

Bayesian estimation of predator diet composition from fatty acids and stable isotopes

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Abstract

Quantitative analysis of stable isotopes (SI) and, more recently, fatty acid profiles (FAP) are useful and complementary tools for estimating the relative contribution of different prey items in the diet of a predator. The combination of these two approaches, however, has thus far been limited and qualitative. We propose a mixing model for FAP that follows the Bayesian machinery employed in state-of-the-art mixing models for SI. This framework provides both point estimates and probability distributions for individual and population level diet proportions. Where fat content and conversion coefficients are available, they can be used to improve diet estimates. This model can be explicitly integrated with analogous models for SI to increase resolution and clarify predator-prey relationships. We apply our model to simulated data and an experimental dataset that allows us to illustrate modeling strategies and demonstrate model performance. Our methods are provided as an open source software package for the statistical computing environment R.

Keywords Stable isotope analysis, quantitative fatty acid analysis, QFASA, lipid profile, diet analysis, Bayesian mixing model, fatty acid signature, dietary marker

1 Introduction

Quantitative estimates of an animals diet are a critical component of predator-prey studies, ecosystem models, and ecosystem-based management. Existing methods of estimating diet proportions all have strengths and weaknesses (Bowen & Iverson, 2012). Traditional stomach content and fecal matter analysis represent a brief snapshot of diet at a particular place and time and can be invasive, time-consuming, and potentially biased by differential rates of digestion of prey or ingestion of identifiable prey parts (Bowen & Iverson, 2012). Chemical markers such as stable isotopes (SI) and fatty acid profiles (FAP) solve some of these problems. For example, both approaches integrate diet composition over an extended time period - typically weeks to months, depending on tissue turnover rates (Tucker *et al.*, 2008). These advantages have led to rapid growth in the use of chemical markers in diet studies (Bowen & Iverson, 2012; Elsdon, 2010; Kelly & Scheibling, 2011; Williams & Buck, 2010). However, chemical dietary markers generally lack the specificity of traditional stomach content analysis. In particular, several prey species often have similar isotopic signatures. More recent studies have sought greater dietary resolution through the use of SI of other elements in addition to carbon and nitrogen (Belicka *et al.*, 2012), compound specific SI

41 ratios (Budge *et al.*, 2008; Jack & Wing, 2011), or a combination of
42 stomach content analysis and SI or FAP (Pethybridge *et al.*, 2012). The use
43 of SI and FAP in combination also holds great promise; however the few
44 studies to date that have used both chemical markers have been qualitative
45 (Guest *et al.*, 2009) or based on positive correlation of results from both
46 methods (Tucker *et al.*, 2008).

47 Analysis tools for SI data have become very sophisticated in recent years,
48 starting with the development of general Bayesian analysis tools for
49 estimating diet proportions, and leading to customized (hierarchical)
50 models for individual applications (Hopkins & Ferguson, 2012; Moore &
51 Semmens, 2008; Parnell *et al.*, 2012). The latter models can, for instance,
52 estimate dietary differences of geographically distinct populations
53 (Semmens *et al.*, 2009), accommodate temporal changes in diets or estimate
54 the effect of covariates (e.g., age, size, sex) on diet proportions (Parnell
55 *et al.*, 2012). While these models provide a considerable step towards
56 ecologically relevant models in diet studies, the underlying SI data is
57 limited in the resolution that it can provide. Since typically only 2-3 SI are
58 measured, the contrast that is achievable from such a low number of
59 variables is necessarily limited, especially when the number of potential
60 prey items increases (Phillips & Gregg, 2003; Ward *et al.*, 2011). Optimally

61 aggregating prey items into prey groups may circumvent this problem
62 (Ward *et al.*, 2011), but may also be less satisfactory in complex food webs.
63 FAP data can, in theory, provide considerably more resolution compared to
64 SI data, due to large number of potential fatty acids that can be measured.
65 Nevertheless, studies employing FAP are either qualitative in their
66 estimates of prey proportions in predator diets, or use Quantitative Fatty
67 Acid Signature Analysis (Iverson *et al.*, 2004) to obtain quantitative
68 estimates of diet proportions. The latter method is the only one available
69 thus far for use with FAP data, and, in contrast to recent (Bayesian) SI
70 mixing models, relies on a distance metric rather than a model based
71 formulation to estimate the most likely diet proportions. This framework
72 provided the first quantitative approach to estimating diet proportions
73 using fatty acids and it has already seen widespread use, particularly in
74 studies of marine mammals (Bowen & Iverson, 2012) and seabirds
75 (Williams & Buck, 2010). Nevertheless, QFASA has a number of
76 limitations. Since it is not based on a probabilistic model, it is difficult to
77 estimate uncertainty associated with estimated diet proportions (Williams
78 & Buck, 2010). The absence of an explicit model also makes it impossible
79 to build ecological mechanisms (e.g., covariates of consumed diets) directly
80 into the model. Furthermore, uncertainty about conversion coefficients

81 representing enrichment and preferential uptake of fatty acids cannot be
82 considered, yet small changes in these coefficients can lead to differences in
83 inferred diet proportions (Wang *et al.*, 2010). Lastly, the QFASA model
84 assumes constant fat content of consumed items, an assumption that will
85 rarely be met.

86 Given the discrepancy in methods applied to SI and FAP data, it is
87 perhaps not surprising that their joint application has commonly relied on
88 qualitative comparisons. Because both markers integrate diet composition
89 over often comparable time-scales, however, an explicit integration of these
90 data types could provide substantial benefits. While FAP data could
91 mitigate the resolution problem in SI data, SI data could provide increased
92 resolution and clarify predator-prey relationships, the knowledge of which is
93 usually a pre-requisite for FAP data. For example, for many non-modified
94 fatty acids, FAP alone cannot discriminate between the case of two species
95 which share a common diet and the situation in which one of these species
96 eats the other. In either case, the two species may have similar FAP. The
97 addition of a stable isotope with trophic fractionation (e.g., ^{15}N), however,
98 can readily distinguish predation from dietary overlap.

99 Here, we present a mixing model for FAP data based on a probabilistic
100 model whose parameters are estimated using Bayesian methods. We

101 demonstrate the suitability of this model for FAP analysis and highlight the
102 potential benefit of explicit integration with SI data to increase the
103 precision of diet estimates. Using both simulated and published data, we
104 show how this model can be extended to ask ecologically relevant questions.

105 **2 Methods**

106 **2.1 A Bayesian mixing model for FAP**

107 Bayesian models for SI data are commonly based on the assumption that SI
108 ratios are normally distributed. This assumption cannot be made for FAP
109 data, since for most methods of analysis, the concentration of individual
110 fatty acids is normalized to the total lipid content of the sample. Thus, the
111 FAP are a collection of proportions (referred to as a composition), which lie
112 between 0 and 1, and are constrained to sum to 1. A common solution to
113 this problem, however, is to consider transformations that make the data
114 approximately normal (Budge *et al.*, 2006). To construct our model, we
115 followed Aitchison & Bacon-Shone (1999) and considered a log ratio
116 transformation, also called alr transformation, such that

$$y_i = alr(\phi_i) = \log \left(\frac{\phi_{i,1...p-1}}{\phi_{i,p}} \right) \quad (1)$$

117 where y_i is the p -variate fatty acid composition of individual i or prey
 118 species s , with $i = 1...n$. We then assumed that the distribution of y is
 119 multivariate normal, with species specific mean μ_s and covariance matrix
 120 Σ_s , or $y \sim N(\mu_s, \Sigma_s)$. A vaguely informative prior on μ_s and Σ_s allows for
 121 uncertainty in prey distributions (Ward *et al.*, 2010) to propagate to
 122 estimates of diet proportions.
 123 Each predator j consumes a proportion π_j of each prey source, and
 124 analogous to stable isotope mixing models, predator FAP are then a linear
 125 combination of prey FAPs, normalised to sum to one. Since predators may
 126 selectively assimilate or metabolize fatty acids (Budge *et al.*, 2006; Iverson
 127 *et al.*, 2004; Rosen & Tollit, 2012), we specify prey-specific conversion
 128 coefficients $\kappa_i = \kappa_{i,1}... \kappa_{i,p}$ (Rosen & Tollit, 2012). Furthermore, the n prey
 129 species likely have different fat content Φ that will affect the relative
 130 amount of fatty acids assimilated by the predator. The FAP of predator j
 131 is then a linear combination of the prey FAP, modified by conversion
 132 coefficients for each fatty acid p and fat content for each prey i . The

signature of predator j is then:

$$\tau_j = C \left\{ \sum_i (\pi_i \Phi_i) (\kappa_i \otimes \phi_{i,j}) \right\} \quad (2)$$

Here, C is the closure operation which normalizes the FAP to sum to one, is the outer (element wise) product, are the diet proportions of predator. We again assume that predator signatures are normally distributed after transformation, with mean and covariance matrix. More complex error formulations including measurement error and prey covariances are possible (Hopkins & Ferguson, 2012), but we restrict ourselves here to a simple formulation that does not depend on prey variances. We assume that and are log-normally and gamma distributed around known mean and variance values (estimated or calculated from controlled diet experiments, see below). Since the sum-to-one constraint on the FAP leads to κ being only determined in terms of relative uptake of fatty acids, we add a sum to one constraint to κ , thus restricting the scale (and implicitly making the overall distribution of κ a Dirichlet distribution). While other parameterizations could be formulated here, we found that the above formulation works well in practice, and makes it straightforward to calculate prior parameters from

149 mean and variance values found in controlled experiments.
 150 The diet proportions predators are the main focus of investigation in diet
 151 studies. It is equally possible to estimate individual diet composition by
 152 simply If data from individual predators are available, but the focus
 153 remains on population level parameters, it is generally advantageous to
 154 model individual as draws from a population level distribution of diet
 155 proportions . Recent approaches to stable isotope mixing have focused on
 156 transformations of to get around the problems associated with the
 157 compositional nature of the diet proportions. This approach is analogous to
 158 that taken in our model for compositional FAPs. The diet proportions are
 159 transformed such that the support of is the real line rather than the
 160 interval $[0;1]$. It is then straightforward to model diet proportions as
 161 function of covariates, such as size, sex, or region (i.e., in a regression
 162 formulation). While this approach is obviously appealing, it adds
 163 considerably to the run-time of Markov Chain Monte Carlo Procedures
 164 employed to estimate model parameters. We therefore use a vague Dirichlet
 165 prior on the proportions when convenient (e.g., when we estimate only
 166 population level parameters), and in our simulations (e.g., Semmens et al.
 167 2009). When estimating individual parameters or for linear model
 168 formulations (see Application 1), a clr transformation approach is used.

169 When estimating population level parameters, the two formulations give
170 near identical results (differences are within the range expected from
171 stochasticity in the MCMC samples).

172 **2.2 Joint diet estimation from FAP and SI**

173 Above, we mentioned three potential benefits of integrating FAP and SI
174 data: i) increased information to discriminate among sources, ii) the
175 potential of SI to resolve predator prey relationships due to trophic
176 enrichment of SI, and iii) the potential reduction in estimation error due to
177 more well-known fractionation coefficients for stable isotopes. It thus
178 appears worthwhile to integrate these types of data in a single model to
179 estimate diet proportions. Our model is conceptually similar to recent
180 models proposed for SI data, and integration of FAP and SI data into a
181 single model is straightforward in the present setting. We again assume
182 that the SI signatures of prey items follow a normal distribution, such that
183 δ^{SI}_i , where the superscript SI denotes that these are stable isotope signatures.
184 Predator SI signatures are again a linear combination of prey SI, this time
185 modified by additive fractionation coefficients and, potentially, by prey C
186 and N concentrations (and/or digestibility, see CITE) . The SI signatures
187 for predator j is then

188 The exact formulation of this integration depends on the assumptions that
189 one is comfortable with in a given setting: identical dietary proportions
190 may be appropriate if diets (and hence SI and FAP) are thought to be
191 stable, or if both chemical tracers are thought to integrate over similar
192 time-scales. If the time scales of these two elements are thought to be
193 different, individual diet proportions for each tracer may be more
194 appropriate, and may be drawn from an overall population distribution of
195 diet proportions. Our models were implemented in JAGS (Plummer *et al.*,
196 2003), called from the statistical computing environment R (R Core Team,
197 2014). Code and data for all models, examples and tutorials are available
198 on the open source repository github.com/philipp-neubauer/fastinR. The
199 models include the above-mentioned formulations for individual diet
200 estimates, population level estimates or both as well as linear model
201 (regression and anova) formulations for diet proportions.

202 **2.3 Simulation studies: accuracy and sensitivities**

203 We explored sensitivities of inferred diet proportions to the source
204 configuration and fatty acid subset selection in a series of simulation
205 experiments. We simulated 100 datasets and varied source separation and
206 the subset of fatty acids retained for the analysis of simulated datasets.

Each dataset was analyzed with subsets retaining 75%-99% of between source variability on the CAP axes, and errors in inferred diet proportions (taken to be the posterior mean of inferred diet proportions) were compared among subsets. We then determined the sensitivity of estimated diet proportions to source separation, collinearity in FAP space and diet evenness (e.g., specialist versus generalist diets). Simulation setup and results are presented in detail in Appendix 1 & 2. To illustrate our method, we also include a simple simulated study, which can be repeated in its entirety from Appendix 3 (this file can also be downloaded as a source file from our project repository).

2.4 Application: Estimating predator diets in a controlled experiment

In this application, we use data from an experimental study published by Stowasser *et al.* (2006), which investigated changes in squid FAP and SI as a function on diet treatments. The treatments consisted of exclusive fish and crustacean diets, as well as switched and mixed diets, with the former switching diets from fish (henceforth SF) to crustacean (SC) after 15 days of the 30 day experiment. In our analysis, we analyzed samples from the switched diet treatments, and used both SI and FAP to investigate whether

226 we can infer diet proportions in either treatments. Since we only had SI for
227 the SC treatment squid, we start by analyzing this treatment in isolation to
228 demonstrate that both SI and FAP can resolve diet proportions, and to
229 demonstrate the benefit of using the two tracers in a joint model. We then
230 analyze the SF and SC treatment squid together in a linear model setup
231 that investigates treatment differences explicitly, and demonstrates how the
232 model based approach to diet estimation can be use to answer ecologically
233 relevant questions about predator diets.

234 In order to apply our model, we first estimated conversion coefficients of
235 FAP and fractionation in SI, using squid from the 30 day diet treatments
236 feeding exclusively crustacean and fish diets. The model for estimation of
237 SI fractionation followed the model in Hussey *et al.* (2014), and used their
238 results as priors for fractionation parameters for $\delta^{15}N$, and results from
239 Caut *et al.* (2009) to construct priors for $\delta^{13}C$. Estimation of FA conversion
240 coefficients used eq 1 with proportions assumed known from feeding trials.
241 Further details on the estimation of conversion coefficients and
242 fractionation is given in Appendix 4.

243 **3 Results**

244 Simulated test cases and our application to squid diets suggest that our
245 model can estimate diet proportions with high accuracy from both SI and
246 FAP, with accuracy depending mainly on source separation and diet
247 evenness (Appendix 1 & 2). These examples further suggest that our
248 selection procedure for FAP works well, allowed models at a fraction of
249 computational cost with little expected loss in accuracy (Figure S1). At
250 very uneven diet proportions, such as in the feeding trials analyzed in the
251 squid example, we found the choice of point estimate for diet proportions
252 inevitably introduced increased error at the margins of the 0-1 proportion
253 interval. This is due to posterior distribution becoming more skewed
254 toward the limits of this interval, and the mean and median, which are
255 intuitive choices for point estimates in symmetrical posteriors, are often
256 placed in relatively unlikely regions of parameter space.

257 **4 Discussion**

258 We presented here a first and very general framework that combines SI and
259 FAP in an extendable, contemporary Bayesian mixing model. While an
260 increasing number of studies combines these two tracer methods (Bank

261 *et al.*, 2011; Guest *et al.*, 2008; Guest *et al.*, 2009; Jaschinski *et al.*, 2008;
262 Stowasser *et al.*, 2006; Tucker *et al.*, 2008), we believe that none have done
263 so in an explicitly quantitative way. Indeed, both approaches have their
264 own limits, and, as mentioned above, their combination may help to
265 overcome each tracers shortcomings. We thus suggest that our study and
266 framework provide a substantial step towards building application specific
267 models that explicitly integrate SI and FAP to achieve robust inference of
268 diet proportions and highlight discrepancies in the two methods that need
269 to be addressed through future research.

270 Recent developments in SI mixing models have led to increasingly realistic
271 models in terms of their error structure (Hopkins & Ferguson, 2012) and
272 incorporation of relevant biology, such as time dependent diet proportions
273 and SI signatures (Parnell *et al.*, 2012). Given that our FAP and combined
274 FAP and SI models are very similar to these models in terms of their
275 underlying structure and assumptions, such developments are readily
276 achievable within this framework. Nevertheless, it should be noted that
277 they present the practitioner with requirements for substantial amounts of
278 data of various kinds (i.e., measurement error estimates, collection of SI
279 and FAP through time, respectively).

280 When working in high dimensional applications such as FAP, where the

number of measured variables can be large (20 FAs is common), one has to balance computation feasibility and model complexity. We opted here for a fully Bayesian analysis that estimates prey and predator distributions, as well as individual proportions. This does not come without a cost: we found that there are limits to the dimensionality that the model (as we formulated it) can deal with. Since the model complexity depends at once on the number of prey items, predators and fatty acids in the analysis, we have found it to be useful to use predator means or relatively few predator signatures first to estimate a single population distribution. Once one has determined that the model can effectively estimate reasonable diet proportions, re-running the model with a larger number of predators is warranted and, although potentially time consuming, may provide additional insights. We also found that using clr (or related) transformations to estimate diet proportions on the real line (Parnell *et al.*, 2012) was a considerable computational burden, and we only used these formulations here when the model structure would not work without such a formulation (i.e., hierarchical models of diet proportions, or a linear model/anova for the diet proportions). Depending on modeling priorities, one may choose to only model predator means, leading to lower computational burden and the possibility to routinely use transformations

301 for diet proportions. Furthermore, more efficient implementations may be
302 possible with tailored and optimized MCMC approaches.

303 We presented an approach to variable selection for FAPs in order to further
304 reduce computational burdens of mixing models. Our suggested method,
305 based on CAP, provides a clear advantage over variable selection by
306 discrimination alone (e.g., by classification success in a linear discriminant
307 analysis). Discrimination is highest when the within class variance is lowest
308 relative to the between class variance. A trivial selection would thus be to
309 select a single FA that is slightly different among prey species, but has
310 minimal variance within species. While classification accuracy would
311 approach 100%, n (the number of prey items) would be greater than the
312 number of selected variables, such that there is no unique solution to the
313 diet estimation problem (Phillips & Gregg, 2003). We found that an
314 optimal subset of variables is usually one that explains the bulk of among
315 prey variance (represented by CAP axes), but eliminates FAs that only
316 contribute minimally to separation among sources. In this case estimation
317 errors may be lower than for the full data set.

318 We refrain from making estimates of relative or absolute error of the
319 proportions themselves, since these depend on the number and
320 configuration of sources in multivariate space in addition to the variance of

conversion coefficients. For many applications, conversion coefficients are not available and would be difficult to obtain, and it is important that practitioners are aware of the increased risk of making erroneous point estimates of diet proportions when setting conversion coefficients to 1. While a similar problem exists with SI fractionation coefficients, more is known about these coefficients, making it easier to construct reasonable priors. Combining SI with FAP may therefore have the additional benefit of reducing errors due to misspecified conversion coefficients.

. What else does this discussion need? A general strategy for modeling FAP and SI data Future research needs: discrepancies and overlap in SI and FAP data. we assumed they integrate over comparable periods and thus represent the same diet proportions CC for FAP desperate need for LOTS of controlled studies. But, when taking into account uncertainty, they are not the deal breakers they appear to be from using just point estimates.

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