bacterial taxa when comparing

high diversity samples (Heikema et al., 2020; Stevens et al., 2023). Thus, it remains unclear to what extent short read Nanopore sequencing is directly comparable to Illumina data.

Recently, metagenomics and shotgun sequencing have gained interest as alternatives to metabarcoding for community analysis (Bernatchez et al., 2024; Theissinger et al., 2023). Shotgun sequencing can bypass some methodological disadvantages that are inherent to metabarcoding such as PCR (Zhou et al., 2013) and primer amplification bias (Leray & Knowlton, 2015), because DNA is directly processed for sequencing. Moreover, shotgun sequencing has been previously suggested to cover the full spectrum of biota in a sample and provide a correlation with morphological biodiversity studies. This method is seen as a viable contestant to metabarcoding methods to monitoring genetic biodiversity (Bista et al., 2018; Lopez et al., 2022; Monchamp et al., 2022; Stat et al., 2017). However, metagenomics can be limited by i) the sequencing depth, which has become more cost-efficient with the advent of current sequencing platforms such as NovaSeq, and ii) the availability of reference sequences within databases, given that the shotgun sequencing process is non-selective. Thus, it is inconclusive whether shotgun sequencing is currently more useful for both diversity detection and relative abundance data for macrobenthos studies.

In this study, we compare different DNA-based methods: pair ended Illumina MiSeq metabarcoding, nanopore MinION metabarcoding and Illumina NovaSeq Metagenomics shotgun sequencing. We used bulk macrobenthos community samples collected from different soft-bottom habitats along the Belgium North Sea. By using different DNA-based methods and sequencing platforms for metabarcoding, we assessed the suitability of these methods for monitoring benthic community composition and diversity. We hypothesized that the metabarcoding data from both sequencing platforms and the shotgun metagenomics method are robust and resemble the morphologically identified community both in alpha and beta diversity, despite incomplete reference databases.

## Materials and methods

### Sample collection

Sampling was conducted at four locations in the Belgian North Sea that contained different macrobenthos communities with high, medium, and low diversity (see Breine et al., 2018) (Figure 1). The bulk samples have been previously used to optimize the metabarcoding protocols and to test the method reproducibility (Derycke et al., 2021; Van den Bulcke et al., 2021, 2023). Samples were collected from a coastal muddy fine-sand habitat with a high taxa diversity of sessile tube-forming organisms and high bioturbation (location 120 - *Abra alba* community). Samples were also collected from a medium sand habitat with a medium taxa diversity of mobile organisms (location 330 - *Nephtys cirrosa* community), a coarse sand habitat with high taxa diversity for sessile interstitial species (location 840 -

154 *Hesionura elongata* community) and lastly, a muddy habitat with low taxa diver-  
155 sity (location ZVL - *Macoma balthica* community) (Breine et al., 2018). A Van  
156 Veen grab was used to collect three biological replicates per location (A, B, C).  
157 All sediment samples were sieved using a 1 mm sieve, and the remaining material  
158 (for example, shells and rocks) was fixed using absolute ethanol and stored at -20  
159 °C prior to further processing.

#### 160 Morphological identification

161 The morphological identification followed the protocols described by Derycke et  
162 al. (2021) and van den Bulcke et al. (2021; 2023). Organisms from one replicate  
163 per location (120 - B, 840 - C, 330 - C, ZVL - A) were identified to species level  
164 and juveniles to genus level, except for specimens belonging to Nemertea, Antho-  
165 zoa and Oligochaeta, which were identified up to phylum, class, and order level,  
166 respectively. The complete list of species identified in each location is available  
167 (Table S1). Species were recorded per individual hence no biomass information  
168 was available for this dataset. To correct for the lack of biomass data, the count  
169 data were multiplied by the average size (from each each size class). This was  
170 done to compare whether there was a correlation between the morphology abun-  
171 dance data and the read count of each DNA based method for the identified spe-  
172 cies.

#### 173 DNA extraction

174 For molecular comparison, all specimens isolated from each field replicate were  
175 retained to obtain a bulk sample. Bulk samples were homogenized with a blender  
176 or, if the sample was < 100 ml, with a mortar and pestle. Subsamples of 2 ml  
177 were taken and stored in Eppendorf tubes at -20 °C before processing at three  
178 institutes (Table S2). Samples used for Illumina MiSeq and Oxford Nanopore se-  
179 quencing were extracted at Naturalis Biodiversity Centre (Leiden, The Nether-  
180 lands) and used by Wageningen University and research (Wageningen, The Neth-  
181 erlands). Samples used for Illumina NovaSeq were processed at Nord University  
182 (Bodø, Norway). DNA was extracted from all samples according to Van den  
183 Bulcke et al. (2021). In short, the Eppendorf tubes were centrifuged for 3 min at  
184 10,000 RPM, and the supernatant was removed. Samples were incubated at 50 °C  
185 for 1 hr to evaporate the remaining ethanol. Three subsamples from each biolog-  
186 ical replicate (3X3) were incubated with 10 µL proteinase K overnight at 56  
187 °C. DNA was extracted from each subsample using the DNeasy PowerSoil kit  
188 (Qiagen, USA) according to the manufacturer's protocol. After extraction, the  
189 DNA extracted from each subsample was pooled and cleaned using the Wizard  
190 DNA clean-up system (Promega, USA) and eluted in 50 µL TE buffer. After pro-  
191 cessing, samples were stored at -20 °C before amplification or shotgun sequencing  
192 (Figure 1).

## 193 PCR amplification

194 For amplification, part of the DNA barcode region, COI Folmer was used (Leray  
195 et al., 2013) with the nanopore extension sequence (Wageningen University) for  
196 the Nanopore metabarcoding results (Table S2). Amplification was performed on  
197 each sample in triplicate. Each reaction contained 8.5 µL nuclease-free water,  
198 12.5 µL 2x KAPA HiFi HotStart ReadyMix (Roche, USA), 0.75 µL (10 µM) for-  
199 ward and 0.75 µL (10 µM) reverse primer and 2.5 µL of DNA template. For Na-  
200 nopore sequencing, DNA template was diluted 10x prior to amplification. PCR  
201 conditions were 3 min at 95 °C, 35 cycles of 30 s at 98 °C, 30 s at 57 °C, 30 s at  
202 72 °C and a final extension for 1 min at 72 °C. PCR replicates were pooled, and  
203 a clean-up was performed using a 2:1 mixture with AMPURE beads (Beckman  
204 Coulter Inc., USA) and >70% ethanol. Amplification was confirmed using gel  
205 electrophoresis (1% gel, ethidium bromide).

## 206 Illumina MiSeq metabarcoding

### 207 Index PCR

208 For the index PCR, 5 µL nuclease-free water, 12.5 µL 2X KAPA HiFi HotStart  
209 ReadyMix (Roche, USA) and 2.5 µL of each index primer (Nextera XT primer 1  
210 and 2) was used with 2.5 µL of initial pooled PCR product. The PCR program  
211 was 3 min at 95 °C, 8 cycles of 30 s at 95 °C, 30 s at 55 °C, 30 s at 72 °C and a  
212 final extension for 3 min at 72 °C. Amplification was confirmed using gel-elec-  
213 trophoresis (1% gel, ethidium bromide). The purified Index PCR products were  
214 equimolarly pooled and sequenced using the Illumina MiSeq 2\*300bp platform  
215 (sequenced by Baseclear BV.).

### 216 Bioinformatics of Illumina MiSeq reads.

217 After Illumina MiSeq sequencing, the quality of the demultiplexed reads was  
218 checked using *MultiQC* (Ewels et al., 2016), and primers were removed using  
219 *Trimmomatic* (Bolger et al., 2014). Amplicon sequence variants (ASV) were gen-  
220 erated using the *DADA2* pipeline in the *Dada2* v1.17.0 package (Callahan et al.,  
221 2016) in R Studio v4.0.2 (R Core Team, 2020). Standard settings were used and  
222 an error rate of 3 mismatches was allowed. Reads with a quality score lower than  
223 30 were removed. Unique paired-end reads were determined, merged, and filtered  
224 for chimeras for each sample. Taxonomy was assigned using the *assignTaxonomy*  
225 function in the *Dada2* package (Q. Wang et al., 2007) using the *Ribosomal Data-*  
226 *base Project* (RDP) (Q. Wang et al., 2007) with a minimum bootstrap confidence  
227 parameter of 80. A public reference database that contains 1992 COI sequences  
228 of 565 North Sea invertebrate species was used for taxonomic identification  
229 ([dx.doi.org/10.5883/DS-GEANS1](https://doi.org/10.5883/DS-GEANS1)).

## 230 Nanopore metabarcoding

### 231 Nanopore sequencing

232 The PCR barcoding kit 96 (EXP-PCB096) was used for the barcoding PCR, and  
233 the sequence library was prepared with the SQK-LSK114 kit (Oxford Nanopore  
234 Technologies, UK). Several adaptations deviated from the manufacturer's instruc-  
235 tions: barcoding PCR was achieved in a total volume of 10 µL using 0.3 µL 10  
236 µM PCR barcode primer pair and 10-50 ng amplicon. The following PCR pro-  
237 gram was used: initial denaturation at 95 °C for 3 min, 15 cycles of 95 °C for 10  
238 s, 62 °C for 15 s, 65 °C for 90 s, followed by a final extension at 65 °C for 180 s.

239 The concentration of the barcoded PCR products was measured using the Qubit  
240 HS kit (Thermo Fisher Scientific, USA) on the non-purified products, after which  
241 barcoded PCR products were pooled in equimolar ratios. The pooled amplicon  
242 sequence library was cleaned twice using AMPURE beads (Beckman Coulter  
243 Inc., USA). The first clean-up step used 70% ethanol and the second used Short  
244 Fragment Buffer (SFB) to enrich for the target size fragments. After end prep and  
245 adapter ligation, the library was again washed with SFB during the final clean-up  
246 of the protocol. A total of 5 µL library containing 98.5ng DNA was loaded onto  
247 an R10.4.1 flow cell (Oxford Nanopore Technologies, UK) mounted on a Minion  
248 Mk1C device. Sequencing continued until an average sequencing depth of 200 k  
249 reads was obtained per barcode.

### 250 Sequence read processing

251 Sequence read processing was performed according to the post-processing proto-  
252 col as described by (Doorenspleet et al., 2023). Base-calling of the fast5 pass files  
253 was performed using Guppy (Version 6.5.7, Oxford Nanopore Technologies, UK)  
254 in super high accuracy (SUP) mode. The Decona pipeline was used  
255 (<https://github.com/Saskia-Oosterbroek/decona>) for trimming, clustering, and  
256 taxonomic assignment of the reads. Raw base-called reads were trimmed to be-  
257 tween 250-400 bases for each sequence. A cluster similarity of 85% was set as the  
258 clustering threshold of the sequences. Medaka consensus sequences were gener-  
259 ated from each cluster larger than 5 reads (Decona -f -q 10 -T 18 -l 300 -m 320 -  
260 c 0.85 -g "GGWACWGGWTGAACWGTWTAYCCYCC;max\_er-  
261 ror\_rate=0.1;min\_overlap=20...GRTTYTTYGGHCAYCCHGAR-  
262 GTHTA;max\_error\_rate=0.1;min\_overlap=19" -n 5 -r 0.99 -R 500 -k 6 -M).

### 263 Taxonomic assignment

264 The consensus sequences were classified using *BLASTn* (NCBI, version 2.11.0)  
265 and the North Sea invertebrate species reference database was used for taxonomic  
266 identification ([dx.doi.org/10.5883/DS-GEANS1](https://doi.org/10.5883/DS-GEANS1)). This database was the same as used for  
267 the Illumina MiSeq metabarcoding taxonomic assignment. Top hits were consid-  
268 ered at species level when there was a minimal alignment length of 250 nucleo-  
269 tides with <4 bp mismatches and >98% identity.

**Commented [RGS1]:** Change formatting in this case to Doorenspleet et al. (2023)

**Commented [RGS2]:** In other parts of the manuscript you use basecalled as one word. It will be better to be consistent

**Commented [RGS3]:** I think you need to clarify a bit more what did you do with the BLAST results. How many alignments did you keep? I would assume there were many matches that aligned with each query sequence. Did you just kept the best match or did you calculate the LCA of the matches clearing a threshold?

## 270 Read abundance correction

271 After taxonomic assignments, a tag correction was performed on the Nanopore  
272 data to correct the tag jumping that had occurred. Tag jumping had occurred when  
273 both forward and reverse barcode tags were on sequences that did not belong to  
274 that barcode. After troubleshooting, most of the contamination could be alleviated  
275 by removing 1% of the total read count of each species from each barcode. This  
276 correction is intended to correct proportionally for the total read abundance of  
277 each taxon. Although the negative PCR control did not show a positive band after  
278 barcode PCR, contamination was detected in the sequence data.

279 First, the total read count was calculated for all species in all barcodes using the  
280 mutate() function in the dplyr v1.1.0 package (R Core Team, 2023). Second, 1%  
281 of the total read count was calculated and rounded to a whole number of reads  
282 using the round() and mutate() functions (R Core Team, 2023). Then 1% of the  
283 total read count of each species was subtracted from each barcode using mutate().

## 284 NovaSeq shotgun sequencing

### 285 Preparations for sequencing

286 After DNA extraction and clean-up, libraries were directly prepared using NEB-  
287 Next® Ultra™ II DNA Library Prep Kit for Illumina (New England Biolabs,  
288 USA). Samples were indexed using NEBNext® Multiplex Oligos for Illumina  
289 (New England Biolabs, USA). The final quality check was conducted using the  
290 Agilent TapeStation system (Agilent Technologies, USA). Samples were pooled  
291 in equimolar concentrations and sent to the Norwegian Sequencing Center in Oslo  
292 to be sequenced using the NovaSeq S4 quarter flow cell.

### 293 Sequence read processing

294 The NovaSeq reads were trimmed using cutadapt (--minimum-length=100, q=30),  
295 and merged with PEAR v 1.7.2 (Zhang et al., 2014) using the default parameters.  
296 In the first iteration of the data analysis, reads were assembled into contigs and  
297 aligned against the complete NCBI database for use in shotgun sequencing. De-  
298 spite the large number of high-quality alignments, many were false positives.  
299 Therefore, this workflow was discarded and instead the merged sequences were  
300 directly aligned against the GEANS ref v4 database (>97 % identity, e-value set  
301 at -10, and alignment length over 100 bp). Single alignments were discarded for  
302 the data analysis.

### 303 Data analysis

304 Data analysis was carried out in RStudio v4.2.2 (R Core Team, 2022). A rarefac-  
305 tion curve (Vegan v2.6.4) was plotted to understand the effect of differential se-  
306 quencing depths between samples. Each sample showed a flattening curve (Figure  
307 S1), which indicated that for each DNA-based method, an appropriate sequencing  
308 depth was achieved. Therefore, the data were not rarefied but normalized using a

**Commented [RG54]:** Did you know this because there was a positive control of known sequence? I am curious as to how this tag jumping happened, as the samples were pooled after the barcodes were added and the ligation of adapters in Nanopore libraries happens afterwards. Would lab contamination rather than tag-jumping be an easier explanation?

**Commented [RG55]:** I have a bit of trouble understanding what was done. Please correct me if I am wrong. You suspect that 99% of the reads of each species are in the right sample, and 1% might be in the wrong sample. So you calculate, for each species, what is 1% of their reads. And for each species-sample combination you subtract the value for that species.

**Commented [RG56R5]:** Also, the dplyr package is not from the R Core team. I think the usage of mutate is not adding information here - I would explain the process, add that you perform it in R, and add the script which does it to the repository or the supplemental

**Commented [RG57]:** Rstudio was not made by the R Core Team. I think you mean in RStudio using R v4.2.2



309 log<sub>10</sub> transformation. For alpha diversity, species level richness, and evenness  
310 (Shannon, log 10 transformed) of the read counts were calculated using the diver-  
311 sity() function (*Vegan* v2.6.4)) and visualized using boxplot (*ggplot2*, v3.4.0).  
312 Normality of the data was tested using Shapiro-Wilk for normal distribution, Q-  
313 Q plots, and a histogram. Based on these results a 2-way ANOVA using the aov()  
314 function (*stats*, v3.6.2) was carried out to determine the differences between sam-  
315 pling locations and the DNA-based method used and whether an interaction effect  
316 could be observed. For a pairwise comparison, a post hoc analysis was performed  
317 using the Tuckey test (HSD) using the TukeyHSD() function (*stats*, v3.6.2). For  
318 beta diversity, non-metric multidimensional scaling ('bray') was performed on  
319 each dataset separately (Nanopore metabarcoding, Illumina MiSeq metabarcod-  
320 ing and Shotgun metagenomics sequencing) in combination with *betadisper* to  
321 check for homogeneity of variance. A PERMANOVA was used (*Adonis2*  
322 *adonis2()*, *Vegan* v2.6.4) to analyse which locations were significantly different from  
323 each other, within each dataset. A Spearman correlation was used (*stats* v3.6.2),  
324 to compare the size class corrected morphological abundance findings with each  
325 DNA-based method.

## 326 Results

### 327 Read processing comparison between DNA-based methods

328 From the Illumina MiSeq metabarcoding samples, a total of 2,538,798 sequences  
329 were obtained with 2,153,086 used after processing. Of these, 1,724,841 reads  
330 were used as ASVs for taxonomy assignment. An overview is available of the  
331 sequencing output of each DNA-based method after sequencing and processing  
332 (Table S3). From the Oxford Nanopore metabarcoding dataset, 2,426,017 reads  
333 were basecalled of which 1,841,385 remained after clustering and consensus  
334 building. A total of 1,191,853 of the remaining reads were used as consensus se-  
335 quences for taxonomy. From the 3,060,417,120 data obtained from the Illumina  
336 NovaSeq metagenomics run, 2,425,520,473 reads passed the quality values for  
337 direct taxonomic assignment of the reads. In total, 42,262 reads could be assigned  
338 to species level, which resembled 0.0017% of the total filtered reads. This illus-  
339 trates that 100 times more reads were used for the taxonomic assignment of the  
340 metabarcoding data, indicating an imbalanced final read count between methods.  
341 This was however, not reflected in the rarefaction curves (Figure S1). All the  
342 curves showed flattening curves and indicated that for both methods, enough se-  
343 quencing depth was reached.

### 344 Alpha diversity obtained with the three DNA-based methods

345 A two-way ANOVA showed a significant interaction effect between sequencing  
346 techniques (Illumina MiSeq, Nanopore, NovaSeq), and location (120, 330, 840  
347 and ZVL) for species richness ( $F = 8.68$ ,  $p < 0.05$ ). Main effects were also ob-  
348 served for both sequencing techniques, ( $F = 9.94$ ,  $p < 0.05$ ) and location ( $F =$   
349  $98.79$   $p < 0.05$ ). Post-hoc analysis using a Tuckey's HSD test showed that there

**Commented [RG58]:** Don't you think that this illustrates that rarefaction curves are not useful to determine whether enough sequencing depth was reached? I think it illustrates that is not worth sequencing each of the samples further, but not that you have an adequate view of the diversity in the sample

350 were significant differences in richness between the NovaSeq metagenomics and  
351 MiSeq metabarcoding ( $p = 0.021$ , Table S5) and between NovaSeq metagenomics  
352 and Nanopore metabarcoding ( $p < 0.001$ , Table S5) but not between Nanopore and  
353 MiSeq metabarcoding ( $p = 0.31$ ). In addition, post-hoc analysis showed a signif-  
354 icant difference between location 120 and all other locations (Table S5), where  
355 120 had the highest richness (Figure 2a). A significant difference was also ob-  
356 served between ZVL and all other locations (Table S5), where ZVL had the lowest  
357 richness. No significant difference was found between location 330 and 840 ( $p =$   
358  $0.99$ ). As for the interaction effect, the NovaSeq had significantly lower richness  
359 in location 120 compared to the other techniques (Nanopore:  $p < 0.01$ ; NovaSeq:  
360  $p < 0.01$ , Figure 2a). A two-way ANOVA showed a significant interaction of  
361 Shannon indices between sequencing techniques and locations ( $F = 4.89$ ,  $p < 0.01$ ,  
362 Table S5). The main effects were only significant for the factor location ( $F =$   
363  $69.76$ ,  $p < 0.01$ , FS5) but not for the factor method ( $F = 0.94$ ,  $p = 0.403$ ). Post-  
364 hoc analysis using a Tuckey's HSD test showed significant differences in Shan-  
365 non indices between location 120, and all other locations (Table S5), where 120  
366 had the highest Shannon index (Figure 2b). A significant difference was also  
367 found between ZVL and all other locations (Table S5), where ZVL had the lowest  
368 Shannon index (Figure 2b). As for the interaction effect, the NovaSeq was signif-  
369 icantly different from both Nanopore and MiSeq for location ZVL (Table S5, fig-  
370 ure 2b), where ZVL was significantly higher than NovaSeq. Overall, these results  
371 highlight that all sequencing techniques similarly observe alpha diversity between  
372 locations, except for the richness in high diversity at location 120, where the No-  
373 vaSeq shotgun metagenomics retrieved less species than the metabarcoding ap-  
374 proaches. Shannon indices were higher for NovaSeq for the low diversity location  
375 ZVL.

#### 376 Beta diversity obtained from the three DNA-based methods

377 The PERMANOVA demonstrated significant differences in macrobenthic com-  
378 munity compositions between locations ( $F = 26.03$ ,  $p < 0.01$ ) and between tech-  
379 niques used ( $F = 6.88$ ,  $p < 0.01$ ) (Table S6, Figure 3). In addition, a significant  
380 interaction effect was observed between location and the DNA-based approach  
381 used ( $F = 2.48$ ,  $p < 0.01$ ), indicating that benthic community composition and  
382 location depend on the DNA-based method used and the other way around (Table  
383 S6). Post-hoc pairwise PERMANOVA tests showed that there was a significant  
384 difference in community composition between all locations ( $p < 0.01$ ) except be-  
385 tween locations 330 and 840 (Table S6,  $p = 0.108$ ). Post-hoc analysis also showed  
386 a significant difference in community composition between Nanopore and No-  
387 vaSeq ( $p < 0.01$ ) but not between Nanopore and Illumina ( $p = 0.99$ ) and Illumina  
388 and NovaSeq ( $p = 0.08$ ). The NMDS plot showed a clear clustering for each lo-  
389 cation, except for locations 330 and 840 (Figure 3). The plot also illustrates that  
390 location is responsible for the biggest contrasts in community composition, indi-

391 cating that the location explains most of the variation between community com-  
392 positions. Similarly, the NMDS plot also indicated that NovaSeq has a different  
393 community composition in some locations. An interaction effect was also ob-  
394 served, as the NovaSeq samples clustered closer to each other within each location  
395 compared to the other DNA-based methods. Clustering between DNA-based  
396 methods was not found in Illumina and Nanopore, as these approaches clustered  
397 together within each location.

#### 398 Comparison of DNA-based methods for assessing location-specific species 399 composition

400 All three DNA-based methods (Figure 4) shared 27 species and an additional 27  
401 species were shared between just the metabarcoding methods (Figure 4, S3). At  
402 location 120, 23 species were shared between the two metabarcoding methods  
403 whereas only 12 species were shared between all three DNA-based methods (Fig-  
404 ure 4, S3). The Nanopore metabarcoding data had 6 unique species for all loca-  
405 tions (Figure 4b, Figure S3), and found the most unique species for each location  
406 (Figure 4b, Figure S3). For example, several species such as, *Crepidula fornicate*,  
407 *Eumida mackiei* and *Magelona mirabilis*, occurred at location 330 using the Na-  
408 nopore dataset but with less reads than in location 120 (Figure 4b). However, these  
409 species were only in location 120 using the MiSeq dataset. Nevertheless, all DNA-  
410 based methods detected unique species with each method. In general, the No-  
411 vaSeq dataset had lower diversity across all the locations compared to the other  
412 DNA-based methods (Figure 2, Figure 4c). Interestingly, *Nyphys cirrosa* occurred  
413 in a high relative abundance in the metabarcoding datasets and is a dominant spe-  
414 cies at location 330 but remained absent in the NovaSeq results. Nevertheless, the  
415 key species of location 840, *Hesionura elongata*, was only detected using the No-  
416 vaSeq method.

#### 417 Comparison of species presence and abundance between DNA-based methods 418 and morphology

419 For the morphological identification, one biological replicate was available  
420 (120B, 330C, 840C and ZVLA) for each location. This resulted in the identifica-  
421 tion of 56 species. A total of 39, 13, 10 and three species were identified at loca-  
422 tions 120, 330, 840 and ZVL, respectively (Table S1). Of the 56 species identified,  
423 25 species were identified using morphology only (Figure 5a). Of these 25 spe-  
424 cies, 19 did not have a reference sequence available in the chosen reference data-  
425 base (Table S4, colour red). In addition, 12 of the species that did not have a ref-  
426 erence sequence available belonged to the phylum Annelida (Table S4, colour  
427 green), which are known to have low primer efficiency and are therefore harder  
428 to include in COI reference databases (Carr et al., 2011). This indicated that a total  
429 of 6 species were unique findings in the morphological dataset (Table S4, orange).  
430 Of the 32 species that were identified using the both the DNA-based methods and

**Commented [RG59]:** I think this interpretation of the nMDS is confusing. An interaction effect would be that the NovaSeq behaves differently in a locality compared to others. I don't think you can conclude that from the nMDS

**Commented [RG510]:** Is *Hesionura elongata* present in your locus-specific database?

431 morphology, 10 species were identified using all three DNA-based methods, 13  
432 species were identified using the metabarcoding-based methods only. Lastly, 5  
433 species were identified in only one of the three DNA-based methods (Figure 5a,  
434 Figure S4).

435 Three species were identified with all three DNA-based methods (Figure 5a), that  
436 were not identified with morphology and an additional six were identified using  
437 only the metabarcoding methods. These six species included *Scoliopsis bonnieri*  
438 and *Cylista troglodytes* which represented a substantial amount of the identified  
439 reads (Figure S2). This indicated that the DNA-based methods can identify spe-  
440 cies that are missed using morphological identification. Nanopore identified an  
441 additional nine species that were unique (Figure 5a) but that were found in low  
442 read count of only one read (Table S4).

443 A Spearman correlation between morphological size class corrected counts and  
444 relative read abundance between each DNA-based method across all locations  
445 showed the highest positive correlation with both the metabarcoding methods  
446 ( $Sp = 0.24$  (MiSeq),  $Sp = 0.27$  (Nanopore)), although this correlation was not sig-  
447 nificant (Figure 5b, c, d). However, the metagenomics method did not show a  
448 correlation with the size class corrected morphological counts (Figure 5b, c).

## 449 Discussion

450 We compared three different DNA-based methods: two metabarcoding ap-  
451 proaches (MiSeq, Nanopore) and a metagenomics approach (NovaSeq). We as-  
452 sessed the robustness between techniques in terms of alpha and beta diversity to  
453 understand the suitability of these techniques for macrobenthos monitoring. We  
454 have demonstrated that the two metabarcoding methods showed a similar diver-  
455 sity richness and evenness as well as location-specific species compositions. The  
456 NovaSeq metagenomics method had lower macrobenthos richness and as a result,  
457 different community compositions than the metabarcoding methods. Interest-  
458 ingly, almost half of the species found in the morphological dataset were not iden-  
459 tified with molecular techniques mostly due to a lack of references in the database.  
460 Nevertheless, all methods showed that most species were shared within each lo-  
461 cation. The NovaSeq metagenomics method correlated best with the morpholog-  
462 ical species count. Nevertheless, improvements can be implemented to optimize  
463 the suitability of DNA methods for macrobenthos monitoring, especially with re-  
464 gards to improving the reference databases.

465 Macrobenthos communities are highly similar using metabarcoding despite us-  
466 ing different sequencing platforms

467 No difference was found between alpha and beta diversity when comparing a  
468 standardized lab protocol with Illumina MiSeq sequencing (Van den Bulcke et al.,  
469 2023) to Nanopore-based metabarcoding. Furthermore, both methods identified  
470 similar species composition and community structure at each location. Therefore,

**Commented [RG511]:** Wasn't it possible to generate refer-  
ence sequences from the morphological dataset? Because if  
the explanation of the differences relies on the un-complete-  
ness of the databases, doesn't that mean that in 2,3,5 years  
time the conclusion of your work would have been different?

471 this study clearly demonstrated that Nanopore and Illumina MiSeq metabarcoding  
472 performed evenly well for monitoring macrobenthos biodiversity. Previous re-  
473 search showed that the Nanopore technique can miss certain taxonomic groups  
474 and therefore does not perform as well as MiSeq (Heikema et al., 2020; Stevens  
475 et al., 2023) which contrasts our results. More recent comparisons (Chang et al.,  
476 2023; van der Reis et al., 2023; Voorhuijzen-Harink et al., 2019) have shown that  
477 the Nanopore datasets are overall comparable with Illumina MiSeq results. Thus,  
478 the findings of this study also suggest that metabarcoding with both sequencing  
479 platforms performs similarly for macrobenthos biodiversity regardless of the ex-  
480 pected richness of an area of interest.

481 Nanopore sequencing had the most unique species (9 vs 2, respectively; Fig S5).  
482 These unique taxa were found mostly in very low relative read abundance and did  
483 not influence the alpha and beta diversity. For this comparison, we used the same  
484 DNA extract; it is therefore likely that either the lab procedure, the sequencing  
485 platform or the bioinformatics method have resulted in slightly different results.  
486 When assessing the reproducibility of laboratories minor variations in detected  
487 species have previously been reported (Van den Bulcke et al., 2021). These de-  
488 tections could be explained as an effect of the stochastic nature of PCR that is  
489 observed in each dataset (van der Loos & Nijland, 2021) or further emphasize the  
490 influence of lab-specific factors.

491 Another potential explanation for these differences is that the Nanopore chemistry  
492 and its protocols might be more prone to introducing false positive detections of  
493 species. This is because the Nanopore dataset had some species with only several  
494 reads in one of the replicates, while in another location this species was abundant.  
495 Using the other methods, the same species was found in only one location. Even  
496 though a simple correction of tag leakage was used for this study (as presented in  
497 the materials and methods), it is possible that tag jumping, or barcode leakage was  
498 still a problem for this dataset. After routine testing, this problem was related to  
499 the temperature at which barcoded samples were pooled for the Nanopore se-  
500 quencing library (personal communication). In addition, barcode leakage prob-  
501 lems have been reported often in metabarcoding studies (Beentjes et al., 2019; van  
502 der Loos & Nijland, 2021). Therefore, it is important to consider protocols that  
503 minimize the possibility of barcode leakage. This includes using negative controls  
504 at each stage, minimizing the handling and amplification of tagged product, or  
505 correcting for a crossover of tags between samples (Beentjes et al., 2019). Similar  
506 other platforms, Nanopore uses two cycles of PCR, one for the amplification of  
507 the region of interest and a second PCR for the barcode attachment using Na-  
508 nopore-specific protocols and kits for barcoding. The protocol used for this study  
509 could be optimized in such a way that individual samples could be amplified with  
510 already tagged initial barcodes to circumvent the second PCR step (Srivathsan et  
511 al., 2021) or by using amplicon-free barcode kits (Toxqui Rodríguez et al., 2023;  
512 van der Reis et al., 2023).

**Commented [RGS12]:** I don't see how a sequencing plat-  
form can perform better or worse in a particular taxonomic  
group.

**Commented [RGS13]:** Are "unique species" in this context  
species that were only found in one platform? I would say  
that the null hypothesis as to why this happened is the com-  
bined stochasticity of PCR and sequencing (What gets ampli-  
fied in a sample is a combination of abundance, affinity with  
the primers and stochasticity - and what gets sequenced is a  
subsample of that PCR product: this will likely explain the  
uniqueness of some taxa to a method, and not some prefer-  
ence or likelihood of sequencing rare things)

**Commented [RGS14]:** I see that you mentioned this: I  
would move it forward

**Commented [RGS15]:** Hard to argue without looking at  
the raw data . I would rather sequence a positive control of  
known composition so you can have two tests of tag jumping:  
do we see something besides the positive control there, and  
do we see positive control sequences inside the normal sam-  
ples

513 The bioinformatics pipeline used in this study could also be responsible for the  
514 little observed difference in metabarcoding results. The newest 10.4.1 flow cells  
515 were used, which greatly improved the quality of the metabarcoding data (Zhang  
516 et al., 2023). Nevertheless, clustering and consensus building of the data with bi-  
517 oinformatics processing might also result in overlooking some elements of the  
518 biodiversity (Brandt et al., 2021). Therefore, the reads that were not included in a  
519 cluster for consensus building were also considered when they met the threshold  
520 for taxonomy assignment. Including this portion of the reads may have led to the  
521 detection of additional species, although this is unlikely since it did not result in  
522 obtaining extra species (data not shown).

523 Despite these minor differences between metabarcoding methods, this did not lead  
524 to significant differences in commonly used biodiversity indices. Therefore, this  
525 study suggests that Nanopore and Illumina MiSeq metabarcoding can be used  
526 equally well for macrobenthos monitoring.

527 NovaSeq Shotgun sequencing identified a reduced number of species com-  
528 pared to metabarcoding

529 The primer and PCR-free shotgun metagenomics method yielded lower richness  
530 compared to the metabarcoding methods and resulted in a significant but slightly  
531 different community compositions. These different community compositions be-  
532 tween methods were mostly due to the reduced number of species, as most species  
533 that were detected by NovaSeq metagenomics were also detected by the two  
534 metabarcoding methods.

535 This study, therefore, does not reflect current environmental metagenomics stud-  
536 ies that show equal or higher levels of biodiversity compared to amplicon-based  
537 approaches (Bista et al., 2018; Garlapati et al., 2019; Monchamp et al., 2022;  
538 Paula et al., 2022). However, in these studies, an environmental sample was taken  
539 that was not targeted to a certain taxonomic group and therefore, reflected a wider  
540 spectrum of biota. In contrast, this study aimed to test whether metagenomics is  
541 suitable for macrobenthos biodiversity monitoring and therefore the data pre-  
542 sented are not directly comparable to other metagenomics studies.

543 For this comparison the reference database that was used contained the most  
544 North Sea macrobenthos and contained only COI rRNA sequences. On average,  
545 ~3,500 reads of the ~200,000,000 reads per sample had a hit within the database.  
546 Considering the relatively low amount of mitogenomic sequences in a DNA ex-  
547 tract (Quiros et al., 2017) let alone sequences that represents the COI region, sug-  
548 gests that searching solely for COI is a needle in a haystack situation. Therefore,  
549 it is not surprising to have such a low retrieval of reads that align with a target  
550 species. These results suggest that with the current available references, a much  
551 higher sequencing depth is needed to improve the performance of this technique.  
552 Regarding costs, the present study's findings align with previous research that

553 suggest that shotgun sequencing metagenomics is hardly feasible for environmen-  
554 tal studies (Ficetola & Taberlet, 2023; Quince et al., 2017). These results also  
555 indicate the necessity to improve reference databases, particularly for full  
556 (mito)genomes of macrobenthos, as the limited availability of references largely  
557 contributed to the reduced number of species found. Currently, reference data-  
558 bases are mainly focused on genetic regions that are popular for metabarcoding  
559 (Weigand et al., 2019) and references of full (mito)genomes are still in their in-  
560 fancy (Blasiak et al., 2020; Leray et al., 2022).

561 Similarly, of the species that were identified using the metagenomics approach,  
562 there was also no correlation with the, for size class corrected read count of the  
563 morphologically identified samples. Unfortunately, no biomass data was obtained  
564 from the morphologically identified samples, which would be a more appropriate  
565 representation of the actual abundance. Nevertheless, a better correlation was  
566 found with the metabarcoding data, which is in contrast with findings that suggest  
567 a better correlation between found metagenomics reads and biomass (Bista et al.,  
568 2018). Since in the study by Bista et. al., the mitogenomes of mock community  
569 was available, the lack of correlations in this study further suggests that the met-  
570 agenomics method is presently not feasible for reliable DNA-based monitoring of  
571 macrobenthos biodiversity. In the future, focussing on reference databases and  
572 especially databases that contain complete (mito)genomes will greatly improve  
573 detection rates and may revolutionize DNA-based monitoring.

574 Morphology identification retrieved more species due to lack of annelid se-  
575 quences in the reference database

576 Most taxa were detected using both morphology and a DNA-based technique, but  
577 there were also 25 species that were not identified using any DNA-based method.  
578 This was especially apparent in the high diversity samples. However, only 6 of  
579 those species were represented in the COI reference database for North Sea mac-  
580 robenthos. The incompleteness of biodiversity databases, especially in relation to  
581 marine invertebrates has often been reported as a limiting factor (Aylagas et al.,  
582 2016; Günther et al., 2018; Steyaert et al., 2020; Willassen et al., 2022). Several  
583 efforts have been made to improve (Lavrador et al., 2023) and increase the cov-  
584 erage of these databases (Leray et al., 2018; Radulovici et al., 2021). Approxi-  
585 mately 22-43% of all European marine species have reference sequences available  
586 in the widely used reference database BOLD (Weigand et al., 2019) and 50% in  
587 a pan-European gap analysis of aquatic invertebrates (Csabai et al., 2023). Multi-  
588 ple studies in the North Sea have emphasized the importance of enhancing these  
589 databases (Christodoulou et al., 2021), indicating a need for sustained long-term  
590 efforts.

591 There were also 15 species from the phylum Annelida that were not identified  
592 using DNA-based methods. Annelida, and especially certain Polychaeta, are  
593 known to be especially difficult to sequence using conventional markers for

**Commented [RG516]:** You mention it later on for An-  
nelida, but the other explanation is not database coverage but  
primer performance.



594 metabarcoding because this group has high variation within the COI region and  
595 therefore, lower primer efficiency (Carr et al., 2011). This also causes the COI  
596 reference databases to be biased towards a lower representation of Annelida. Us-  
597 ing multiple markers that are more specific to certain taxonomic groups might  
598 therefore greatly improve the capability to detect species from metabarcoding  
599 methods. However, consequently this may increase laboratory time and costs  
600 (Cordier et al., 2019; Gielings et al., 2021; A. Meyer et al., 2021). Metagenomic  
601 methods can also improve the detection of annelids as this technique doesn't rely  
602 on the amplification of specific regions. Nevertheless, the metagenomics method  
603 in this study did not result in the retrieval of more annelids and this is probably  
604 due to the chosen reference database that is solely based on the commonly used  
605 region of the COI gene. Especially, the low percentage (0.002%) of reads eventu-  
606 ally used for taxonomic identification suggests that the lack of a reference data-  
607 base for this method has strongly hampered the power of the metagenomics  
608 method used in the present study.

609 The DNA-based methods also found taxa with a high read count (>13000 reads)  
610 that were not reported during the morphological analysis. These taxa include soft  
611 bodied organisms such as the Anthozoa *Sagartia*, whose tissue becomes hard or  
612 impossible to recognize when not intact. It is, therefore, not surprising that these  
613 species are easier to identify with molecular methods while only classified to a  
614 high taxonomic rank during morphological analysis (Robinson et al., 2022). In  
615 conclusion, although DNA-based methods missed 25 species compared to mor-  
616 phological analysis, the DNA-based methods detected an additional 17 species  
617 that were otherwise undetected. This is in line with previous reports, also con-  
618 firming that DNA-based methods and morphology should remain complementary  
619 (Cahill et al., 2018; Kelly et al., 2017; A. Meyer et al., 2021). However, improve-  
620 ments to the databases and the choice of multi-marker approach for specific tax-  
621 onomic groups might further improve detection sensitivity and at some point, may  
622 surpass morphological identification.

## 623 Conclusions

624 In recent years, there has been increased interest in implementing DNA-based  
625 tools into routine biodiversity monitoring practices. To achieve this, standardized  
626 protocols are necessary to ensure reproducibility and data robustness across stud-  
627 ies and regions, particularly as sequencing technology is evolving rapidly (Van  
628 den Bulcke et al., 2023).

629 In this study, we showed that similar alpha and beta diversity patterns were found  
630 regardless of the metabarcoding platform used. Thus, Illumina MiSeq and Na-  
631 nopore sequencing results are, at this stage, highly similar and can both be used  
632 to monitor macrobenthos biodiversity. Incomplete reference databases still ham-  
633 per detection, as most morphologically identified species did not have a repre-  
634 sentative sequence in the database. NovaSeq metagenomics has the potential for

**Commented [RGS17]:** It is here when I realize that the GEANS ref v4 database is a COI database. So it seems that the experiment is playing for metabarcoding advantages and not to metagenomics strengths. I see the reason is the rate of false positives, which I think should be addressed, but I think the experiment as it is now, could be summarised as: If you want to use COI for species detection, then amplify COI.



environmental monitoring especially for better representation of abundance data but is at this stage not ideal for macrobenthos monitoring of bulk samples as fewer species were identified compared when using the metabarcoding methods. These findings demonstrate that newer next-generation sequencing platforms are ready to be integrated for standard monitoring practices. We emphasize the importance of improving sequence reference databases to implement and enhance next-generation of sequencing methods for robust and harmonized monitoring practices.

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#### Author contributions

Karlijn Doorenspleet: Laboratory work, analysis, writing and reviewing with emphasis on writing the draft. Amalia Mailli: Laboratory work, analysis, writing and reviewing with emphasis on visualization of the results. Annelies de Backer Concept. Writing and reviewing, project administration, funding acquisition. Sofie Derycke concept, methodology writing and reviewing, project administration, funding acquisition. Berry van den Hoorn: writing and reviewing. Kevin Beentjes: laboratory work, writing and reviewing. Henning Reis: Writing, reviewing and supervision Albertinka Murk: Supervision, writing and reviewing Reindert Nijland: Concept, supervision, project administration writing and reviewing.

#### Data availability

The raw data as well as the processed data and the used scripts are available including descriptive metadata are available under DOIXXXXXX in the Marine data ~~Archive~~Archive (MDA) <https://marinedataarchive.org/> Customs R scripts used for the Data Analysis can be accessed at: [https://github.com/ama-lia03/GEANS\\_Platform\\_Comparison\\_Scripts/blob/main/tax\\_geans.R](https://github.com/ama-lia03/GEANS_Platform_Comparison_Scripts/blob/main/tax_geans.R).

The data generated from the metabarcoding approach with Illumina MiSeq, as well as the morphological identification have been previously used for the publication by van der Bulke et al. 2023. The data has been used to compare datasets generated from the same samples with the same protocol in different labs. This was to show whether the methods were robust between institutes. In our approach however, we use the dataset of one lab only and the morphology data to compare

675 this with other DNA based methods and sequencing platforms and therefore  
676 serves another purpose.

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