

1 **Title:** The long and short of it: Benchmarking viromics using Illumina, Nanopore and PacBio
2 sequencing technologies

3

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34 **Keywords**

35 Viral metagenomics, Viromics, Nanopore, PacBio, Hybrid sequencing, Long reads, Bacteriophage,
36 Phage

37

38 **Repositories**

39 All reads from virome sequencing were submitted to the ENA under the study PRJEB56639.

40 **Abstract**

41

42 Viral metagenomics has fuelled a rapid change in our understanding of global viral diversity and
43 ecology. Long-read sequencing and hybrid approaches that combine long and short read
44 technologies are now being widely implemented in bacterial genomics and metagenomics. However,
45 the use of long-read sequencing to investigate viral communities is still in its infancy. While Nanopore
46 and PacBio technologies have been applied to viral metagenomics, it is not known to what extent
47 different technologies will impact the reconstruction of the viral community.

48

49 Thus, we constructed a mock phage community of previously sequenced phage genomes and
50 sequenced using Illumina, Nanopore, and PacBio sequencing technologies and tested a number of
51 different assembly approaches. When using a single sequencing technology, Illumina assemblies
52 were the best at recovering phage genomes. Nanopore- and PacBio-only assemblies performed
53 poorly in comparison to Illumina in both genome recovery and error rates, which both varied with the
54 assembler used. The best Nanopore assembly had errors that manifested as SNPs and INDELs at
55 frequencies ~4x and 120x higher than found in Illumina only assemblies respectively. While the best
56 PacBio assemblies had SNPs at frequencies ~3.5 x and 12x higher than found in Illumina only
57 assemblies respectively. Despite high read coverage, long-read only assemblies failed to recover a
58 complete genome for any of the 15 phage, down sampling of reads did increase the proportion of a
59 genome that could be assembled into a single contig.

60

61 Overall the best approach was assembly by a combination of Illumina and Nanopore reads, which
62 reduced error rates to levels comparable with short read only assemblies. When using a single
63 technology, Illumina only was the best approach. The differences in genome recovery and error rates
64 between technology and assembler had downstream impacts on gene prediction, viral prediction,
65 and subsequent estimates of diversity within a sample. These findings will provide a starting point
66 for others in the choice of reads and assembly algorithms for the analysis of viromes.

67

68 **Data Summary**

69 All reads from virome sequencing were submitted to the ENA under study PRJEB56639. The
70 assemblies are provided via FigShare (<https://figshare.com/s/2d9b5121eb421d370455>).

71

72 **Author Notes**

73 Eight Supplementary Tables and nine Supplementary Figures are available with the online version
74 of this article.

75

76 **Abbreviations**

77 INDEL, Insertion or Deletion; LASL, Linker Amplified Shotgun Library; MDA, Multiple Displacement
78 Amplification; ONT, Oxford Nanopore Technology; SNP, Single Nucleotide Polymorphism; TFF,
79 Tangential Flow Filtration; vOTU, Viral Operational Taxonomic Unit
80

81

82 Introduction

83

84 Viruses play critical roles in all environments they inhabit, as evidenced by their distribution and
85 abundance. In particular viruses that infect bacteria, bacteriophages (from hereon phages), are
86 known to play important roles in regulating the abundance of their bacterial hosts, facilitating
87 horizontal gene transfer and playing crucial roles in global biogeochemical cycles by augmenting
88 host metabolism [1–3].

89

90 It is now over 40 years since sequencing of the first phage genome [4]. The number of complete
91 phage genomes from phage isolates is now >22,000 [5]. However, millions more phage genomes
92 have been sequenced through metagenomics sequencing and are available through a variety of
93 databases [6–8]. Viral metagenomics (viromics) has revolutionised our understanding of the diversity
94 of phages and their potential ability to augment host metabolism. Initial virome studies required DNA
95 to be cloned into a vector and the clone sequenced by Sanger sequencing. As new sequencing
96 technologies developed that did not require the cloning of DNA, such as Solexa (becoming Illumina),
97 454 and SOLiD, the field of viromics expanded. With Illumina sequencing becoming the dominant
98 technology, more and more viromes have been sequenced spanning pristine ocean environments
99 [9], abyssal depths [10], and even the faeces of a wide variety of animal species [11–13].

100

101 Whilst viromes produced using Illumina short-read sequencing have provided new insights into viral
102 diversity, short reads are not able to resolve all viral genomes within a virome. Phages that contain
103 hypervariable regions and/or possess high microdiversity are known to cause virome assemblies to
104 fragment, resulting in reduced contig sizes and exclusion from further analyses [14]. To overcome
105 such problems, alternative approaches to viromics can be taken including single cell viromics or the
106 cloning of viral genomes into fosmids [15]. Whilst both of these approaches are beneficial, they are
107 technologically challenging compared to more standard viromics workflows.

108

109 Recent technological developments have led to the production of long read sequences by both
110 Oxford Nanopore Technology (ONT) [16] and PacBio [17]. While the technologies differ in their
111 approach, both platforms sequence single molecules and are capable of producing sequences of
112 tens of kilobases in length [17]. The ability to sequence long DNA molecules offers the ability to
113 overcome the issues of microdiversity and or hypervariable regions found within phage genomes
114 [14]. To date there have been limited studies using ONT sequencing for viromics. One of the first
115 was able to acquire complete phage genomes from single ONT reads, utilising tangential flow
116 filtration (TFF) of marine samples to obtain the significant amounts of DNA required for library
117 preparation [18]. Extraction of such quantities of phage DNA is likely prohibitive from more viscous
118 and heterogeneous environments where multiple displacement amplification (MDA) is already used

119 to obtain enough DNA for library preparation for short read sequencing. While MDA provides a
120 solution to the amount of input material, it does not come without problems. It has been well
121 documented that MDA can introduce biases in metagenomic libraries, in particular over
122 representation of ssDNA phages within samples [19–21]. To overcome the problem of library input
123 requirements, MDA for ONT library preparation, combined with unamplified short read libraries for
124 quantification have been utilised [22]. Alternatively, ONT sequencing (minION) of long-read linker
125 amplified shotgun libraries (LASL), to sequence PCR products on a minION, combined with Illumina
126 short reads were used in an approach dubbed virION [14, 23]. Both approaches were successful in
127 increasing the number and completeness of viral genomes.

128

129 While the number of viromes that utilise ONT alone or in combination with Illumina sequencing is
130 slowly increasing [14, 22–25], reports of utilising PacBio sequencing for viromes are scarce [26]. A
131 recent study predicted phages from a bacterial metagenome assembled from PacBio reads,
132 identifying phages not identified when the same sample was sequenced with short reads [26]. It is
133 not clear why there are not more viromes sequenced with long read technologies, as has become
134 commonplace for sequencing of bacterial metagenomes. Even for the sequencing of individual
135 phage isolates there are relatively few studies that have utilised long reads [27–30]. In part, this is
136 likely because the vast majority of phage genomes can be assembled from short read Illumina
137 sequences alone [31]. Thus, unlike sequencing their bacterial hosts, long reads do not provide the
138 immediate benefit of a better genome assembly for an isolate and thus the need to use them is
139 reduced. The lack of long-read data generally for phage isolates, combined with the lack of a
140 comparative benchmarked dataset comparing different methods is likely contributing to long read
141 sequencing not being widely adopted for viromes, despite clear benefits from the limited studies
142 performed to date. We aimed to understand how different sequencing technologies affect the
143 recovery of viral genomes from communities and the quality of the assembled genomes.

144

145 Here then, we sequenced a mock community of phages with three different sequencing technologies
146 (PacBio, minION and Illumina) in order to benchmark these different approaches and identify the
147 benefits and limitations of each approach.

148 **Methods**

149 **Mock Virome Community Preparation and Sequencing**

150 Phages (vB_Eco_SLUR29, vB_EcoS_swan01 [32], vB_Eco_mar001J1 [32], vB_Eco_mar002J2 [32], KUW1 (OQ376857), PARMAL1 (OQ376857), HP1 [31], DSS3_PM1, vB_Eco_mar005P1 [32], S-RSM4 [33], vB_Eco_mar003J3 [32], vB_Vpa_sm033, vB_VpaS_sm032, CDMH1 [31]) were propagated as previously described and DNA was extracted using the method of Rihtman et al (2016). DNA was quantified with the Qubit dsDNA high sensitivity kit. Φ X174 DNA was obtained from the spike in control provided with Illumina library preparation kits. Genomic DNA was combined to produce a mock community of fifteen phages that covered a range of lengths (44,509 - 320,253 bp) and molGC content (38% - 61%). Genomes were combined across a range of abundances (169,000 - 684,329,545 genome copies) within the mock community (Supplementary Table 1). Genome copies were estimated by using the formula: $(\text{ng of DNA} * 6.022 \times 10^{23}) / (\text{Genome Length} * 660 * 1 \times 10^9)$. The genomes were chosen to include both highly divergent and highly similar phages (Supplementary Table 2; Supplementary Figure 1).

162

163 Illumina library preparation was carried out using the NexteraXT library preparation kit, with a minor 164 modification to the number of PCR cycles as described previously [32]. In addition, no Φ X174 spike 165 was added to the library as it is part of the normal Illumina library preparation protocol. Sequencing 166 was carried out with a MiSeq 2 x 250 bp kit. For minION and PacBio sequencing, the DNA was 167 amplified prior to sequencing with the GenomiPhi V3 DNA Amplification Kit, following the 168 manufacturer's instructions. Eight individual amplification reactions were performed with 10 ng DNA 169 input for each amplification. Following amplification, DNA was treated with S1 nuclease with 10 U 170 per μ g of input DNA and the enzyme deactivated, prior to cleanup and concentration with a DNA 171 Clean & Concentrator-25 column (Zymo Research). Three independent amplification reactions were 172 sequenced via PacBio or ONT sequencing.

173

174 Libraries were prepared for minION sequencing using SQK-LSK109 (Version: 175 NBE_9065_v109_revB_23May2018) with the native barcoding kit, following the manufacturer's 176 instructions (Oxford Nanopore Technologies, Oxford, UK) with omission of the initial g-tube 177 fragmentation step. Base calling was carried out with Guppy v2.3.5, with reads demultiplexed using 178 Porechop [34]. PacBio sequencing was carried out at NU-OMICS (Northumbria University). Briefly, 179 genomic DNA was sheared using g-TUBE (Covaris, USA) to an average size of 8-10 kb and then 180 libraries were prepared using SMRTbell Template Prep Kit 1.0 (Pacific BioSciences, USA) as per 181 manufacturer's instructions and sequenced on the Sequel I system (Pacific BioSciences, USA). 182 Circular consensus reads were created in SMRTLink v6 (Pacific BioSciences, USA) and fastq files 183 were generated using the BAM to FASTX pipeline.

184

185 **Bioinformatics Analyses**

186 To determine coverage and depth, reads from each library were mapped to the 15 reference
187 genomes using Minimap2 v2.14-r892-dirty with “-ax sr”, “-ax map-ont”, or “-ax map-pb” for Illumina,
188 ONT and PacBio reads respectively [35]. Minimap2 output was piped and sorted using the Samtools
189 sort command to produce sorted bam files [36]. Coverage and depth were taken from the bam files
190 using the Samtools coverage command [36].

191

192 Assemblies were separately produced for the three libraries, and additional assemblies were
193 produced by pooling the three libraries together, resulting in four assemblies per read/assembler
194 combination. Illumina reads were trimmed with Trim Galore v0.4.3 prior to assembly [37]. Illumina
195 reads were assembled using SPADes v3.12.0 with parameters “--meta -t 16” [38]. Flye assemblies
196 were produced with parameters “--nano-raw/or --pacbio-raw --threads 90 --meta” [39]. Unicycler
197 assembly of long reads was used with default parameters [40], that utilise miniasm [41] for an overlay
198 consensus assembly followed by racon for polishing [42]. wtdbg2 was used with the parameters “-p
199 21 -k 0 -AS 4 -K 0.05 -s 0.05 -L 1000 --edge-min 2 --rescue-low-cov-edges -t 90” [43].

200

201 To determine whether using long and short reads together improved the assemblies, three methods
202 that utilised a hybrid approach were used. (1) Long read-only assemblies were polished with multiple
203 rounds of polishing using Pilon [44] (hereafter referred to as “polished”). (2) For a hybrid assembly
204 with Unicycler, long and short reads were provided with default parameters (hereafter referred to as
205 “hybrid”). (3) The hybrid Unicycler assemblies were combined with the Illumina-only assemblies and
206 de-replicated at 95% average nucleotide identity (ANI) over 80% genome length using the
207 ClusterGenomes script [45].

208

209 To assess completeness and quality, assemblies were compared to the 15 reference genomes using
210 metaQUAST v5.0.2 with default parameters [46]. All resultant plots were produced using ggplot2 in
211 R v3.5.1. When investigating the fidelity of assemblies to the reference genomes, we included
212 assemblies for which 50% of the genome was covered by contigs, no matter how fragmented the
213 assembly was (i.e., if 100 individual contigs mapped to 50% of genome length, despite the longest
214 contig only being 10% of genome length, this was still included. This was to exclude misassembly
215 data for which only small portions of genomes were assembled, potentially leading to under-
216 estimation of error frequencies). To investigate the effect of sequence depth on long read assembly,
217 reads mapping to the genome of interest were extracted and downsampled using seqtk sample with
218 -s100 to the desired depth.

219

220 To determine the effect of polishing long-read assemblies with short-reads on viral prediction
221 software, we processed the long-read assemblies and their polished counterparts using VIBRANT
222 v1.2.1 [47] with the following parameters “-t 8 -l 10000 -virome” and compared against DeepVirFinder

223 v1.0 [48] with contigs >10 kb and a P-value <0.05. Prodigal v2.6.2 with default settings was used for
224 predicting open reading frames on the vOTUs and the 15 reference genomes [49].

225

226 To investigate the effect of different sequencing platforms and assemblers on estimates of viral
227 diversity, we applied a typical virome analysis workflow to the assemblies. Each assembly was
228 separately processed using DeepVirFinder v1.0 [48]. Contigs \geq 10 kb or circular were included as
229 viral operational taxonomic units (vOTUs) if they obtained a P-value of <0.05. Reads from the
230 corresponding Illumina library were mapped to the assembly using Bbmap v38.69 at 90% minimum
231 ID and the ambiguous=all flag [50]. vOTUs were deemed as present in a sample if they obtained
232 \geq 1x coverage across \geq 75% of contig length [51]. The number of reads mapped to present vOTUs
233 were normalised to reads mapped per million. Relative abundance values were analysed using
234 Phyloseq v1.26.1 [52] in R v3.5.1 to calculate diversity statistics [53]. The number of predicted
235 vOTUs and alpha diversity statistics were compared to the genome copy numbers used in the
236 original mock community.

237 **Results**

238

239 **Mock Virome Composition**

240 To assess the performance of short, long, and hybrid sequencing approaches for viromic analyses,
241 we sequenced a mock community of 15 bacteriophage genomes with an Illumina MiSeq, PacBio
242 Sequel, and ONT minION. For Illumina sequencing, no MDA was used to provide a library as free
243 as possible from bias. For PacBio and ONT sequencing, the mock community was first amplified
244 with MDA to obtain sufficient material for library preparation and sequencing. The Illumina and ONT
245 libraries yielded similar amounts of data with 0.5 - 1.1 Gb and 0.6 - 1.1 Gb respectively, and 0.3 -
246 0.5 Gb from PacBio libraries. Pooling the libraries resulted in 2.4, 2.7 and 1.1 Gb for Illumina, ONT
247 and PacBio libraries respectively (Supplementary Table 3).

248

249 **Limits of Detection by Read Mapping**

250 First, we assessed the limits of detection of each sequencing platform using a mapping-based
251 approach, with detection of a genome set at 1x coverage across $\geq 97\%$ of a genome. Four phage
252 genomes were not detected at all (CDMH1, HP1, vB_Eco_mar005P1 and Φ X174) by any
253 sequencing technology (Figure 1A). The Illumina and ONT libraries detected a similar number of
254 genomes (8-10 genomes), with PacBio detecting 7-8 genomes (Figure 1B). Although Illumina and
255 ONT both recovered 8-10 genomes across all libraries, the average number of genomes detected
256 in a single Illumina library was higher than that of a single ONT library (Figure 1B). The least
257 abundant phage to be detected was S-RSM4 (465,530 copies) and was only detected by Illumina
258 sequencing, although a small percentage of the genome was covered in the PacBio and ONT
259 libraries. The least abundant phages detected in ONT and PacBio libraries were vB_VpaS_sm032
260 (52,465,265 copies) and J1 (53,672,906 copies), respectively.

261

262 The use of unamplified DNA for Illumina libraries allowed any effects of MDA to be identified in the
263 long read assemblies. Encouragingly, the abundance of a genome within a sample generally
264 correlated across different sequencing platforms, even after MDA for PacBio and ONT sequencing
265 (ONT vs Illumina $r=0.9903948$, PacBio vs Illumina $r=0.9883086$, ONT vs PacBio $r=0.9996938$)
266 (Figure 2A, B, C; Supplementary Table 4). However, it should be noted that phage Φ X174 was not
267 detected in any sample, suggesting we may have been overly cautious in the amount we added to
268 the mock community.

269

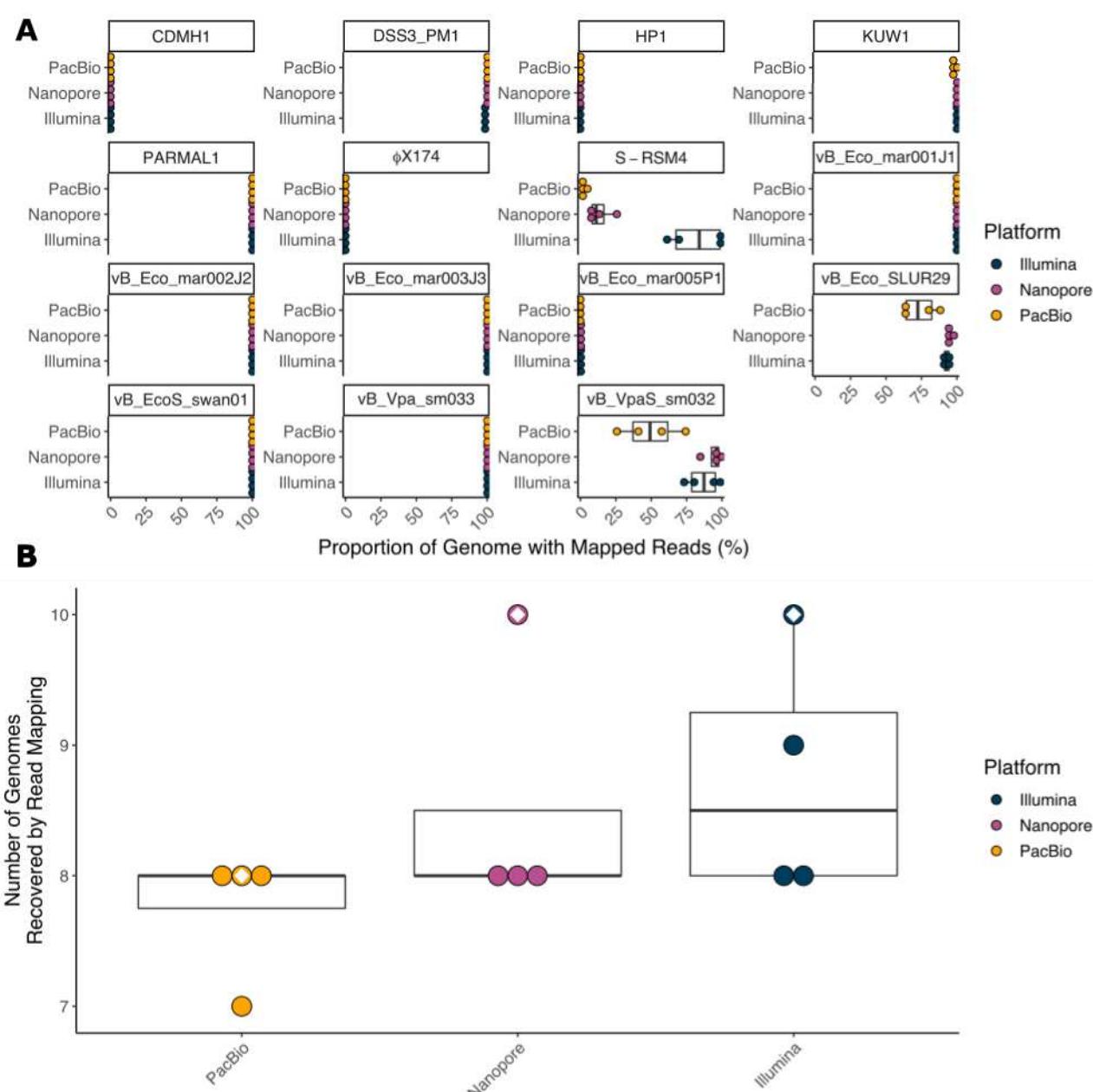
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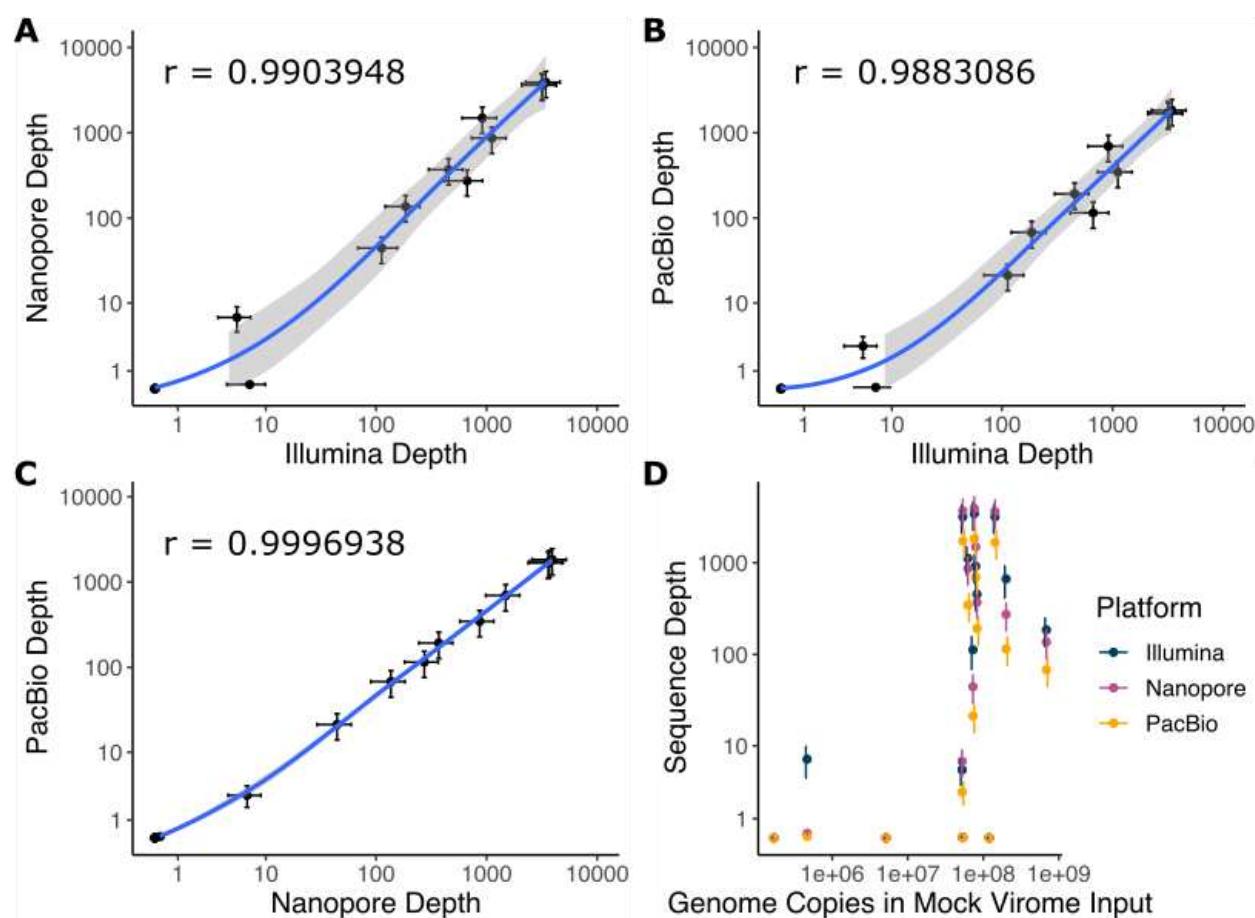
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275

276 **Figure 1.** Detection of genomes by read mapping. (A) Dot and boxplots showing the proportion of
277 each genome to which reads were mapped from each of the three sequencing platforms for library
278 repeats, and (B) the number of genomes detected by read mapping by each sequencing platform at
279 1x coverage over $\geq 97\%$ of genome length with the white diamond indicating the pooled library.

280



281

282 **Figure 2.** Comparison of sequencing depth between platforms. Correlation plots showing average
283 sequence depth of a genome between (A) Illumina and ONT, (B) Illumina and PacBio, and (C) ONT
284 and PacBio. An additional plot (D) shows sequence depth for the three sequencing platforms versus
285 the estimated number of genome copies in the original mock community from which DNA libraries
286 were prepared and sequenced. Values shown are the mean across three libraries and a pooled
287 library, with bars showing standard error.

288 **Assembly Results - Genome Recovery**

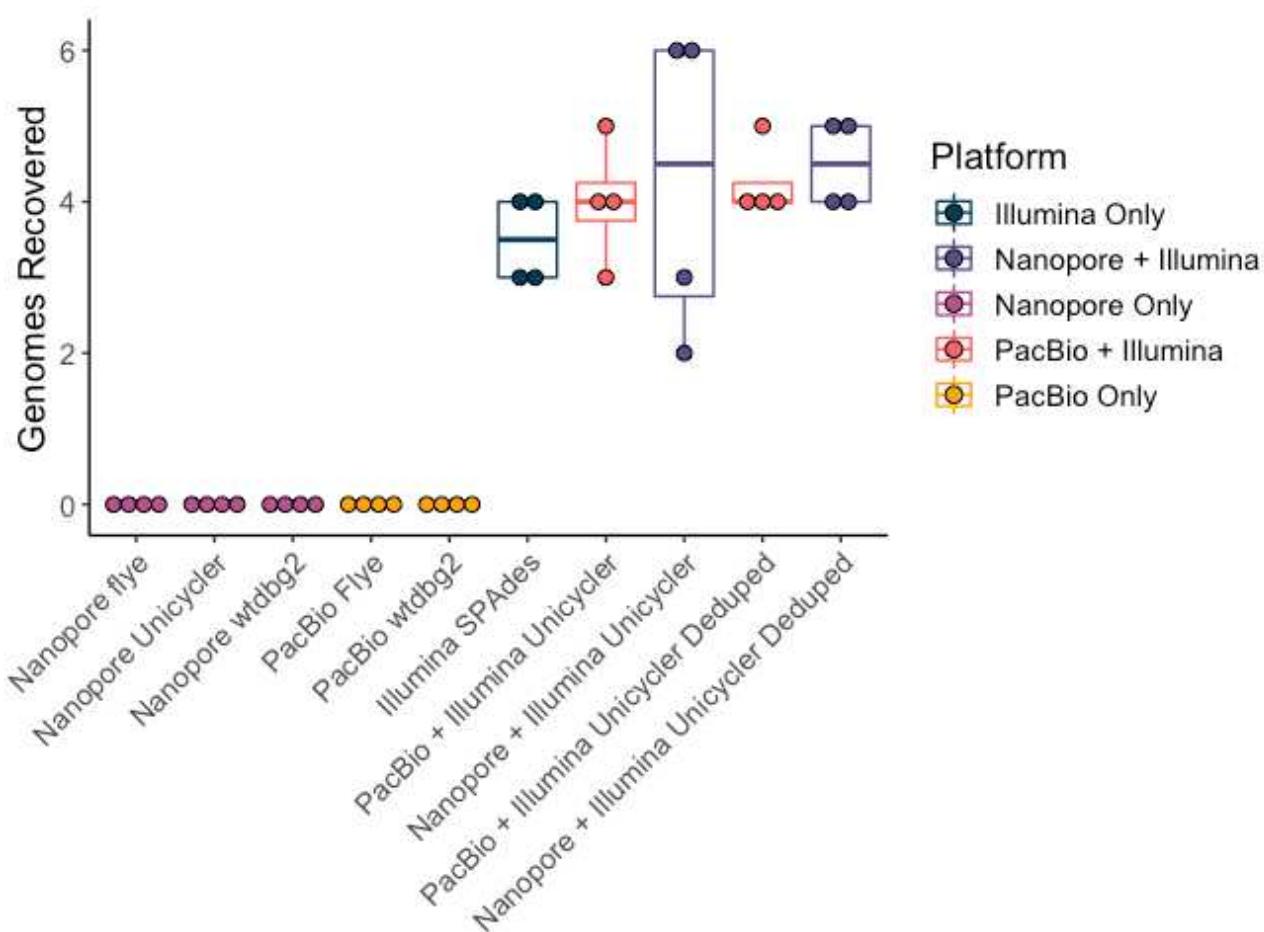
289 As assembly options for each read type were tested to optimise assembly methods, assemblies
290 were obtained for all samples and assemblers tested, with the exception of PacBio reads using
291 Unicycler (miniasm + racon) so these were excluded from further analysis. To investigate whether
292 combining read technologies led to more complete assemblies, PacBio and ONT reads were
293 separately assembled alongside Illumina reads using Unicycler to produce “hybrid” assemblies. The
294 hybrid assemblies were separately combined with Illumina only assemblies and de-replicated at 95%
295 average nucleotide identity (ANI) over 80% length to produce “deduped” assemblies [54].

296

297 For individual sequencing platforms, only short reads (Illumina) resulted in any completely
298 assembled genomes (3-4) (Figure 3; Supplementary Figure 2). Despite having >1,000x coverage of
299 some genomes in long-read-only libraries the reads did not assemble into complete genomes,
300 suggesting that coverage is not a limitation and may well be a hindrance to assembly
301 (Supplementary Table 4). The Illumina + ONT hybrid assembly (Unicycler) recovered the most
302 genomes (2-6 genomes) (Figure 3; Supplementary Figure 2). The addition of long reads to short
303 reads increases the number of genomes recovered (particularly ONT).

304

305



306

307 **Figure 3.** Comparison of genome recovery across sequencing technologies and assemblies. Dot
308 and boxplot showing the number of genomes fully assembled within each assembly (successful
309 assembly defined as a single contig covering 97% of genome length), with the reads used for
310 assembly shown in different colours.

311 **Assembly Results - Limits of Detection for Assembled Genomes**

312 The phage with the lowest input abundance to be recovered in a single contig within any assembly
313 was vB_Eco_mar001J1 (53,672,905 genome copies), which was recovered in the ONT + Illumina
314 hybrid assembly. The least abundant genome to be recovered from an Illumina only assembly, and
315 a PacBio + Illumina hybrid assembly was KUW1 (72,995,151 genome copies), suggesting the
316 addition of ONT reads to Illumina reads improves the recovery of lowly abundant genomes, but the
317 addition of PacBio reads to the same Illumina reads did not.

318

319 Whilst not the genome with lowest input abundance, KUW1 was recovered from Illumina libraries at
320 a lower average sequence depth than any other genome (139 x coverage in the largest Illumina
321 library, 225 x coverage in the pooled library). Furthermore, KUW1 was not assembled in the two
322 smaller Illumina libraries (37 and 49 x coverage obtained), suggesting that the depth of Illumina
323 sequencing impacts the limits of detection.

324

325 As previously discussed (**Limits of Detection by Read Mapping**), the least abundant genomes to
326 be detected by read mapping were vB_VpaS_sm032 and S-RSM4. Summed Illumina contigs from
327 the pooled library mapped to 87% and 97% of vB_VpaS_sm032 and S-RSM4 respectively. However,
328 the longest individual contigs only covered a small fraction of the genomes (22% and 9%
329 respectively). The average read depth for vB_VpaS_sm032 and S-RSM4 contigs was 10 x over
330 98.7% and 14 x over 99.6% of genome lengths respectively in the pooled Illumina library. Manual
331 inspection of alignments revealed that breaks in the assemblies typically coincided with a drop in
332 read coverage which was often associated with a sudden and sharp change in mol%GC (either
333 upwards or downwards; Supplementary Figure 3; Supplementary Table 4) [55–57].

334

335 The longest genome to be recovered in a single contig, vB_Vpa_sm033 (320,253 bp), was
336 assembled in Illumina-only, Illumina + PacBio, and Illumina + ONT assemblies. The shortest genome
337 to be recovered in a single contig, KUW1 (44,509 bp), was assembled in Illumina-only, Illumina +
338 PacBio, and Illumina + ONT assemblies. Whilst KUW1 was assembled from only one individual
339 Illumina library, it was assembled in two each of the ONT + Illumina, and PacBio + Illumina hybrid
340 assemblies. Furthermore, dereplicating these hybrid assemblies with the Illumina-only assemblies
341 led to KUW1 being assembled in all individual libraries.

342 **Assembly Results - Resolution of Highly Similar Genomes**

343 It was possible to assemble a single genome that was representative of vB_Eco_mar001J1 and/or
344 vB_Eco_mar002J2 from Illumina + ONT hybrid assemblies, rather than two genomes, perhaps
345 unsurprisingly given there is >99% ANI between them (Supplementary Figure 1). A single genome
346 of vB_EcoS_swan01 was obtained using an Illumina + ONT hybrid assembly, which has ~80% ANI
347 with vB_Eco_SLUR29 (Supplementary Figure 1). However, the genome of vB_Eco_SLUR29 could
348 not be resolved.

349

350 **Assembly Results - Comparison of Long Read Assemblers**

351 Despite high read coverage, long-read only assemblies failed to recover a complete genome for any
352 of the 15 phage (Figure 3; Supplementary Table 4). To identify the optimal long-read only
353 assemblies, we used the NGA50 statistic (Supplementary Figure 4 & 5). While nine genomes were
354 detected by mapping long reads in at least one library, only eight are included in this analysis due to
355 the very low coverage of vB_Eco_SLUR29 recovered from any assembly. For this comparison, we
356 also included long read assemblies that were polished with Illumina reads, as this was found to affect
357 the results.

358

359 The NGA50 values averaged across the eight genomes and four libraries obtained from ONT
360 assemblies were higher than those from PacBio. Again this varied depending on the assembler
361 used. ONT reads assembled with Flye, wtdbg2 and Unicycler obtained average NGA50 values of
362 28%, 10% and 8% respectively, whereas PacBio reads obtained values of 5% and 4% for wtdbg2
363 and Flye assemblies respectively. ONT reads assembled with Flye typically produced the longest
364 alignments in relation to reference genomes. The performance of Flye with individual libraries was
365 higher than that in the pooled library, with the average NGA50 values as a proportion of genome
366 length being 27%, 39% and 30% for individual libraries, and only 16% for the pooled library
367 (Supplementary Figure 4 & 5). Conversely, the highest NGA50 values for ONT reads assembled
368 with Unicycler were obtained from the pooled library (26%), and 3%, 1% and 0.1% from individual
369 libraries (Supplementary Figure 4 & 5). Thus, pooling reads was both detrimental or advantageous,
370 depending on the assembler used.

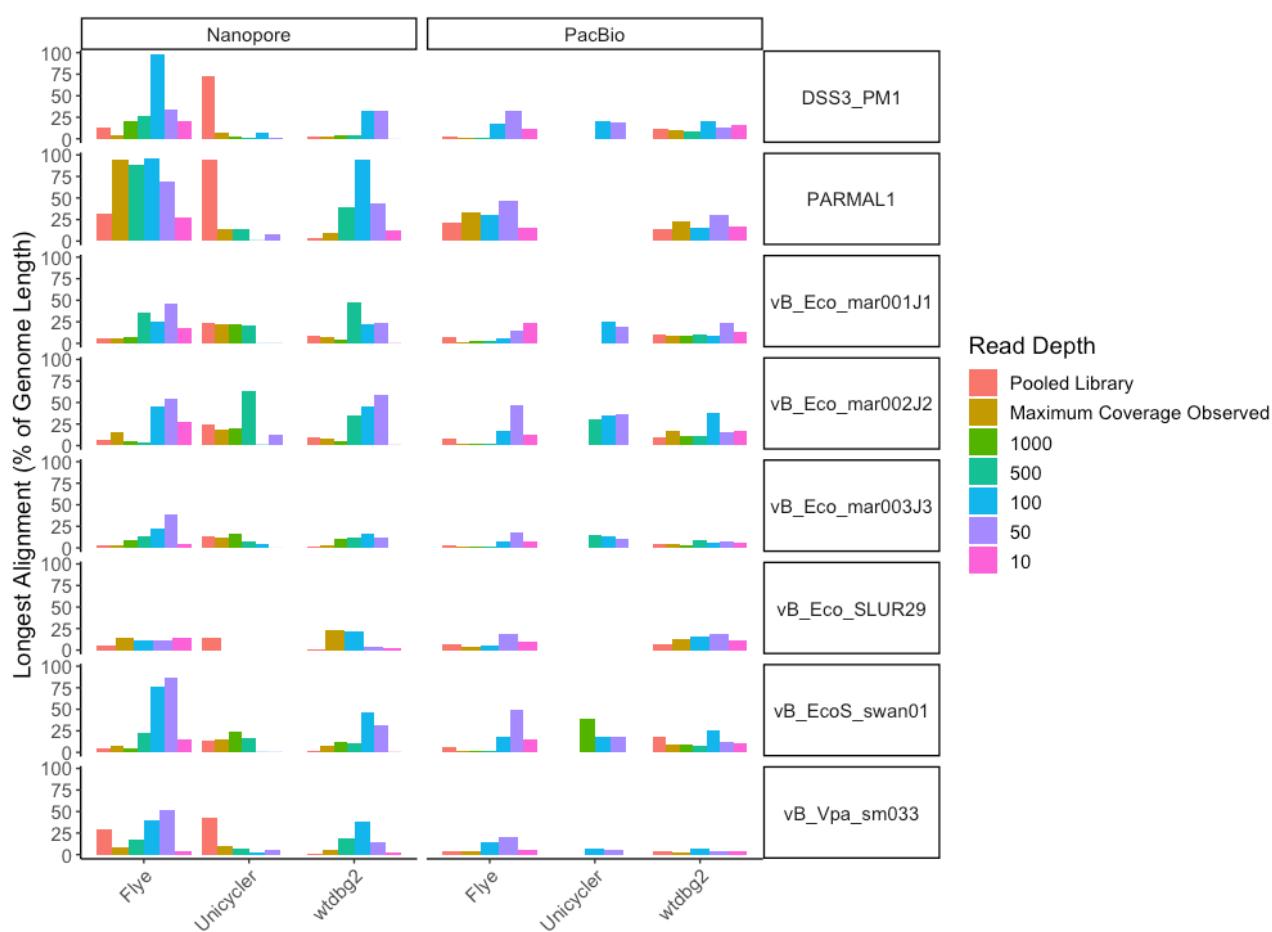
371

372 For all five long-read only assemblies, its polished counterpart typically obtained more complete
373 assemblies than before polishing (Supplementary Figure 4 & 5). This is particularly apparent with
374 the individual ONT libraries assembled with Unicycler which went from obtaining some of the lowest
375 average NGA50 values to having some of the highest (3%, 1% and 0.1% increasing to 43%, 35%
376 and 29% respectively), suggesting the ONT-Unicycler assemblies contained contigs below the 90%
377 ANI threshold required for mapping and were only aligned to the reference genomes post-polishing
378 (Supplementary Figure 4 & 5). A post-polish increase was more modest in PacBio assemblies, which
379 increased from 3.7% to 3.8% and from 4.9% to 5.1% for the Flye and wtdbg2 assemblies respectively

380 (Supplementary Figure 4 & 5). Manual inspection of contig alignments from long-read only
381 assemblies to the reference genomes revealed large numbers of overlapping misassembled contigs
382 that were not resolving into a single assembly. The lack of contiguity is potentially due to the higher
383 error frequency associated with ONT and PacBio reads.

384

385 To determine if the long-read assemblies were failing due to high sequencing depth, reads mapping
386 to genomes with ≥ 100 x coverage were extracted, randomly downsampled to different coverage
387 levels, and re-assembled. For both ONT and PacBio, and all assemblers used, downsampling the
388 reads prior to re-assembly led to more complete assemblies (Figure 4; Supplementary Table 5).
389 Furthermore, successful assemblies using PacBio reads with Unicycler were only obtained after
390 downsampling. However, Nanopore reads assembled with Unicycler obtained the most complete
391 assemblies using the original mixed community reads (i.e., rather than reads mapping to that
392 genome only).



393

394 **Figure 4.** Effect of read depth on long-read assembly. To determine if read depth was a factor in
395 genome assembly when using long reads. Reads were first mapped to individual genomes, then
396 randomly subsampled from the Maximum coverage obtained in a sample, down to give 1000x, 500x,
397 100x, 50x and 10x coverage per genome, before being assembled. The proportion of the original
398 reference genome (%) that was assembled into a single contig was then determined.

399

400 **Assembly Results - SNPs, INDELs and Mis-assemblies**

401 To investigate the fidelity of assemblies, we compared assembled contigs to the mock community
402 reference genomes to identify the frequency of SNPs and INDELs per 100 kb. Assemblies with the
403 highest fidelity would be expected to have the smallest number of SNPs and INDELs compared to
404 the known references. Both SNPs and INDELs were calculated for genomes where $\geq 50\%$ of the
405 genome was covered by contigs. Using Illumina only reads resulted in the lowest number of SNPs
406 per 100 kb (503) with ONT long-read only assemblies having the highest number of SNPs. The
407 number of SNPs in long read assemblies was also dependent on the assembler used. Using ONT
408 reads with Flye (2038) resulted in fewer SNPs than wtdbg2 (3545) or Unicycler (4159)
409 (Supplementary Figure 6A & 7). Conversely, PacBio reads assembled with Flye had a higher SNP
410 frequency (2180) than those produced using wtdbg2 (1806) (Supplementary Figure 6A & 7).

411

412 A similar pattern of results was observed for the number of INDELs per 100 kb, although a much
413 larger difference between the different read technologies was observed. Again, the assembler used
414 had an impact on the frequency of INDELs. ONT assemblies produced by far the largest number of
415 INDELs when using Unicycler (miniasm + racon; 4521) compared with Flye (1702) and wtdbg2
416 (1982) assemblies (Supplementary Figure 6B & 8). PacBio assemblies had far fewer INDELs than
417 ONT with far fewer INDELs observed in Flye assemblies (176) than wtdbg2 assemblies (946).
418 Illumina only assemblies had by far the smallest number of INDELs (14) (Supplementary Figure 6B
419 & 8).

420

421 Whilst long-read-only assemblies had a high frequency of SNPs and INDELs, hybrid assemblies
422 produced with Unicycler that combined Illumina reads with ONT or PacBio reads obtained SNP and
423 INDEL levels comparable to Illumina only assemblies (Supplementary Figure 6B). Thus, there is a
424 clear advantage to using a hybrid assembly as it reduces the number of errors.

425

426 **Effect of Polishing Long-Read Assemblies on SNPs, INDELs and ORF Prediction**

427 Using short reads to polish contigs produced from long read assemblies generally reduced the
428 number of SNPs per 100 kb, although this was dependent on the specific assembly. Polishing ONT
429 assemblies produced with Unicycler and wtdbg2 decreased the frequency of SNPs by 42% and
430 26%, respectively (Figure 5A). Polishing the Flye assembly resulted in a small increase in the
431 number of SNPs (Figure 5A). Rather than introducing errors, this is likely as a result of contigs prior
432 to polishing having SNP frequencies that prevented recruitment to a reference genome at 90%
433 identity by mapping. Post polishing, these contigs are now recruited to genomes, but still contain a
434 number of SNPs (Figure 5A). With PacBio reads assembled with Flye, polishing had no effect on the
435 number of SNPs (Figure 5A). For the PacBio wtdbg2 assembly, the number of SNPs increased, as
436 observed with ONT reads assembled with Flye. Again, this increase is likely due to the increased
437 number of contigs that are mapped to the reference genome (Figure 5A).

438

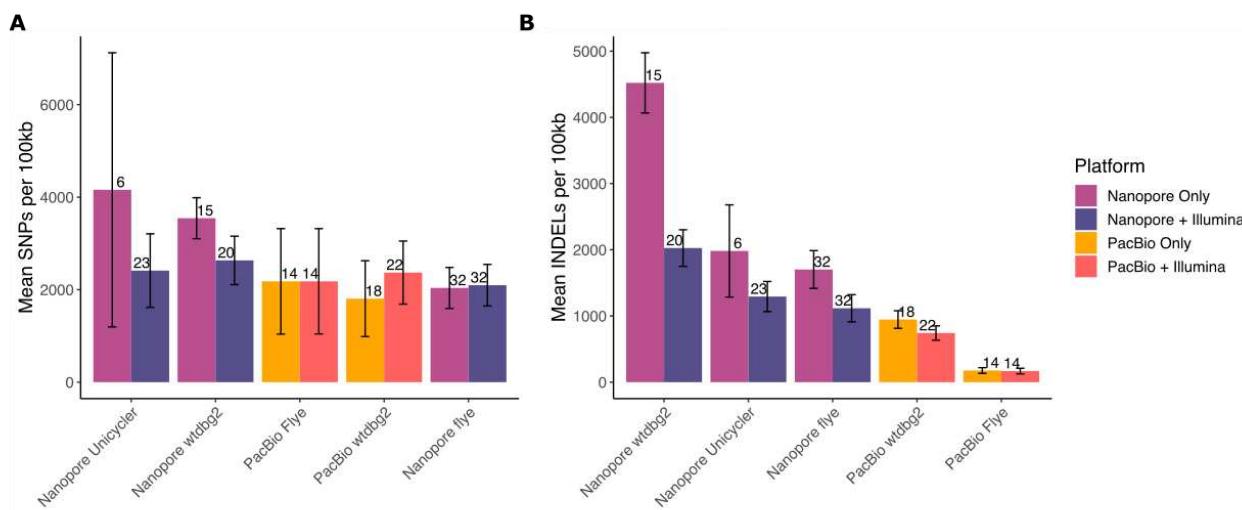
439 The effect of polishing on the frequency of INDELs was more apparent. The ONT assemblies had a
440 higher number of INDELs than PacBio assemblies prior to polishing (Figure 5B) and thus were of
441 lower quality. For ONT reads assembled with Unicycler (miniasm + racon), which had the highest
442 frequency of INDELs initially, there was a 55% decrease in INDELs post polishing (Figure 5B). For
443 ONT reads assembled with wtgb2 and Flye, there was a ~34% decrease in the number of INDELs
444 per 100 kb (Figure 5B). For PacBio assemblies the starting frequency of INDELs was lower than
445 ONT prior to polishing but polishing with Illumina reads still resulted in a 21% and 4.5% decrease in
446 INDEL frequency for wtgb2 and Flye assemblies respectively (Figure 5B).

447

448 As assembly errors can have an effect on ORF prediction and functional annotation [58], we
449 investigated the number and length of predicted ORFs on contigs which mapped to reference
450 genomes before and after polishing. Polishing with short reads had the greatest effect on ONT data
451 regardless of the assembler used, with mean ORF length increasing for all assemblies. Both
452 Unicycler and wtgb2 observed mean ORF length increases of ~66%, with a ~24% increase for Flye
453 (Figure 6). For PacBio assemblies, the increases in mean ORF length were more modest at ~11%
454 for wtgb2 assemblies and ~0.2% for Flye assemblies (Figure 6). While there was an increase in
455 mean ORF length for all combinations of reads and assemblers post-polishing, all combinations were
456 still smaller than the value obtained for the 15 reference genomes (Figure 6).

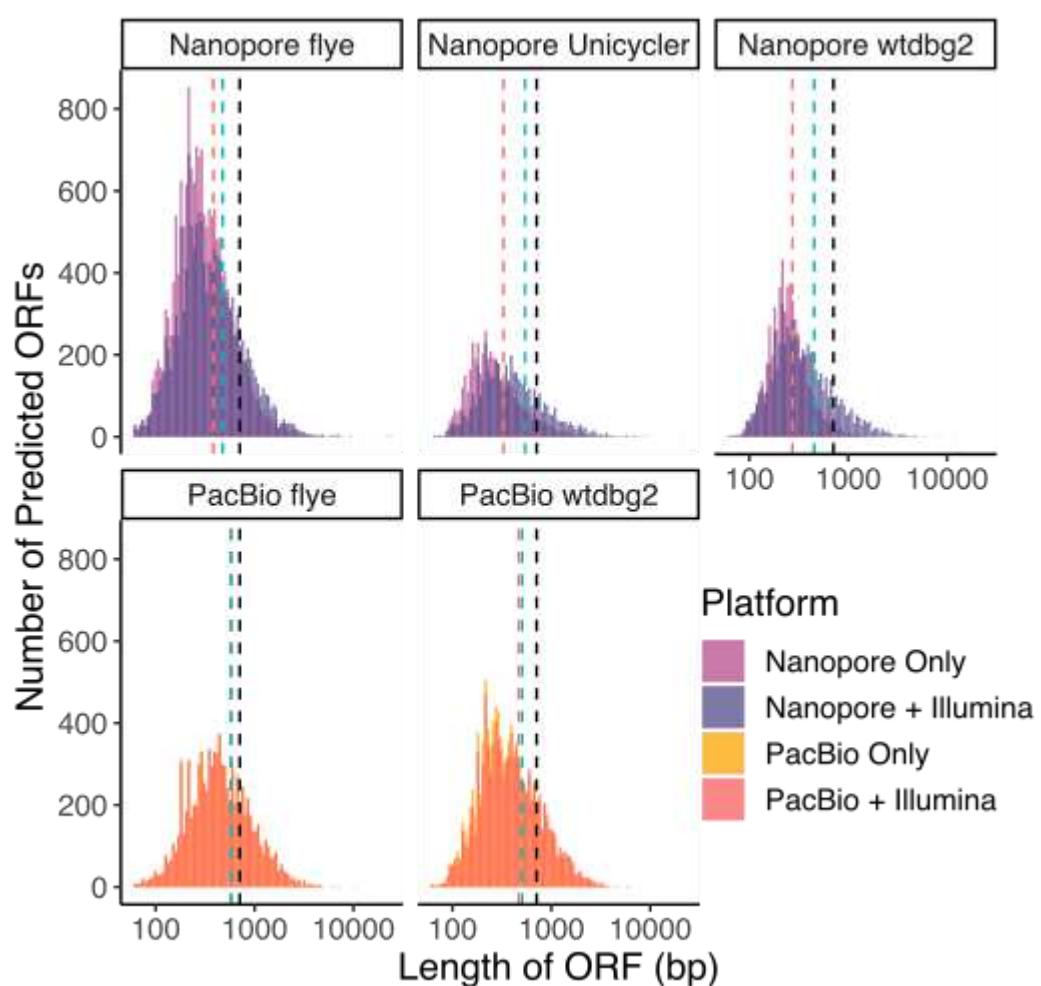
457

458



459

460 **Figure 5.** Effect of polishing on error rate. SNPs and INDELs were identified in contigs from
461 nanopore only, nanopore contigs polished with illumina reads, PacBio only and PacBio contigs
462 polished with illumina reads. The number of SNPs (A) and INDELs are expressed as the number
463 per 100 kb of reference genome, where at least 50% of the reference genome was recovered by
464 contigs, where at least 50% of the reference genome was recovered by contigs. Error bars are
465 standard error of the mean, and the number above the bar indicates the number of genomes included
466 in the mean calculation (from a total possible maximum of 60 (15 genomes, 4 assemblies)).



467

468 **Figure 6.** The effect of polishing long-read assemblies on predicted ORF lengths. ORF length was
469 calculated from nanopore only contigs, nanopore contigs polished with illumina reads, PacBio only
470 contigs and PacBio contigs polished with illumina reads. With contigs obtained using Flye, wtdbg2
471 and Unicycler assemblers. Histograms show the distribution of predicted ORF length for sequencing
472 type (Nanopore or PacBio) and assembly algorithm. The expected mean ORF length from the
473 reference genomes is represented as dashed vertical line (709 bp; black), compared to the mean
474 value before (red) and after (blue) polishing.

475 **Effect of Polishing Long-Read Assemblies on Viral Prediction**

476 Many viral prediction programs use similarity of predicted proteins to known hallmark proteins for
477 virus prediction. Thus, truncated proteins may alter the ability to predict viral contigs from viromes.
478 To test if truncated proteins affect virus prediction, we compared VIBRANT [47] which in part uses
479 predicted proteins, and DeepVirFinder [48] a K-mer based prediction system on all assembled
480 contigs. Although we utilised purified phage isolates to create the mock community, up to 20% of the
481 reads from Illumina libraries did not map to the reference genomes. Therefore, we utilised this
482 unfortunate level of contaminating host bacterial DNA for benchmarking viral prediction. To
483 determine how many predictions represented “true” viral predictions, we mapped the predicted
484 vOTUs against the reference genomes.

485

486 For DeepVirFinder predictions, there were minimal differences in the number of predicted viral
487 contigs (vOTUs) before and after polishing for all assemblies. The largest difference was observed
488 for ONT reads assembled using Flye (61 before, 52 after; Supplementary Figure 9; Supplementary
489 Table 7). However, there was a marked increase in the number of vOTUs that could be verified as
490 phage. For Flye, the number that could be verified as phage increased from 82% to 96% after
491 polishing, wtdbg2 assemblies increased from 83% to 98%, and Unicycler assemblies increased from
492 93% to 99%. Thus, polishing ONT assemblies with Illumina reads led to an overall decrease in the
493 number of erroneous viral predictions when using DeepVirFinder (Supplementary Figure 9;
494 Supplementary Table 7). For the PacBio assemblies, there was no difference in the number of
495 predicted vOTUs and those that could be verified as phage when using DeepVirFinder
496 (Supplementary Figure 9; Supplementary Table 7).

497

498 When using VIBRANT for prediction, polishing of PacBio assemblies had no or minimal effect on the
499 number of predictions or the number of verified predictions (Supplementary Figure 9; Supplementary
500 Table 7). However, the polishing of ONT assemblies led to vastly different numbers of predicted
501 vOTUs, and this varied with the assembler used. The largest difference was for the ONT wtdbg2
502 assembly, decreasing from 199 to 133 predicted vOTUs, and the proportion of verified phages
503 increased for all ONT assemblies after polishing. For Flye, the number of verified phages increased
504 from 75% to 81%, Unicycler increased from 72% to 96%, and wtdbg2 increased from 51% to 87%
505 (Supplementary Figure 9; Supplementary Table 7).

506

507 Thus, when using DeepVirFinder there was minimal impact of polishing on the prediction of vOTUs
508 from either PacBio or ONT assemblies. However, there were clear benefits to the polishing of ONT
509 assemblies when using VIBRANT for vOTU prediction, as the percentage of vOTUs that could be
510 verified to be phage increased post polishing.

511

512

513 **Effect of sequencing technology on predicted virome diversity**

514 Having established DeepVirFinder generally performed better for all sequencing technologies, we
515 utilised the output of DeepVirFinder predictions to assess how diversity statistics of the mock
516 community varied with sequencing technology and assembly.

517

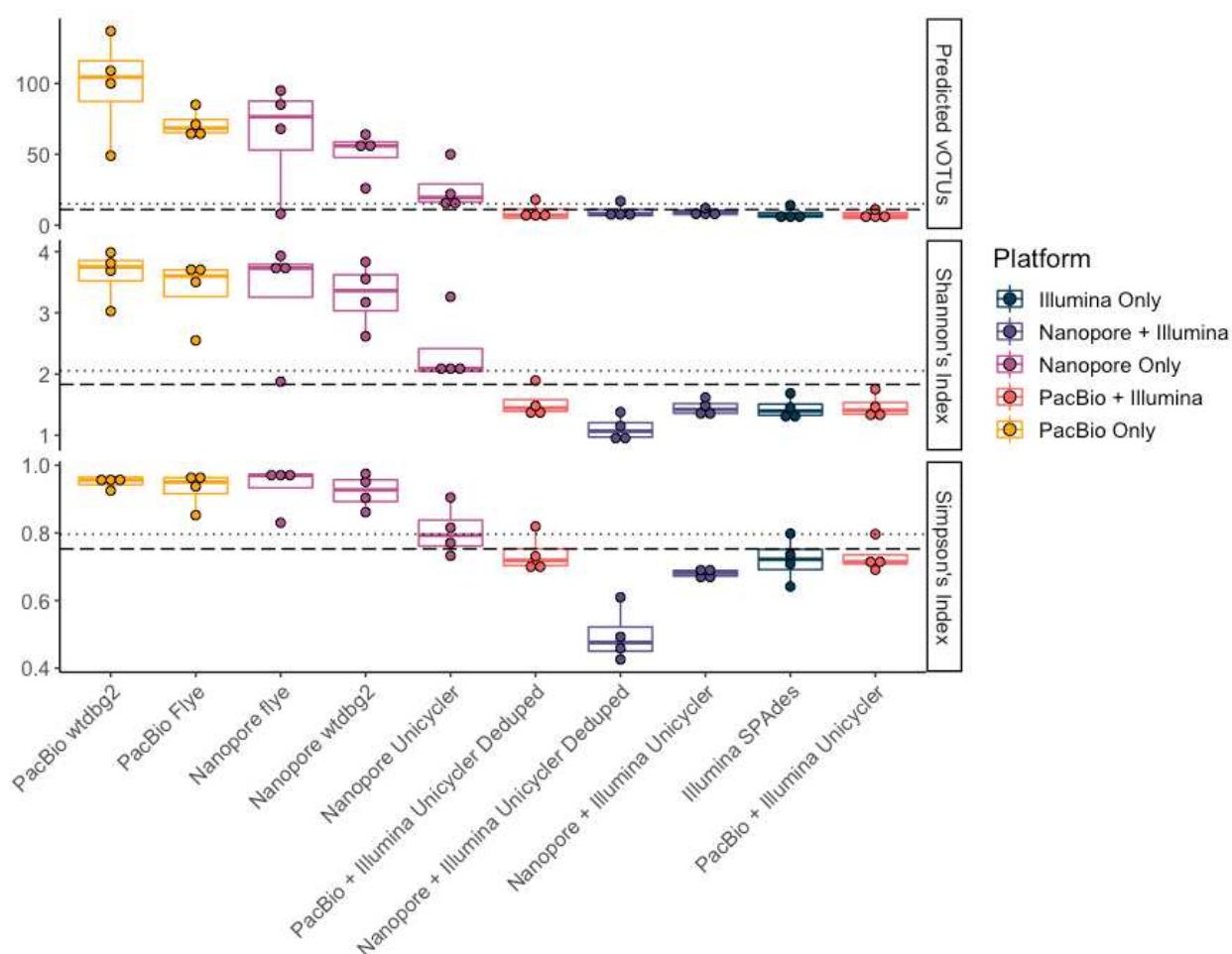
518 Alpha diversity was assessed using predicted vOTUs, Shannons's index and Simpson's index;
519 overall the same general trend was observed for each metric (Figure 7; Supplementary Table 8).
520 When using long read assemblies there was an overprediction of alpha diversity (ONT: median
521 vOTUs 54.5, PacBio: median vOTUs 77.5; Known number vOTUs 15). In contrast, when using
522 Illumina and Illumina + ONT/PacBio hybrid there was an underestimation of alpha diversity (ONT-
523 Illumina hybrid: median vOTUs 8.5, PacBio-Illumina hybrid: median vOTUs 6.5, Illumina: median
524 vOTUs 6.5). Within this general trend, there was further variation with the method used for assembly.
525 While the use of Illumina or Illumina +ONT/PacBio generally led to an underestimation of diversity,
526 it was closer to the known diversity measurement than the use of long reads alone. When using long
527 reads alone, using ONT assembled with Unicycler give the closest estimate of the true diversity of
528 the mock community.

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534 **Figure 7.** The effect of sequencing platform and assembler on diversity estimates. Boxplots showing
535 the number of predicted vOTUs for mock virome analysis (top), and Shannon's index (middle) and
536 Simpson's index (bottom) alpha diversity measures. Dotted lines indicate true values for mock
537 virome input, and dashed lines indicate true values excluding genomes that were not detected by
538 read mapping in any library.

539 **Discussion**

540 The use of long read sequencing technologies is becoming increasingly common for the sequencing
541 of metagenomics samples, in particular those that focus on the bacterial community. A number of
542 studies have demonstrated the advantage of long-reads in assembling complete genomes from a
543 variety of samples [25, 59–61]. There have also been a number of studies benchmarking the
544 assembly and/or recovery of bacteria from mock communities using long-reads [62, 63], along with
545 benchmarking of assembly algorithms for prokaryotic genomes (excluding phages) [64, 65].
546 However, there are no such comprehensive studies that have directly compared Illumina, ONT, and
547 PacBio sequencing technologies for the study of viromes.

548

549 Previous benchmarking of short-read assemblers has demonstrated minimal differences in genome
550 recovery of phage genomes when comparing multiple assemblers on a mock viral community [51].
551 For this reason, we chose only one short-read assembly algorithm: SPAdes. For long-read
552 assembly, we chose three frequently used approaches of Unicycler (miniasm + racon), Flye, and
553 wtdgb2 as well as using Unicycler for a direct hybrid assembly. For long read sequencing alone, we
554 were unable to obtain assemblies from PacBio reads with Unicycler, even when combining all three
555 libraries, suggesting it was not a lack of coverage.

556

557 When using a single sequencing technology, only Illumina reads resulted in the complete assembly
558 of a phage genome within any sample. Utilising a hybrid approach increased the number of genomes
559 that could be assembled, with ONT + Illumina reads assembled with Unicycler (miniasm + racon)
560 recovering the largest number of genomes, whereas the addition of PacBio reads did not result in
561 the same increased recovery of genomes. However, this may well be due to the reduced yield of
562 PacBio reads compared to ONT reads. Thus, increased yield of PacBio data might improve this
563 metric. However, it was clear for both ONT and PacBio that very high coverage of specific genomes
564 within a sample was detrimental to genome assembly, with subsampling of reads improving the
565 length of the contig recovery. Thus, digital normalisation of reads may improve recovery of longer
566 contigs as has been found in other systems [66]

567

568 The combination of long and short reads improving recovery of assembled genomes is consistent
569 with previous benchmarking of a mock viral community using a virION approach [14]. Unlike the
570 virION approach, we were only able to assemble a complete genome with just long-reads after
571 downsampling to lower read depths prior to assembly. However, direct comparison between the
572 studies is difficult given the different phages used in each mock community. Here, we utilised MDA
573 application to provide sufficient material for long-read sequencing, whereas the virION utilises PCR
574 to provide sufficient material [14, 23]. The virION approach has comprehensively demonstrated that
575 the relative abundance of phages is maintained due to the LASL-PCR approach [14, 23]. Here, we
576 observed a strong correlation in the abundance of phages in the un-amplified Illumina viromes and

577 amplified long-read viromes. However, we are cautious in the interpretation of this data. The DNA
578 from a ssDNA phage (Φ X174) was spiked into our mock community at a deliberately low level, as
579 we wanted to avoid flooding our amplified DNA with ssDNA given known biases of MDA. However,
580 given the lack of detection of Φ X174 in any samples, we may have been overly cautious in the
581 amount added. Thus, when ssDNA phages are present in a community, it is likely the biases
582 observed previously are still likely to hold true [19–21].

583

584 When assessing any individual sequencing technology alone, the lowest number of SNPs or INDELs
585 observed when using Illumina reads, with ONT assemblies having a larger number of SNPs, and in
586 particular INDELs, compared to PacBio assemblies. Thus, the short read assembly produced the
587 highest fidelity genomes. Both INDELs and SNPs were also affected by the method used for
588 assembly. For ONT reads, Flye produced assemblies with the lowest number of INDELs or SNPs
589 compared to wtgb2 and Unicycler (miniasm + racon). It is likely for ONT data that the number of
590 SNPs and INDELs will further decrease with improvements in accuracy reported for both R10 flow
591 cells and the latest base calling algorithms that have been developed since this data was collected,
592 as this data was generated with R9 flow cells. In contrast, Flye assemblies of PacBio reads had the
593 lowest number of SNPs, but the highest number of INDELs. Thus, the choice of assembly method
594 should be adjusted for the type of long-reads being used. The addition of short reads to polish the
595 long read assemblies resulted in a reduction of both SNPs and INDELs, as has been observed in
596 other studies [14, 22, 26].

597

598 While the combination of both short Illumina reads with long reads resulted in the “best” overall
599 assemblies, it may well not be feasible to sequence samples with both technologies. Therefore, we
600 treated the assemblies from multiple approaches to assess how the different approaches affected
601 the predicted diversity of the sample. Although polishing long read assemblies had a significant
602 impact on reducing the number of SNPs and INDELs, there was minimal effect on the number of
603 predicted contigs that were viral when using DeepVirFinder for prediction. However, VIBRANT,
604 which in part utilises the identification of hall-mark phage genes and was more sensitive to the higher
605 error rates of un-polished long-read assemblies, obtained far fewer erroneous viral predictions post-
606 polishing. Thus, choice of sequencing technology may have ramifications for downstream choices
607 in viral prediction software.

608

609 **Conclusions**

610 We have benchmarked Illumina, ONT, and PacBio sequencing platforms for virome analysis using
611 a number of read and assembler combinations and offer recommendations for the community: (i) if
612 only using one sequencing platform, Illumina performs best at genome recovery and has the lowest
613 error rates; (ii) the addition of long-reads to Illumina reads improves the assembly of lowly abundant
614 genomes, particularly ONT; (iii) whilst long read assemblies, particularly ONT, have higher error

615 frequencies, polishing with Illumina reads can reduce these errors to levels comparable with Illumina-
616 only assemblies; (iv) down-sampling of long reads may aid assembly; and (v) the choice of
617 sequencing platform should be considered when making downstream analysis decisions, such as
618 assembler algorithm and viral prediction software.

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624 **Data Availability**

625 All reads from virome sequencing were submitted to the ENA under study PRJEB56639. The
626 assemblies are provided via FigShare ([10.25392/leicester.data.21346935](https://doi.org/10.25392/leicester.data.21346935))

627

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632

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634 Some text

635

636 **Author Contributions**

637

638 NB &, DS, AM conceived the idea. AM, BR, SM, TR, AN, YC, MC and DJS provided funding
639 and/or strains. AM, DJS, DS, MJ and JH supervised the work. RC analysed the data. RC and AM
640 drafted the manuscript, with all authors contributing to editing of the final manuscript.

641

642

643 **Conflicts of Interest**

644 The authors declare that there are no conflicts of interest.

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