# Responses to reviewers' comments

We would like to thank the reviewers for their valuable and constructive feedbacks and comments, which helped us to improve the manuscript.

Referee comments are given in black, and our responses are in blue. Changes made to the manuscript are marked in underlined blue. The line number referred here is for the new revised manuscript.

## Anonymous Referee #1

This manuscript reports a novel "binPMF" method that can be used to improve the deconvolution of organic factors using atmospheric mass spectral data that don't have adequate mass resolution for unambiguous ion speciation. The authors applied this method to both ambient and synthetic data and demonstrated that the combination of mass spectral binning with positive matrix factorization is an effective approach to better resolve chemical information and to improve the separation of different sources and processes. This is an exciting new development in data analysis for real-time mass spectrometry and this work is of very high quality. The manuscript is very well written and the topic is a good fit for AMT. I thus recommend the manuscript be accepted for publication as is.

**Response:** We greatly appreciate this positive feedback on our work.

## Anonymous Referee #2

This paper introduces a new method of interpreting ambient mass spectrometer data, binPMF. This is an extension of existing PMF techniques to sub-unity resolution mass spectra without the usual peak fitting stage before this. The advantage of this approach is that it can utilise the extra mass spectrometric information without having to specify the peaks that are expected to be present. I can foresee a number of applications for this technique; it could conceivably be used deliver more accurate factorisations than UMR-PMF, but I strongly suspect that it may prove more useful in identifying peaks to use for HR-PMF. However, time will tell on that. Presented as a proof-of-concept, this is likely to stimulate activity and further development within the community of users of ARI/Tofwerk instruments, but I would anticipate that this may have applications beyond this. The paper is certainly relevant to AMT and is very well written and presented. I have a few reservations (see below) but these are minor, so subject to these I recommend publication.

Comments: Generally, the authors are very bullish about the capabilities of the technique, but I can foresee a number of fundamental limitations. In the interests of properly exploring this method on a conceptual level, I would recommend that the authors discuss these so as to create realistic expectations of what this is capable of. The issues I can think of are as follows, but there may be others:

**Response:** We thank the reviewer for the comments and will answer them point-by-point below. We acknowledge already at this stage that our aim was not to present binPMF as a method without limitations. For example, any fundamental limitations inherent to PMF will obviously still apply to binPMF. Instead, we want here to emphasize the word "simple" in our title. HR fitting of spectra can be extremely laborious, and with enough ions at a single integer mass, HR fitting can become impossible. BinPMF can still be run in such cases, with data preparation requiring the same amount of work as for a simpler data set, informing the analyst about various aspects of his/her data, while still utilizing more spectral information than simply running UMR PMF.

* Peak shape - It must be explicitly stated that this technique assumes that the peak shape model is consistent throughout a dataset. While this should remain constant if the instrument is working properly, if it drifts somehow, then this will likely cause unpredictable behaviour here.

**Response:** For the technique of binPMF itself, it only tries to separate different bins based on their temporal behaviors, and the narrow bins help to preserve the high-resolution information. Thus, the technique does not assume anything about the peak shape. However, the reviewer is correct that in the way we present the results and their interpretation, we as analysts have assumed a constant peak shape throughout our data sets. Any variability in the peak shape, or resolution for that matter, will cause signal to "leak" different amounts into adjacent bins at different times. The larger this variation is, the harder the factor and peak separation becomes in binPMF.

An inconsistent peak shape in a data set will be a much larger issue for traditional peak fitting, and an invariable peak shape is a basic assumption in the routines of tofTools or Tofware. With problematic peak shape issues, only UMR results will be completely unaffected, but binPMF will be less affected, and thus likely provide a better result, compared to any method based on high-resolution peak fitting.

Ultimately, variable peak shapes over time are an indication that some large change has occurred in the instrument, and data before and after this change should likely not be analyzed together in the first place. Luckily, in our experience, the peak shape typically stays very consistent.

We added the following sentence (underlined) on Line 545-547 in Section 3.3 in the manuscript in order to briefly discuss this issue about peak shape:

"…… variation could also be considered for error estimation. Similarly, although generally rare and suggestive of some instrumental problem, if the peak shape or resolution shift over time, this would also require an improved error estimation in order to account for increased variability."

* Aliasing - the act of binning the mass spectra through over- followed by under-sampling may introduce artificial smoothing of the data. This is unlikely to be an issue for peaks at low m/z ratios where the fundamental resolution of the instrument is high, but where the resolution of the mass spectrometer starts to become comparable to the target bin width, I imagine this could be an issue. This would be unlikely to cause problems if the mass calibration of the spectrometer were constant, but as this is known to subtly drift over time, this means that any aliasing artefacts could (in theory) be variable with time, even if the changes in calibration were properly accounted for, which in turn could create artificial factors in the dataset. This should be discussed, if only conceptually.

**Response:** In the binning process of binPMF, the data are first linearly interpolated with certain interpolation interval, and then binned with certain bin width. The bin width is much larger than the interpolation interval. The binning process considers all the interpolated data points within the bin width by averaging their signals, instead of just taking one data point as representative for this bin. In addition, in the manuscript section 3.3., we also suggest that the bin width should be mass-dependent and defined in such way that each peak can be covered by 7 bins, considering the instrument resolution (Th/Th).

While any resampling of data will inevitably lead to some smoothing, it should be minor with this approach. For the aliasing effect suggested by the reviewer, the fact that the bin widths are always clearly narrower than the peak widths, should make this effect negligible. We added a note on this into Section 3.3 on Line 516:

"Too few bins per peak would mean that we may lose valuable information in the binning, and potentially risk introducing aliasing effects, while too many points……"

* Complexity - the analysis may not be able to adequately factorise systems where there is a large number of degrees of freedom in the chemistry, e.g. studying SOA formation in a chamber. This is a fundamental limitation of PMF and applies equally to the other established methods as well. However, I suppose this technique could still be of use in peak identification, even if it can't explain all the variance.

**Response:** Yes, we agreed with the reviewer that factorization analysis cannot separate every pathway/source. PMF itself, as a factorization analysis method, has its own fundamental limitations and problems and binPMF cannot improve on these problems. We added one sentence (underlined) in the manuscript in Line 173-174 in Section 2.1,

"……considering their rotational uniqueness. Finally, we note that in addition to rotational ambiguity, binPMF also inherits all other fundamental limitations and strengths of the underlying PMF method."

* Covariance - as with all PMF, the ability to separate components is contingent on them showing different trends. If (hypothetically) two adjacent peaks were to covary, then this technique would fail to separate them.

**Response:** Yes, the reviewer is correct. However, we do not find this to be a problem, and it would not impact the separation of factors.

Even so, for example, if there are $C_{10}H_{16}O_7$ and $C_9H_{12}O_8$ in the same mass spectrum, which will go to the same factor, we can still get the HR information in this factor, as it will now be a double peak at m/z of 310 Th in the factor. Thus, compared to UMR, we get more information. Compared to traditional HR fitting, assuming one knows the two ions are present at this mass, they can be fitted and separated, but will not contribute much more to the separation of different factors than the binPMF approach. In addition, if the two adjacent peaks are very close in mass, the attribution of signal between the two fitted peaks may become variable. This, in turn, may cause covarying ions to have different, anti-correlating behavior from improper HR fitting. This, again, highlights the robustness of binPMF, which requires no identification of ions beforehand, and is much less sensitive to variations in mass calibration, resolution or peak shapes.

Line 196: If the noise is based on signal-free regions of the mass spectrum, would this not be underestimated because of the thresholding applied by the data acquisition system?

**Response:** For the error estimation, we use this equation $S_{ij} = \sigma_{ij} + \sigma_{noise}$ .The signal dependent part $\sigma_{ij}$ represents the poisson counting error. The noise term $\sigma_{noise}$ is to represent the background noise, stray counts etc. Exactly how good our method of noise estimation is, will depend on a wide variety of factors, including the frequency of ions measured at a given mass, the type of data acquisition card (compare e.g. TDC vs ADC), the ratio of the threshold level compared to the electronic noise, etc. . If the reviewer is suggesting that the electronic noise is "thresholded away" in the signal-free region, but that this noise is superimposed on the signal when an actual ion is detected, then there are a few effects counteracting this potential problem. At low count rates a given bin, most acquired spectra (sampled at ~10 kHz) will lack ions, and the majority of noise will arise from stray counts in the spectra, which were signal-free in reality. When the count rate becomes higher, the spectra with real signal become more dominant,

but at this stage the signal-dependent error term $\sigma_{ij}$ will start to dominate the total error. In other words, for low (or no) signal bins, and for high signal bins, the error estimation approach is expected to work correctly. For intermediate count rates, there might be an effect as suggested by the reviewer. However, this cannot be addressed by simply increasing the noise term, since this would cause the low signals to have over-estimated noise. Thus, this simple error model is concluded to be adequate for the purpose of binPMF.

Line 535: I disagree that mass calibration could be accounted for by an error term; according to the PMF data model, the errors are supposed to be random and independent of one another, however a shift in mass calibration would cause deviations that are dependent on adjacent points.

**Response:** Uncertainty in PMF analyses arises from three main causes, as described in Paatero et al., 2014: (1) random errors in data values; (2) rotational ambiguity; and (3) modeling errors. This question by the reviewer is discussed in great detail in Paatero et al., 2014. Variations in mass calibration are one example of a modeling error. The assumptions underlying PMF are completely fulfilled if there are no modelling errors, and this is often the case in simulation studies. Then the results obtained from PMF obey rather strict mathematical rules, e.g. the Q contributions from individual columns or individual rows obey rather narrow chi-square distributions.

However, in real data, modeling errors are usually present, often in significant amounts. This means that statistical properties of PMF results are undefined. On the other hand, PMF analysis may still be used even in presence of modeling errors. It is common practice to include expected effect of modeling errors of data values so that the uncertainties $S_{ij}$ specified for erroneous data values are artificially increased. In this way, the effect of modeling errors is constrained although it cannot be totally eliminated.

We added the following sentences in Line 536-544 in Section 3.3 in the manuscript,

"Uncertainty in PMF analyses arises from three main causes, random errors in data values, rotational ambiguity, and modeling errors (Paatero et al., 2014). Variations in mass calibration are one example of a modeling error, It is common practice to increase uncertainty values $S_{ij}$ specified for data values disturbed by modeling errors. This increase does not account for the mass calibration error in the sense that the effect of mass calibration variation would disappear. The increase simply balances residuals in different data values so that the best possible result may be obtained. In addition to the two error estimation terms discussed in section 2.3, $\sigma_{ij}$ and $\sigma_{noise}$, a third form of error, to balance the mass calibration variation could also be considered for error estimation."

Reference

Paatero, P., Eberly, S., Brown, S. G., and Norris, G. A.: Methods for estimating uncertainty in factor analytic solutions, Atmos. Meas. Tech., 7, 781-797, doi:10.5194/amt-7-781-2014, 2014.

# A Novel Approach for Simple Statistical Analysis of High-Resolution Mass Spectra

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**Abstract.** Recent advancements in atmospheric mass spectrometry provide huge amounts of new information, but at the same time present considerable challenges for the data analysts. High-resolution (HR) peak identification and separation can be effort- and time-consuming, yet still tricky and inaccurate due to the complexity of overlapping peaks, especially at larger mass-to-charge ratios. This study presents a simple and novel method, mass spectral binning combined with positive matrix factorization ('binPMF') to address these problems. Different from unit mass resolution (UMR) analysis or HR peak fitting, which represent the routine data analysis approaches for mass spectrometry datasets, binPMF divides the mass spectra into small bins and takes advantage of PMF's strength in separating different sources or processes based on different temporal patterns. In this study, we applied the novel approach to both ambient and synthetic datasets to evaluate its performance. It not only succeeded in separating overlapping ions, but was found to be sensitive to subtle variations as well. Being fast and reliable, binPMF has no requirement for a priori peak information and can save much time and effort from conventional HR peak fitting, while still utilizing nearly the full potential of HR mass spectra. In addition, we identify several future improvements and applications for binPMF, and believe it will become a powerful approach in the data analysis of mass spectra.

**Keywords.** (Atmospheric) mass spectrometry, binned positive matrix factorization (binPMF), high-resolution (HR) mass spectra, peak fitting, chemical ionization mass spectrometer (CIMS), highly oxygenated molecules (HOM)

## 1. Introduction

Volatile organic compounds (VOC) are emitted to the atmosphere both from biogenic and anthropogenic sources (Guenther et al., 1995;Wei et al., 2008). After oxidation, these gaseous species can partition to the particle phase and contribute to atmospheric organic aerosol (OA), a major component of tropospheric particulate matter (Zhang et al., 2007). The chemical components, both in particulate (OA) and gaseous phase (VOC and their oxidation products), play important roles in many atmospheric physical and chemical processes. They can deteriorate air quality causing adverse health effects, and aerosol particles can influence Earth's climate by altering the radiative balance, as well as decrease visibility (Stocker et al., 2013;Zhang et al., 2016;Pope III et al., 2009;Shiraiwa et al., 2017).

Recent instrumental advances in mass spectrometry have greatly enhanced our capability to investigate the chemical composition and evolution of aerosol particles and their precursors. The Aerodyne aerosol mass spectrometer (AMS) is widely applied in atmospheric research (Canagaratna et al., 2007), measuring the bulk composition and temporal behavior of the non-refractory aerosol, and has successfully identified different/unique OA sources utilizing factor analysis (Jimenez et al., 2009;Zhang et al., 2011). With the development of gas-phase chemical ionization mass spectrometry (CIMS) (Huey, 2007), and the commercially available ToF-CIMS (Bertram et al., 2011) and CI-APi-TOF (chemical ionization atmospheric pressure interface time-of-flight mass spectrometer (Jokinen et al., 2012)), these instruments are becoming more popular in atmospheric chemistry research. Due to these new advances, the detection methods for aerosol precursor vapors and the understanding of their formation mechanisms have been greatly improved. For example, the discovery of highly oxygenated molecules (HOM) by the CI-APi-TOF has led to increased knowledge regarding atmospheric oxidation pathways, with large implications on secondary organic aerosol (SOA) and new particle formation (Ehn et al., 2014;Jokinen et al., 2015;Kirkby et al., 2016;Yan et al., 2016). In particular, biogenic VOC such as monoterpenes ($C_{10}H_{16}$), promptly produce HOM upon ozonolysis, e.g. $C_{10}H_{16}O_7$ and $C_{10}H_{16}O_9$.

While a mass spectrum can contain large amounts of information representing the highly complex nature of the atmospheric sample, it also presents considerable challenges for the analysis and interpretation of the data. One example of such a challenge is the identification and separation of peaks with a similar but not identical masses. A single integer mass can contain tens of distinct ions, with mass-to-charge ratios (*m/z*) close to each other. In all cases, specific spectral fitting techniques are needed to resolve the overlapping peaks at the same integer mass. Typically, a least squares fit is made to the spectrum, using analysis software such as Squirrel/PIKA (http://cires1.colorado.edu/jimenez-group/ToFAMSResources/ToFSoftware/), tofTools (Junninen et al., 2010) or Tofware (https://www.tofwerk.com/software/tofware/). However, these techniques require a pre-defined list of ions. This makes the analysis resource-intensive, and it can easily introduce subjective bias in determining the peak list.

Figure 1 depicts a concrete example, measured by a nitrate-based CI-APi-TOF, where peak separation is not large enough to allow unambiguous fitting of all the ions, and the final result will depend on which ions the analyst chooses to include. As the *m/z* increases, the number of possible ions at a certain unit mass increases rapidly (Kroll et al., 2011;Stark et al., 2015). Too closely overlapping peaks will sometimes lead to ambiguously fitted peaks and arbitrarily resolved ions, resulting in unreliable separation of signals. Additionally, mass calibration errors can also affect correct peak

assignment or fitting. A few recent studies discuss in more detail the uncertainties of ion identification and separation in HR mass spectra (Stark et al., 2015;Corbin et al., 2015;Cubison and Jimenez, 2015).

Another typical analysis approach is to utilize only the unit mass resolution, or UMR data. As opposed to high resolution fitting, where the signals of individual ions are separated from the total measured signal, in UMR analysis all signals at a given integer mass is integrated and treated together. This approach is more straightforward and less subjective than HR fitting, but loses all possible high resolution details in the spectrum (see Figure 2).

Even with perfect high resolution peak fits, a spectrum typically contains information of hundreds, if not thousands, of ions, many of which come from similar sources. This wealth of data itself presents a challenge for data analysis. Factor analysis enables the reduction of data dimensions and can help to apportion the signals to factors. These factors may correspond to different sources or formation processes. Positive matrix factorization (PMF) (Paatero and Tapper, 1994) has been widely utilized in environmental sciences, applied to UMR and HR AMS data, succeeding in identifying multiple OA sources (Lanz et al., 2008;Ulbrich et al., 2009;Sun et al., 2011;Zhang et al., 2011). Compared to AMS data, PMF has been applied to CIMS data analysis much less frequently. To our knowledge, only Yan et al. (2016) and Massoli et al. (2018) have reported PMF analysis on nitrate-based CI-APi-TOF, utilizing UMR and HR data, respectively.

UMR-PMF cannot utilize the full information content provided by HR mass spectrometers, but is more straightforward to apply. In contrast, accurate HR peak fitting can better preserve the information content of the raw data than UMR, and thus provide more information to PMF, resulting in more interpretable results. However, incorrectly fitted peaks can severely disturb the PMF modeling and the factor interpretation. In addition, mass spectra from iodide-adduct Tof-CIMS (Lee et al., 2014), often contain more peaks per mass than the $NO_3^-$-CI-APi-TOF, making HR fitting much more complex (or in some cases, even unmanageable), severely limiting the potential of HR PMF.

In this study, a novel, yet simple and reliable, data analysis method, binned mass spectra combined with PMF (binPMF), is proposed to try to tackle the abovementioned problems in both HR and UMR PMF. Instead of using traditional UMR or HR fitting techniques to the mass spectra, we binned the mass spectra prior to PMF analysis (Figure 2). We applied binPMF to both ambient and synthetic datasets, succeeding in separating the key components of different sources/processes. Compared to UMR PMF, binPMF preserves more of the high resolution information content of the mass spectra, without the immense effort and subjectivity associated with high-resolution peak fitting. As a result,

this novel method can improve our understanding of sources/formation processes governing the particulate and gaseous phases in more detail and in a less subjective manner.

## 2. Methodology

We divided the mass spectra into narrow bins as presented in Figure 2, and carried out PMF analysis to extract more information from the dataset. Details on the data preparation (binning the mass spectra), and error estimation for the PMF input are discussed in the Sections 2.2 and 2.3. To test the performance of binPMF under different scenarios, we first constructed synthetic datasets, using a simple one-/two-mass system (Section 2.4.1). In the second step, we applied binPMF to an ambient dataset measured with a $NO_3^-$-CI-APi-TOF in a boreal forest site located in Southern Finland (Section 2.4.2).

### 2.1. Positive matrix factorization

The PMF model was developed by Paatero and Tapper (Paatero and Tapper, 1994) in the 1990s and has been widely applied in the analysis of various types of environmental data ever since (Zhang et al., 2017;Yan et al., 2016;Ulbrich et al., 2009;Song et al., 2007). By decomposing the observed dataset into different factors, PMF helps to simplify the complex data matrix and extract useful information contained within it. Compared to other common source apportionment tools, like chemical mass balance (CMB) (Schauer et al., 1996), PMF requires no prior knowledge of source information as essential input. Nevertheless, as a statistical method, PMF does require more data as input, which is typically not a problem for environmental mass spectrometry datasets. The main distinction of PMF from other factor analysis techniques is that PMF utilizes a least squares minimization scheme weighted with data uncertainties, and non-negative constrains, to minimize the ambiguity caused by rotation of the factors (Huang et al., 1999;Paatero and Tapper, 1994).

In PMF modelling, a measurement of chemical species is assumed to be a sum of contributions from several relatively fixed sources/processes. The measured data matrix is broken down to two smaller matrices, and a residual term as follows:

$$X_{(m\times n)} = \mathrm{TS}_{(m\times p)} \times \mathrm{MS}_{(p\times n)} + R_{(m\times n)} \quad (1)$$

where $X$ represents an $m\times n$ data matrix of original measurement for species $n$ (e.g. $m/z$) at time point $m$, TS is the $m\times p$ time series matrix of factor contributions, MS is the $p\times n$ matrix of factor profiles or the factor mass spectra, and $R$ is the residual between the modelled and the measured data. $p$ is the number of factors, which needs to be determined based on the interpretability of the PMF results,

among other criteria. Thus, in PMF, the original data matrix is approximated in terms of *p* factors, each of which has a distinct mass spectrum and time series.

To find the solution, the PMF model utilizes uncertainty estimates for each element in the data matrix X. These uncertainty estimates are used to weight the residuals (*R*), in order to calculate the *Q* value as

$$Q = \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{R_{ij}}{S_{ij}}\right)^2 \quad (2)$$

where $S_{ij}$ is the estimated uncertainty of species/mass *j* at time point *i*, and $R_{ij}$ is the residual of that mass at the same time. *Q* is then minimized iteratively to find the mathematically optimal solution. An expected *Q* value ($Q_{exp}$) can be calculated as the number of non-down-weighted data values in X minus the sum of elements in TS and MS. If the data follows the requirements of PMF, the solution with the correct number of factors should have a $Q/Q_{exp}$ value near unity. When this is true, the residuals on average fall within the expected uncertainties for each time point and variable. More details about uncertainty estimation will be discussed in Section 2.3. The PMF analysis in this study was performed with the toolkit of Source Finder (SoFi, v6.3) (Canonaco et al., 2013) by multi-linear engine (ME-2) (Paatero, 1999). Masses with low signal-to-noise ratio (SNR < 0.2, see Section 2.3 on error estimation) were down-weighted by a factor of 10, and masses with 0.2 < SNR < 2 were down-weighted by a factor of 2, as suggested by Paatero and Hopke (Paatero and Hopke, 2003). The down-weighting effect was considered in the $Q_{exp}$ calculation. In this study, PMF was operated in robust mode, where outliers ($\left|\frac{R_{ij}}{S_{ij}}\right| > 4$) were dynamically down-weighted (Paatero, 1997).

One of the problems in any factorization analysis is rotational ambiguity, which is caused by an infinite number of similar solutions generated by PMF (Paatero et al., 2002;Henry, 1987). Generally, the non-negativity constraint alone is not sufficient for solution uniqueness. Rotating a certain solution and assessing the rotated results is one possible way to determine the most physically reasonable solution. Known source profiles or source contributions can also serve as constrains. In addition, if there is a sufficient number of time points when the contribution of a source is nearly zero, independent of other sources, rotational uniqueness of solutions can be achieved (Paatero et al., 2002). The same is true if specific variables in the profiles go to zero. Otherwise, the correct solution (correct rotation) may only be obtained by skillful use of rotational tools. Ambient measurement data can often contain zero values in most sources/processes, greatly reducing rotational ambiguity of the PMF results. The issue of rotational ambiguity is not explored in detail in this manuscript, as it is common to all PMF approaches, and the main purpose here is to illustrate the new methodology of

binPMF. All the solutions shown in this study were achieved without considering their rotational uniqueness. Finally, we note that in addition to rotational ambiguity, binPMF also inherits all other fundamental limitations and strengths of the underlying PMF method.

### 2.2. binPMF data matrix preparation

Instead of UMR or HR fitting of the mass spectra, the mass spectra were divided into small bins after mass calibration (Figure 2 and Figure S1 in the Supplement). Data were first linearly interpolated to a mass interval of 0.001 Th, and then divided into bins of 0.02 Th width. At an integer mass *N*, only the signals between *N*-0.2 Th and *N*+0.3 Th ("the signal region") were binned to avoid unnecessary computation of masses without any signal. With the binning, there were 25 data points for each nominal mass, instead of only one signal in UMR or several fitted peaks in HR analysis. All the parameters mentioned above, e.g. bin width and signal region size, should be adjusted to suit the mass spectrometer and the data being analyzed. Further details on binning procedures are discussed in Section 3.3.

### 2.3. binPMF error matrix preparation

Beside the data matrix, an error matrix describing the expected uncertainty for each element in the data matrix is also required as input in PMF analysis. Here, the error matrix (Polissar et al., 1998) is estimated as

$$S_{ij} = \sigma_{ij} + \sigma_{\text{noise}} \quad (3)$$

where the uncertainty of mass $j$ at time point $i$, $S_{ij}$, is composed of analytical uncertainty $\sigma_{ij}$ and instrument noise $\sigma_{noise}$. $\sigma_{ij}$ is the uncertainty arising from counting statistics and is estimated as

$$\sigma_{ij} = a \times \frac{\sqrt{I}}{\sqrt{t_s}} \quad (4)$$

in which $I$ is the signal intensity, in counts per second, $t_s$ is the averaging time in seconds and $a$ is an empirical parameter incorporated to include unaccounted uncertainties (Allan et al., 2003;Yan et al., 2016). In our study, we applied binPMF with CI-APi-TOF data as an example, and the same $a$ value of 1.28 was utilized as estimated previously from laboratory experiments in the work of Yan et al. (2016). The $\sigma_{noise}$ is calculated as the median of the standard deviation of instrument noise, calculated from the bins between two nominal masses that should be least influenced by real signals (the noise region), i.e. *N*+0.5 - *N*+0.8 Th (see Figure S1 in the Supplement).

### 2.4. Data sources and description

This study utilized both ambient and synthetic datasets to test the performance of binPMF. The ambient data was collected at the SMEAR II station (Station for Measuring Ecosystem–Atmosphere Relations (Hari and Kulmala, 2005)) in the boreal forest in Hyytiälä, Southern Finland. Located in a rural forest area, the station has a wide range of continuous measurements of meteorology, aerosol and gas phase properties year-round. There are no strong anthropogenic sources close to the site, but two sawmills 5 km to southeast and the city of Tampere 60 km to the southwest. Detailed meteorological parameters and concentrations of trace gases during this campaign have been presented earlier (Zha et al., 2018). Before the application to ambient data, we constructed a simple synthetic dataset, to examine how well binPMF can separate overlapping ions under different conditions.

### 2.4.1. Synthetic dataset

As a first test of the performance of binPMF, we generated a series of synthetic datasets based on two distinct sources. Each synthetic dataset $Y$ was created by summing up the signals of the two sources. Each source consisted of a constant source profile (represented as the matrix MS), and had a unique temporal behavior (represented as the matrix TS). Each source was the multiplication of MS (mass spectra / source profile) and TS (time series). The two TS for the two sources were generated randomly and independently from each other, as shown in Figure S2 in the Supplement (correlation coefficient $R$ = 0.375). To avoid rotational ambiguity (See section 2.1) in these tests, we added zero values to the time series of the two sources, independently of each other.

As shown in Figure 3, each source profile (MS) was generated to consist of either one or two separate peaks, covering either one or two unit masses, respectively. The peaks were generated as Gaussians of known width and centroid position. The peaks of the different sources/profiles were partially overlapping, with the exact overlap, i.e. the distance (*m/z* difference) between the overlapping peaks, being varied from one experiment to another.

Peaks in the synthetic MS profiles were first generated as perfect smooth peaks (fine *m/z* interval of 0.00001 Th), with mass resolution of 5000 Th/Th. We define the resolution R of a peak as $R = M/\Delta M$, where M is the mass of the ion, and $\Delta M$ is the full width at half maximum signal intensity, FWHM. As an example, with R = 5000 Th/Th, an ion at *m/z* of 300 Th will have a FWHM of 0.06 Th, corresponding to 200 ppm. Multiplying the source profiles and the time series, we generated an ideal data matrix. From this ideal matrix, we sampled with *m/z* interval of 0.015 Th to simulate the real measurement data. The interval selected was close to that typically used for the HTOF mass analyzer on a CI-APi-TOF. After the sampling, Gaussian distributed noise, both from background

random noise and signal dependent noise were added to make up the data matrix *Y'*, point by point, as shown in Eq. 6 below. The variance of the Gaussian distributed noise was estimated as one hundredth of the coefficient '*c*', which is the average value of *Y*.

$$Y = \mathrm{TS} \times \mathrm{MS} \tag{5}$$

$$Y'_{ij} = Y_{ij} + \mathrm{Gaussian}\,(0, 0.01 \times c) + \mathrm{Gaussian}\,(0,1) \times \sqrt{Y_{ij}} \tag{6}$$

Finally, random *m/z* shift within ± 10 ppm was added to simulate mass calibration error, spectrum by spectrum. This error, resulting from inaccurate conversion of the time-of-flight into mass-to-charge ratio, is one of the main causes of ambiguous or incorrect peak assignment or fitting. In our study, with the bin width of 0.02 Th and the mass calibration error of 10 ppm, a maximum of 15% of one bin's signal may incorrectly shift to the adjacent bin, for a mass at 300 Th ((10 ppm × 300 Th) / 0.02 Th × 100 % = 15%). The impact of this mass shift will effectively be smaller, due to the high temporal correlation of adjacent bins, as the signal from an ion will spread to several adjacent bins (the FWHM is ~3 times the bin width). In the case of HR fitting of peaks, a 10 ppm mass calibration error may cause much more dramatic changes than merely shifting 15% of the signal. There is also no reason for ions from a given source to selectively end up at the same integer mass, meaning that the signal is likely to be shifted to another ion from a completely different source.

Twenty-one synthetic experiments were designed, varying the mass difference between peaks (*m/z* difference) and number of unit masses included in the MS, as shown in Table S1 and Figure 3. For experiments 1-10, each of the two source profiles consisted of one peak (A1 and B1), both located at the same unit mass (chosen to be 310 Th in this study), with varying separation of the peak centroids. In experiments 11-20, we added one more peak to each profile (peaks A2 and B2), in addition to peaks A1 and B1. The additional peaks were added at another unit mass (311 Th) and their *m/z* difference was fixed at 0.05 Th (161 ppm), while the position of peak B1 was varied as in experiments 1-10. For experiment 21, peaks A2 and B2 were added at two different masses (311 Th and 312 Th), corresponding to a *m/z* difference sufficiently large that there was no meaningful overlap between them. In the MS (i.e. mass spectra profiles), all peaks had the same intensity level initially. The variation of the peak intensity ratio comes from variations in the time series (Figure S2 in Supplement). The same time series for each of the two sources was used in all experiments 1-21.

With this approach of only using two masses, we purposefully provide a challenging dataset for binPMF, as in most real datasets there would be many more masses to help to constrain the final solutions. Nevertheless, as we will show, this simple synthetic dataset already provided a wealth of

useful information in the results attainable with binPMF, and provided a good comparison to the traditional HR fitting approach.

#### 2.4.2. Ambient dataset

The ambient dataset was measured at ground level during the Influence of Biosphere-Atmosphere Interactions on the Reactive Nitrogen budget (IBAIRN) campaign (Zha et al, 2018) in September, 2016. The measurements were conducted using a $NO_3^-$-CI-APi-TOF that has been described in detail elsewhere (Jokinen et al., 2012;Junninen et al., 2010;Yan et al., 2016). Here, the ambient gas-phase molecules clustered with the nitrate ion were measured with about 4000 Th/Th mass resolving power. Data from September 1$^{st}$ to 26$^{th}$, averaged to 1-hour time resolution, in the mass range of 300 - 350 Th (a typical monoterpene HOM "monomer" range, Ehn et al., 2014) were utilized for the binPMF analysis. A baseline subtraction was applied to the mass spectra, which caused some small signals next to large peaks to become negative. In our analysis, any *m/z* bin where the median signal was negative was excluded from the data matrix.

## 3. Results and discussion

### 3.1. Synthetic dataset

#### 3.1.1. Experiment settings

As introduced in Section 2.4.1, the synthetic datasets were constructed to assess the response of binPMF to varied *m/z* difference, peak intensity ratios, and number of masses included, as shown in Table S1 and Figure 3. The smaller the distance between the two peaks, the harder it is to accurately separate them with traditional HR peak identification and fitting. In our experiments, the *m/z* difference was decreased stepwise from 0.050 Th (161 ppm) to 0.001 Th (3 ppm), in a system where the FWHM was roughly 200 ppm.

The analysis procedure of the synthetic dataset is briefly described here. In all cases, the parameter of interest is to see how well binPMF is able to deconvolve the adjacent peaks A1 and B1 at *m/z* 310 Th. First, binPMF was applied to the synthetic datasets, and factors profiles (mass spectra) were extracted. The optimal number of factors for the synthetic dataset is two, the same as the number of sources, so only the two-factor solution was studied with binPMF. The results of the diagnostic parameter $Q/Q_{exp}$ for each experiment are included in Table S1. Gaussian fitting was then performed on the factor profiles to retrieve the locations of peaks A1 and B1, and thereby assess how well binPMF was able to retrieve the original peak positions.

In addition to applying binPMF to the synthetic datasets, traditional HR peak fitting was also conducted as comparison (by tofTools in our study). For the tofTools fits, we constrained the peak locations and widths to those originally used for generating the data (Table S1). Peaks fitted by tofTools and peaks fitted to the binPMF factors were compared, as well as the retrieved time series correlation with the original datasets. More details are presented and discussed in the following sections.

### 3.1.2. Comparison of peak fitting

We examined the performance of traditional HR fitting and binPMF by comparing their results to the original input data. In Figure 4, the shaded areas depict the original data, the dashed lines the traditional HR peak fitting result, and the solid lines the binPMF factors. Red and blue represent source/factor A and B, respectively. Panels a-d (in Figure 4) show four scenarios of peak fitting results from experiments 1, 5, 10 and 20, at the 79$^{th}$ time point, where the two peaks had similar signal intensities. When the two peaks were separated by 0.05 Th (Figure 4a), both methods captured the peak intensities quite well. However, as the *m/z* difference narrowed, the performance of both methods declined, with the HR fitting results deteriorating faster than those from binPMF. As *m/z* difference reached 0.001 Th (3 ppm), the traditional HR fitting method completely failed to fit the two peaks (panels c and d), instead attributing all the signal to just one fitted mass. In panels e-h, the peak fitting results at the 21$^{st}$ time point are displayed, where the ratio of the two peaks was roughly 1:6. Here, the traditional fitting method failed to extract the two peaks already at a *m/z* difference of 0.01 Th (30 ppm), attributing all signal to Peak B1 (panels g and h). As shown in panels d and h, when a second set of peaks, separated by 0.05 Th, was introduced for the two sources in the datasets, binPMF was able to utilize the temporal behavior of peaks A2 and B2, performing much better, even in the extremely difficult cases when the *m/z* difference for the two peaks was only 0.001 Th (3 ppm). It is an inherent advantage of binPMF over traditional peak fitting methods that the temporal behavior and the correlations between different variables can be utilized.

Figure 5 shows an overview of all the results of peaks fitted with binPMF. Experiments 1-10 for the one-mass system are shown with green lines, and experiments 11-20 for the two-mass system in yellow. Mass accuracy was calculated as the difference between fitted peak center mass and the original mass, divided by the original mass, in ppm. When the *m/z* difference got smaller, the mass accuracy of peaks fitted to binPMF factors declined (Figures 5a and 5c). At a *m/z* difference of 0.01 Th (32 ppm), the mass accuracy was -4±2 ppm and 7±2 ppm for peaks A1 and B1, respectively. The uncertainties were estimated by repeating the analysis with 10 different random time series for the two sources (Brown et al., 2015). For comparison, this separation approximately corresponds to that

between $C_{10}H_{16}O_7 \cdot NO_3^-$ (310.0780 Th) and $C_9H_{16}N_2O_6 \cdot NO_3^-$ (310.0892 Th). With *m/z* difference decreasing, the position of peak A1 (the left red peak in Figure 3), as identified by binPMF, shifted gradually to the left, while peak B1 (the right blue peak) shifted to the right. When peaks A2 and B2 were introduced to the sources, the mass accuracy improved (< 6 ppm). The resolution of the peaks fitted to binPMF factor profiles stayed fairly constant, but had degraded compared to the original input data (5000 Th/Th), explained at least partially by the data binning (Figures 5b and 5d). Overall, binPMF performs relatively well in peak separation, with reasonable mass accuracy and peak resolution compared to the original datasets.

#### 3.1.3. Correlation of time series

In addition to the peak positions, we also compared the temporal behavior of both the binPMF factors and the time series obtained through traditional fitting, to the original time series. When *m/z* difference was larger than 0.02 Th (65 ppm), both methods worked similarly well in reproducing the original time series (Figure 6). As the *m/z* difference decreased below 0.02 Th (65 ppm), correlations decreased rapidly (panels a and c), with that of the traditional method decreasing faster. However, as shown by the yellow lines, when peaks A2 and B2 were added to each source profile, the time series correlation coefficients between original data and peaks extracted by binPMF were close to unity in experiments 11-20. The coefficients stayed similar to that from the experiment with *m/z* difference of 0.05 Th (161 ppm), which was the fixed *m/z* difference for the two new peaks added at 311 Th in experiments 11-20. This means that the separation of the factor time series was mainly driven by the additional, better separated peaks. Again, the traditional HR fitting method could not utilize the information at 311 Th, and therefore no improvement to the peak deconvolution at 310 Th was seen. In addition to the correlation analysis, also the assignment of absolute signal to peaks A1 and B1 was evaluated. This was done by a linear fit (through zero) to the data points retrieved by the different methods as a function of the original input data. The slopes of the fitted lines are plotted in Figures 6b and 6d, and show that the signal was for the most part correctly attributed to within a few percent. The largest scatter in the determined slopes were observed for binPMF experiments with only one mass, at low peak separations.

#### 3.1.4. Summary and discussion

Based on the results shown above, binPMF was found to be as capable of separating different peaks as traditional peak fitting techniques when the two peaks were separated by more than the mass calibration uncertainty (yet still in all cases by less than the FWHM of the peaks). As the *m/z* difference of the two overlapping peaks decreased, the performance of the traditional method declined

faster than that of binPMF. This was shown for signal attribution of fitted peaks and time series correlation with original data. When masses with co-varied temporal behavior of the targeted overlapping peaks were introduced in the dataset, the performance of binPMF improved significantly.

The peak fitting principle of the traditional method and binPMF are very different. For example, tofTools fits peaks based on pre-determined instrument parameters (e.g. peak shape and peak width), as well as the peak location, either as a numeric value, or a chemical composition from which the location is calculated (Junninen et al., 2010). HR peak fitting by tofTools can be effective if the majority of the components (peaks) are known and provided in a peak list, which is valuable information for peak separation that was not provided to binPMF in this study. However, this information can be hard to achieve due to unknown numbers and/or identities of all the ions at a given mass, in combination with the limited mass resolving power of the mass spectrometer. HR peak fitting is also sensitive to mass calibration error, increasingly so when many ions in close proximity to each other need to be fit. On the contrary, in binPMF, peaks are separated based on the temporal variation of masses, which is an inherent advantage of PMF, though no information of the peaks is provided beforehand. To be more specific, a conceptual illustration is shown in Figure S3 in the Supplement. The red peaks belong to Source A and the blue peaks to Source B. As mentioned before, the time series of sources A and B were totally independent and random. The shaded areas (the tails of the peaks), e.g. red shaded area in Figure S3a, contained masses that only had significant signal from peak A1 (left red peak). Similarly, the blue shaded area in Figure S3a was mostly from peak B1. The different temporal behaviors of the red and blue shaded areas helped the separation and correct attribution also in the regions with overlapped signals. When the *m/z* difference of peaks A1 and B1 decreased, shown in Figure S3b, the two shaded areas also became smaller. This is the main reason why the fitted masses of binPMF had lower mass accuracy and lower correlation coefficients compared to the original data, as the *m/z* difference decreased.

When peaks A2 and B2 (*m/z* difference of 0.05 Th) were added in the dataset, peaks A1 and B1 were better separated and fitted by binPMF compared to the scenarios with only one mass. This is because, as shown in Figure S3c, the red and blue shaded areas became larger due to the addition of two more peaks. In this case, it was peaks A2 and B2 that dominated the separation of sources A and B. In experiment 21, three integer masses were included in the dataset. Though it was still equally difficult for the traditional HR method to separate and fit peaks A1 and B1 with *m/z* difference of 0.001 Th (3 ppm), it was the easiest experiment for binPMF out of all the experiments because of the large *m/z* difference of peaks A2 and B2 (1.000 Th, 3225 ppm). In experiment 21, the mass accuracies for peaks A1 and B1 were -3.2 ppm and 2.6 ppm, respectively, and the time series correlation with original data

was 1.000 and 0.999, respectively. In most real-world applications, individual sources typically contain multiple peaks, and the correlations of these can be utilized by binPMF.

We note once more that the results of binPMF and traditional HR peak fitting are not totally comparable. Information about the peaks, like the exact peak centroid position, peak width (resolution) and number of peaks, was provided to the traditional fitting method. For binPMF, no prior information about the peaks was given, except for the optimal number of factors, i.e. two.

### 3.2. Ambient dataset

With the success of binPMF for the synthetic datasets, we applied the new method to a real ambient dataset. Here we used data collected in September 2016, from Hyytiälä in Finland. The SMEAR II station is a forest site dominated by monoterpene ($C_{10}H_{16}$) emissions (Hakola et al., 2006). Previous CI-APi-TOF measurements of HOM at the site (Ehn et al., 2014;Yan et al., 2016) have presented bimodal distributions, with one mode corresponding to HOM monomers (range 300-400 Th) and the second to HOM dimers (450-650 Th). For testing the binPMF analysis on our ambient dataset, we selected the HOM monomer range of 300-350 Th. While the synthetic dataset primarily compared binPMF to traditional HR fitting analysis, in this section, we compare the binPMF results with that of traditional UMR-PMF, as employed by Yan et al. (2016). HR fitting was not performed for the ambient dataset, for all reasons mentioned in earlier sections, including the difficulty and efforts of producing a proper unambiguous peak list, as well the limitations of overlapping peaks.

As mentioned above, no prior knowledge was provided to PMF before the analysis. To determine the number of factors for further analysis, we conducted runs with two to eight factors. As the number of factors increased, more information could be extracted from the raw data. However, after the optimal number of factors, the additional factors may split the physically reasonable factors into meaningless fragments. There has been many studies on evaluations of PMF runs and selections of PMF factor number (Zhang et al., 2011;Craven et al., 2012). This is an inherent challenge in any PMF analysis, and not specific to binPMF, and therefore we do not put emphasis on this here. In this study, based on commonly used mathematical parameters and physical interpretation, we chose the seven-factor result, as presented below. Our main aim with this work is to present a 'proof of concept' for the binPMF methodology, and we will therefore not provide a detailed interpretation of all the factors (though several of the factors are easily validated based on earlier studies). The factor evolution from two to eight factors are briefly discussed below.

From two to six factors, $Q/Q_{exp}$ showed a dramatic decrease from 6.5 to 2.7. Then for seven and eight factors, $Q/Q_{exp}$ decreased to 2.3 and 2.0, respectively. The unexplained variation also declined from

14% to 8.8% going from two to six factors, then reached 8.0% for seven factors, and 7.6% for eight factors. The two-factor solution first split the data into a daytime factor and a nighttime factor, with very distinct mass spectral profiles. The daytime factor was characterized by signals at 307 Th, 311 Th, 323 Th, 339 Th and other odd masses, while the nighttime factor was dominated by 308 Th, 325 Th, 340 Th and 342 Th. The odd masses are typical signatures of day-time monoterpene-derived organonitrates at the site, while the even masses, and specific odd masses e.g. a radical at 325 Th, have been identified as monoterpene ozonolysis products (Ehn et al., 2014;Yan et al., 2016). As the number of factors increased, the daytime factor was further split into new daytime factors, with diurnal profiles having various peak times around noon or early afternoon. When the number of factors increased to seven, a clear sawtooth shape in the diurnal trend was resolved with marker masses at 308 Th, 324 Th, 325 Th, and 339 Th. Many of the profiles resolved in the seven-factor solution are similar to those found by Yan et al. (2016), and separating more factors did not yield new factors that we could interpret. Therefore, we opted to use this seven-factor result for the main discussion below, as it provided us with enough information to evaluate the binPMF method for this dataset.

Figure 7 shows the mass spectral profiles and factor time series for the 7-factor result, while Figure 8 displays the diurnal trends and factor contributions to the total signal. As shown in Figure 8a , the seven factors separated by binPMF consist of one nighttime factor (Factor 1), five daytime factors (Factors 2, 3, 4, 5 and 7) and a sawtooth-pattern factor (Factor 6).The same dataset was also analyzed by UMR-PMF, and the corresponding seven-factor results are also included in Figures 7 and 8 for comparison.

Overall, the results between UMR-PMF and binPMF are very similar. UMR-PMF also resolved one clear nighttime factor, and additionally six daytime factors. For the nighttime factor, both binPMF and UMR-PMF showed comparable temporal behavior, diurnal trend (peak at 17:00), mass spectral profiles (peaks at 340 Th, 308 Th, 325 Th, 342 Th) and factor contribution (~ 20%). This factor has been validated in both chamber and ambient studies to be formed from monoterpene ozonolysis (Ehn et al., 2014;Yan et al., 2016). As shown in Figure 7a, both methods also resolved similar, though not identical, mass spectral profiles for the other six factors, with mostly comparable time series (Figure 7b) and peak times in the diurnal trends (Figure 8a).

Despite the similarities, there also existed distinct differences between the results from binPMF and UMR-PMF. As the most distinctive dissimilarity, binPMF Factor 6 revealed a “contamination factor”. This factor was found to be related to automated instrument zeroing every three hours, giving rise to the distinct three-hour sawtooth pattern. The ~~zero measurements had been removed from the~~

~~data matrix, but the~~ zeroing system introduced some additional compounds into the sampling lines, and the semi-volatile nature of these compounds caused them to linger, and slowly decay, in the tubing even after the instrument had returned to sampling ambient air. binPMF accurately retrieved the 3-hour interval of the zero measurements. However, with the same mass range (300-350 Th), UMR-PMF failed to extract the contamination factor, regardless of the number of factors retrieved (up to 20 factor solutions were evaluated). Instead, these contamination signals were always mixed into the other factors. Factor 6 from UMR-PMF contributed almost twice as much as that estimated by binPMF due to the inaccurate factor separation (Figure 8b). The time series of other factors, e.g. Factors 5 and 7 in UMR-PMF, were clearly influenced by Factor 6. Compared to UMR-PMF, binPMF thus showed a clear advantage in providing more information out of the data by being more sensitive to subtle variations.

In addition to better resolving certain factors from the data, the binPMF mass spectral profiles will still contain more information than visible in Figure 7, due to the multiple bins at each unit mass. As an example, binPMF Factor 6 showed masses with clear negative mass defects, e.g. at 324 Th and 339 Th (Figure 9). We identified many ions in this factor as different fluorinated carboxylic acids, common interference signals in negative ion CIMS, outgassing from e.g. Teflon tubing (Brown et al., 2015;Ehn et al., 2012;Heinritzi et al., 2016). The exact source of these products in our setup was not established, but it is not surprising that the additional valves, filters and/or tubing in the zeroing line could have caused this type of signal to be introduced to the instrument with the zero air. In general, this finding highlights the usefulness of the binPMF approach, where factor separation can be performed first, and the specific factor profiles can be utilized in interpreting the physical meaning of the different factors. This is in complete contrast to the more traditional approach, where all ions need to be identified first, and only then can HR PMF be attempted. As not all ions are going to be observable at all times, many ions may remain unidentified. For example, if peak identification would only have been done during periods when the HOM signals were high, as in the case shown in Figure 9a, the fluorinated ion at 339 Th would not have been found (contributing only 0.45% to the total signal at this time point), even though it on average contributes nearly 10% of the signal at this mass over the entire campaign. binPMF, on the other hand, utilized the full dataset for the identification, and was able to separate several ions at 339 Th. By fitting gaussian signals to the factor profiles, similar to the synthetic data in section 3.1.2, we see that the two major peaks were fitted with decent resolution (Figure 9). Also the contamination factor (Factor 6) was clearly separated and fitted, and the resolution (3136 Th/Th) is slightly underestimated by the fit, as only one gaussian was fitted to each profile, yet there are clearly more than one ion at 339 Th in Factor 6. As shown in Figure 9c,

there is also clear indication that Factors 3 and 5, which together make up as much signal at 339 Th as the contamination Factor 6, mainly contain signals from another molecule ($C_{10}H_{13}O_9$) than the dominant signals at this mass ($C_{10}H_{15}NO_8$). However, further work will be needed to validate this. Factor 1 has marginal contribution to the signal at 339 Th (as seen in Figure 9b) throughout the campaign, and we expect it does not contain useful signal, as is suggested by the unreasonably high resolution, i.e. narrow peak width, of the fitted peak. The resolving power of the instrument was around 4000 Th/Th, and thus any apparent peak resolution above that will be unrealistic. However, as this factor contains signal at the outer edges of the main peaks at this *m/z*, it is possible that this factor relates to some instrumental variability affecting the peak shape. This is highly speculative, but such a phenomenon may be worth looking into in later studies utilizing binPMF. In summary, resolving multi-overlapping peaks by traditional methods is time-consuming and can be tricky and ambigous. Here, binPMF greatly simplified this problem, by providing additional separation between the ions.

### 3.3. Future improvements and applications

The new technique for mass spectra analysis, binPMF, as presented above, shows clear promise in utilizing HR information while saving time and effort, as well as decreasing ambiguity related to conventional HR peak fitting. It is also more sensitive to subtle variation than standard UMR analysis. We consider this study a succesful proof-of-concept, and note that several future improvements and applications are still foreseeable. We list some of these below:

(1) **Varied bin width.** The full width at half maximum of an individual peak in a mass spectrometer is mass dependent, with peaks getting wider at higher masses. In binning the mass spectrum with a constant bin width, like in this study, the average number of bins per peak increases as a function of mass. To represent the peaks in a comparable manner, the bin width should thus be dependent on the mass. Varying the bin width as a function of the mass, and the mass resolution of the instrument, would enable a constant number of bins (e.g., seven) per peak. Too few bins per peak would mean that we may lose valuable information in the binning, and potentially risk introducing aliasing effects, while too many points per peak would lead to an unnecessarily high number of variables, without noticeable gain in information content. This would also result in high computational cost. If targeting 7 bins per peak, then the function for determining bin width based on *m/z* and resolution (R, which is mass-dependent) could be

$$\because \quad R\ (m/z) = \frac{m/z}{\Delta m}$$

$$Bin\ width\ \times 7 = 2 \times \Delta m$$

$$\therefore\ Bin\ width = \frac{2}{7} \times \frac{m/z}{R(m/z)}$$

$\Delta m$ is the full peak width at half maximum signal intensity. If we consider an instrument with approximate constant resolution of 5000 Th/Th for masses from 200 Th to 600 Th, the bin width at 200 Th and 600 Th should be around 0.01 Th and 0.03 Th, respectively.

(2) **Optimization of binning region**. Similarly to bin width, the binning region, i.e. the signal region ([N-0.2,N+0.3] in this study, introduced in section 2.2), should also be mass-dependent. Due to the widening of the peaks with increasing mass, the binning region should also get wider. In addition, the typical mass defect of measured ions typically varies with mass. This means that the binning regions should not necessarily be defined with respect to the integer masses, but to some chosen mass defect. Another approach would be to bin all the data, and remove the bins not meeting a certain criterion, such as one related to the signal to noise ratio in that bin, afterwards. In this case, there would be no need for a pre-defined mass defect or region width, and one could utilize the signals that do not fall within the expected regions.

(3) **Error estimation.** Good error estimation is crucial to PMF calculation. Uncertainty in PMF analyses arises from three main causes, random errors in data values, rotational ambiguity, and modeling errors (Paatero et al., 2014). Variations in mass calibration are one example of a modeling error. It is common practice to increase uncertainty values $s_{ij}$ specified for data values disturbed by modeling errors. This increase does not account for the mass calibration error in the sense that the effect of mass calibration variation would disappear. The increase simply balances residuals in different data values so that the best possible result may be obtained. In addition to the two error estimation terms discussed in section 2.3, $\sigma_{ij}$ and $\sigma_{noise}$, a third form of error, ~~caused by~~to balance the mass calibration variation could also be considered for error estimation.~~.~~ Similarly, although generally rare and suggestive of some instrumental problem, if the peak shape or resolution shift over time, this would also require an improved error estimation in order to account for increased variability.

(4) **Multi-peak fitting.** As discussed, peak identification is one of the most time-consuming and potentially ambiguous tasks in HR analysis, and with binPMF this may not always be a necessary task. However, as binPMF often resolves several peaks (chemical components) at each integer mass, peak identification can be made easier if peak identification is constrained to several binPMF factor profiles rather than just the initial HR spectrum. The optimal approach for this will be the target of a future study.

Most likely several other improvements to the approach will be identified in future studies, and simplicity of the analysis remains a critical consideration. We propose that binPMF is a good tool for initial exploration of new datasets, at which stage optimizing all parameters is not necessarily crucial, if the results can help guide further analysis directions. However, for maximizing the information content that can be extracted from a given data set, optimized routines are important.

## 4. Conclusions

While recent advances in mass spectrometry have greatly enhanced our understanding of atmospheric chemistry, the increased information content in mass spectra also brings difficulties and challenges to the data analysis. Peak identification and separation can be challenging and ambiguous, as well as extremely time-consuming and involving large uncertainties. Constructing peak-lists, i.e. deciding which ions to fit to the mass spectra, and validating the results is becoming one of the most labor-intensive parts of the entire work. In this study, we propose a simple and reliable method, binPMF, to try to avoid many of these problems, while still being able to distinguish different chemical pathways/sources in the atmosphere.

Different from traditional analysis, binned positive matrix factorization (binPMF), divides the mass spectra into smaller bins, before applying PMF to distinguish different types of factors and behavior in the data. This method utilizes more available information than classical UMR-PMF, and requires no prior peak information as in the case of traditional HR-PMF. We applied binPMF successfully to both ambient and synthetic datasets to test its usefulness under different circumstances.

Traditional HR analysis fits peaks to each mass according to a pre-defined list, and is not able to utilize any information across masses or time. In our analysis of a simple synthetic data set with two overlapping ions at a single integer mass, we found that binPMF was able to separate the contributions of each ion even in cases where the HR analysis failed completely. This was the case for overlapping ions where binPMF had help in constraining the time series from another integer mass. When applied to an ambient dataset of HOM measured by a CI-APi-TOF, binPMF identified more physically meaningful factors than UMR-PMF. Additionally, for factors where the two PMF approaches agreed, binPMF still contained more mass spectral information for ion identification, as compared to UMR-PMF.

We provide a proof-of-concept for the utility of binPMF, showing that it can outperform the two traditional analysis approaches, UMR and HR. We identify several future improvements and applications for binPMF, including an approach to greatly facilitate the time-consuming process of peak-list construction. We expect binPMF to become a powerful tool in the data exploration and analysis of mass spectra.

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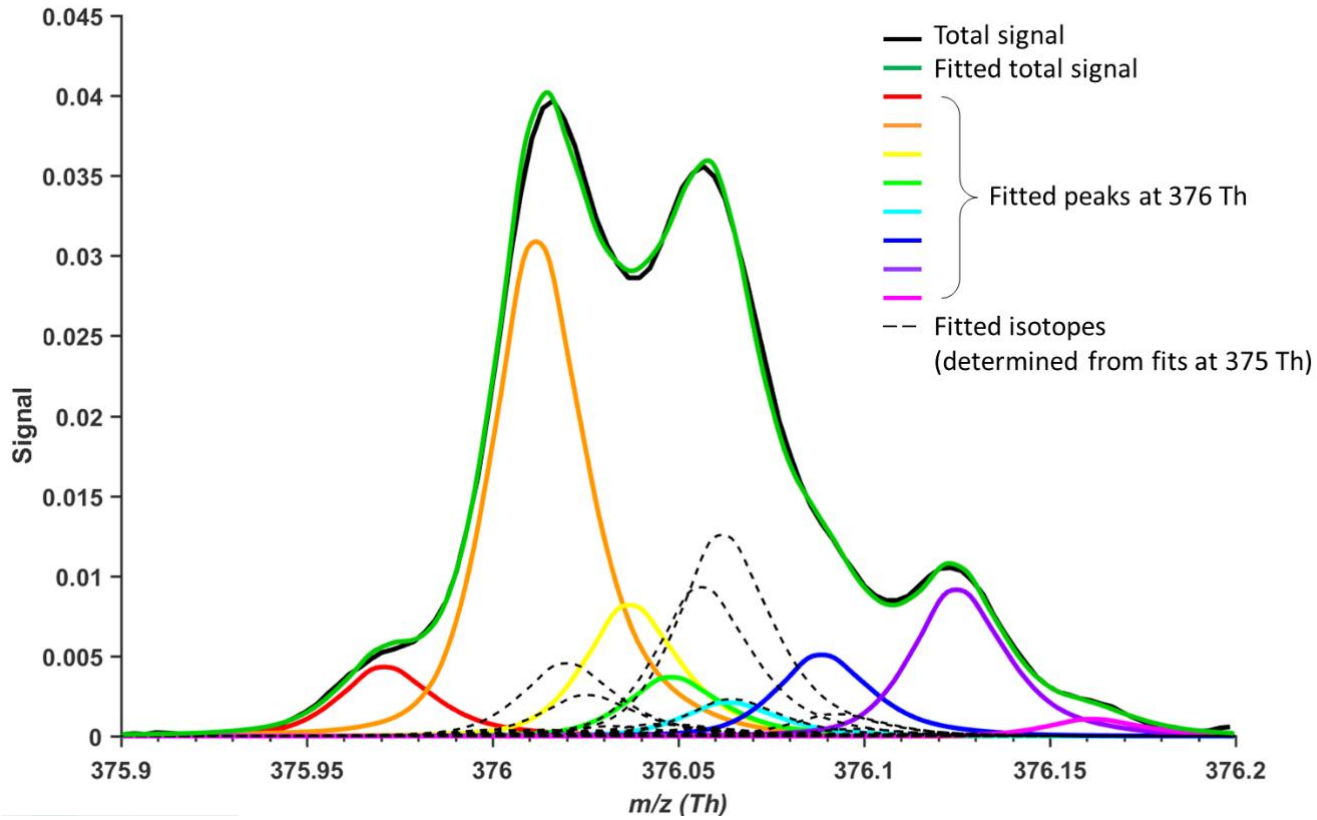
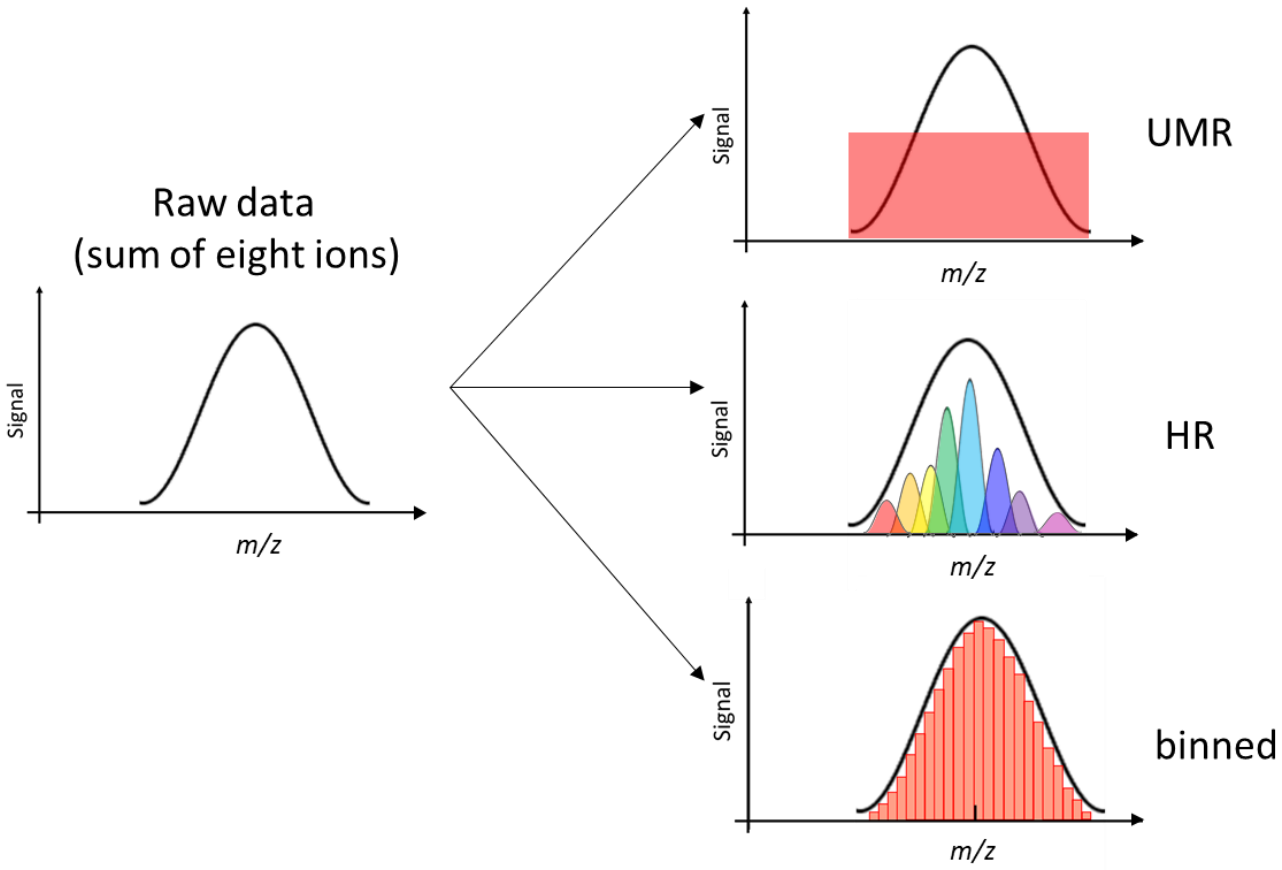



Figure 1. Example of traditional HR peak fitting. Potential peak fitting at *m/z* 376 Th (10-h average) in an atmospheric simulation chamber during a monoterpene ozonolysis experiment, utilizing a nitrate-based CI-APi-TOF (resolving power of 13000 Th/Th). Even a minor shift in the mass axis calibration could cause the signals of especially the yellow, green and blue peaks to change dramatically. Similarly, adding or removing an ion would alter the amount of signal attributed to the other fitted peaks.




602

603 Figure 2. Conceptual comparison of traditional methods (UMR and HR) and binned mass spectra for
604 PMF analysis. The raw data signal is shown in the left and contains eight ions. By UMR analysis, the
605 information of the eight ions is totally lost. Using an analyst-determined peak-list, HR analysis
606 attempts to separate signals at this mass by fitting selected ions. By binning the spectra, we utilize the
607 HR information without any a priori information required.

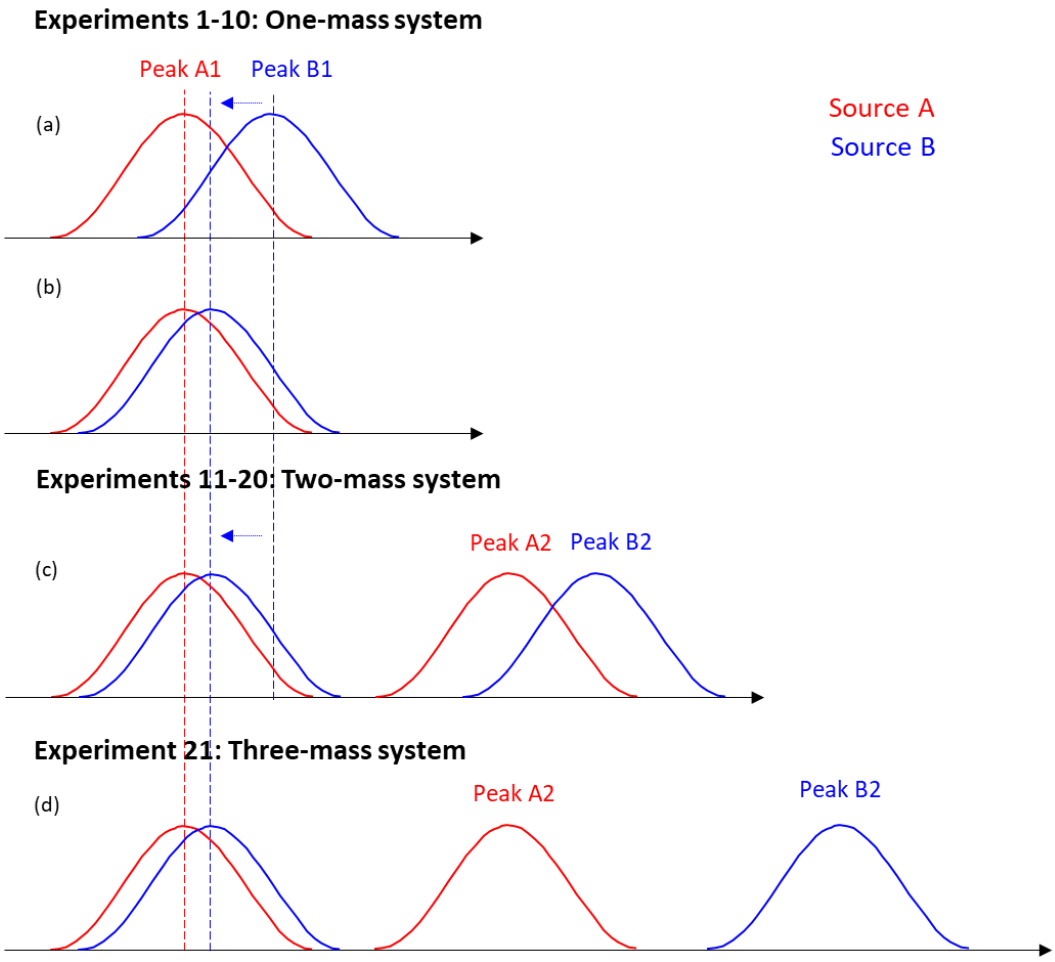



Figure 3. Conceptual schematic diagram for the synthetic datasets. Panels a and b describe experiments 1-10 in the one-mass system, panel c is experiments 11-20 in the two-mass system. Panel d shows experiment 21, with peaks A2 and B2 at separate integer masses (see text for details).

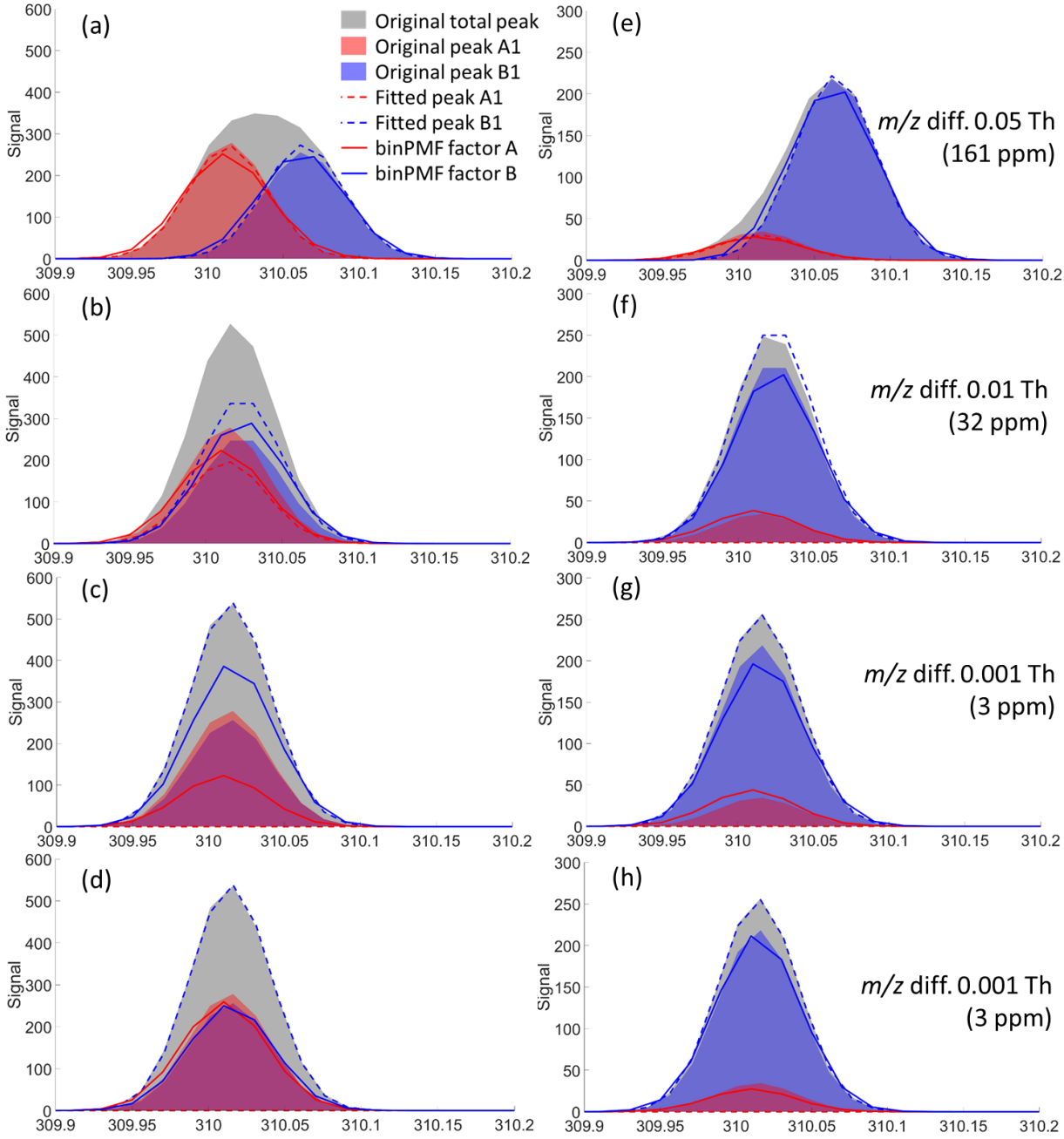



Figure 4. Peak separation results by a traditional HR fitting method (dashed lines) and binPMF (solid lines), at the 79$^{th}$ time point (panels a-d) and at the 21$^{st}$ time point (e-h) for experiment numbers 1 (a, e), 5 (b, f), 10 (c, g), and 20 (d, h). The signal intensity ratio of peaks A1 and B1 were about 1:1 and 1:6, respectively, at the 79$^{th}$ and the 21$^{st}$ time points. Panels a-c and e-g are for the one-mass system, while panels d and h are for the two-mass system.

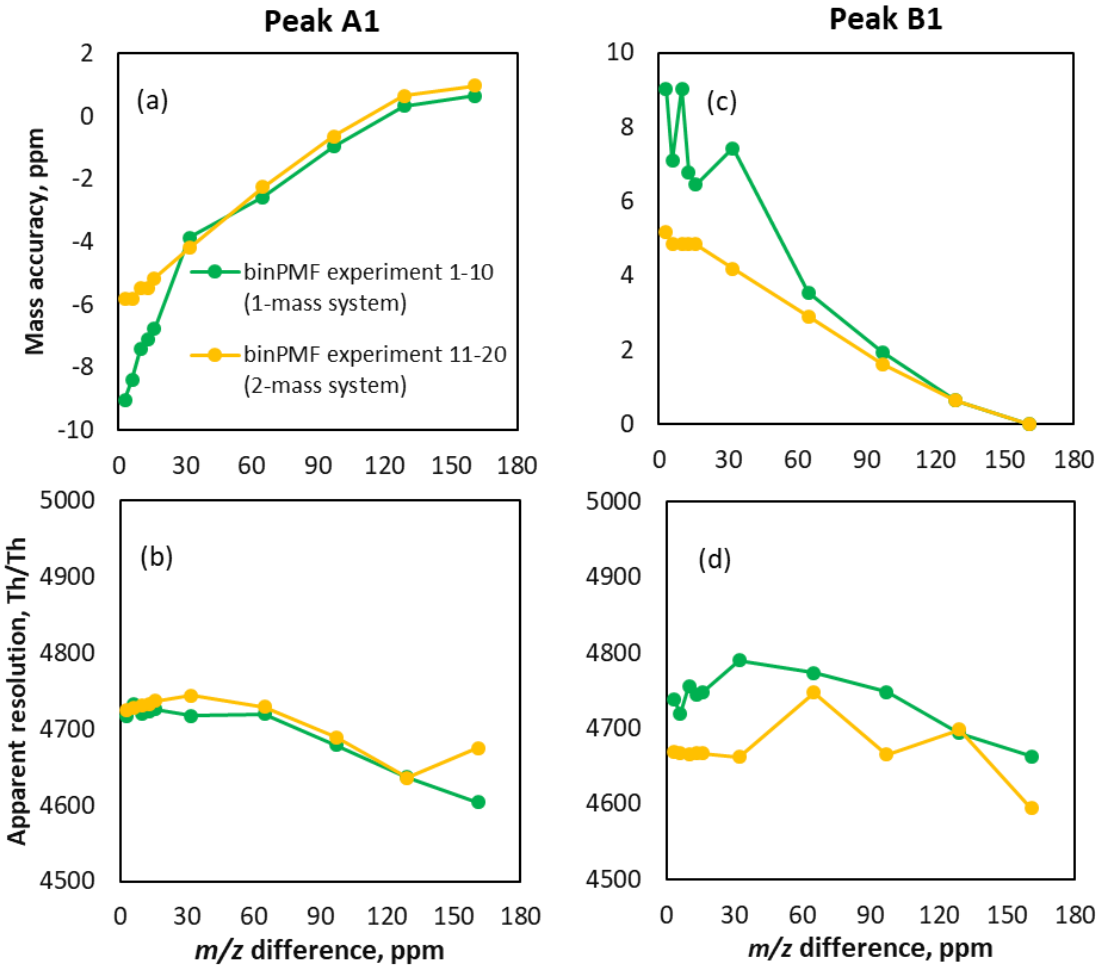
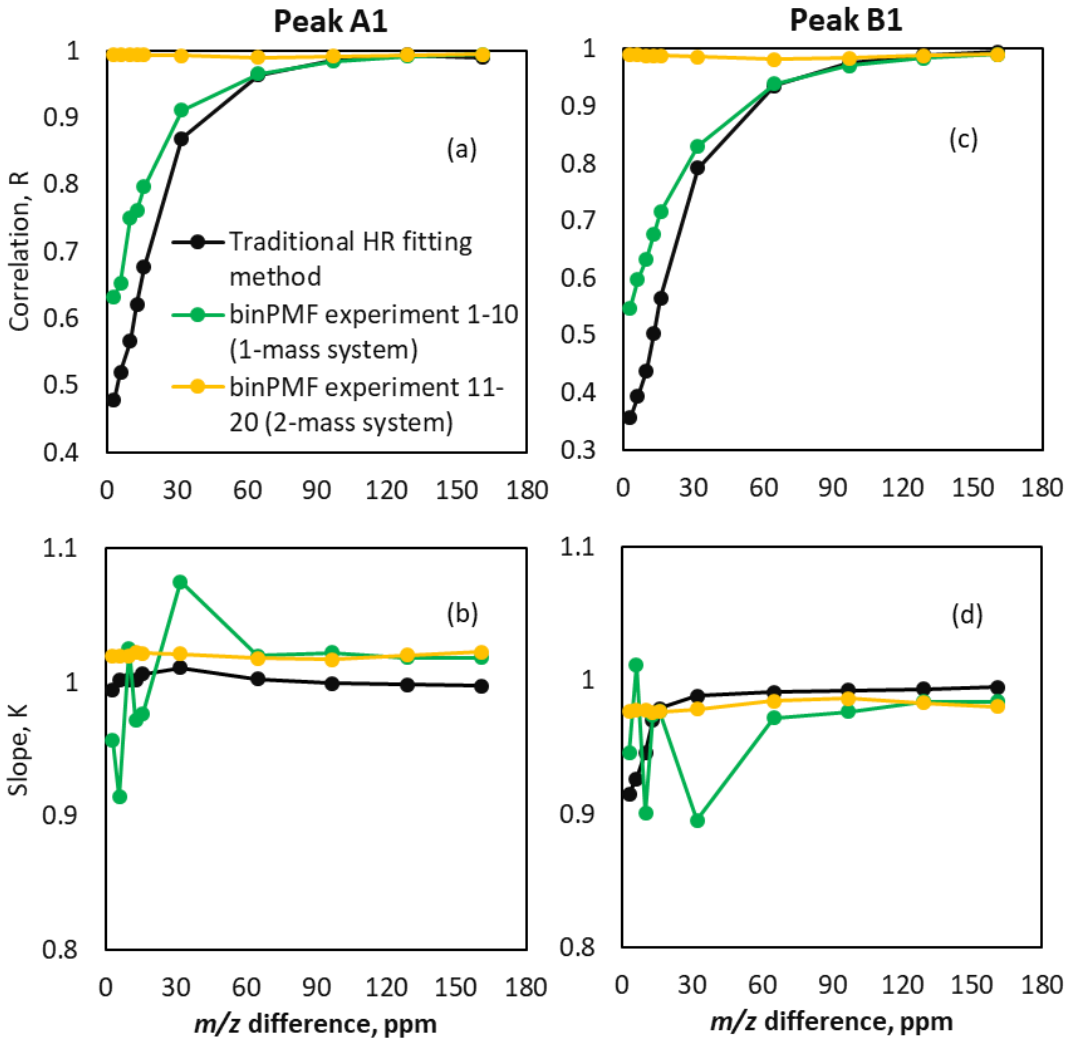
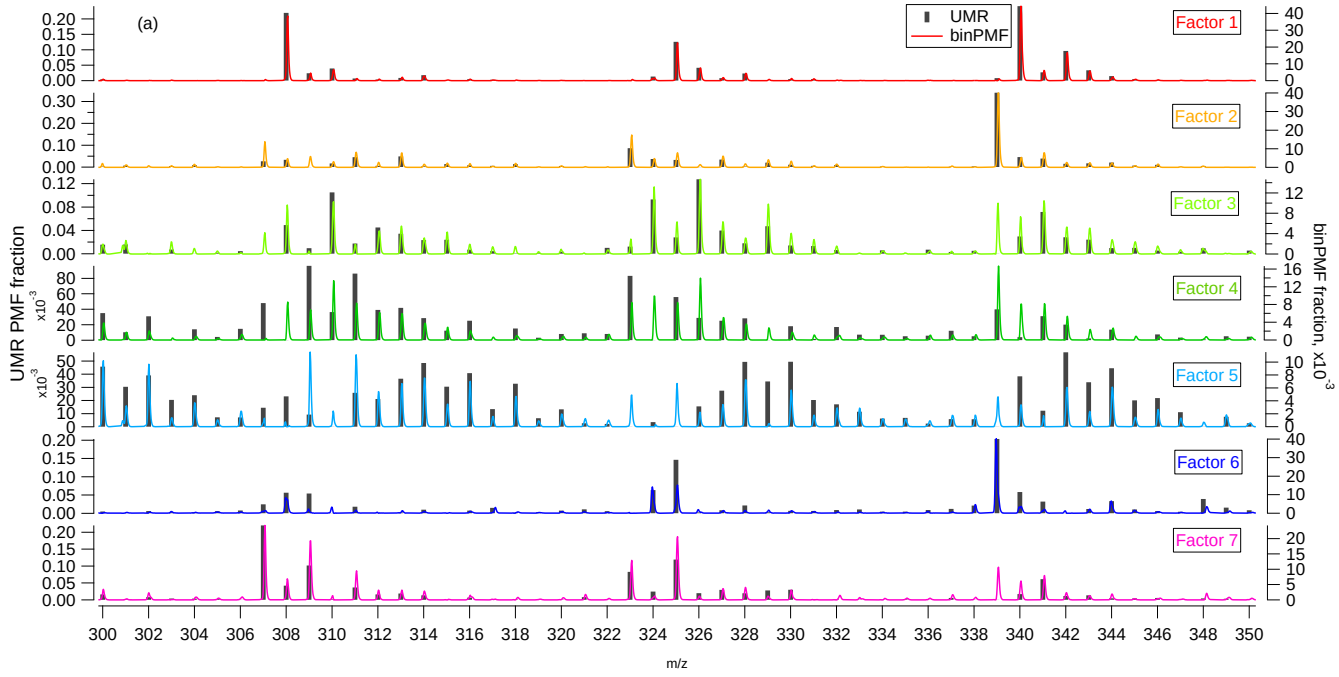



Figure 5. Characteristics of peaks fitted to binPMF factors. Panel a and b show results for peak A1, and c and d for peak B1. In panels a and c, the mass accuracy of peaks resolved by binPMF are compared to the original data. Panels b and d depict the resolution of the two fitted peaks. The original resolution of the input data was 5000 Th/Th.




623

624 Figure 6. Comparison of time series of binPMF and HR fitting. Panel a and b show results for peak
625 A1, and c and d for peak B1. Correlation of time series (panels a and c) retrieved by binPMF (green
626 lines for experiments 1-10, yellow for 11-20) and traditional HR fitting (black lines) compared to
627 original input data. Panels b and d depict the slope K of the linear fit y = k×x, where y is the signal
628 retrieved from the synthetic data by either binPMF or the HR fitting, and x is the original input signals.



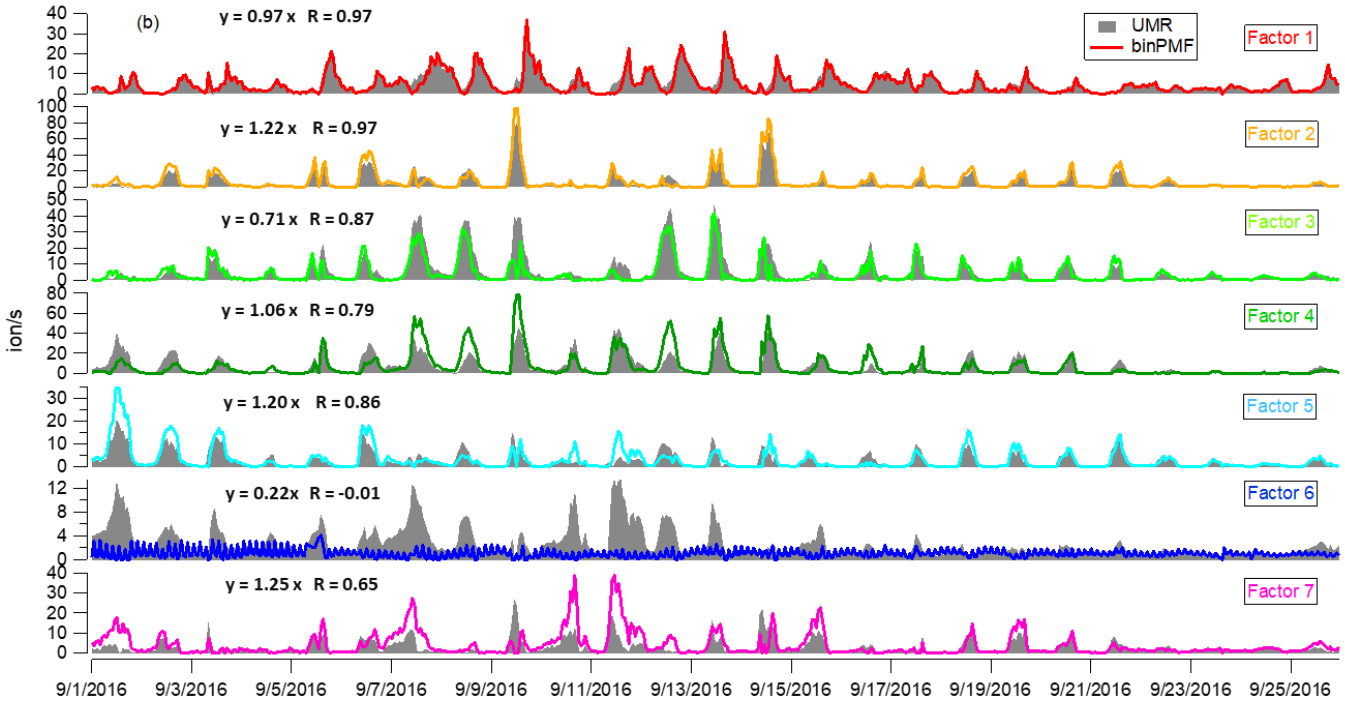
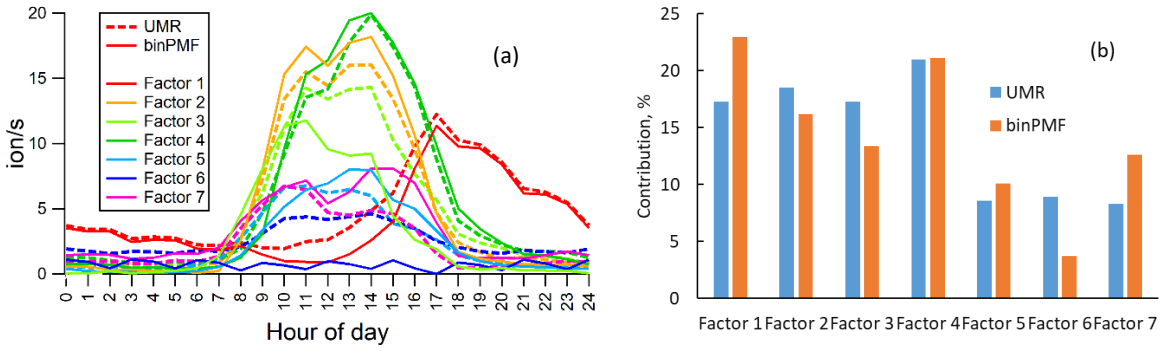




Figure 7. Comparison of binPMF and UMR-PMF for factor mass spectral profiles (panel a) and time series (panel b). The equations in each panel describe how signals from binPMF (y) compare with the UMR-PMF solution (x). R is the correlation coefficient between the time series.

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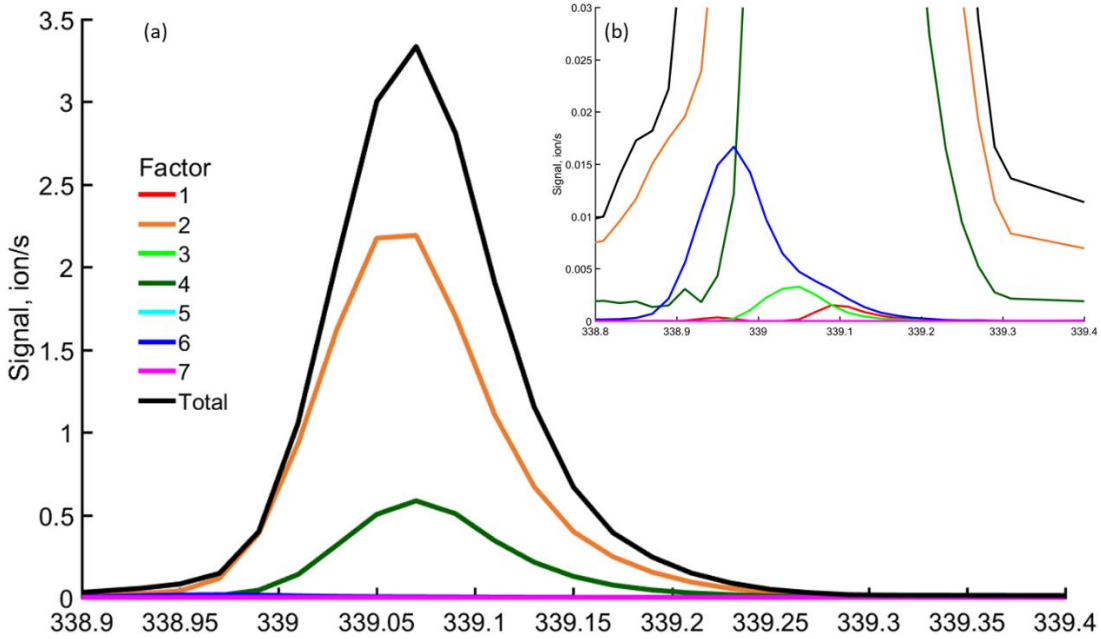
635 Figure 8. Comparison of binPMF and UMR-PMF for (a) diurnal trend and (b) factor contribution

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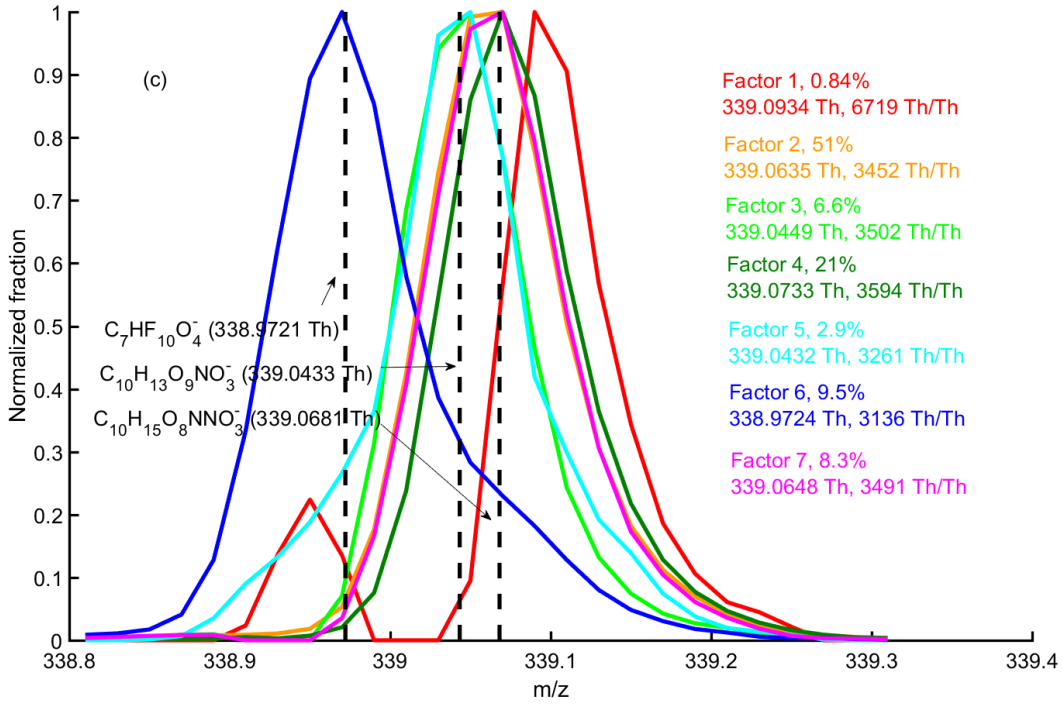


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638 Figure 9. binPMF factor profiles at m/z 339 Th at 12:00 on September 9th. Panels a and b show the
639 absolute concentrations of each factor, while in panel c, the factor profiles are normalized to the same
640 maximum peak heights. The fitted peak location (Th) and the apparent resolution (Th/Th) for each
641 factor is given in panel c,. The contribution of different factors to the integer *m/z* 339 Th is shown as
642 a percentage. Three potential chemical compositions were marked with black vertical dashed lines.

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