

1 **A critical review of the use and performance of different function types for modeling**
2 **temperature-dependent development of arthropod larvae**

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9 **Highlights:**

- 10 • Temperature-dependent development functions of arthropod larvae were reviewed
- 11 • 79 published datasets were re-tested and fit with 33 different function types
- 12 • 91.1 % of published studies did not fit their data with the best function of those tested
- 13 • Performance differed among functions and was related to taxon and temperature range tested
- 14 • Function type impacted predicted development times, so using the best function matters

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ABSTRACT

Temperature-dependent development influences production rates of arthropods, including crustaceans important to fisheries and agricultural pests. Numerous candidate equation types (development functions) exist to describe the effect of temperature on development time, yet most studies use only a single type of equation and there is no consensus as to which, if any model predicts development rates better than the others, nor what the consequences of selecting a potentially incorrect model equation are on predicted development times. In this study, a literature search was performed of studies fitting development functions to development of arthropod larvae (99 species). The published data of most (79) of these species were then fit with 33 commonly-used development functions. Overall performance of each function type and consequences of using a function other than the best one to model data were assessed. Performance was also related to taxonomy and the range of temperatures examined. The majority (91.1 %) of studies were found to not use the best function out of those tested. Using the incorrect model lead to significantly less accurate (e.g., mean difference \pm SE 85.9 ± 27.4 %, range: -1.7 to 1725.5 %) predictions of development times than the best function. Overall, more complex functions performed poorly relative to simpler ones. However, performance of some complex functions improved when wide temperature ranges were tested, which tended to be confined to studies of insects or arachnids compared with those of crustaceans. Results indicate the biological significance of choosing the best-fitting model to describe temperature-dependent development time data.

Key Words: Temperature; arthropod; larval development; development functions; molting rate

47 **1. Introduction:**

48 Temperature affects biota at all levels, ranging from effects at the fundamental
49 biochemical and physiological levels (Bělehrádek, 1935; Coutant and Talmage 1976; Somero,
50 2004) to effects on individual organisms (Brière et al., 1999; MacKenzie, 1988), populations
51 (Aiken and Waddy, 1986; Cooper et al., 2012; McLaren et al., 1969), communities, and
52 ecosystems (Menge, 1978; McQuaid and Branch, 1985). Through its effects on the physical and
53 chemical properties of biologically active molecules, such as enzymes, temperature affects the
54 rate at which numerous life processes occur, including metabolism, oxygen consumption,
55 photosynthesis, movement, survival, growth, and embryonic development (Bělehrádek, 1935;
56 Brière et al. 1999; Corkett, 1972; Coutant and Talmage 1976; Du et al., 2007; Geffen and Nash,
57 2012; Herzig, 1983; McLaren et al., 1969). Temperature also significantly affects larval
58 development rate of poikilothermic animals, including some vertebrate larvae (Lind and
59 Johansson, 2007; Kang et al., 2009; Miller et al., 2006) and those of invertebrates (e.g., de
60 Severyn et al., 2000; Jenkins et al. 2006; Singh and Sharma, 1994). Temperature has particularly
61 strong impacts on moulting and development of arthropods (Anger, 1984; Corkett and McLaren,
62 1970; Easterbrook et al., 2003; Hamasaki et al., 2009; Koda and Nakamura, 2010; MacKenzie,
63 1988; Marchioro and Forester, 2011; McLaren, 1963).

64 Within certain tolerance limits (Bělehrádek, 1935; Brière et al., 1999; Campbell et al.,
65 1974; Shi and Ge, 2010) rates of biological processes of poikilotherms, including larval
66 development, are positively correlated with temperature; thus, higher temperatures generally
67 result in more rapid development than lower temperatures. This has important ecological
68 implications, as environmental temperatures can influence generation times, production cycles,
69 and population dynamics of such organisms. Higher or lower temperatures could, for example,

70 lead to changes in the amount and/or timing of peak secondary marine production of copepods
71 (Huntley and López, 1992; McLaren, 1963), outbreaks of agricultural pests (Easterbrook et al.,
72 2003) or vector-borne diseases (Bayoh and Lindsay, 2003), or introduction and establishment of
73 invasive species into new areas (de Rivera et al., 2007). Water temperatures could also influence
74 patterns of recruitment to populations of marine invertebrates, including crustaceans such as
75 lobsters and crabs, on which human fisheries depend (Aiken and Waddy, 1986; Anger, 1984;
76 Caddy, 1986; MacKenzie, 1988; Rothlisberg, 1979).

77 When modeling ecology and population dynamics of arthropods, equations are used to
78 represent the functional relationship between environmental temperature and development rate or
79 time of larvae. These equations, hereafter referred to as development functions, are derived by
80 rearing larvae at different controlled temperatures in a lab or hatchery setting, observing
81 development times of multiple larvae at each temperature, and then using regression analyses to
82 fit an equation relating temperature to development time (or its inverse, rate) to the data obtained.
83 There are countless potential forms of equation that can be used to fit such data, including
84 various linear, simple curvilinear, and complex non-linear functions (e.g., see reviews by Anger,
85 2001; Angilleta Jr., 2006; Blanco et al. 1995; Guerrero et al., 1994; Heip, 1974; Kontodimas et
86 al., 2004; McLaren, 1995; Shi and Ge, 2010; Smits et al. 2003). These functions differ in form,
87 assumptions, procedures used to derive their parameters, and most importantly in terms of the
88 development times predicted. For example, development times of American lobster, *Homarus*
89 *americanus* (H. Milne Edwards, 1837), larvae predicted with 33 of these development function
90 types can differ from each other and the data used to derive them by ≥ 50 days at the same
91 temperatures (see Fig. 1; Table S1). However, this is no clear standard rule or consensus as to
92 what is the “best” type of development function to apply to these kinds of data. Researchers are

93 generally left to choose the type of development function to use on their own, and will often
94 select one or a very few forms that have the best apparent match to their characters of their data
95 or has been used by other studies on the same or related species (e.g., Edgar and Andrew, 1990;
96 McLaren et al., 1969). Given the potential for different functions to make very different
97 predictions of development times (e.g., Fig. 1), however, development function choice should be
98 given more consideration in studies on these species.

99 It is possible that certain function types may in general be better representations of the
100 relationship between temperature and development of arthropod larvae, or specific sub-groups
101 within the Arthropoda (e.g., arachnids vs. crustaceans vs. insects), for example because they
102 come closer to capturing thermal performance relations of enzymes and other biomolecules
103 mediating moulting and development cycles in these taxa (Brière et al., 1999; Huey and
104 Stevenson, 1979; Somero, 2004). As a result, such functions might also achieve better fit to
105 development data, be able to more-closely match real observed development times, and make
106 better predictions of development in nature. Differences in methodologies used in studies on
107 different taxa, for example the fact that the range of temperatures tested is generally wider for
108 insects and arachnids than crustaceans; (reviewed by Hartnoll, 1982; Quinn and Rochette, 2015),
109 might also lead to apparent taxonomic differences in function performance and should be
110 investigated. Several previous studies have compared the characteristics of different
111 development function types in general (Anger, 2001; Blanco et al., 1995; Guerrero et al., 1994;
112 McLaren, 1995). Others have examined performance of one or two specific functions on
113 multiple species (e.g., Logan et al., 1976), or attempted to fit multiple function types to data for
114 one or two specific species under study to select the best function for their data (e.g., Angilletta
115 Jr., 2006; Heip, 1974; Kontodimas et al., 2004; Shi and Ge, 2010; Smits et al., 2003). Many other

116 studies seem to choose one or very few function(s) semi-arbitrarily, without discussing
117 alternatives (e.g., de Oliveria et al., 2009; Thompson 1982; see also Results). However, no
118 previous study has attempted to assess the degree to which one versus multiple types of
119 development functions are used in published studies, compared performance of different types of
120 development functions across multiple species, or assessed the overall impact of function choice
121 to predictions made with such functions. Such a large-scale analysis is needed, though, because it
122 could potentially allow functions that tend to better represent development data in general to be
123 identified, which can then allow for more informed decisions by future studies on arthropod
124 larval development.

125 In this study, a critical literature review was conducted to assess whether and to what
126 extent studies of temperature-dependent development of arthropod larvae attempt to represent
127 their data with more than one development function type, and also which specific types of
128 functions tend to be used. Then, data from previously published studies were extracted and
129 retested to derive multiple different development functions for the same datasets. The best model
130 type for each dataset was determined, and whether or not published studies actually used the best
131 function type for their data was recorded. Overall performance of different function types were
132 assessed by comparing overall function rankings, proportion of variance explained, and
133 information loss across datasets. Any taxonomic patterns (e.g., whether particular function types
134 performed better for arachnids than for crustaceans and/or insects) and whether performance was
135 related to the range of temperatures tested were also noted. The consequences of using different
136 function types were then tested by comparing the difference of predicted versus observed
137 development times, fit, and information loss of the function type used in original studies versus
138 that of the best function for the data.

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140 **2. Materials and methods:**

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142 2.1. Literature review:

143 A literature search was conducted through Web of Science (Thompson Reuters, 2015) for
144 the terms “temperature” AND “development”. An initial search was carried out on 12 September
145 2012, through which the majority of the data in the present study were obtained; this search
146 yielded 1,052 results. A second search was carried out on 19 November 2014, which returned 35
147 additional results not available or published online at the time of the initial search. These 1,087
148 total search results were then further examined, and several criteria were used to remove non-
149 relevant results. Accessible peer-reviewed studies that reported larval development rates or times
150 of arthropods at different temperatures and derived a regression equation(s) (i.e., development
151 function) from their data were sought out. Studies that looked exclusively at growth (size
152 increase), which is a distinct process from development (Forster et al., 2011), were excluded.

153 After applying these criteria, 81 studies of 96 different arthropod species were obtained,
154 which provided a total of 99 species datasets for subsequent examination and analyses (Table S2).
155 Several specific types of development function were frequently utilized in these studies (Table
156 S2); these functions are presented in Table 1 and discussed in the next section (2.2.1, below).
157 Studies were published between 1970 and 2014, and conducted in several different countries on
158 marine, freshwater, and terrestrial species (Table S2) of various taxa within the Arachnida
159 (Phylum Arthropoda: Subphylum Chelicerata), Crustacea, and Insecta (Table S2). To assess
160 whether published studies tested multiple development functions on their data, each study was
161 carefully read and the number and types of development functions used to fit the data for each

162 study species were noted. Even if results from multiple functions were not reported, if alternative
163 functions than reported were at least mentioned in the Methods sections of studies they were
164 counted as having considered > 1 function. Also if any study tested multiple development
165 functions on their data and concluded one of these to be the “best” function for their data this
166 was also noted. The percent (%) of the 99 species datasets from the literature search on which
167 one, two, or more functions were tested, and the % of datasets on which different types of
168 functions were tested, were then calculated.

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170 2.2. Meta-analysis:

171 *2.2.1. Development functions considered in this study:*

172 In the present study, 33 development function types were examined (Table 1; Figure 1).
173 These functions were used because they were found in the literature review in the present study
174 (see section 2.1 and Results) to be used quite frequently in studies of arthropod larvae, and were
175 discussed in reviews and studies on the topic of arthropod temperature-development functions by
176 Anger (2001), Guerrero et al. (1994), Heip (1974), Kontodimas et al. (2004), and Shi and Ge
177 (2010). Three linear and 30 nonlinear functions were examined, with k -values (k = numbers of
178 parameters + 1; Anderson, 2008) ranging from 3 to 8 (Table 1). Eight of these functions are fit
179 directly to development time data, while the remaining 25 functions are typically fitted to
180 development rate data, which are the inverse of time (Table 1); in some cases, the same function
181 form (e.g., quadratic) is applied to either development rate (function #15, Table 1) or time (#16),
182 yielding distinct functions (Fig. 1). 12 of these functions included a nonzero minimum
183 temperature (T_{\min}) for development at which development rate is zero and development time
184 becomes infinite (see Fig. 1), 15 included a similar maximum temperature for development

185 (T_{\max}), and 8 functions included both of these thresholds (Table 1). Linear functions can be used
186 to derive starting estimates for the values of T_{\min} and T_{\max} (Campbell et al., 1974; Kontodimas et
187 al., 2004; Table 1) to be used in deriving more complicated nonlinear functions. Attempts were
188 also made to test three additional functions found in these reviews: the Exponentially Modified
189 Gaussian (Naish and Hartwell, 1988), Sharpe-Schoolfield-Ikemoto (SSI; Sharpe and DeMichele,
190 1977; Schoolfield et al., 1981), and Weibull (Angilletta Jr., 2006) functions. However, these
191 three functions have very complex structures requiring specialized fitting procedures not readily
192 applicable in many statistical software packages (see review by Shi and Ge, 2010), and in the
193 present study they could not be fit to the datasets used; as such, they were not considered further
194 in this study.

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197 *2.2.2. Re-analysis of species datasets from published studies:*

198 To assess whether the function(s) used in published studies were actually the “best”
199 functions for these published datasets, data were extracted for re-analysis from as many of the
200 studies obtained through the literature search described above as possible. Studies from the
201 literature search that did not present their data in a way that allowed it to be extracted for
202 retesting (e.g., only mean development times resented, without any measure of error), had to be
203 excluded. Therefore, only 79 species datasets out of the 99 initially obtained from the literature
204 search could be retested (Table S2); these included 10 arachnids (9 mites in the Subclass Acari
205 and one spider in Subclass Aranea), 28 Crustaceans (9 copepods and 19 decapods), and 41
206 insects in 8 orders (8 Coleoptera, 6 Diptera, 9 Hemiptera, 1 Homoptera, 1 Heteroptera, 8
207 Hymenoptera, 6 Lepidoptera, and 2 Thysanoptera) (Table S2). Raw data or means \pm error

208 (standard deviation (SD), standard error (SEM), etc.) and sample sizes were extracted from
209 tables or figures in published papers for each of these 79 species and used to generate datasets
210 for reanalysis.

211 Each study dataset was analyzed with linear and nonlinear regressions (Table 1) between
212 temperature and development time or rate, as appropriate. These regression were carried out
213 using IBM SPSS Statistics 22 (SPSS Inc., 2014). To simplify analyses, only total development
214 times or rates (i.e., summed across multiple larval stages) were examined and data for individual
215 stages were not. For development functions including thermal limits or other parameters with
216 biological meaning (e.g., T_{\min} or T_{\max} ; see Table 1 and section 2.2.1), unconstrained regressions
217 were initially carried out, with starting values for these parameters set to values estimated from
218 linear functions (see Table 1 and section 2.2.1, above). However, results were not accepted if this
219 yielded biologically unrealistic estimates, such as $T_{\min} < 0^{\circ}\text{C}$ in a species not known to survive
220 and develop at sub-zero temperatures, unreasonably low T_{\min} (e.g., -100°C) or high T_{\max} (e.g.,
221 100°C), or T_{\min} or T_{\max} within the temperature range for which successful development was
222 reported in the original study. In this case, constrained regressions were carried out (e.g., $T_{\min} \geq$
223 0°C , $T_{\min} < \text{minimum T with successful development}$, $T_{\max} > \text{maximum T with successful}$
224 development, etc.) until satisfactory values were obtained.

225 Once a regression equation corresponding to each development function was obtained for
226 each dataset, AIC_C values (Akaike's Information Criterion (AIC) corrected for finite sample size;
227 Akaike, 1973; Anderson, 2008) were calculated using the residual sum of squares (RSS) between
228 observed development times and those predicted by each function for each study (Anderson,
229 2008). Development functions were then ranked for each species dataset based on AIC_C -values.
230 The "best" possible rank was 1, corresponding to the lowest AIC_C value, and the "worst"

231 possible rank – if there were no ties – was 33, which corresponded to the highest AIC_C value
232 among the functions tested. The percentage of retested datasets for which each of the 33
233 functions was concluded to be “best” was recorded. For each species dataset, whether or not the
234 function used in its original published study and concluded to be the “best” function for the data
235 was the same as that determined to be the “best” function in this study was noted. If more than
236 one function was used in an original study, whether the actual best function was among all these
237 functions was also noted. RSS values were also used to calculate R^2 -values for each function, on
238 each dataset. These values were used as a measure of function performance (see next section,
239 2.2.3), indicating the proportion of the variation in observed development times that was
240 explained by each temperature-dependent development function.

241

242 *2.2.3. Assessing and comparing the overall performance of different functions:*

243 To determine whether any particular type(s) of function tended to do “better” than others,
244 the overall performance of each development function across species datasets was assessed using
245 three measures: average ranking (determined using AIC_C), R^2 , and Δ_i values. These measures of
246 performance were also compared across different taxonomic groups (arachnids, crustaceans, and
247 insects) as it was possible that certain functions might better represent development of animals in
248 a certain group(s) better than animals in others; this could be due to real biological differences
249 among taxa or to different experimental methodologies used for their rearing.

250 Calculation of function rankings and R^2 -values for each function on each dataset was
251 described above (previous section). Δ_i values were calculated once the best function for a given
252 dataset was determined to assess the information potentially lost by using a function other than
253 the best one (Anderson, 2008); a lower Δ_i value is better, and indicates less information loss. The

254 Δ_i value for a given function, “i”, is calculated by subtracting the AIC_C value of the best function
255 of those tested from its AIC_C value (Anderson 2008); therefore, the best function will have $\Delta_i =$
256 0. A function with a lower Δ_i , higher R^2 , or lower (better) ranking value on average than other
257 functions was considered to have performed better overall than other functions.

258 Separate two-way ANOVAs were carried out in IBM SPSS Statistics 22 (SPSS Inc.,
259 2014) to compare each of these three measures of performance (rankings, R^2 , and Δ_i) across
260 different development functions (factor with 33 levels; Table 1), as well as among different
261 taxonomic groups (factor with 3 levels: Arachnida, Crustacea, and Insecta). R^2 -values were
262 arcsine-square root transformed to meet the assumptions of parametric tests. If a statistically-
263 significant ($p \leq 0.05$) interaction between function and taxon was found, the data for that
264 measure were split by taxon and then separate one-way ANOVAs comparing different functions
265 were carried out for each taxon. If significant differences among functions were found, Tukey’s
266 Honestly Significant Difference (HSD) test was used to perform post-hoc comparisons among
267 specific function types.

268

269 *2.2.4. Assessing the consequences of development function choice:*

270 The consequences of choosing one function versus another to predict larval development
271 at different temperatures were assessed by comparing whether and how much the best or only
272 function originally used in the study from which each species dataset was obtained (“original
273 best” function) predicted observed development times relative to the best function identified in
274 this study (“actual best” function). Three measures, described in detail below, were calculated for
275 each of the 79 species datasets to assess consequences of function choice. These were mean error,
276 R^2 decrease, and Δ_i resulting from using the original study function instead of the actual best one.

277 To calculate the first of these, error, the absolute deviance (in days) between predicted
278 (using a development function) and observed development time was calculated for both the best
279 and original study functions, at each temperature tested in original studies. The absolute deviance
280 for the actual best function was then subtracted from that for the original best/used function at
281 each temperature, to determine how much predictions were worse (i.e., further from observed
282 values) when using the original versus best function. These differences were then averaged
283 across all temperatures and data points to calculate a mean absolute error (in days) per each
284 dataset that was due to using the original versus actual best functions. Mean error per dataset was
285 also expressed as a percent improvement by performing the aforementioned calculations, but
286 before averaging differences between deviance of original and actual best functions across
287 temperatures these differences were divided by the best function's deviance and multiplied by
288 100 %; this translated the error from a "raw" measure (in days) to a percentage (%).

289 R^2 decrease was simply calculated for each dataset by subtracting the R^2 -value of that
290 dataset's actual best function from that of its original used function. Percent R^2 increase was also
291 calculated for each dataset by dividing the R^2 change by the best function's R^2 , and then
292 multiplying by 100 %. A large R^2 decrease implied that a lower proportion of the variation in
293 development time was explained by the original function than the best one.

294 The Δ_i of the original function for each dataset was also examined to assess the extent of
295 potential information lost by using these, rather than the best functions, to fit the data. As
296 described above, a lower Δ_i (closer to 0 = Δ_i of best function) is better, and implies the function
297 retains more useful information than a function with a higher Δ_i . Generally a function with $\Delta_i < 2$
298 contains some useful information, even if it is not the "best" function, whereas a function with Δ_i

299 > 14 is highly unlikely to be informative (Anderson 2008). A high original function Δ_i value
300 would imply that the original function was considerably less informative than the best function.

301 If the best function for a given dataset was the same as the original function, all of the
302 measures described above would have a value of zero; if any measure were not significantly
303 different from zero, then, it would imply that using the best versus original function did not result
304 in meaningfully different predicted development times. Therefore, the distributions of each
305 measure of the consequences of using a function other than the best one (mean errors and R^2
306 decrease (both raw and % versions), as well as original function Δ_i values) across all species
307 datasets were compared to zero (null hypothesis of no differences) using five one-sample *t*-tests.
308 If the null hypothesis comparing these data against zero-values could be rejected, then a
309 significant ($p < 0.05$) impact of function choice was concluded.

310

311 2.3. Potential relationship between thermal range and function performance:

312 One interesting pattern noted during the literature review in this study was that studies of
313 temperature-dependent development differed considerably in their methodology, particularly
314 regarding the range of temperatures tested. Thermal ranges varied considerably among studies in
315 general, from as narrow as 6°C to as wide as 38°C (Table S2). Differences also appeared to exist
316 between studies of different taxonomic groups, particularly between studies of crustaceans
317 versus those of arachnids and insects (Hartnoll, 1982; Quinn and Rochette, 2015; Table S2). To
318 confirm whether such taxonomic differences were significant, the thermal range for each species
319 dataset obtained in the initial literature search ($n = 99$ total) was calculated as the maximum
320 temperature tested in its original study minus the minimum temperature tested; this included any
321 temperatures at which successful development was not observed (i.e., survival = 0 %), as this

322 implies a developmental threshold (i.e., T_{\min} and T_{\max} ; see Table 1). One-way ANOVA was then
323 used to compare thermal ranges among the three major taxonomic groups of arthropods.

324 More complex functions with more parameters have lower power to model smaller
325 datasets (Angilletta Jr., 2006; Shi and Ge, 2010). This is especially true for functions containing
326 threshold temperatures (T_{\min} and T_{\max}) if these are fit to data recorded over narrow thermal
327 ranges not approaching a species' real thermal limits (Shi and Ge, 2010). In such cases, thermal
328 thresholds have to be extrapolated too far beyond actual observations, resulting in excessively
329 extreme estimates for these parameters. One could thus expect that more complex functions may
330 perform better when wider thermal ranges are tested, potentially approaching or encompassing
331 real thermal limits. To test whether or not more complex functions would be selected as better
332 functions when wider thermal ranges were tested, Pearson's correlation coefficients (R) were
333 calculated between the thermal ranges calculated for each dataset and the ranking of each
334 function per dataset. Thus, 33 separate correlation analyses were carried out (one for each type of
335 development function), each consisting of 99 thermal range-ranking pairs (one pair per dataset).
336 Whether correlations were significant ($p \leq 0.05$), and if significant R-coefficients were positive
337 or negative was examined. As lower ranking values implied better function performance (see
338 above), a positive correlation for a given function implied that the function did worse when a
339 wider range of temperatures was tested, whereas a negative correlation meant that the function
340 did better when a wider thermal range was tested.

341

342 **3. Results:**

343

344 3.1. Results of literature review – usage of different functions:

345 Out of 99 different species datasets, over half (59.6 %) were reported to have been fit
346 with only one development function and the vast majority (96.0 %) were fit with five or fewer
347 functions (Fig. 2). In most cases studies that used 2-5 functions examined insects or arachnids
348 (Fig. 2) and used 1-3 more complex functions plus the linear rate (function #5) or Ikemoto and
349 Takai (#4) functions to derive starting values for T_{\min} and T_{\max} parameters in these complex
350 functions (Table S2; see also below and Fig. 3). The only taxonomic group for which > 5
351 different functions were tested was Insecta, for which 4.0 % of all species datasets (representing
352 7.8 % of insects) were tested with 5-17 different development functions (Fig. 2).

353 The most frequently-used development function overall, and particularly among studies
354 of the Insecta and Arachnida, was the Linear rate function (#5), which was used in 34.9 % of all
355 datasets and representing 28.4 and 15.2 % of insect and arachnid datasets, respectively (Fig. 3A;
356 Table S2). Seven other function types were used for arachnids, and for insects a wide range of 24
357 further functions types were used (Fig. 3A). Functions used on insects and arachnids ranged in
358 complexity from relatively simple ($k = 3$) to very complex (#33, $k = 8$), but with no particular
359 function aside from the linear rate one (#5) predominating (Fig. 3A). Studies of Crustacea used a
360 more limited set of 8 functions, all but one of which (function #16, $k = 4$) were relatively simple
361 (#1-3 and 5-8, $k = 3$) (Fig. 3A). The Heip power function (#2) was the most commonly-used
362 function for Crustacea (9.4 % of all datasets, or 35.1 % of crustaceans), followed by the
363 Bělehrádek (#8, 6.6 % of datasets or 24.6 % of crustaceans) and Tauti or exponential (#7, 4.7 %
364 of datasets, 17.5 % of crustaceans) functions (Fig. 3A). The distribution of best functions as
365 concluded in reviewed studies showed a similar pattern, with the linear rate function (#5)
366 dominating for insects and arachnids and the Heip power function (#2) most often being
367 concluded best for crustacean data (Fig. 3B). Among insects and arachnids, the Brière-1 function

368 (#9) showed a slight tendency to be selected as best more often than other nonlinear functions, as
369 it was for 7.0 % of all datasets, representing 6.7 % of insects and 18.2 % of arachnids (Fig. 3B).

370

371 3.2. Results of meta-analysis – did previous studies use the “best” function for their data?

372 The development function(s) used to fit species datasets and/or concluded to have been
373 the “best” function for these data in their original studies were found, in the vast majority of
374 cases, not to be the best function for the data out of the 33 functions examined (Fig. 4). When
375 AIC_C was used to rank functions, the best function for 91.1 % of 79 retested study datasets was
376 concluded to be a different one than that selected in previous studies (Fig. 4A), and for 86.1 % of
377 datasets the actual best function was not even included in the set of all functions used in original
378 studies (Fig. 4B). The actual best function was found to be different from that concluded to be
379 best in original studies for all (100 %) arachnid and insect studies examined, and for most
380 (75.0 %) crustacean studies (Fig. 4A). Also, for all taxonomic groups a considerable majority of
381 datasets (100 % of Arachnida, 67.9 % of Crustacea, and 95.1 % of Insecta) were found to be best
382 fit using a function that was not used in original studies of these species (Fig. 4B).

383

384 3.3. Overall performance of different functions:

385 No one function was found to always be the “best” or “worst” for all reanalyzed datasets,
386 but some functions did tend to perform better than others (Fig. 5). Those that were ranked as the
387 best function by AIC_C particularly often (i.e., for ≥ 10 % of datasets) were the Heip power (#2),
388 hyperbola (#3), Bělehrádek (#8), quadratic time (#16), and 3rd order polynomial time (#19)
389 functions (Fig. 5). There were no clear taxonomic patterns in terms of which functions tended to
390 be ranked best, although function #19 did perform particularly well for insect datasets, and more

391 complex functions with $k > 5$ were rarely concluded to be best (Fig. 5). Of the 33 functions tested,
392 16 were also never concluded to be the best of those tested (Fig. 5).

393 There were significant interactions between the effects of taxonomic group and
394 development function type on overall performance of the 33 different development functions as
395 assessed with R^2 -values ($F_{64, 2508} = 1.377$, $p = 0.026$) and by ranking functions with AIC_C ($F_{64,$
396 $2508} = 2.362$, $p < 0.001$). Therefore differences in R^2 and rank among functions were compared
397 for each taxonomic group separately. In all three taxonomic groups, R^2 -values (Arachnida: $F_{32,$
398 $297} = 1.783$, $p = 0.007$; Crustacea: $F_{32, 891} = 3.721$, $p < 0.001$; Insecta: $F_{32, 1320} = 2.868$, $p < 0.001$)
399 and ranks significantly differed among different development functions (Arachnida: $F_{32, 297} =$
400 5.724 , $p < 0.001$; Crustacea: $F_{32, 891} = 14.707$, $p < 0.001$; Insecta: $F_{32, 1320} = 17.823$, $p < 0.001$).
401 However, overall Δ_i values were found to not differ significantly among functions ($F_{32, 2508} =$
402 0.278 , $p > 0.999$) or taxonomic groups ($F_{2, 2508} = 1.0$, $p = 0.368$), nor was there a significant
403 interaction between the effects of these factors on Δ_i values ($F_{64, 2508} = 0.448$, $p > 0.999$).

404 Differences in fit (R^2) and rankings among functions were actually very similar across the
405 different taxonomic groups (Fig. 6A-F; Table 2). Most function had relatively high overall
406 average R^2 -values between 0.7 and 0.9 or higher (Fig. 6A-C), so on average, all temperature-
407 dependent development functions tested were able to explain the majority of variation in
408 observed development times. Functions with notably lower fit compared to others (lowest mean
409 $= 0.476$) did occur, though, and included the linear time (#6) Logan-6 (function #25), Logan-10
410 (#30), and W-L-D (#33) functions on arachnid and insect data (Fig. 6A, C; Table 2), and the
411 Ratkowsky (#27), Brière-1 (#9) and Brière-2 (#20) functions on crustacean data (Fig. 6B; Table
412 2). The explanatory power of development functions therefore differed by as much as ca. 10-
413 50% on average depending on which was used (Fig. 6A-C). Functions with lower (better) overall

414 ranks for all taxonomic groups included the Heip (#2), Hyperbola (#3), Bělehrádek (#8),
415 quadratic time (#16), and 3rd order polynomial time (#19) functions (Fig. 6D-E; Table 2), and
416 those with high (poor) overall ranks included those with low R²-values described above and the
417 Holling Type III (#21) functions (Fig. 6D-E; Table 2). All mean Δ_i values were high (mean $\Delta_i \geq$
418 22.7) because each function was not selected as the best function by AIC_C at least once, and in
419 many cases the difference between the AIC_C values of the best function and the 2nd best function
420 (Δ_i) were quite large (as evidenced by the variance in Fig. 6G-I). There were therefore large
421 differences in the amount of information attained depending on which function was used, but no
422 clear pattern among functions or taxa (Fig. 6G-I).

423

424 3.4. Consequences of function choice:

425 All measures of prediction error, decreased fit, and increased information loss resulting
426 from using the best original rather than the actual best functions on species datasets were
427 significantly different from zero (one-sample *t*-tests, $p < 0.05$; Table 2). Development times
428 predicted with original studies' functions disagreed with observed developmental duration by
429 about 4 days or 85.9 % on-average, but could be off by as much as 132 days or 1725.5 % (Table
430 3). Fit (R²) of original functions to arthropod datasets was lower by 0.091 on-average compared
431 with best functions (Table 3), meaning that nearly 10 % of the variation in the data would remain
432 unexplained if the original rather than the actual best function was used. The difference in R²-
433 values between originally-used and best functions could be much greater in many cases, though,
434 as percent decrease in R² by using the best function was as high as 100 % for certain study
435 datasets (Table 3; Table S2). Additionally the mean Δ_i of the originally-used functions was 225

436 and could be as high as 3958.7 for some datasets (Table 3), indicating a substantial loss of
437 information relative to the actual best function as determined in the present study.

438

439 3.5. Range of temperature tested in studies versus function performance:

440 Thermal ranges tested in original studies differed significantly among studies of different
441 taxonomic groups ($F_{2, 96} = 16.533$, $p < 0.001$; see also Table S2). Interestingly, studies of
442 crustaceans tended to be carried out over significantly smaller thermal ranges (mean \pm 95% C.I.
443 = 11.9 ± 0.8 °C, range = 6.0-22.5°C) than those of arachnids (20.0 ± 1.1 °C, range = 12.5-
444 30.0°C; Tukey's HSD test, $p < 0.001$) or insects (17.5 ± 1.2 °C, range = 8.0-38.0; Tukey's HSD
445 test, $p < 0.001$) implying notable differences in the way thermal effects are investigated in these
446 taxa; thermal ranges studied for Insects and Arachnids did not differ, however (Tukey's HSD test,
447 $p = 0.328$).

448 The range of temperatures examined in previous studies was significantly correlated with
449 performance (ranking) of 13 of the 33 development functions tested in this study (Fig. 7). With
450 one exception (function # 30), all functions for which rankings by AIC_C were significantly and
451 positively correlated with temperature range were those (#1, 2, 5-7, 13, 15, and 16) that had
452 fewer parameters ($k \leq 4$) (Fig. 7). This means that these relatively simpler functions tended to do
453 more poorly (higher value = poorer rank, further from 1) when larger thermal ranges were tested.
454 Conversely, rankings of more complex functions with $k = 5$ (#20, 24, and 27) or $k = 7$ (#32) were
455 negatively correlated with temperature range (Fig. 7), meaning that these functions performed
456 better (lower value = better rank, closer to 1) when studies tested a wider range of temperatures.

457

458 **4. Discussion:**

459

460 4.1. Use and performance of different development functions in previous studies:

461 Modeling functional relationships between temperature and life history characters is an
462 essential component of studying the biology of poikilothermic organisms (Angilletta Jr., 2006;
463 Bělehrádek, 1935; Papnikolaou et al., 2013; Shi and Ge, 2010). Predictions of generation times
464 (Huntley and Lopez, 1992), timing of seasonal events (Bayoh and Lindsay, 2003), dispersal
465 potential (de Rivera et al., 2007), and recruitment to adult populations of Arthropoda (Aiken and
466 Waddy, 1986; Caddy, 1986) produced by such modeling efforts are thus sensitive to the types of
467 temperature-dependent larval development functions incorporated in these. Development times
468 of arthropod larvae predicted for the same species and temperatures by different function types
469 can differ substantially, which has important impacts on predictions made. Using the best
470 possible function to represent a given species' and/or study's dataset should thus be a crucial
471 component of the study of temperature-dependent arthropod larval development, which should
472 precede reporting and use of the results of such studies in models. However, in the present study
473 this important step was found to be largely bypassed by the majority of studies. Particular
474 function types tended to be used more often than others for particular taxonomic groups with
475 little or no clear justification for the choice made, while consideration of alternative function
476 types was rarely reported in published papers. In most cases the function used in original
477 published studies was not actually the best one for the datasets presented. Further, fitting these
478 data with the best model resulted in better fit, less disagreement between predicted and observed
479 development times, decreased information loss, and presumably also better predictive ability.
480 These results demonstrate that development function choice is an important but often-ignored

481 step in research on arthropod larval development, which should be given greater consideration in
482 future studies.

483 Choosing one particular development function might have some justification if any
484 function(s) could be said to be better overall than others. In the present study, no single function
485 type was found to be the best or worst, although some did tend to perform better or worse than
486 others (see Fig. 5, 6 in Results). Functions that performed well overall might be recommended as
487 good starting points for fitting development data, and those that did poorly overall could
488 conversely be used with caution. (Table S1). Also, the more complex functions with high k -
489 values and including T_{\min} and T_{\max} parameters, which performed poorly overall, did somewhat
490 better on insect data than for other taxa and actually was among the best models for some insect
491 species datasets (Table S2). Therefore, it is difficult to make general statements about which
492 function is always best to use; this must rather be assessed on a case-by-case basis, for each
493 species and study. Results in this study showed that not using the best function for a given
494 dataset can result in very different predicted development times, which could lead to very
495 different (and potentially erroneous) inferences and predictions of species biology by modeling
496 studies (Miller et al., 1998; Miller et al., 2006; Quinn, 2014; Reitzel et al., 2004). The practice
497 among many fields of study has been to fit data with a development function type that has been
498 used in previous studies on similar species; for example, the frequent use of the Bělehrádek
499 function on copepod crustaceans (Anger, 2001; Corkett and McLaren, 1970; Hamasaki et al.
500 2009) or linear rate + complex function(s) on insects and arachnids (Golizadeh and Zalucki,
501 2012; Shi and Ge, 2010; Smits et al., 2003; Table S2). However, based on results of the present
502 study this practice should be discontinued.

503

504 4.2. Importance of temperature range tested to function performance:

505 An interesting finding in the present study was that overall performance of several
506 function types was correlated with the range of temperatures tested in original published studies.
507 Specifically, as the range of temperatures tested increased performance (i.e., likelihood to be
508 ranked as the best model) of the simpler functions examined decreased while that of more
509 complex functions increased. This result does make sense, however, if one considers the “real”
510 nature of temperature-biological rate relationships. Because the actual performance of the
511 enzymes mediating larval development most certainly have upper and lower functional threshold
512 temperatures, beyond which development cannot progress (Brière et al., 1999; Quinn and
513 Rochette, 2015; Somero, 2004), one can assume that for most species the “true” relationship
514 between temperature and development time resembles the Brière-2 function, or similar complex
515 asymmetrical curves (e.g., Huey and Stevenson, 1979; Shi and Ge, 2010). A study carried out
516 over a very wide range of temperatures should be able to approach or exceed thermal thresholds
517 and therefore identify these limiting temperatures, and thus be best explained by a complex
518 function. However, if one carries out their study over a more narrow thermal range, they will
519 only be able to observe a certain section of the development curve, which could be located
520 relatively far from one or both threshold temperatures. This could result in the observed
521 temperature-development data having a distinctly linear, quadratic, or power function-like shape,
522 such that one of these alternative, simpler functions would be identified as the “best” function for
523 the data over this specific range. Indeed, this seems to have been the case in several of the
524 datasets examined, in which thermal ranges and/or sample sizes were relatively small (e.g.,
525 Quinn et al., 2013; Corkett and McLaren, 1970; Hamasaki et al., 2009; Carlotti et al., 2007;
526 Table S1, S2) and the best function was determined to be one of the simpler functions, such as

527 the linear time (#6) or Heip power (#2) function, even though these should be the least-realistic
528 (Bělehrádek, 1935; Brière et al., 1999; Somero, 2004). Importantly, when this occurs the best
529 function will be the one that provides the most informative description of development times
530 over a very specific range of temperatures, but its performance is likely to degrade if
531 extrapolation beyond this range is attempted. Ultimately the “best” function should be of a
532 complex form resembling functions with T_{\min} and T_{\max} parameters, but most studies, especially
533 of Crustacea, are not conducted over sufficiently wide temperature ranges to be allow good
534 estimates of such functions’ parameters to be derived.

535 The vast majority of insects and arachnids have terrestrial and/or freshwater aquatic
536 habitats, in which temporal variability in air and water temperatures can be very large (Pakyari et
537 al., 2011; Sanchez-Ramos et al., 2007; Stavrinides et al. 2010). As a result, the likelihood of
538 these organisms and their larvae being exposed to extreme temperatures exceeding thresholds for
539 moulting, development, and/or survival can be high. Conversely, many crustaceans (and all of
540 those examined in the present review; Table S2) inhabit the marine realm as larvae and/or adults
541 (Paul and Paul, 1999; Roberts et al., 2012; Thompson, 1982). While it is not impossible that
542 marine crustacean larvae could encounter temperatures too high for development or survival (e.g.,
543 such warm extremes could occur in shallow coastal areas, highly-stratified water columns,
544 intertidal zones at low tide, or more generally due to future climate change; Caffara et al., 2012;
545 Quinn and Rochette, 2015), they are thought to be far more likely to encounter lower limiting
546 temperatures, especially in the deeper ocean or temperate regions (Hartnoll, 1982; MacKenzie,
547 1988; Quinn, 2016). This perceived difference in limiting temperatures appears to have lead
548 studies on temperature-dependent development in these groups along different paths. Studies of
549 insects and arachnids often use very wide temperature ranges with the intent of capturing lower

550 and upper limiting temperatures for development in their species because these physiological
551 limits are known to be essential to modeling these species in their natural environments (Shi and
552 Ge, 2010; Smits et al., 2003). Studies of crustaceans, to the contrary, tend to be limited to more
553 narrow thermal ranges deemed “ecologically-relevant” (i.e., likely to be encountered by the
554 species in nature); occasionally these include lower limits, but in general physiological limits,
555 especially upper ones, are rarely sought (Hartnoll, 1982; Quinn, 2016).

556 While there is certainly logic behind the use of narrower, more-relevant thermal ranges in
557 studies of Crustacea, this approach still has potential to result in errors for two main, related
558 reasons. First, the type of development function used changes predicted development times both
559 at and between (interpolation) observed temperatures and especially outside of these
560 (extrapolation) (Angilletta Jr., 2006; Campbell et al., 1974; Quinn and Rochette, 2015). Second,
561 thermal development limits actually change the shape of the “real” and estimated (i.e., fitted by
562 regression) development curve, for example by decreasing its curvature when lower and upper
563 limits are further apart and increasing curvature when these are closer together (Bělehrádek,
564 1935; Brière et al., 1999; Shi and Ge, 2010; personal observations by author). All else being
565 equal, these difference in curvature can result in very different development times at the same
566 temperatures. As a result, it is important to know the physiological limits of a given species when
567 modeling its development (Quinn, 2016). Even if a species rarely encounters temperatures close
568 to these limits, development times calculated at intermediate temperatures will be impacted by
569 the values of these limits; if one ignores these limits and uses a different function type, or
570 attempts to estimate limits by extrapolation from a narrow thermal range, there is great potential
571 for erroneous predictions of development times to be made.

572

573 4.3. Discussion of potential limitations and next steps:

574 In the present review, published studies on arthropod larvae were obtained through
575 literature searches through Web of Science (Thompson Reuters, 2015). These searches were by
576 no means comprehensive – many other studies of temperature-dependent development of
577 arthropod larvae exist that were not indexed in this search engine – but it was extensive and did
578 provide a good sample of such studies encompassing many different years, regions, and
579 arthropod taxa (Table S2). This sample of the relevant literature was thus appropriate and useful
580 for the purposes of the present review of development function usage and performance. An
581 expanded search using additional search tools in a future study could obtained data for other
582 taxonomic groups within the Arthropoda (e.g, myriapods, more arachnids, other orders of
583 Crustacea and Insecta, etc.); indeed, an Insect Developmental Database has been created by
584 Nietschke et al. (2007) that could be used to obtain considerably more insect data for reanalyses.
585 Performance of development functions on data from species outside of the arthropod phylum
586 (e.g., molluscs: de Severyn et al., 2000; nematodes: Jenkins et al., 2006; Singh and Sharma,
587 1994; urochorates: Kang et al., 2009; vertebrates: McLaren and Cooley, 1972; Miller et al. 2006)
588 may also be attempted, and reveal additional patterns in study design, taxonomy, and function
589 usage of interest. However, overall patterns and conclusions of the present study would likely
590 hold true. To simplify analyses, this study conducted analyses on total larval development time
591 data rather than on individual larval stages. However, in most species development time of each
592 larval stages has a distinct response to temperature, requiring different developmental equations
593 to be derived for each stage (Corkett and McLaren, 1970; Hartnoll, 1982). Often survival to and
594 through later larval stages is very low, so power to fit more complex functions to later-stage
595 development data can be limited. As a result, the best function can potentially differ among

596 larval stages of the same species, in the same study; indeed, this was noted for American lobster
597 data in the present study (data not shown). A future study should investigate stage-specific
598 changes in the “best” development function(s), to confirm whether such patterns could impact
599 the overall performance of different function types, prediction error, and so on. However, it
600 would make mathematical sense for similar patterns to be found through such a detailed review
601 to those noted in the present study, given that similar factors (e.g., sample sizes and thermal
602 ranges tested) would impact function performance. There are also countless other development
603 function types in existence which were not included in the present study (e.g., Angilletta Jr.,
604 2006; Schoolfield et al., 1981; Shi and Ge, 2010). It is possible that one or more of the functions
605 not examined herein could actually be the closest to “real” development relationships and/or
606 perform better overall than all others. However, findings of this review that one or few functions
607 are used by most studies, the best function was not the one used in most original published
608 studies, and that using the non-best function results in poorer predictions would not change
609 through consideration of such additional functions.

610 In this study function performance was assessed mainly in terms of fit (R^2 and observed
611 versus predicted values) and information loss (AIC_C and Δ_i). These gave good indications of how
612 appropriate each function and its parameter estimates were for particular datasets (e.g., how well
613 sample sizes supported estimation of more complex functions). However, future studies could
614 take more thorough approaches to assessing predictive ability of different functions. One
615 approach to be used in the future to assess function performance could be cross-validation
616 (Picard and Cook, 1984; Anderson, 2008). Even better would be actually testing development
617 functions on new data, for example by predicting development times for a particular species at
618 different temperatures using different functions derived in a prior study, and then measuring new

619 development times and comparing these to predictions. If future studies attempted this, very
620 thorough tests and new evidence in favour of one function or another might be obtained.

621

622 4.4. Implications of development time predictions based on different functions:

623 Differences in development times predicted for the same species and temperature among
624 development functions have potential to impact various types of predictions relevant to arthropod
625 biology and ecology. Larval survival is usually inversely related to larval duration, such that
626 slower development results in fewer potential recruits to adult populations (Reitzel et al., 2004;
627 Roberts et al., 2012). Most life history and bio-physical models account for this by reducing
628 larval numbers in simulated cohorts by a certain percentage at each model time step, resulting in
629 substantial, exponential losses per each additional step spend in larval development (e.g., Miller
630 et al., 1998; Quinn, 2014). In many crustaceans, the larval phase of the life cycle is the main
631 dispersive phase (Anger, 1984; de Rivera et al., 2007; MacKenzie, 1988). Lengthening the larval
632 developmental period of such larvae can dramatically alter how far and to where larvae drift in
633 simulations with ocean currents; for example, simulations by Quinn (2014) showed that slowing
634 larval development (and thus lengthening drift time) of American lobster larvae by 60 % could
635 result in increased drift distances of larvae by up to ca. 500 km. If drift were overestimated in
636 such models, for instance due to use of inappropriate development functions, then the degree of
637 population mixing would be overestimated and an incorrect estimate of population structure
638 obtained; underestimation by the same means could also lead to considerable errors. Likewise if
639 dispersal ability of larvae of an invasive species, such as the green crab *Carcinus maenas* (L.) (de
640 Rivera et al., 2007), were underestimated in this way potential invasions to new regions that
641 could be predicted may be missed. Using development functions to estimate the timing of

642 seasonal peaks in abundance of disease vectors (Bayoh and Lindsay, 2003), agricultural pests
643 (Campbell et al., 1994; Easterbrook et al., 2003; Stavrinos et al., 2010), or species that serve as
644 important food sources to others (e.g., copepod secondary productivity in the ocean: Carlotti et
645 al., 2007) also depends on being able to make good estimates of larval development. For many
646 species very small differences in development time similar to the difference in “errors” of best
647 and original studies’ functions are enough to dramatically alter the nature and implications of
648 modeled predictions (e.g., ≤ 1 -5 days; Gadino and Walton, 2012). The type of development
649 function used can thus have large impacts on predictions, so it is important that studies attempt to
650 find the best model for their data. Importantly, much research is now being initiated to assess
651 how future climate change will impact many species, including arthropods and their larvae
652 (Caffara et al., 2012; Quinn and Rochette, 2015). Use of non-best development functions within
653 such research clearly could result in erroneous predictions as well and so should be avoided.

654

655 4.5. Recommendations and conclusions:

656 Based on results of this study, it is recommended that future studies examining effects of
657 temperature on development of arthropod larvae consider and attempt to fit multiple alternative
658 development function types to their data to determine the best way to model their results and
659 report that this was attempted. No one function type is better or worse overall, but the range of
660 temperatures to be considered and potential use of results (e.g., for extrapolation to temperatures
661 not observed) can be used as a guide when deciding which functions are most likely to provide
662 good representations of data. In general simpler functions could provide better descriptions of
663 development observed over relatively narrow thermal ranges, but provide poor extrapolation
664 ability. Conversely, wider ranges encompassing lower and/or upper limiting temperatures for

665 development can support more complex functions, which potentially resemble more closely true
666 enzymatic and biological thermal performance curves (Brière et al., 1999; Somero, 2004) and
667 may allow modeling over all temperatures potentially encountered. Studies on crustaceans in
668 particular should be conducted over wider thermal ranges in the future so that limiting
669 temperatures of these species can be identified and more complex, presumably realistic
670 development functions reliably fit to data for these organisms. Considering different potential
671 function types to find the best for each dataset should lead to better predictions of larval
672 development times in support of subsequent research on these important species.

673

674 **Acknowledgements:**

675

676 Thanks are due to Rémy Rochette, Joël Chassé, Jeff Houlihan, and Heather Hunt for advice and
677 guidance during this project, and the University of New Brunswick, Saint John Campus, for
678 providing resources that made the review and analyses possible. The author also thanks two
679 anonymous reviewers for providing comments that improved the scope and quality of the
680 manuscript.

681

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1083 **Electronic Supplementary Material:**

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1085 **Table S1.** Development function parameter estimates, R^2 , and AIC_C for American lobster data
1086 plotted in Figure 1.

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1088 **Table S2.** List of studies and species obtained for the literature review and meta-analyses,
1089 including taxonomic grouping, function type(s) used, best function, whether the best and used
1090 function were the same, temperature range tested, performance (R^2 , AIC_C rank, and Δ_i) of each
1091 of the 33 functions tested ('na' = study not possible to retested in meta-analysis), and
1092 consequences of using original studies' rather than the actual best function to fit datasets in terms
1093 of prediction error, R^2 decrease, and information loss (Δ_i).

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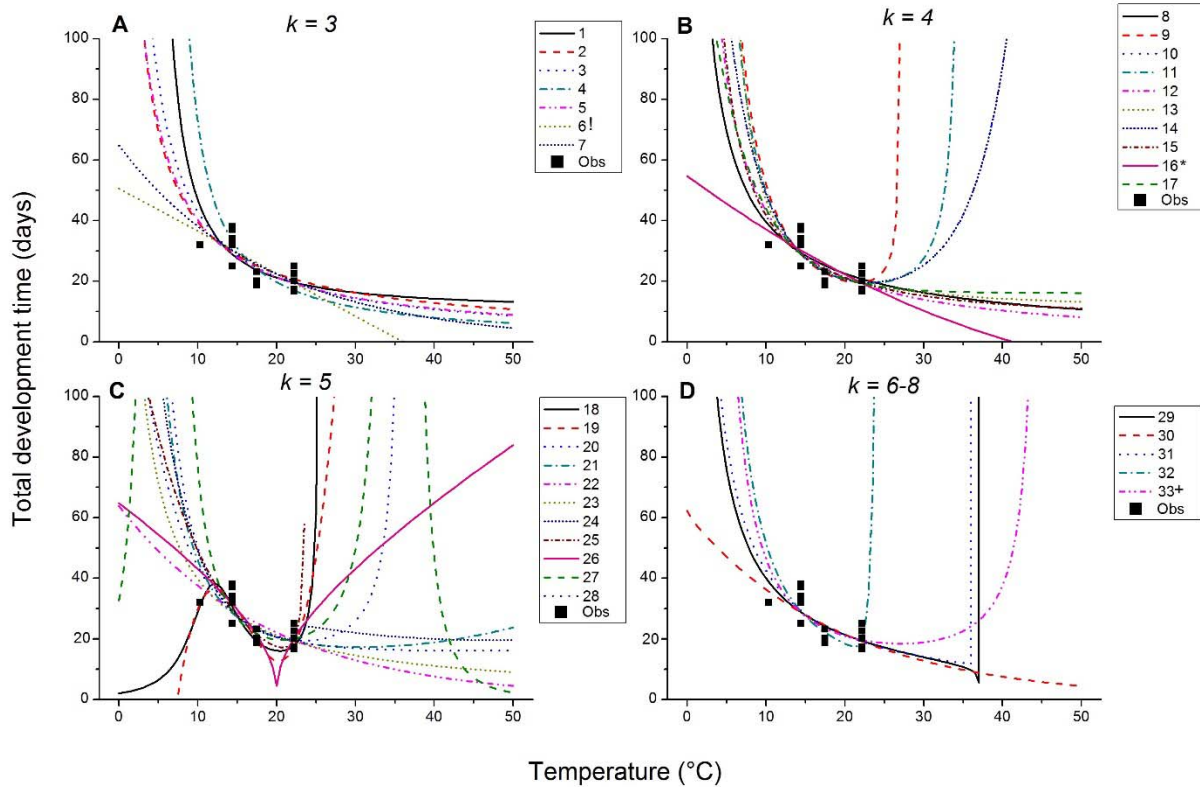
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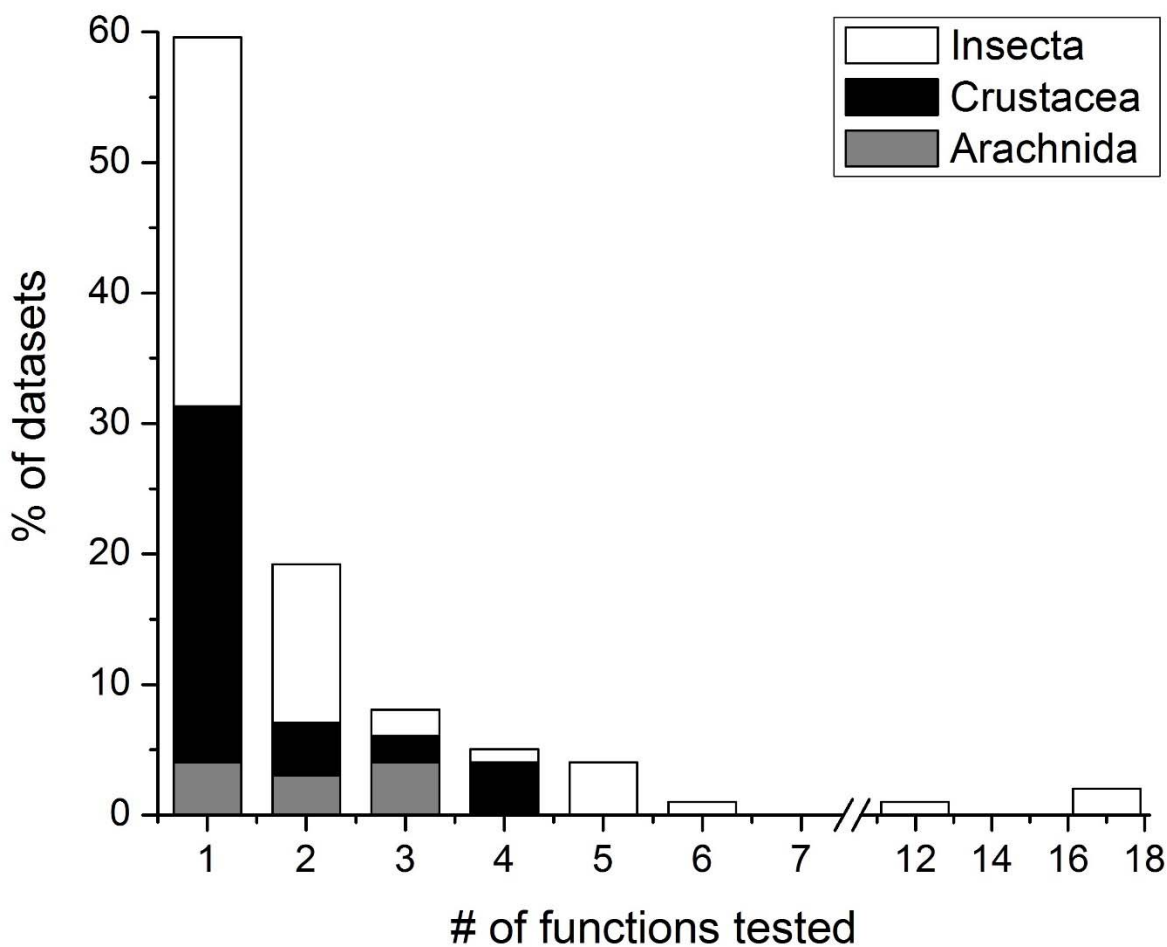
1106 **Tables and Figures:**



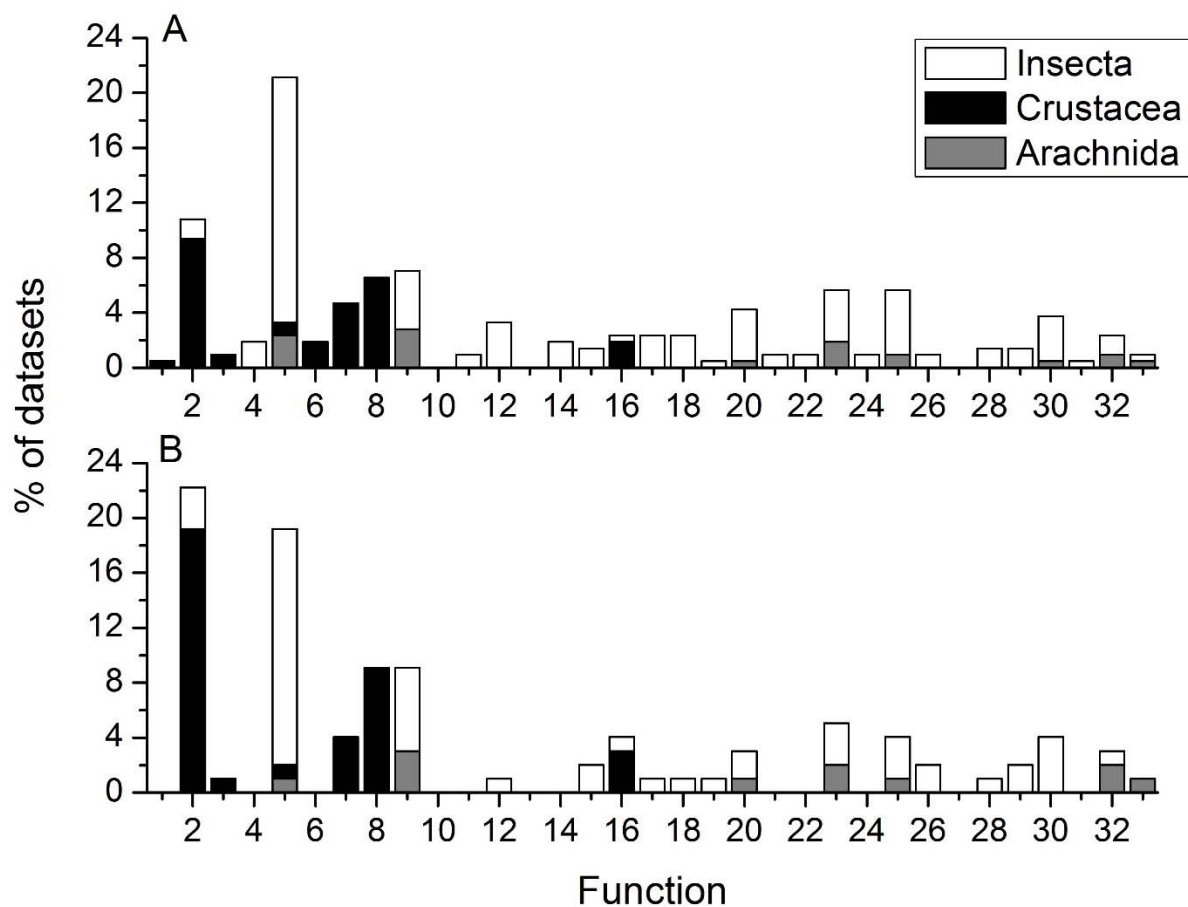
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1108 **Figure 1.** Examples of the curves formed by different development functions, when these are
 1109 used to calculate development time (y-axes, days) at different temperatures (x-axes, °C). Types
 1110 of functions plotted here are those presented in Table 1, separated into those with k -values
 1111 (number of parameters + 1) of (A) 3, (B) 4, (C) 5, or (D) 6-8. Actual functions (see Table S1)
 1112 were derived from and fitted to data for total development times (combined time to complete
 1113 larval stages I-III) of American lobster (*Homarus americanus* (H. Milne Edwards, 1837)) larvae,
 1114 as reported by Quinn et al. (2013); observed development times are plotted (squares) along with
 1115 predictions of development functions (lines). Coefficients, R^2 , AIC_C , and Δ_i values for these
 1116 functions are presented in Table S1. ‘*’ = function used by Quinn et al. (2013) to fit the data, ‘!’
 1117 = actual “best” function for these data, and ‘+’ = worst function for these data.

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1119
1120 **Figure 2.** Usage in each development study reviewed of one or more different types of
1121 development function. The percentage (%) of species datasets obtained in initial literature review
1122 (n = 99 total, see Table S2) that were tested with each number of functions is plotted on the y-
1123 axes and broken down by taxa (gray bars = arachnids, black = crustaceans, and white = insects).
1124 For names and details of development functions (#1-33) the reader is referred to Table 1.
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1127 **Figure 3.** Usage in each development study reviewed of specific development function types.

1128 The percentage (%) of the 99 species datasets obtained in initial literature review (see Table S2)

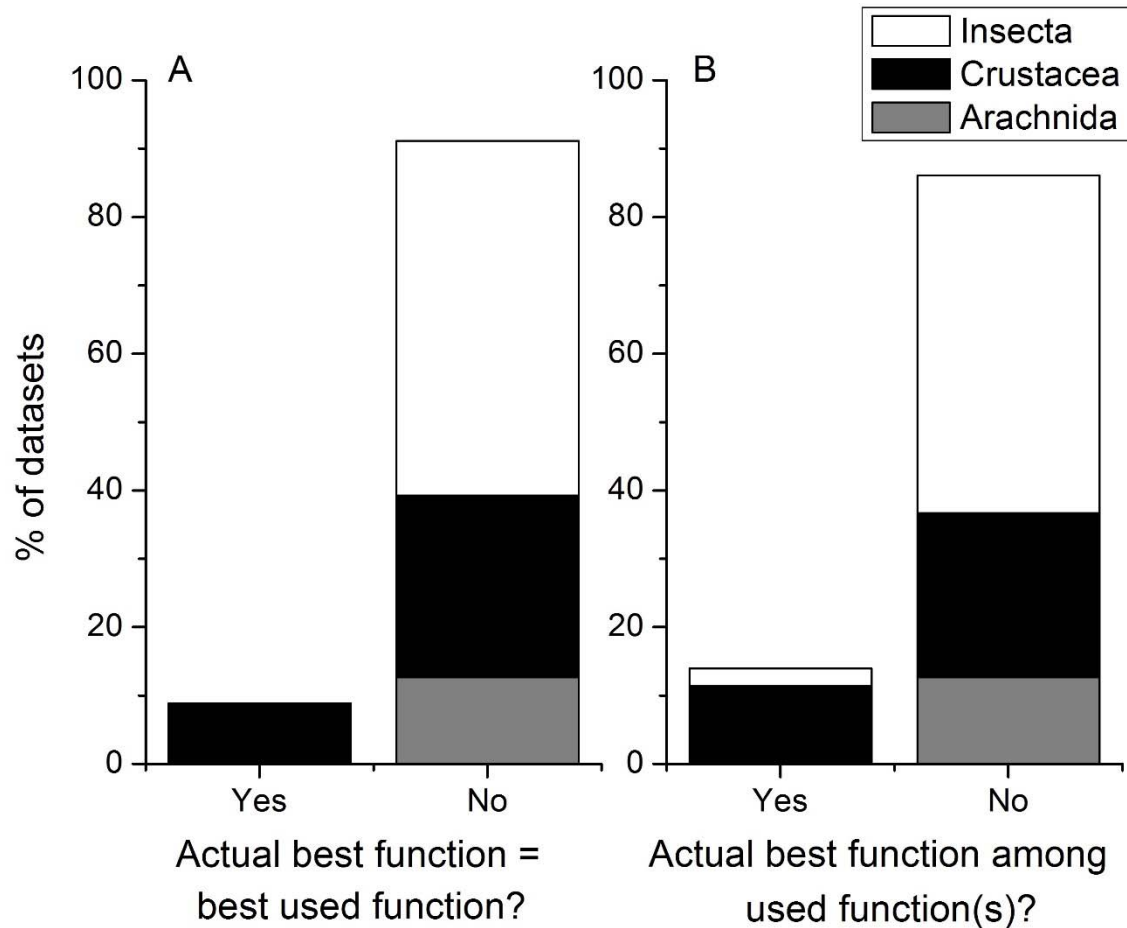
1129 that were (A) tested with each type of function (i.e., all used functions) and (B) concluded to be

1130 best represented by each type of function (i.e., best used function) is plotted on the y-axes.

1131 Results are also broken down by taxonomic group, as in Fig. 2. For names and details of

1132 development functions (#1-33) the reader is referred to Table 1.

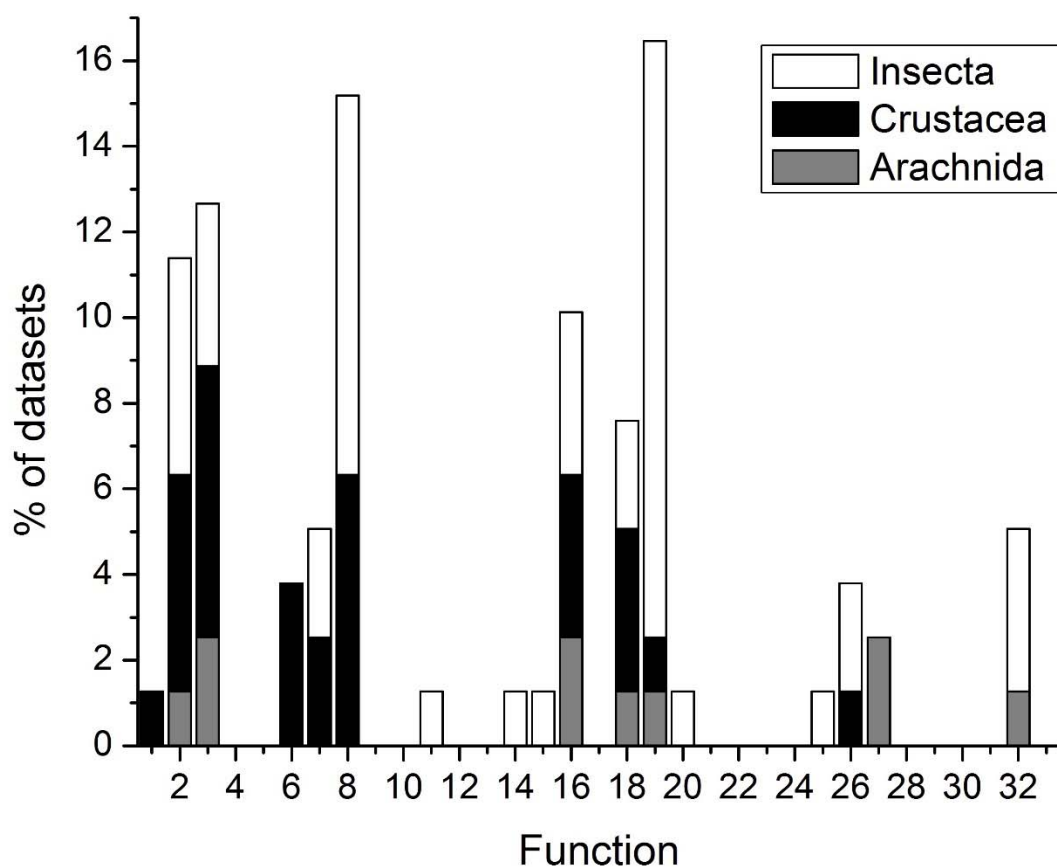
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1135 **Figure 4.** Percentage (%) of species datasets re-analyzed for meta-analysis (n = 79) for which the
1136 development function found to be best for the data (lowest AIC_C value, ranking based on AIC_C =
1137 1) in this study (i.e., actual best function) (A) agreed or not with the best function as used in its
1138 original published study or (B) was among the set of all function(s) used within its original
1139 published study. Results are also broken down by taxonomic group, as in Fig. 2. For names and
1140 details of development functions (#1-33) the reader is referred to Table 1.

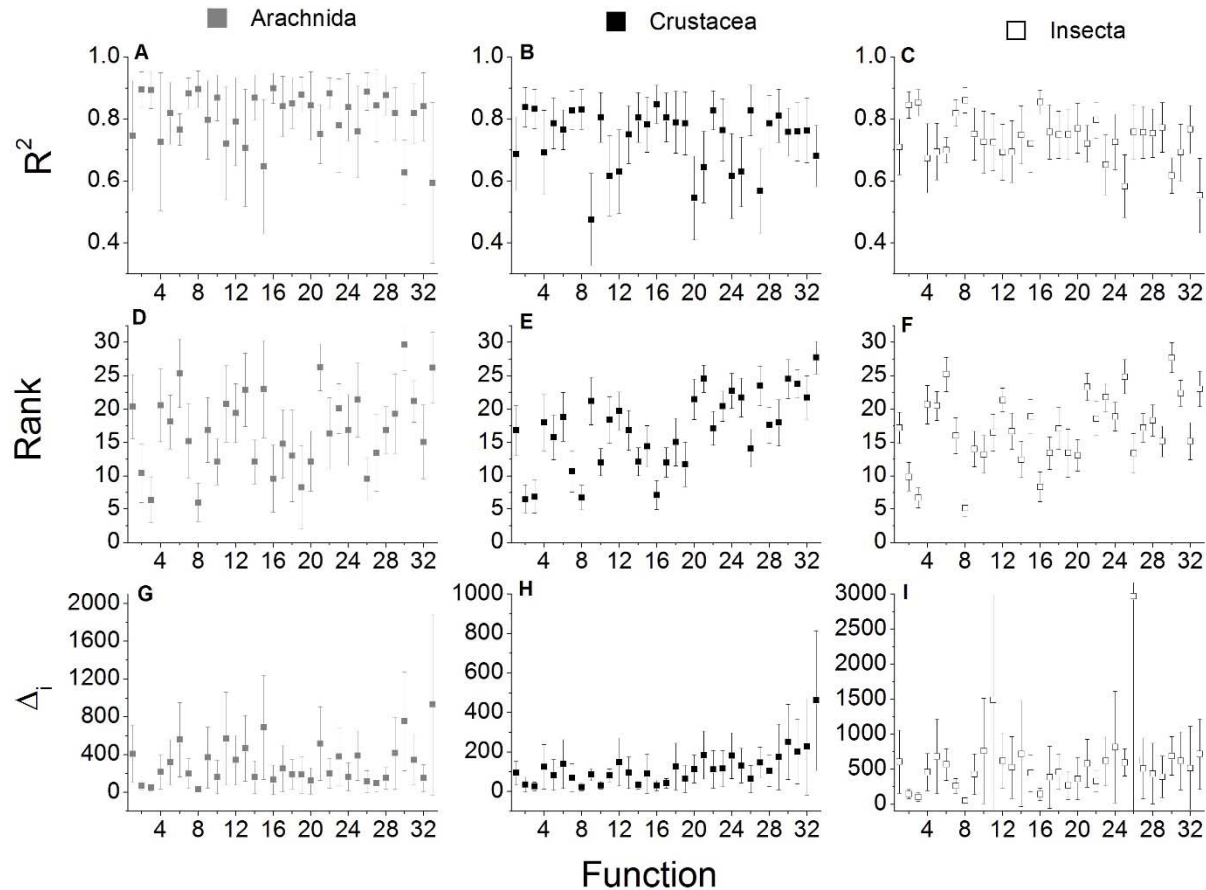
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1143 **Figure 5.** Percentage (%) of species datasets re-analyzed for meta-analysis (n = 79) for which
1144 each development function type was found to be best for the data (lowest AIC_C value, ranking
1145 based on $AIC_C = 1$) in this study. Results are broken down by taxonomic group, as in Fig. 2. For
1146 names and details of development functions (#1-33) the reader is referred to Table 1.

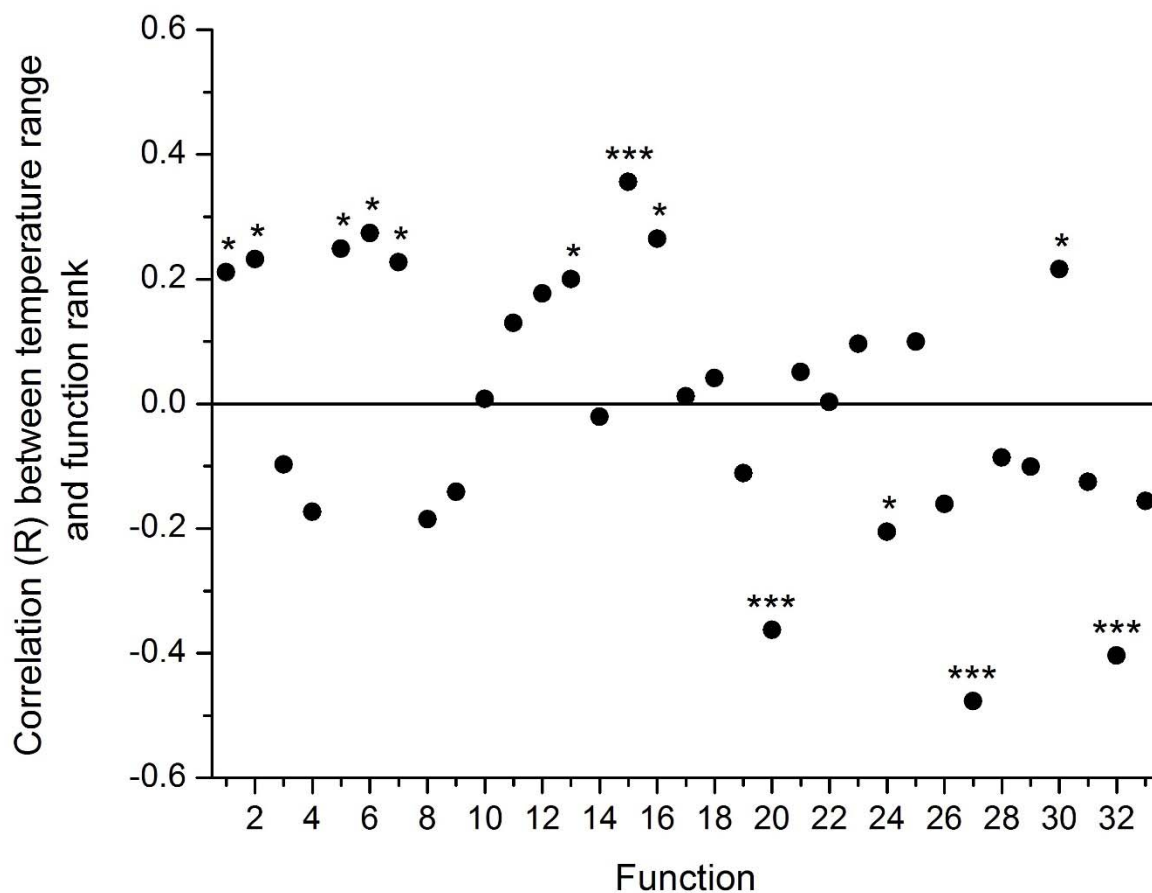
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1149 **Figure 6.** Overall performance of different development functions (x-axes) assessed based on
1150 (A-C) R^2 values, (D-F) ranking based on AIC_C values, and (G-I) Δ_i values (y-values). Function
1151 performance was assessed separately for each taxon: (A, D, G) arachnids ($n = 10$ species for each
1152 function), (B, E, H) crustaceans ($n = 28$), and (C, F, I) insects ($n = 41$). Possible rankings ranged
1153 from 1 (“best” model) to 33 (“worst”). Values plotted are mean values per function and
1154 taxonomic group taken across all species datasets within that group $\pm 95\%$ C.I.s. For names and
1155 details of development functions (#1-33) the reader is referred to Table 1. Results of post-hoc
1156 comparisons among functions with Tukey’s HSD test for each taxonomic group are presented in
1157 Table 2.

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1160 **Figure 7.** Pearson's correlation coefficient values (R) calculated between the ranges of
1161 temperatures (°C) tested in all original studies (n = 99) and rank (out of 33) of development
1162 functions based on AIC_C for each species dataset. Statistical significance of correlation
1163 coefficients is indicated by labels above each plotted point as follows: * p ≤ 0.05, ** p ≤ 0.01,
1164 *** p < 0.001; non-significant (p > 0.05) results are not labelled. For names and details of
1165 development functions (#1-33) the reader is referred to Table 1.

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1169 **Table 1.** Names and forms of the 33 different development functions examined in this study. Functions are arranged and numbered
1170 first in order of their value of k (number of parameters + 1, used in AIC_C analyses), and then alphabetically by their common name. In
1171 all equations D is development time (in days), T is temperature ($^{\circ}C$), A , B , C , F , a , b , c , d , f , and g are fitted constants. Additional
1172 fitted constants in some equations with biological meaning and constrained values are as follows: T_{min} = biological minimum
1173 temperature; T_{max} = biological maximum temperature; T_{opt} = temperature at which development rate is maximized; K = thermal
1174 constant, or the number of degree days required to complete development (Kontodimas et al., 2004); ΔT = range of temperatures over
1175 which development occurs; D_{min} = minimum development time. Functions that are fitted to development rate ($1/D$) are here
1176 represented in their inverted form, from which D can be directly calculated. For clarity lowercase letters are used for functions fitted to
1177 development rate, and uppercase letters are used for functions fitted directly to time (D).
1178

Function	k	Equation	Reference(s)
(1) Arrhenius	3	$D = 1/(a*EXP(b/(T)))$	Guerrero et al., 1994
(2) Heip or power	3	$D = A*T^B$	Anger, 2001; Heip, 1974; Guerrero et al., 1994
(3) Hyperbola	3	$D = A/(T-T_{min})$	Hamasaki et al., 2009; Heip, 1974
(4) Ikemoto and Takai	3	$D*T = K+T_{min}*D$ $D = 1/((T-T_{min})/K)$	Ikemoto and Takai, 2000; Papanikolaou et al., 2013

(5) Linear rate, or thermal summation	3	$D = 1/(a+b*t)$ $D = K/(T-T_{min})$ $T_{min} = -a/b$ $K = 1/b$	Campbell et al., 1974; Guerrero et al., 1994; Kontodimas et al., 2004
(6) Linear time, or sum of temperatures	3	$D = A+B*T$ $T_{max} = -A/B$	Guerrero et al., 1994; Winberg, 1971
(7) Tauti or exponential	3	$D = A*EXP(B*T)$ $D = 1/(a*EXP(b*t))$ $A = 1/a, B = -b$	Anger, 2001; Guerrero et al., 1994; Tauti, 1925
(8) Bělehrádek	4	$D = A*(T-T_{min})^B$	Anger, 2001; Bělehrádek, 1935; Guerrero et al., 1994; Heip, 1974; McLaren, 1963
(9) Brière-1	4	$D = 1/(a*T*(T-T_{min})*SQRT(T_{max}-T))$	Brière et al., 1999; Shi and Ge, 2010
(10) Gaussian	4	$D = 1/(a*EXP(-0.5*((T-b)/c)^2))$	Shi and Ge, 2010; Taylor, 1981
(11) Kontodimas-	4	$D = 1/(a*(T-T_{min})^2*(T_{max}-T))$	Kontodimas et al., 2004

(12) Lactin-1	4	$D = 1/(\text{EXP}(a*T)-\text{EXP}(a*T_{\max}*((T_{\max}-T)/\Delta T)))$	Lactin et al., 1995; Zhao et al., 2014
(13) Modified Arrhenius	4	$D = 1/(a*\text{EXP}(b/(T-T_{\min})))$	Guerrero et al., 1994
(14) Pradham-Taylor, or Taylor	4	$D = 1/(a*\text{EXP}(-0.5*((T-T_{\text{opt}})/b)^2))$	Golizadeh and Zalucki, 2012; Mobarakian et al., 2014; Roy et al., 2002
(15) Quadratic rate	4	$D = 1/(a*T^2+b*T+c)$	Mehrnejad, 2012
(16) Quadratic time	4	$D = A*T^2+B*T+C$	de Oliveira et al., 2009; Quinn et al., 2013
(17) Sigmoid, logistic, or Davidson	4	$D = 1/(c/(1+\text{EXP}(a-b*T)))$	Davidson, 1942; Kontodimas et al., 2004
(18) 3 rd order polynomial rate, or Harcourt	5	$D = 1/(a*T^3+b*T^2+c*T+d)$	Harcourt and Yee, 1982; Kontodimas et al., 2004
(19) 3 rd order	5	$D = A*T^3+B*T^2+C*T+F$	Bayoh and Lindsay, 2003; Harcourt and Yee, 1982

polynomial time

(20) Brière-2	5	$D = 1/(a*T*(T-T_{min})*(T_{max}-T)^{(1/b)})$	Brière et al., 1999; Shi and Ge, 2010
(21) Holling Type III, or Hilbert and Logan	5	$D = 1/(a*((T^2/(T^2+b^2))*EXP((T_{max}-T)/\Delta T)))$	Hilbert and Logan, 1983; Holling, 1965; Kontodimas et al., 2004
(22) Janisch	5	$D = (D_{min}/2)*(EXP(K*(T-T_{max}))+EXP(-A*(T-T_{max})))$	Analytis, 1981; Janisch, 1932; Kontodimas et al., 2004
(23) Lactin-2	5	$D = 1/(EXP(a*T)-EXP(a*T_{max}*((T_{max}-T)/\Delta T))+b)$	Kontodimas et al., 2004; Lactin et al., 1995
(24) Lamb, or Taylor non-symmetric Gauss	5	$D = 1/(a*EXP(-0.5*((T-T_{opt})/T_{min})^2)), \text{ if } T \leq T_{opt}$ $D = 1/(a*EXP(-0.5*((T-T_{opt})/T_{max})^2)), \text{ if } T > T_{opt}$	Kontodimas et al., 2004; Lamb et al., 1984; Taylor, 1981
(25) Logan-6 (or Logan-1)	5	$D = 1/(a*(EXP(b*T)-EXP(b*T_{max}-((T_{max}-T)/\Delta T))))$	Logan et al., 1976; Shi and Ge, 2010; Kontodimas et al., 2004
(26) Modified Gaussian	5	$D = 1/(a*EXP(-0.5*(ABS(T-b)/c)^d))$	Angilletta Jr., 2006; Naish and Hartwell, 1988; Shi and Ge, 2010
(27) Ratkowsky	5	$D = 1/((a*(T-T_{min})*(1-EXP(b*(T-T_{max}))))^2)$	Ratkowsky et al., 1983; Shi and Ge, 2010

(28) Stinner	5	$D = 1/(c/(1+EXP(a+b*T))), \text{ if } T \leq T_{opt}$ $D = 1/(c/(1+EXP(a+b*(2*T_{opt}-T))))), \text{ if } T > T_{opt}$	Kontodimas et al., 2004; Stinner et al., 1974
(29) Analytis	6	$D = 1/(a*(T-T_{min})^b*(T_{max}-T)^c)$	Analytis 1977, 1981; Kontodimas et al., 2004
(30) Logan-10 (or Logan-2)	6	$D = 1/(a*((1/(1+K*EXP(-b*T)))-EXP(-(T_{max}-T)/\Delta T)))$	Kontodimas et al., 2004; Logan, 1988; Logan et al., 1976; Shi and Ge, 2010
(31) Performance	6	$D = 1/(m*(T-T_{min})*(1-EXP(K*(T-T_{max}))))$	Huey and Stevenson, 1979; Shi and Ge, 2010
(32) Sharpe and DeMichele	7	$D = 1/(T*(EXP(a-(b/T)))/(1+EXP(c-(d/T))+EXP(f-(g/T))))$	Kontodimas et al., 2004; Schoolfield et al., 1981; Sharpe and DeMichele, 1977
(33) Wang-Lan-Ding (W-L-D)	8	$D = 1/((K*(1-EXP(-a*(T-T_{min}))))*(1-EXP(b*(T-T_{max}))))/(1+EXP(-c*(T-d)))$	Shi and Ge, 2010; Wang et al., 1982

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1181 **Table 2.** Results of post-hoc comparisons of fit (R^2) and rank (based on comparisons of AIC_C
 1182 values) among different development functions within each arthropod subphylum using Tukey's
 1183 HSD test. Functions with different letters in a particular column had significantly different values
 1184 of R^2 or rank; comparisons were not made among subphyla (i.e., among columns). Functions
 1185 labelled with the letter 'A' had the overall best performance (highest mean R^2 , rank closest to 1)
 1186 while letters from B to M indicate progressively poorer function performance. Means of the R^2
 1187 and rank data compared in this table are plotted in Fig. 6. Post-hoc comparisons were not made
 1188 of Δ_i values because these did not differ significantly overall among functions. For names and
 1189 details of development functions (#1-33) the reader is referred to Table 1.
 1190

Function	R^2			Rank		
	Arachnida	Crustacea	Insecta	Arachnida	Crustacea	Insecta
1	AB	ABCD	ABCD	BCDEF	CDEFGH	EFGHIJ
2	A	AB	AB	ABC	A	ABCD
3	A	AB	AB	A	A	AB
4	AB	ABCD	ABCD	BCDEF	CDEFGH	FGHIJKL
5	AB	ABC	ABCD	ABCDEF	CDEFG	FGHIJKL
6	B	ABC	ABCD	DEF	DEFGH	LM
7	AB	ABC	ABC	ABCDE	ABC	DEFGH
8	A	AB	A	A	A	A
9	A	D	ABCD	ABCDEF	EFGHI	CDEF
10	AB	ABC	ABCD	ABCD	ABCD	BCDE
11	A	ABCD	ABCD	BCDEF	CDEFGH	DEFGHI

12	AB	ABCD	ABCD	ABCDEF	DEFGH	GHIJKLM
13	AB	ABC	ABCD	CDEF	CDEFGH	EFGHIJ
14	A	ABC	ABCD	ABCD	ABCD	BCDE
15	AB	ABC	ABCD	CDEF	ABCDE	EFGHIJKL
16	A	A	AB	AB	AB	ABC
17	A	ABC	ABCD	ABCDE	ABCD	BCDE
18	A	ABC	ABCD	ABCDE	BCDEF	EFGHIJ
19	A	ABC	ABCD	ABC	ABCD	BCDE
20	AB	CD	ABCD	ABCD	EFGHI	BCDE
21	A	ABCD	ABCD	EF	HI	JKLM
22	AB	ABC	ABC	ABCDEF	CDEFGH	EFGHIJKL
23	AB	ABC	ABCD	BCDEF	EFGHI	GHIJKLM
24	AB	ABCD	ABCD	ABCDEF	FGHI	EFGHIJKL
25	AB	ABCD	CD	BCDEF	EFGHI	KLM
26	A	AB	ABCD	ABC	ABCDE	BCDE
27	AB	BCD	ABCD	ABCDE	GHI	EFGHIJ
28	A	ABC	ABCD	ABCDEF	CDEFGH	EFGHIJK
29	AB	ABC	ABC	ABCDEF	CDEFGH	DEFG
30	B	ABC	BCD	F	HI	M
31	AB	ABC	ABCD	BCDEF	GHI	HIJKLM
32	AB	ABC	ABC	ABCDE	EFGHI	DEFG
33	AB	ABCD	D	EF	I	IJKLM

1192 **Table 3.** Consequences of fitting development data with functions used or found to be best in
 1193 original published studies rather than the best function for each of 79 reanalyzed species datasets,
 1194 as determined in this study. Consequences were assessed by calculating differences between
 1195 used and actual best functions in terms of (1) increased mean error (absolute, in days) between
 1196 observed and predicted development times, (2) increased percent (%) prediction error, (3)
 1197 usually poorer fit (R^2), (4) poorer percent (%) fit (R^2), and (5) information loss (Δ_i of used
 1198 models; $\Delta_i = 0$ is the best model). resulting. Mean values \pm 95 % confidence intervals (95 % C.I.)
 1199 for each difference measure taken across all retested datasets are shown (with the range of values
 1200 in parentheses), as well as the results of one-sample t-tests comparing these differences to zero;
 1201 statistically-significant p-values ($p \leq 0.05$) are presented in bold text.

1202

Measure of difference between used and actual best functions	Mean \pm 95 % C.I. (Minimum – Maximum)	Significance of difference from zero
Mean error (days)	4.042 \pm 3.696 (-0.024 – 132.342)	$t_{78} = 2.144$, p = 0.035
Mean error (%)	85.913 \pm 53.666 (-1.690 – 1725.529)	$t_{78} = 3.138$, p = 0.002
R^2	-0.091 \pm 0.039 (-0.873 – 0.002)	$t_{78} = -4.620$, p < 0.001
R^2 (%)	-10.736 \pm 4.595 (-100 – 0.172)	$t_{78} = -4.579$, p < 0.001
Δ_i of used function	225.011 \pm 118.316 (0 – 3958.691)	$t_{78} = 3.727$, p < 0.001

1203