

1 MinION™ nanopore sequencing of environmental metagenomes: a synthetic approach

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27 28 29 30 31 15 **Abstract**

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33 16 **Background:** Environmental metagenomic analysis is typically accomplished by assigning

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35 17 taxonomy and/or function from whole genome sequencing (WGS) or 16S amplicon sequences.

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37 18 Both of these approaches are limited, however, by read length, among other technical and

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39 19 biological factors. A nanopore-based sequencing platform, MinION™, produces reads that are

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41 20 $\geq 1 \times 10^4$ bp in length, potentially providing for more precise assignment, thereby alleviating some

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43 21 of the limitations inherent in determining metagenome composition from short reads. We tested

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45 22 the ability of sequence data produced by MinION (R7.3 flow cells) to correctly assign taxonomy

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47 23 in single bacterial species runs and in three types of low complexity synthetic communities: a

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49 24 mixture of DNA using equal mass from four species, a community with one relatively rare (1%)

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51 25 and three abundant (33% each) components, and a mixture of genomic DNA from 20 bacterial

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53 26 strains of staggered representation. Taxonomic composition of the low-complexity communities

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27 was assessed by analyzing the MinION sequence data with three different bioinformatic
28 approaches : Kraken, MG-RAST, and One Codex.

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30 **Results:** Long read sequences generated from libraries prepared from single strains using the
31 version 5 kit and chemistry, run on the original MinION device, yielded as few as 224 to as many
32 as 3,497 bidirectional high-quality (2D) reads with an average overall study length of 6,000 bp.
33 For the single-strain analyses, assignment of reads to the correct genus by different methods
34 ranged from 53.1% to 99.5%, assignment to the correct species ranged from 23.9% to 99.5%, and
35 the majority of mis-assigned reads were to closely related organisms. A synthetic metagenome
36 sequenced with the same setup yielded 714 high quality 2D reads of approximately 5,500 bp that
37 were up to 98% correctly assigned to the species level. Synthetic metagenome ~~from~~ MinION
38 libraries generated using version 6 kit and chemistry yielded 899-3,497 2D reads with lengths
39 averaging 5,700 bp with up to 98% assignment accuracy at the species-level. The observed
40 community proportions for “equal” and “rare” synthetic libraries were close to the known
41 proportions, deviating from 0.1 – 10% across all tests. For a 20-species mock community with
42 staggered contributions, a sequencing run detected all but 3 species (each included at <0.05% of
43 DNA in the total mixture); 91% of reads were assigned to the correct species, 93% of reads were
44 assigned to the correct genus, and >99% of reads were assigned to the correct family.

45
46 **Conclusions:** At the current level of output and sequence quality (just under 4×10^3 2D reads for a
47 synthetic metagenome), MinION sequencing followed by Kraken or One Codex analysis has the
48 potential to provide rapid and accurate metagenomic analysis where the consortium is comprised
49 of a limited number of taxa. Important considerations noted in this study included: high
50 sensitivity of the MinION platform to the quality of input DNA, high variability of sequencing
51 results across libraries and flow cells, and relatively small numbers of 2D reads per analysis limit.
52 Together, these limited detection of very rare components of the microbial consortia, and would
53 likely limit the utility of MinION for the sequencing of high-complexity metagenomic

1 54 communities where thousands of taxa are expected. Furthermore, the limitations of the currently
2 55 available data analysis tools suggest there is considerable room for improvement in the analytical
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4 56 approaches for the characterization of microbial communities using long reads. Nevertheless, the
5
6 57 fact that the accurate taxonomic assignment of high quality reads generated by MinION is
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8 58 approaching 99.5% and, in most cases, the inferred community structure mirrors the known
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10 59 proportions of a synthetic mixture, warrants further exploration of practical application to
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12 60 environmental metagenomics as the platform continues to develop and improve. With further
13
14 61 improvement in sequence throughput and error rate reduction, this platform shows great promise
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16 62 for precise real-time analysis of the composition and structure of more complex microbial
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18 63 communities.
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23 65 **Keywords**

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26 66 MinION™, Oxford Nanopore Technologies, metagenome, whole-genome sequencing, long-read
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28 67 sequencing
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31 69 **Background**

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33 70 Environmental metagenomics, employing whole genome sequence analysis to identify ecologically
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35 71 and epidemiologically important components of sediments, soils, waters, and surfaces, is rapidly
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37 72 evolving through advances in both hardware and software [1]. Knowledge of the consortia that
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39 73 inhabit these ecosystems allows for better understanding of the organisms and their ecological roles,
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41 74 provides for the development of effective strategies to mitigate ecosystem damage, and facilitates
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43 75 evaluation of the responses of species to environmental change. One common approach in
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45 76 environmental metagenomics involves sequencing and subsequent annotation of whole genome
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47 77 nucleic acid fragments (WGS) extracted directly from environmental samples to discover major
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49 78 microbial members of the ecosystem; if sequenced deeply enough, rare species can be detected [2].
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51 79 For well-studied members of the microbial community, such metagenomic data also can be used to
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53 80 characterize the functional potential of complex communities.
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1 81 One technique for characterizing environmental metagenomes is to use short-read high-
2 82 throughput sequencing followed by mapping the reads to reference genomes. Profiling the taxonomic
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4 83 composition of the community also can be accomplished by the analysis of the distribution of k-mers
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6 84 (e.g., using Kraken or One Codex). Although these methodologies are very powerful due to the depth
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8 85 of sequencing, the capacity to resolve the taxonomy of the community to the species level is limited
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10 86 by read length. One approach to overcome this limitation is to assemble short reads into contigs prior
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12 87 to analysis and annotation. If assembled correctly, the longer sequence lengths of the contigs have a
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14 88 greater chance of accurately identifying the members of the community; however, due to the mixed
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16 89 nature of the samples, such assembly approaches are challenged by many artifacts including chimeric
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18 90 contigs that inappropriately combine sequence reads from multiple species. The high information
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20 91 content of very long reads such as those provided by MinION™ (Oxford Nanopore Technologies,
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22 92 Inc., Oxford, UK) has the potential to overcome some of the limitations of short reads by allowing for
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24 93 longer alignments that potentially can contribute to higher taxonomic specificity, functional
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26 94 characterization, and resolution. Although conceived almost two decades ago [3], nanopore-based
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28 95 whole-molecule sequencing has only recently become available to MinION™ Access Programme
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30 96 (MAP) participants for exploration and practical application [4]. Data generated by early access
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32 97 MinION™ flow cells have been assessed for whole genome sequencing [5, 6, 7, 8, 9], gene
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34 98 expression and transcriptome studies [10, 11, 12], clinical applications such as inferring antibiotic
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36 99 resistance of bacterial strains and the detection of influenza and Ebola virus [13, 14, 15], bacterial
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38 100 and viral serotyping [16], and clinical metagenomes of viral pathogens [17]. Efforts to use this
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40 101 technology to study diverse environmental communities have been limited [18] and there has not
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42 102 been, to our knowledge, any cross-validation of the results or any systematic assessment to determine
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44 103 the best data analysis strategies for nanopore-based environmental metagenomics. To investigate the
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46 104 potential of this platform for broader applications, we performed a set of experiments to quantify the
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48 105 ability of MinION™ long-read sequence data to accurately characterize the taxonomic composition
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50 106 and structure of metagenomes by assessing its performance in the characterization of low complexity
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52 107 synthetic metagenomes.
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2 **109 Data description**
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4 110 The raw MinION data [19] collected during sequencing by MinKNOW software (versions 0.49.2.9
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6 111 through 0.51.3.40 b201605171140) were immediately uploaded as FAST5 packets to Metrichor
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9 112 Agent (r7.3 2D basecalling, ver rx-2.22-44717-dg-1.6.1-ch-1.6.3; Mk1 2D base-calling, ver WIMP
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11 113 Bacteria k24 for SQK-MAP006), after which base-called data [19] were returned to the host
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13 114 computer, also in the form of FAST5 files. The programs poRe [20], Poretools [21], and NanoOK
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15 115 [22] were used to extract and characterize the numbers of reads and channels, after which only the 2D
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17 116 reads were stored in FASTQ and FASTA files for downstream analyses. The base-called data sets
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19 117 were scrutinized by methods commonly employed in metagenome analysis of short reads including
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21 118 MG-RAST [23], which assigns taxonomy based on predicted proteins and rRNA genes. The data sets
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23 119 also were analyzed by tools that have been shown to work for long-read data including: (1) WIMP
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25 120 [24], which assigns taxonomy by comparing read sequences against a database of bacteria, (2) Kraken
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27 121 [25], which uses exact alignments of *k-mers* and indexes more than 5000 genomes and plasmids, (3)
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29 122 One Codex [26], which uses exact *k-mer* alignment to classify sequences against a reference database
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31 123 of ~40,000 complete microbial genomes (including bacteria, viruses, fungi, protists, and archaea), and
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33 124 (4) by principal components analysis (PCA) based on the frequency of 5-mers in each read followed
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35 125 by annotation of reads with the top BlastN [27] hit (carried out in R [28]). Specific parameters are
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37 126 described in Methods.
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44 **128 Results**
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46 129 MinION™ WGS libraries were generated from 1 µg of fresh DNA isolates (see Methods) of separate
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48 130 cultures of two Proteobacteria, *Escherichia coli* and *Pseudomonas fluorescens*, and two
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50 131 Cyanobacteria, *Microcystis aeruginosa*, and *Synechococcus elongatus*, and from two different DNA
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52 132 mixtures of these four species. One mixture combined an equal mass of genomic DNA (gDNA) from
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54 133 each of the four species. The other mixture was created by combining 33% mass of gDNA from each
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56 134 of three species and only 1% of gDNA mass from the other species. The preparation of these libraries
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135 yielded sufficient Pre-sequencing Mix for multiple loads of each flow cell. An additional library was
136 derived from a commercially prepared 20-species mock community. Because only 100 ng of material
137 was provided by the supplier, genome pre-amplification using Φ 29 polymerase was required to
138 generate sufficient mass of DNA to create the sequencing library (see Methods).

139 To assess the purity of the cultures used in this study, we used the Sanger method to sequence
140 full-length (~1500 bp) 16S amplicons from each (Table 1). Inspection of those data revealed varying
141 degrees of genomic uniqueness at the species level. For the strain of *M. aeruginosa* used in this
142 study, the top 16S hit had a low sequence identity to any reference sequence in the database (90%).
143 In contrast, the input strain of *S. elongatus* was 99% identical to two different species of
144 *Synechococcus* (*S. elongatus* and *S. UTEX 2973*). In addition, whole-genome alignment indicated
145 that the input strain of *P. fluorescens* was highly similar to multiple species of *Pseudomonas*.
146 However, all of the input organisms were distinct at the genus level, thus that taxonomic level was
147 used for downstream analysis of the single-species and ‘Equal’ and ‘Rare’ synthetic samples.

148 MinION sequencing of the single-species libraries generated up to 31×10^3 reads (0.2 – 1.1×10^3 2D
149 reads that passed the quality filter) ranging from as short as 5 bp to as long as 267×10^3 bp (data
150 include both 2D pass and fail reads), and the resulting average length of single-species read subjected
151 to downstream analysis was 6×10^3 bp. Using MG-RAST, Kraken, and One Codex, up to 99.5% of
152 the high quality 2D reads obtained from the sequencing of the single-species libraries of *E. coli*, *P.*
153 *fluorescens*, *S. elongatus*, and *M. aeruginosa* were taxonomically assigned to the corresponding input
154 taxa (Table 3). The least accurate assignments were for *M. aeruginosa*, where at best 58% of 2D
155 reads were correctly assigned to the level of species, although more than half of the mis-assigned
156 reads were to closely related cyanobacteria genera and other prokaryotes known to break down
157 microcystin [29] (data not shown). All three methods of analysis assigned sequence reads of the *P.*
158 *fluorescens* single-species library to *Stenotrophomonas*. Over all of these analyses, MG-RAST
159 generally showed the lowest rate of correct taxonomic assignment and, although One Codex and
160 Kraken provided similar results, Kraken showed a lower rate of correct assignment for *M. aeruginosa*
161 (85%) compared to One Codex (95%).

162 In the second round of validation, using three synthetic communities containing mixtures of the
163 previously described species, $6\text{--}12\times 10^3$ reads ($0.7\text{--}1.3\times 10^3$ 2D reads) were generated per run, ranging
164 in length from $0.6\text{--}56.8\times 10^3$ bp (Table 2). For the two communities comprised of equal DNA
165 contribution from four bacteria (25% each species), WGS proportions accurately aligned with the
166 known proportions 87–99% of the time when analyzed using Kraken or One Codex and 65–85%
167 using MG-RAST (Table 3). Specifically, taxonomic assignment of reads obtained from the
168 sequencing of the equal mixture of four species (25% of each) using version 5 chemistry and run on
169 an original MinION device identified the following taxa: 27% *E. coli*, 16% *M. aeruginosa*, 30% *P.*
170 *fluorescens*, 21% *S. elongatus*, 3% Enterobacteriaceae, and 3% misclassified. In a subsequent test
171 (version 6 chemistry), classification results for the equal mixture were: 26% *E. coli*, 18% *M.*
172 *aeruginosa*, 30% *P. fluorescens*, 22% *S. elongatus*, and 3% Enterobacteriaceae, and 1% misclassified
173 (Figure 1). For the community with three common (33% of each) and one rare (1%) representative,
174 classifications were: 33% *E. coli*, 34% *P. fluorescens*, 29% *S. elongatus*, 1% *M. aeruginosa*, 2%
175 misclassified (a third of those latter category of reads were assigned to *Shigella*). For both the
176 “Equal” and “Rare” community data sets, the 5-mer frequency profiles were computed and visualized
177 using the top BlastN hit for each full read, revealing that 5-mer profiles for these long-read sequences
178 were shared within species. This was reflected in the 5-mer frequency analysis which revealed
179 distinct per-species clusters in the PCA plots (Figure 2).

180 In the final round of testing, the mock microbial community with 20 species included in
181 “staggered” proportions (i.e., 1,000 to 1,000,000 16S rRNA operon copies per organism per μL of
182 material supplied by BEI Resources, Catalog # HM-783D) yielded 14.7×10^3 reads (3.5×10^3 2D reads)
183 ranging in length from $0.5\text{--}20.9\times 10^3$ bp, sufficient to detect all of the high and moderate abundance
184 species, but the sequencing run failed to detect 3 of 5 species that were included at very low mass
185 ($0.6\text{--}1.0$ pg/ μL of material supplied; Table 4). For that run, misclassifications accounted for only
186 0.2% of read assignments but greatly overrepresented in the results for this run were reads assigned to
187 *E. coli* (included as 20% of DNA but observed as 46–52% of read assignments), whereas greatly
188 underrepresented in the results were reads assigned to *R. sphaeroides*, which was putatively included

189 as 41% of DNA mass but accounted for only 1% of read assignments (Figure 3). Although 75% of
 190 the read assignments made by WIMP were to genera known to comprise the mock community, 93%
 191 of the read assignments made by One Codex matched the correct genera.

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194 **Table 1** Identity of single-species used in this study as determined by Sanger sequencing of
 195 16S rDNA amplicons from different DNA preparations of each species.

Culture ^a	Final sequence Length (bp)	Sequence matches in BlastN	
		%	Organism
<i>Escherichia coli</i>	1440–1696 ^a	98	<i>E. coli</i> numerous strains
<i>Microcystis aeruginosa</i>	1418	90	<i>M. aeruginosa</i> NIES-843 and NIEHS-2549, and <i>M. panniformis</i> FACHB-1757
<i>Pseudomonas fluorescens</i>	1478–1570	96	<i>P. fluorescens</i> A506 and LBUM223
<i>Synechococcus elongatus</i>	1431–1719	99	<i>S. elongatus</i> PCC 7942, PCC 6301, UTEX 2973

196 ^a Multiple DNA preparations from bacterial cultures were used during the progress of the study, and each was tested,
 197 yielding for each strain slightly different final 16S sequence lengths, but the same BLAST matches.

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200 **Table 2** Details of MinION™ whole genome sequencing output for single-species and
 201 synthetic mixtures. Sequencing experiments used the MinION device and new R7.3
 202 flow cells. Libraries were prepared with kit SQK–MAP005 as indicated by (5) and
 203 SQK–MAP006 chemistry, indicated by (6). Columns relating to “2D” indicate bi-
 204 directional reads with quality above Q9.

Experiment (chemistry)	Pores with reads	Run time (hr) ^a	Total bp (Mbp)	Total reads	Number of 2D pass reads	Mean 2D read length (bp)	MG-RAST accession	ENA accession
Single species								
<i>E. coli</i> ⁽⁵⁾	430	42	83.6	26590	1112	5274	4629367.3	ERR1713483
<i>P. fluorescens</i> ⁽⁵⁾	453	48	119.4	25228	777	7784	4629445.3	ERR1713487

<i>M. aeruginosa</i> ⁽⁵⁾	377	18	40.8	22760	569	5676	4629369.3	ERR1713486
<i>S. elongatus</i> ⁽⁵⁾	367	23	18.3	6163	224	5101	4629381.3	ERR1713489
Mixtures								
Equal ⁽⁵⁾	129	24	26.5	10592	714	5527	4614572.3	ERR1713484
Equal ⁽⁶⁾	437	44	77.1	12174	1358	5202	4685746.3	ERR1713485
Rare ⁽⁶⁾	449	18	39.0	6728	899	6194	4685745.3	ERR1713488
Staggered ⁽⁶⁾	300	33	39.0	14711	3497	2612	4705090.3	ERR1713490

^a Runs were set to either 24 or 48 hours and were allowed to continue until either sufficient sequence data were collected or until the 2D pass rate was greatly reduced.

Table 3 Taxonomic assignment accuracy of metagenomic reads across three analysis methods.

Accuracy of assignment to known genus (%)			
Experiment	MG-RAST	Kraken	One Codex
Single species			
<i>E. coli</i> ⁽⁵⁾	74.4 ^a	99.5	98.7
<i>P. fluorescens</i> ⁽⁵⁾	84.9 ^b	84.6 ^b	84.2 ^b
<i>M. aeruginosa</i> ⁽⁵⁾	53.1	85.8	95.1
<i>S. elongatus</i> ⁽⁵⁾	87.9	98.1	97.6
Mixtures			
Equal ⁽⁵⁾	65.0 ^b	97.6	87.4 ^c
Equal ⁽⁶⁾	85.9	98.0	98.7
Rare ⁽⁶⁾	92.9	99.1	98.7

^a 15% of reads assigned to *Shigella*

^b 7-15% of reads assigned to *Stenotrophomonas*

^c 7% of reads assigned to *Stenotrophomonas*

Accuracy was calculated as the proportion of reads assigned to the known input organism at the genus level out of the total number reads given any assignment at that rank.

Table 4 Known composition of 20-species mock staggered community compared with analysis results for WIMP and One Codex. “nd”: not detected.

Organism	Operon count/μL ^a	Quantity pg/μL ^b	% DNA in template ^c	WIMP % species	WIMP % genus	One Codex % species	One Codex % genus
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<i>Acinetobacter baumannii</i>	10,000	8.2	0.24	0.14	0.14	0.29	0.29
<i>Actinomyces odontolyticus</i>	1,000	1	0.03	nd	nd	nd	nd
<i>Bacillus cereus</i>	100,000	45	1.33	0.53	0.53	0.66	0.75
<i>Bacteroides vulgatus</i>	1,000	0.8	0.02	0.1	0.1	0.07	0.12
<i>Clostridium beijerinckii</i>	100,000	44	1.30	0.19	0.19	0.29	0.35
<i>Deinococcus radiodurans</i>	1,000	1	0.03	0.05	0.05	0.07	0.06
<i>Enterococcus faecalis</i>	1,000	0.7	0.02	nd	nd	nd	nd
<i>Escherichia coli</i>	1,000,000	680	20.04	45.61	45.66	52.15	52.52
<i>Helicobacter pylori</i>	10,000	8.6	0.25	1.68	1.68	3.43	2.72
<i>Lactobacillus gasseri</i>	10,000	3.2	0.09	0.14	0.14	0.22	0.23
<i>Listeria monocytogenes</i>	10,000	5	0.15	0.38	0.38	0.58	0.52
<i>Neisseria meningitidis</i>	10,000	5.8	0.17	0.24	0.24	0.44	0.41
<i>Propionibacterium acnes</i>	10,000	8.8	0.26	0.48	0.48	0.07	0.64
<i>Pseudomonas aeruginosa</i>	100,000	160	4.71	1.25	1.25	3.07	3.18
<i>Rhodobacter sphaeroides</i>	1,000,000	1,400	41.25	1.01	1.01	1.46	1.27
<i>Staphylococcus aureus</i>	100,000	59	1.74	0.38	3.88	1.31	12.74
<i>Staphylococcus epidermidis</i>	1,000,000	510	15.03	7.67	7.72	6.65	
<i>Streptococcus agalactiae</i>	100,000	32	0.94	0.96	1.01	0.95	16.97
<i>Streptococcus mutans</i>	1,000,000	420	12.38	10.17	10.17	19.50	
<i>Streptococcus pneumoniae</i>	1,000	0.6	0.02	nd	nd	nd	
Other		0	0	29.02 ^d	25.37 ^e	8.77 ^f	7.24 ^g
Correct assignments				70.98	74.63	91.23	92.76

^aTheoretical copy number provided by BEI Resources certificate of analysis

^bgDNA content provided by BEI Resources certificate of analysis

^cProportion of individual species within the mock community.

^dOf these, 12.7% were correctly assigned to genus, 86.4% were Enterobacteriaceae, and only 0.7% were misclassifications.

^eOf these, 86.4% were Enterobacteriaceae and only 0.7% were misclassified.

^fOf these, 56.8% were *Shigella*.

^gOf these, 63.3% were species of *Escherichia* and *Shigella*.

Discussion

Sequencing of whole genome libraries can enhance environmental metagenomic analysis by providing more precise identification of the composition and structure of the community than is

228 possible by amplicon sequencing of marker genes (e.g., 16S) [2, 30]. Typical environmental samples
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2 229 contain tens of thousands to millions of organisms, yet the resulting metagenomes almost certainly
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4 230 underrepresent this diversity and, often due to short-read strategy, the resulting data sets can be
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6 231 confidently assigned only to higher taxonomic levels [31, 32]. One strategy to improve the accuracy
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8 232 of taxonomic assignment is to carefully assemble metagenomic data, which despite the potential for
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10 233 chimeric contig formation has been shown to greatly enhance species call correctness [33]. However,
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12 234 even with enhanced sequencing and bioinformatic strategies, many public database accessions contain
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14 235 sequences that are not innate to the species that was analyzed; these include symbionts, parasites,
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16 236 pathogens, and sequencing linkers/primers/adapters (unbeknownst to those who have accessed the
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18 237 data) that can lead to false discovery rates [34]. Contaminated and mis-annotated reference sequences
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20 238 can affect environmental metagenome analyses that are derived from short reads to a greater extent
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22 239 than would be expected from analyses based on long reads. Long reads can circumvent these issues
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24 240 [31, 35, 36], so long as much of the genome for each component organism is represented in the
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26 241 sequencing library and there are few errors in the sequences and the reference database. The results
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28 242 reported here allow us to consider the potential utility of MinION long read sequencing and
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30 243 subsequent bioinformatic analysis for shotgun environmental metagenomics.

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33 244 The primary challenge of microbial metagenomic sequence analysis using long reads is the
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35 245 comparison of input sequences against a large reference database of whole genomes from bacteria,
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37 246 viruses, fungi, etc. Although a number of algorithms have been developed for alignment of long,
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39 247 error-prone reads [37, 38], those sensitive algorithms are not optimized for the challenge of
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41 248 comparison against the large and ever-expanding universe of microbial genomes. The bioinformatic
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43 249 methods used in this analysis, MG-RAST, Kraken, One Codex, and WIMP, each compare the input
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45 250 reads against their own more concise reference databases, providing an assignment for the most likely
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47 251 origin of each individual sequence.

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53 252 We found that for low complexity synthetic communities, long reads generated by MinION
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55 253 provided sufficiently precise sequence data to assign organisms represented at or above 1%. In fact,
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57 254 two out of five species included at <0.05% in a mock community (and 9 out of 9 species included at
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59 255 0.05-1.00%) were detected. Furthermore, for un-amplified whole genome preparations, read
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256 assignments were observed to be within about 10% of their proportional occurrence in the
1 metagenome. Ultimately, we saw that although the reads were longer, because the sequence coverage
2 257 was not as deep, the improvement in specificity of assignment was offset by a reduction in the
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4 258 sensitivity, and some of the genomes present at low concentration were not detected.
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9 260 By comparing the output of multiple analysis methods, we were able to gain insight into the
10 performance of various bioinformatic approaches for analyzing error-prone MinION reads. Overall,
11 261 MG-RAST provided the lowest level of accuracy and detected multiple organisms that were not a part
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13 262 of the known input set. This is not surprising given that MG-RAST is optimized for analyzing short-
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15 263 read, low-error data. Kraken and One Codex performed similarly for the single-species samples
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17 264 except in the case of *M. aeruginosa*, in which case One Codex correctly identified this taxon at a
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19 265 higher rate than Kraken (95% vs. 85%). For the equal mixture with the version 5 chemistry, Kraken
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21 266 showed a higher rate of correct assignment than One Codex (97.6% vs 87.4%), although the two
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23 267 methods were generally comparable (actually One Codex was slightly more accurate) for the equal
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25 268 mixture when using version 6 of the MinION chemistry. An unexpected finding of this study was the
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27 269 detection by all three methods of *Stenotrophomonas* in the *P. fluorescens* single-species sample.
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29 270 Interestingly, *Stenotrophomonas* was classified as *Pseudomonas* when it was first discovered, based
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31 271 on similar metabolic capabilities, and was later moved to its own genus based on molecular data [39].
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33 272 Our 16S sequences derived from laboratory cultures used in this study did not identify
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35 273 *Stenotrophomonas*, suggesting that its identification in the mixed metagenomes is not a result due to a
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37 274 contaminant but rather, an artifact caused by assigning taxonomy to reads with multiple sequencing
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39 275 errors. Also contributing to its identification is the fact that both *Pseudomonas* and
40
41 276 *Stenotrophomonas* share functional phenotypic characteristics, indicating they may share homologous
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43 277 genes coding for those characteristics. The sharing of homologous genes, similar GC contents (both
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45 278 species genomes have 66% GC), and the higher error rate are the most likely factors responsible for
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47 279 the assignment of *Pseudomonas* sequence reads to *Stenotrophomonas*.
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51 281 The fact that the estimated proportions of community members in synthetic mixtures were not
52
53 282 precise despite careful DNA quantitation could indicate differences across library preparation (all
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55 283 libraries were prepared by BLB), reagent kits, flow cells, MinKNOW control scripts, the quality of
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284 DNAs used to create the synthetic metagenomes, and the methods used for quantification (Qubit for
1 the home-grown mixtures and UV spectrophotometry for the 20-species mixture). Because DNA
2 285 the home-grown mixtures and UV spectrophotometry for the 20-species mixture). Because DNA
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4 286 quality is of paramount importance for MinION sequencing, PreCR (used in the version 5 protocol) or
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6 287 FFPE Repair Mix (used in the version 6 protocol) was included in the preparation of all libraries. The
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8 288 potential for profound effects related to library preparation recently was examined by Jones and
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10 289 collaborators [30], leading to the recommendation that studies of complex metagenomes should be
11
12 290 based on PCR-free approaches. The current data indicate that the MinION lends itself well to a PCR-
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14 291 free approach but its utility for the analysis of complex metagenomes is presently limited by the small
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16 292 number of reads that pass the quality filtering process. The current study also provides data for
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18 293 considering alternatives to PCR for amplification, in this case GenomiPhi™, which was used to
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20 294 generate sufficient DNA for one library in the current study (“Staggered”). This method is optimized
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22 295 for linear DNA and was intended to generate unbiased copies of the 20-species genomes.
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24 296 Nevertheless, the Φ29 pre-amplification step is one possible reason for the overrepresentation of *E.*
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26 297 *coli* and underrepresentation of *R. sphaeroides* in the sequencing of the 20 species mock community.
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28 298 Also, a consequence of Φ29 pre-amplification combined with putative differences in DNA quality,
29
30 299 chimeric amplicons (known to occur with Φ29 amplification of microbial communities [40]) could
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32 300 have been formed predominantly from higher quality *E. coli* DNA re-priming itself [41] leading to
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34 301 overrepresentation of the *E. coli* component. Notably, a novel low input DNA approach recently
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36 302 reported [42] could enhance MinION analyses of samples with low DNA yields. Although the pre-
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38 303 amplification step is the most likely culprit, an additional effect that could contribute to incongruence
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40 304 of known and estimated proportions in the 20 species mock community is that organisms for which
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42 305 there are many accessions in the public databases provide for more precise classification (e.g., NCBI
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44 306 has more than 6×10^5 *E. coli* complete genome accessions) and that *vice versa*, organisms with
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46 307 relatively few accessions (e.g., NCBI has only 116 *R. sphaeroides* complete genome accessions)
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48 308 result in less precise classification.
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56 309 Despite the rather small number of 2D reads that were observed to pass the quality filter across all
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58 310 MinION runs, there was a strong biological signal in the data (Figure 2). Thus, as investigators have
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1 found MinION useful for single genome introspection [6, 9, 15], 16S and other amplicon resolution
2 [16, 43], cDNA sequencing [11], and assembly [5, 44, 45], our findings imply that this platform has
3 immediate utility for analysis of very simple mixtures (e.g., serum testing for pathogens). Over the
4 18-month period of MinION use for this set of experiments, 2D pass rates increased from 2% to 24%.
5 Because the rate of improvement is concurrent with Moore's Law [46], we speculate that future
6 improvements will make the MinION platform very useful in the analysis of complex metagenomic
7 samples in the near future. The cloud-based WIMP base-calling and taxon prediction program
8 associated with the device provides a method of real-time analysis of metagenomic data. However,
9 because we had no control over the comparative database, the cloud implementation of WIMP was far
10 less flexible for environmental metagenomic analysis than Kraken or One Codex, and we note that
11 use of an incomplete database can lead to false positives and negatives. By the time of submission of
12 this study, the R7.3 flow cells and sequencing chemistry were no longer available. Subsequent
13 versions of the platform have shown dramatically lower error and higher throughput. This study
14 nevertheless provides a baseline for considering nanopore metagenomics and provides an impetus for
15 further development of MinION output and data analysis, specifically with regard to evaluation of the
16 informative value of 1D reads, scrutiny of reference data, alternative alignment algorithms, and more
17 sophisticated k-mer analyses. As the quality rate for this platform improves, the potential will
18 increase for MinION to accurately resolve the diversity and composition of many of the taxa in an
19 environmental metagenome.

20 **Methods**

21 To set a baseline of expectations for MinION metagenomic analysis, we performed single-species
22 sequencing runs with four organisms. Cell cultures at log phase were harvested by spinning 15 mL
23 culture tubes at $3,000 \times g$ for 30 min, and DNA was isolated using the PowerSoil DNA kit (MoBio,
24 Carlsbad, CA, USA) according to the manufacturer's instructions. Nucleic acid quality and quantity
25 were checked via Nanodrop 2000 and Qubit, whereafter 1 μg of DNA was used to prepare sequencing
26 libraries. For the first two mixtures, equal portions of DNAs from all four organisms (250 ng each)

338 were used (“equal”) and, for the third mixture (“rare”), equivalent amounts of three of the species
339 were used (330 ng each) and *M. aeruginosa* was included as only 1% of the mixture (10 ng). An
340 additional preparation of a mock community containing DNA of 20 bacterial species in staggered
341 amounts was obtained from a commercial source (Catalog # HM-783D, BEI Resources, ATCC,
342 Manassas, VA, USA). This mock community preparation was chosen because it previously has been
343 used to test the ability of the R7.3 version MinION to study microbial diversity via 16S amplicon
344 approach [43]. However, because sequencing libraries for this study required 1 µg of DNA, to
345 generate sufficient starting material 1 µL of the mock community sample (5.5 ng of template, the
346 amount recommended by the supplier for a typical reaction) was pre-amplified using Φ29 enzyme
347 from the GenomiPhi V3 kit (25-6601-24, GE Healthcare Bio-Sciences, Pittsburgh, PA, USA)
348 according to the manufacturer’s recommendations. This version of Φ29 enzyme was chosen for
349 isothermal pre-amplification due to the high-fidelity proof-reading aspects of its replication process
350 [47].

351 The composition of each microbial mixture was calculated on the basis of the relative DNA mass
352 contributed from each organism. Due to the random nature of shotgun sequencing, this library
353 construction strategy is expected to result in a relative proportion of reads sequenced from each
354 organism that corresponds to the relative input mass. In other words, the relative genome size of each
355 organism should not have impacted the relative proportion of reads recovered from each organism.

356 Sequencing libraries were prepared for R7.3 flow cells run on an original MinION device using
357 the Genomic DNA Sequencing Kit SQK–MAP005 (version 5 chemistry) according to the base
358 protocol from Oxford Nanopore with slight modifications [48] and for flow cells run using the
359 Nanopore Sequencing Kit SQK–MAP006 (version 6 chemistry) according to the manufacturer’s
360 recommendations. The steps for library SQK–MAP005 preparation included in this order: shearing 1
361 µg in a Covaris g-TUBE (Covaris, Inc., Woburn, MA, USA) at 2,000 × g for 2 min, treatment with
362 PreCR (New England Biolabs, Beverly, MA, USA), cleanup with 1X AMPure beads (Agencourt,
363 Beckman Coulter, Brea CA, USA), end-repair with NEBNext End Repair Module (New England
364 Biolabs), cleanup with 0.5X AMPure beads, dA-tailing with NEBNext dA-Tailing Module (New

1 365 England Biolabs), ligation to a cocktail of both the leader and hairpin sequencing adapters (Oxford
2 366 Nanopore Technologies) using Blunt TA Ligase (New England Biolabs), cleanup using his-tag
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4 367 Dynabeads (Life Technologies, City, State, USA), and recovery of the pre-sequencing mix in 25 μ L
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6 368 of Elution Buffer (Oxford Nanopore Technologies). After priming the flow cell with EP solution
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9 369 according to the manufacturer's recommendations, an initial 6 μ L aliquot of the pre-sequencing mix
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11 370 (at 10-20 ng/ μ L) was combined with 141 μ L EP Solution and 3 μ L Fuel Mix and applied to the flow
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13 371 cell. Thereafter, at 6-8 hr intervals, additional pre-sequencing mix aliquots (held on ice) combined
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16 372 with EP Solution and Fuel Mix were added to the flow cell at times roughly coinciding with re-
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18 373 programmed pore "remux," which is a process that adjusts the bias voltage and mux channels to
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20 374 maximize yield performance. Modified scripts (J. Tyson, pers. comm.) caused the MinION device to
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22 375 perform four remux steps at 8 h intervals to maintain regular increases in data (Figure 4).

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25 376 Steps for library SQK-MAP006 preparation included in this order: shearing in a Covaris g-TUBE
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27 377 (Covaris, Inc., Woburn, MA, USA) at 2,000 \times g for 2 min, treatment with PreCR (New England
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29 378 Biolabs, Beverly, MA, USA), cleanup with 1X AMPure beads (Agencourt, Beckman Coulter, Brea
30
31 379 CA, USA), combined end-repair and dA-tailing with NEBNext UltraII End Repair/dA-Tailing
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33 380 Module (New England Biolabs), cleanup with 1X AMPure beads, ligation to a cocktail of both the
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36 381 leader and hairpin sequencing adapters (Oxford Nanopore Technologies) using Blunt TA Ligase
37
38 382 (New England Biolabs), addition of a tether to the hairpin segment, cleanup using MyOne
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40 383 Streptavidin C1 Beads (Life Technologies, Carlsbad, CA, USA), and recovery of the pre-sequencing
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42 384 mix in 25 μ L of Elution Buffer (Oxford Nanopore Technologies). After priming the flow cell with
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45 385 running buffer and fuel according to the manufacturer's recommendations, an initial 6 μ L aliquot of
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48 386 the pre-sequencing mix (at 10-20 ng/ μ L) was combined with 75 μ L Running Buffer, 65 μ L water, and
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50 387 4 μ L Fuel Mix and applied to the flow cell. Thereafter, at 8 hr intervals, additional pre-sequencing
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52 388 mix aliquots (held on ice) were combined with Running Buffer and Fuel Mix and added to the flow
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55 389 cell at times roughly coinciding with re-programmed pore remux (modified scripts from J. Tyson,
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57 390 pers. comm.) Modified remux scripts were not used for the final MinION run (Staggered community
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59 391 analysis) because that run was controlled by a new version of MinKNOW.
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392 Whole genome sequence data (2D FASTQ) from the MinION R7.3 flow cells were accessed on
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2 393 the MG-RAST server [23] and annotated based on their predicted proteins and rRNA genes using the
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4 394 BLAT annotation algorithm [49] against the M5NR protein Db, screened to remove any sequences
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6 395 matching *H. sapiens* (none found), and without dereplication or dynamic trimming. Although
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8 396 optimized for short read data, the MG-RAST tools were implemented because they allow query of a
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10 suite of comprehensive nonredundant genetic databases and because this server provides a means to
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12 share both raw data and computational results. Raw read counts were later accessed from MG-RAST
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14 using the API endpoint for organism summaries. The recommended parameters “hit_type=single”,
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16 “source=RefSeq”, and “evaluate=15” were used to generate the appropriate read-level abundance
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18 information. The same read sets (2D FASTA) also were analyzed by Kraken [25] using the default k-
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20 mer size, minimizers, and other parameters, and accessing a local database created from archaea,
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22 bacteria, fungi, virus, protozoa, human, and invertebrate genomes. The Kraken tool was implemented
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24 because it is much faster than MG-RAST and allowed use of a smaller, more targeted reference
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26 database. The results were translated (kraken-translate) and summarized (kraken-report) to provide
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28 full taxonomic names for each classified sequence. Metagenomic analysis using One Codex was
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30 performed by uploading the 2D FASTQ data to the One Codex platform at <https://app.onecodex.com>.
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32 This cloud-based k-mer method was selected because it is reportedly more accurate than either the
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34 MG-RAST or the Kraken tools and because like MG-RAST, it provides for community access to the
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36 data and analytical results. Because of the high error rate of the R7.3 version MinION nucleotide
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38 data, the unfiltered One Codex results were used for this analysis, which do not include an automated
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40 error-filtering step. The One Codex read-level classification results were accessed by selecting the
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42 “unfiltered” option in the web-based results display and downloading a data table for each sample to
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44 generate appropriate read-level abundance information for tabulation.
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51 415 Comparative data sets were generated for each of the four single species templates using full
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53 length ~1500 bp Sanger sequencing of a 16S amplicons [50]. Reads from the 16S analysis were
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55 subjected to BlastN for taxonomic assignment.
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Figure 1 Result of “What’s in my pot” analysis of a mixture with equal DNA mass from four bacterial strains.

Rendering of real-time analysis using WIMP [20] of whole genome sequences from a synthetic mixture prepared from equal DNA quantities of four cultured microbe species (experiment “Equal ⁽⁶⁾” in Tables 1 and 2) and run on the MinION™ sequencing platform. Arc angle is proportional to the number of reads assigned to the indicated species. Colors (scale at bottom of diagram) refer to the classification score threshold (for this analysis the threshold for inclusion was 0.01).

Figure 2 Principal component analysis of normalized 5-mer frequency (i.e., percentage) within each MinION™ read for a mixture with equal DNA mass from four bacterial strains and a mixture with one rare component.

A: Sequencing run with equal DNA mass from four species. B: sequencing run with three equally represented (33% DNA mass each) and one rare (1% DNA mass) species included in the DNA pool. “none”: read had no BlastN hits. “other”: read had BlastN hits but not one of the four species included in the mix.

Figure 3 Log abundance of reads assigned from staggered mixture.

DNA of 20 species mixed in various proportions (BEI Resources, ATCC, HM-783D, operon counts μL^{-1} in original mixture indicated along bottom margin of bars) was pre-amplified with $\Phi 29$ polymerase prior to library preparation and sequenced with MinION™ R7.3 flow cells. The 2D reads that passed quality filtering were assigned to taxa using Kraken. Colored bars are species included in the mix whereas gray bars indicate species detected but not included in the original DNA mixture.

Figure 4 Read production using a MinION™ device and an R7.3 flow cell.

445 Illustration of reads collected from a synthetic metagenome made with equal DNA mass from
446 four microbias species and a library prepared using SQK-MAP006 kit. Arrows indicate
447 approximate times when additional aliquots of library and fuel were added.

449 **Availability and requirements**

- 450 • Project name: Experimental Metagenome on MinION
- 451 • Project home page: <https://github.com/gigascience/paper> link will be here.
- 452 • Operating system: Unix
- 453 • Programming language: Bash and R
- 454 • Other requirements: Unix
- 455 • License: N/A

457 **Availability of supporting data**

458 The datasets supporting the results of this article are available in the GigaDB repository [19],
459 on the MG-RAST server 4629367.3, 4629445.3, 4629369.3, 4629381.3, 4614572.3,
460 4685746.3, 4685745.3, 4705090.3, and at the European Nucleotide Archive as primary
461 accessions PRJEB8672 and PRJEB8716. One Codex results are available at
462 https://app.onecodex.com/projects/bb_minion_env.

464 **Competing interests**

465 BLB, MW, MCR, and RBF are enrolled in the Oxford Nanopore MinION™ Access
466 Programme (MAP) and received free materials for this research. SSM is an employee of One
467 Codex.

469 **Authors' contributions**

1 470 BLB conceived of the study, performed the DNA extraction and sequencing, directed the
2 471 data analysis, and drafted the manuscript. MW provided bioinformatic analyses and
3
4 472 statistical analyses. MCR participated in study design, sequence alignment, and
5
6
7 473 bioinformatic analysis. RBF participated in study design, sequencing, data analysis, and
8
9
10 474 manuscript preparation. SSM performed some of the bioinformatic analyses and data
11
12 475 interpretation. All authors read and approved the final manuscript.
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15 476

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43
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45
46 489 NIAID, NIH as part of the Human Microbiome Project: Genomic DNA from Microbial
47
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49 490 Mock Community B (Staggered, Low Concentration), v5.2L, for 16S rRNA Gene
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51 491 Sequencing, HM-783D.
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53 492 **List of abbreviations**

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58 494 MAP: MinION™ Access Programme
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495 2D: refers to sequences where both the template and the complement were completed

496 (bidirectional) and passed the Metrichor quality threshold (Q9)

497 PCA: principal components analysis

498 gDNA: genomic DNA isolates from putatively pure cultures of bacterial strains

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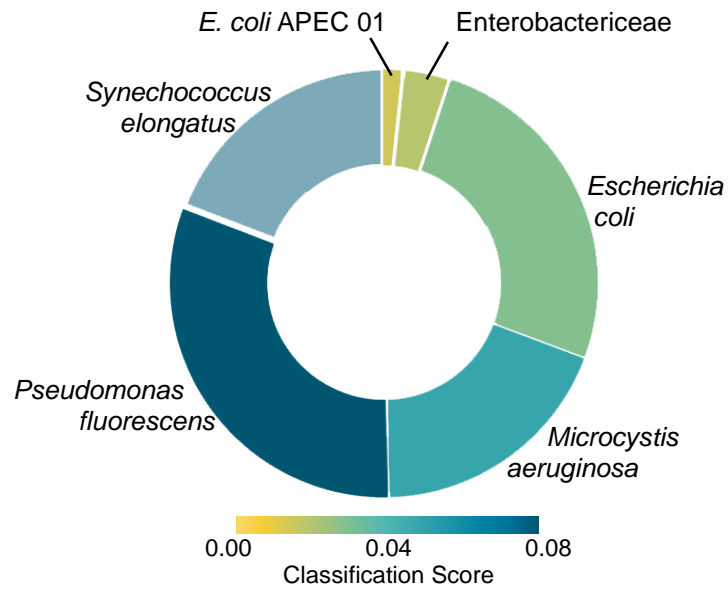
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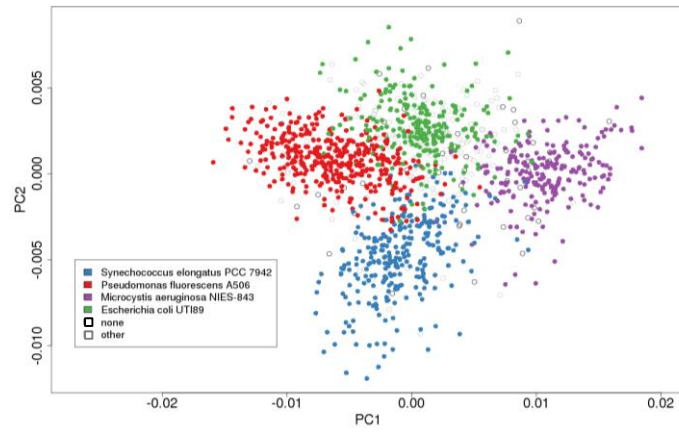
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