Experimental Set Up and Data Analysis Considerations for DNA- and RNA-SIP Experiments in the Omics Era

Roey Angel

Careful and thoughtful experimental design is crucial to the success of any SIP experiment. This chapter discusses the essential aspects of designing a SIP experiment, focusing primarily on DNA- and RNA-SIP. The design aspects discussed here begin with considerations for carrying out the incubation, such as, the effect of choosing different stable isotopes and target biomolecules, how enriched should a labelled substrate be, what concentration to use and how long the incubation should take. Then tips and pitfalls in the technical execution of SIP are listed, including how much nucleic acids should be loaded, how many fractions to collect and what centrifuge rotor to use. Lastly, a brief overview of the current methods for analysing SIP data is presented, focusing on high-throughput amplicon sequencing, together with a discussion on how the choice of analysis method might affect the experimental design.

**Running head:** Experimental set-up and data analysis

**Keywords:** DNA-SIP, RNA-SIP, amplicon sequencing, omics, network analysis

# Introduction

The success of any lab experiment hinges on a thoughtful design of the experimental system, careful execution of protocols and statistically-sound data analysis. While SIP protocols have matured and become standardised over the past 20 years since their introduction, what surrounds the gradient generation and fractionation, i.e., the experimental design and data analysis, have been somewhat neglected. Other chapters in this book provide detailed protocols on how to perform SIP in the lab and how to analyse the data using specific methods. This chapter, on the other hand, discusses general considerations in conceptualising a SIP experiment, designing the experimental set-up and choosing the right analysis method. The focus here is on DNA- and RNA-SIP experiments since these are the most flexible and most widely-used forms of SIP. **Table**??? summarises the main points to consider during each of the various steps in designing a SIP experiment.

# Choice of stable isotope

Every SIP experiment is based on incubating the sample in the presence of a heavy isotope labelled substrate. In theory, every element that is present in the target biomolecule – DNA, RNA,  phospholipid-derived fatty acids, or proteins – can be labelled and therefore be used in a SIP experiment. The only exception is, of course, phosphorus for which the common form – 31P – is the only stable isotope that exists. In practice, however, SIP experiments almost exclusively use 13C as the isotope of choice, with a tiny minority using 18O and 15N.  The choice of substrate and stable isotope as labelling compounds in a SIP experiment is of course directly related to the metabolic process or microbial guild of interest. Naturally, in SIP target microbes can only be isotopically labelled through assimilatory processes. This is somewhat unfortunate because many of the microbially-mediated biogeochemical processes of interest are energy-yielding dissimilatory processes, involving only electron transfer between two compounds and leave no trace in the biomass. In such cases, the microbial guild of interest can only be labelled indirectly through an assimilatory process that is powered by the dissimilatory process of interest (e.g., using 18O-H2O or 13C-CO2 as general substrates for all active organisms and for autotrophs, respectively).

Beyond the question of which biological process or microbial target group to study, the different stable isotopes used for SIP differ in their ability to label nucleic acids and therefore lead to buoyant density (BD) changes. **Table**??? lists and compares the number of additional neutrons gained per nucleotide in a DNA or RNA molecule by replacing all the atomic positions of a particular element with its heavier stable isotope. The table shows that theoretically the highest mass increase from labelling is achieved by using 18O, with added 12 or 14 neutrons on average for a hypothetical DNA or RNA molecule, respectively. This is, of course, thanks to the fact that labelling with 18O adds two neutrons per atom compared to only one for either 13C, 15N or D, therefore leading to higher overall mass increase despite the lower number of atoms in the molecule. In contrast, N is, unfortunately, the rarest in nucleic acids compared to C, O or H and labelling with 15N can lead to a maximum of 3.75 added neutrons per base, on average, or 2.5 times less in mass increase compared to labelling with 13C. This was confirmed experimentally already over 40 years ago when it was shown that fully 15N-labelled DNA in CsCl has a BD gain of ca$. $0.016 g ml−1 compared to a BD gain of ca$. $0.036 g ml−1 with 13C (Birnie and Rickwood 1978). Similarly, RNA fully labelled with 15N showed a BD gain of ∼0.015 g ml−1 (Angel et al. 2018) compared to 0.035 for 13C (Lueders, Manefield, and Friedrich 2004). The lower maximum mass addition to DNA and RNA through 15N-labelling means a smaller shift of labelled nucleic acids away from unlabelled nucleic acids in an isopycnic gradient compared to 13C-labelling. Still, this more modest shift in BD is nevertheless sufficient to detect labelling in DNA originating from a single organism, as was shown already in the classical work of Meselson and Stahl (Meselson and Stahl 1958). However, for DNA-based SIP this creates a major challenge since double-stranded DNA migrates in a BD gradient not only as a function of its mass but also as a function of its hydration state. The latter is ultimately determined by the G+C content of the DNA and causes an undesired migration of unlabelled high-GC DNA towards the denser regions of the gradient (Rolfe and Meselson 1959). Already in the first attempts to develop 15N-SIP, it was noticed that due to the relatively small migration of 15N-labelled DNA, unlabelled DNA with high-G+C content could overlap with even fully-labelled DNA of lower G+C content, and obscure the ability to differentiate labelled from unlabelled taxa (Cupples et al. 2007; Youngblut and Buckley 2014). This is further intensified by the fact that A-T base pairs contain only seven nitrogen atoms compared to eight in a G-C base-pair, resulting in a lower, albeit minor labelling of the A-T base pair (Cadisch et al. 2005).

Surprisingly, while 18O labelling should theoretically increase the mass of DNA by 23% and of RNA by 47% compared to labelling with 13C, in practice the observed shifts in BD in 18O-SIP gradients are not much different than in 13C-SIP gradients (0.04 g ml-1)(Aanderud and Lennon 2011; Angel and Conrad 2013), indicating that not all positions can be replaced with a heavy isotope.

Deuterium has been used in SIP experiments coupled with either Raman microspectroscopy (Berry et al. 2014) or metabolomics (Baran et al. 2017), but because of the toxicity of deuterated water (heavy water) at high concentrations, it is probably not suitable for DNA or RNA-SIP.

Considering these, it is easy to understand why carbon is the most widely used isotope in SIP. Carbon is abundant enough in biomolecules to allow for easy labelling. In many cases, carbon-based substrates are used for both assimilatory and dissimilatory processes in the cell, so biomass labelling is easily achieved using any of a selection of different substrates. In contrast,  many N-transforming processes are dissimilatory, while at the same time many N-assimilation processes are common between different functional groups of microorganisms and therefore provide relatively little differentiating power. Similarly, oxygen is also found abundantly in various terminal electron acceptors used for respiration, which are therefore unsuitable for SIP, or alternatively in water, which is assimilated into the biomass by all known organisms.

# Setting up an experiment

SIP experiments are usually relatively complex, laborious and time-consuming, and can, therefore, fail because of various reasons and at different stages. Thus, the experimental design of a SIP experiment should be carefully considered in advance and cover all aspects and phases, including preliminary knowledge of the environment and the targeted process, the nature and duration of the incubation, through possible pitfalls and down to the desired method of data analysis. Before deciding on a SIP experiment, it is important to gain some preliminary knowledge of the system in questionand the microbial guild to be targeted. For SIP to be successful, sufficient substrate needs to be processed and assimilated by the microbes during the incubation period. Therefore, one of the first and most important preliminary tests to perform is to measure the rate and dynamics of the process in question to estimate the length of the incubation period that is needed. Although the relationship between substrate consumption and level of labelling depends on the assimilation efficiency and the size of the active microbial guild and is therefore difficult to establish, some insights and ballpark estimates can nevertheless be made. Also, it is advisable to measure the enrichment level of the total DNA or RNA extracted from the sample to assess if detection of labelled microbes will be feasible (Angel et al. 2018; Manefield et al. 2002; Blazewicz and Schwartz 2011). Again, while it is impossible to draw a general direct relation between the level of enrichment of nucleic acids and the outcome of the SIP, because this will depend on whether or not the label is concentrated within a small group of highly labelled microbes or shared amongst many members, but a qualitative relationship can nevertheless easily be drawn for specific environments and microbial guilds.

## Which bio-molecule to target

SIP was first designed to identify labelled microbes through the incorporation of a stable isotope into their DNA (Radajewski et al. 2000). While this is still the most commonly used ‘flavour’ of SIP, other types of SIP quickly followed, since in essence nearly every stable bio-molecule in the cell can be used as a target for SIP. Targeting DNA is advantageous because DNA is the gold-standard for taxonomic classification of organisms and for hypothesising about potential functions. It is also popular because DNA amplification and sequencing technologies are affordable and wide spread in most molecular and microbiological labs. A protocol for targeting RNA instead of DNA in a SIP experiment (Manefield et al. 2002) then quickly followed. RNA-SIP offers the same taxonomic resolution power as DNA-SIP but because RNA synthesis is uncoupled to cell replication it offers higher sensitivity, though at the cost of a somewhat more laborious and sensitive lab work. A further advantage of RNA-SIP is that unlike DNA, RNA does not migrate based on its G+C content in a density gradient, so the potential for detecting false-positives is theoretically lower (see **Sections**???**,**???**and**??? and in **Chapter 9**of this book). Targeting PLFA (Boschker et al. 1998) is another popular way for running SIP that even predates the use of DNA-SIP for detecting active microbes in the environment.  Because of the use of an isotope-ratio mass spectrometer (IRMS), which is capable of a much finer mass separation compared to density gradient, PLFA-SIP offers significantly higher sensitivity over DNA or RNA SIP, which can be important when studying organisms with very low specific activity such as deep subsurface microorganisms (Pelz et al. 2001)  or bacteria that oxidise atmospheric methane (Knief, Lipski, and Dunfield 2003). However,  in addition to excluding the use of  15N-labelled substrates, PLFA inherently offers a much limited capacity for taxonomic affiliation of microbes compared to DNA or RNA and can only differentiate between groups at broad level (Evershed et al. 2006). Targeting proteins and metabolites is also an option (e.g. (Baran et al. 2017; Jehmlich et al. 2008)),  thus providing a direct and unquestionable proof of processing a labelled substrate. However these methods are very laborious, low throughput and require significant in-house experience in sample processing, and analysis of the output data. Lastly, identification of isotopically labelled microbes at the single-cell levels is also gaining interest lately using tools such as NanoSIMS (Li et al. 2008) and SIP-Raman (Wang et al. 2016) microspectroscopy, however their application is still limited because they are costly, low-throughput and relay on equipment that is found in only a handful of labs around the world.

## Duration of incubation

As mentioned, incubation length will depend on the one hand on the rate in which the process in question is proceeding and its specific assimilation efficiency. Incubation in the presence of the labelled substrate should allow enough time for the nucleic acids to become sufficiently labelled to be detected above the background. For very fast processes such as water uptake, incubation time can be as short as a few hours (Blazewicz, Schwartz, and Firestone 2014; Angel and Conrad 2013), while for very slow processes, such as nitrogen fixation, incubation can be as long as several days to weeks (Angel et al. 2018; Buckley et al. 2007; Pepe-Ranney et al. 2015)*.*Incubation time should also vary if targeting DNA or RNA. Labelling of RNA can be detected earlier because it does not require cell replication and because its synthesis is not semi-conservative as DNA replication (although this does not preclude a significant dilution of newly synthesised RNA with light isotope as a result of recycling of building blocks within the cell). In general, it is assumed that DNA or RNA molecules should be labelled to at least 30 atomic % to differentiate them from unlabelled molecules in a BD gradient (Buckley et al. 2007; Cadisch et al. 2005). On the other hand, long incubation times bear the risk of labelling community members that do not perform the metabolic activity in question but were labelled through cross-feeding. Because microbes are interlinked through a network of trophic interactions, any labelled element will eventually be spread amongst many members of the community, regardless of how specific the process in question is. Cross-feeding in isotope-labelling experiments has been acknowledged from the start and has been shown for nitrogen as well as carbon  (e.g., (McDonald, Radajewski, and Murrell 2005; Adam et al. 2015)). Although typically considered to be an unwanted side effect in SIP experiments, cross-feeding has also been taken advantage of many times to study substrate flow patterns microbial interactions on a temporal scale (DeRito, Pumphrey, and Madsen 2005; Pepe-Ranney et al. 2016). Since cross-feeding in a microbial community cannot simply be put to a halt, the typical way of dealing with this issue is to sample at several time points, limit the incubation time to the minimum necessary for labelling and combine complementary lines of evidence when concluding that a specific taxon indeed performs the metabolism in question.

## Substrate enrichment level and concentration

Substrates used in SIP experiments are in almost all cases “fully” labelled, i.e., all positions are enriched with the labelled isotope to the highest level possible (>97 atomic %). This, of course, stems from the need to achieve high levels of labelling in nucleic acids to detect labelled microbes. However, labelling of carbon only at specific positions could also be employed, for example, to study microbial guilds that would attack the substrate at a specific position of interest, while excluding others. The substrate concentration can also affect the rate and strength of labelling, however, presenting a sample with unrealistically high-concentrations can lead to undesired consequences such as drastic community changes or a rapid enrichment of a fast-growing sub-population with low substrate affinity. Therefore it is best to remain within the range (typically on the higher end) of substrate concentrations that are expected to be found in the environment.

## Amount of nucleic acids to load

Typical DNA-SIP gradients are prepared with 0.5**–**5 µg  of DNA, but there does not seem to be a hard limit for the amount of DNA that can be loaded on a gradient. For PCR purposes this amount should be more than enough to target the rRNA or any other functional gene. For metagenomic or metatranscriptomic sequencing of the fractions larger amounts of the template will be needed. This can be achieved either by pooling together several fractions from several different gradients or by multiple displacement amplification (e.g., (Chen et al. 2008)). In RNA-SIP gradients, overloading with RNA will cause aggregation that will prevent efficient separation. The typical recommended amount is around 500 ng for a 5.5 ml gradient (Lueders, Manefield, and Friedrich 2003). However, this issue was never been studied systematically.

## Number of fractions to collect, and sequencing depth

Regardless of which method is used for analysing the data, success in a SIP experiment is determined by the ability to detect microbial phylotypes that are present in the denser fractions of a labelled gradient and are either absent or have lower abundance in the lighter fractions of the same gradient, or in the denser fraction of a control gradient. The detection limit in SIP experiments is itself not a fixed value but will depend on the sequencing depth, the number of fractions being collected from each gradient, and on which method is being used to analyse the data (see **Section**???). Using state of the art sequencing technologies it is now easy to obtain thousands of sequences per fraction. However, this, of course, comes at a cost, which might not be necessary. It is therefore advisable, if possible, to first obtain an estimate of the size of the microbial guild in question in relation to the total microbial population, using for example qPCR with primers targeting a functional gene or fluorescent microscopy. The smaller the size of the target community, the harder it will be to detect its labelling above the detection limit. Naturally, this will almost inevitably be an overestimation since only a part of the population will be active during the experiment and will eventually incorporate the substrate, but this will at least give a minimum threshold for the sequencing depth needed. The number of fractions collected can also affect the detection limit. While a higher number of fractions will most likely increase the sensitivity, it also entails higher sample processing efforts and costs. In addition, more fractions also mean less template per fraction and thus also an increased difficulty to amplify the target and a higher chance of contamination with foreign nucleic acids from the environment. Typically 12–20 fractions are collected, of which about 10–16 end up being analysed because the lightest and heaviest fractions contain little to no nucleic acids.

## Unlabelled controls

As in any lab experiment, appropriate label controls should be set up in parallel to minimise the detection of false-positives. Many of the older published works included only one or two controls, usually at the last time point or at the highest amendment level.  Recently, however, particularly with the growing use of high-throughput sequencing and statistical models to detect labelled OTUs the need to include more no-label controls in the experiment to correctly detect labelled phylotypes has been growing, but on the other hand also became easier to achieve. The exact number and type of no-label controls will depend on the exact statistical method used to analyse the data, but also on the type of SIP being performed since DNA-SIP is more prone to detecting false positives than RNA-SIP because of the effect of the G+C-content on DNA BD (see **Section**???). Ideally, every labelled sample will have its parallel no-label control. However, this is very laborious and costly, and might not be needed. Since RNA-SIP does not suffer from the bias caused by G+C-based migration as in DNA-SIP, it is possible to compare fractions within a gradient, rather than between gradients, and thus reduce the number of controls (see **Section**???). Similarly, methods that are only interested in identifying labelling of a phylotype (e.g., differential abundance) but not necessarily quantifying it (e.g., qSIP) remain robust even when some controls are omitted (see **Section**??? and **Chapter 11**).

## Type of rotor

Traditionally a vertical rotor was preferred over a fixed-angle one for SIP experiments because it provides a shallower gradient and therefore a higher degree of separation between densities. Recent modelling work suggests, however, that this comes at the cost of a higher diffusion of nucleic acids throughout the gradient (and thus leading to a higher background) (Youngblut, Barnett, and Buckley 2018). Both rotor types were successfully used for 15N-SIP, but to date, no experimental comparison was published.

# Data analysis

## Analysis of barcoded amplicon data for SIP

Arguably, the most significant advancement in the field of DNA- and RNA-SIP  in recent years came from the introduction of high-throughput sequencing techniques and their adoption to the study of microbial communities using barcoded amplicon sequencing (Xia et al. 2011; Lee et al. 2011; Pilloni et al. 2011).  The ability to sequence dozens of samples simultaneously to a very high depth meant that it was now possible to identify rare taxa that were labelled but also taxa that are only partially labelled. Before the adoption of high-throughput sequencing (HT-sequencing), successful labelling of DNA or RNA was done visually, either by detecting a second band of nucleic acids under UV light following ethidium bromide staining or fractionating the gradient into multiple fractions, amplifying the nucleic acids using PCR or qPCR and evaluating the intensity of the bands or copy numbers. The use of fingerprinting techniques such as DGGE and TRFLP enabled not only a more sensitive comparison between fractions but also a direct, albeit qualitative, insight into how many phylotypes were labelled. However, it still suffered from low resolution and a high degree of noise that are inherent to these methods. Moreover, the unequivocal identification of the labelled microbes was still low-throughput, laborious and costly since it required the construction of clone libraries followed by Sanger sequencing. Barcoded amplicon sequencing allows for robust, semi quantitative comparison of different fractions along a density gradient, as well as an identification of the identity of which microbes became labelled and which did not. Moreover, the ability to obtain thousands of sequences per sample meant that even labelling of minor members of the community could be detected — something that could not be achieved with standard molecular fingerprinting techniques or Sanger sequencing. The adoption of HT-sequencing technologies also called for new analytical methods that could take advantage of this increase in sensitivity through statistical modelling and enable robust detection of either minor or partially labelled members of the active guild (Zemb et al. 2012; Zumsteg, Schmutz, and Frey 2013). However, alongside with added sensitivity barcoded amplicon sequencing also presents some challenges for comparing samples because it is difficult to control the number of sequences per sample, also known as the library depth. The problem is not unique to analysing SIP experiments and poses a major analytical challenge in the field of microbiome studies and comparative transcriptomics (RNA-Seq). In essence, most statistical methods used for comparison assume that across different samples, templates with identical relative abundance should have equal chances of being sequenced and thus any observed differences are an indication that the true abundance of the given sequence differs between the samples. In ecology, the issue is known as “sampling effort”. Traditionally, the most common way to alleviate the problem of unequal sequencing depths was to randomly sub-sample sequences from each sample down to the smallest sample size so that all samples become equal (a process sometimes called “rarefaction”). This practice, however, came under scrutiny in recent years and sparked some heated polemic papers on how to best handle microbiome data (McMurdie and Holmes 2014). While the severity of the bias caused by random sub-sampling is debated, it is generally accepted that this is a sub-optimal way to deal with the problem. Another common approach is to convert all abundances to relative abundances and compare the different sequences on a fraction (or percentage) basis. This, however, leads to other problems since it maintains the correlation between sequencing depth and the number of unique sequences (or OTUs) while at the same time drastically reducing the number of degrees of freedom by coercing the sum of abundance in each sample to 100% (Faust and Raes 2012). More recent methods try to “eat the cake and leave it whole” by attempting to equalise the variance between samples through a scaling factor while not discarding any data (covered in (Weiss et al. 2017)). Whichever method is chosen, it is important to remember that no statistical trick can solve the inherent problems that stem from large differences in library sizes and these should be handled at the level of sample preparation or sequencing and not data analysis.

## Differential abundance analysis and quantitative analysis

The most common methods for comparing fractions in SIP experiments were developed for analysing RNA-Seq datasets. The parallels are apparent; typical RNA-Seq experiments are designed as a case-control study and the analytical challenge is to identify which sequences are differentially expressed (either up-regulated or down-regulated) compared to the control, while overcoming the natural variance and differences in library sizes. Similarly, in SIP experiments one would like to identify which sequences are “differentially abundant” in the fractions where labelled nucleic acids are expected to be present compared to those where unlabelled nucleic acids are present. An important difference to RNA-Seq experiments is, however, that only enriched sequences in the ‘heavy’ fractions are of interest, while depleted sequences should only occur when labelling is strong enough to displace unlabelled sequences from the ‘light’ fractions to a noticeable degree. Nearly all existing data analysis methods should apply to both DNA- and RNA-SIP, albeit with some differences. This book offers two recent and very robust ways to analyse SIP datasets: quantitative SIP (qSIP; **Chapter 11**) and High-Resolution SIP (HR-SIP; **Chapter 9**). Both yield similar results, but they nevertheless differ in some details (discussed in (Youngblut, Barnett, and Buckley 2018)). While High-Resolution SIP, like all other differential abundance methods, aims only at detecting labelled phylotypes, qSIP also attempts to quantify the level of enrichment per phylotype, but requires additional quantitative data from qPCR and also a matching unlabelled control sample for every labelled sample, to reliably detect growth.

## Data analysis for RNA-SIP experiments

Since both HR-SIP and qSIP are carefully detailed in this book, repeating the steps here would be redundant. However, because the methods were published for DNA-SIP, some differences to RNA-SIP should be noted. In principle, both methods rely on a comparison of the gradient fractions from labelled samples to those from unlabelled control samples (between-gradient comparison). Moreover, both assume and make use of the fact that while DNA and RNA will concentrate around their theoretical BD, they diffuse throughout the gradient in a Gaussian shape so that amplifiable amounts of nucleic acids are present in every fraction in the gradient (Angel et al. 2018; Youngblut, Barnett, and Buckley 2018). However, because the course of development of a microbial community is controlled by stochastic processes in addition to deterministic ones, parallel incubations from the same parent community often lead to different communities after a while, even if conditions are kept as similar as possible. Consequently, it was demonstrated that these stochastic variations reduce the detection accuracy and it was recommended that the Bray-Curtis dissimilarity between communities of labelled and unlabelled samples that are being compared should ideally be >0.2 (Youngblut, Barnett, and Buckley 2018). Between-gradient comparisons are crucial for DNA-SIP because as mentioned above, the DNA of different taxa will migrate in the gradient also based on their G+C content. Moreover, the migration based on G+C content is not constant per phylotype. Instead, it will vary based on the size of the DNA fragment surrounding the gene of target, which varies stochastically in most DNA extraction methods (Youngblut and Buckley 2014). In RNA-SIP however, the buoyant density of RNA is less affected by G+C content, and one can assume that in a gradient from an unlabelled sample the relative abundance of each taxon should remain relatively constant throughout the different fractions. In contrast, in a gradient from a labelled sample, some taxa will be more abundant in the heavy fractions compared to the lighter ones, while the relative abundance of unlabelled taxa will remain constant throughout the gradient or decline in the heavy fractions if the labelled taxa make up a significant proportion of the entire community. In any case, since in RNA-SIP differential migration of taxa is only expected as a response of labelling, detection of labelled taxa can also be done in a within-gradient fashion by comparing the relative abundances of taxa in the heavy fractions (i.e., ca$. $1.72–1.76 g ml-1 for DNA-SIP or 1.80–1.84 g ml-1 for RNA-SIP) with those in the light fractions (i.e., ca$. $1.68–1.72 g ml-1 for DNA-SIP or 1.77–1.80 g ml-1 for RNA-SIP). However, some label-free controls should nevertheless be set up (e.g., paralleling the beginning and end time points or the highest and lowest treatment extremes) and analysed because they can help to fine-tune the statistical cutoff parameters so that false positives can be avoided (Angel et al. 2018).

## Network analysis using SIP data

Network analysis – the prediction of microbial associations from presence-absence or abundance data is gaining popularity in ecological studies in general and microbiome studies in particular (Faust and Raes 2012). This type of analysis has also been used in concert with SIP to detect, for example, positive and negative correlation between phylotypes of ammonia-oxidising archaea, nitrite oxidising bacteria and methanotrophs (Daebeler et al. 2014), clusters of anaerobic and aerobic bacteria in rewetted biological soil crusts (Angel and Conrad 2013), or to identify community members that interact with methane-oxidizing bacteria (Ho et al. 2016). However, in contrast to a standard network analysis on microbiome data, the interpretation of the results from a SIP experiment might not be so straightforward. First, most probably only the “heavy”  fractions from the labelled gradients should be analysed because changes in the “light” fractions are either already reflected in the “heavy” fractions (i.e., phylotypes becoming labelled and hence depleted in the “light” fractions), or not directly related to substrate incorporation (e.g., growth and death of phylotypes in the general community). Secondly, while the interpretation of positive correlations in the heavy fractions are relatively easy to interpret (i.e., two phylotypes acquire label under similar conditions), it is not entirely clear what negative interactions mean if anything at all. Thirdly, it is important to bear in mind that network analysis does not reveal the mode of the interaction between two interacting phylotypes and a positive correlating could mean that both use the same substrate, that there is cross feeding occurring (and thus the interaction is positive-positive or at least positive-neutral), or that one phylotype is praying on another (positive-negative interaction). Lastly, it should be noted that many replicates are required for a network to be stable (at least 25) and that communities should be reasonably similar in all samples (Berry and Widder 2014). For SIP studies this probably translates into an analysis of at least 25 “heavy” gradient fractions, coming from both labelled and no-label control incubations. However, when analysing data from DNA-SIP experiments care should be taken when analysing multiple fractions from the same gradient since this could simply be a result of similar G+C contents.

**Acknowledgements**

The manuscript for this chapter was written online using [authorea](https://www.authorea.com/). RA was supported by BC CAS, ISB & SoWa RI (MEYS; projects LM2015075, EF16\_013/0001782 – SoWa Ecosystems Research).

**Tables**

 What should be considered during each of the various steps in the design of a SIP experiment.

|  |  |
| --- | --- |
| **Experimental design step** | **What to consider** |
| Which stable isotope to use? | Choice of stable isotope primarily depends on the substrate being used, but different stable isotopes differ in their ability to label nucleic acids and lipids |
| Prior to incubation | Measure or estimate the turnover rate of the substrate that will be used for labelling |
| Target molecule | Will dramatically affect what type of data will be produced and what can be learned from it |
| Incubation duration | Short incubation times might lead to insufficient labelling of the target molecule but long incubation times increase the risk of cross-feeding |
| Substrate enrichment level and concentration | Substrate should almost always be fully labelled, concentration should be within a realistic range for the sample |
| Amount of nucleic acids to load | Varies for DNA- and RNA-SIP. Will also depend on the downstream application |
| Number of fractions to collect and sequencing depth | More fractions means higher sensitivity but also higher contamination potential and sequencing costs |
| Unlabelled controls | Should always be included but the exact number will depend on the requirements of the data analysis method |
| Type of rotor | Traditionally vertical but fixed angle has been recently suggested to be advantageous |
| Data analysis | Consider how many gradients, fractions and types of samples (e.g. controls, time series, various concentration levels etc.) will be needed for the chosen data analysis pipeline |

 Number of additional neutrons per nucleotide in a DNA or RNA molecule given full labelling (all respective atoms are replaced by a heavier stable isotope).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Carbon-13** | **Oxygen-18** | **Nitrogen-15** | **Deuterium** |
| Adenine | 10 | 10/12 | 5 | 9 |
| Guanine | 10 | 12/14 | 5 | 10 |
| Cytosine | 9 | 12/14 | 3 | 9 |
| Thymine/Uracil | 10/9 | 14/16 | 2 | 8 |
|  Mean | 9.75/9.5 | 12/14 | 3.75 | 9 |

# References

Birnie, G. D., and D. Rickwood. 1978. “Isopycnic Centrifugation in Ionic Media”. In *Centrifugal Separations: Molecular and Cell Biology*, edited by G. D. Birnie and D. Rickwood, 169–217. Butterworth & Co Publishers Ltd.

Angel, Roey, Christopher Panhölzl, Raphael Gabriel, Craig Herbold, Wolfgang Wanek, Andreas Richter, Stephanie A. Eichorst, and Dagmar Woebken. 2018. “Application of Stable-Isotope Labelling Techniques for the Detection of Active Diazotrophs”. *Environmental Microbiology* 20 (1): 44–61. <https://doi.org/10.1111/1462-2920.13954.>

Lueders, Tillmann, Mike Manefield, and Michael W. Friedrich. 2004. “Enhanced Sensitivity of DNA- and RRNA-Based Stable Isotope Probing by Fractionation and Quantitative Analysis of Isopycnic Centrifugation Gradients”. *Environmental Microbiology* 6 (1): 73–78. <https://doi.org/10.1046/j.1462-2920.2003.00536.x.>

Meselson, M., and F. W. Stahl. 1958. “The Replication of DNA in ”. *Proceedings of the National Academy of Sciences* 44 (7): 671–82. <https://doi.org/10.1073/pnas.44.7.671.>

Rolfe, R., and M. Meselson. 1959. “The Relative Homogeneity of Microbial DNA”. *Proceedings of the National Academy of Sciences* 45 (7): 1039–43. <https://doi.org/10.1073/pnas.45.7.1039.>

Cupples, Alison M., Elizabeth A. Shaffer, Joanne C. Chee-Sanford, and Gerald K. Sims. 2007. “DNA Buoyant Density Shifts during 15N-DNA Stable Isotope Probing”. *Microbiological Research* 162 (4): 328–34. <https://doi.org/10.1016/j.micres.2006.01.016.>

Youngblut, Nicholas D., and Daniel H. Buckley. 2014. “Intra-Genomic Variation in G+C Content and Its Implications for DNA Stable Isotope Probing”. *Environmental Microbiology Reports* 6 (6): 767–75. <https://doi.org/10.1111/1758-2229.12201.>

Cadisch, Georg, Mingrelia Espana, Rachel Causey, Michael Richter, Eve Shaw, J. Alun W. Morgan, Clive Rahn, and Gary D. Bending. 2005. “Technical Considerations for the Use of15N-DNA Stable-Isotope Probing for Functional Microbial Activity in Soils”. *Rapid Communications in Mass Spectrometry* 19 (11): 1424–28. <https://doi.org/10.1002/rcm.1908.>

Aanderud, Zachary T., and Jay T. Lennon. 2011. “Validation of Heavy-Water Stable Isotope Probing for the Characterization of Rapidly Responding Soil Bacteria”. *Applied and Environmental Microbiology* 77 (13): 4589–96. <https://doi.org/10.1128/aem.02735-10.>

Angel, Roey, and Ralf Conrad. 2013. “Elucidating the Microbial Resuscitation Cascade in Biological Soil Crusts Following a Simulated Rain Event”. *Environmental Microbiology* 15 (May): 2799–2815. <https://doi.org/10.1111/1462-2920.12140.>

Berry, David, Esther Mader, Tae Kwon Lee, Dagmar Woebken, Yun Wang, Di Zhu, Marton Palatinszky, et al. 2014. “Tracking Heavy Water (DO) Incorporation for Identifying and Sorting Active Microbial Cells”. *Proceedings of the National Academy of Sciences* 112 (2): E194–E203. <https://doi.org/10.1073/pnas.1420406112.>

Baran, Richard, Rebecca Lau, Benjamin P. Bowen, Spencer Diamond, Nick Jose, Ferran Garcia-Pichel, and Trent R. Northen. 2017. “Extensive Turnover of Compatible Solutes in Cyanobacteria Revealed by Deuterium Oxide (D2O) Stable Isotope Probing”. *ACS Chemical Biology* 12 (3): 674–81. <https://doi.org/10.1021/acschembio.6b00890.>

Manefield, Mike, Andrew S. Whiteley, Nick Ostle, Philip Ineson, and Mark J. Bailey. 2002. “Technical Considerations for RNA-Based Stable Isotope Probing: an Approach to Associating Microbial Diversity with Microbial Community Function”. *Rapid Communications in Mass Spectrometry* 16 (23): 2179–83. <https://doi.org/10.1002/rcm.782.>

Blazewicz, Steven J., and Egbert Schwartz. 2011. “Dynamics of 18O Incorporation from H 2 18O into Soil Microbial DNA”. *Microbial Ecology* 61 (4): 911–16. <https://doi.org/10.1007/s00248-011-9826-7.>

Radajewski, Stefan, Philip Ineson, Nisha R. Parekh, and J. Colin Murrell. 2000. “Stable-Isotope Probing as a Tool in Microbial Ecology”. *Nature* 403 (6770): 646–49. <https://doi.org/10.1038/35001054.>

Boschker, H. T. S., S. C. Nold, P. Wellsbury, D. Bos, W. de Graaf, R. Pel, R. J. Parkes, and T. E. Cappenberg. 1998. “Direct Linking of Microbial Populations to Specific Biogeochemical Processes by 13C-Labelling of Biomarkers”. *Nature* 392 (6678): 801–5. <https://doi.org/10.1038/33900.>

Pelz, Oliver, Antonis Chatzinotas, Annatina Zarda-Hess, Wolf-Rainer Abraham, and Josef Zeyer. 2001. “Tracing Toluene-Assimilating Sulfate-Reducing Bacteria Using 13C-Incorporation in Fatty Acids and Whole-Cell Hybridization”. *FEMS Microbiology Ecology* 38 (2-3): 123–31. <https://doi.org/10.1111/j.1574-6941.2001.tb00890.x.>

Knief, C., A. Lipski, and P. F. Dunfield. 2003. “Diversity and Activity of Methanotrophic Bacteria in Different Upland Soils”. *Applied and Environmental Microbiology* 69 (11): 6703–14. <https://doi.org/10.1128/aem.69.11.6703-6714.2003.>

Evershed, Richard P, Zoe M Crossman, Ian D Bull, Hazel Mottram, Jennifer AJ Dungait, Peter J Maxfield, and Emma L Brennand. 2006. “13C-Labelling of Lipids to Investigate Microbial Communities in the Environment”. *Current Opinion in Biotechnology* 17 (1): 72–82. <https://doi.org/10.1016/j.copbio.2006.01.003.>

Jehmlich, Nico, Frank Schmidt, Mathias Hartwich, Martin von Bergen, Hans-Hermann Richnow, and Carsten Vogt. 2008. “Incorporation of Carbon and Nitrogen Atoms into Proteins Measured by Protein-Based Stable Isotope Probing (Protein-SIP)”. *Rapid Communications in Mass Spectrometry* 22 (18): 2889–97. <https://doi.org/10.1002/rcm.3684.>

Li, Tianlun, Ting-Di Wu, Laurent Mazéas, Laurent Toffin, Jean-Luc Guerquin-Kern, Gérard Leblon, and Théodore Bouchez. 2008. “Simultaneous Analysis of Microbial Identity and Function Using NanoSIMS”. *Environmental Microbiology* 10 (3): 580–88. <https://doi.org/10.1111/j.1462-2920.2007.01478.x.>

Wang, Yun, Wei E Huang, Li Cui, and Michael Wagner. 2016. “Single Cell Stable Isotope Probing in Microbiology Using Raman Microspectroscopy”. *Current Opinion in Biotechnology* 41 (October): 34–42. <https://doi.org/10.1016/j.copbio.2016.04.018.>

Blazewicz, Steven J., Egbert Schwartz, and Mary K. Firestone. 2014. “Growth and Death of Bacteria and Fungi Underlie Rainfall-Induced Carbon Dioxide Pulses from Seasonally Dried Soil”. *Ecology* 95 (5): 1162–72. <https://doi.org/10.1890/13-1031.1.>

Buckley, D. H., V. Huangyutitham, S.-F. Hsu, and T. A. Nelson. 2007. “Stable Isotope Probing with N Reveals Novel Noncultivated Diazotrophs in Soil”. *Applied and Environmental Microbiology* 73 (10): 3196–3204. <https://doi.org/10.1128/aem.02610-06.>

Pepe-Ranney, Charles, Chantal Koechli, Ruth Potrafka, Cheryl Andam, Erin Eggleston, Ferran Garcia-Pichel, and Daniel H Buckley. 2015. “Non-Cyanobacterial Diazotrophs Mediate Dinitrogen Fixation in Biological Soil Crusts during Early Crust Formation”. *The ISME Journal* 10 (2): 287–98. <https://doi.org/10.1038/ismej.2015.106.>

Buckley, D. H., V. Huangyutitham, S.-F. Hsu, and T. A. Nelson. 2007. “Stable Isotope Probing with N Achieved by Disentangling the Effects of Genome G+C Content and Isotope Enrichment on DNA Density”. *Applied and Environmental Microbiology* 73 (10): 3189–95. <https://doi.org/10.1128/aem.02609-06.>

Cadisch, Georg, Mingrelia Espana, Rachel Causey, Michael Richter, Eve Shaw, J. Alun W. Morgan, Clive Rahn, and Gary D. Bending. 2005. “Technical Considerations for the Use of N-DNA Stable-Isotope Probing for Functional Microbial Activity in Soils”. *Rapid Communications in Mass Spectrometry* 19 (11): 1424–28. <https://doi.org/10.1002/rcm.1908.>

McDonald, Ian R., Stefan Radajewski, and J. Colin Murrell. 2005. “Stable Isotope Probing of Nucleic Acids in Methanotrophs and Methylotrophs: A Review”. *Organic Geochemistry* 36 (5): 779–87. <https://doi.org/10.1016/j.orggeochem.2005.01.005.>

Adam, Birgit, Isabell Klawonn, Jennie B Svedén, Johanna Bergkvist, Nurun Nahar, Jakob Walve, Sten Littmann, et al. 2015. “N-Fixation Ammonium Release and N-Transfer to the Microbial and Classical Food Web within a Plankton Community”. *The ISME Journal* 10 (2): 450–59. <https://doi.org/10.1038/ismej.2015.126.>

DeRito, C. M., G. M. Pumphrey, and E. L. Madsen. 2005. “Use of Field-Based Stable Isotope Probing To Identify Adapted Populations and Track Carbon Flow through a Phenol-Degrading Soil Microbial Community”. *Applied and Environmental Microbiology* 71 (12): 7858–65. <https://doi.org/10.1128/aem.71.12.7858-7865.2005.>

Pepe-Ranney, Charles, Ashley N. Campbell, Chantal N. Koechli, Sean Berthrong, and Daniel H. Buckley. 2016. “Unearthing the Ecology of Soil Microorganisms Using a High Resolution DNA-SIP Approach to Explore Cellulose and Xylose Metabolism in Soil”. *Frontiers in Microbiology* 7 (May). <https://doi.org/10.3389/fmicb.2016.00703.>

Chen, Yin, Marc G. Dumont, Josh D. Neufeld, Levente Bodrossy, Nancy Stralis-Pavese, Niall P. McNamara, Nick Ostle, Maria J. I. Briones, and J. Colin Murrell. 2008. “Revealing the Uncultivated Majority: Combining DNA Stable-Isotope Probing Multiple Displacement Amplification and Metagenomic Analyses of Uncultivated Methylocystis in Acidic Peatlands”. *Environmental Microbiology* 10 (10): 2609–22. <https://doi.org/10.1111/j.1462-2920.2008.01683.x.>

Lueders, Tillmann, Mike Manefield, and Michael W. Friedrich. 2003. “Enhanced Sensitivity of DNA- and RRNA-Based Stable Isotope Probing by Fractionation and Quantitative Analysis of Isopycnic Centrifugation Gradients”. *Environmental Microbiology* 6 (1): 73–78. <https://doi.org/10.1046/j.1462-2920.2003.00536.x.>

Youngblut, Nicholas D., Samuel E. Barnett, and Daniel H. Buckley. 2018. “SIPSim: A Modeling Toolkit to Predict Accuracy and Aid Design of DNA-SIP Experiments”. *Frontiers in Microbiology* 9 (March). <https://doi.org/10.3389/fmicb.2018.00570.>

Xia, Weiwei, Caixia Zhang, Xiaowei Zeng, Youzhi Feng, Jiahua Weng, Xiangui Lin, Jianguo Zhu, et al. 2011. “Autotrophic Growth of Nitrifying Community in an Agricultural Soil”. *The ISME Journal* 5 (7): 1226–36. <https://doi.org/10.1038/ismej.2011.5.>

Lee, Tae Kwon, Jaejin Lee, Woo Jun Sul, Shoko Iwai, Benli Chai, James M. Tiedje, and Joonhong Park. 2011. “Novel Biphenyl-Oxidizing Bacteria and Dioxygenase Genes from a Korean Tidal Mudflat”. *Applied and Environmental Microbiology* 77 (11): 3888–91. <https://doi.org/10.1128/aem.00023-11.>

Pilloni, Giovanni, Frederick von Netzer, Marion Engel, and Tillmann Lueders. 2011. “Electron Acceptor-Dependent Identification of Key Anaerobic Toluene Degraders at a Tar-Oil-Contaminated Aquifer by Pyro-SIP”. *FEMS Microbiology Ecology* 78 (1): 165–75. <https://doi.org/10.1111/j.1574-6941.2011.01083.x.>

Zemb, O., M. Lee, M.L. Gutierrez-Zamora, J. Hamelin, K. Coupland, N.H. Hazrin-Chong, I. Taleb, and M. Manefield. 2012. “Improvement of RNA-SIP by Pyrosequencing to Identify Putative 4-n-Nonylphenol Degraders in Activated Sludge”. *Water Research* 46 (3): 601–10. <https://doi.org/10.1016/j.watres.2011.10.047.>

Zumsteg, Anita, Stefan Schmutz, and Beat Frey. 2013. “Identification of Biomass Utilizing Bacteria in a Carbon-Depleted Glacier Forefield Soil by the Use of13C DNA Stable Isotope Probing”. *Environmental Microbiology Reports* 5 (3): 424–37. <https://doi.org/10.1111/1758-2229.12027.>

McMurdie, Paul J., and Susan Holmes. 2014. “Waste Not Want Not: Why Rarefying Microbiome Data Is Inadmissible”. Edited by Alice Carolyn McHardy. *PLoS Computational Biology* 10 (4): e1003531. <https://doi.org/10.1371/journal.pcbi.1003531.>

Faust, Karoline, and Jeroen Raes. 2012. “Microbial Interactions: from Networks to Models”. *Nature Reviews Microbiology* 10 (8): 538–50. <https://doi.org/10.1038/nrmicro2832.>

Weiss, Sophie, Zhenjiang Zech Xu, Shyamal Peddada, Amnon Amir, Kyle Bittinger, Antonio Gonzalez, Catherine Lozupone, et al. 2017. “Normalization and Microbial Differential Abundance Strategies Depend upon Data Characteristics”. *Microbiome* 5 (1). <https://doi.org/10.1186/s40168-017-0237-y.>

Youngblut, Nicholas D., Samuel E. Barnett, and Daniel H. Buckley. 2018. “HTSSIP: An R Package for Analysis of High Throughput Sequencing Data from Nucleic Acid Stable Isotope Probing (SIP) Experiments”. Edited by Chongle Pan. *PLOS ONE* 13 (1): e0189616. <https://doi.org/10.1371/journal.pone.0189616.>

Daebeler, Anne, Paul LE Bodelier, Zheng Yan, Mariet M Hefting, Zhongjun Jia, and Hendrikus J Laanbroek. 2014. “Interactions between Thaumarchaea Nitrospira and Methanotrophs Modulate Autotrophic Nitrification in Volcanic Grassland Soil”. *The ISME Journal* 8 (12): 2397–2410. <https://doi.org/10.1038/ismej.2014.81.>

Ho, Adrian, Roey Angel, Annelies J. Veraart, Anne Daebeler, Zhongjun Jia, Sang Yoon Kim, Frederiek-Maarten Kerckhof, Nico Boon, and Paul L. E. Bodelier. 2016. “Biotic Interactions in Microbial Communities as Modulators of Biogeochemical Processes: Methanotrophy as a Model System”. *Frontiers in Microbiology* 7 (August). <https://doi.org/10.3389/fmicb.2016.01285.>

Berry, David, and Stefanie Widder. 2014. “Deciphering Microbial Interactions and Detecting Keystone Species with Co-Occurrence Networks”. *Frontiers in Microbiology* 5 (May). <https://doi.org/10.3389/fmicb.2014.00219.>