1	Identifying mixed Mycobacterium tuberculosis infection and
2	laboratory cross-contamination during Mycobacterial sequencing
3	programs
4	
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18	Keywords
19	Mycobacterium tuberculosis, next generation sequencing, quality control, mixed infection, cross-

20 contamination

## 21 ABSTRACT

- 22 Introduction: Detecting laboratory cross-contamination and mixed tuberculosis infection are
- 23 important goals of clinical Mycobacteriology laboratories.
- 24 **Objectives:** To develop a method detecting mixtures of different *M. tuberculosis* lineages in
- 25 laboratories performing Mycobacterial next generation sequencing (NGS).
- 26 Setting: Public Health England National Mycobacteriology Laboratory Birmingham, which performs
- 27 Illumina sequencing on DNA extracted from positive Mycobacterial Growth Indicator tubes.
- 28 **Methods:** We analysed 4,156 samples yielding *M. tuberculosis* from 663 MiSeq runs, obtained
- 29 during development and production use of a diagnostic process using NGS. Counts of the most
- 30 common (major) variant, and all other variants (non-major variants) were determined from reads
- 31 mapping to positions defining *M. tuberculosis* lineages. Expected variation was estimated during
- 32 process development.
- 33 **Results:** For each sample we determined the non-major variant proportions at 55 sets of lineage
- 34 defining positions. The non-major variant proportion in the two most mixed lineage defining sets
- 35 (F2 metric) was compared with that in the 47 least mixed lineage defining sets (F47 metric). Three
- 36 patterns were observed: (i) not mixed by either metric, (ii) high F47 metric suggesting mixtures of
- 37 multiple lineages, and (iii) samples compatible with mixtures of two lineages, detected by
- 38 differential F2 metric elevation relative to F47. Pattern (ii) was observed in batches, with similar
- 39 patterns in the H37Rv control present in each run, and is likely to reflect cross-contamination.
- 40 During production, the proportions of samples in each pattern were 97%, 2.8%, and 0.001%,
- 41 respectively.
- 42 Conclusion: The F2 and F47 metrics described could be used for laboratory process control in
   43 laboratories sequencing *M. tuberculosis*.
- 44 (249 words)

### 45 INTRODUCTION

46 Mycobacterium tuberculosis is an organism which has co-evolved with humans during the early 47 migrations of modern man, diverging from a common *M. tuberculosis* ancestor about 75,000 years 48 ago (1). Distinct lineages, corresponding to evolution occurring during these early migrations, are 49 readily identified by next generation sequencing (NGS), with each lineage characterised by ancient 50 single nucleotide variants (SNV) which define deep branches in the *M. tuberculosis* phylogeny (1, 2). 51 Multiple M. tuberculosis lineages: Infection by multiple lineages of TB is well described, and has 52 been detected by observing mixed results on fractional sequencing (e.g. spoligotyping, MIRU-VNTR) 53 and validated by characterisation of multiple individual picks from solid media (3). Multi-lineage 54 infection is characterised by isolates differing by many hundreds of SNVs, in which respect it differs 55 from the increasingly recognised and more common in-host microevolution (4). Reported rates of 56 mixed infection vary markedly as reviewed (3, 5), with between 10 and 30% reported in areas of

current (5-7) or historical (8, 9) high prevalence. Much lower rates are reported in low incidence
countries (3), although systematic under-detection is likely to occur due to both to the limited

59 representation of bacteria in single sputum samples of pulmonary disease, and to the decrease in

60 diversity occurring during differential strain growth in broth culture (10).

61 Implications of mixed infection: Mixed infection, assessed by either MIRU-VNTR polymorphisms (7) or by heterogeneity in drug susceptibility testing (11), is independently associated with reduced drug 62 treatment response, so there are compelling clinical reasons to try to identify it. There are also 63 64 important technical implications of isolating mixed TB strains from a culture. Firstly, such a finding 65 may reflect cross-contamination within the laboratory (3). Secondly, mixed infection complicates 66 the interpretation of drug resistance tests, whether phenotypic or genotypic, as one or other co-67 infecting strain may dominate the results from these tests. Thirdly, it complicates the understanding 68 of relatedness when techniques such as SNV distance computation are applied, as these generally 69 assume a single sequence is present when base-calling (5, 12-14), marking mixed sites as uncertain. 70 Maximal likelihood tree drawing algorithms assume such 'uncertain' sites contain no information 71 and impute a single nucleotide at each of such positions, an approach which may be inappropriate in 72 the presence of mixtures.

73 Increasingly, NGS based species and resistance determination is becoming routine in

74 Mycobacteriology laboratories, and has been deployed in reference laboratories in England (15, 16).

As part of the quality control and accreditation of the routine process now operating in these

76 laboratories, we describe an approach to identifying mixed samples using Illumina next generation

- 77 sequencing data, illustrating its use by studying over 4,000 consecutive positive cultures from a
- 78 single reference laboratory.
- 79

## 80 METHODS

#### 81 Isolation of DNA from Mycobacteria and sequencing

- 82 This study includes all mycobacteria processed between 01/06/2015 and 30/12/2017 in the Public
- 83 Health England Midlands and North reference laboratory, whose catchment is approximately 15
- 84 million people, or about one third of England. Clinical specimens were decontaminated and
- 85 inoculated into Mycobacterial Growth Indicator Tubes (MGIT) tubes. During the process (Fig. 1)
- 86 positive MGIT tubes were batched when they became available, either following growth in the local
- 87 laboratory, or following receipt from another laboratory. Positive control samples (H37Rv strain)
- 88 were also grown in MGIT cultures. Batches of positive samples were extracted using a manual
- 89 process, exactly as described in the Supplementary Methods in (16). Illumina sequencing libraries
- 90 were prepared using Nextera XT chemistry from equal amounts of 12 (20.04.15-01.08.15) or 16
- 91 (01.08.15-30.12.17) Mycobacterial DNA extracts (16), using manual steps (Table 1). Positive control
- 92 DNA (H37Rv, obtained from ATCC) was included as one of the 12 or 16 extracts in all libraries, either
- 93 from a contemporaneously extracted broth culture, or from stored DNA. Libraries were loaded into
- an Illumina MiSeq instrument and sequenced (16).

## 95 Bioinformatic processing

- 96 The routine bioinformatics pipeline deployed by Public Health England has been previously
- 97 described (15). Briefly, reads were first processed using the Mykrobe predictor tool, which identifies
- 98 *Mycobacterium tuberculosis* using species specific k-mers (17). Specimens identified as containing
- 99 M. tuberculosis were further processed (16), mapped to the H37Rv v2 genome (NC\_000962.2) (18),
- as described (16), and vcf files generated using Samtools mPileup, with additional basecalling using
- 101 GATK VariantAnnotator v2.1. A consensus base is called from high-quality bases provided one base
- accounts from >90% of the pileup; otherwise, the base is recorded as uncertain ('N') (15). In this
- analysis, high quality base counts (identified by the BaseCounts VCF tag) were extracted and
- 104 summarised using code available at <u>https://github.com/davidhwyllie/VCFMIX</u>.

### 105 Nucleotides identifying lineage

- 106 Coll et al (2) described the M. tuberculosis phylogeny and identified 62 sets of nucleotide positions
- 107 defining the deep branches of the *Mycobacterium tuberculosis* lineage. At each position within a
- 108 nucleotide set, in one particular clade, one nucleotide is uniquely present (i.e. is not present in any

109 other of the known clades). These sets contain a median 108 nucleotide positions (range 1 - 898). 110 In this analysis, we considered 55 branches, excluding branches 1.2, 3.1, 3.1.2, 4.1.2, 4.3.4.2.1, 4.6 111 and 4.7 because they contain fewer than 20 positions, making estimates of minor variation in these 112 positions less reliable than estimates in other branches. We identified lineage using consensus 113 basecalling in these 55 branches. If the signature SNV of a branch was called as uncertain, we called 114 only to the level of the branch deeper (i.e. closer to the root) than the uncertain call. If more than one different lineage defining variant was called, or we could not call any lineage defining positions, 115 116 we reported the samples as 'lineage not defined'.

## 117 Estimation of the minor variant frequency within a set

118 The minor variant frequency at a set of bases can be due to sequencing error, mapping error and/or bong fide inter-lineage mixtures (Supplementary Figure 1, panels A and B). Minor variant 119 120 frequencies were determined as follows: if there are *n* bases in a lineage defining set, we count the 121 high quality depths d at each base, e.g. if n=3 and  $d_1 = 30$ ,  $d_2 = 70$ ,  $d_3 = 100$ , then the total depth  $D = \sum_{i=1}^{n} d_i$  = 200. For each position, we also identify the most common base; the minor depth m 122 123 is the total depth minus the most common base depth. If the minor depths are  $m_1 = 3$ ,  $m_2 = 7$ ,  $m_3 = 1$ 10, then total minor depth  $M = \sum_{i=1}^{n} m_i = 20$ ; we estimate the minor allele fraction p in the set as 124 M/D = 0.1.125

### 126 F2 and F47 metrics

If sequences from two different *M. tuberculosis* lineages are mixed together, then the sets which 127 uniquely define these lineages will be mixed (depicted in Supplementary Figure 1C); there will be a 128 129 minimum of two and maximum of eight sets affected (e.g. a Lineage 5/7 mixture will mix two sets of 130 lineage defining nucleotides, a 2.1/4.2.1 will mix five sets, and a 4.1.1.1 / 3.1.2.1 mixture will mix 8 131 sets). Only if more than two samples are mixed will more than 8 sets be mixed. In this work, we 132 describe two metrics reflecting mixing. Having computed the minor allele frequency estimates,  $p_{1}$  $p_2$ , ...  $p_{55}$  we can sort these in descending order, identifying the sets with the highest and lowest 133 134 minor allele frequencies. We then estimate the minor variant frequency across the nucleotides in 135 the top two (F2 metric) and lowest 47 sets (F47 metric) as described above. The underpinning 136 assumptions are that mixtures of biological origin are most likely to occur between two lineages, and therefore F2 is the most sensitive metric for identifying these. Since between two and 8 sets will be 137 mixed in such genuine co-infections, then the lowest 47 (55 - 8) sets will not be mixed, and thus the 138 139 F47 metric is more sensitive for identifying laboratory contamination involving more than two 140 samples.

## 141 Regression modelling

- 142 Because of high leverage by a small number of observations, we used quantile regression to
- 143 estimate the relationship between median values of log-transformed non-callable base numbers and
- 144 log-transformed F47, using the quantreg R package (R 3.3.1).
- 145 Ethical framework
- 146 Only anonymised data was used in this work; ethical approval is not required.
- 147 Data availability
- 148 The data analysed is available at https://ora.ox.ac.uk/objects/uuid: 5e4ec1f8-e212-47db-8910-
- 149 161a303a0757.

#### 150 RESULTS

#### 151 Samples studied

- 4,156 samples were included since they (i) were identified using MyKrobe (17) as belonging to the
- 153 *M. tuberculosis* complex, and (ii) had at least 0.5 x 10<sup>6</sup> read pairs mapped to the H37Rv reference
- 154 genome, a criterion reflecting successful DNA extraction and sequencing. These sequences were
- highly diverse, originating from six branches of lineage 1 (n=320), five branches from lineage 2
- 156 (n=278), five branches of lineage 3 (n=1,010), thirty lineage 4 branches (n=2,266). 106 samples were
- 157 from *M. bovis* or *africanum*, and 176 did not have their lineages defined.
- 158 The laboratory processes operated under three different phases: in the first, *development*,
- 159 laboratory processes were being actively refined; in the second, *pre-production*, laboratory
- 160 processes were fixed and controlled by standard operating procedures, with version controlled
- 161 changes. The third *production* state was similar to the second, except that the process had received
- 162 ISO15189 accreditation.

## 163 Variation in lineage defining positions in H37Rv controls

- 164 The F2 mixture metric reflects the estimated mixture in the two most mixed lineage defining sets; in
- the H37Rv controls, this follows a distribution skewed to the right (Figure 2A). The MiSeq runs with
- 166 H37Rv controls with F2 mixture metrics in the top 5% (Fig. 2A) are temporally clustered (red lines on
- 167 Fig. 2B, C) with a number of examples in the Development phase. Among clinical (non-control)
- 168 samples, variation in F2 metric is explained in part by MiSeq run (Kruskal-Wallis test,  $p < 10^{-16}$ ), and a
- strong correlation exists between the F2 metric in H37Rv controls and that in clinical samples on the
- same plate ( $\rho$  = 0.61, 95% CI 0.56-0.61, Spearman's Rank Correlation). That is, in plates with
- 171 elevated F2 metrics in the H37Rv control, the clinical samples are more likely to have elevated F2, as
- is evident visually (e.g. Fig 2B and C, around run 2301).

### 173 Different patterns of mixtures were observed during Development

174 We ordered specimens first by the order of the plates analysed and the order in which the

- bioinformatics processing was completed, which is the order that an automated quality control
- 176 monitoring system would encounter output. During the Development phase (Fig. 3), blocks of
- samples derived from runs with elevated mixtures in the H37Rv control are seen (red bars in Fig. 3A),
- 178 coincident with clear increases in both F2 and F47 metrics (Fig. 3B, C), reflecting elevations in mixed
- bases across most or all lineage defining positions (Fig. 3D). These blocks of samples typically span
- 180 multiple MiSeq runs (Fig 3A,B). In addition to the blocks of samples with elevated F2 and F47
- 181 metrics, we also observed small numbers of single samples with elevated F2, but not F47, metrics
- 182 (Fig. 3B, Arrow). This latter pattern is expected in cases of inter-lineage mixtures of only two

## 183 samples (Supp. Fig 1, and Methods). These patterns were also seen in the subsequent phases

184 (Supplementary Figures S2-5, yellow dots).

#### 185 Mixtures of multiple lineages are common

- 186 Based on the pattern observed in the Development phase, we categorised samples as having one of
- 187 (i) neither F2 nor F47 raised, (ii) raised F47, or (iii) raised F2 without raised F47. We defined a raised
- 188 F2 and F47 as more than 10x and 5x the respective median metric during Development in all control
- and clinical samples, cutoffs which correspond to 4.7% (F2) and 0.2% (F47) minor variant frequencies
- across the relevant lineage-defining sets, respectively. In the Pre-production and Production phases,
- 191 F2 and F47 values below these thresholds (reflecting unmixed samples) were observed in 97.5% of
- the samples studied, raised F47 and F2 values (reflecting a mixture of multiple samples) in 2.5%,
- 193 while six samples (0.001%) had raised F2 but normal F47 values (Table 2).

#### 194 Isolated F2 metric elevation is rare

- 195 Isolated elevation of F2 is expected if bacteria from two different lineages are mixed. In Fig. 4, we
- show the minor variant frequencies from all samples from the six individuals with raised F2, but
- 197 normal F47, metrics. In one case, patient 3, two technical repeats of the same sample (#2) showed
- the same pattern, as did a separate sample taken contemporaneously. In other cases (patients 1, 5,
- 199 6) the mixed pattern was only observed in one out of two positive samples taken on the same day,
- and in two cases (2, 3) only a single sample was positive. Thus, between 1 and 6 samples of the
- 201 4,156 studied may truly reflect mixed co-infections.

### 202 Impact of inter-lineage variation on basecalling

203 One obvious question is whether very low level cross-contamination impacts the consensus

- 204 sequence which can discerned from the pileup. As cross-contamination increases, at some point
- 205 minor variant frequencies in some parts of the genome will start to rise above the 10% cutoff
- 206 specified by the basecalling algorithm. The numbers of uncalled bases will then rise; this
- relationship can be observed in Figure 5: the number of uncallable bases rises rapidly when F47
- exceeds the cutoff value, but only slowly below it. Below the cutoff value of 4.7% (red line in Fig. 5),
- which is 10 times the median (black line in Fig. 5), the number of uncallable bases increased by 1.25
- fold (95% Cl 1.22, 1.28) for every 10-fold increase in F47; above the cutoff, the corresponding
- 211 increase was 9.24 (95% CI 5.5, 11.2).

#### 213 DISCUSSION

214 In this work, we describe methods for monitoring the presence of mixtures of Mycobacterium 215 tuberculosis of different lineages. It assumes that multiple lineages and sublineages of M. 216 tuberculosis are being sequenced contemporaneously; this is the case in our setting, and is also true globally (19, 20). Using single nucleotide variants, each of which uniquely defines a branch in the 217 218 phylogenetic tree of *M. tuberculosis*, we can show two patterns of mixtures. The first, which 219 occurred in about 2.5% of samples during the pre-production and production phases of our project, 220 is indicative of multiple samples being mixed together, since mixtures are seen in most or all of the 221 lineage defining branches. This occurred in batches, was characterised by cross-contamination at 222 levels of less than 1%, and can be monitored by a metric we term F47. This pattern likely reflects 223 process failures. The strength of the F47 metric is that the depth analysed is very high, as about 5,000 nucleotides typically contribute across the lineage-defining sets included in it. If there is a 224 225 sequencing depth of 50-100 at each of these, the effective sequencing depth analysed is of the order 226 of 25,000 – 50,000, making detection of minor variation at sub- 1% levels readily feasible with high 227 statistical confidence.

Such low level cross-contamination, as observed during our production process and illustrated in
 Supplementary Figures 2-4, is likely to have minimal influence on inference drawn from the
 sequence, unless highly sensitive assays for heteroresistance are required. A sensitive metric such as
 F47 will, however, allow early detection of emerging problems and allow review of process, as part
 of continuous quality improvement.

233 A second class of mixture, which we found was rarely detected in this setting, is compatible with co-234 infection with two organisms of differing lineage within the patient. This kind of mixture is clinically 235 relevant (7, 11), and may be under-detected using the laboratory process we describe here, since 236 culture based amplification can reduce diversity in the sample inoculated (10). Its frequency may 237 rise if direct-from-sample sequencing is employed, or if samples from high-endemicity areas are 238 studied, but here we identified only one probable case of such mixtures, and five other possible 239 cases. Confirmatory approaches are available: microbiological techniques conducted separately on 240 multiple picks from the same samples have been used as validation(3); a limitation of this study is that we could not undertake such work as only multiply sub-cultured stored isolates exist for 241 242 historical samples. Techniques for reconstructing the contributing sequences also have been 243 described in detail (21-23), and we did not study them here. Another limitation is that we were not 244 able to consider six of the lineage defining sets in Coll *et al* because they covered <20 nucleotide 245 positions and therefore we considered that they did not contain sufficient information to be used in

- F2 or F47 metrics. A consequence is that our method would not identify mixtures of samples if theyonly involved mixtures in these excluded branches.
- 248 The clinical of use of bacterial genome sequencing is rising (16, 17, 24), and given the importance of
- 249 *M. tuberculosis* and the complexity of treatment, *M. tuberculosis* has been one of the first organisms
- tackled (15). The processes followed involve multiple steps at which the opportunity for cross-
- 251 contamination exists. The availability of tools monitoring critical aspects of laboratory process is
- 252 required for accreditation under ISO15189, and the F2 and F47 metrics described here will
- 253 contribute to this.

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- and not necessarily those of the NHS, the NIHR, the Department of Health or Public Health England.
- 263 The sponsors of the study had no role in study design, data collection, data analysis, data
- interpretation, or writing of the report. The corresponding author had full access to all the data in
- the study and had final responsibility for the decision to submit for publication.

## 266 FIGURE LEGENDS

- 267 Figure 1 Laboratory and Bioinformatic processing
- 268 Figure 2 Mixtures in H37Rv controls
- 269 Histogram showing the F2 metric, which reflects the mixture in the two most mixed lineage
- associated sets, in H37Rv control DNA (A). Median F2 metric among clinical samples other than
- 271 H37Rv is shown in (B); red lines indicate that the F2 mixture metric in H37Rv controls is raised (as
- shown in A). (C) shows F2 metric for each *M. tuberculosis* sequence from a clinical sample.
- 273 Figure 3 Mixture metrics in the Development phase
- 274 Samples arranged first by the order of the MiSeq runs (depicted as solid gray blocks, in A), and the
- 275 order bioinformatics processing completed. Only samples yielding *M. tuberculosis* are shown, which
- is why some blocks in A are longer than others. If the H37Rv control samples had increased F2
- statistics, a red bar is shown above each sample in A. We depicted the F2 (B) and F47 metrics (C), as
- 278 well as the estimated mixture F in each of the 58 lineage defining sets (D). The arrow illustrates a
- sample with elevated F2, but low F47 metric.

### **280** Figure 4 Consistency of isolated F2 elevation in individuals

- 281 Six individuals with elevated F2, but not F47, statistics were identified during the pre-production and
- 282 production phases. The observed minor variant proportion for all deep branches analysed are
- shown in a heatmap. For example, patient #4 had two samples taken in December 2015; sample 2
- was analysed twice (sequencing ids 0d9d5,9276f) and sample 3 once. A similar pattern of minor
- 285 variation is seen in all three samples.

### **286** Figure 5 F47 metric and the number of callable bases

- 287 The relationship between the F47 metric and the number of uncallable bases. The red line
- corresponds to the cutoff used to define F47 as being elevated.

#### 289 Supplementary Figures

#### **290** Supplementary Figure 1

- 291 Illustrates the computation of variation between samples of two different lineages, Lineage 1 (black
- text) and Lineage 2 (blue text) (A). When a mixture of these samples is present, and mapped to a
- reference sequence, a major base and minor base(s) are present in the pileup (B). Variation may be
- 294 due to either sequencing error (underlined) or to lineage associated variation; the non-major variant
- frequency included both classes of variation. Lineage defining sites, as defined by Coll *et al* (2), mark
- branches of the phylogenetic tree. If a lineage 4.1.1.1 *M. tuberculosis* is mixed with a lineage 3.1.2.1
- 297 *M. tuberculosis*, eight sets of lineage defining sites will be mixed (red boxes).

## **298** Supplementary Figures 2-5

- 299 These illustrate mixture patterns observed during the Production stage. The layout is similar to
- 300 Figure 3; samples arranged first by the order of the MiSeq runs (depicted as solid gray blocks, in A),
- and the order bioinformatics processing completed. Only samples yielding *M. tuberculosis* samples
- 302 are shown, which is why some blocks in A are longer than others. If the H37Rv control samples had
- 303 increase F2 statistics, a red bar is shown above each sample in A. We depicted the F2 metric (B) and
- 304 F47 metrics (C), as well as the estimated mixture F in each of the 58 lineage defining sets (D).

305

## 307 TABLES

## 308 Table 1 Samples analysed

Development	Total	Date range	Number of	MiSeq run	Number of	Number of
Stage	sequences		individuals	range	clinical	MiSeq Runs
	(samples and		providing		samples	
	controls)		samples			
Development	938	20.04.2015-	630	101 291	776	154
		15.12.2015				
Pre-Production	1167	01.04.2016-	753	1152	919	163
		06.12.2016		1522		
Production	2191	07.12.16-	1481	1523	1794	346
		30.12.2017		2307		

309

## 310 Table 2 Detection of mixtures in clinical samples

Development	Neither F2 nor	F2 raised, but	F47 raised
Stage	F47 raised	F47 normal	
Pre-Production	900 (98%)	5 (0.003%)	14 (1.1%)
(n=919)			
Production	1741 (97%)	1 (0.001%)	52 (2.8%)
(n=1794)			

311

312

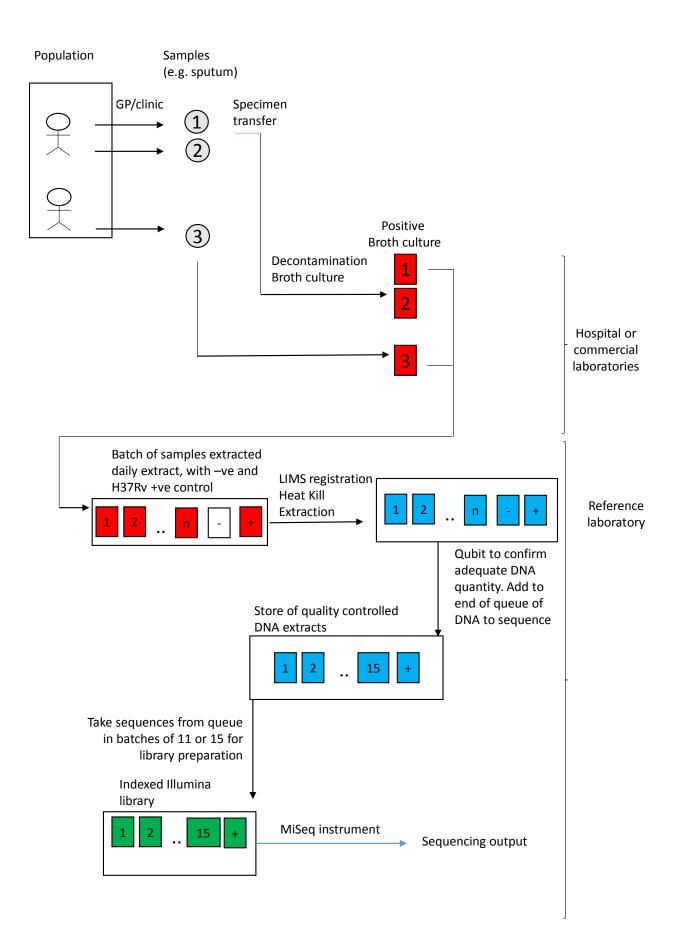
313

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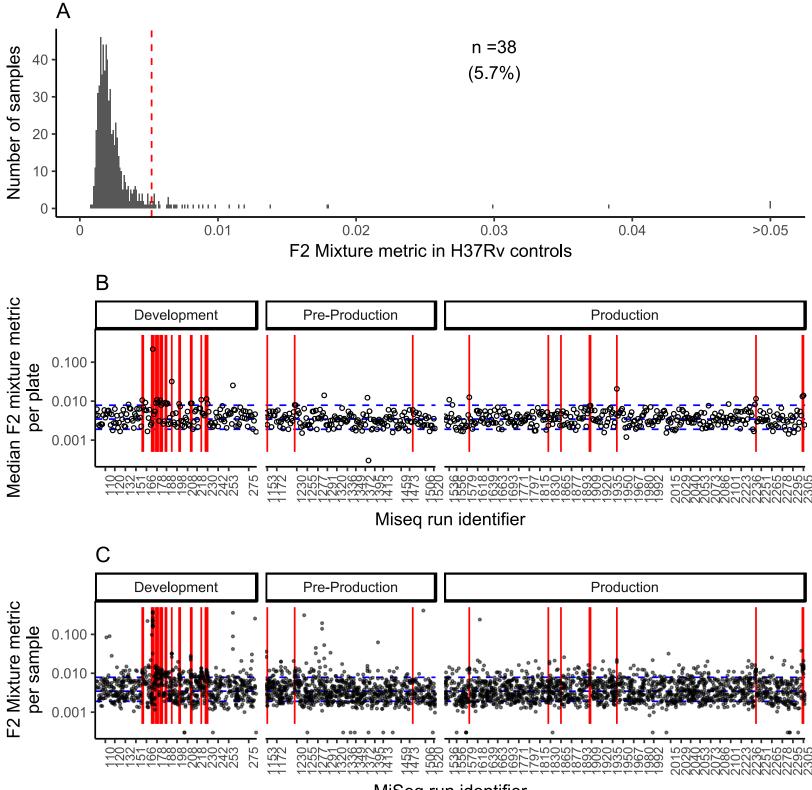
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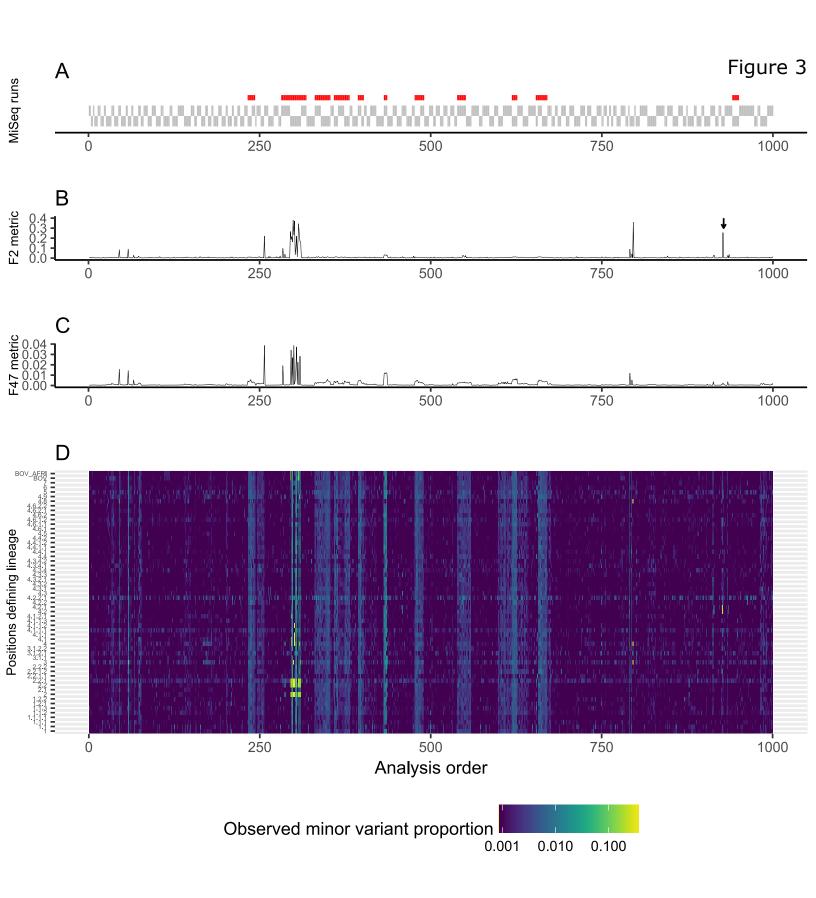
# FIGURE 1

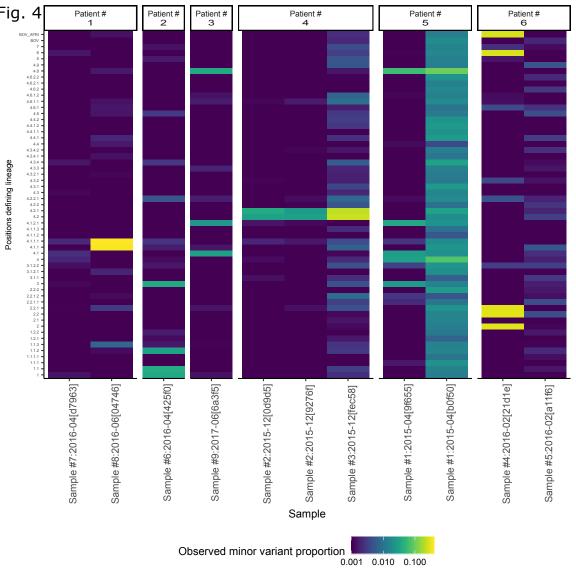


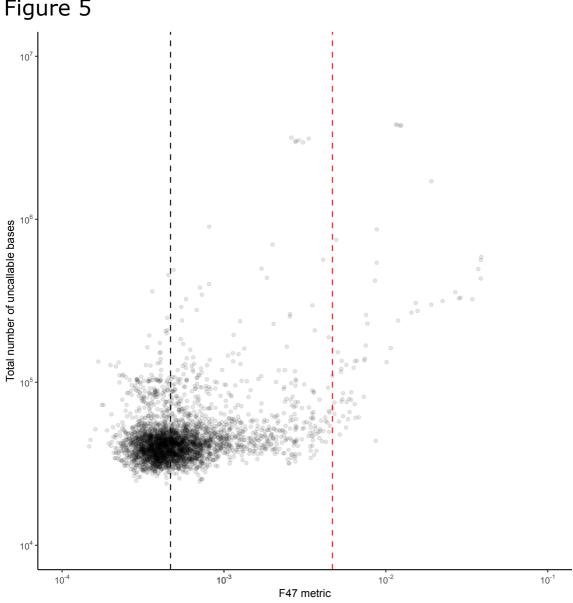
# FIGURE 2



MiSeq run identifier







# Supp. Fig. 1



# ACATACGTACGTACGTACGT ACGTACGT**TCA**TACGTACGT

ACATACGTACGT GTACGTACGTACGT CGTACGTACTTACGT GTACGTACGTACGT ACGTACGT**T**C**A**TACGTACGT AAGTACGT**T**C**A**TACGTCCG CGGACGTTCATACGTACGT Sequence of lineage 1 lineage 2

## Reads from lineage 1 lineage 2

(bold) lineage Т defining variant

(underlined) Τ Variation due to error

