

1 **Unlocking the potential of historical abundance datasets to study**
2 **biomass change in flying insects**

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4 Rebecca S. Kinsella¹, Chris D. Thomas¹, Terry J. Crawford¹, Jane K. Hill¹, Peter J. Mayhew¹
5 and Callum J. Macgregor¹

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7 ¹: Department of Biology, University of York, Wentworth Way, York, YO10 5DD

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9 *Running head: Predicting moth biomass from abundance*

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11 Corresponding author:

12 Callum J. Macgregor; tel: (+44) 01904 328632; email: callumjmacgregor@gmail.com.

13

14 **Abstract**

15

16 1. Insect abundance changes are well-established in some datasets, but far less is
17 known about how this translates into biomass changes. Moths (Lepidoptera)
18 provide particularly good opportunities to study trends and drivers of biomass
19 change at large spatial and temporal scales, given the existence of long-term
20 abundance datasets for moths. This requires estimation of the body mass of moths
21 sampled over time, but such data do not currently exist.

22 2. We collected empirical data in 2018 on the forewing length and dry mass of
23 sampled moths, and used these to train and test a statistical model that predicts the
24 body mass of moth species from their forewing lengths (with refined parameters for
25 Crambidae, Erebidae, Geometridae and Noctuidae). We tested the relationships
26 between biomass, abundance and species richness of samples of moths for our
27 2018 samples, and over a 16-year period using long-term historical moth data (with
28 model-estimated biomass) from a single site.

29 3. Modelled biomass was positively correlated with measured biomass of moth
30 species ($R^2 = 0.910$) and mixed-species samples of moths ($R^2 = 0.915$), showing
31 that it is possible to predict biomass accurately. Biomass correlated with moth
32 abundance and species richness in our 2018 data and in the historical dataset,
33 revealing biomass declined by 65.9 % over a 16-year period.

34 4. By allowing biomass to be estimated for historical moth abundance datasets, our
35 approach creates opportunities to investigate trends and drivers of insect biomass
36 change over long timescales and broad geographic regions.

37

38 **Keywords**

39

40 Biodiversity decline, body mass, forewing length, Lepidoptera, moths, predictive model

41 **Introduction**

42

43 Several recent studies have reported that insect biomass is in decline (Hallmann *et al.*, 2017;
44 Lister & Garcia, 2018; Sánchez-Bayo & Wyckhuys, 2019), but with substantial spatial and
45 taxonomic variation in the existence and strength of such declines (Shortall *et al.*, 2009). The
46 reasons for such variation are not yet known, and it is therefore possible that declines in
47 insect biomass are not always symptomatic of equivalent declines in abundance, or vice
48 versa. Biomass could remain stable even in the face of declining abundance if communities
49 became increasingly comprised of larger-bodied species. Likewise, changes in community-
50 level biomass could be attributable to changes in community composition, even in the
51 absence of an overall abundance change. This might occur if communities became more
52 biased towards larger- or smaller-bodied species, e.g. through size-bias in strength of
53 selection for or against particular traits (Coulthard *et al.*, 2019), such as faster or slower life-
54 histories, degree of habitat specialization (Mattila *et al.*, 2011; Davis *et al.*, 2013), and
55 strength of attraction to artificial light at night (van Langevelde *et al.*, 2011). However, the
56 relationships between biomass, abundance and community composition have not yet been
57 examined at large spatial and temporal scales because of a lack of suitable data on
58 biomass.

59

60 Opportunities to investigate changes over time and space in insect communities are
61 provided by several large-scale, long-term abundance datasets for moths (Lepidoptera) in
62 the UK, including the Rothamsted Insect Survey (RIS; Storkey *et al.*, 2016), the National
63 Moth Recording Scheme (NMRS; Fox *et al.*, 2011), and the Garden Moth Scheme (GMS;
64 Bates *et al.*, 2014a; Wilson *et al.*, 2018), and elsewhere (e.g. the *Noctua* database;
65 Groenendijk & Ellis, 2011). However, these datasets do not record measurements of body
66 mass, and in most cases do not retain specimens. To address questions of biomass change
67 using these abundance datasets requires reliable body-mass data for all species, but such
68 empirical data are currently available for only a limited set of species (García-Barros, 2015).

69 An alternative approach is to use empirical data from a subset of all species to model the
70 expected body mass of all species from some other, more readily-available, trait. Such
71 models have previously been formulated to predict the body mass of moths and other
72 insects from their body length (Sage, 1982) and variants thereof (García-Barros, 2015),
73 chosen because it is easily measurable from museum specimens (García-Barros, 2015).
74 However, for moths, body length data are not widely available and in any case may be
75 influenced to a greater degree by contraction in dried specimens than other traits (García-
76 Barros, 2015). The only morphological trait for which existing data on many species is
77 readily available is forewing length: for example, an expected range of forewing lengths is
78 included for all British species of macro-moths, and most British species of micro-moths, in
79 standard field guides (Sterling & Parsons, 2012; Waring & Townsend, 2017), and it may
80 therefore be possible to predict body mass based on forewing length. The existence of
81 substantial interfamilial variation in body plan (e.g. between Saturniidae and Sphingidae;
82 Janzen, 1984) may provide opportunities to fine-tune such a model without requiring further
83 data, but no previous model has included any refinement based on taxonomic relationships
84 between moths. Therefore, a model to predict body mass based on forewing length, with
85 family-level refinements where possible, may therefore have the broadest potential
86 application, but no such model currently exists.

87

88 Two-thirds of British species of macro-moths show negative abundance trends in the long-
89 term (Conrad *et al.*, 2006), with similar patterns observed elsewhere in Europe (e.g.
90 Groenendijk & Ellis, 2011). The potential drivers of these declines are diverse (Fox, 2013),
91 and likely to include habitat loss and fragmentation, agricultural intensification and
92 associated agrochemical use, increased prevalence of artificial light at night and other
93 factors associated with urbanisation, and climate change (Wickramasinghe *et al.*, 2004;
94 Morecroft *et al.*, 2009; Fox, 2013; Fox *et al.*, 2014; Gilburn *et al.*, 2015; van Langevelde *et*
95 *al.*, 2018). Moths contribute to important ecosystem functions, including nocturnal pollination
96 (Macgregor *et al.*, 2015, 2019) and energy transfer from producers to higher-level

97 consumers (e.g. Franklin *et al.*, 2003; Hooks *et al.*, 2003; Singer *et al.*, 2012). Thus, moths
98 can be important to the conservation of their predators, such as bats (Vaughan, 1997;
99 Threlfall *et al.*, 2012) and some birds (Sierro *et al.*, 2001; Denerley *et al.*, 2018). In
100 transferring energy, the quantity of vegetation consumed by caterpillars and the biomass of
101 insects available to predators may be functionally important determinants of ecosystem
102 processes (Brose *et al.*, 2005). Similarly, the body size of individual species can play a
103 substantial role in structuring networks of interspecific interactions (Woodward *et al.*, 2005).
104 Therefore, understanding changes in the biomass of moths at the community level is vital,
105 requiring biomass data over long time-periods.

106

107 In this study, we develop an approach to estimate the body mass of individual moths from
108 their forewing length, and hence quantify the biomass of samples of moths. We have three
109 aims: (i) collection of empirical data (during 2018 on the University of York campus, UK) to
110 test the relationship between forewing length and body mass in moths; (ii) construction and
111 testing of a predictive model for estimating body mass from species identity and associated
112 forewing length; (iii) demonstration of our model's potential applications by investigating
113 changes over time in biomass, abundance and species richness, using a 16-year historical
114 abundance dataset (RIS records from the University of York campus during the period 1991-
115 2006) for which no body mass data or specimens are available.

116

117 **Materials and methods**

118

119 *Field sampling, identification and measurement of moths*

120

121 We sampled moths at three sites (Fig. S1) on the University of York campus, UK (53°56'41"
122 N 1°2'2" W) between 11th June and 20th July 2018 (Appendix S1.1). Moths were collected
123 using Heath-style moth traps (Heath, 1965), each operating a 15 W actinic fluorescent tube
124 and powered by a 12 V battery (Anglian Lepidopterist Supplies, Hindolveston, UK). Moths

125 were euthanised and returned to the laboratory for identification and measurement. Moths
126 were identified to species-level where possible using standard field guides (Sterling &
127 Parsons, 2012; Waring & Townsend, 2017). Where species-level identification would have
128 required dissection of the genitalia, identification was made to aggregate level (e.g. Common
129 Rustic agg. *Mesapamea secalis/didyma*). After identification, moths were allowed to air-dry
130 at room temperature for a minimum of one week (Appendix S1.2, Fig. S2). After drying, we
131 measured the forewing length and dry mass of each moth. Forewing length was measured
132 from wing base to wing-tip, using calipers and a ruler, to the nearest 1 mm. Dry mass was
133 measured using an A&D HR-202 balance (A&D Instruments Ltd., Abingdon, UK), to the
134 nearest 0.01 mg. Measurements were precise to within $\pm 6\%$ of the true value (Appendix
135 S1.2).

136

137 *Modelling forewing length – body mass relationship from empirical data*

138

139 To investigate the relationship between forewing length (mm) and body mass (mg; both
140 variables ln-transformed) in moths, we constructed a generalized linear mixed-effects model
141 (GLMM) using our 2018 field data, with species as a random effect and the fixed-effect
142 structure: body mass is explained by the interaction between forewing length and taxonomic
143 family (i.e. $\ln(\text{body mass}) \sim \ln(\text{wing length}) \times \text{family}$). We tested the significance of model
144 terms, including the interaction between wing length and family, using Likelihood Ratio
145 Tests.

146

147 In order to refine the model for making predictions, we then simplified the family variable to
148 analyse four families which had more than five species in our 2018 samples (Crambidae,
149 Erebidae, Geometridae and Noctuidae), grouping all other families together as ‘others’ (n = 7
150 families). This allowed the predictive model’s parameters to be refined for the four families
151 with sufficient data, whilst also making overall predictions for all other families. We fitted a
152 GLMM to the dataset as above, using this aggregated version of the family variable, and

153 extracted all parameters from the GLMM to form the predictive model. We did not include
154 information on whether individuals were male or female, even though male and female
155 moths can differ substantially in size, because this information is not recorded in historical
156 abundance datasets. Our model therefore used overall slope and intercept to predict body
157 mass from forewing length, with a refined slope and intercept for moths from the most
158 speciose (and therefore data-rich) four families in our dataset.

159

160 To test the accuracy of the predictive model when making predictions based on forewing
161 length data from field guides, we used it to estimate the dry body mass of every moth in our
162 dataset. For each moth, we obtained an expected forewing length by taking the midpoint
163 between the minimum and maximum expected forewing lengths given by field guides (micro-
164 moths: Sterling & Parsons, 2012; macro-moths: Waring & Townsend, 2017), and applied our
165 predictive model to these expected forewing lengths to generate estimated body masses
166 that were independent of our empirical data. From these estimated body masses, we
167 calculated the total estimated biomass of each sample of moths (i.e. all moths captured at
168 one site in one night) in our study, and compared this estimate with the true biomass of the
169 same samples that we had measured. We also calculated the mean dry body mass of each
170 moth species in our dataset. At both species- and sample-level, we tested the relationship
171 between measured and predicted biomass, using model II regressions with a Major Axis
172 approach because neither biomass variable was dependent upon the other. Significance of
173 relationships from random was tested using one-tailed permutation tests (with 100
174 permutations), and relationships were also compared to the desired 1:1 (i.e. estimated =
175 measured) relationship by calculation of 95% confidence intervals around the estimated
176 slope and intercept. The strength of the relationships between measured and estimated
177 biomass at species- and sample-level were determined by model R^2 values.

178

179 *Testing biomass – abundance relationships and trends across samples and over time*

180

181 We investigated the relationships between sample-level biomass, abundance and species
182 richness across our three study sites in 2018 using sample-level data, and over time using a
183 16-year historical dataset also collected on the University of York campus. We obtained this
184 long-term historical abundance data from the Rothamsted Insect Survey (RIS), covering the
185 period 1991–2006. In the RIS, moths are collected in the same location on every night of the
186 year using standard-design light-traps operating a 200 W tungsten bulb (Storkey *et al.* 2016).
187 Samples of moths are identified and counted daily or every few days, generating long-term,
188 high-temporal resolution abundance data for a fixed site which can reveal site-level trends in
189 abundance over many years (e.g. Fox *et al.* 2013). An RIS trap, “Heslington”, was operated
190 between 1991–2006 on the roof of the Department of Biology, University of York (53°56’51”
191 N 1°3’26” W), at approximately 500 m distance from 2018 sampling site 1 (Fig. S1). This trap
192 was emptied daily and abundance records are available, but specimens were not stored. We
193 used our predictive model to estimate the body mass of all British species of macro-moths
194 and all British species of the micro-moth families Crambidae and Pyralidae (Fig. S3), which
195 collectively included all species that had ever been recorded in the Heslington trap, and also
196 provides a useful resource for other users of insect abundance data (Table S1). From these
197 estimates, we calculated the total annual biomass of moths captured in this trap in each year
198 from 1991–2006.

199
200 For the 2018 samples, we used generalised linear mixed-effects models (GLMMs) to
201 investigate the relationships between sample biomass, abundance, and species richness,
202 with site as a random effect. We tested significance using a Likelihood Ratio Test. For the
203 Heslington RIS data, we tested the same relationships (with no random effects) using
204 generalised linear models (GLMs), testing significance using an F-test. We also confirmed
205 significance of all relationships using model II regressions with a Major Axis approach, as
206 above, because it was unclear which variable should be viewed as the independent variable.
207

208 We used linear regression to test for significant trends over time in biomass, abundance and
209 species richness in the historical dataset, and checked significance of these trends using
210 non-parametric Spearman's rank correlation because trends over time might not be linear.
211 We calculated the absolute change in biomass, abundance and species richness between
212 1991 and 2006, as a percentage of the 1991 value.

213

214 All statistical analyses were conducted in R version 3.5.0 (R Core Team, 2018) using the
215 following packages: *lme4* to fit and assess linear mixed-effects models (Bates *et al.*, 2015);
216 *lmodel2* to conduct model II regressions (Legendre, 2018); and *ggplot2* to plot figures
217 (Wickham, 2016). All R scripts used in the analysis, and all data except the Heslington RIS
218 data and its derivatives (which can be obtained independently by application to Rothamsted
219 Research), are archived online at Zenodo (doi: [10.5281/zenodo.2645026](https://doi.org/10.5281/zenodo.2645026)).

220

221 **Results**

222

223 *Sampled moths*

224

225 We sampled 614 individual moths in 2018, of which 13 could not be identified beyond family
226 level. One micro-moth (*Narycia duplicella* [Goeze, 1783], Psychidae) could not be detected
227 by our balance (and therefore weighed less than 0.005 mg). These 14 individual moths were
228 excluded from further analyses. The remaining dataset contained exactly 600 individual
229 moths, representing 94 species from 11 families (Table S2).

230

231 *Testing forewing length – body mass relationships in field data*

232

233 Body mass and forewing length were significantly related to each other at both species and
234 individual levels (Fig. 1), with variation among the eleven families in the slope and intercept
235 of this relationship ($\chi^2 = 35.9$, d.f. = 10, $P < 0.001$; marginal $R^2 = 0.819$) revealing that

236 interfamilial variation in body plan significantly influences the scaling of forewing length to
237 body mass. To reduce the risk of our model overfitting for families represented by only a few
238 species in our dataset, we refitted this model with an aggregated family variable, in which
239 seven families represented by fewer than five species in our dataset were grouped together
240 as 'other' (effectively reducing the family variable from $n = 11$ to $n = 5$). The significance of
241 the model (and almost all of its explained variance) was retained when fitting this simplified
242 model ($\chi^2 = 30.7$, d.f. = 4, $P < 0.001$; marginal $R^2 = 0.812$), resulting in a set of parameters
243 from which body mass could be predicted based on forewing length (Table 1). All four
244 families with refined estimates had larger intercepts and shallower slopes than the overall
245 prediction across the other families (Table 1), implying that within families, body mass may
246 increase more gradually as forewing length increases than between families.

247

248 We found that our estimates of biomass significantly predicted the measured biomass at
249 both species- and sample-levels (Fig. 2), even though body mass varied widely both within
250 and between species (within-species s.d. of body mass = 34.6 mg, between-species s.d. of
251 body mass = 74.7 mg). At sample-level, the relationship between estimated and measured
252 biomass was not significantly different a 1:1 relationship (Table 2), with 91.5 % of variation
253 explained. At species-level, estimated biomass explained 91.0 % of variation, but the
254 relationship was shallower than the expected 1:1 relationship (Table 2). However, when we
255 excluded the 34 smallest species (i.e. only included species weighing > 15 mg, $n = 60$
256 species), the relationship no longer deviated from a 1:1 relationship, indicating that our
257 predictive model may slightly overestimate the body mass of very small species of moths.

258

259 *Testing biomass – abundance relationships and trends*

260

261 Amongst the samples of moths collected in 2018 for this study, we found that sample
262 biomass was significantly predicted by abundance and species richness across the three
263 study sites (Fig. 3), with the strongest relationship to abundance ($R^2 = 0.566$). These results

264 were qualitatively unchanged and quantitatively similar when the biomass of samples was
265 estimated from the predictive model (Table S3), illustrating that conclusions drawn from
266 estimated biomass (rather than direct measurements of biomass) are likely to be robust.
267 Similarly, both abundance and species richness were strongly correlated with estimated
268 biomass in the Heslington RIS data, with the strongest relationship between biomass and
269 abundance ($R^2 = 0.961$).

270

271 Using the Heslington RIS dataset, we found that both abundance and species richness
272 declined significantly between 1991–2006 (Table 3), but changes were not necessarily linear
273 (Fig. 4). These declines were matched by a significant decline in biomass of 445.6 ± 153.0
274 mg per year (i.e. annual reductions of 3.1 % of the total biomass in 1991). Biomass declined
275 by 65.9 % over the 16-year period.

276

277 **Discussion**

278

279 The strong relationship between forewing length and body mass in moths enables prediction
280 (to a useful level of accuracy) of the biomass of samples of moths when specimens have not
281 been kept. Data generated using this approach will allow researchers to address pressing
282 and policy-relevant questions about ongoing declines in insect biomass (Hallmann *et al.*,
283 2017; Lister & Garcia, 2018; Sánchez-Bayo & Wyckhuys, 2019) using long-term recording
284 datasets, or to include estimates of moth body mass in comparative studies and trait-based
285 analyses, despite the general lack of empirical data of this nature (García-Barros, 2015). In
286 particular, these data will facilitate studies of the relationships between biomass, abundance
287 and community composition, asking questions such as: do biomass declines indicate a
288 general decline in the abundance of the majority of species, or a severe decline in the
289 biomass of a few key species (e.g. Shortall *et al.*, 2009), or a shift in community composition
290 towards smaller-bodied species, all of the above, or something else entirely?

291

292 *Evaluation of the predictive model's current and future utility*

293

294 Overall, the estimates of body mass calculated using the predictive model's parameters
295 performed relatively well during testing, with > 90 % of variation in measured biomass
296 explained by predicted biomass at both species- and sample-levels. Therefore, using
297 estimated body masses from the model (Table S1) to calculate the combined biomass of
298 large samples of moths should yield accurate results (for example, when summed to
299 generate annual totals; c.f. Fig. 4). However, our sampled dataset was only sufficiently data-
300 rich to allow refined parameter estimates for four families (Crambidae, Erebidae,
301 Geometridae and Noctuidae). Further improvement of the model's accuracy may be possible
302 with the collection of additional data on body masses from a greater number of species from
303 other families. These species are less abundant in moth-trap samples than the dominant
304 family, Noctuidae, and so collection of sufficient data using field sampling may be
305 challenging. An alternative may be to use museum collections to measure individuals of a
306 much wider range of species and families, where methods exist to account for the mass of
307 entomological pins when taking such measurements (Gilbert, 2011). Taking such an
308 approach might allow for more data to be collected even from rarely-trapped families (e.g.
309 Sphingidae), or those which are speciose globally but have few (e.g. Saturniidae) or no (e.g.
310 Hedylidae) species extant in Britain, thereby allowing for incorporation of family-specific
311 refinements for every family, even at a global scale. However, inspection of Fig. 1 indicates a
312 'valley' in the data for the relationship between forewing length and body mass; two parallel
313 relationships indicating two "ways to be a moth" (Janzen, 1984), whereby different moth
314 families may have substantially different body-plans. For example, the Noctuidae generally
315 have high body mass for a given forewing length, while Geometridae might have lower body
316 mass for the same forewing length. In some cases it may, therefore, be sufficient to identify
317 which relationship is appropriate for a given family, rather than to derive a separate
318 relationship for every family. Such refinement could potentially be supported by a
319 phylogenetic imputation approach (Penone *et al.*, 2014). However, in some families (most

320 notably Erebidae), species are distributed across both parallel relationships with little
321 obvious influence of phylogeny, and so it may be necessary to identify which “way to be a
322 moth” is most relevant at genus- or even species-level.

323

324 One source of potential error when using published forewing lengths to estimate biomass is
325 that 19% of individuals in our 2018 dataset had a measured forewing length which was
326 outside the expected range given by field guides. Nevertheless, there was an overall
327 correlation ($R^2 = 0.942$) between the mean forewing length at species-level derived from our
328 2018 empirical measurements and the midpoint of the range of forewing lengths for each
329 species, taken from the published field guides (Fig. S4). This suggests sufficient accuracy in
330 our approach, particularly considering that our largest measured species, *Laothoe populi*
331 (Sphingidae) had a forewing length 524 % larger than that of our smallest species, *Eudonia*
332 *pallida* (Crambidae).

333

334 An alternative source of possible error in our models is sexual dimorphism in moths. Some
335 moth species, including some sampled in our study (e.g. Drinker *Euthrix potatoria*;
336 Lasiocampidae), exhibit substantial sexual dimorphism in wing length (Waring & Townsend,
337 2017) and in body mass (Allen *et al.*, 2011). However, we did not quantify or adjust for
338 sexual dimorphism in this study because long-term recording schemes rarely include
339 information on sex of individual moths, even for dimorphic species, although the majority of
340 such records are likely to be males (Altermatt *et al.*, 2009). Therefore, for estimation of
341 sample-level biomass, it will be of most use to provide a single average estimate of body
342 mass per species, regardless of size dimorphism.

343

344 *Future research using our predictive model to study biomass change*

345

346 The fact that sample biomass correlated strongly with moth abundance, and that both
347 declined over time in the Heslington RIS dataset (abundance: absolute decline of 56.5 %

348 between 1991 and 2006; biomass: absolute decline of 65.9 % over the same period), is
349 consistent with other studies showing insect biomass declines in recent decades (Hallmann
350 *et al.*, 2017; Lister & Garcia, 2018; Sánchez-Bayo & Wyckhuys, 2019). However, questions
351 remain regarding temporal, spatial, and taxonomic variation in these declines (Shortall *et al.*,
352 2009), the potential drivers of declines (Grubisic *et al.*, 2018; Komonen *et al.*, 2019), and the
353 challenges of extrapolating across data types, geographic locations, and temporal and
354 spatial scales (Thomas *et al.*, 2019; Wagner, 2019). Our study illustrates the power of
355 predictive models of body mass to tackle these challenges. Applying our estimates of body
356 mass to RIS datasets across the UK (Storkey *et al.*, 2016), or to other long-term moth
357 abundance datasets, such as the National Moth Recording Scheme or the Garden Moth
358 Scheme (Fox *et al.*, 2011; Bates *et al.*, 2014a), will facilitate investigation of declines over
359 longer time-periods and broader geographical scales than has previously been feasible.
360 Moreover, the same model parameters could be used to estimate body mass of moths in
361 other databases, including macro-moth recording schemes from other regions (e.g. the
362 Noctua database; Groenendijk & Ellis, 2011) and micro-moths, which were incorporated into
363 the NMRS in 2016. This would allow comparison of biomass losses across multiple datasets
364 at a global scale.

365

366 Declines in biomass and abundance have been identified in some studies (Conrad *et al.*,
367 2006; Hallmann *et al.*, 2017; Sánchez-Bayo & Wyckhuys, 2019), but the drivers of these
368 trends have not been identified. Our study is consistent with the hypothesis that changes in
369 insect biomass correlate with changes in abundance and species richness of insects (Fig. 3).
370 However, declines in biomass within the 1991–2006 Heslington RIS dataset were greater
371 than abundance declines, which in turn were greater than species richness declines (Table
372 3). Thus, estimating biomass of samples has the potential to add to information held in
373 abundance datasets, such as the RIS. Changes in community composition could also
374 contribute to biomass loss; investigating changes in biomass over time at continuously-
375 recorded sites, using our approach, will be important for examining relationships between

376 biomass change and community composition. Similarly, the environmental drivers causing
377 changes in insect biomass have not been fully established (Fox, 2013), and our approach
378 will permit their effects to be investigated at a broader scale, in a similar manner to many
379 studies of changes in abundance (Conrad *et al.*, 2006; Pescott *et al.*, 2015; Wilson *et al.*,
380 2018).

381

382 Our approach will be of use for conducting trait-based analyses of moths (e.g. van
383 Langevelde *et al.*, 2018), where it is important that trait data have high precision (Middleton-
384 Welling *et al.*, 2018). Our predictive model offers a means to estimate body mass
385 reproducibly, potentially across multiple data sources, using a trait (forewing length) that is
386 straightforward to measure using basic equipment, and therefore can be robustly applied to
387 other datasets. Previous trait-based analyses have used forewing length as a proxy for body
388 size, but we have shown that there is interfamilial variation in this relationship (Fig. 1), which
389 can be incorporated by using our approach.

390

391 *Conclusions*

392

393 We have developed a predictive model to estimate the dry body mass of moths based on
394 their forewing length, using it to generate body masses for all British species of macro-moth
395 and demonstrating its potential for use in the investigation of historical changes in biomass
396 at large temporal and spatial scales. The predictions of sample biomass made by our model
397 correlated strongly with measured biomass of the same samples ($R^2 = 0.915$). We use these
398 predicted body masses to show that biomass of moths has declined by 65.9 % at a site in
399 Britain over a 16-year period between 1991–2006. Our approach unlocks new opportunities
400 to study trends in moth biomass over time and over large geographic regions.

401

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403

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407

408 **Contribution of authors**

409

410 The study was conceived by C.J.M. and C.D.T., and designed by those authors in
411 discussion with J.K.H. Field and laboratory work was conducted by R.S.K., who also carried
412 out the statistical analysis with C.J.M. Data was collected from the Heslington RIS trap by
413 T.J.C. The first draft of the manuscript was written by R.S.K. and C.J.M., and all authors
414 contributed to subsequent revisions.

415

416

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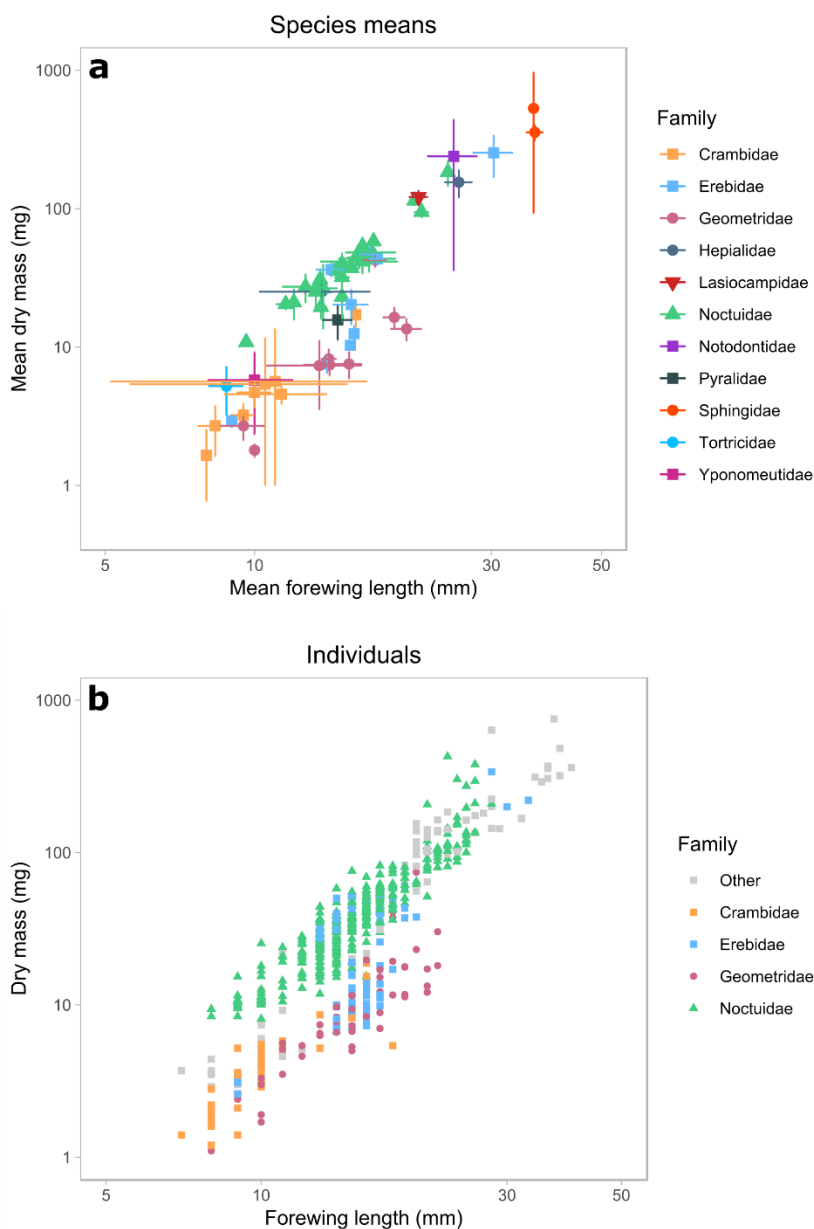
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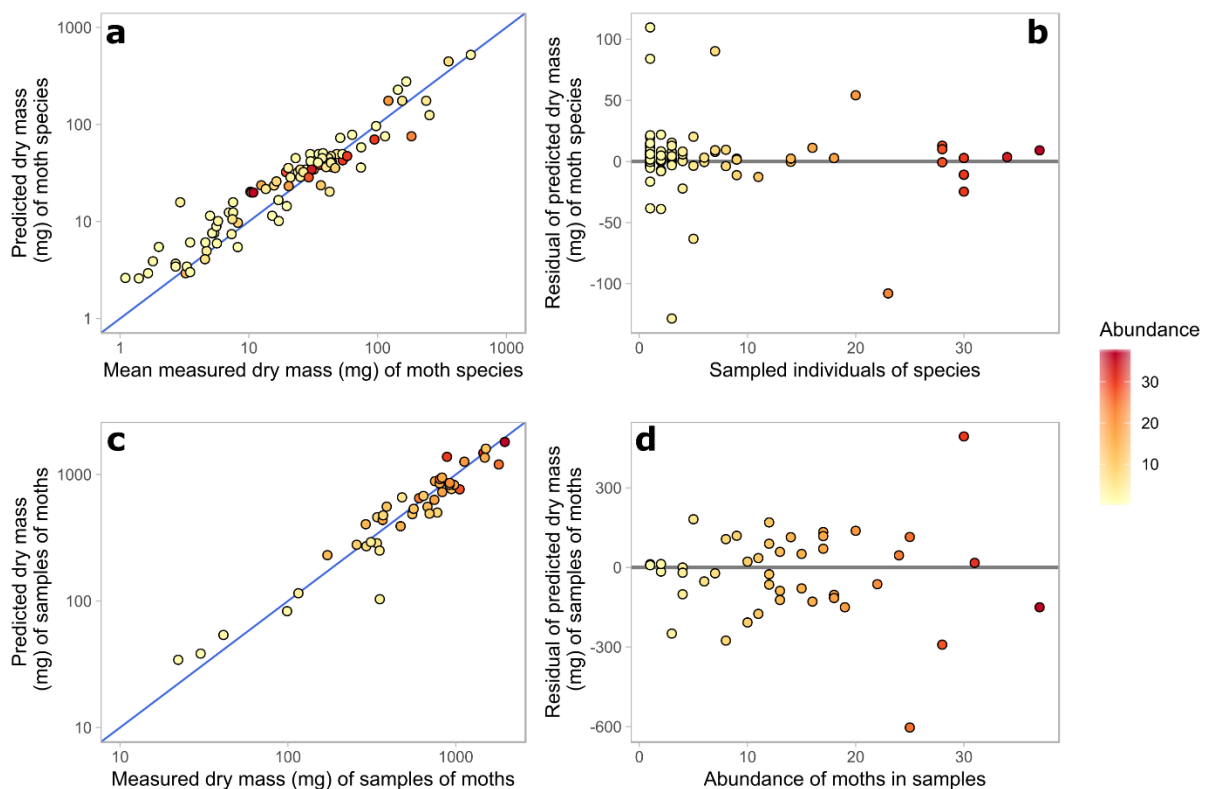
553 **Figures and tables**

554 **Figure 1:** Relationship between forewing length (mm) and dry mass (mg). In the top panel,
555 the mean forewing length and dry mass of each species sampled in the study is shown on
556 logarithmic axes, with error bars showing standard errors and family indicated by the
557 combination of point colour and shape. In panel (b), the forewing length and dry mass of
558 every individual moth sampled in the study is shown on logarithmic axes, with the four most
559 speciose families in our sample (Crambidae, Erebidae, Geometridae and Noctuidae)
560 indicated as above by point colour and shape.



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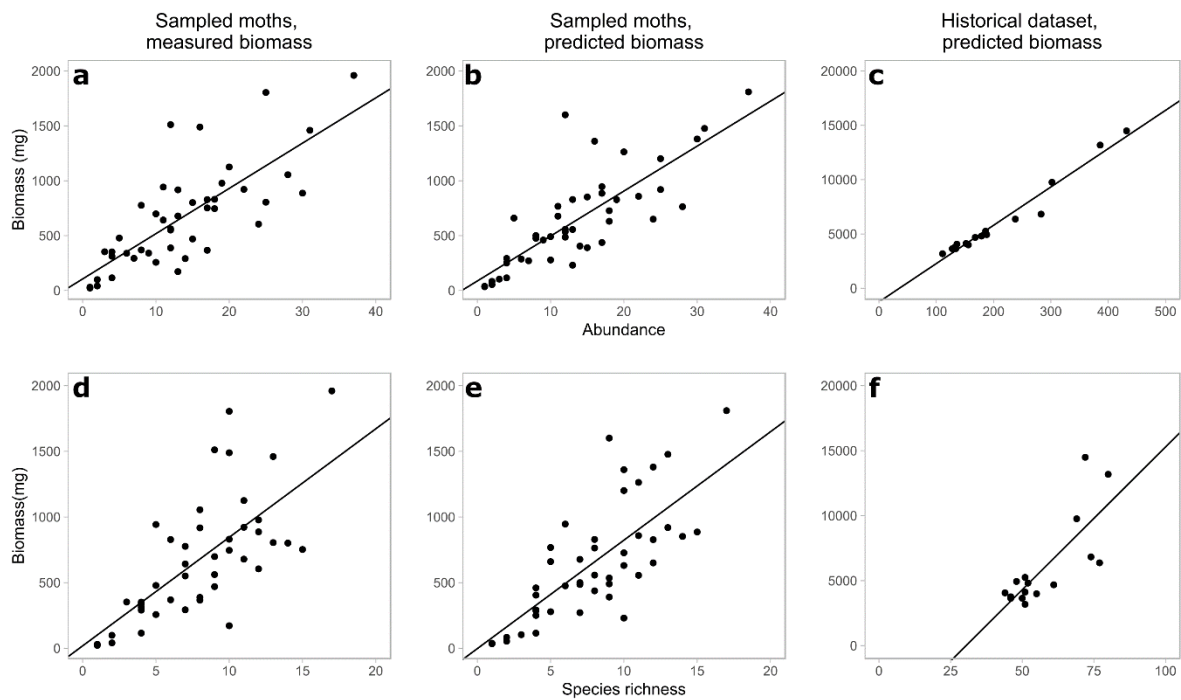
562 **Figure 2:** Accuracy of predicted biomass of moth species and samples of moths compared
563 to the true, measured biomass. (a) Predicted dry mass of species (mg) is plotted against
564 mean measured dry mass (mg); the 1:1 relationship is plotted as a blue line, and points are
565 coloured by the number of individual moths from which the measured mean was calculated.
566 (b) The absolute difference between mean measured dry mass and predicted dry mass of
567 each moth species is plotted against the number of individuals from which the measured
568 mean was calculated; a horizontal line is plotted at $y = 0$. (c) Predicted dry mass of samples
569 (mg) is plotted against measured dry mass (mg); the 1:1 relationship is plotted as a blue line,
570 and points are coloured by the number of individual moths contained in the sample. (d) The
571 absolute difference between measured and predicted dry mass of each sample of moths is
572 plotted against measured dry mass (mg); a horizontal line is plotted at $y = 0$.
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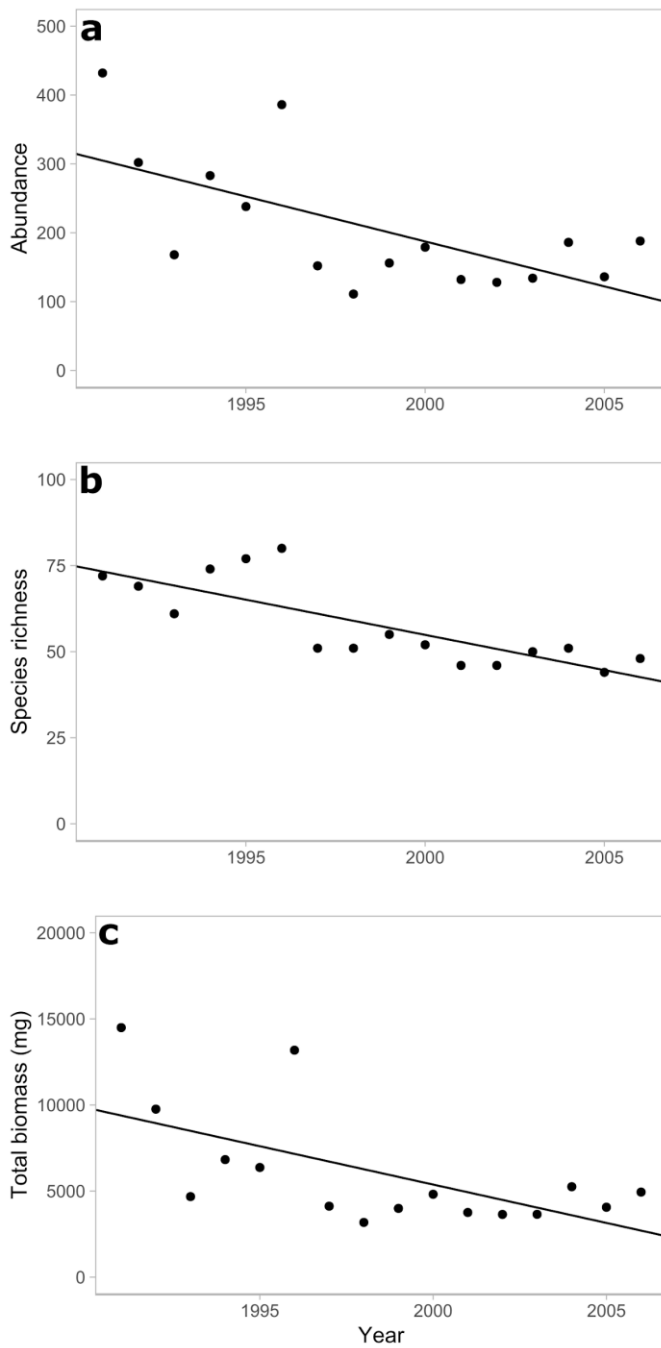
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576 **Figure 3:** Relationship between sample biomass (mg) and abundance and species richness
577 of moths, for (a,d) measured biomass of samples of moths captured in this study; (b,e)
578 predicted biomass of samples of moths captured in this study; and (c,f) predicted biomass of
579 samples of moths recorded in a historical dataset. All relationships are significant ($P < 0.05$)
580 and are plotted as solid lines. Each point represents a single night for the 'sampled moths'
581 data, whereas historical point samples are much larger, representing year-long totals.
582



583

584 **Figure 4:** Changes in total biomass (mg), abundance and species richness of moths
585 captured in the Heslington RIS trap over a 16-year period between 1991 and 2006. All
586 trends are significant ($P < 0.05$) and are plotted as solid lines (significance of all trends was
587 also confirmed by a non-parametric Spearman's rank correlation; Table 3).
588



589

590 **Table 1:** Parameters of the predictive model, extracted by fitting a GLMM with the fixed-effects structure: $\log(\text{body mass}) \sim \log(\text{forewing length})$
591 \times family, to data from 600 individual moths. Overall model parameters are given, including the χ^2 and P -values of a Likelihood Ratio Test of the
592 model's overall significance. Family-specific slope and intercept values are refinements to be added to the parameters for 'other families'
593 (rather than taken in isolation). To predict body mass of a moth from its forewing length, these parameters should be applied to the following
594 formula: $\log(\text{body mass}) = (\log(\text{forewing length}) \times (\text{'other families' slope} + \text{family slope adjustment})) + (\text{'other families' intercept} + \text{family}$
595 $\text{intercept adjustment})$.

596

Family adjustment	n species (n individuals)	χ^2 , d.f. (P)	Slope estimate (s.e.)	Intercept estimate (s.e.)
Overall model	94 (600); 11 families	30.7, 4 (<0.001)	-	-
'Other families' (no adjustment)	15 (67); 7 families	-	3.056 (0.180)	-5.016 (0.540)
Crambidae	11 (38)	-	-0.904 (0.311)	1.361 (0.813)
Erebidae	10 (79)	-	-0.601 (0.360)	1.294 (1.029)
Geometridae	22 (52)	-	-0.492 (0.322)	0.344 (0.891)
Noctuidae	36 (364)	-	-1.297 (0.239)	3.788 (0.694)

597

598 **Table 2:** Details of statistical models testing the relationships between measured biomass and estimated biomass at species- and sample-level.
 599 Relationships were tested using a model II regression, and significance was determined by a one-tailed permutation test with 100 permutations.
 600 The R^2 of each model is also given, alongside the estimated intercept and slope of each model, with associated 95% confidence intervals.

601

Level	Data subset	<i>n</i>	Model R^2	Model intercept (95% CI)	Model slope (95% CI)	<i>P</i>
Sample	Full dataset	44	0.915	0.275 (-0.310, 0.810)	0.952 (0.865, 1.047)	0.010
Species	Full dataset	94	0.910	0.545 (0.369, 0.712)	0.877 (0.822, 0.936)	0.010
	Species > 15 mg only	60	0.823	0.168 (-0.311, 0.595)	0.964 (0.853, 1.090)	0.010

602

603

604 **Table 3:** Details of statistical models testing the trends over time in annual measures of estimated biomass, abundance and species richness,
605 using historical samples recorded from the Heslington RIS trap over the 16-year period 1991–2006. Absolute % change over this period is the
606 absolute difference between values in 1991 and 2006, given as a percentage of the 1991 baseline value. Trends were tested both with a
607 parametric linear regression tested using an *F*-test, and a non-parametric Spearman’s rank correlation, because some trends appeared to be
608 non-linear (Fig. 4). *F*-statistics are shown for linear regressions, and *S*-statistics for Spearman’s rank correlations. The R^2 of each linear
609 regression model is also given, alongside the effect size, which represents the annual change detected in each metric.

610

Dependent variable	Absolute % change	<i>n</i>	<i>S</i> (<i>P</i>)	Model R^2	Effect size (s.e.)	<i>F</i> (<i>P</i>)
Abundance	-56.48	16	1046 (0.034)	0.401	-13.05 (4.12)	10.05 (0.007)
Species richness	-33.33	16	1234 (<0.001)	0.611	-2.05 (0.42)	23.6 (<0.001)
Sample biomass (mg)	-65.92	16	1046 (0.034)	0.361	-445.6 (153.0)	8.48 (0.011)

611

612