

1 **Evaluation of strategies for the assembly of diverse bacterial genomes using MinION long-**
2 **read sequencing**

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12 **Abstract**

13 **Background:** Short-read sequencing technologies have made microbial genome sequencing
14 cheap and accessible. However, closing genomes is often costly and assembling short reads
15 from genomes that are repetitive and/or have extreme %GC content remains challenging. Long-
16 read, single-molecule sequencing technologies such as the Oxford Nanopore MinION have the
17 potential to overcome these difficulties, although the best approach for harnessing their
18 potential remains poorly evaluated.

19 **Results:** We sequenced nine bacterial genomes spanning a wide range of GC contents using
20 Illumina MiSeq and Oxford Nanopore MinION sequencing technologies to determine the
21 advantages of each approach, both individually and combined. Assemblies using only MiSeq
22 reads were highly accurate but lacked contiguity, a deficiency that was partially overcome by
23 adding MinION reads to these assemblies. Even more contiguous genome assemblies were
24 generated by using MinION reads for initial assembly, but these were more error-prone and
25 required further polishing. This was especially pronounced when Illumina libraries were biased,
26 as was the case for our strains with both high and low GC content. Increased genome contiguity
27 dramatically improved the annotation of insertion sequences and secondary metabolite
28 biosynthetic gene clusters, likely because long-reads can disambiguate these highly repetitive
29 but biologically important genomic regions.

30 **Conclusions:** Genome assembly using short-reads is challenged by repetitive sequences and
31 extreme GC contents. Our results indicate that these difficulties can be largely overcome by
32 using single-molecule, long-read sequencing technologies such as the Oxford Nanopore
33 MinION. Using MinION reads for assembly followed by polishing with Illumina reads generated

34 the most contiguous genomes and enabled the accurate annotation of important but difficult to
35 sequence genomic features such as insertion sequences and secondary metabolite biosynthetic
36 gene clusters. The combination of Oxford Nanopore and Illumina sequencing is cost effective
37 and dramatically advances studies of microbial evolution and genome-driven drug discovery.
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39

40 Introduction

41 Microbial genome sequencing has revealed how microorganisms adapt, evolve, and
42 contribute to health and disease [1, 2]. Although these were once enterprise-level projects,
43 technological advances have now reached the point where microbial genomes can be
44 sequenced routinely by small teams for a few hundred dollars [1]. These advances have
45 particularly been driven by the maturation of short-read sequencing technologies such as those
46 marketed by Illumina, which generate highly accurate reads (>99%) with lengths ranging from
47 75-300bp [1]. Although Illumina technologies currently dominate the sequencing market [1, 2],
48 difficulties remain that require further technological advances to fully realize the potential of
49 microbial genome sequencing.

50 By their very nature, short reads alone cannot disambiguate repetitive genomic regions
51 that are longer than their read length. Unfortunately, such repetitive regions are common in
52 microbial genomes [3–6], and include ribosomal genes, transposons, insertion sequences,
53 CRISPR arrays, *rhs* toxins, secondary metabolite biosynthetic gene clusters, and many others
54 [5]. Repeats lead to unresolvable loops in the underlying genome assembly graph that are
55 ultimately fragmented into contigs [5, 7]. Because of this, short reads are theoretically
56 incapable of closing most microbial genomes.

57 Genome assembly using most short-read datasets is also challenged by biases that occur
58 during library preparation and that cause some genomic regions to be excluded from
59 sequencing libraries. Common short-read library preparation methods (e.g., the Illumina
60 Nextera protocol) include PCR amplification steps that are biased against regions of the genome
61 with extreme GC contents [8–12]. Such regions are common among bacteria, whose average

62 GC content ranges widely from 25% to 75% [13]. Library preparation protocols that use
63 transposases to fragment DNA may also non-randomly shear genomes during library
64 preparation [14], causing further biases that limit the utility of short-read sequencing.

65 *De novo* genome assembly algorithms struggle to assemble genomes when intergenic
66 repeats are present and GC biases skew sequencing coverage [15, 16]. Fragmentation of such
67 genomes prevents the accurate identification of mobile elements, the detection of horizontal
68 gene transfers, the determination of gene copy number, and the discovery of biotechnologically
69 important gene clusters such as those that encode for the production of secondary metabolites
70 [16, 17]. These deficiencies significantly lower the informational value of draft-quality genomes
71 [18, 19].

72
73 Recently, long-read, single-molecule sequencing has overcome some of the deficiencies
74 of short-read sequencing. Library preparation protocols for single-molecule sequencing
75 typically avoid bias-prone PCR steps, and long read lengths span genomic repeats to
76 unambiguously resolve complex genomic regions. Some Illumina-based technologies such as
77 mate pair libraries and linked reads (e.g., as commercialized by 10X Genomics) can also
78 generate positionally linked sequences that span complex genomic repeats [1], but these
79 technologies still require library preparation protocols that are subject to the biases discussed
80 above. Pacific Biosciences (PacBio) currently markets the most widely used single-molecule
81 sequencing technology, which can produce > 7 Gb per run with read lengths averaging >12 kbp
82 [1]. Although the error rate for PacBio sequencing is high (~13%), these errors are near-
83 randomly distributed and can largely be corrected during assembly with adequate sequencing
84 coverage [7]. Unlike some Illumina sequencers (e.g., the MiSeq and MiniSeq), all PacBio

85 sequencers require considerable capital investment, limiting general access to these
86 technologies in individual laboratories. Nevertheless, PacBio sequencing has shown the
87 enormous potential for long-read, single-molecule sequencing to routinely produce high-quality
88 microbial genome assemblies that overcome many of the deficiencies of short-read sequencing.

89 The Oxford Nanopore Technologies (ONT) MinION is a more recently developed long-
90 read, single-molecule sequencing instrument. The MinION is a small benchtop device that can
91 plug directly into a laptop via a USB3 port [20] and that requires a relatively small upfront
92 financial investment relative to PacBio instruments [1]. This affordability and simplicity has
93 enabled the rapid uptake of MinION sequencing by individual labs worldwide, and facilitated
94 new applications such as tracking disease outbreaks in low-resource environments [21].
95 MinION read lengths have no theoretical limit and reads >2 million bp long have been reported
96 [22]. As with PacBio, MinION read quality is low compared to short read sequencing
97 technologies [23, 24]. These errors are less randomly distributed than for PacBio sequencing
98 [25], meaning that increased read depth alone cannot completely overcome this high error
99 rate, at least currently. However, error rates and bias profiles are expected to improve as the
100 MinION and its associated base-calling software continues to develop, e.g., as demonstrated by
101 the increased accuracy of the new Scrappy base caller that is currently under development by
102 ONT [26].

103 Two main strategies have been used to assemble bacterial genomes using MinION
104 sequencing [27, 28]. In the first, MinION reads are used to enhance genome assemblies that are
105 generated from short-read Illumina data. Here, MinION reads can scaffold contigs generated by
106 Illumina sequencing [29–31] or be directly used in the assembly process to disambiguate

107 regions of the assembly graph that cannot be resolved by Illumina sequencing alone (e.g., as
108 implemented in the popular SPAdes and Unicycler software [32, 33]). Alternatively, MinION
109 reads alone are used to generate an initial genome assembly [34, 35] that can then be further
110 polished using either MinION or Illumina reads [34, 36]. Such polishing is highly recommended
111 for MinION-based genome assemblies due to their higher error rates relative to assemblies
112 based on Illumina data [17, 26, 27, 37, 38]. The increasing maturity and throughput of MinION
113 sequencing is leading to its adoption for routine microbial genome sequencing [39–41].

114 Both MinION-only [34, 35] and Illumina-hybrid methods [32, 33] have been validated
115 extensively for bacteria with low and average GC contents. However, whether these
116 approaches offer advantages when assembling bacterial genomes with high GC content
117 remains unclear [42] (but see [43]). We therefore compared the ability of Illumina and MinION
118 sequencing technologies to produce high-quality assemblies of genomes from three bacterial
119 genera (*Flavobacterium*, *Aeromonas*, and *Pseudonocardia*) that range in GC content from 31-
120 73% (Table 1). *Flavobacterium* spp. are gliding bacteria that can be found in diverse
121 environments and that include important fish pathogens. *Aeromonas* spp. are ubiquitous in
122 aquatic environments and can cause diseases in humans and fish or form beneficial symbioses,
123 e.g., with fish and leeches [44]. *Pseudonocardia* sp. are members of the Actinobacteria and, like
124 many other members of this class, are important producers of antibiotics such as those
125 involved in defensive symbioses with ants (e.g., [45]). Our results validate MinION sequencing's
126 ability to generate high-quality assemblies for all of these genomes, and especially emphasize
127 the advantages of MinION sequencing when unbiased Illumina sequencing libraries are difficult
128 to generate, e.g., for Actinobacteria with high GC content. These improved genome assemblies

129 dramatically improve the annotation of repetitive genomic regions such as insertion sequences
130 and secondary metabolite biosynthetic gene clusters (BGCs). MinION sequencing therefore has
131 strong potential to overcome current limitations of short-read sequencing technologies and
132 catalyze improved understanding of genome evolution and exploitation of genomic data for
133 drug discovery.

134 135 **Methods**

136 **Description of Strains**

137 Three *Aeromonas* strains were used in this study. *Aeromonas hydrophila* str. CA-13-1
138 (hereafter *Ah* CA-13-1) was isolated from the wound of a patient undergoing post-operative
139 leech therapy in 2013 [46]. *Aeromonas veronii* str. CIP107763^T (hereafter *Av* CIP107763^T) was
140 isolated from a mosquito midgut in France in 2015 and sequenced previously [47]. *A. veronii* str.
141 JG3 (hereafter *Av* JG3) is a derivative of a medicinal leech isolate Hm21 [48]. All *Aeromonas*
142 strains were grown either in LB broth or on agar plates for 16 hours at 30°C.

143 The *Flavobacterium* strains used in this study were all isolated from necrotic gill tissues
144 of farmed rainbow trout, *Onchorhyncus mykiss*. *Flavobacterium* sp. str. ARS-166-14 (hereafter
145 *Fs* ARS-166-14) was isolated in October 2014, *Flavobacterium columnare* str. FC-081215-1
146 (hereafter *Fc* FC-081215-1) was isolated in August 2015, and *F. columnare* str. FC-100715-19
147 (hereafter *Fc* FC-100715-19) was isolated in October 2015, all on TYES agar. Frozen cells were
148 grown on TYES agar, incubated for three days at 20°C, and then grown in liquid TYES broth for
149 another 3 days at 15°C for *Fs* ARS-166-14 and 25°C for *Fc* FC-100715-19 and *Fc* FC-08-1215-1
150 [49].

151 The *Pseudonocardia* bacteria sequenced during this study were isolated from individual
152 *Trachymyrmex septentrionalis* ants collected from three locations within the United States:
153 Paynes Creek Historic State Park, FL (*Pseudonocardia* sp. str. JKS002056, hereafter *Ps*
154 JKS002056), Magnolia Springs State Park, GA (*Pseudonocardia* sp. str. JKS002072, hereafter *Ps*
155 JKS002072), and Jones Lake State Park, NC (*Pseudonocardia* sp. str. *Ps* JKS002128).
156 *Pseudonocardia* were visible as white patches on the ants' propleural plates, which were
157 scraped using a sterile needle under a dissecting microscope to isolate *Pseudonocardia*
158 following Marsh [50].

159 **DNA Isolation**

160 DNA was extracted from *Aeromonas* and *Flavobacterium* isolates following a modified
161 version of a previously published protocol for large scale genomic DNA isolation [51, 52]. DNA
162 in solution was not micropipetted during these extractions to minimize DNA fragmentation.
163 DNA was extracted from single *Pseudonocardia* colonies using the Epicentre MasterPure
164 Complete DNA and RNA kit following the manufacture's protocol. Each *Pseudonocardia*
165 extraction was performed in triplicate using wide bore tips and taking care to pipette slowly to
166 prevent DNA shearing.

167 **Library Preparation and Sequencing**

168 The quality of all extracted DNA was assessed using an Agilent TapeStation 2200
169 protocol for genomic DNA, an Agilent 2100 Bioanalyzer (High sensitivity DNA chip), and/or a
170 Nanodrop spectrophotometer. All libraries were quantified using a Qubit® 2.0 fluorometer. For
171 the *Aeromonas* and *Flavobacterium* strains, NexteraXT Illumina sequences were constructed by
172 following the manufacturer's instructions for genomic tagmentation, PCR of tagged DNA, and

173 PCR product cleanup. Libraries were diluted to 4nM for loading onto an Illumina MiSeq. TruSeq
174 DNA PCR-Free libraries were created for each *Pseudonocardia* strain following the
175 manufacturer's protocol, shearing the DNA to 550 bp fragments using a Covaris M22 Focused-
176 ultrasonicator. All Illumina libraries were sequenced on an Illumina MiSeq using the 2x250bp
177 protocol at the University of Connecticut Microbial Analysis Research and Services (MARS)
178 facility. Demultiplexing was performed using Illumina Basespace
179 (<https://basespace.illumina.com/home/index>).

180 All genomes were also sequenced on a MK1B MinION device using R9.4 flow cells.
181 *Aeromonas* and *Flavobacterium* libraries were prepared using the ONT EXP-NBD103 Barcode kit
182 and the ONT "Native Barcoding Genomic DNA Sequencing for the MinION Device" protocol
183 (downloaded from <https://nanoporetech.com/resource-centre/protocols> on Oct 20, 2017) and
184 performed without optional shearing steps to select for long reads. *Pseudonocardia* libraries
185 were prepared using the ONT "1D gDNA Selecting for Long Reads Using SQK-LSK108" protocol
186 (downloaded from <https://nanoporetech.com/resource-centre/protocols> on Dec 20, 2016) All
187 strains were sequenced using the ONT MinKNOW NC_48h_Sequencing_Run_FLO-MIN107_SQK-
188 LSK108 protocol, except for JKS002056, which was sequenced using the older
189 NC_48h_Sequencing_Run_FLO-MIN106_SQK-LSK108 MinKNOW protocol. The run duration
190 ranged from 12 to 48 hours. Strains *Av* JG3, *Fc* FC-100715-19, and *Ps* JKS002072 were
191 sequenced using two separate MinION runs that were combined for all analyses, except for the
192 *Av* JG3 Canu+Nanopolish assembly where the few MinION reads (<3000) from the first run were
193 excluded because of their being processed using base calling software that was incompatible
194 with Nanopolish.

195 **Base calling and Read Preparation**

196 MinION reads for *Ps* JKS002056 and the first *Av* JG3 run were base-called using the ONT
197 Metrichor 1D protocol and locally using MinKNOW (ONT; Oct 20, 2017 release) respectively. All
198 other MinION reads were based-called using Albacore (v.1.2.4). These software choices were
199 determined by changes made by ONT to their cloud-based base calling system. All raw data was
200 deposited in the NCBI database under the BioProject number PRJNA477342.

201 We assessed Illumina read quality using FastQC (v.0.11.5, available from
202 <http://www.bioinformatics.babraham.ac.uk/projects/fastqc/>). Trimmomatic (v.0.36; [53]) was
203 used remove Illumina adapters, bases at each end of the read with an average Phred score <15
204 over a 4 bp window, and reads ≤ 36 basepairs long. Poretools version 0.6.0 [54] was used to
205 assess the quality of each MinION dataset and to generate fastq files from basecalled fast5 files.
206 Barcodes and reads that contained an internal barcode adapter sequence were removed using
207 Porechop version 0.2.3 (available from <https://github.com/rrwick/Porechop>). Nanofilt (v.1.0.5,
208 available from, <https://github.com/wdecoster/nanofilt>) was used to remove reads shorter than
209 500 basepairs or having an average quality score <9.

210 **Genome Assembly**

211 We used several approaches to construct *de novo* assemblies of each genome. First, we
212 constructed MiSeq-only short read assemblies using SPAdes (v.3.11.1) [33] and Unicycler
213 (v.0.4.3) [32] (v.0.4.3), representing the current state of the art. Second, we added MinION
214 reads to these MiSeq-based assemblies to disambiguate ambiguous regions in the MiSeq
215 sequencing graph, creating SPAdes-hybrid and Unicycler-hybrid assemblies. Third, we
216 constructed MinION-only long-read assemblies using Canu (v.1.5) [35]. These MinION-only

217 Canu assemblies were polished using the same MinION reads to create Canu+Nanopolish
218 assemblies by aligning MinION reads to the Canu assembly using BWA (v.0.7.15) [55] and
219 Samtools (v.1.3.1) [56], and then using Nanopolish (v.3.2.5) [34] for assembly polishing. A
220 second iteration of Nanopolish was completed for strain *Ps* JKS002128 but did not significantly
221 improve its accuracy (data not shown), and so this strategy was not pursued further. The Canu
222 assemblies were alternatively polished using MiSeq reads to create Canu+Pilon assemblies.
223 MiSeq reads were aligned to the Canu genome using BWA (v.0.7.15) and Samtools (v.1.3.1) and
224 then Pilon (v.1.22) [36] was used for assembly polishing. In total, we created seven assemblies
225 for each genome: four based primarily on MiSeq data (SPAdes, Unicycler, SPAdes-hybrid, and
226 Unicycler-hybrid) and three based primarily on MinION data (Canu, Canu+Nanopolish,
227 Canu+Pilon). All commands used for the computational analyses in this study are included in
228 the Supplementary Material.

229 **Depth of Coverage**

230 MinION data was subsampled from *Av* JG3, *Fs* ARS-166-14, and *Ps* JKS002128 to
231 determine the minimum read depth required to create contiguous MinION-based assemblies.
232 Fast5-formatted reads for each strain were subsampled in the order that they were acquired
233 from the MinION sequencer to achieve 10X, 20X, 30X, 40X, 50X, (for *Fs* ARS-166-14, *Av* JG3 and
234 *Ps* JKS002128), 60X (*Fs* ARS-166-14 and *Ps* JKS002128 only), and 70X (*Ps* JKS002128 only)
235 coverage of the Canu assembly for each strain, calculated using the mean MinION read length
236 for each strain (Table 2). This strategy was used to simulate runs stopped after achieving each
237 level of coverage. All data was processed and assembled using Canu as described above.

238 **Quality assessment**

239 The contiguity and quality of each genome assembly was assessed using Quast (v.4.6.3)
240 [57]. Because we lacked reference genomes for comparison, we instead assessed the quality of
241 our genomes using two strategies, focusing on the *Pseudonocardia* genomes for detailed
242 comparison. First, we compared all genome assemblies to each other based on their shared k-
243 mer composition using Mash (v2.0) [58]. These Mash distances were used to construct a
244 phylogeny using Mashtree (v.0.33, available at <https://github.com/lskatz/mashtree>). Second,
245 we aligned each assembly to their respective Canu+Pilon assembly using MUMmer (v3.1) [59]
246 to identify SNPs and indels relative to the Canu+Pilon assembly. We selected the Canu+Pilon
247 assemblies as references because of their high contiguity and error profiles that were similar to
248 the MiSeq assemblies. However, we stress that this does not comprise a “gold standard”
249 comparison and the relative nature of these comparisons.

250 **Biosynthetic gene cluster prediction**

251 Secondary metabolite biosynthetic gene clusters (BGCs) were annotated in each *Ps*
252 JKS002128 assembly using antiSMASH (v.4.1.0) [60]. Fragmented BGCs were annotated by their
253 occurring at contig ends. This likely overestimates the number of fragmented BGCs due to
254 antiSMASH’s tendency to conservatively extend BGCs past their true boundaries. Identical BGCs
255 were identified using the ClustCompare pipeline (available from, [https://github.com/klassen-](https://github.com/klassen-lab/ClustCompare)
256 [lab/ClustCompare](https://github.com/klassen-lab/ClustCompare)). Briefly, PfamScan (v.1.6) [61] was used to annotate protein domains
257 encoded by each BGC and these domains were compared to each other using BLASTp [62].
258 BGCs were considered to be homologous based on their sharing a minimum ClustCompare
259 similarity score of 0.3 calculated using a 70% similarity threshold between domains in different
260 BGCs, a minimum of two homologous domains shared between BGCs, and a minimum of 50%

261 of the domains in the smaller BGC being homologous to domains in the larger BGC. The
262 resulting homology networks were visualized using Cytoscape (v.3.6.1) [63] to identify clusters
263 of homologous BGCs. Singleton clusters were aligned to the Canu+Pilon genome and individual
264 Canu+Pilon antiSMASH BGCs using MUMmer v3.1 [59] to identify homologies that occurred at
265 the nucleotide level but not at the protein level (e.g., due to high error rates that might
266 confound gene prediction). Nucleotide-level BGC comparisons were also conducted using Mash
267 (v.2.0) [58].

268 **Insertion Sequence identification**

269 Insertion sequences (ISs) were annotated in the *Fs* ARS-166-14 Canu, Canu+Pilon,
270 SPAdes, and Unicycler assemblies using ISSaga2 [64]. Full and partial IS sequences were
271 identified by comparing each assembly genome sequence to the ISfinder database. The default
272 detection algorithm and parameters were used for all assemblies in this experiment, and both
273 the total number of hits and those with >70% amino acid similarity to ISs in the ISfinder
274 database were recorded.

275 **Results**

276 **Sequencing**

277 We sequenced the genomes of nine bacterial strains using both Oxford Nanopore
278 MinION and Illumina MiSeq technologies, together spanning a wide range of GC content
279 (*Flavobacterium*: 31%; *Aeromonas*: 59-61%; *Pseudonocardia*: 74%). MinION sequencing
280 coverage ranged from 40-135X and generated median read lengths of 1,629-9,665 bps (Table
281 2). Median MinION read lengths for *Ah* CA-13-1 and *Av* CIP107763^T were considerably shorter
282 than for the other MinION libraries due to difficulties in extracting high molecular weight DNA

283 from these strains. Illumina Nextera libraries were sequenced for all *Aeromonas* and
284 *Flavobacterium* strains with coverage ranging from 30-169X (Table 3). Preliminary Nextera
285 libraries were also constructed for the *Pseudonocardia* strains, but these were highly biased
286 and generated extremely fragmented assemblies (1000s of contigs; data not shown). We
287 therefore instead generated Illumina TruSeq PCR-free libraries for these strains, with coverage
288 ranging from 71-246X (Table 3).

289 **Genome Assembly**

290 Seven assemblies were generated for each strain, four based on MiSeq data either alone
291 (SPAdes, Unicycler) or with MinION data to deconvolute the MiSeq assembly graph (SPAdes-
292 hybrid, Unicycler-hybrid), and three based on MinION data either alone (Canu), polished using
293 the same MinION data (Canu+Nanopolish), or polished using MiSeq data (Canu+Pilon). Both the
294 SPAdes and Unicycler assemblies had the largest number of contigs out of all assemblies
295 generated for each strain (Figure 1). These assemblies also typically had the lowest N50 values
296 compared to the other assemblies. *Ah* CA-13-1 and *Av* CIP107763^T were exceptions to this
297 trend, likely due to their lower quality MinION libraries. The addition of MinION reads to
298 deconvolute the SPAdes and Unicycler assembly graphs lowered the number of contigs and
299 increased the N50 for all assemblies (Figure 1). This highlights the ability of long MinION reads
300 to resolve genomic repeats that otherwise stymied assembly of these genomes from short
301 reads. Unicycler consistently outperformed SPAdes during hybrid assembly (the only exception
302 being *Av* CIP107763^T) but not when assembling MiSeq reads only.

303 Canu assemblies were more contiguous and had higher N50 values than all MiSeq-based
304 assemblies, except for *Av* CIP107763^T Unicycler-hybrid and SPAdes-hybrid assemblies and the

305 *Ah* CA-13-1 Unicycler-hybrid assembly (Figure 1A, B). These two strains had lower quality
306 MinION libraries (Table 2) that likely compromised the Canu assemblies, even if they were still
307 more contiguous than the MiSeq-only SPAdes and Unicycler assemblies. Canu assemblies were
308 used as the base for polishing with either Nanopolish or Pilon, and so the number of contigs
309 was the same for the Canu, Canu+Nanopolish, and Canu+Pilon assemblies (Figure 1). The Canu
310 assembly sizes were greater than those of any MiSeq-based assembly for all *Flavobacterium*
311 and *Pseudonocardia* strains (up for ~14% for *Ps* JKS002128; Figure 1), likely reflecting the
312 MinION's ability to overcome biases in the Illumina libraries for these genomes with low (31%)
313 and high (74%) GC content, respectively. This was not true for the *Aeromonas* assemblies, likely
314 reflecting fewer biases in the Illumina libraries for these strains with more moderate GC
315 content (59-61%). Taken together, these assemblies demonstrate that MinION sequencing
316 improves assembly contiguity, especially where Illumina sequencing libraries are the most
317 biased.

318 **Assembly Accuracy**

319 Because we lacked high-quality reference genomes for our strains, we instead used several
320 comparative analyses to assess the accuracy of our assemblies. We focused on *Pseudonocardia*
321 for these analyses because these appeared to be the most challenging to assemble based on
322 the substantial differences in their assembly sizes and contiguities (Figure 1). We used Mash
323 [58] to compare all of our *Pseudonocardia* assemblies to each other according to their shared k-
324 mer content and to construct a distance-based phylogeny (Figure 2). Canu assemblies were the
325 least similar to the MiSeq-based assemblies, followed by the Canu+Nanopolish assemblies. This
326 suggests that MinION data alone cannot produce accurate *Pseudonocardia* assemblies using

327 current technologies. These data might alternatively be interpreted to mean that the MiSeq-
328 based assemblies have lower accuracy compared to the Canu and Canu+Nanopolish assemblies,
329 but we consider this unlikely based on previous research that argues against this interpretation
330 [17, 27, 37, 38]. Canu+Pilon assemblies were more similar to the MiSeq-based assemblies,
331 suggesting that polishing MinION-based assemblies with MiSeq reads is an effective strategy to
332 generate microbial genome assemblies that are both accurate and contiguous. However, some
333 divergence was observed between the Canu+Pilon and MiSeq-based genome assemblies. This
334 was especially true for *Ps* JKS002128, which appeared to have the most biased MiSeq library in
335 our study based on differences in the sizes of the MiSeq-based and MinION-based assemblies
336 for this strain (Figure 1). These differences are consistent with the existence of regions in the
337 Canu assembly that lacked mapping MiSeq reads, leaving these regions uncorrected [65]. All
338 genome assemblies for the same strain clustered together in the Mash tree analysis (Figure 2),
339 indicating that even the high error rates of the Canu and Canu+Nanopolish assemblies did not
340 obscure strain-level phylogenetic differences.

341 Based on the Mash analysis, the Canu+Pilon assemblies were used as a reference
342 against which to compare the other assemblies based on their higher contiguity and substantial
343 accuracy. The high accuracy of MiSeq sequencing meant that all MiSeq-based assemblies had
344 few SNPs and indels relative to the Canu+Pilon assembly (Figure 3). In contrast, the Canu
345 assemblies had many more SNPs and indels relative to the Canu+Pilon assembly, especially for
346 *Ps* JKS002056 (Figure 3). Polishing these Canu assemblies using Nanopolish reduced the number
347 of indels, and the number of SNPs to a lesser extent (Figure 3). However, the numbers of SNPs
348 and indels were still much higher than for the MiSeq-based assemblies.

349 **MinION Sequencing Depth**

350 Canu assemblies were performed using 5-7 different levels of coverage for strains *Av*
351 *JG3*, *Fs* ARS-166-14, and *Ps* JKS002128. These assemblies suggest that the amount of coverage
352 needed for a high-quality MinION-based genome assembly is relatively low, but also depends
353 somewhat on the complexity of each genome. Assemblies for strains *Av* *JG3* and *Fs* ARS-166-14
354 did not improve substantially above 30X coverage, consistent with previous findings [66].
355 However, assemblies for strain *Ps* JKS002128 improved incrementally up to 70X coverage
356 (Figure 4), suggesting that higher coverage may be necessary for genomes with high GC
357 content. Even though they were assembled into a few contigs, these assemblies were not error-
358 free based on the different genome sizes and N50 values obtained for assemblies using
359 different high-coverage datasets. The single 50X *Av* *JG3* assembly also lacked a plasmid that was
360 present in assemblies for the lower coverage datasets (data not known). Researchers should
361 therefore assess their goals for MinION sequencing before progressing with a run and consider
362 stopping data collection at a certain threshold to conserve flow cells and to decrease
363 sequencing time and cost.

364 **Biosynthetic gene cluster prediction**

365 One expected benefit of high quality genome assemblies is that they will substantially
366 improve the annotation of repetitive genomic regions relative to lower quality assemblies. To
367 test this, we compared antiSMASH [60] secondary metabolite biosynthetic gene cluster (BGC)
368 annotations for all of our *Ps* JKS002128 assemblies. Actinobacteria such as *Pseudonocardia*
369 typically possess many BGCs, although they are often difficult to assemble correctly [16].
370 AntiSMASH consistently predicted 12 and 13 BGCs for the SPAdes and Unicycler assemblies,

371 respectively, and 12 BGCs for both the SPAdes-hybrid and Unicycler-hybrid assemblies (Figure
372 5). The extra BGC in the Unicycler assembly is due to there being two separate fragments of
373 BGC 1 annotated in this assembly. More BGCs were predicted for the Canu (17),
374 Canu+Nanopolish (19), and Canu+Pilon (18) assemblies, including 4 BGCs that were found in at
375 least two of these genomes but not in any of the MiSeq-based genomes (Figure 5A). These
376 BGCs may lie at particularly repetitive or bias-prone regions of the *Ps* JKS002128 genome such
377 that they are omitted from MiSeq-based assemblies but present in MinION-based assemblies
378 that are much less sensitive to these issues. Despite their greater contiguity, the Canu,
379 Canu+Nanopolish, and Canu+Pilon assemblies lacked some combination of BGCs 1, 9, 12, and
380 13, all of which were found in all of the MiSeq-based assemblies (Figure 5A). The Canu assembly
381 lacked all 4 of these BGCs, the Canu+Nanopolish assembly lacked BGCs 9, 12, and 13, and the
382 Canu+Pilon assembly only lacked BGC 13. These omissions are likely due to gene prediction
383 errors that decreased the ability of antiSMASH to detect these BGCs. Such errors may have also
384 been responsible for the prediction of BGCs 18 and 19 solely in the Canu and Canu+Nanopolish
385 assemblies (Figure 5A), which are likely false positive annotations based on these BGCs only
386 appearing in individual error-prone assemblies. MinION-based genome assemblies therefore
387 substantially increase the sensitivity of BGC annotation, but require polishing to limit
388 annotation errors.

389 Improved genome assembly also reduced the number of BGCs that were fragmented,
390 i.e., that overlapped with a contig end (Figure 5B). Approximately half of all BGCs in the SPAdes
391 and Unicycler assemblies were fragmented, reflecting the inability of short-read Illumina data
392 to resolve these repetitive genomic regions. The Unicycler hybrid, and to a lesser extent the

393 SPAdes hybrid, assemblies produced fewer fragmented BGCs, reflecting the increased
394 contiguity of these assemblies. The Canu, Canu+Nanopolish, and Canu+Pilon assemblies all had
395 very few fragmented BGCs, based on BGCs overlapping with contig ends. MinION-based
396 genome assemblies therefore do not only increase the frequency of BGC detection, but also
397 more completely assemble these BGCs and thus increase their value for genome-guided drug
398 discovery. The Canu, Canu+Nanopolish, and Canu+Pilon assemblies did have several annotated
399 gene clusters that were aggregated into a single BGC in other assemblies (Figure 5A). Whether
400 these represent single BGCs that were fragmented in the MinION-based assemblies or multiple
401 BGCs that were located adjacent to each other on the *Ps* JKS002128 genome is difficult to
402 predict computationally.

403 **Insertion Sequence Prediction**

404 To further investigate the effect of genome assembly on the annotation of repetitive
405 genetic regions, insertion sequences were predicted in the *Fs* ARS-166-14 Canu, Canu+Pilon,
406 SPAdes, and Unicycler assemblies using ISSaga2 and the ISfinder database [64]. The total
407 number of full or partial hits to the ISfinder database and the number of hits with amino acid
408 sequence similarities >70% are reported in Figure 6. The Canu+Pilon assembly had the most
409 unique insertion sequences with 70% or greater sequence similarity to the ISfinder database
410 (20), followed by the Canu assembly with 15, and then the Unicycler and SPAdes assemblies
411 with 4 and 3, respectively. Interestingly, the Canu+Pilon assembly also had the greatest total
412 number of hits, but these likely contain many false positive results that require further curation.

413

414 **Discussion**

415 Single-molecule, long-read sequencing technologies such as the Oxford Nanopore
416 MinION have strong potential to revolutionize the sequencing and *de novo* assembly of
417 bacterial genomes. Existing short-read sequencing technologies frequently produce genome
418 assemblies that are broken into 10s-100s of contigs, such as in our assemblies generated using
419 only short-read MiSeq data (Figure 1). Fragmented genome assemblies prevent accurate
420 annotation of important genome features such as insertion sequences and secondary
421 metabolite biosynthetic gene clusters (Figures 5 and 6). Technological improvements are
422 therefore necessary to fully understand and exploit these genomic features to cure disease and
423 foster biotechnology.

424 One key reason for poor genome assembly is the inherently limited length of short-
425 reads. By increasing the read length, long-read sequencing technologies such as the MinION
426 disambiguate genomic repeats and generate fewer contig breaks (e.g., [38]). This was clearly
427 evident from our SPAdes- and Unicycler-hybrid assemblies, where the long MinION reads were
428 able to deconvolute the assembly graph produced from the MiSeq data and yielded fewer and
429 longer contigs compared to the MiSeq-only assemblies (Figure 1). Such improvements are likely
430 to continue as MinION-compatible extraction methods for high-molecular weight DNA are
431 refined.

432 However, this approach assumes that the entire genome is represented in the Illumina
433 sequencing graph, which may not be true because of biases in short-read sequencing library
434 preparation. As a result, some regions of the genome are sequenced to low coverage or
435 excluded entirely, resulting in assembly fragmentation due to missing data. These problems
436 include PCR biases against extreme %GC sequences [8–12] and due to biased insertion of

437 transposases during library preparation [14]. Reflecting such biases, our initial *Pseudonocardia*
438 sequencing experiments that used the Illumina Nextera library preparation method (which
439 includes both transposases and PCR) produced genome assemblies with 1,000s of contigs (data
440 not shown), compared to the 10s-100s of *Pseudonocardia* contigs produced using Illumina
441 TruSeq PCR-free libraries (Figure 1). Single-molecule sequencing methods such as the MinION
442 avoid many of these biases by sequencing individual template DNA molecules without using
443 PCR. This is reflected by the higher contiguity of our *Pseudonocardia* Canu genome assemblies
444 compared to the SPAdes- and Unicycler-hybrid assemblies that used MinION reads to
445 deconvolute the potentially biased Illumina assembly graphs (Figure 1). All of our
446 *Flavobacterium* and *Pseudonocardia* Canu assemblies are also larger than those based on
447 Illumina reads, reflecting the inclusion of sequences that were missing from the Illumina
448 sequencing libraries. For *Pseudonocardia*, these differences were sometimes substantial (up to
449 a 13.7% increase in genome size). These results point to library preparation bias as a second
450 source of error common to short-read sequencing that can be overcome by long-read, single-
451 molecule sequencing technologies such as the MinION, in addition to the ability of MinION
452 reads to span long genomic repeats.

453 Our results also highlight the importance of efficient high molecular weight DNA
454 extraction methods for MinION sequencing. Of the 9 genomes that we sequenced during this
455 study, the two with the lowest median read length (*Ah* CA-13-1 and *Av* CIP107763^T) produced
456 the least contiguous Canu assemblies (14 and 32 contigs, respectively). However, this is still
457 more contiguous than the MiSeq-only SPAdes and Unicycler assemblies for these strains.
458 MinION reads also improved these SPAdes and Unicycler assemblies when run in hybrid mode,

459 demonstrating the utility of long reads even if DNA extraction remains suboptimal. There is a
460 current need for reliable protocols to produce high molecular weight genomic DNA that is
461 compatible with the MinION sequencer, and the Oxford Nanopore Voltrax and Ubik devices
462 (<https://nanoporetech.com/about-us/news/clive-g-brown-cto-plenary-london-calling>) show
463 strong potential to overcome these issues. The degree to which such devices are compatible
464 with diverse cell wall chemistries remains to be validated.

465 Although most of our MinION-based assemblies were more contiguous than the MiSeq-
466 based assemblies, they were less accurate. Assemblies generated using Canu contained a large
467 number of SNP and indels relative to our Illumina-based assemblies (Figures 2 and 3). These
468 differences were reduced by using Nanopolish to correct the Canu assembly using MinION
469 reads, and even better results were obtained using Pilon to correct the Canu assembly using
470 MiSeq reads (Figures 2 and 3). However, differences still existed between these polished
471 assemblies and the Illumina assemblies in some cases (most obviously for *Pseudonocardia* sp.
472 JKS002128). Although it is possible that the MiSeq assemblies contained errors relative to the
473 MinION assemblies, this would be inconsistent with previous work comparing MinION
474 assemblies to high-quality reference genomes [17, 27, 37, 38]. Illumina reads are also unable to
475 correct repetitive genome sequences that cannot be unambiguously mapped using short reads,
476 and so these regions will be uncorrected even in Canu+Pilon assemblies [65]. A tradeoff
477 therefore exists between the higher contiguity of MinION-based assemblies relative to their
478 higher number of SNP and indel errors. Minimizing such errors is a current technological focus
479 of ONT (<https://nanoporetech.com/about-us/news/clive-g-brown-cto-plenary-london-calling>)
480 and so this tradeoff may lessen in the near future.

481 The importance of these assembly trade-offs is highlighted by our analysis of repetitive
482 genomic regions. For example, antiSMASH annotated $\sim 1/3$ more secondary metabolite
483 biosynthetic gene clusters (BGC) in the MinION-based assemblies of *Pseudonocardia* sp.
484 JKS002128 compared to the MiSeq-based assemblies (Figure 5), confirming our previous
485 observations that BGCs are poorly resolved by Illumina sequencing [16]. Similar results were
486 obtained when annotating insertion sequences in *Flavobacterium* sp. *Fs* ARS-166-14, as
487 expected due to the highly repetitive nature of these genomic regions (Figure 6). The BGCs that
488 were annotated in the Illumina-only assemblies were highly fragmented, highlighting the
489 challenge of sequencing these complex genomic regions (Figure 5). Interestingly, the genome
490 assemblies that contained the highest number of SNP and indel errors (Figure 2) contained
491 several BGCs that were unique to those particular genomes (Figure 5), and lacked several BGCs
492 that were annotated in the MiSeq-based assemblies. These differences are likely due to the
493 difficulty in accurately predicting gene structures in highly error-prone genomes due to gene
494 truncation or misplaced start sites. Indeed, our initial ClustCompare analysis to compare BGCs
495 based on their protein sequences did not detect many true homologies between BGCs
496 annotated in the Canu and Canu+Nanopolish assemblies to those annotated in assemblies that
497 were generated or polished using MiSeq data due to the large number of misannotated gene
498 structures in the Canu and Canu+Nanopolish assemblies (data not shown). These homologies
499 only became clear using comparisons between nucleotide sequences. High numbers of SNP and
500 indel errors can therefore prevent accurate genome annotation due to errors in gene structure
501 prediction. Several homologous BGCs were also annotated as having different biosynthetic
502 classes in different genomes (represented by the different colors in Figure 5). Together, these

503 analyses highlight the importance of contiguous and accurate genome assemblies for the
504 prediction of repetitive elements such as BGCs, and highlight the utility of MinION sequencing
505 in this application, especially when polished using accurate Illumina reads.

506 In summary, our data highlights the ability of long-read, single-molecule MinION
507 sequencing to overcome current limitations of short-read sequencing, particularly its inability to
508 disambiguate repetitive genome regions and avoid biases introduced during library
509 preparation. Overcoming these limitations greatly improves the annotation of many clinically-
510 and biotechnologically-important genomic regions such as insertion sequences and BGCs
511 (Figures 5 and 6). However, SNP and indel errors remain problematic in *de novo* assemblies
512 generated from MinION data. This is likely to improve in the near future given the extensive
513 research underway in this area. Because twelve microbial genomes can currently be sequenced
514 to sufficient coverage (40-50X; Figure 3) on a single MinION or MiSeq flowcell, combining these
515 data currently requires ~\$100-\$200 for the MinION and ~\$150 for Illumina sequencing in
516 reagent and consumable costs per genome. Combining these two data types is therefore an
517 affordable means to dramatically increase the quality of any bacterial *de novo* genome
518 assembly, regardless of their genome complexity or %GC content, and compares favorably to
519 the cost of PacBio sequencing. Future technical advances will likely decrease these costs
520 further, and we anticipate that highly contiguous and accurate *de novo* assembly of bacterial
521 genomes will become standard in the field in the very near future.

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530 for Cool and Cold Water Aquaculture, Agriculture Research Service, Kearneysville, West
531 Virginia, USA for providing the *Flavobacterium* strains.

532 List of Figures

533 **Figure 1:** MinION reads improve assembly contiguity. The number of contigs (left), N50 (in Mbp,
534 center), and assembly length (in Mbp, right) are shown for each of the MiSeq-based (SPAdes,
535 Unicycler, SPAdes-hybrid, and Unicycler-hybrid) and MinION-based (Canu, Canu+Nanopolish,
536 Canu+Pilon) genome assemblies. Results for *Pseudonocardia*, *Aeromonas*, and *Flavobacterium*
537 are shown in blue, red, and green, respectively.

538 **Figure 2:** Comparison of *Pseudonocardia* assemblies generated during this study. (A): Heatmaps
539 depicting Mash distances between the assemblies of each *Pseudonocardia* strain based on their
540 shared k-mer content. Whiter colors indicate greater Mash distances between assemblies. (B):
541 Mashtree analysis showing the relationships of all *Pseudonocardia* assemblies to each other,
542 based on Mash distances. The scale bar represents a Mash distance of 0.003.

543 **Figure 3:** Quantification of insertion/deletions (indels, left) and single nucleotide
544 polymorphisms (SNPs, right) in all *Pseudonocardia* strains sequenced during this study, as
545 determined by aligning each assembly to the Canu+Pilon assembly for that strain as a
546 reference.

547 **Figure 4:** The effect of coverage on Canu genome assembly contiguity. The number of contigs
548 (Left), N50 (in Mbp, Center), and assembly length (in Mbp, Right) are shown for subsets of the
549 *Ps* JKS002128 (blue), *Av* JG3 (red), and *Fs* ARS-166-14 (green) MinION reads used in Figure 1.

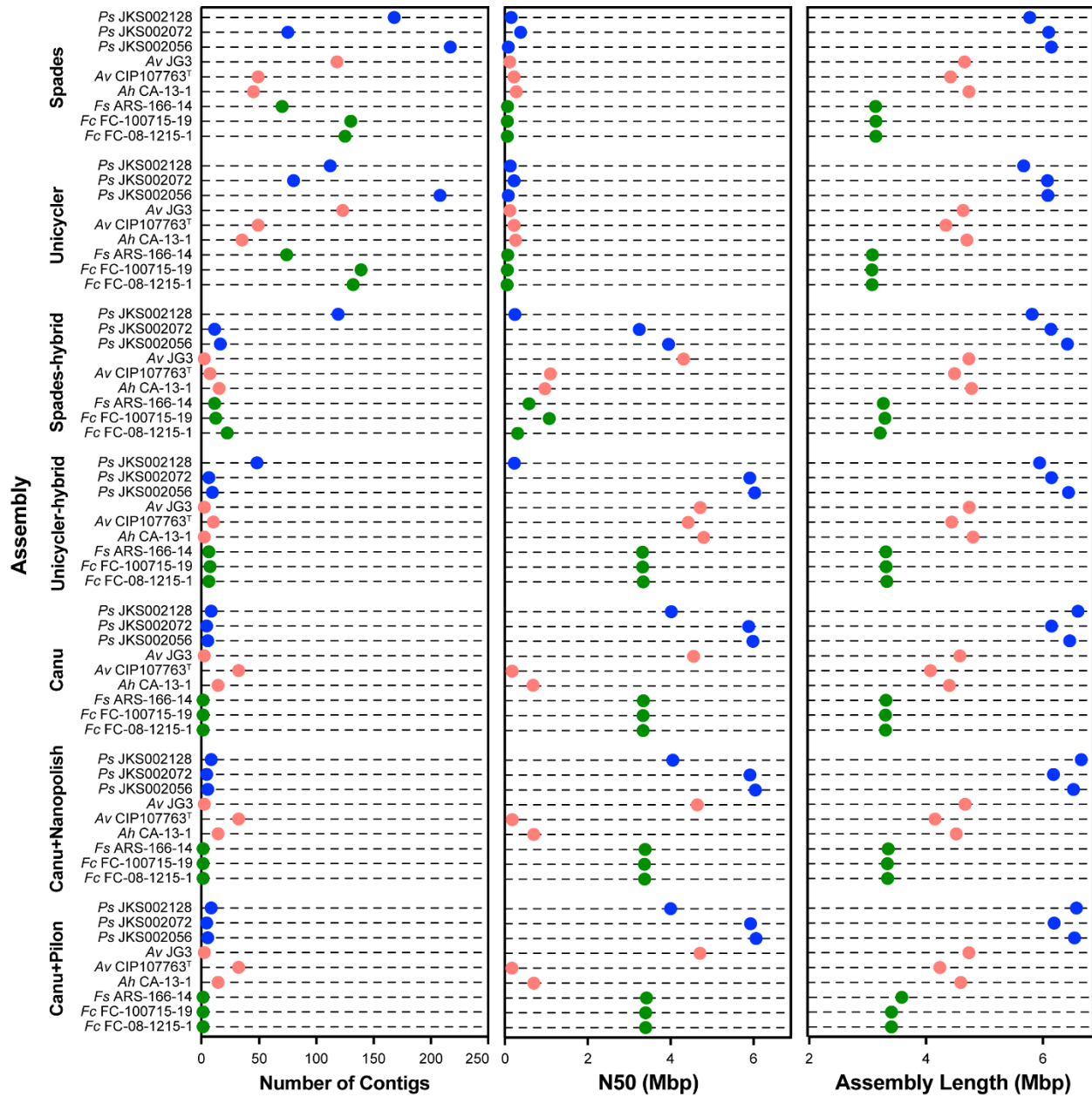
550 **Figure 5:** *Ps* JKS002128 genome assembly quality affects secondary metabolite biosynthetic
551 gene cluster annotation. (A) Homologies between BGCs predicted for each *Ps* JKS002128

552 assembly, with each row representing a unique BGC in the *Ps* JKS002128 genome. Filled boxes
553 indicate the BGCs found in each assembly, colored according to the type of secondary
554 metabolite that it is predicted to encode. White boxes indicate BGCs that were not found in
555 that assembly. Some BGCs occur on multiple contigs or are separated into multiple gene
556 clusters on the same assembly, indicated by either two or three polygons within a single box.
557 BGCs may still be fragmented even if represented by a single box. (B) The total number of
558 complete and fragmented BGCs predicted in each *Ps* JKS002128 genome assembly.

559 **Figure 6:** *Fs* ARS-166-14 genome assembly quality affects insertion sequences annotation. Both
560 the total number of hits and hits with >70% amino acid identity to insertion sequences in the
561 ISfinder database are shown. The former likely includes false-positive annotations while the
562 latter is more conservative.

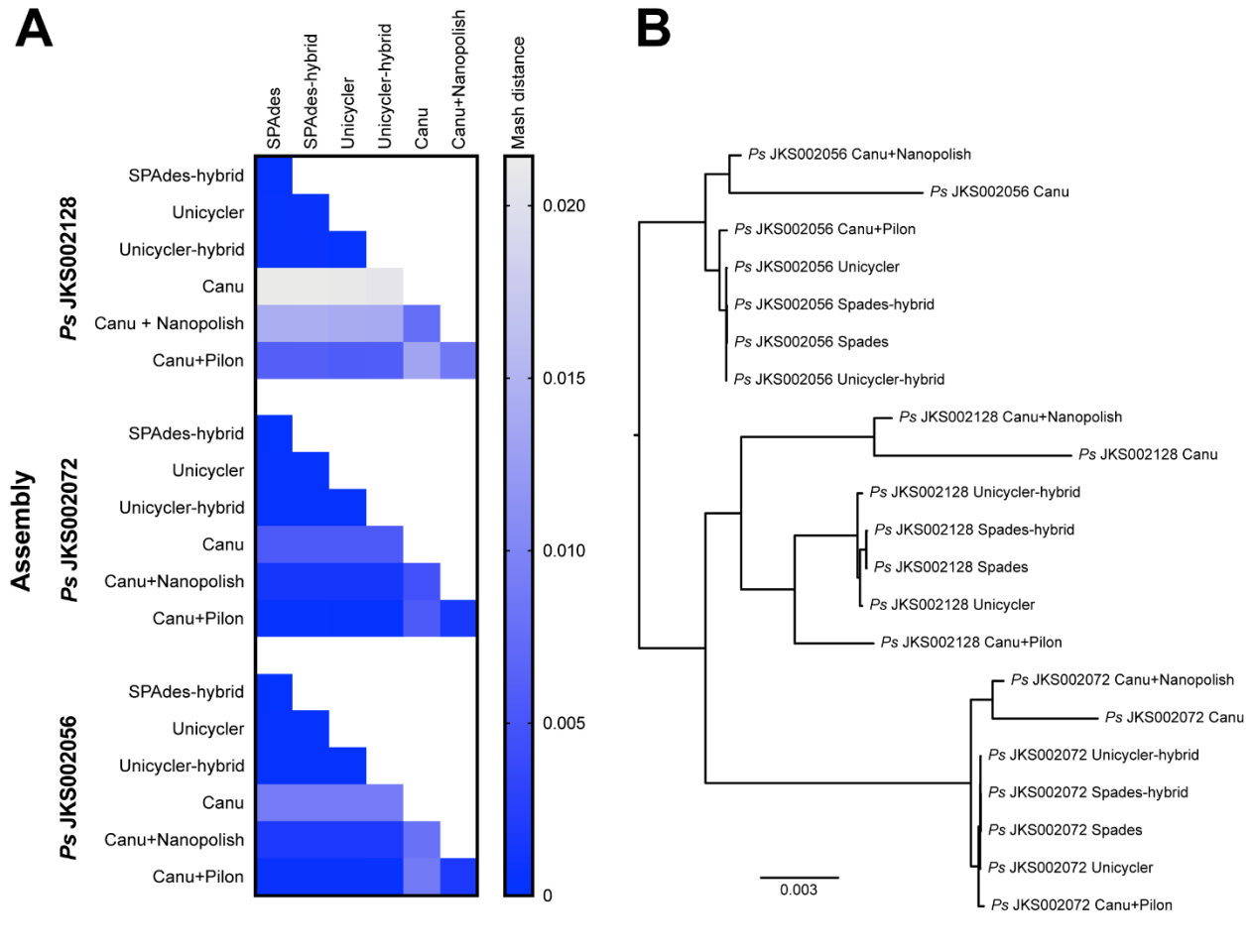
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564 **Figure 1.**
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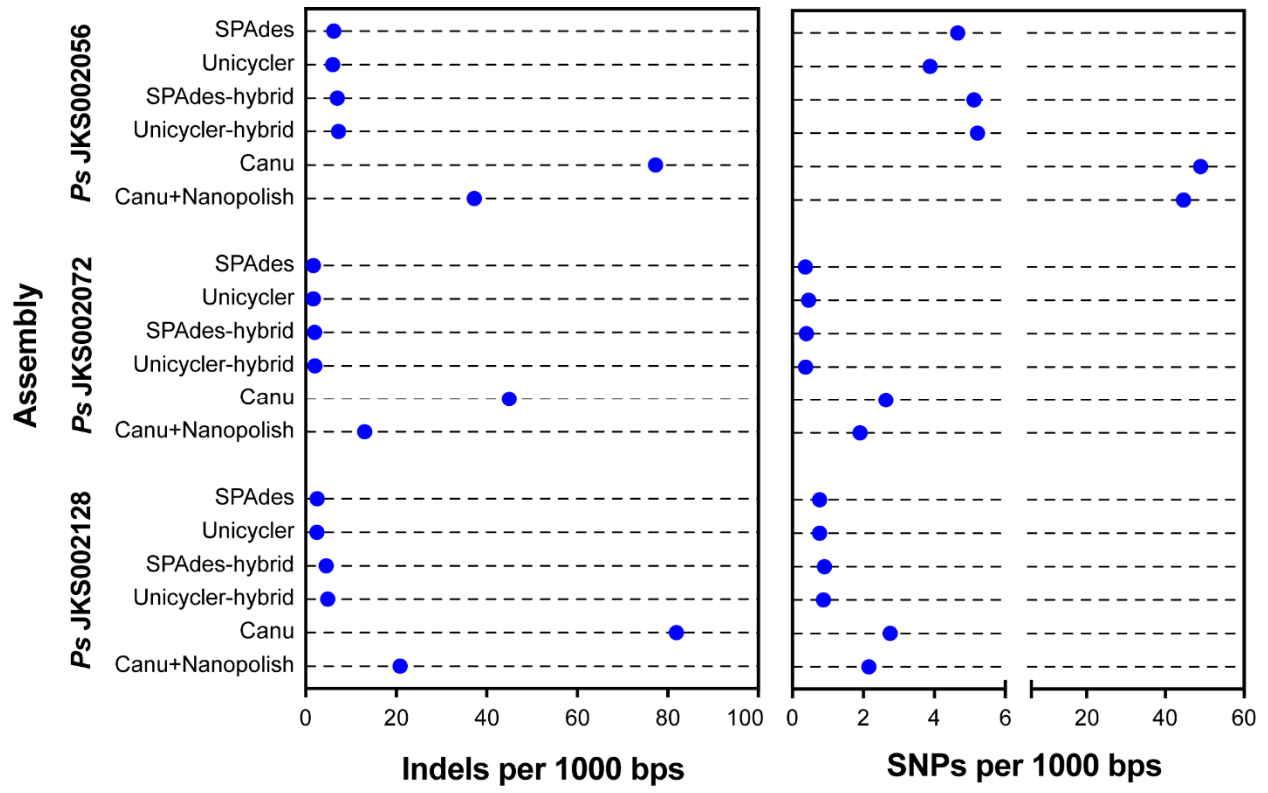
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568 **Figure 2.**
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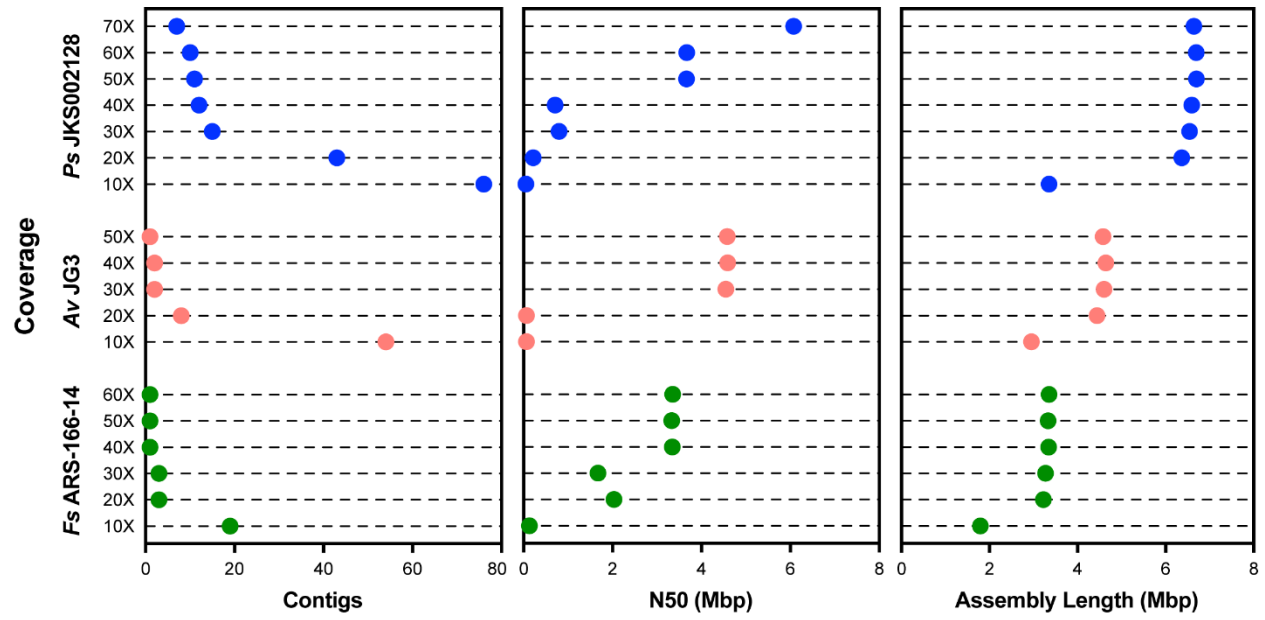
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572 **Figure 3.**
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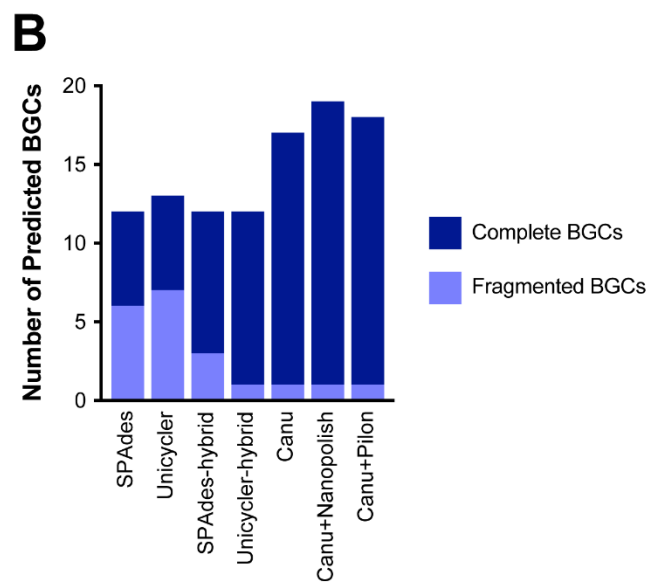
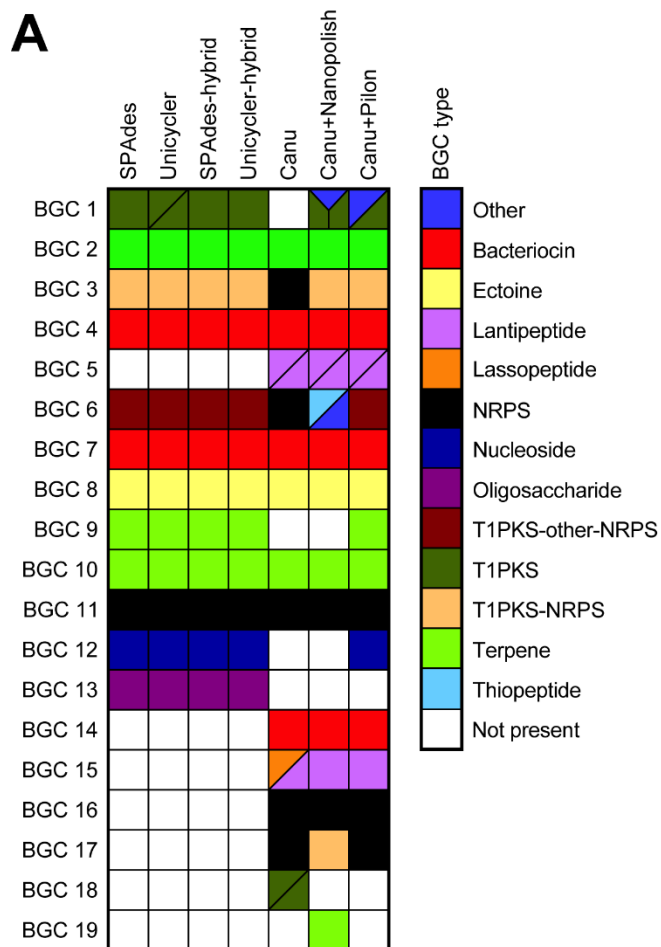
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576 **Figure 4.**
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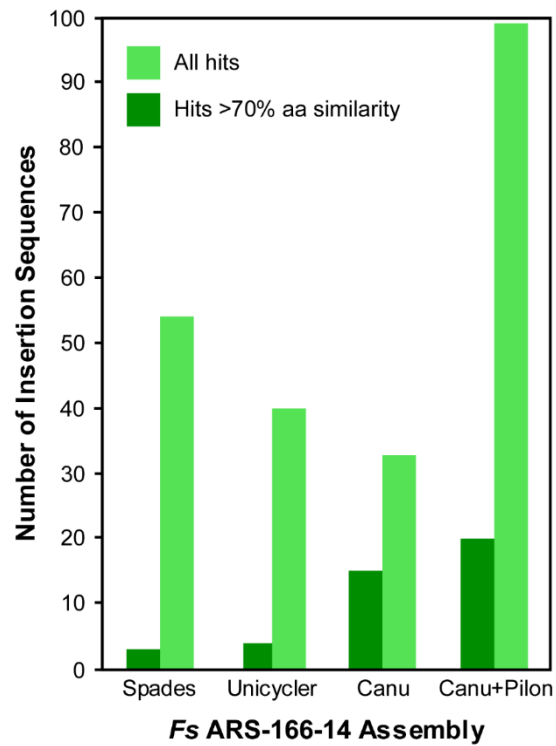
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580 **Figure 5.**
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Ps JKS002128 Assembly

584 **Figure 6**
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586
587

588 **List of Tables**

589 **Table 1.** Bacteria used in this study

590 **Table 2.** Summary of MinION sequencing

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592

Table 1. Bacteria used in this study

Strain ID	Phylum	Genus	Species	% GC Content	Expected Genome Size (Mbps)
<i>Ps</i> JKS002128	Actinobacteria	<i>Pseudonocardia</i>	<i>sp</i>	73.12	6.60
<i>Ps</i> JKS002072	Actinobacteria	<i>Pseudonocardia</i>	<i>sp</i>	73.69	6.21
<i>Ps</i> JKS002056	Actinobacteria	<i>Pseudonocardia</i>	<i>sp</i>	73.31	6.54
<i>Av</i> JG3	Proteobacteria	<i>Aeromonas</i>	<i>veronii</i>	58.64	4.49
<i>Av</i> CIP107763 ^T	Proteobacteria	<i>Aeromonas</i>	<i>culicicola</i> ^a	58.80	4.34
<i>Ah</i> CA-13-1	Proteobacteria	<i>Aeromonas</i>	<i>hydrophila</i>	61.29	4.76
<i>Fs</i> ARS-166-14	Bacteroidetes	<i>Flavobacterium</i>	<i>sp</i>	31.61	3.31
<i>Fc</i> FC-100715-19	Bacteroidetes	<i>Flavobacterium</i>	<i>columnare</i>	31.59	3.32
<i>Fc</i> FC-08-1215-1	Bacteroidetes	<i>Flavobacterium</i>	<i>columnare</i>	31.56	3.31

^aCIP107763^T is the type strain for *Aeromonas culicicola*, which is a later subjective synonym of *A. veronii*.

Table 2. Summary of MinION sequencing

Strain ID	Total Raw Reads	Total bases (Mbps)	Mean Length (bps)	Median Length (bps)	Max Length (bps)	N50 (bps)	Coverage (fold)	Total Reads After Filtering
<i>Ps</i> JKS002128	119,358	499	9,665	2,510	244,268	7,797	80	87,836
<i>Ps</i> JKS002072	135,898	311	2,289	729	678,379	7,142	50	70,035
<i>Ps</i> JKS002056	41,096	397	4,184	6,207	105,595	16,572	64	21,874
<i>Av</i> JG3 (run1)	2,718	25	7,232	5,710	85,387	17,143	5	34,473*
<i>Av</i> JG3 (run2)	42,301	306	9,176	4,807	90,470	11,741	63	
<i>Av</i> CIP107763 ^T	200,362	645	1,629	1,299	98,351	7,545	135	110,391
<i>Ah</i> CA-13-1	136,486	222	1,629	808	62,567	2,840	46	65,195
<i>Fs</i> ARS-166-14	53,171	289	5,442	1,583	1,149,252	18,107	90	36,648
<i>Fc</i> FC-100715-19 (run1)	39,376	146	3,709	836	84,881	17,593	45	45,194*
<i>Fc</i> FC-100715-19 (run2)	31,121	187	5,996	1,137	157,214	26,227	58	
<i>Fc</i> FC-08-1215-1	39,938	236	5,908	1,252	106,525	22,063	74	26,486

* indicates the combined total of both runs for that strain

Table 3. Summary of Illumina sequencing

	Total Raw Reads	Total Bases (Mbps)	Coverage (fold)	Total Reads After Filtering
<i>Ps</i> JKS002128	6,120,982	1,536	246	5,475,000
<i>Ps</i> JKS002072	1,766,572	443	71	1,638,060
<i>Ps</i> JKS002056	5,038,846	1,265	203	4,736,206
<i>Av</i> JG3	1,488,761	372	79	942,391
<i>Av</i> CIP107763^T	566,606	142	30	536,504
<i>Ah</i> CA-13-1	950,886	238	51	873,417
<i>Fs</i> ARS-166-14	2,164,975	541	169	890,703
<i>Fc</i> FC-100715-19	2,072,592	518	162	1,130,797
<i>Fc</i> FC-08-1215-1	1,145,425	286	89	987,428

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