



Ecological analysis of metabarcoding data

Data preparation

Clarisse Lemonnier

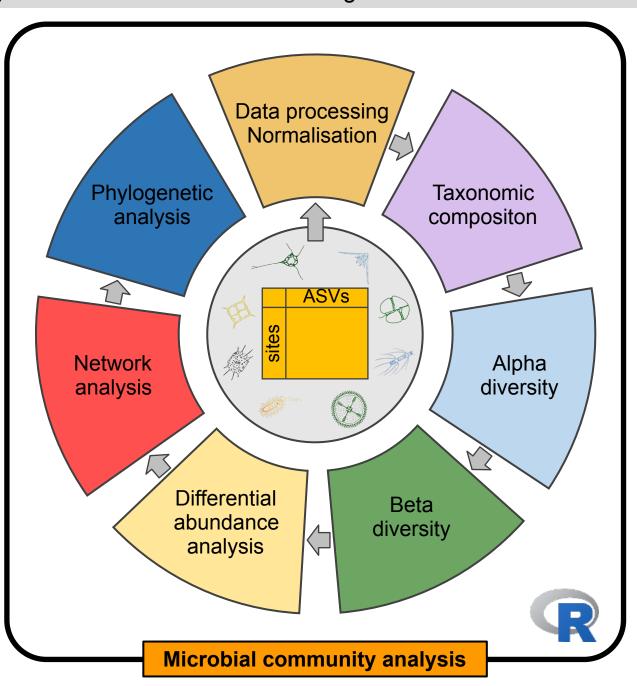




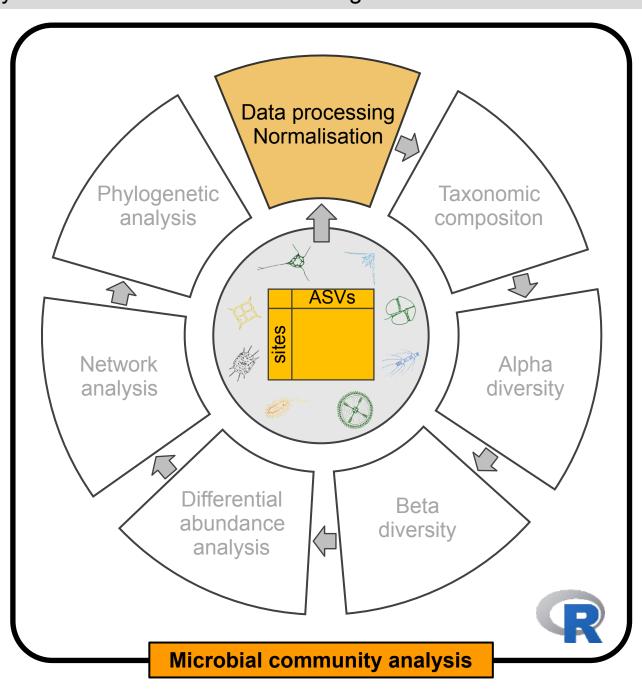




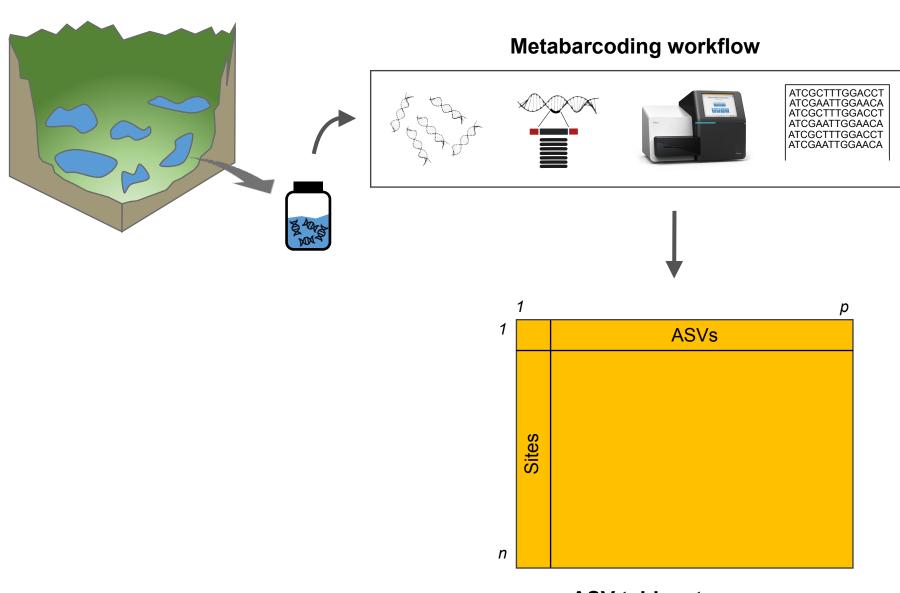






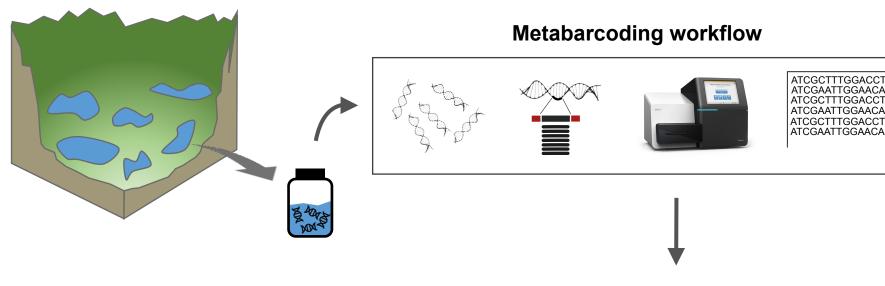






ASV table + taxonomy





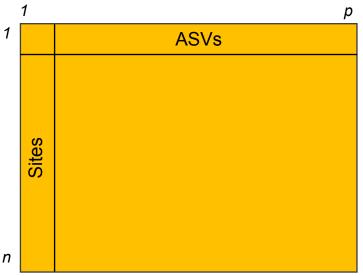
Metabarcoding specificities

Unwanted taxa

Uneven sequencing depth

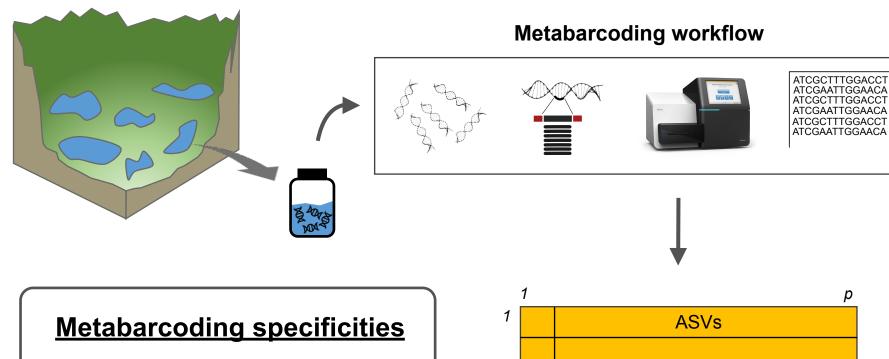
Compositionality

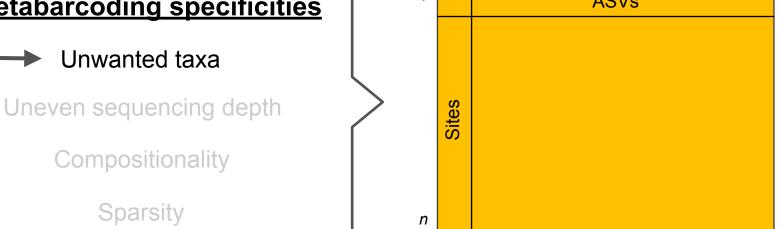
Sparsity



ASV table + taxonomy

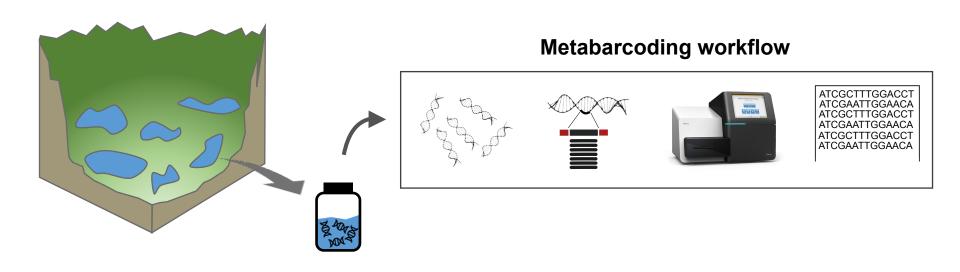




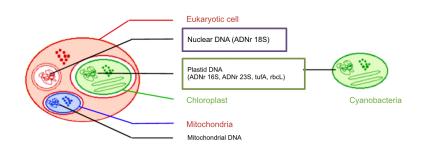


ASV table + taxonomy





Exemple: you study bacterial communities through 16S metabarcoding



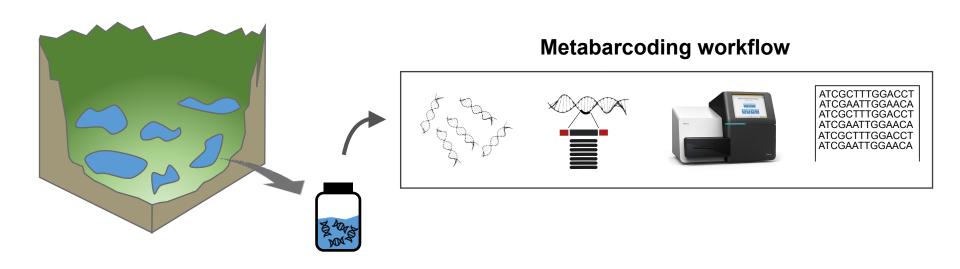
Bacteria + Chloroplasts

Archaea

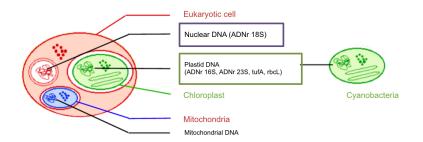
Chloroplasts

Mitochondria





Exemple: you study bacterial communities through 16S metabarcoding



Bacteria + Chloroplasts

Archaea

Chloroplasts

Archaea

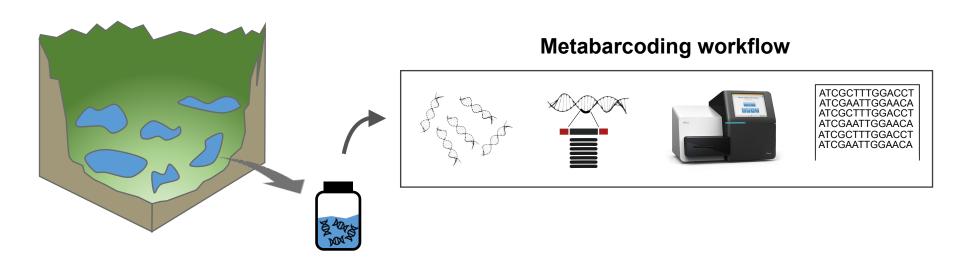
Presence of reads affiliated to nontargeted taxa can be due to several reasons:

Sequencing errors

Aspecific amplification

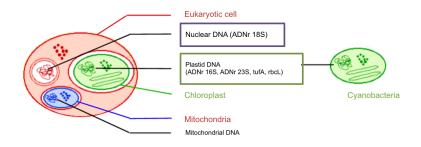
. . .





And for 23S sequencing of phytoplankton, what unwanted taxa could we get?

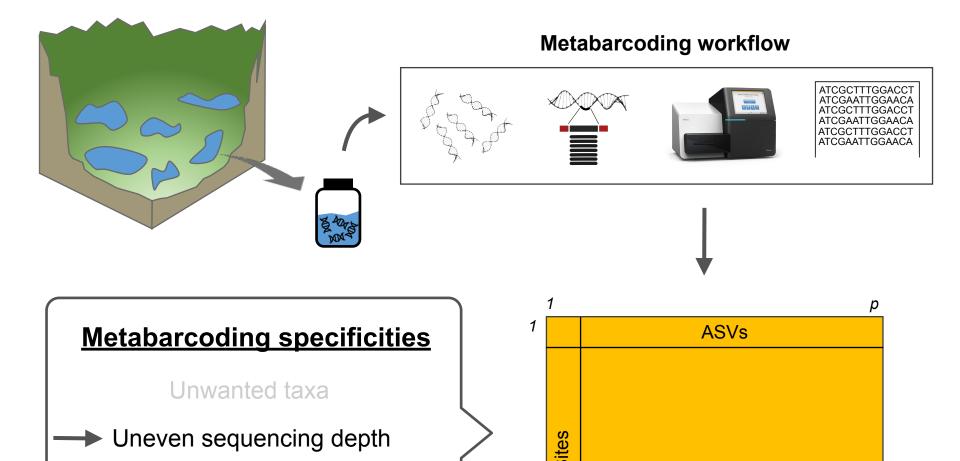
Let's see during the practice!



Compositionality

Sparsity

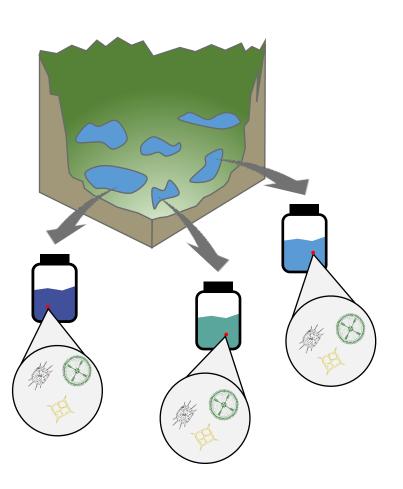


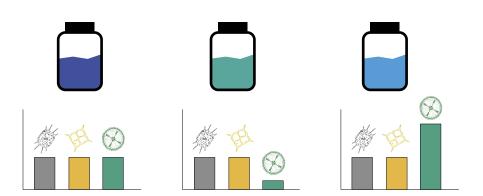


n

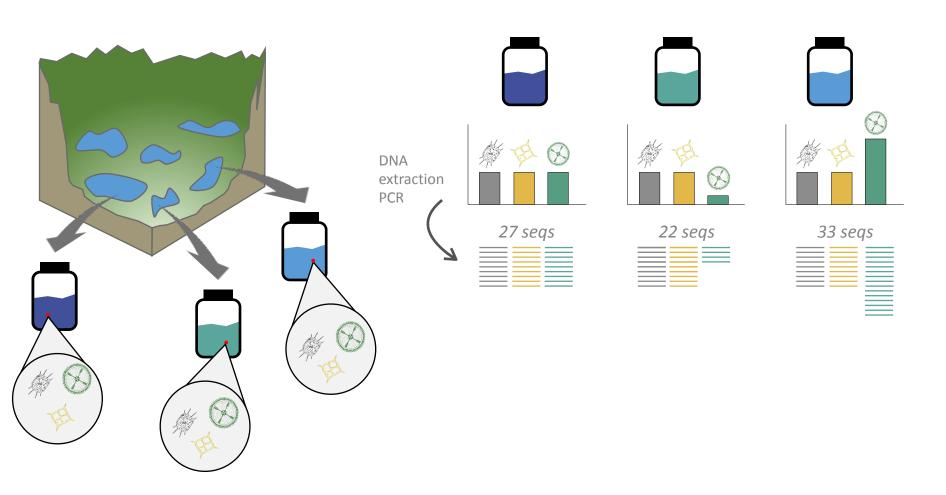
ASV table



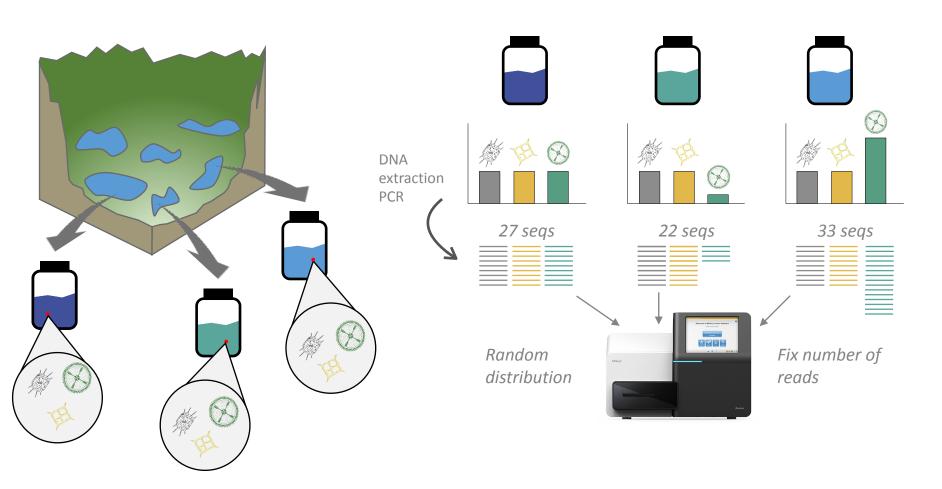




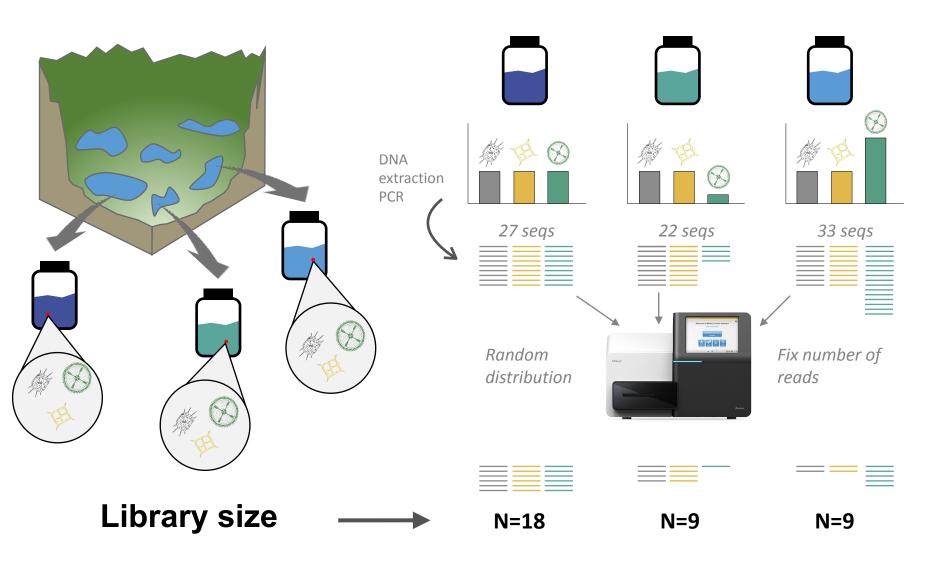




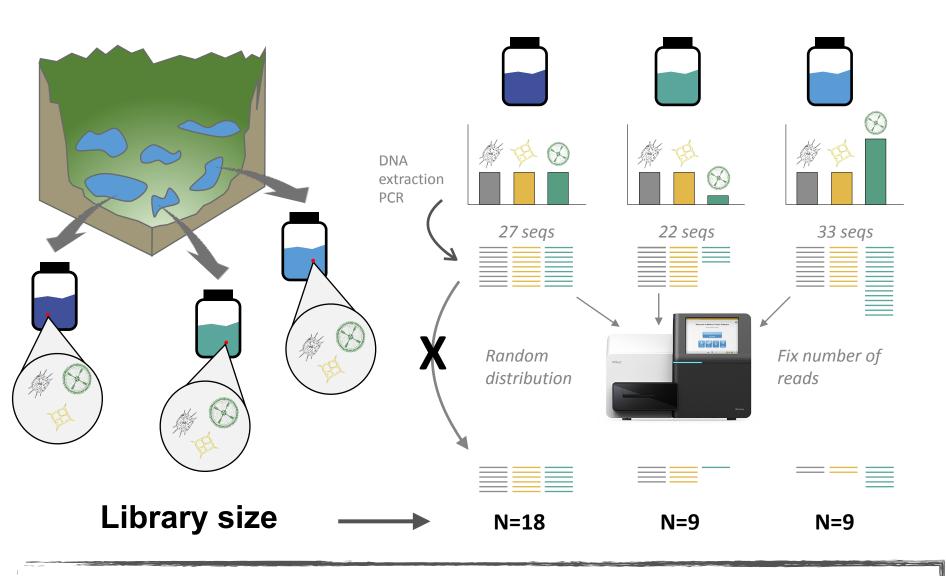






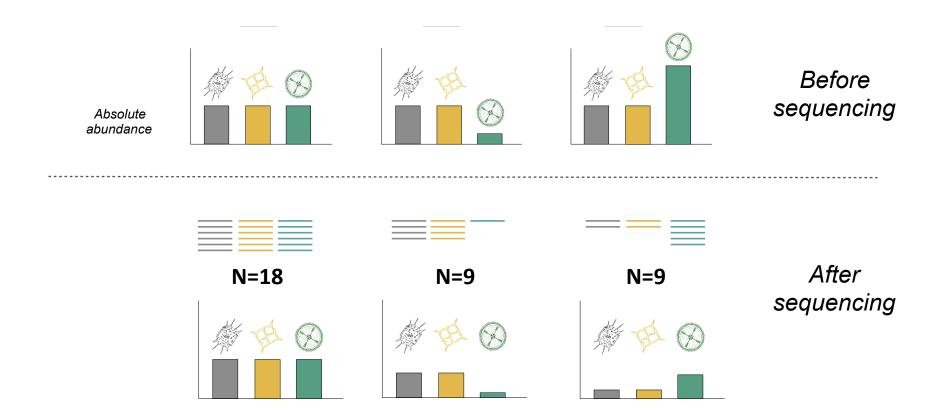






The library size is uneven due to the sequencing technology. This is not related to actual biological differences. It can change of more than 10s fold!!









Samples cannot be compared directly based on read counts

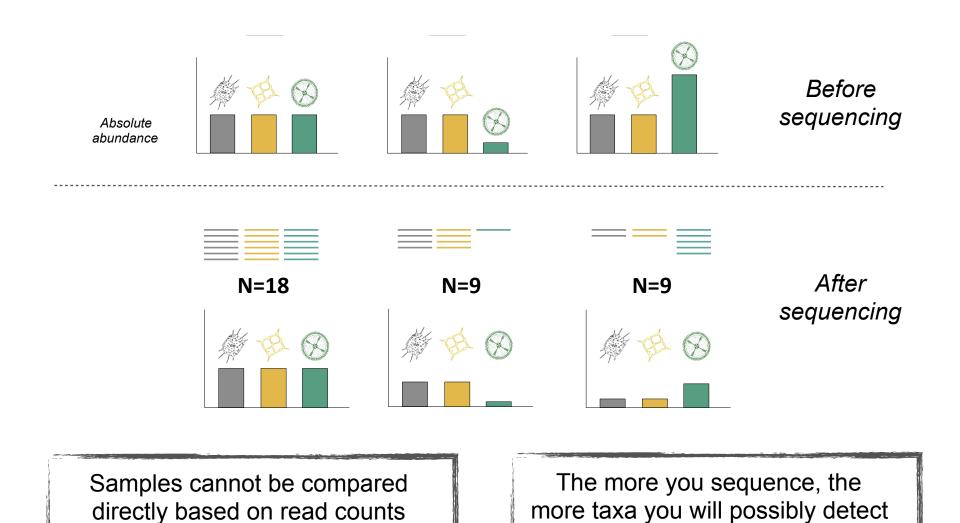




Samples cannot be compared directly based on read counts

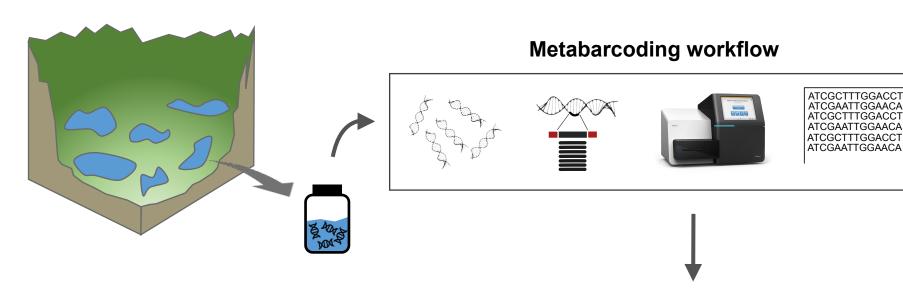
The more you sequence, the more taxa you will possibly detect





A normalisation step is mandatory before doing any ecological analysis





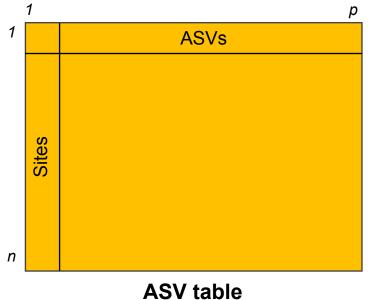
Metabarcoding specificities

Unwanted taxa

Uneven sequencing depth

Compositionality

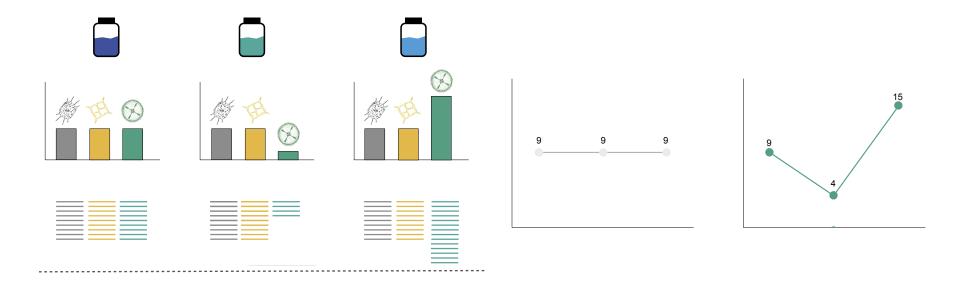
Sparsity





Data is compositional

« A data set is compositional when the parts in each sample have an arbitrary or non-informative sum »





Data is compositional

« A data set is compositional when the parts in each sample have an arbitrary or non-informative sum »

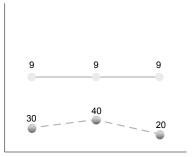


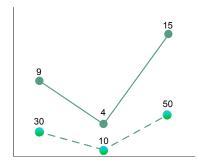


Data is compositional

« A data set is compositional when the parts in each sample have an arbitrary or non-informative sum »



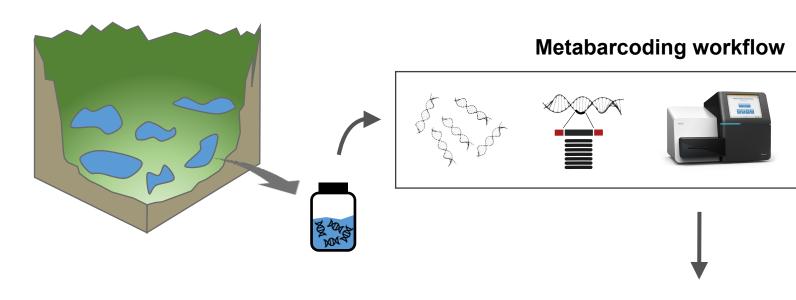




- Induce spurious correlations
- Problematic for differential abundance analysis
- Problematic for network analysis and correlations between taxas



ATCGCTTTGGACCT ATCGAATTGGAACA



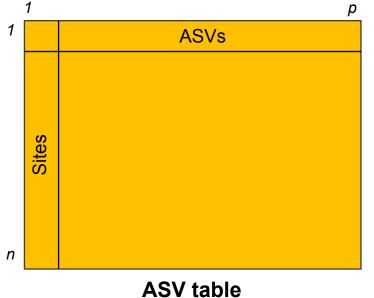
Metabarcoding specificities

Unwanted taxa

Uneven sequencing depth

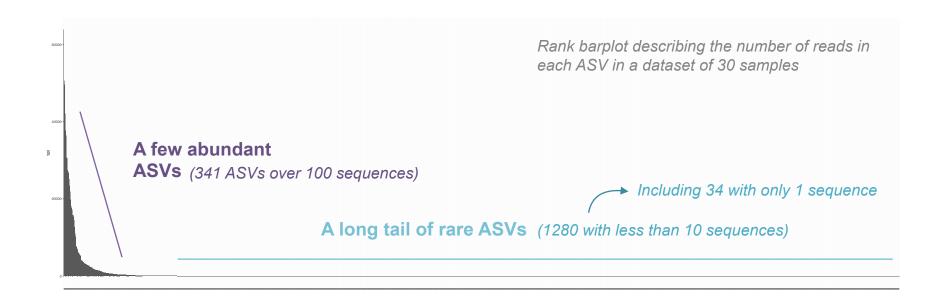
Compositionality

Sparsity





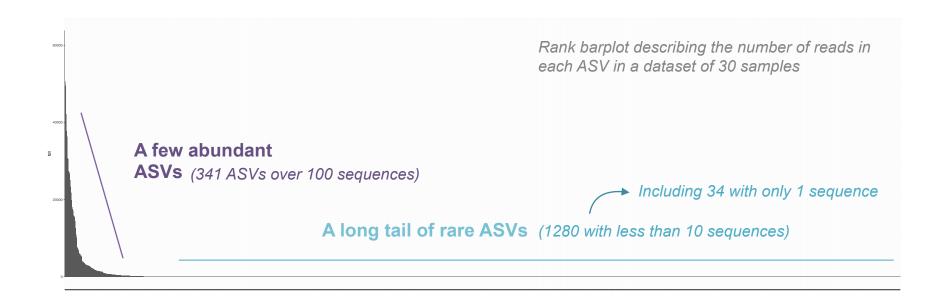
Data is sparse



In some studies, data can be composed of more than 80% of 0s!



Data is sparse



Why?

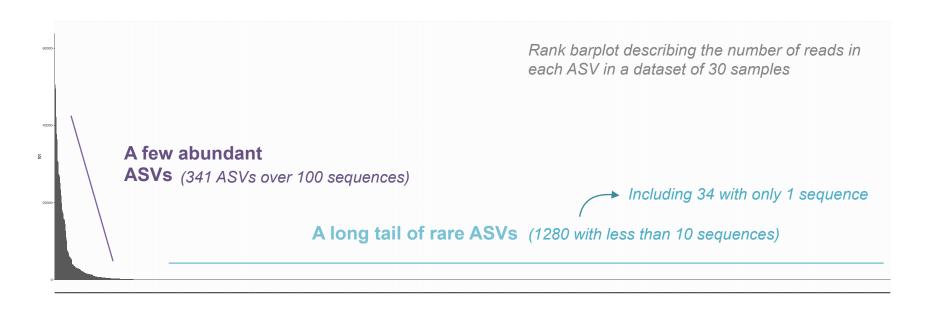
Because metabarcoding is very sensitive and can detect rare species or variants

Because of sequencing errors

Because microbial communities are highly diverse



Data is sparse



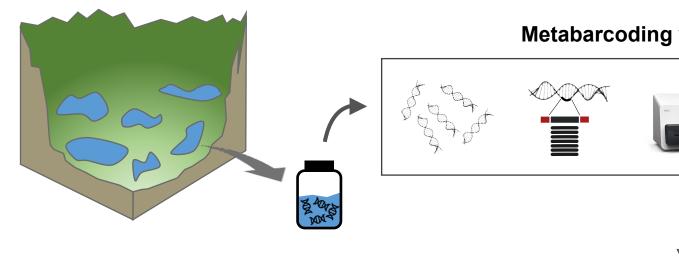
Problematics

A 0 does not mean the **absence** of a species (e.g. low sequencing depth).

Some statistical analysis can be impacted (due to « double zeros »)

It is complex to decipher true rare species from sequencing errors





Metabarcoding workflow



ATCGCTTTGGACCT ATCGAATTGGAACA



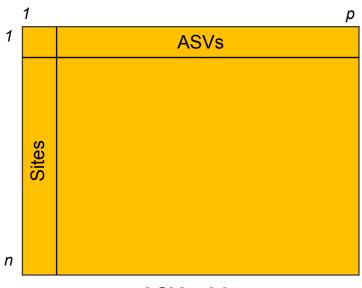
Metabarcoding specificities

Unwanted taxa

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Compositionality

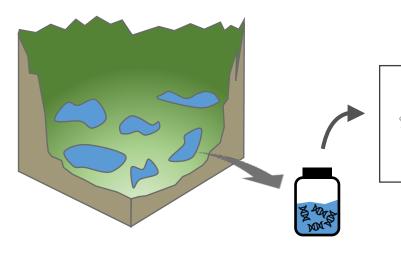
Sparsity



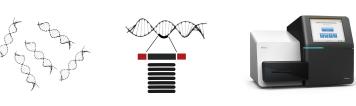
ASV table



ATCGCTTTGGACCT ATCGAATTGGAACA



Metabarcoding workflow





Metabarcoding data needs to
Metabarcoding data needs to
Metabarcoding data needs to
be normalized and prepared
be normalized and prepared
before doing any ecological
before analysis

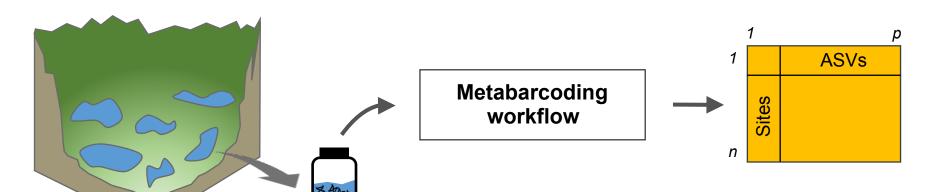
1 ASVs

Sites

n

ASV table

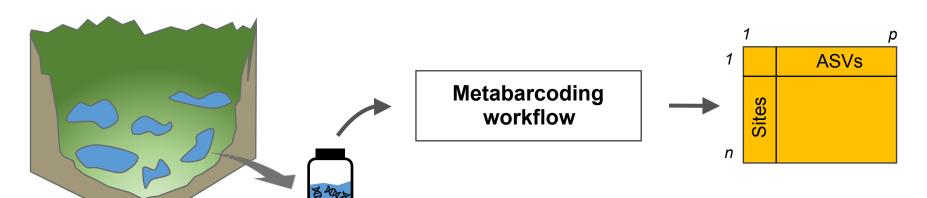




Filter ASVs based on taxonomy

Keep only ASVs assigned to the targeted organisms (e.g. Diatoms)





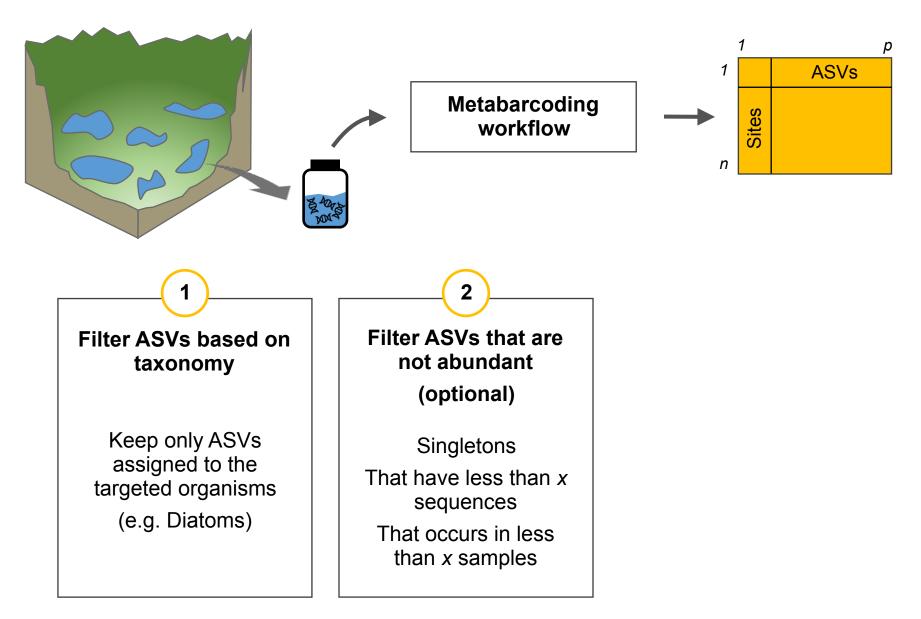
Filter ASVs based on taxonomy

Keep only ASVs assigned to the targeted organisms (e.g. Diatoms) Filter ASVs that are not abundant (optional)

Singletons
That have less than *x* sequences

That occurs in less than *x* samples



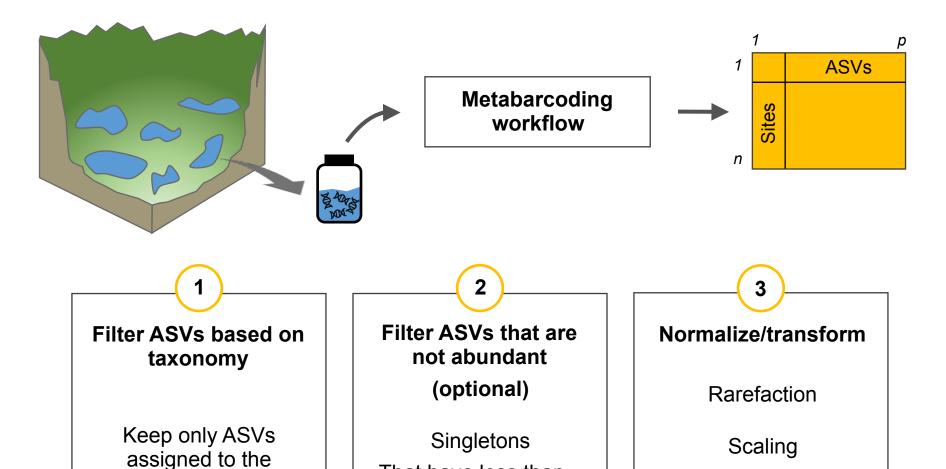


Limit sparsity and sequencing errors

targeted organisms

(e.g. Diatoms)





That have less than x

sequences

That occurs in less

than x samples

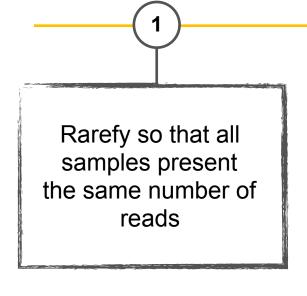
Limit sparsity and sequencing errors

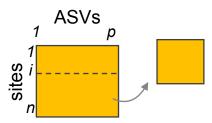
Deal with library size and/or compositionallity

Log ratio

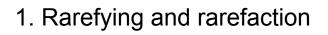


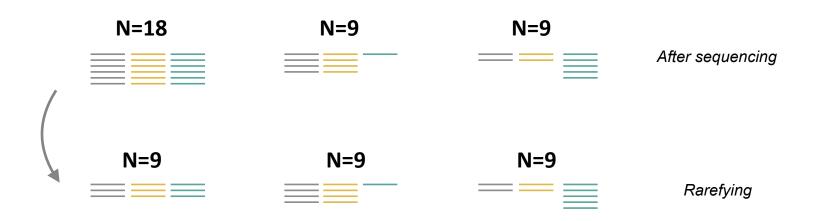
Different strategies exist to deal with uneven sequencing depth in metabarcoding data



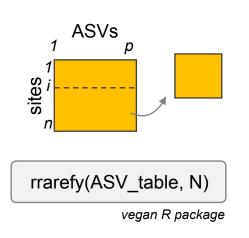




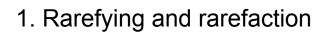


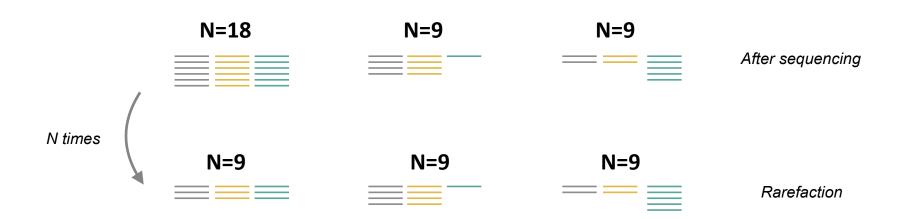


Rarefying: randomly subsample read counts of each sample to a common read depth (often taken from the smallest sample)



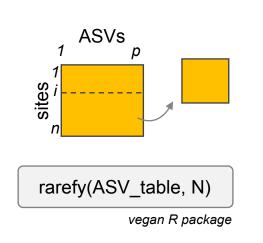






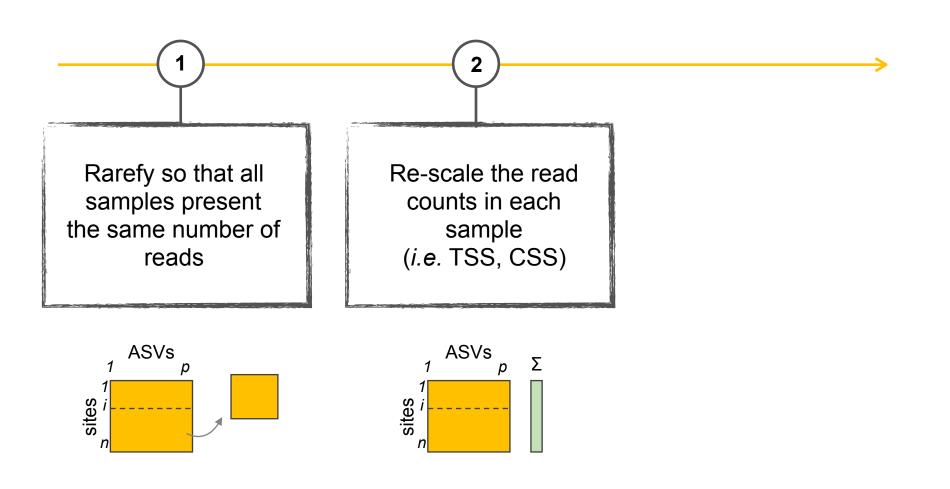
Rarefying: randomly subsample read counts of each sample to a common read depth (often taken from the smallest sample)

Rarefaction: repeat the subsampling a high number of time (e.g. 100, 1000 times) and calculate the mean of the alpha or beta diversity metrics (more robust !!).



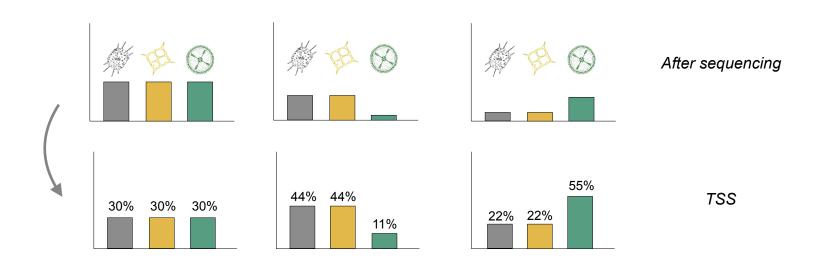


Different strategies exist to deal with uneven sequencing depth in metabarcoding data



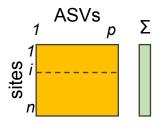






Divide ASVs read counts by the total number of reads in each samples

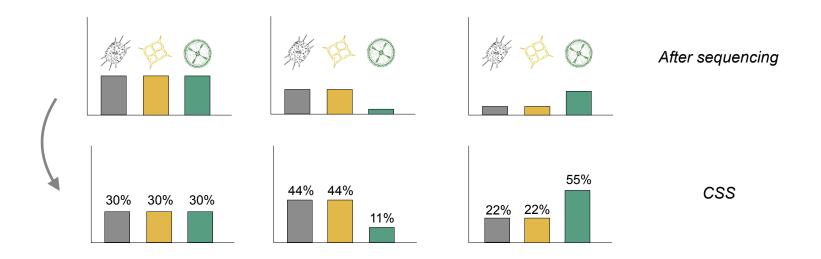
All values are summed up to 100%



ASV_table/rowSums(ASV_table)

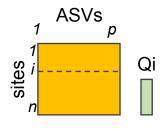


3. Cumulative Sum Scaling (metagenomeSeq)



Re-scales the samples by using a subset of lower abundant taxa (quantile), thereby excluding the impact of highly abundant taxa

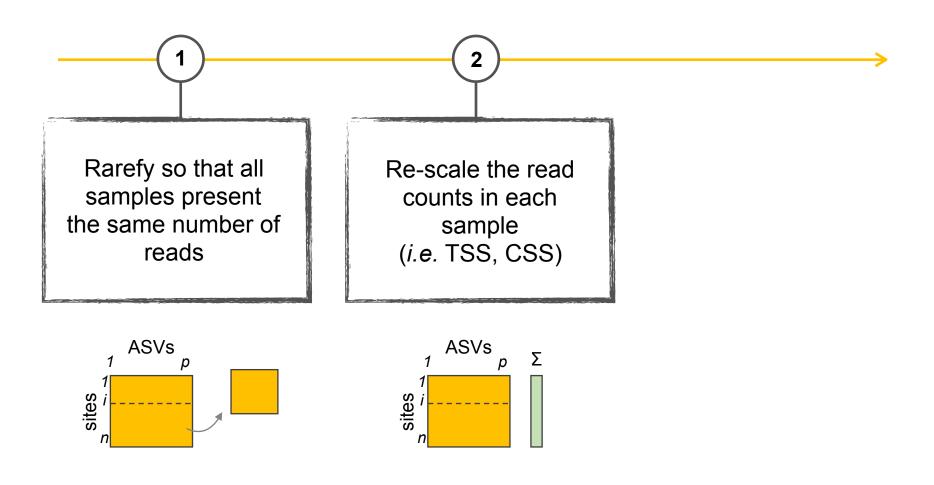
Number of reads in each samples are kept different



cumNorm(ASV_table,
p=cumNormStatFast(ASV_table))



Different strategies exist to deal with uneven sequencing depth in metabarcoding data



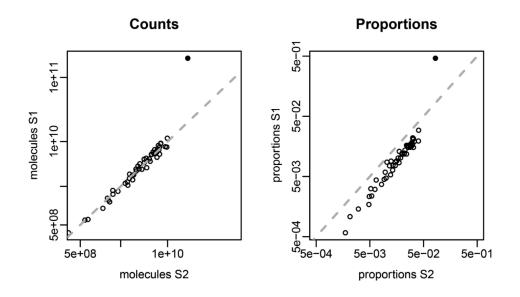
Deal with uneven sequencing depth

Compositionality



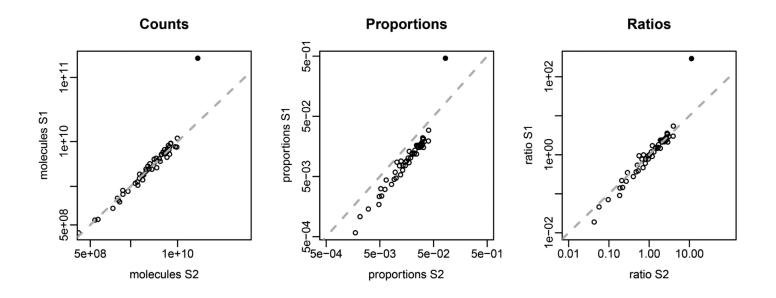


One main strategy to deal with compositional data: use ratios



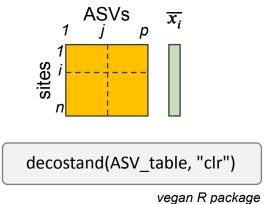


One main strategy to deal with compositional data: use ratios



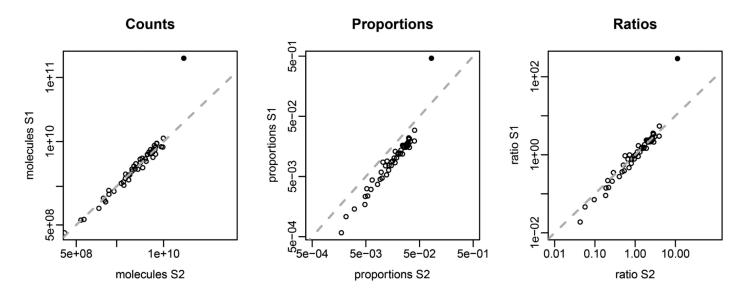
Ratios are conserved, regardless of the library size

For metabarcoding data, the most widely used transformation is the center log ratio





One main strategy to deal with compositional data: use ratios



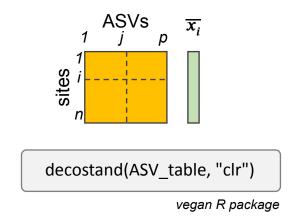
BUT, log(0) = infinity

And metabarcoding are sparse!

Different solutions:

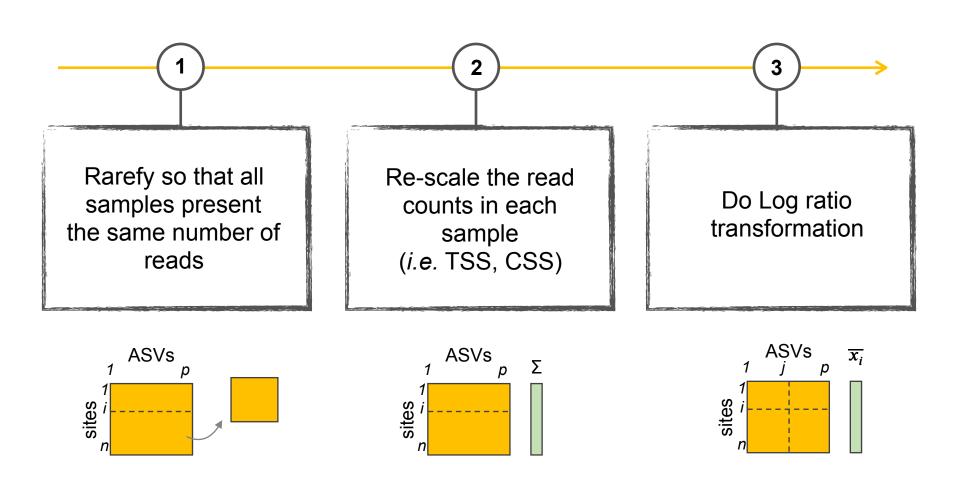
Either remove all 0s (not recommended)

Re-estimate their abundance using pseudocounts





Different strategies exist to deal with uneven sequencing depth in metabarcoding data

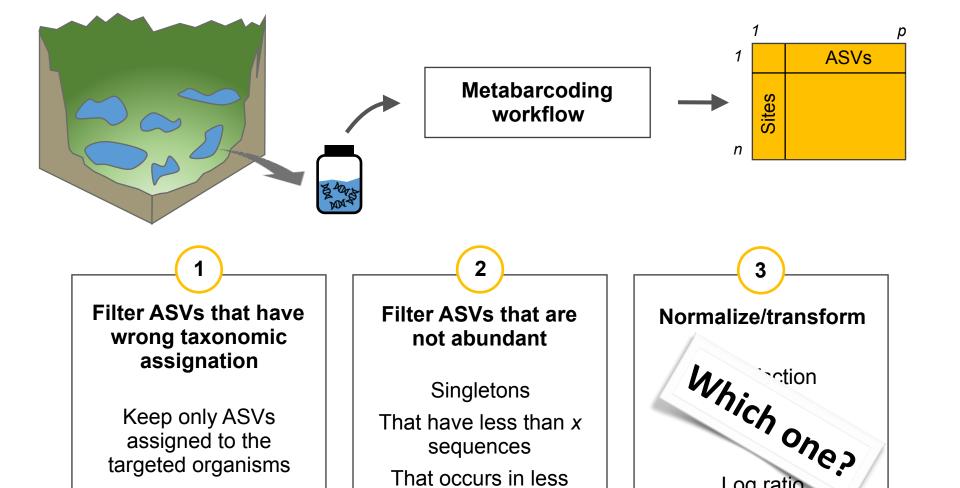


assigned to the

targeted organisms

(e.g. Diatoms)





That have less than x

sequences

That occurs in less

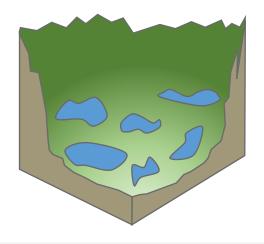
than x samples

Limit sparsity and sequencing errors

Deal with library size and/or compositionallity

Log ratio





It is important to consider that normalization is a highly debated topic and there is currently no consensus from experts on which normalization method is better

> Methods for normalizing microbiome data: An ecological perspective

Donald T. McKnight¹ | Roger Huerlimann¹ | Deborah S. Bower^{1,2} |

Microbiome Datasets Are Compositional: And This Is Not Optional

Jean M. Macklaim¹ Vera Pawlowsky-Juan J. Egozcue³

A review of normalization and differential abundance methods for microbiome counts data

Dionne Swift¹ | Kellen Cresswell² | Robert Johnson¹ | Spiro Stilianoudakis¹ | Xingtao Wei¹



Alpha and beta-diversities performance comparison between different normalization methods and centered log-ratio transformation in a microbiome public

David Bars-Cortina^{1,2,3}

dataset

Waste Not, Want Not: Why Rarefying Microbiome Data Is Inadmissible

Paul J. McMurdie, Susan Holmes

Published: April 3, 2014 • https://doi.org/10.1371/journal.pcbi.1003531

Rarefaction is currently the best approach to control for uneven sequencing effort in amplicon sequence analyses



Developping transformation tools to account for problematics in sequencing data is an active domain of research

More and more sophisticate tools are developed, initially for RNAseq data / metagenomic data and differential abundance analysis...

... wich are not always optimal for metabarcoding data and alpha/beta diversity analysis

TABLE 1 Summary of normalization methods

Methods	Scale factor	Normalizing covariate/method	Availability (bioconductor/R)	Correction	
TSS	$S_j = \frac{Y_{ij}}{n_j}$	Total number of sample reads	Topics	Total reads	
CSS	$S_j = rac{\sum_{i:Y_{ij} \leq q_j^i} Y_{ij} + 1}{N}$	Cumulative sum of counts (up to threshold q)	metagenomeSeq	Sequencing depth	2013
TMM	$\log_2(S_j) = \sum_{i \in G*} w_{ij} \log_2\left(\frac{X_{ij}}{X_{ir}}\right)$	Trimmed mean of logged expression ratios/ Inverse Variance	edgeR	Sequencing depth	2010
DESEq2	$S_{j} = med_{i} rac{Y_{ij}}{\left(\prod_{j'=1}^{N} Y_{ij'} ight)^{1/N}}$	Median ratio of gene counts relative to geometric mean per gene	DESeq2	Sequencing depth and compositionality	2010
GMPR	$S_{j} = \left(\prod_{k=1}^{n} Median_{i Y_{ij}Y_{ik}} \neq 0 \left\{ rac{Y_{ij}}{Y_{ik}} ight\} ight)^{1/N}$	Geometric mean of the pairwise ratio of nonzero counts	GMPR	Sequencing depth, compositionality, and sparsity	2018
Wrench	$S_j = \frac{1}{p} \sum_{ij} w_{ij} \frac{X_{ij}}{\overline{X_{i}}}.$	Group-wise and sample-wise compositional bias factor	Wrench	Sequencing depth, compositionality, and sparsity	2023
ANCOM-BC	$\log(S_j) = \frac{1}{p} \sum_{i=1}^{p} \left(y_{ij} - x_j^T \widehat{\beta}_i \right)$	Ratio of expected absolute abundance to ratio of library size to microbial load	ANCOM-BC	Sequencing depth and compositionality	2020
CLR ^a transformation	$\log\!\left(\!rac{Y_{ij}}{\left[\prod_{i}\!Y_{ij} ight]^{1/p}}\! ight)$	Log ratio of observed values and their geometric means		Compositionality	



Regardless which method you choose, you need to normalize before doing ecological analysis

1

Filter ASVs based on taxonomy

Keep only ASVs assigned to the targeted organisms (e.g. Diatoms) 2

Filter ASVs that are not abundant (optional)

Singletons
That have less than *x* sequences
That occurs in less than *x* samples

3

Normalize/transform

Rarefaction

or

Scaling

or

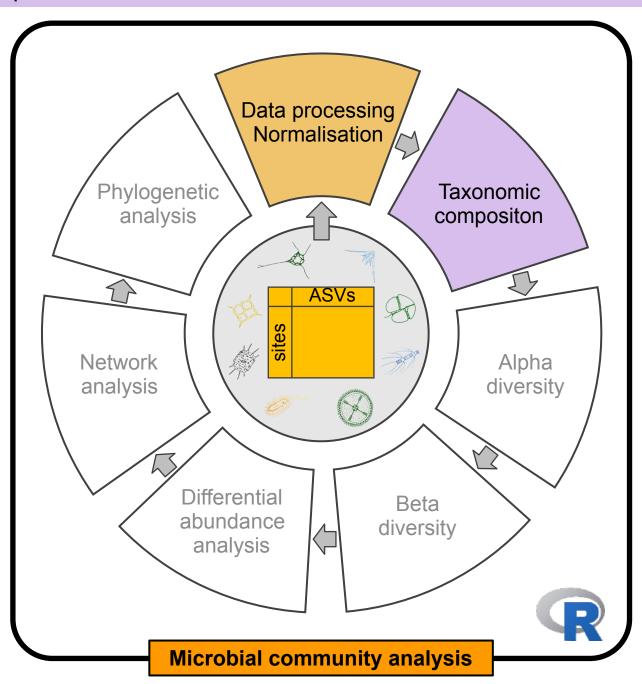
Log ratio

. . .

Limit sparsity and sequencing errors

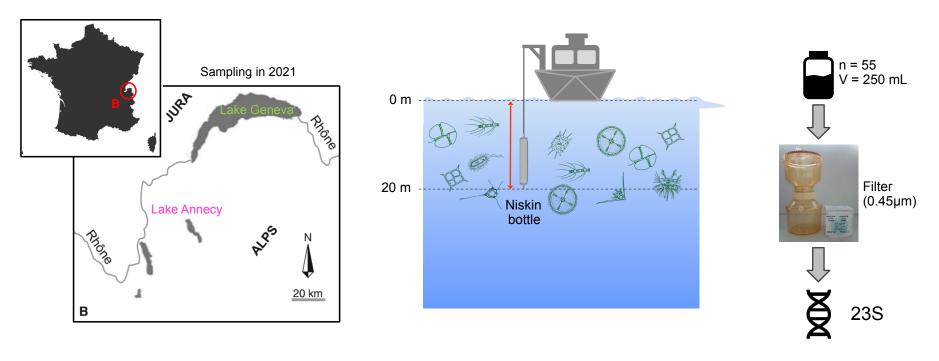
Deal with library size and/or compositionallity







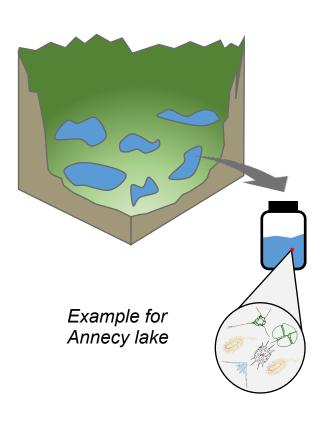
To illustrate alpha and beta-diversity analysis we will use a dataset of phytoplankton dynamic over one year (2021) from 2 alpine lakes



- Sampling 1 or 2 time per month
- 250mL of water filtered on 0.45µm filters
- Targeting 23S barcode

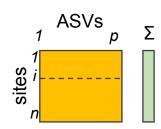
- Illumina MiSeq
- Data analysed with DADA2 pipeline (ASVs)

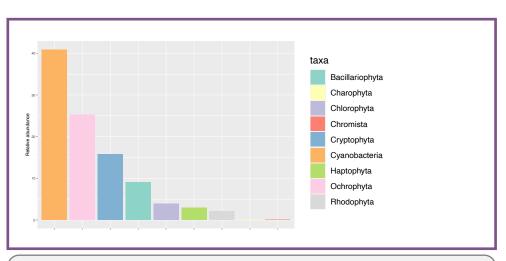




Who's there? And when?

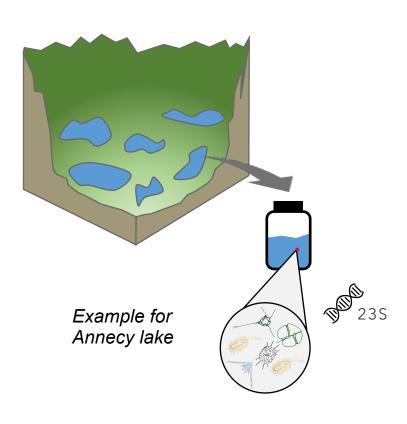
Using relative abundance





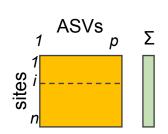
gg <- ggplot(dASV, aes(x=reorder(taxa, perc, decreasing=T), y=perc)) +
 geom_bar(stat="identity",position="stack", aes(fill=taxa))
 scale_fill_brewer(palette="Set3") + xlab("Lake") + ylab("Relative abundance") +
 theme(strip.text.y = element_text(angle = 0), axis.text.x = element_text(angle = 90))</pre>

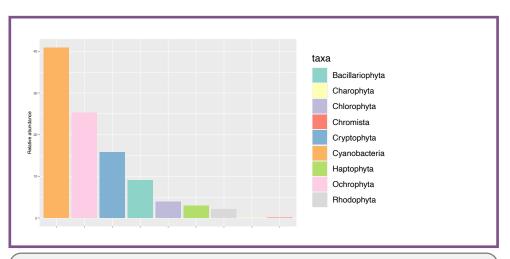




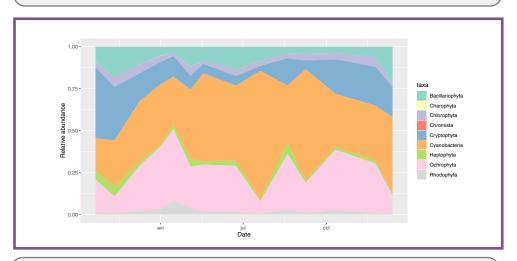
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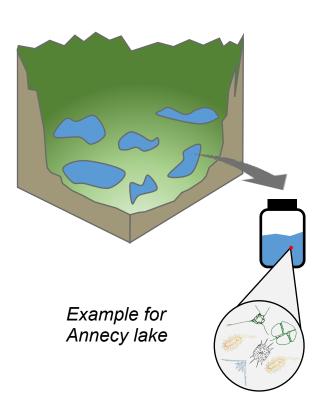


gg <- ggplot(dASV, aes(x=reorder(taxa, perc, decreasing=T), y=perc)) +
 geom_bar(stat="identity",position="stack", aes(fill=taxa))
 scale_fill_brewer(palette="Set3") + xlab("Lake") + ylab("Relative abundance") +
 theme(strip.text.y = element_text(angle = 0), axis.text.x = element_text(angle = 90))</pre>



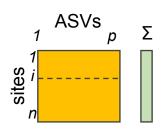
 $\label{eq:gg} $$ $$ $ = s(x=as.Date(Date,format="%d/%m/%Y"), y=value), group=taxa) + geom_area(stat="identity", position="fill", aes(fill=taxa)) + scale_fill_brewer(palette="Set3") + xlab("Date") + ylab("clr abund") \\$

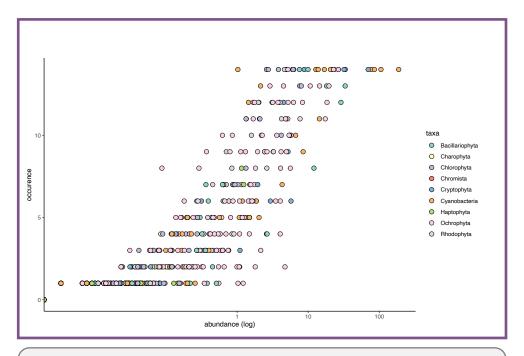




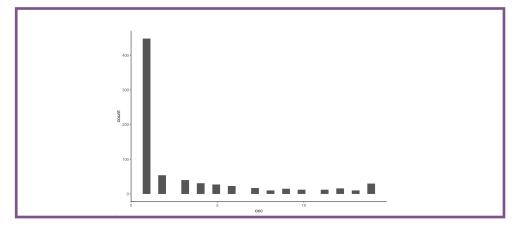
Who's there? And when?

Using relative abundance

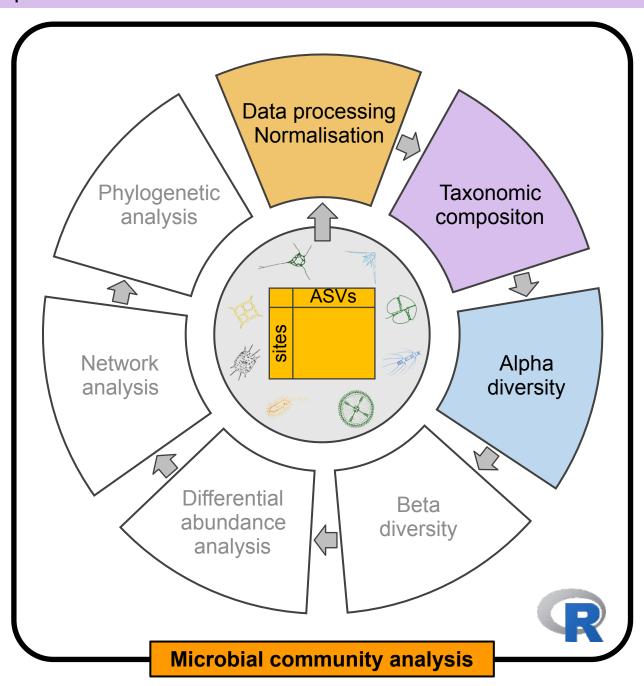




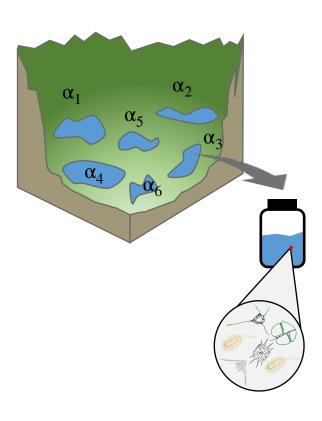
```
gg <- ggplot(ASV_table_occ, aes(x=occ, y=tot)) +
geom_point(aes(fill=taxa), shape=21, size=3) +
scale_y_continuous(trans="log", breaks=c(1,10,100)) + theme_classic() +
scale_fill_brewer(palette="Set3") + xlab("occurence") + ylab("abundance (log)")
```





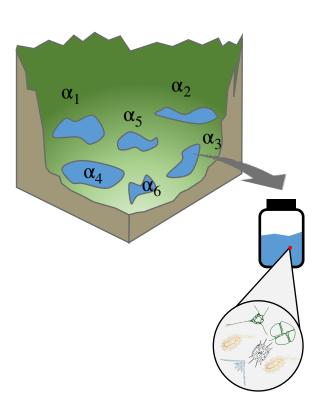






Alpha diversity





Alpha diversity

There are 2 component of diversity: richness and evenness





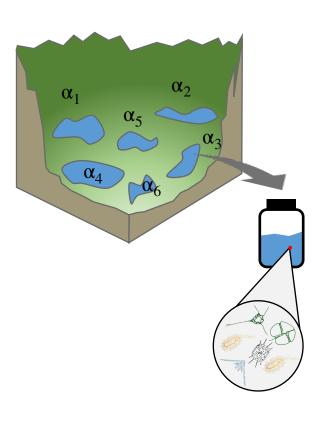


Rich, not even



Not rich, not even





Alpha diversity

There are 2 component of diversity: richness and evenness







Rich and even

Rich, not even

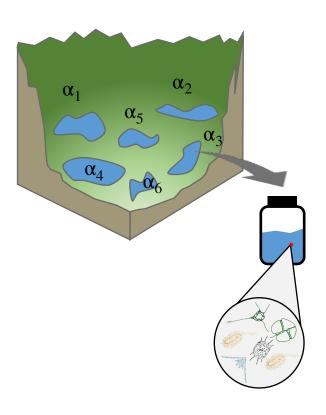
Not rich, not even

There are different index

	Richness	Evenness	R function*
Observed	X		specnumber (ASV_table)
Shannon	x	Х	diversity(ASV_table, « shannon »)
Simpson	Х	х	diversity(ASV_table, « simpson »)
Pielou		Х	shannon/log(specnumber(ASV_table))

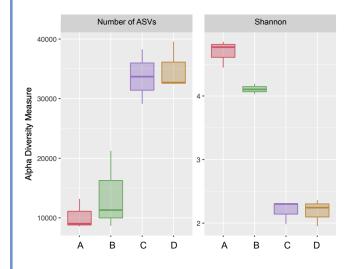
* Package vegan





Alpha diversity

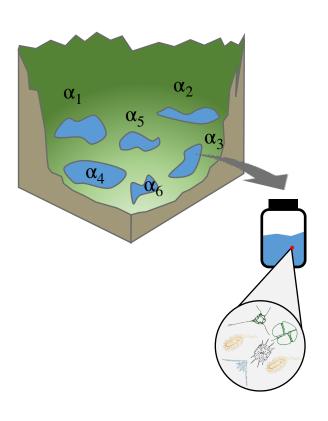
Exemple with bacterial communities composition of biofilm in seawater



Alpha-diversity measured based on richness only or with Shannon index gives opposite results...

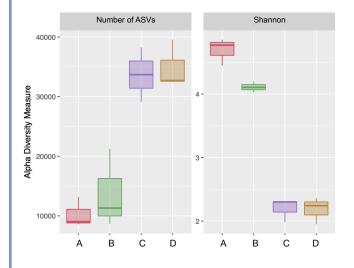
Trigodet et al., 2019





Alpha diversity

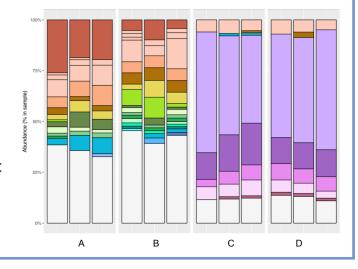
Exemple with bacterial communities composition of biofilm in seawater



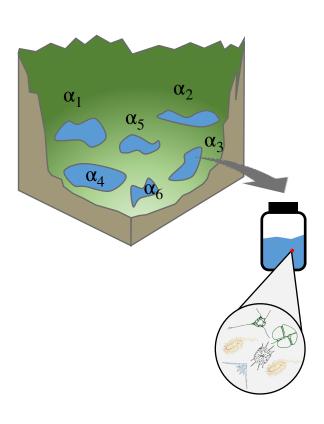
Alpha-diversity measured based on richness only or with Shannon index gives opposite results...

...This is because samples of condition A and B are even while samples of conditions C and D have highly dominant taxa (low evenness)

Trigodet et al., 2019







Alpha diversity

There are 2 component of diversity: richness and evenness







Rich and even

Rich, not even

Not rich, not even

Two components are essential in the calcul of alpha diversity indexes



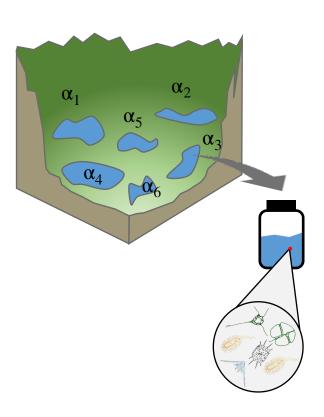
Number of ASVs

Abundance of ASVs











There are 2 component of diversity: richness and evenness







Rich and even

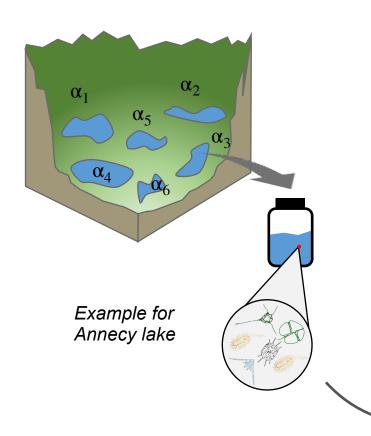
Rich, not even

Not rich, not even

Two components are essential in the calcul of alpha diversity indexes







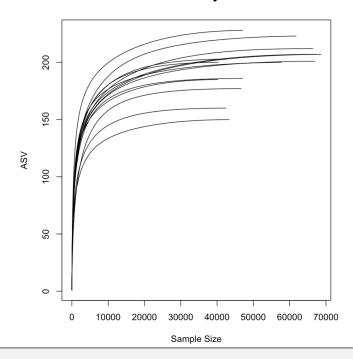
Alpha diversity

Problem to estimate **richness** with metabarcoding data

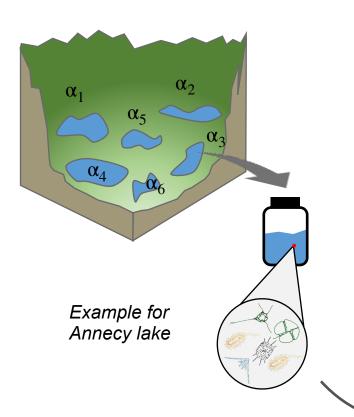
Different library size

Rarefaction curve:

Is the sequencing effort enough to recover phytoplankton diversity?







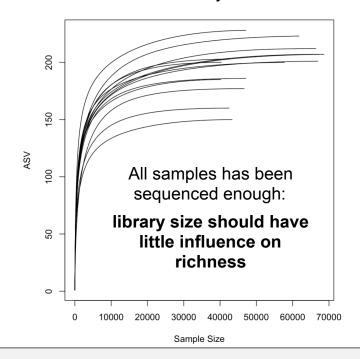
Alpha diversity

Problem to estimate **richness** with metabarcoding data

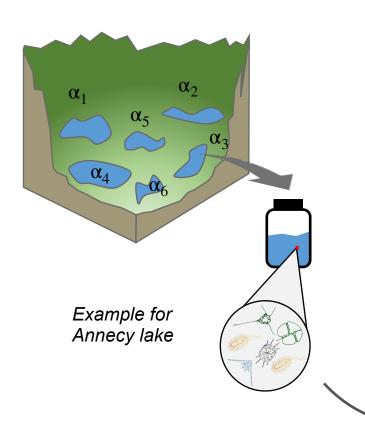
Different library size

Rarefaction curve:

Is the sequencing effort enough to recover phytoplankton diversity?







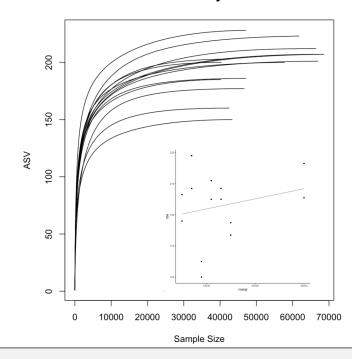
Alpha diversity

Problem to estimate **richness** with metabarcoding data

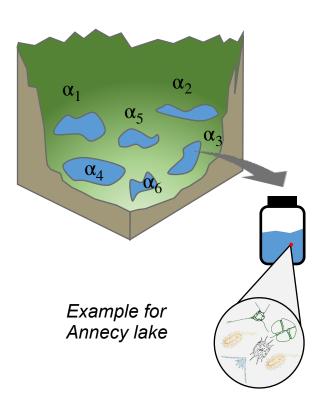
Different library size

Rarefaction curve:

Is the sequencing effort enough to recover phytoplankton diversity?







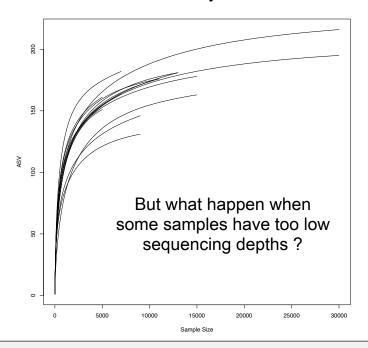
Alpha diversity

Problem to estimate **richness** with metabarcoding data

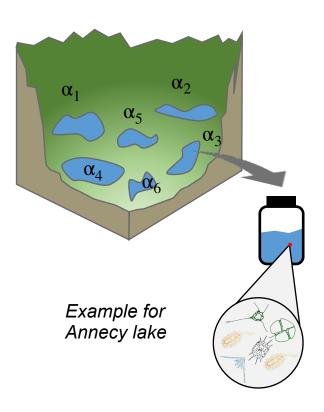
Different library size

Rarefaction curve:

Is the sequencing effort enough to recover phytoplankton diversity?







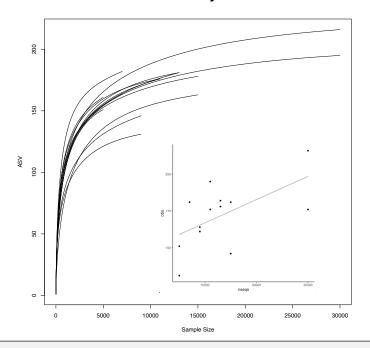
Alpha diversity

Problem to estimate **richness** with metabarcoding data

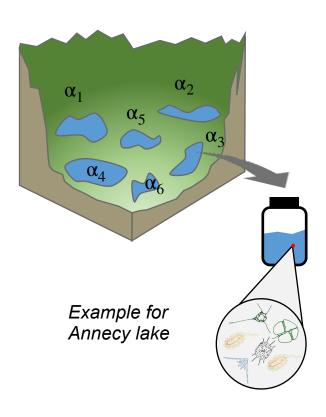
Different library size

Rarefaction curve:

Is the sequencing effort enough to recover phytoplankton diversity?



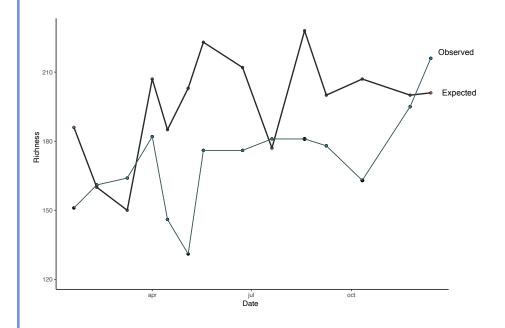




Alpha diversity

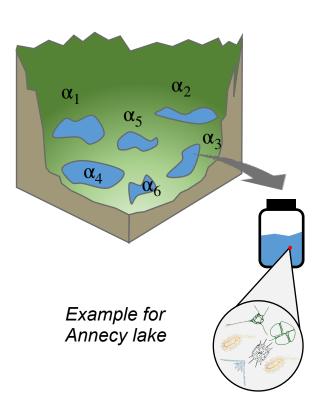
Problem to estimate <u>richness</u> with metabarcoding data

Different library size



Estimation of richness is incorrect

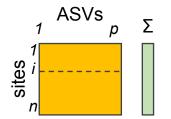


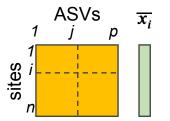


Alpha diversity

Problem to estimate **richness** with metabarcoding data

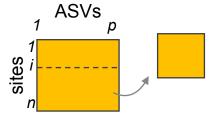
Different library size



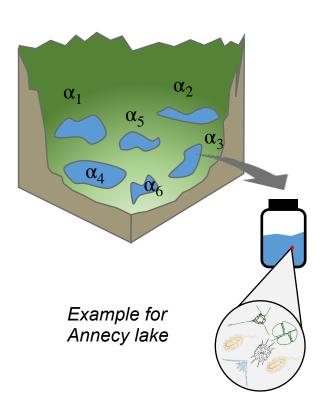


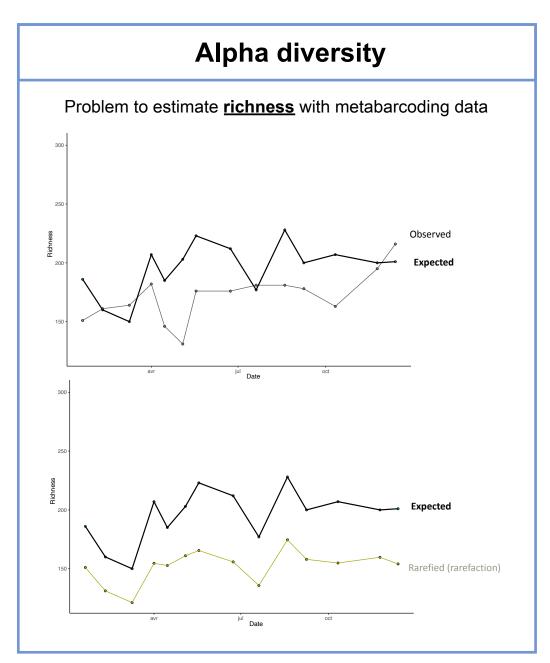
Most normalisation methods (TSS, CSS) won't change anything in the number of ASVs within a sample.

Rarefaction is often suggested to be a good way to prepare data for alpha-diversity analysis, particularly if you have high variation in library size (more than 10x)

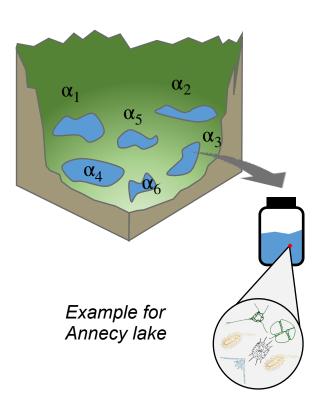












Alpha diversity

Problem to estimate richness with metabarcoding data

Different library size

Another possibility: estimating diversity

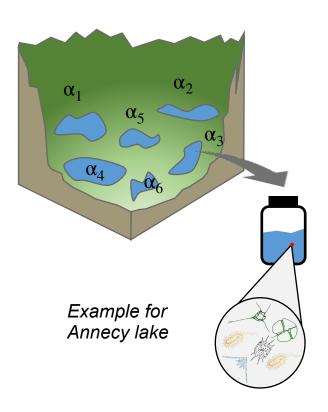
« I encourage ecologists to use estimates of diversity that account for non-observed species » Willis, 2019

A very famous richness estimator is Chao1 which is a nonparametric analysis that extrapolate the number of species present in a sample, based on the number of rare species.

(Chao, 2004)

Amy Willis also developed another index, parametric this time available in breakaway R package
(Willis, 2019)





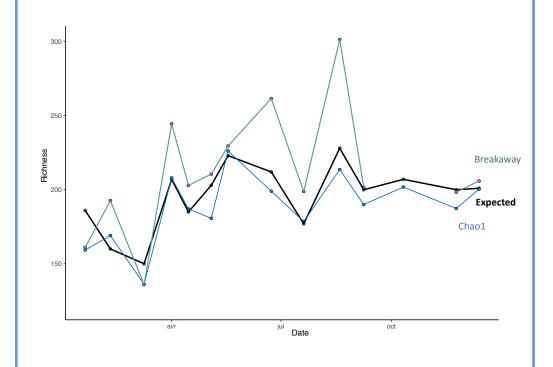
Alpha diversity

Problem to estimate <u>richness</u> with metabarcoding data

Different library size

Another possibility: estimating diversity

« I encourage ecologists to use estimates of diversity that account for non-observed species » Willis, 2019





Questions?