

# **Metabarcoding processing pipelines and considerations**

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**FROM THE COVER**

**MOLECULAR ECOLOGY  
RESOURCES** WILEY

## A pile of pipelines: An overview of the bioinformatics software for metabarcoding data analyses

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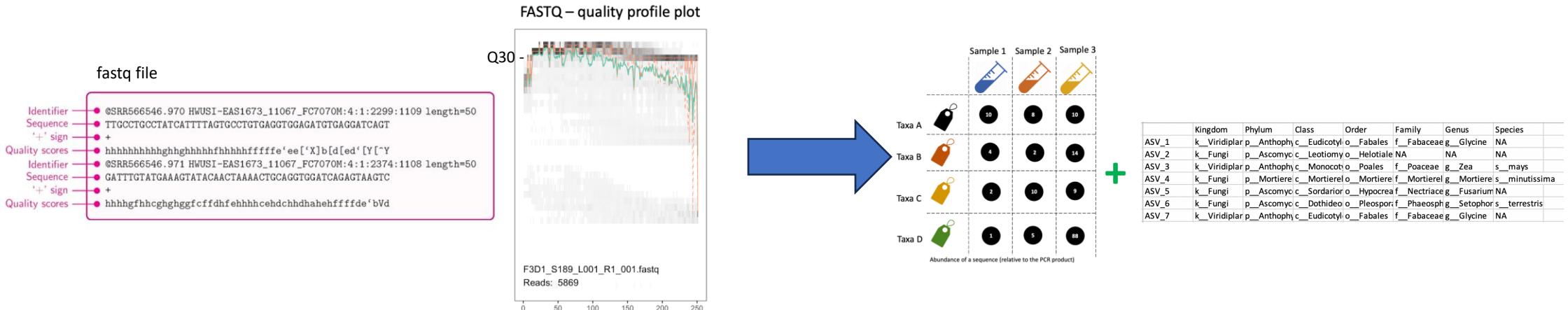
# **Metabarcoding processing and analysis pipelines**

**1. From raw-reads to OTU-table**

**2. Statistical analysis**

# Metabarcoding processing and analysis pipelines

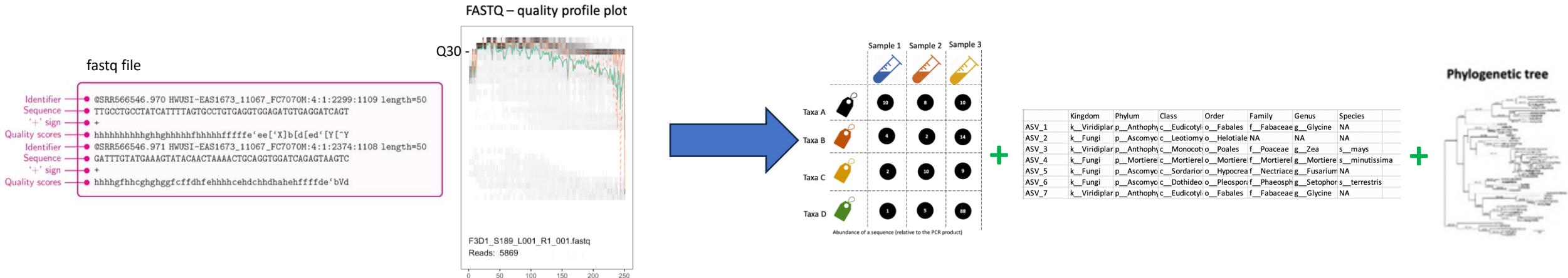
## 1. From raw-reads to OTU-table



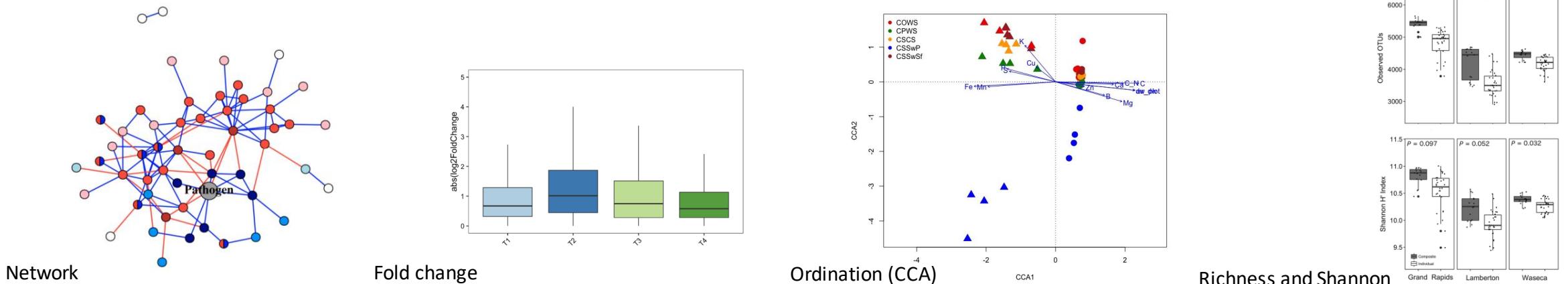
## 2. Statistical analysis

# Metabarcoding processing and analysis pipelines

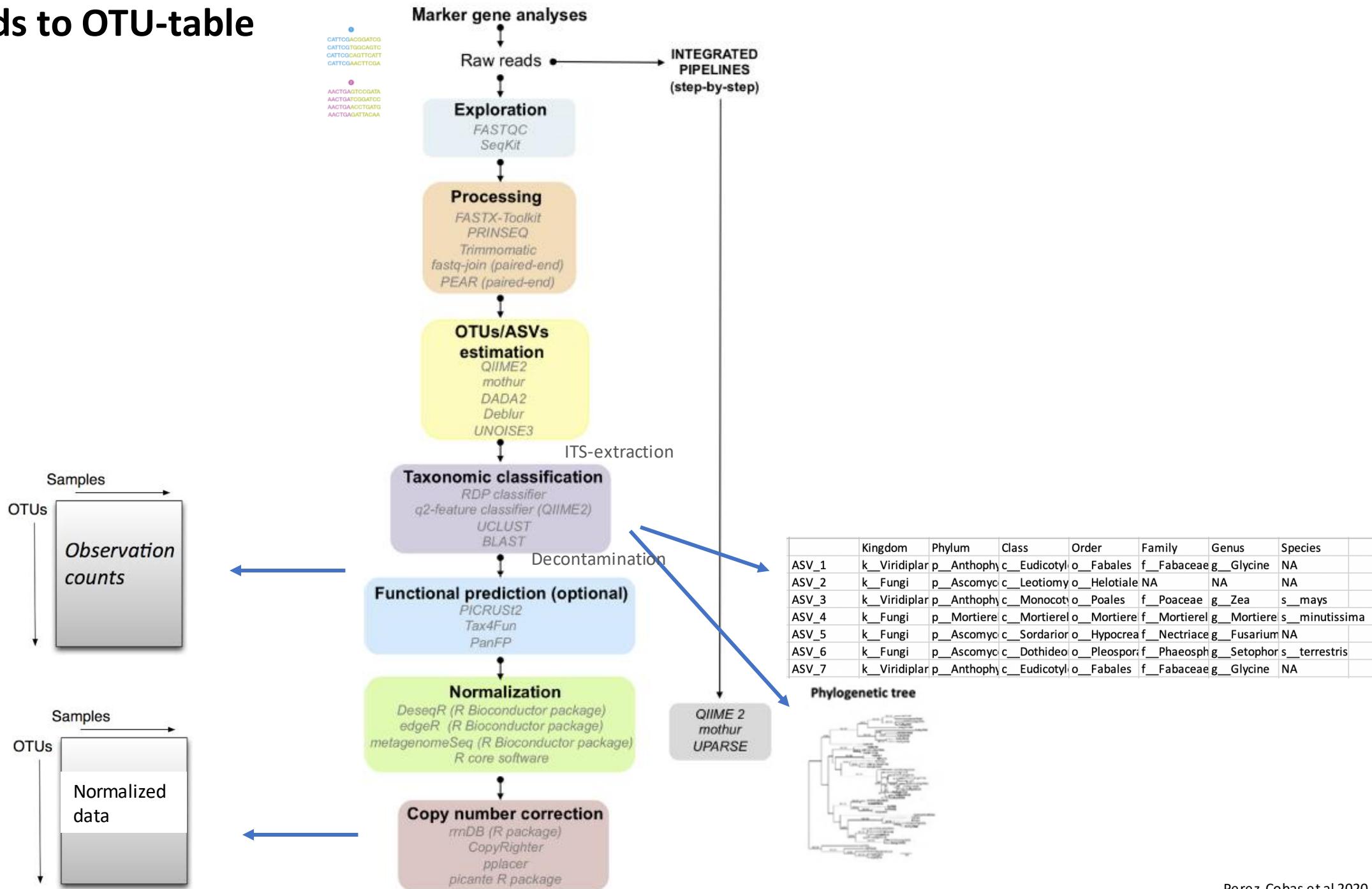
## 1. From raw-reads to OTU-table



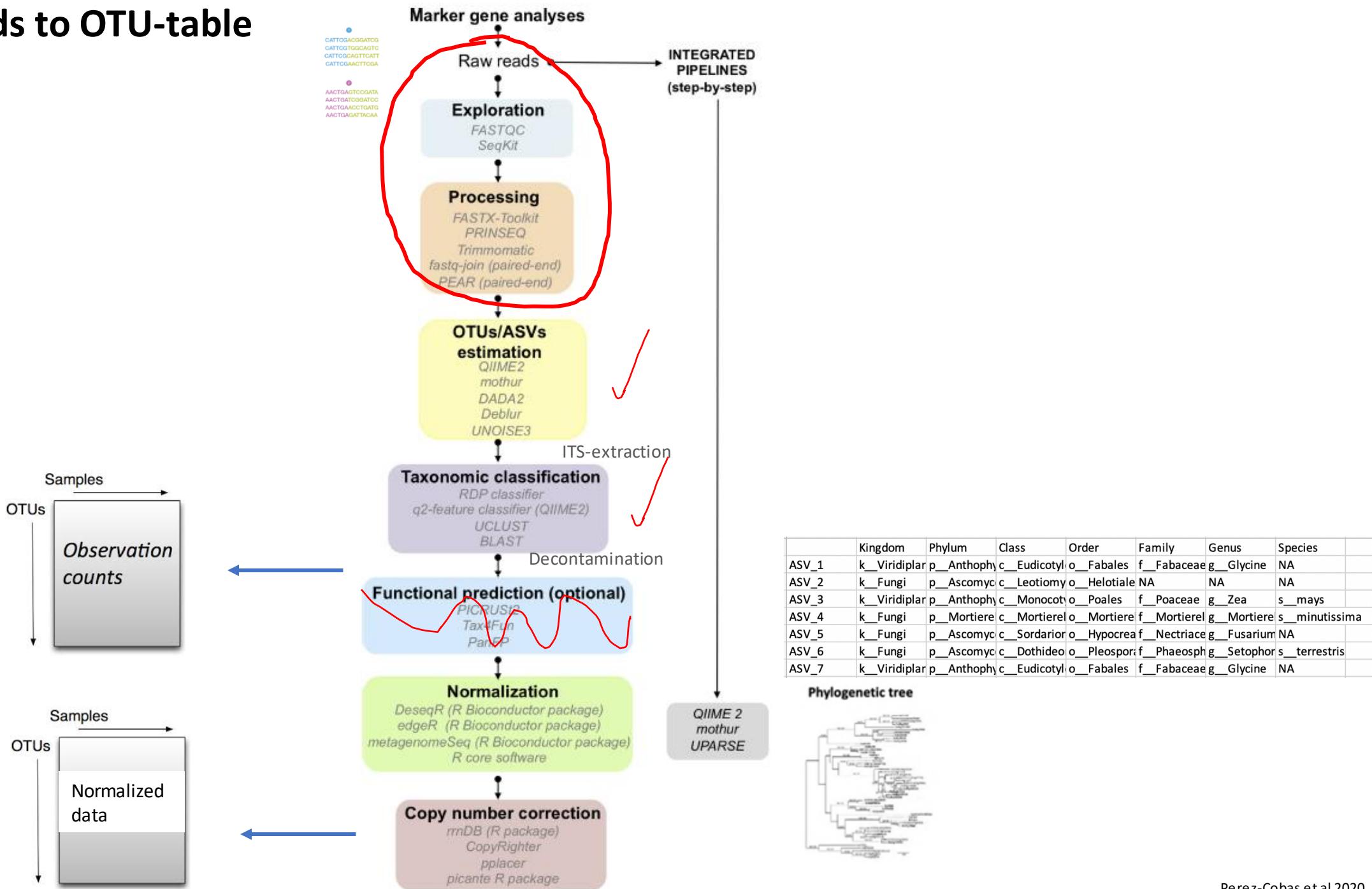
## 2. Statistical analysis (examples)



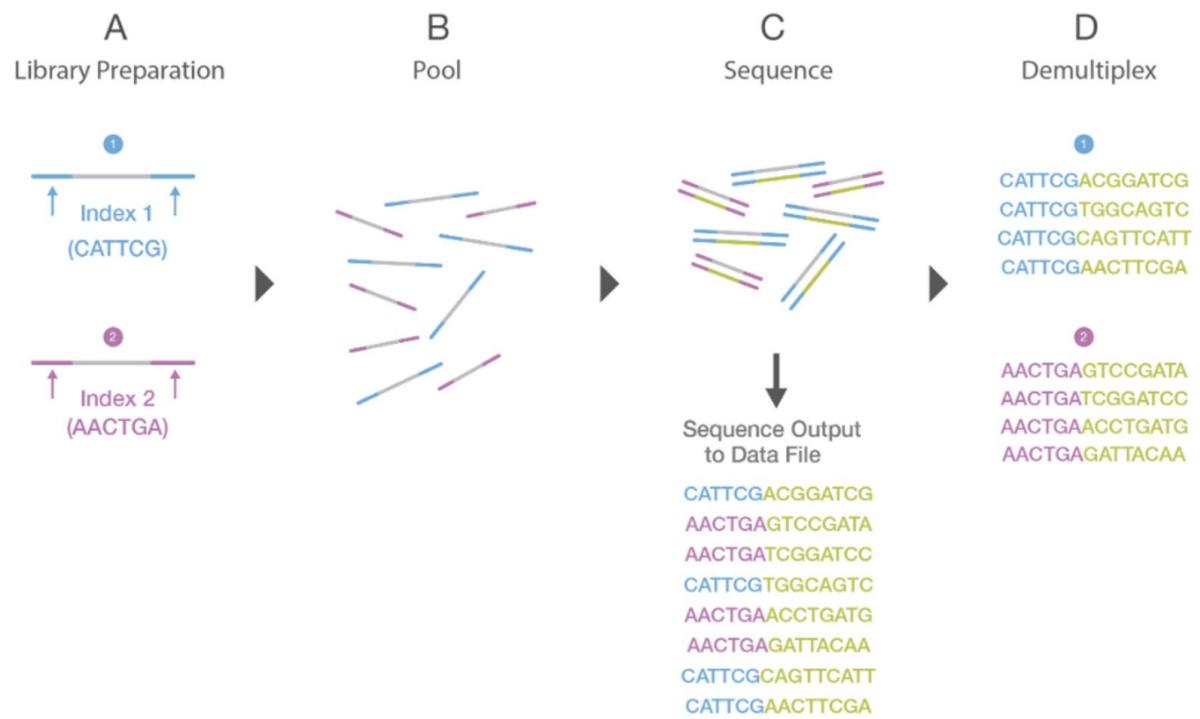
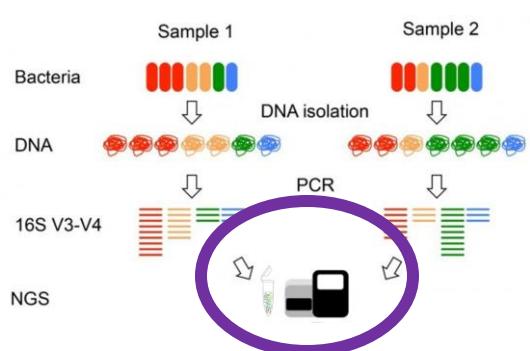
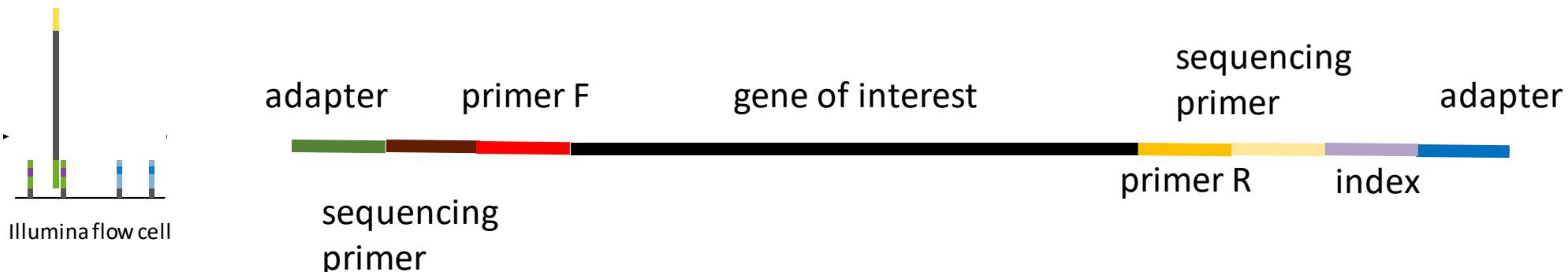
## From raw-reads to OTU-table



# From raw-reads to OTU-table



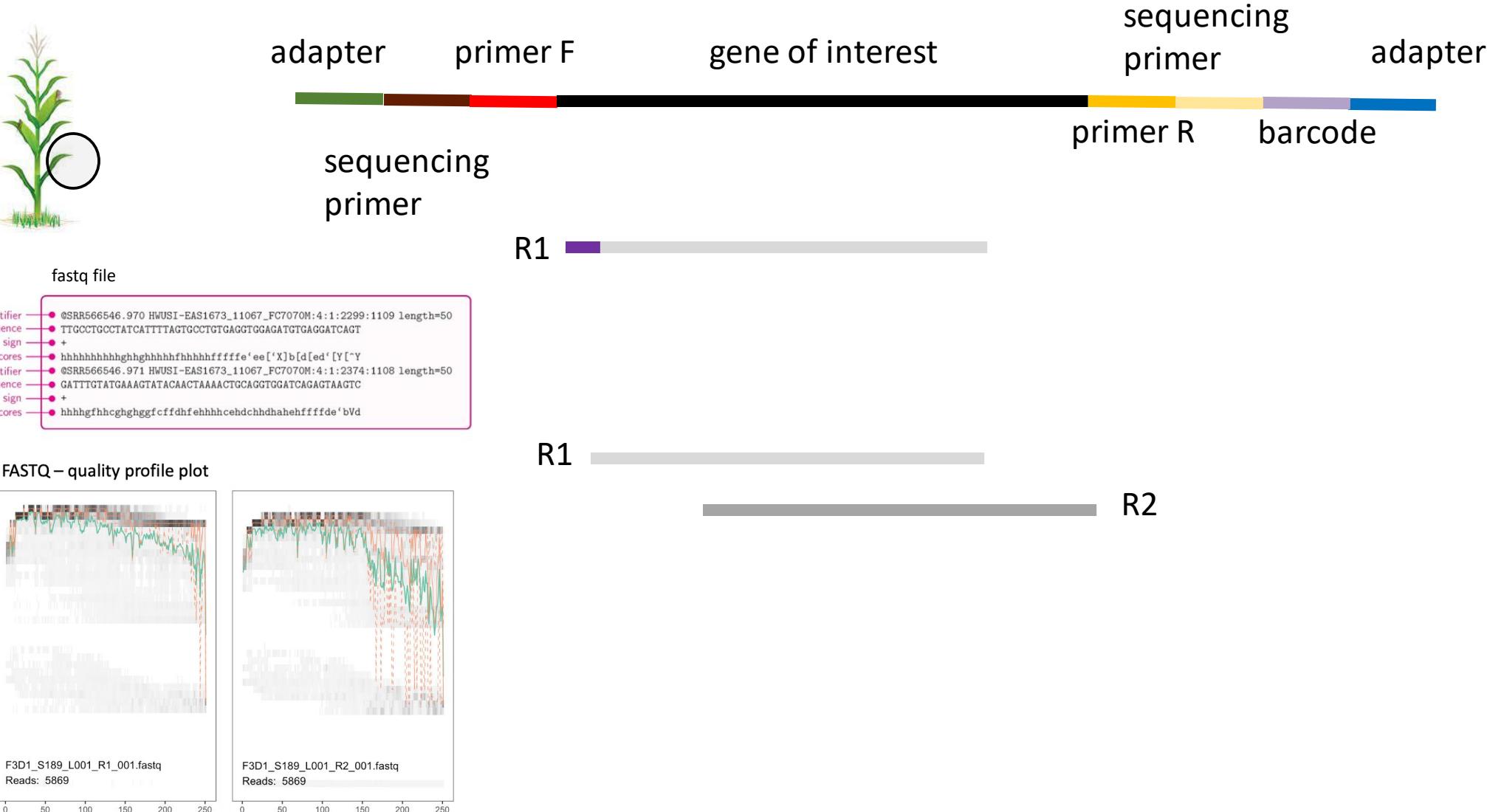
# Structure of the amplicon (sequencing read)



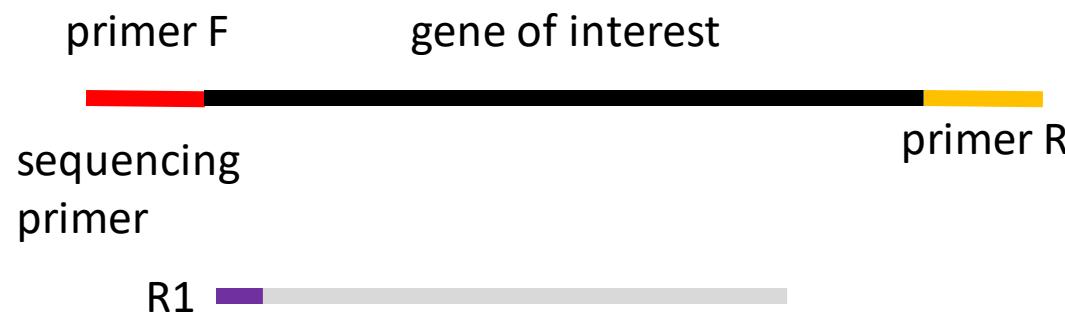
Metabarcoding – different indexes allows the sequencing of multiple samples at once

Lundberg et al 2013, Caporaso et al 2011, www.illumina.com

# Exploration and processing of reads

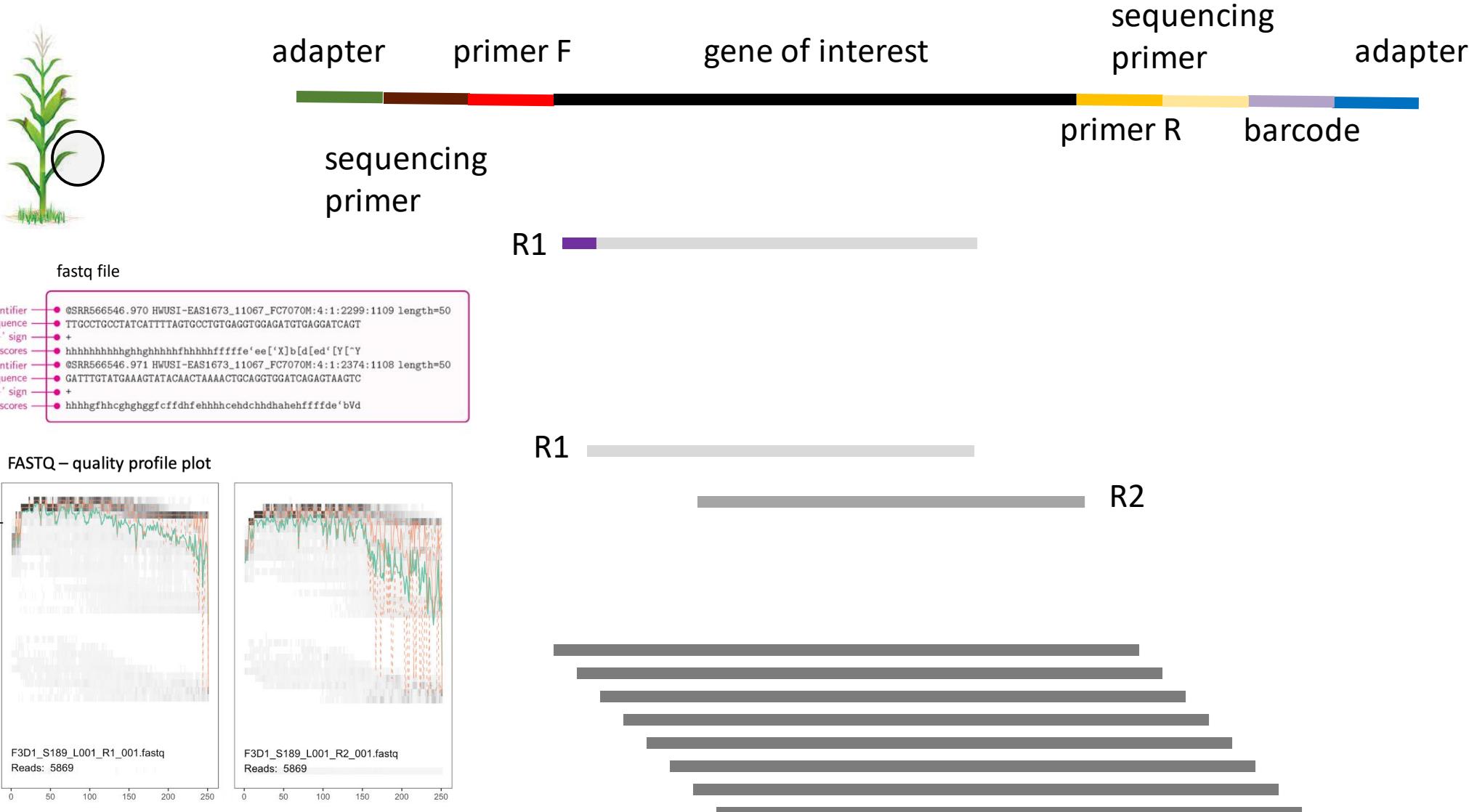


# Comparison with Sanger sequencing

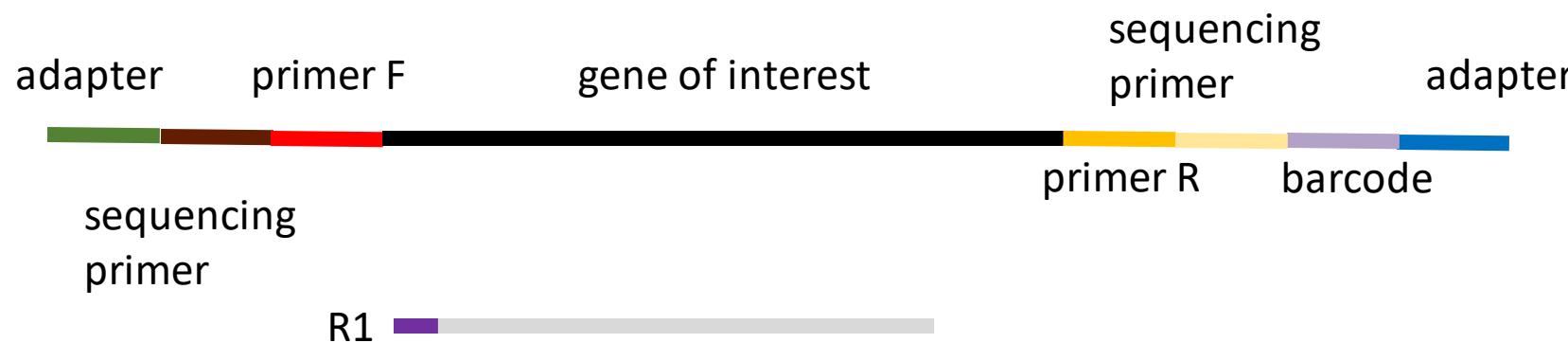
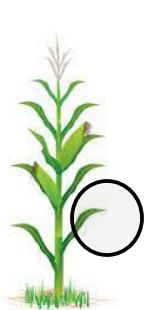


unite  
community

# Exploration and processing of reads



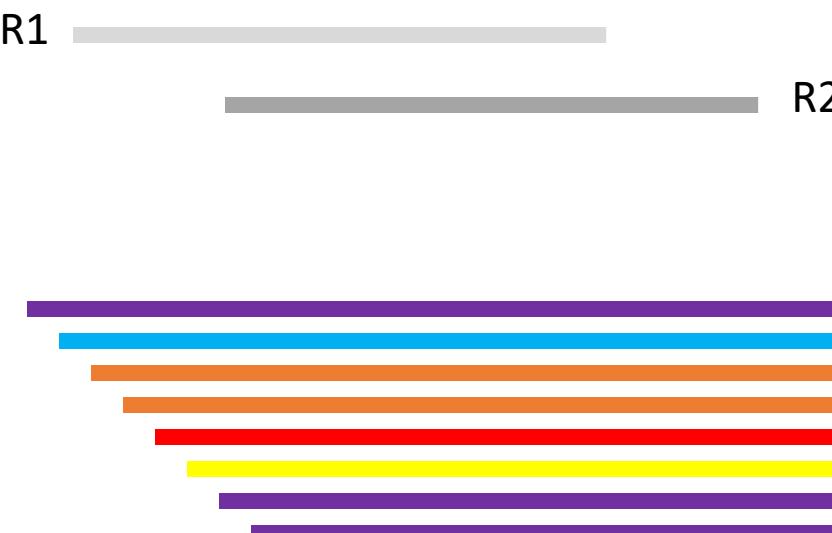
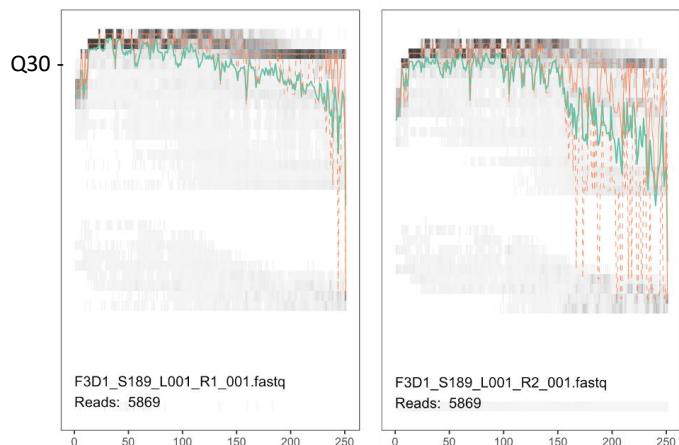
# Exploration and processing of reads



## fastq file

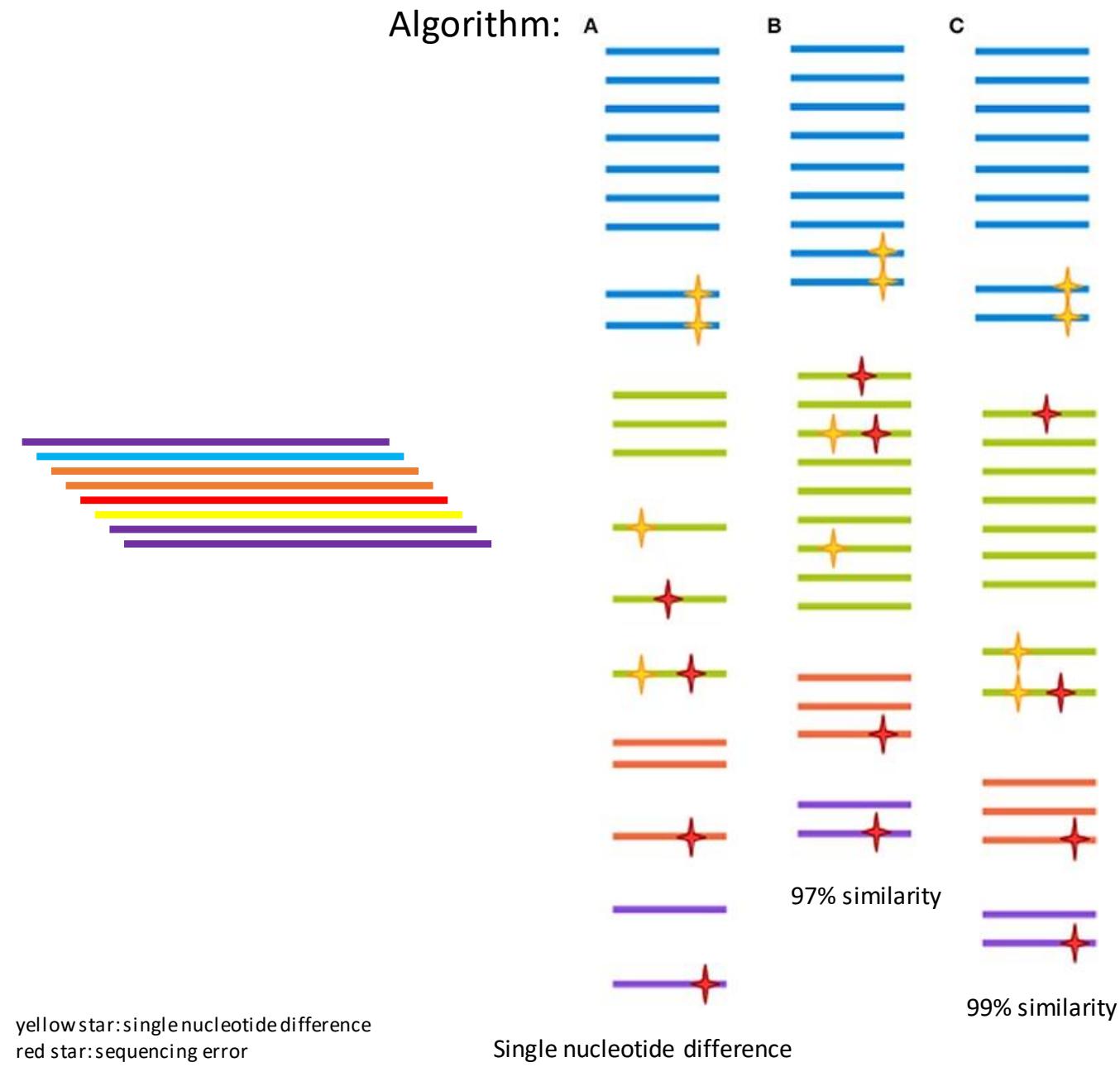
```
Identifier  • @SRR566546.970 HWUSI-EAS1673_11067_FC7070M:4:1:2299:1109 length=50
Sequence   • TTGCTCTGCCTATCATTITAGTGCCTGTGAGGTGGAGATGTGAGGATCAGT
'+' sign   • +
Quality scores • hhhhhhhhhhhggghhhhhhhhhfffffe'ee[X]b[d|ed][Y~Y
Identifier  • @SRR566546.971 HWUSI-EAS1673_11067_FC7070M:4:1:2374:1108 length=50
Sequence   • GATTGTATCAAAGTATAACAACTAAAATCGCAGGTGGATCAGAGTAAGTC
'+' sign   • +
Quality scores • hhggfhhgcggghggfcffdfhfehhhhcehdchddhahheffffe'bVd
```

## FASTQ – quality profile plot

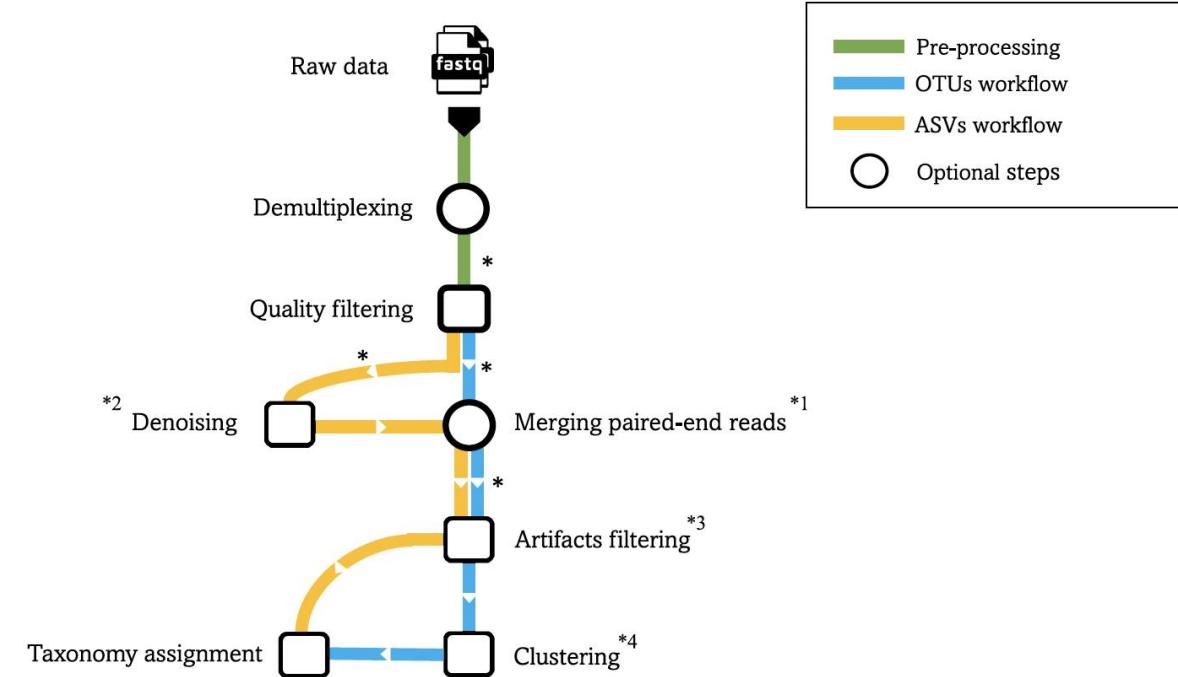
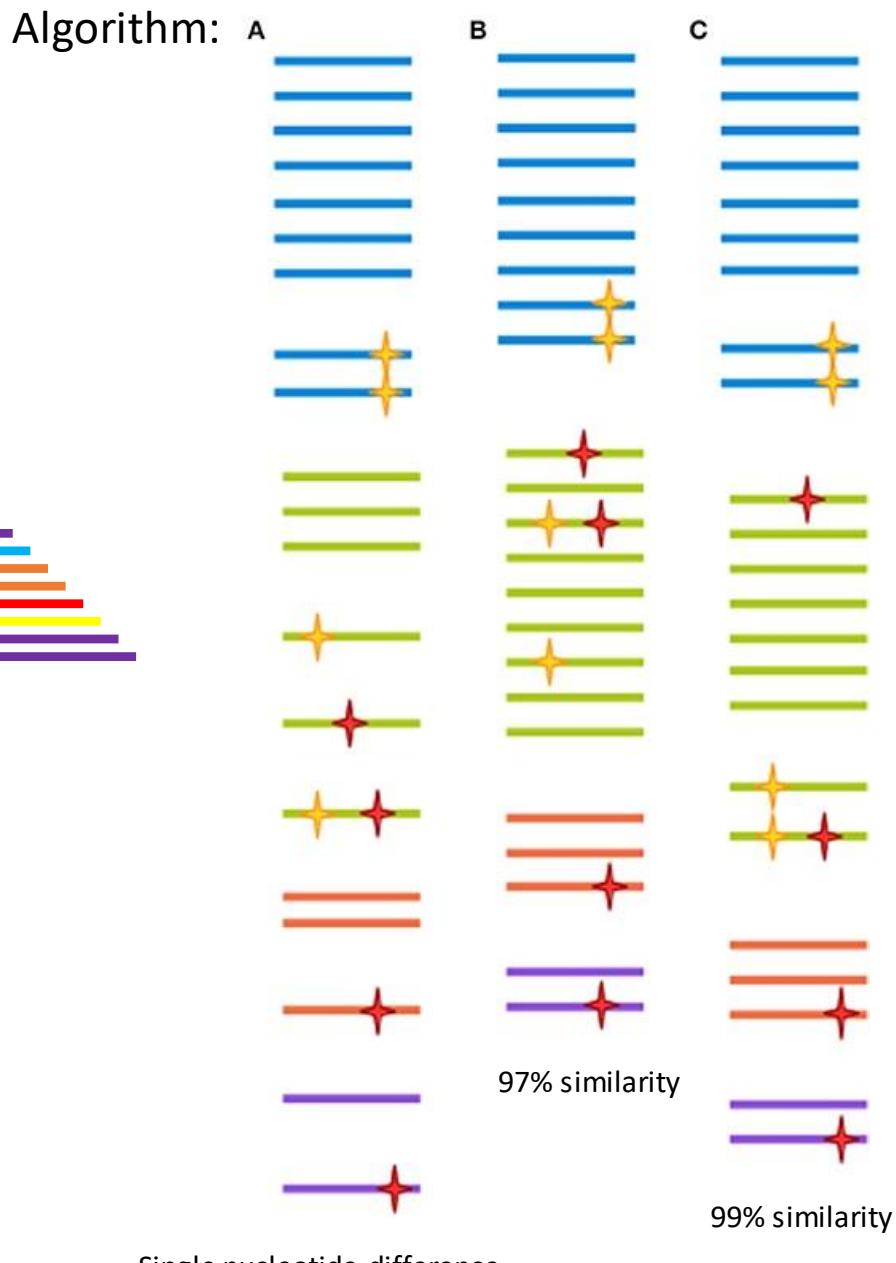


## Taxonomic unit of analysis

# Estimation of the taxonomic unit of analysis (*De novo*)



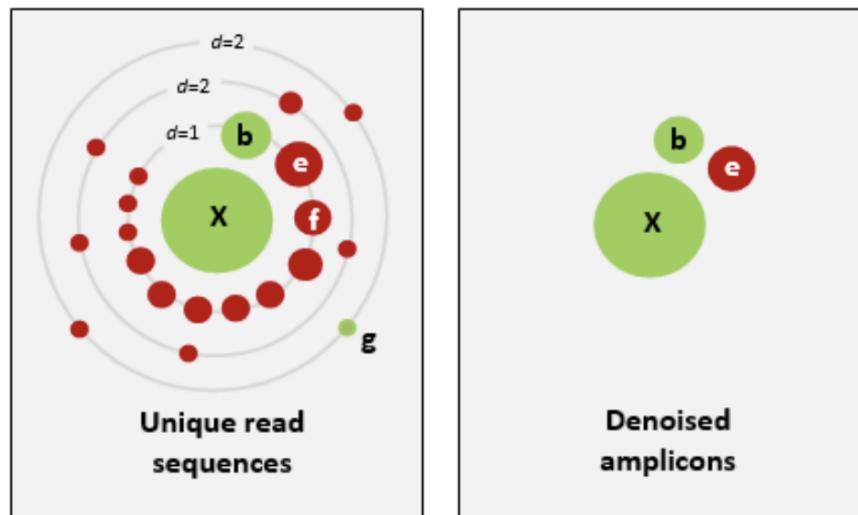
# Estimation of the taxonomic unit of analysis (*De novo*)



Hakimzadeh et al 2023

Hugerth and Andersson 2017

# Denoising and error correction



**Figure 1. Schematic of the UNOISE2 denoising strategy.** The left panel shows the neighborhood close to a high-abundance unique read sequence **X**, grouped by the number of sequence differences ( $d$ ). Dots are unique sequences, the size of a dot indicates its abundance. Green dots are correct biological sequences; red dots have one or more errors. Neighbors with small numbers of differences and small abundance compared to **X** are predicted to be bad reads of **X**. The right panel shows the denoised amplicons. Here, **X** and **b** were correctly predicted, **e** is an error with anomalously high abundance that was wrongly predicted to be correct, **f** is an error that was correctly discarded but has an abundance almost high enough to be a false positive, and **g** is a low-abundance correct amplicon that was wrongly discarded. The abundances of **b**, **e**, and **f** are similar, illustrating the fundamental challenge in denoising: how to set an abundance threshold that distinguishes correct sequences from errors. \*zOTUs (zero radius) or ESV (exact sequence variant)

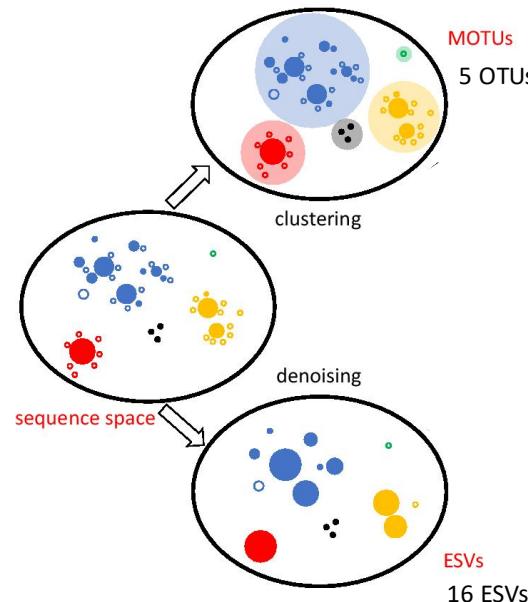
# **ASVs or OTUs?**

# ASVs or OTUs?

Does the pipeline incorporate denoising and error correction?

“ASVs are identical denoised reads with as few as 1 base pair difference between variants, representing an inference of the biological sequences prior to amplification and sequencing errors (Callahan et al., 2017)”.

OTUs represent clusters of sequences based on a specified similarity threshold. One sequence representative is chosen for further analysis.

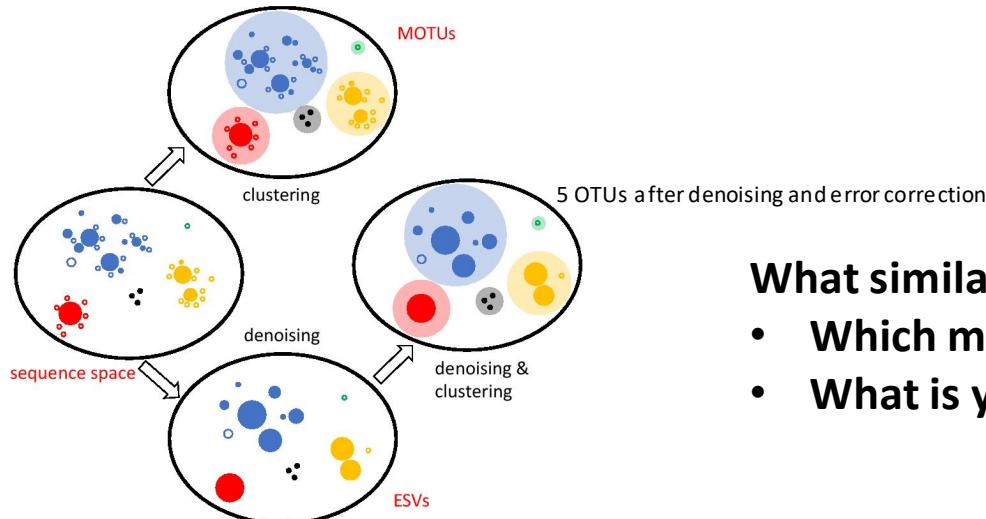


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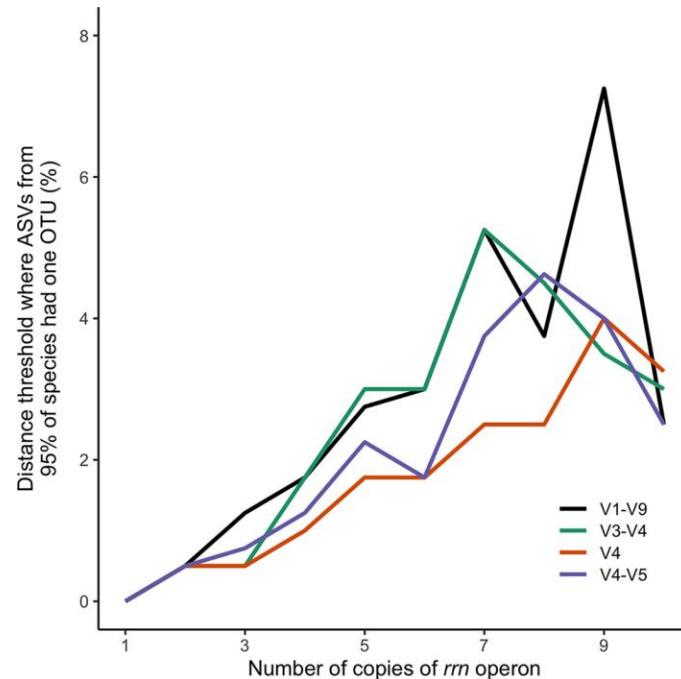
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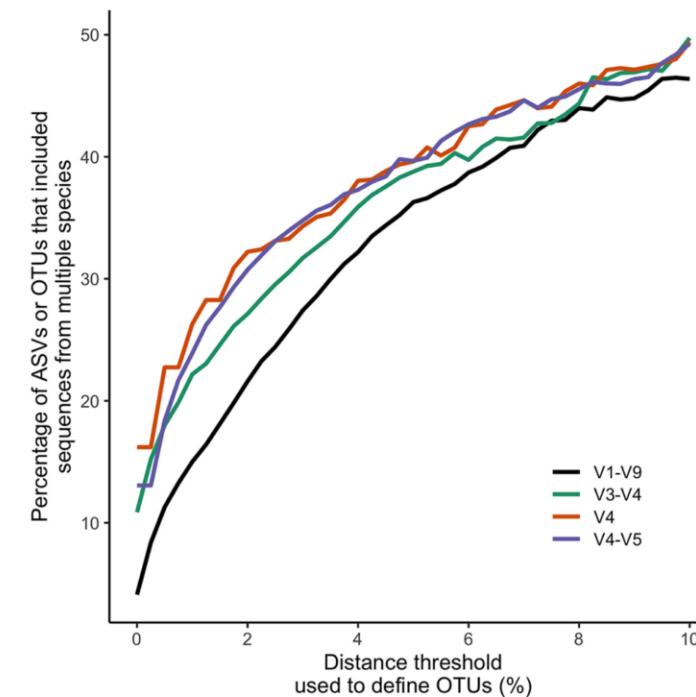
**What similarity threshold to cluster with?**

- **Which marker gene did you use?**
- **What is your desired taxonomic resolution?**

# Relationship between gene region variability, % similarity, and ‘genome splitting’

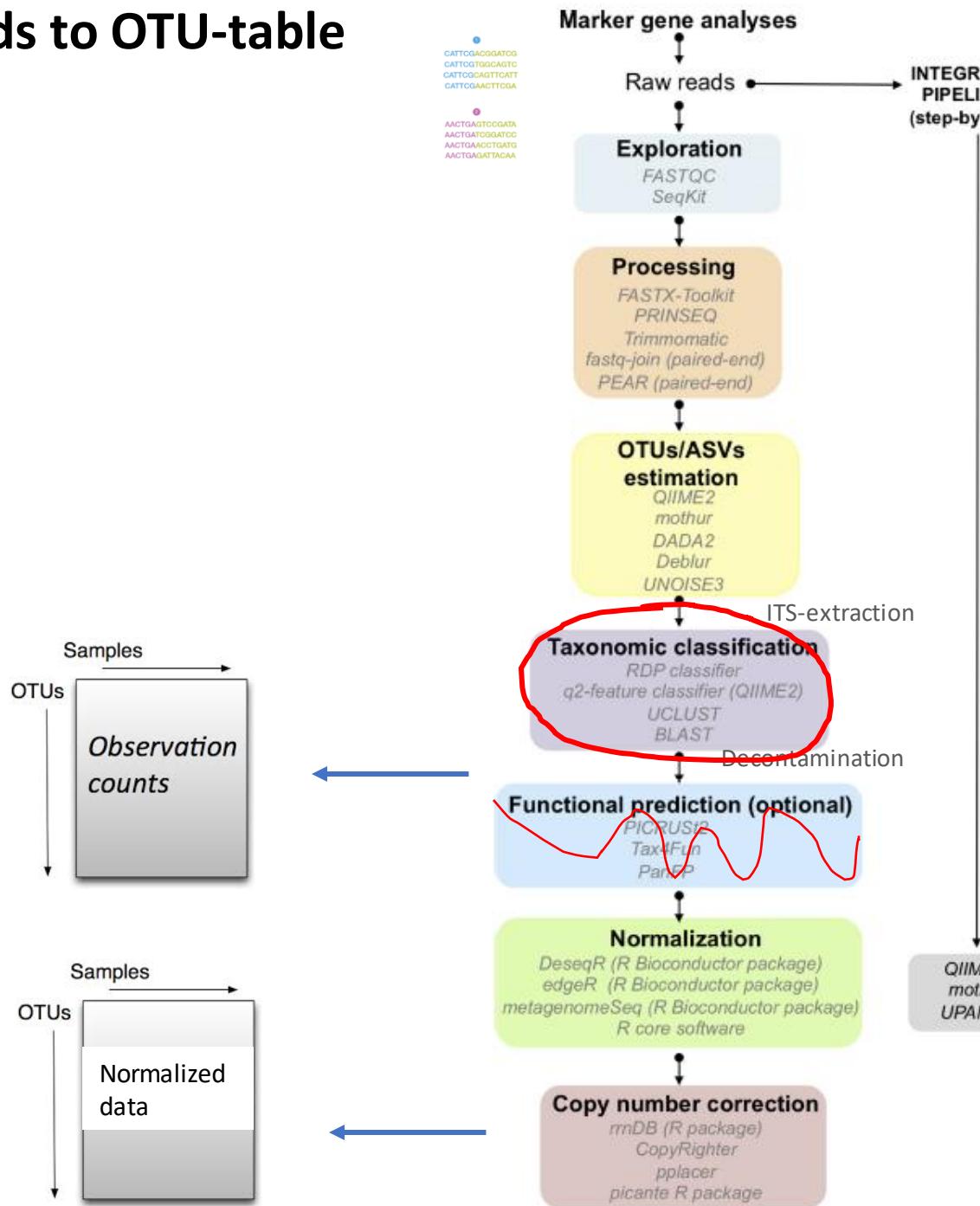


**FIG 1** The distance threshold required to prevent the splitting of genomes into multiple OTUs increased as the number of *rrn* operons in the genome increased. Each line represents the median distance threshold for each region of the 16S rRNA gene that is required for 95% of the genomes with the indicated number of *rrn* operons to cluster their ASVs to a single OTU. The median distance threshold was calculated across 100 randomizations in which one genome was sampled from each species. Only those numbers of *rrn* operons that were found in more than 100 species are included.



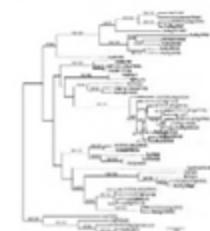
**FIG 2** As the distance threshold used to define an OTU increased, the percentages of ASVs and OTUs representing multiple species increased. These data represent the median fractions for both measurements across 100 randomizations. In each randomization, one genome was sampled from each species.

# From raw-reads to OTU-table



	Kingdom	Phylum	Class	Order	Family	Genus	Species
ASV_1	k_Viridiplar	p_Anthophy	c_Eudicotyl	o_Fabales	f_Fabaceae	g_Glycine	NA
ASV_2	k_Fungi	p_Ascomyc	c_Lecotomy	o_Helotiale	NA	NA	NA
ASV_3	k_Viridiplar	p_Anthophy	c_Monocot	o_Poales	f_Poaceae	g_Zea	s_mays
ASV_4	k_Fungi	p_Mortiere	c_Mortierel	o_Mortiere	f_Mortierel	g_Mortiere	s_minutissima
ASV_5	k_Fungi	p_Ascomyc	c_Sordarior	o_Hypocreaf	f_Nectriace	g_Fusarium	NA
ASV_6	k_Fungi	p_Ascomyc	c_Dothideo	o_Pleosporf	f_Phaeospf	g_Setophor	s_terrestris
ASV_7	k_Viridiplar	p_Anthophy	c_Eudicotyl	o_Fabales	f_Fabaceae	g_Glycine	NA

Phylogenetic tree



# Taxonomic classification and databases

## Example

```
>ASV1
GAGTTTGATCCTGGCTCAGGATGAACGCTGGCGGTGCTAACACATGCAAGTCGAAACGGTGAAGCAG
GAGCTTGCTCTTGTGGATCAGTGGCGAACGGGTGAGTAACACGTGAGCAACCTGCCCGAACTCTGGGA
TAAGCGCTGGAAACGGCGTCTAATACTGGATATGCACCAGGGAGGCATCTTACTGGTGGGAAAGATT
TTGGTTGGGATGGGCTCGCGGCCTATCAGCTTGTGGTAGGTAACGGCTACCAAGGGCGTCGACGGG
TAGCCGGCCTGAGAGGGTGACCGGCCACACTGGGACTGAGACACGGCCCAGACTCCTACGGGAGGCAG
CAGTGGGAAATTGCACAATGGCGGAAGCCTGATGCAGCAACGCCGC
```

## Classification

Bacteria

Firmicutes

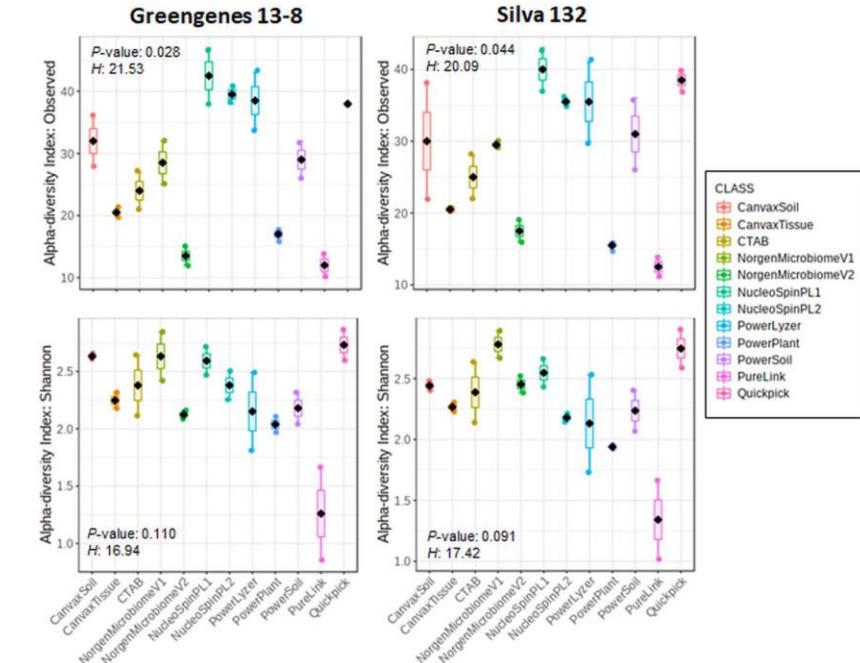
Bacilli

Bacillales

Bacillaceae

Bacillus

Bacillus subtilis



\*depends on the taxonomic resolution of your marker gene (and its length)

# Taxonomic classification and databases

## Example

>ASV1

```
GAGTTTGATCCTGGCTCAGGATGAACGCTGGCGGTGCTAACACATGCAAGTCGAACGGTGAAGCAG  
GAGCTTGCTCTTGTGGATCAGTGGCGAACGGGTGAGTAACACGTGAGCAACCTGCCCGAACTCTGGGA  
TAAGCGCTGGAAACGGCGTCTAATACTGGATATGCACCAGGGAGGCATCTTACTGGTGGGAAAGATT  
TTGGTTGGGATGGGCTCGCGGCCTATCAGCTTGTGGTAGGTAACGGCTACCAAGGCCTGACGGG  
TAGCCGGCCTGAGAGGGTGACCGGCCACACTGGGACTGAGACACGGCCCAGACTCCTACGGGAGGCAG  
CAGTGGGAAATTGCACAATGGCGGAAGCCTGATGCAGCAACGCCGC
```

## Classification

Bacteria

Firmicutes

Bacilli

Bacillales

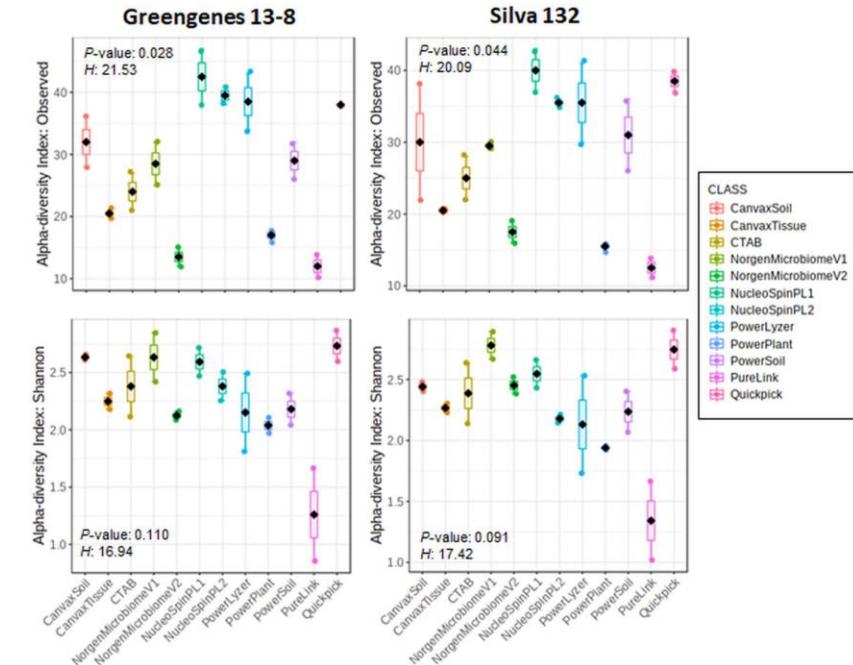
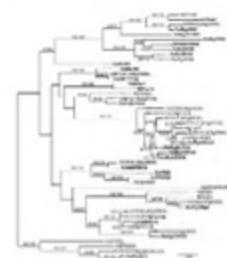
Bacillaceae

Bacillus

Bacillus subtilis

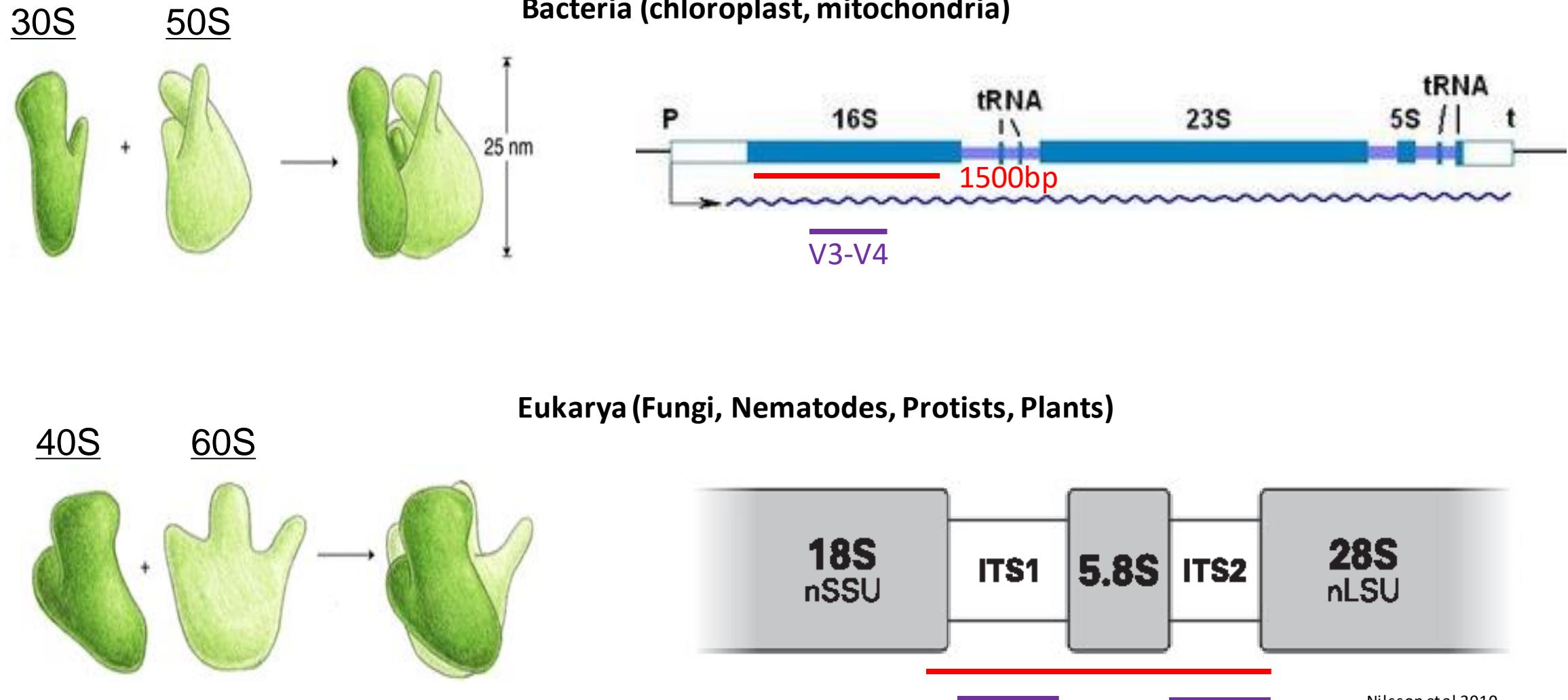
## Tree building (all ASVs)

Phylogenetic tree



\*depends on the taxonomic resolution of your marker gene (and its length)

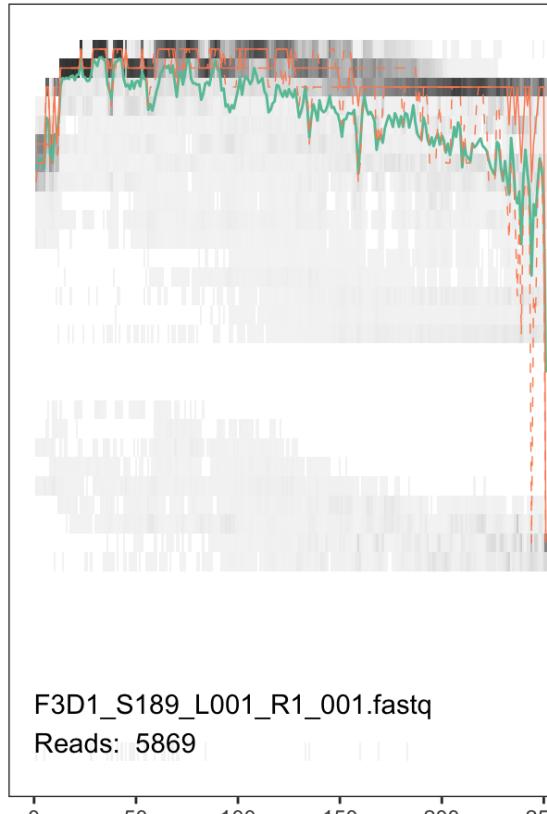
# Ribosomal markers as taxonomic barcodes



# Things to look for in a pipeline

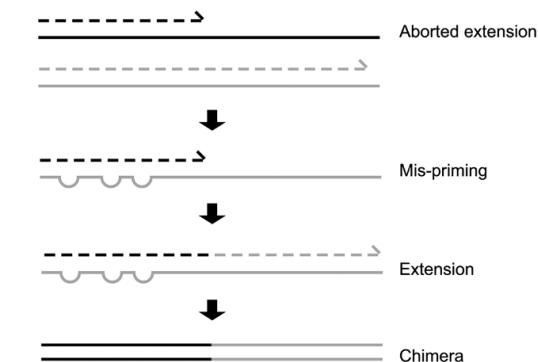
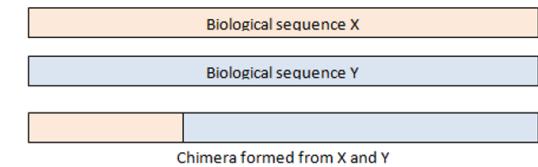
- Different quality control steps:
  - Sequence length (trimming)
  - Low quality reads (filtering)
  - Deal with sequencing errors (denoising/error correction)
  - Homopolymers
  - Chimeras
- OTU vs SV
- Deal with controls
- Documentation
- Format/compatibility with downstream analysis

FASTQ – quality profile plot



[https://benjineb.github.io/dada2/tutorial\\_1\\_6.html](https://benjineb.github.io/dada2/tutorial_1_6.html)

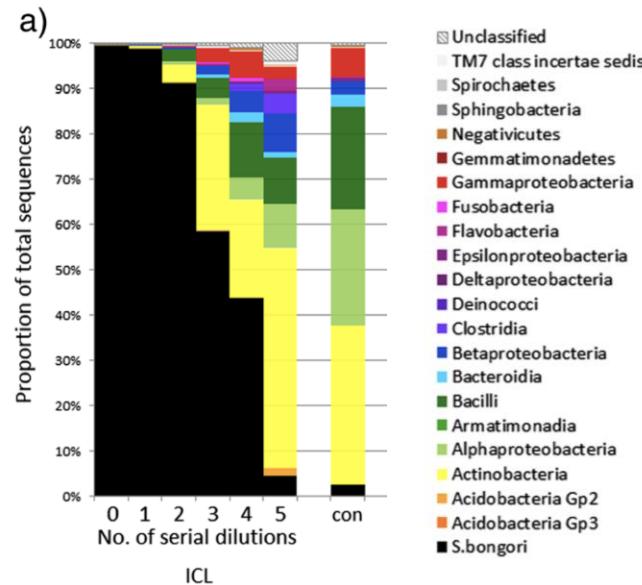
PCR and Chimeras



Bahram et al (2019) doi:[10.1111/1758-2229.12684](https://doi.org/10.1111/1758-2229.12684): Haas et al 2011

# Negative controls and identifying contaminants

## Contaminants in low biomass samples



con=template free PCR  
<http://www.biomedcentral.com/1741-7007/12/87>

Davis et al. *Microbiome* (2018) 6:226  
<https://doi.org/10.1186/s40168-018-0605-2>

Microbiome

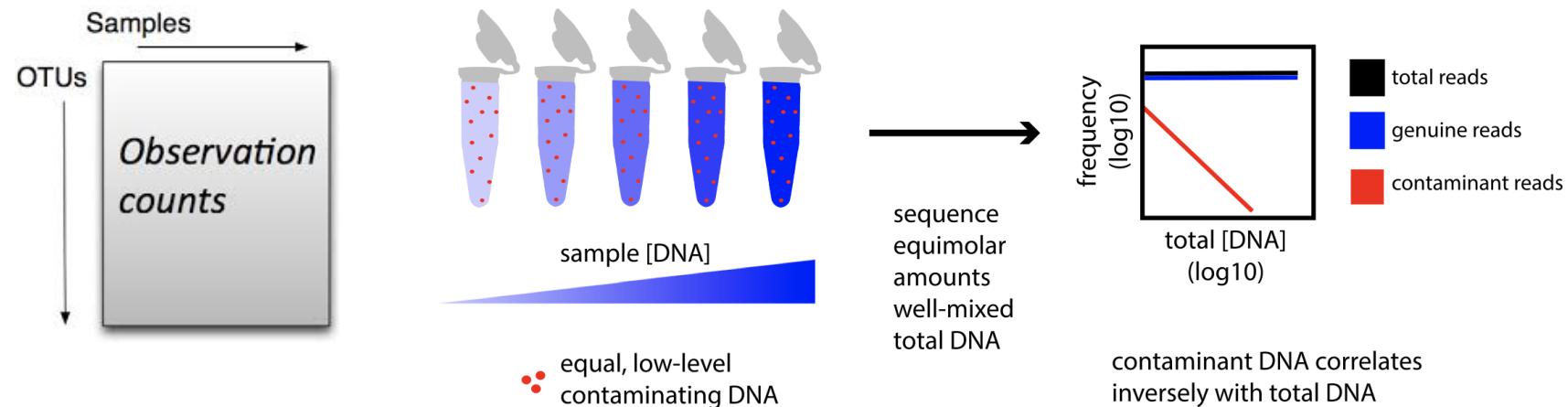
## METHODOLOGY

Open Access



Simple statistical identification and removal of contaminant sequences in marker-gene and metagenomics data

Nicole M. Davis<sup>1</sup>, Diana M. Proctor<sup>2,3</sup>, Susan P. Holmes<sup>4</sup>, David A. Relman<sup>1,2,5</sup> and Benjamin J. Callahan<sup>6,7\*</sup>



# Technical replicates or other standards

Phytobiomes • 2018 • 2:165-170

<https://doi.org/10.1094/PBIOIMES-09-17-0041-R>



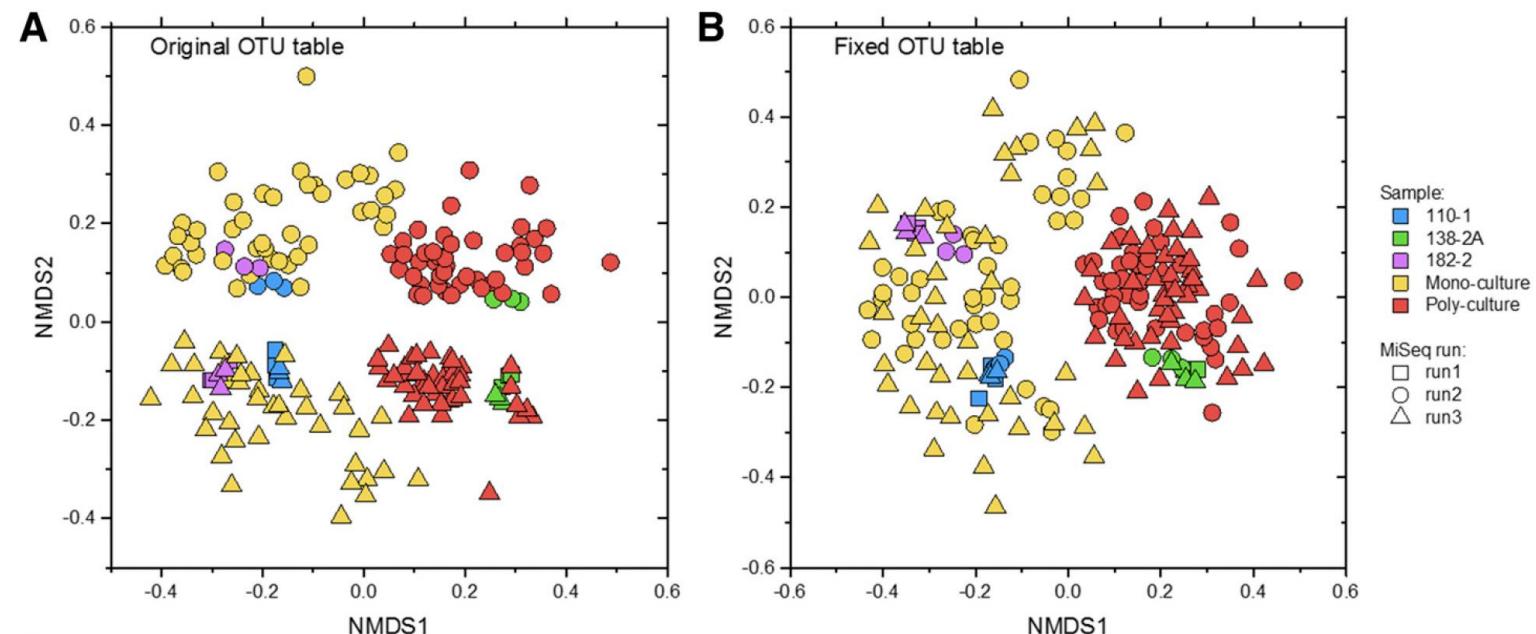
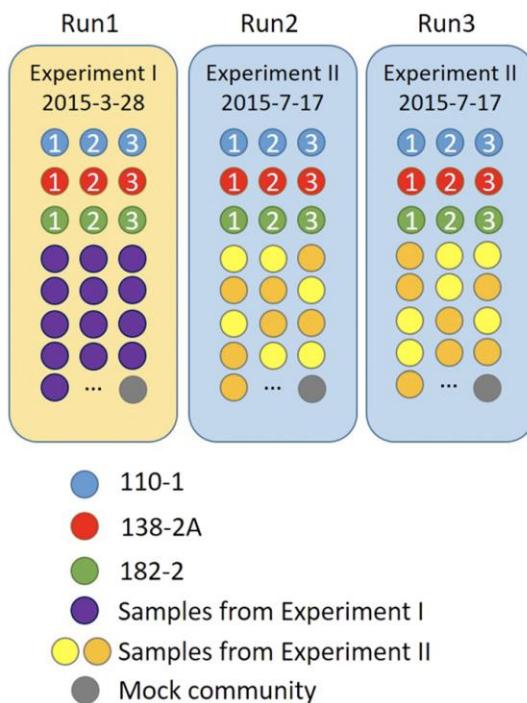
RESEARCH

eXtra\*

## Run-to-Run Sequencing Variation Can Introduce Taxon-Specific Bias in the Evaluation of Fungal Microbiomes

Zewei Song<sup>†</sup> and Dan Schlatter, Department of Plant Pathology, University of Minnesota, Saint Paul; Daryl M. Gohl, University of Minnesota Genomics Center, Minneapolis; and Linda L. Kinkel, Department of Plant Pathology, University of Minnesota, Saint Paul

## Experiment design

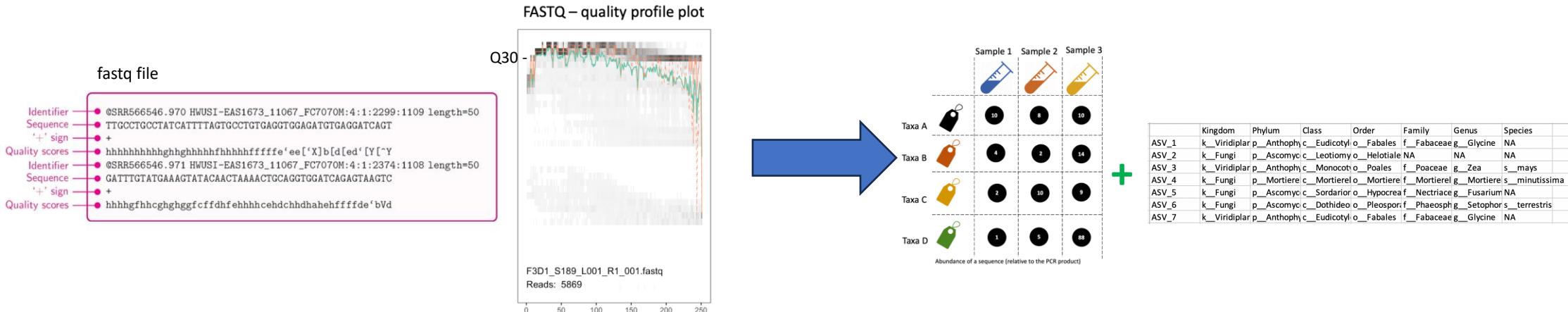


# Mock communities and positive controls

Product	Catalog #	Composition	Format
<b>Microbial Community Standard</b>	D6300	Even Distribution	Microbial
<b>Microbial Community DNA Standard</b>	D6305/6306	Even Distribution	Isolated DNA
<b>Microbial Community Standard II</b>	D6310	Log Distribution	Microbial
<b>Microbial Community DNA Standard II</b>	D6311	Log Distribution	Isolated DNA
<b>Spike-in Control I (High Microbial Load)</b>	D6320/D6320-10	Even Distribution	Microbial
<b>Spike-in Control II (Low Microbial Load)</b>	D6321/D6321-10	Log Distribution	Microbial
<b>HMW DNA Standard</b>	D6322	Even Distribution	Isolated DNA
<b>Gut Microbiome Standard</b>	D6331	Staggered Abundance	Microbial

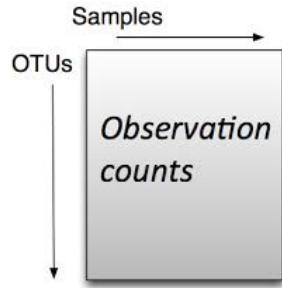
# Metabarcoding processing and analysis pipelines

## 1. From raw-reads to OTU-table

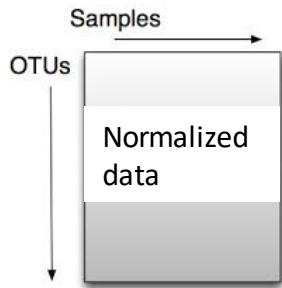


## 2. Statistical analysis

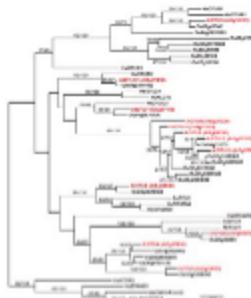
# Analysing and interpreting your data



	A	B	C	D	E	F
1		sample01	sample01	sample02	sample02	sample03
2	OTU0001	528	68	1755	773	2167
3	OTU0002	138	68	559	2588	1198
4	OTU0003	36	533	673	351	815
5	OTU0004	1	2618	5	17	19
6	OTU0005	224	237	81	271	313



Phylogenetic tree



	Kingdom	Phylum	Class	Order	Family	Genus	Species
ASV_1	k_Viridiplar	p_Anthophy	c_Eudicotyl	o_Fabales	f_Fabaceae	g_Glycine	NA
ASV_2	k_Fungi	p_Aскомyc	c_Leotiomyc	o_Helotiale	NA	NA	NA
ASV_3	k_Viridiplar	p_Anthophy	c_Monocot	o_Poales	f_Poaceae	g_Zea	s_mays
ASV_4	k_Fungi	p_Mortiere	c_Mortierel	o_Mortiere	f_Mortierel	g_Mortiere	s_minutissima
ASV_5	k_Fungi	p_Aскомyc	c_Sordarior	o_Hypocreaf	f_Nectriace	g_Fusarium	NA
ASV_6	k_Fungi	p_Aскомyc	c_Dothideo	o_Pleosporf	f_Phaeosph	g_Setophor	s_terrestris
ASV_7	k_Viridiplar	p_Anthophy	c_Eudicotyl	o_Fabales	f_Fabaceae	g_Glycine	NA

## Metadata

Phytobiomes Journal • 2020 • 4:115-121

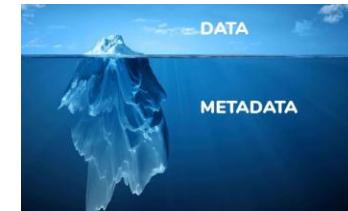
<https://doi.org/10.1094/PBIOMES-09-19-0051-P>



### PERSPECTIVE

#### Community-Driven Metadata Standards for Agricultural Microbiome Research

J. P. Dundore-Arias,<sup>1,†</sup> E. A. Eloe-Fadros,<sup>2</sup> L. M. Schriml,<sup>3</sup> G. A. Beattie,<sup>4</sup> F. P. Brennan,<sup>5</sup> P. E. Busby,<sup>6</sup> R. B. Calderon,<sup>7</sup> S. C. Castle,<sup>8</sup> J. B. Emerson,<sup>9</sup> S. E. Everhart,<sup>10</sup> K. Eversole,<sup>11</sup> K. E. Frost,<sup>12</sup> J. R. Herr,<sup>13</sup> A. I. Huerta,<sup>14</sup> A. S. Iyer-Pascuzzi,<sup>15</sup> A. K. Kalil,<sup>16</sup> J. E. Leach,<sup>17</sup> J. Leonard,<sup>18</sup> J. E. Maul,<sup>19</sup> B. Prithiviraj,<sup>20</sup> M. Potrykus,<sup>21</sup> N. R. Redekar,<sup>22</sup> J. A. Rojas,<sup>23</sup> K. A. T. Silverstein,<sup>24</sup> D. J. Tomso,<sup>25</sup> S. G. Tringe,<sup>26</sup> B. A. Vinatzer,<sup>27</sup> and L. L. Kinkel<sup>28</sup>

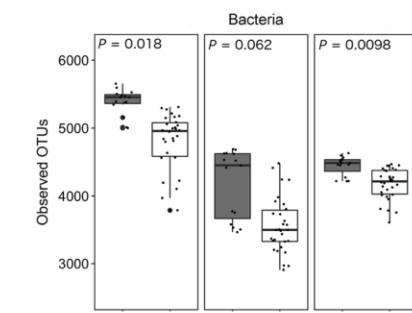
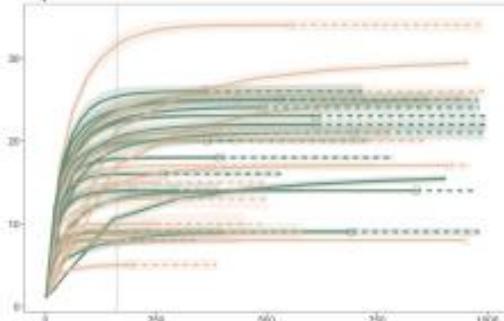


\**phyloseq* object

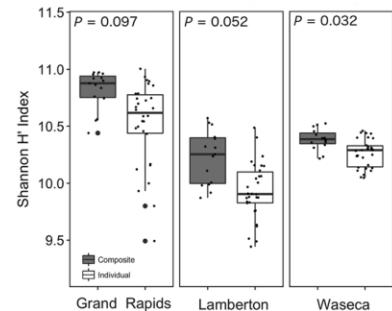
# Which analyses to apply?

## Alpha-diversity: within a community

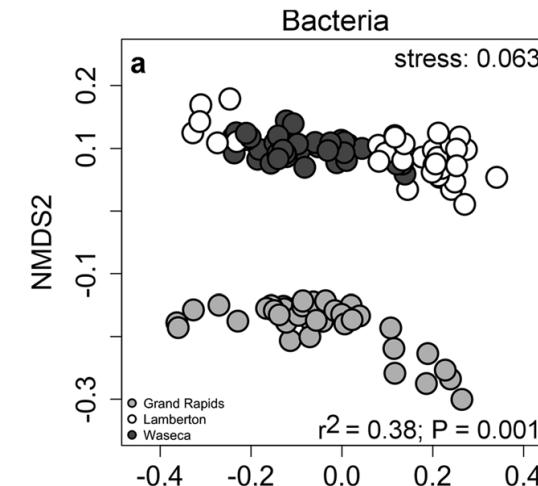
a) Root bacteria



Richness  
Evenness  
Phylogenetic diversity  
...

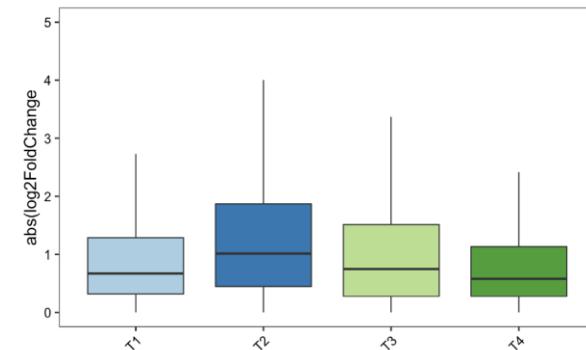


## Beta-diversity: between communities

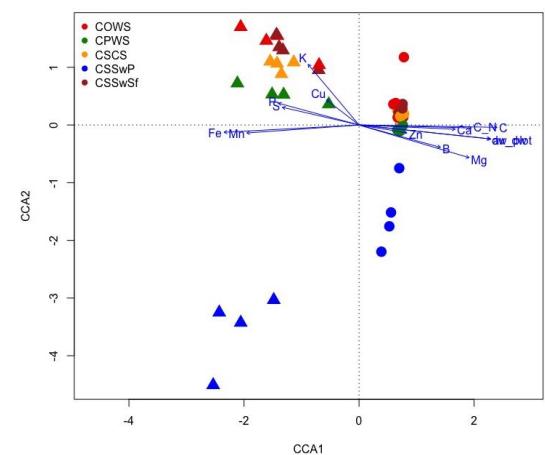
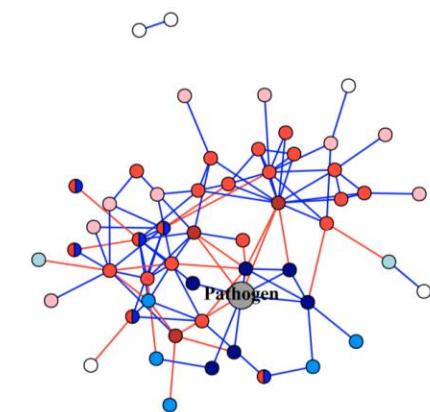


Similarity/dissimilarity indices  
E.g: Bray-Curtis, Unifrac...

## Differential abundance tests



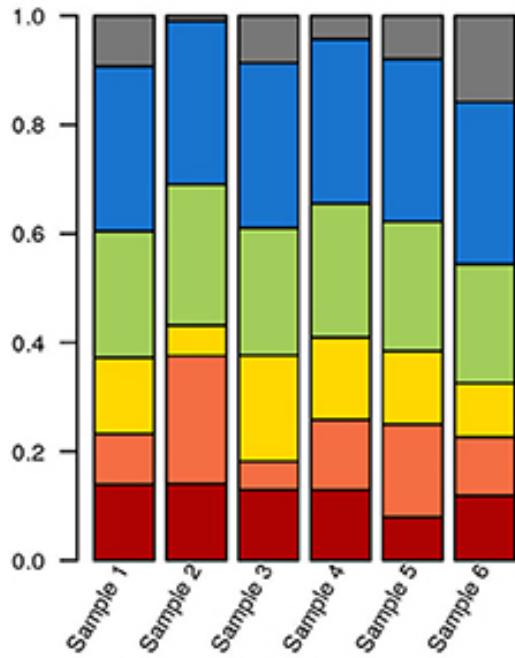
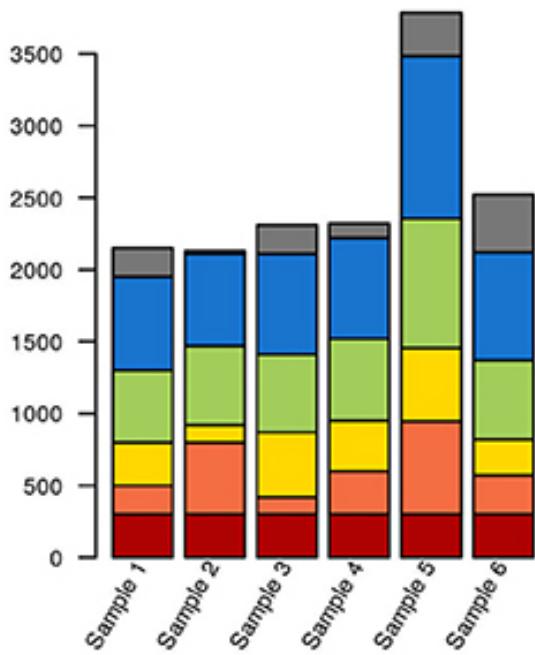
## Co-occurrence and interactions between microbes; and correlation with environmental variables



# To normalize or not?

What is your question and hypothesis?

McMurdie, Paul J., and Susan Holmes. "Waste Not, Want Not: Why Rarefying Microbiome Data Is Inadmissible." *PLoS Comput Biol* 10, no. 4 (2014): e1003531.



Weiss, Sophie, Zhenjiang Zech Xu, Shyamal Peddada, Amnon Amir, Kyle Bittinger, Antonio Gonzalez, Catherine Lozupone, et al. "Normalization and Microbial Differential Abundance Strategies Depend upon Data Characteristics." *Microbiome* 5, no. 1 (March 3, 2017): 27. <https://doi.org/10.1186/s40168-017-0237-y>.

Schloss PD. 2024. Waste not, want not: revisiting the analysis that called into question the practice of rarefaction. *mSphere* 9:e00355-23. <https://doi.org/10.1128/msphere.00355-23>

# Variation in RNA operon copy number

## rrndb: the Ribosomal RNA Operon Copy Number Database



**Table 1.**

Intra-genomic 16S rRNA variability for Bacteria and Archaea with full-genome sequence availability

Organism	No. rRNA <sup>a</sup> operons	Diff. (nt) <sup>b</sup>	% difference <sup>c</sup>
<i>Aquifex aeolicus</i> VF5	2	-	-
<i>Bacillus subtilis</i> ATCC 23857	10	1-15	0.97
<i>Campylobacter jejuni</i> ATCC 700819	3	-	-
<i>Deinococcus radiodurans</i> ATCC 13939	3	0-2	0.13
<i>Escherichia coli</i> ATCC 10798	7	0-19	1.23
<i>Haemophilus influenzae</i> ATCC 51907	6	-	-
<i>Helicobacter pylori</i> 26695	2	-	-
<i>Methanococcus jannaschii</i> DSMZ 2661	2	3	0.20
<i>Methanococcus thermoautotrophicum</i> ATCC 29096	2	2	0.14
<i>Neisseria meningitidis</i> MC 58	4	-	-
<i>Treponema pallidum</i> ATCC 25870	2	-	-
<i>Ureaplasma urealyticum</i> serovar 3	2	1	0.07
<i>Vibrio cholerae</i> ATCC 39315	8	0-14	0.91
<i>Xyella fastidiosa</i> 9a5c	2	-	-

<sup>a</sup>Number of rRNA operons per genome.

<sup>b</sup>Pairwise difference range between 16S rRNA genes per genome.

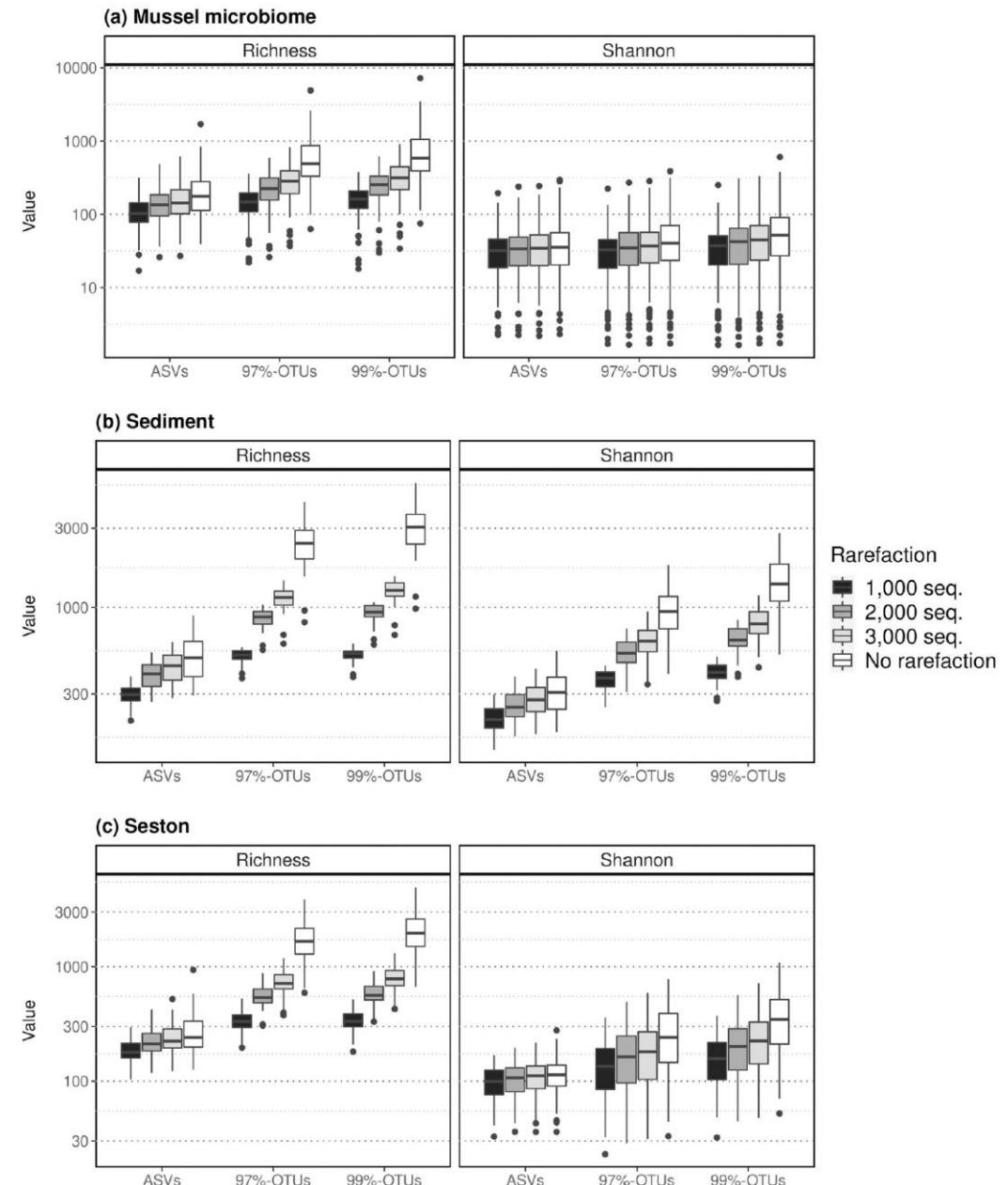
<sup>c</sup>Pairwise difference range between 16S rRNA genes per genome calculated as a percentage. -, no nucleotide differences.

# Ranking the biases: The choice of OTUs vs. ASVs in 16S rRNA amplicon data analysis has stronger effects on diversity measures than rarefaction and OTU identity threshold

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**Fig 2. Effect of sequence processing methodology on alpha diversity metrics for microbiome analyses.** Measure of taxonomic richness (expressed as the number of OTUs or ASVs) and Shannon alpha diversity depending on the methodology used, namely ASV, 97%-OTU, and 99%-OTU, at three different levels of rarefaction (1,000; 2,000 and 3,000 sequences per sample) within each sample type studied (a-c). To ease the visualization of differences across methods and rarefaction levels, the y-axis of plots has been log transformed. The effect of methodological choices on other alpha diversity metrics is available in S3 Fig in [S1 File](#).

