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# Can we predict ectotherm responses to climate change using thermal performance curves and body temperatures?

Brent J Sinclair

Katie E Marshall

Mary A Sewell

Danielle L Levesque

Christopher S Willett

*See next page for additional authors*

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**Authors**

Brent J Sinclair, Katie E Marshall, Mary A Sewell, Danielle L Levesque, Christopher S Willett, Stine Slotsbo, Yunwei Dong, Christopher D G Harley, David J Marshall, Brian S Helmuth, and Raymond B Huey

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3 1 REVIEWS AND SYNTHESSES  
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6 2 **Can we predict ectotherm responses to climate change using thermal**  
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8 **performance curves and body temperatures?**  
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11 4 Brent J. Sinclair<sup>1\*</sup>, Katie E. Marshall<sup>2‡</sup>, Mary A. Sewell<sup>3</sup>, Danielle L. Levesque<sup>4†</sup>, Christopher S.  
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13 5 Willett<sup>5</sup>, Stine Slotsbo<sup>6</sup>, Yunwei Dong<sup>7</sup>, Christopher D.G. Harley<sup>2</sup>, David J. Marshall<sup>8</sup>, Brian S.  
14  
15 6 Helmuth<sup>9</sup> and Raymond B. Huey<sup>10</sup>  
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20  
21 8 <sup>1</sup>Department of Biology, University of Western Ontario, London, ON, Canada  
22  
23 9 <sup>2</sup>Department of Zoology, University of British Columbia, Vancouver, BC, Canada  
24  
25 10 <sup>3</sup>School of Biological Sciences, University of Auckland, Auckland, New Zealand  
26  
27 11 <sup>4</sup>Institute of Biodiversity and Environmental Conservation, Universiti Malaysia Sarawak, Kota  
28  
29 12 Samarahan, Sarawak, Malaysia  
30  
31 13 <sup>5</sup>Department of Biology, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA  
32  
33 14 <sup>6</sup>Department of Bioscience, Aarhus University, Aarhus, Denmark  
34  
35 15 <sup>7</sup>State Key Laboratory of Marine Environmental Science, Xiamen University, Xiamen, China  
36  
37 16 <sup>8</sup>Faculty of Science, Universiti Brunei Darussalam. Gadong, Brunei Darussalam  
38  
39 17 <sup>9</sup>Department of Marine and Environmental Sciences and School of Public Policy and Urban  
40  
41 18 Affairs, Northeastern University Marine Science Center, Nahant, MA, USA  
42  
43 19 <sup>10</sup>Department of Biology, University of Washington, Seattle, WA, USA  
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45 20 <sup>‡</sup>Present Address: Department of Biology, University of Oklahoma, Norman, OK, USA  
46  
47 21 <sup>†</sup>Present Address: School of Biology and Ecology, University of Maine, Orono, ME, USA  
48  
49 22 <sup>\*</sup>Corresponding Author: email: [bsincla7@uwo.ca](mailto:bsincla7@uwo.ca); tel. 519-661-2111 x83138; fax 519-661-3935  
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**Abstract**

Thermal performance curves (TPCs), which quantify how an ectotherm's body temperature ( $T_b$ ) affects its performance or fitness, are often used in an attempt to predict organismal responses to climate change. Here we examine the key – but often biologically unreasonable – assumptions underlying this approach; for example, that physiology and thermal regimes are invariant over ontogeny, space, and time, and also that TPCs are independent of previously experienced  $T_b$ . We show how a critical consideration of these assumptions can lead to biologically useful hypotheses and experimental designs. For example, rather than assuming that TPCs are fixed during ontogeny, one can measure TPCs for each major life stage and incorporate these into stage-specific ecological models to reveal the life stage most likely to be vulnerable to climate change. Our overall goal is to explicitly examine the assumptions underlying the integration of TPCs with  $T_b$ , to develop a framework within which empiricists can place their work within these limitations, and to facilitate the application of thermal physiology to understanding the biological implications of climate change.

**Introduction**

Anthropogenic climate change is causing demonstrable and accelerating biological impacts on organisms and ecosystems, and biologists are attempting to understand and predict these impacts (Pacifi *et al.* 2015). Inevitably, these effects are mediated in large part by the behavioral and physiological responses of organisms to changing abiotic variables. Most organisms are ectotherms and thus have body temperatures ( $T_b$  – see Box 1 for a glossary of terms) that reflect their environments to varying degrees (Angilletta 2009). Extremely high or low temperatures are lethal, and temperature determines the rate of biochemical and physiological reactions. Indeed, all cellular and physiological functions, including metabolism, development, growth, movement, and reproduction, are temperature-dependent; and this has profound consequences at organismal, community, and ecosystem levels (e.g. Grigaltchik *et al.* 2012). Thus, addressing the impacts of climate change through the lens of ectotherm thermal biology allows us to draw conclusions relevant to almost all of the Earth’s species.

A standard way to evaluate the ecological consequences of temperature involves (1) measuring (or predicting) actual body temperatures of ectotherms in nature and (2) determining how body temperature affects organismal-level performance (generally, the rate at which an organism can perform an ecologically-relevant activity) or fitness (Huey & Slatkin 1976). Then one can either predict instantaneous performances associated with those  $T_b$ , or, by integrating over a temperature distribution for a time interval or habitat, estimate the average performance level over a given time or habitat (see Angilletta 2009, and the references therein). More recently, this approach has also been used to predict the ecological consequences of climate warming on performance or fitness (e.g. Deutsch *et al.* 2008; Vasseur *et al.* 2014; Levy *et al.* 2015). This

examination of  $T_b$  through the lens of physiological (or physiologically-mediated) responses sometimes yields counter-intuitive surprises: for example, several studies have predicted that climate warming will have relatively large and negative effects on tropical ectotherms, even though the rate of warming is slower in the tropics than at higher latitudes (Deutsch *et al.* 2008; Dillon *et al.* 2010; Thomas *et al.* 2012; Sunday *et al.* 2014).

Measuring instantaneous physiological rates ('performance') across temperature generally yields a curve where performance (assumed to be a proxy for fitness) rises slowly with temperature up to a maximum level ( $T_{opt}$ ), and then drops rapidly (Fig. 1). These Thermal Performance Curves (TPCs) describe how  $T_b$  affects an ectotherm's performance or fitness (Huey & Stevenson 1979) over the range of  $T_b$  for which performance is positive (i.e. between the critical thermal minimum and maximum,  $CT_{min}$  and  $CT_{max}$ ). In studies with ecological applications, TPCs typically quantify whole-organism performance (e.g., speed, stamina, feeding rate, or growth) or sometimes fitness proxies (e.g. reproductive output), because such integrative, higher-level, traits are more directly related to ecological performance than are lower-level ones such as enzyme activity.

Mapping  $T_b$  onto performance provides an intuitive heuristic model of impacts of temperature or temperature change on organism physiology and ecology. This mapping is not, however, without hazards. Here we explore assumptions and complications associated both with quantifying  $T_b$  and TPCs, and specifically when integrating them to predict impacts of climate change. These factors can fundamentally alter predictions of the likely impacts of climate change, but our initial goal is to identify the assumptions underlying TPC-based models, and to encourage analyses of

how sensitive the models are to those assumptions. Our central conclusion is that the TPC- $T_b$  approach – despite many limitations – remains a useful exploratory tool for evaluating responses to climate change.

**Using TPCs to predict the consequences of climate change**

In principle, TPCs and  $T_b$  distributions can be used to predict the performance or fitness consequences of an organism's thermal environment. First, one empirically estimates how fitness,  $w$ , changes instantaneously with  $T_b$ , giving  $w(T_b)$ . Next, one estimates the frequency distribution of body temperatures,  $p(T_b)$ , experienced by the animal during some time period. The total fitness ( $W$ ) in a given environment can then be integrated via Eqn. 1, which is, in effect, a rate summation of fitness over  $T_b$  (Huey & Slatkin 1976; Deutsch *et al.* 2008; Vasseur *et al.* 2014):

$$W \sim \int_{CT_{\min}}^{CT_{\max}} [w(T_b) \cdot p(T_b)] dT_b \tag{1}$$

Fitness will approach a maximum if most  $T_b$  match the optimal  $T_b$  ( $T_{\text{opt}}$ , see Fig. 2), which should (theoretically) be the preferred temperature (but see Martin & Huey 2008). A shift in the mean of  $p(T_b)$  – caused by behavior, seasonality, habitat selection, or climate change – can increase, have no impact, or decrease total fitness, depending on the magnitude, direction, and position of the shift relative to  $T_{\text{opt}}$  (Huey 1991). Similarly, a shift in the variance or skewness of  $p(T_b)$  will also have positive or negative effects on  $W$ , again depending on the magnitude and position of the shift relative to  $T_{\text{opt}}$  and to the degree of thermal specialization versus generalization (Angilletta 2009; Vasseur *et al.* 2014), in part as a consequence of Jensen's inequality (discussed below).

Equation 1 evaluates fitness as a function of the  $T_b$  experienced by an ectotherm during some time period, but  $T_b$  can sometimes reach or exceed the  $CT_{max}$  – for example, if temperatures warm, or if the animal moves into the sun – with deleterious and potentially lethal consequences. Because the TPC is asymmetric,  $T_{opt}$  is much closer to the  $CT_{max}$  than it is to the  $CT_{min}$  (Fig. 1). A risk-avoidance hypothesis (Martin & Huey 2008) proposes that ectotherms should avoid  $T_b$  that approach  $CT_{max}$ : thus they should maintain an ample “thermal safety margin (TSM).” [Note: TSM has been defined in several ways. In Fig. 1 and Box 1, we use the distance between the optimal  $T_b$  and the  $CT_{max}$ ]. The smaller the thermal safety margin in a given environment, the greater the likelihood that an organism will overheat (and possibly die) as climate warms. Because among-species variation in  $CT_{max}$  is relatively small, tropical species – assumed to experience relatively stable, warm, temperatures (Janzen 1967) – should have very small TSMs and therefore be disproportionately affected by small increases in mean temperature with climate change (Deutsch *et al.* 2008). Parallel arguments have extended this concept to other stenotherms, for example polar fishes (Peck *et al.* 2010). Importantly,  $CT_{min}$  and  $CT_{max}$  bound the TPC, but are not necessarily survival limits, especially during short-term exposures. For example, freeze-tolerant sub-Antarctic *Pringleophaga marioni* caterpillars stop moving at around  $-0.6\text{ }^{\circ}\text{C}$ , but only die at temperatures below c.  $-7.5\text{ }^{\circ}\text{C}$  (Klok & Chown 1997). Some intertidal gastropods lose mobility at  $CT_{max}$ , but still survive brief exposures to higher temperatures (e.g. Marshall *et al.* 2015).

The curvilinear relationship between performance and temperature over much of the TPC (Fig. 1) means that the effects of small changes in temperature can be small, negligible, or large,



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depending on where on the TPC those changes occur (Jensen’s inequality – see Ruel & Ayres 1999). Jensen’s inequality has two significant implications for ectotherms under climate change. First, thermal variability becomes a central determinant of ectotherms’ responses to environmental change independent of changes in mean temperature (e.g. Helmuth *et al.* 2014; Vasseur *et al.* 2014; Colinet *et al.* 2015). Second, because metabolic rates increase exponentially with temperature below the inflection point, for a given shift in temperature the metabolic rates of ectotherms in regions with high mean temperatures (i.e. the tropics) may increase more than those of ectotherms in regions with a relatively low mean temperature (e.g. terrestrial Arctic habitats), even though temperature increases in the tropics have been relatively small (Dillon *et al.* 2010). By contrast, Kingsolver *et al.* (2013) and Vasseur *et al.* (2014) argued that temperate species may be more vulnerable to climate warming than are tropical species because of higher thermal variability in temperate zones, which increases the incidence of lethal temperatures, despite lower mean temperatures. Variability can be important even at non-lethal temperatures in temperate species; for example, driving evolution of metabolic suppression in butterflies (Williams *et al.* 2012).

**Do TPCs really estimate fitness?**

The relationships between  $T_b$  and fitness in Eqn. 1 are simple and appealing. If one knows the TPC and how climate change will affect  $p(T_b)$ , one can predict the fitness consequences of climate change for an ectotherm. However, fitness is notoriously hard to define, let alone to measure. Classical life history measures of fitness (e.g., net reproductive rate,  $R_0$ ; intrinsic rate of population growth,  $r$ ) must be measured at least over an organism’s lifespan (Huey & Berrigan 2001; Thomas *et al.* 2012). Not surprisingly, actual measurements of the thermal

dependence of fitness have generally been limited to short-lived taxa in the laboratory or to organisms studied by – possibly hypothetical – biologists with long careers and reliable funding. Such data exist as life tables (age-specific table of survival and reproduction) primarily of economically-important insects raised at multiple temperatures (Huey & Berrigan 2001). Importantly, TPCs for  $r$  and  $R_0$  have different shapes, even when based on the same life table, because  $r$  is inversely related to generation time, which in turn decreases at high temperatures: consequently,  $T_{\text{opt}}$  for  $r$  is often higher than that for  $R_0$  (Huey & Berrigan 2001), and analyses using  $r$  vs.  $R_0$  can yield conflicting predictions (Deutsch *et al.* 2008; Kingsolver *et al.* 2011). These life table studies also require exposing animals throughout their lives to fixed temperatures (see Assumption 9 in Table 1). Two problems arise here. First, fixed temperature exposures are inappropriate if life stages live in different micro-environments and thus experience different body temperatures in nature, which is true for insects and many other taxa (Kingsolver *et al.* 2011; Colinet *et al.* 2015; Levy *et al.* 2015). Second, long exposure to fixed temperatures may induce pathologies, especially at high temperature (Kingsolver & Woods 2016).

Because of the above issues, an instantaneous measure of performance, such as locomotor speed or feeding rate, is often used as a proxy for  $w(T_b)$  (Assumption 1, Table 1; Figures 3, 4, 5). Often the choice of performance traits for TPC analyses is driven by expediency, rather than by validated links to fitness. Importantly, TPCs estimated for different traits can differ markedly even in a single species (Fig. 3), which means that contrasting conclusions about fitness could easily be derived from TPCs for different traits acquired on the same organism. Maximal sprint speed has been measured across the most taxa, but its relationship to fitness is rarely established (Miles 2004). Feeding rate can determine an organism's ability to meet and exceed metabolic

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3 184 demands but, above some threshold, mechanical limits to food processing or physiological limits  
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5 185 to absorption mean that additional food does not necessarily increase fitness (Riisgard 2001), and  
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8 186 it is unclear where this threshold occurs relative to  $T_{\text{opt}}$ . Trait differences may arise from  
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10 187 physical constraints or evolutionary and behavioral selection of different thermal regimes that  
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12 188 mean they have been optimized for specific  $p(T_b)$ ; for example locusts enhance digestion by  
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14 189 selecting high temperatures after a meal, but choose cooler regimes to reduce energetic costs  
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17 190 when starved (Clissold *et al.* 2013). TPCs can also shift with food resources (Fig. 6a; Brett  
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19 191 1971), and are not, as Eqn. 1 implies, fixed. One approach to resolve this issue may be to  
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21 192 integrate a composite panel of TPCs that use different  $w(T_b)$  relationships for different activities,  
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23 193 habitats, or times of day.  
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29 195 Finally, some temperature-dependent traits may be poor proxies for fitness. For example,  
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31 196 although resting or standard metabolic rates increase with temperature, higher rates indicate  
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33 197 higher energetic expenditures as well as higher activity, and may not therefore translate to higher  
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35 198 fitness, particularly during non-feeding life stages (Clarke 1991). Thus, identifying the most  
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37 199 relevant fitness proxies is necessary when parsing contrasting – or even contradictory – signals  
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39 200 from different traits (e.g. Fig. 3).  
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46 202 **Breaking down  $w(T_b)$ : What are the implicit and explicit assumptions of using TPCs to**  
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48 203 **predict fitness?**  
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50 204 Equation 1 provides a simple way to conceptualize how organismal thermal sensitivity (TPC)  
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52 205 and body temperature map to organismal fitness ( $W$ ). However, doing so makes a number of  
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54 206 assumptions about the relationship between temperature and fitness. In particular, biologists  
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tend to assume that their chosen trait reflects fitness (Assumption 1 in Table 1), that TPCs are evolutionarily fixed (Assumptions 2-5 in Table 1), that the well-documented physiological adjustments to temperature can be ignored (Assumptions 6-9 in Table 1), and that temperature is the primary driver of fitness (Assumptions 10 & 11 in Table 1). Below we critically address each assumption.

### *Are TPCs invariant in space and time?*

Macrophysiological analyses generally assume that the TPC of a species (or sometimes of an Order or Class) can be adequately described by a single curve. This is valid only if numerous – and unlikely – conditions are met (Assumptions 2-11 in Table 1). The shape, maximum, limits, and breadth of TPCs can vary with habitat, nutritional state, developmental stage, and acclimation history (Figures 4, 5, 6). In addition, individuals within a population may differ significantly, due to both genetic and non-genetic causes (Kingsolver *et al.* 2011; Logan *et al.* 2014; Assumption 10 in Table 1).

The use of ‘one species, one TPC’ also assumes that the TPC is invariant over both geographical range and evolutionary time (Assumptions 3 and 4 in Table 1). In fact, the thermal sensitivity of ectotherms sometimes varies markedly across their range, often in concert with local conditions. This variation can alter predictions of population dynamics at range edges under climate change (Pearson *et al.* 2009). For example, thermal tolerance of barnacles is higher in subpopulations that experience more extreme temperatures (Schmidt *et al.* 2000), and thermal tolerances can vary widely among insect populations (reviewed by Sinclair *et al.* 2012). This local adaptation illustrates the evolutionary potential of thermal biology to shift over relatively short time scales –

less than a century in the case of the cabbage white butterfly, *Pieris rapae*, in North America (Kingsolver *et al.* 2007). Thus, natural selection might conceivably alter  $w(T_b)$  for species with short life cycles by the 2050 and 2100 dates used for most climate change projections.

The capacity for  $w(T_b)$  to evolve in this timeframe will vary among taxa, habitats, and traits (Hoffmann & Sgrò 2011), and will also depend on the extent to which climate change affects  $p(T_b)$  – see below. The importance of evolution in altering responses to climate change is widely acknowledged (Munday *et al.* 2013), but unfortunately the sensitivity of predicted outcomes to either evolution or plasticity has rarely been incorporated into models (but see Dowd *et al.* 2015 for an example). Sensitivity analyses will be required to develop ‘rules’ about how robust predictions are to evolutionary change and (conversely) how much evolutionary capacity or plasticity is necessary to offset climate change impacts.

*Do TPCs reflect the realities of the thermal environment?*

TPCs for fitness traits are typically constructed using exposure to fixed temperatures, but extrapolating TPCs to field conditions can be complicated by thermal environments that are often highly heterogeneous in space and time, affecting  $p(T_b)$  (see below). Thus, both  $w(T_b)$  and the experiments we use to derive TPCs carry important assumptions that must be accounted for when using TPCs to derive predictions about the thermal performance of ectotherms in nature.

Importantly, temperature exposures in nature vary in duration, and the duration of exposure to a given temperature can determine performance and fitness. For example, a 30-min exposure to 36 °C initiates a protective molecular cascade (the ‘heat shock response’) in *Drosophila*

253 *melanogaster*, but exposure to 29 °C for more than a few hours renders flies sterile (David *et al.*  
254 2005). These duration effects are particularly significant at high temperatures, where  
255 performance usually declines with exposure time (Rezende *et al.* 2014). Even so, mortality and  
256 damage accumulation can also result from long exposure to low temperatures (Nedvěd *et al.*  
257 1998; Rezende *et al.* 2014). Such duration effects imply that TPCs are temporally dynamic, but  
258 this has been generally ignored in models (Assumptions 6, 7, 11 in Table 1; but see Kingsolver  
259 & Woods 2016).

261 Animals in nature usually experience temperatures in a certain order; a change in  $T_b$  from  
262 temperature  $x$  to temperature  $x+3$  necessarily involves exposure to temperatures  $x+1$  and  $x+2$ .  
263 Thus, thermal regimes usually do not shift suddenly, except in instances where the animal moves  
264 from shade to sun or air to water, or in subtidal environments subject to strong tidal currents,  
265 which all can lead to abrupt changes in  $T_b$  (Leichter *et al.* 2006). In experiments where  
266 performance of individual animals is measured at multiple temperatures, the sequence of body  
267 temperatures is usually randomized (although the highest temperature often comes last to avoid  
268 any heat shock response affecting performance at other temperatures; e.g. Williams *et al.* 2012).  
269 These randomized protocols have some empirical support: for example, thermal sensitivity of  
270 instantaneous cricket metabolic rate calculated from ramped, ordered or randomized temperature  
271 did not significantly differ (Lake *et al.* 2013). Nevertheless, animals in nature have had prior  
272 thermal experience that is largely unaccounted for in TPCs (Assumption 6 in Table 1).

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274 Prior thermal experience can modify the TPC directly. For example, acclimation responses can  
275 substantially modify the shape and position of the entire TPC (e.g. Fig. 5), including thermal

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3 276 limits (Angilletta 2009). Although the broad physiological and biochemical mechanisms  
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5 277 underlying these changes are reasonably well-understood, predicting how TPCs will shift is  
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8 278 challenging, even in broad geographic comparisons (Somero 2010). Tropical *Drosophila* appear  
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10 279 to have sufficient plasticity to maintain an adequate thermal safety margin (Overgaard *et al.*  
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12 280 2011), whereas porcelain crabs do not (Stillman 2003). Predicting TPCs is made even more  
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14 281 complicated by cross-generation effects on TPCs. For example, female blow flies exposed to  
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16 282 relatively warm autumn temperatures produce larvae with reduced cold hardiness, which likely  
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18 283 reduces overwinter survival (Coleman *et al.* 2014). The capacity for plastic responses to  
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20 284 changing temperatures can also depend on the rate of temperature change: emerald ash borer  
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22 285 prepupae have relatively high heat tolerance when shifted slowly to a high temperature, because  
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24 286 slow warming allows them to mount a heat shock response (Sobek *et al.* 2011). Whether or not  
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26 287 acclimatization is an effective strategy in nature will thus depend on how temporally  
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28 288 autocorrelated thermal regimes are over the scale of days, i.e. whether preparing for an extended  
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30 289 heat wave or cold snap is an effective use of physiological resources.  
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38 291 Both the order of thermal exposure and the rate of temperature change can affect  $w(T_b)$ , but  
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40 292 neither is usually accounted for in models (Assumptions 6 and 8 in Table 1), even though both  
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42 293 vary in nature. Plastic responses to temperature fluctuations will likely bear costs and elicit  
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44 294 trade-offs, not just as simple shifts in the instantaneous value of  $w(T_b)$ , but in terms of long-  
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46 295 lasting accumulation of fitness. This will particularly be the case when organisms are exposed to  
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48 296 temperature extremes. For example, the heat shock response requires energy for the synthesis  
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50 297 and ATP-dependent activity of heat shock proteins (Feder & Hofmann 1999), and recovery from  
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298 being cooled to below the  $CT_{\min}$  has a measurable metabolic cost in insects (MacMillan *et al.*  
299 2012).

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301 Finally, thermal regimes in nature often repeat themselves (but see above for exceptions); for  
302 most habitats, diel thermal cycles mean that an ectotherm that lives for more than a few hours  
303 will be exposed to repeated warm-cold fluctuations (Colinet *et al.* 2015). Given that prior  
304 experience can modify the TPC, the degree to which TPCs remain constant across multiple  
305 thermal cycles will depend in part on the temporal autocorrelation of the environment, which  
306 may be modified with climate change (Assumption 6 in Table 1). Fitness can decline because of  
307 repeated exposure to deleterious temperatures – in insects and lizards, this effect may be more  
308 important than the duration or intensity of exposure to extreme temperatures (Kearney *et al.*  
309 2012; Marshall & Sinclair 2015). Conversely, thermal cycles under permissive temperatures  
310 often increase growth rates (and presumably fitness; Colinet *et al.* 2015). Overall, a predictive  
311 understanding of how thermal fluctuations affect ectotherm fitness is still elusive (Kingsolver *et*  
312 *al.* 2013; Vasseur *et al.* 2014; Colinet *et al.* 2015), and empirical responses might well prove  
313 idiosyncratic.

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315 Thus, in reality,  $w(T_b)$  is not a fixed curve but a shifting multi-dimensional envelope with an  
316 explicit temporal history. Estimates may need to incorporate threshold-crossing events plus  
317 duration and frequency of exposure to stressful temperatures (Assumptions 7 and 9 in Table 1).  
318 The consequences of exposure to temperature extremes have been included in models in several  
319 ways. Deutsch *et al.* (2008) assumed that fitness was temporarily zero when  $T_b > CT_{\max}$  (or  
320  $< CT_{\min}$ ), Kingsolver *et al.* (2011) assumed that individuals died under these same conditions, and



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3 321 Buckley and Huey (2016) assumed that survival declined exponentially to zero between the  
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5 322  $CT_{\max}$  and 60°C. Roitberg and Mangel (in press) have proposed splitting the TPC in two, with  
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8 323 fitness costs accumulating (and the  $w(T_b)$  curve modified) after exceeding  $CT_{\max}$ , but not the  
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10 324  $CT_{\min}$ . This latter approach reflects modifications to the TPC by the heat shock response (Feder  
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12 325 & Hofmann 1999), and perhaps provides a template for how other thermal-history-based  
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15 326 modifications to the TPC can be modelled. Alternatively, perhaps we need to shift entirely from  
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17 327 a TPC approach to a time series model that reflects the time  $\times$  sequence  $\times$  duration  $\times$  temperature  
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19 328 interaction implicit in thermal biology in nature – Woodin et al. (2013) begin to take this  
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21 329 approach by applying a time component when  $T_b > CT_{\max}$ . In the short term, determining the  
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23 330 relative importance of these components could allow the key drivers of the  $w(T_b)$  relationship to  
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25 331 be identified and incorporated. For example, the number of cold exposures has a bigger effect on  
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27 332 fitness than either the duration or intensity of those exposures in overwintering spruce budworm:  
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29 333 thus, a term quantifying exposure-number could account for most effects of thermal variability  
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32 334 on this species (Marshall & Sinclair 2015).

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39 336 *Beyond temperature: TPCs in a multi-stressor world*  
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41 337 Environmental physiology of ectotherms often focuses on temperature as a “master variable” that  
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43 338 dominates the performance, survival, and fitness of organisms (Assumption 11, Table 1).  
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46 339 Nevertheless, interactions involving numerous other environmental and biological factors can  
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48 340 alter the shape of an organism’s TPC and thus how an organism relates to its thermal  
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50 341 environment (e.g. Fig. 4; Denny *et al.* 2009; Todgham & Stillman 2013; Gunderson *et al.* 2016).  
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52 342 Furthermore, performance curves can just as readily be constructed with respect to other  
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55 343 environmental variables such as salinity, pH, and water vapor deficit, and to other anthropogenic  
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3 344 stressors, such as pollutants, each of which can modify the effect of temperature on performance  
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5 345 (Gunderson *et al.* 2016). Some of these abiotic factors are themselves temperature-dependent;  
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8 346 for example, oxygen saturation and  $p\text{CO}_2$  for aquatic organisms (Deutsch *et al.* 2015; Gunderson  
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10 347 *et al.* 2016). When such interactions occur, the combined effect of two variables usually cannot  
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12 348 be predicted merely by summing the individual effects from single parameter experiments. Non-  
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14 349 additive (synergistic) or even antagonistic outcomes in multiple stressor scenarios appear to be  
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16 350 the norm, and varying a larger number of environmental parameters yields more substantial  
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18 351 effects (Denny *et al.* 2009; Todgham & Stillman 2013; Brennan & Collins 2015; Deutsch *et al.*  
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20 352 2015). Fractional factorial designs may be required to deal with multiple factors (Porter *et al.*  
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22 353 1984).  
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29 355 In most cases, the physiological mechanisms underlying non-additive outcomes in multi-stressor  
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31 356 scenarios are not yet fully understood. However, one proposed mechanism linking two stressors  
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33 357 in a predictive fashion is oxygen and capacity limited thermal tolerance (OCLTT), which relates  
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35 358 performance both to temperature and to the supply of oxygen to the tissues, and therefore to  
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37 359 aerobic scope (Pörtner 2010). The generality of OCLTT is debated (e.g. Verberk *et al.* 2016). For  
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39 360 example, in contrast to the OCLTT, where extreme temperatures reduce the capacity to deal with  
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41 361 a second stressor (reduced oxygen), exposure to thermal extremes can also increase tolerance to  
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43 362 other stressors, including hypoxia and hyperoxia, leading to cross-tolerance among multiple  
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45 363 stressors (Todgham & Stillman 2013). Nevertheless, the OCLTT approach is an excellent  
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47 364 example of a mechanism-based integration of two interacting stressors, and has been used to  
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49 365 generate global-level predictions about responses of some aquatic species to climate change  
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53 366 (Deutsch *et al.* 2015)..  
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6 368 *Biotic interactions and TPCs*  
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8 369 Because of high interspecific variability in thermal performance, climate change is expected to  
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10 370 result in “winners” and “losers” (Somero 2010). When performance differs among ecologically-  
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12 371 important species such as structuring species, ecosystem engineers, and keystone predators,  
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15 372 differential vulnerability among interacting species can translate into differential vulnerability of  
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17 373 entire assemblages (Monaco & Helmuth 2011; Dell *et al.* 2014). Similarly, TPCs can be  
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19 374 modified by interactions among species: shifts in food abundance (e.g. via predator-prey  
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21 375 interactions, or competition) can modify the TPC (Figure 6); non-consumptive effects (‘fear of  
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23 376 being eaten’) can reduce foraging success and efficiency, or elicit other physiological costs  
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26 377 (Rovero *et al.* 1999; Nelson *et al.* 2004); and parasites and pathogens can induce direct  
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28 378 physiological costs (Vernberg & Vernberg 1963) that might modify the TPC. Community  
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30 379 interactions can themselves be determined by temperature, creating feedback loops between  
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32 380 TPCs and interspecific interactions. For example, elevated temperatures can increase or decrease  
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34 381 foraging rates of predators, depending on whether temperature increases occur below or above an  
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36 382 organism's  $T_{opt}$  (Monaco & Helmuth 2011).  
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41 384 Animals carry with them communities of microbes that can affect behavioral and physiological  
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43 385 phenotypes (McFall-Ngai 2015). Although the effect of symbionts on TPCs has not, to our  
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45 386 knowledge, been directly explored, there is substantial evidence that symbionts can modify  
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47 387 thermal limits. For example, mutations in endosymbiotic *Buchnera* determine the thermal  
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49 388 tolerance of their aphid hosts (Dunbar *et al.* 2007), and thermally-tolerant strains of  
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51 389 endosymbiotic *Symbiodinium* increase the thermal tolerance of their host corals by more than  
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1°C (Berkelmans & van Oppen 2006). Interactions between immunity and pathogens will also help to shape the TPC; for example, crickets deactivate low temperature immunity during cold acclimation in a trade-off with other physiological activities that contribute to  $w(T_b)$  (Ferguson *et al.* 2016). Thus,  $w(T_b)$  and  $p(T_b)$  can be altered by numerous interactions involving hosts and symbiotic or pathogenic microbiota.

### Breaking down $p(T_b)$

Global models of ectotherm responses to climate change depend on the relationship between fitness and  $T_b$ , and thus the distribution of  $T_b$  animals experience,  $p(T_b)$ . Although  $T_b$  has been extensively measured and modelled for animals, empirical  $T_b$  distributions are seldom incorporated in global-scale analyses, which tend to substitute large-scale meteorological air- or water-temperature datasets for  $T_b$ , and thus ignore behavioural thermoregulation and micro-scale environmental variation (Kearney *et al.* 2009; Sears *et al.* 2011; Potter *et al.* 2013). In the simplest cases, such as a soil ectotherm that does not thermoregulate,  $p(T_b)$  will be very close – if not identical – to the distribution of operative temperatures,  $p(T_e)$ , measured in the soil. However, the assumption that  $T_e = T_b$  is often extended into heterogeneous situations, to animals with significant capacity to regulate  $T_b$ , or to animals whose  $T_b$  is affected by morphology, thermal inertia, or surface coloration; in these situations, instantaneous  $T_e \neq T_b$ . Moreover, behavioral thermoregulation and physiology can decouple  $T_b$  from  $T_a$  in space and time (Fig. 7; Sunday *et al.* 2014). Interspecific interactions can also shift  $p(T_b)$ : grasshoppers exposed to avian predators move to lower (cooler) positions in the vegetation (Pitt 1999). Thus, properly quantifying  $p(T_b)$  is essential for improving the accuracy and precision of conclusions about ectotherm responses to climate change.

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414 Many ectotherms can actively behaviorally thermoregulate to maintain a  $p(T_b)$  with a mean and

415 variance that are substantially different from  $p(T_e)$ . Behavioral thermoregulation can be highly

416 active, such as in lizards that shuttle from shade to sun (Kearney *et al.* 2009), or more passive,

417 such as the periwinkle *Echinolittorina peruviana*, which orients its narrower sides towards the

418 sun on hot days (Muñoz *et al.* 2005). There are hard limits to plasticity of  $CT_{max}$  in at least some

419 species (Stillman 2003), which means that behavioral thermoregulation will be essential for

420 survival of tropical stenotherms with limited plasticity and small TSMs (Kearney *et al.* 2009;

421 Sunday *et al.* 2014).

422

423 In many animals,  $T_b$  can be measured directly in nature and thus generate accurate values for

424  $p(T_b)$ . Methods for estimating  $T_b$  of free-ranging animals in nature include telemetry (e.g.

425 Mitchell *et al.* 1997; Briscoe *et al.* 2014) as well as instantaneous measurements of  $T_b$  in freshly-

426 captured animals (e.g. 'grab and stab' in insects; Bartholomew & Heinrich 1973). Telemetry

427 does not interfere with an organism's thermoregulation and movements, and allows

428 measurements during both active and inactive periods, but can only be used on species large

429 enough to surgically implant a sensor. However, small data loggers can also be attached or

430 implanted, but must later be collected (Davidson *et al.* 2003).

431

432 Alternatively,  $p(T_b)$  can be estimated via physical models ('biomimetic sensors'), such as

433 'robomussels' (Helmuth *et al.* 2002): such models can accurately mimic the physical properties –

434 and thus equilibrium heat exchange – of specific organisms in a given microclimate (Bakken

435 1992). Most such models are dry-skinned, so assume negligible evaporative heat loss (but see

436 Köhler *et al.* 2011; Monaco *et al.* 2015), but do account for size, shape, and color in generating  
437 maps of  $T_b$ . Automatic recordings from biomimetic sensors can easily provide long-term (even  
438 multi-year) records (Helmuth *et al.* 2010); but (except for completely sessile organisms such as  
439 intertidal bivalves), they necessarily ignore behavioral thermoregulation. Other approaches  
440 deploy biomimetics in multiple potential habitats, and then estimate realized  $p(T_b)$  using a series  
441 of behavioral rules, such as optimization of performance or avoidance of extremes (e.g. Monaco  
442 *et al.* 2015).

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444 An alternative (or adjunct) to using direct biomimics to estimate  $p(T_b)$  is to develop biophysical  
445 (e.g. heat budget) models that predict  $T_b$  from environmental variables (e.g. wind speed, air  
446 temperature, and solar radiation) and the physical properties of the organism, and then use  
447 climate projections to develop an overall heat budget and thus estimate  $p(T_b)$  (Kearney *et al.*  
448 2009). These relationships are not necessarily simple: the size, color, morphology, and  
449 orientation of organisms alters heat exchange with their environments (and thus  $T_b$ ); the thermal  
450 properties of materials vary (e.g. shell has a lower specific heat capacity than wet tissues), as do  
451 the properties of surfaces presented to the environment. Similarly, body size can buffer rapid  
452 changes in temperature (larger animals have higher thermal inertia), but even large animals can  
453 modify heat exchange via thermal windows such as large bills, fins, or ears (e.g. Tattersall *et al.*  
454 2009). To account for all of this variety, biophysical models must be developed in a species-  
455 specific (and maybe even a life-stage-, morph-, or sex-specific) manner, making it difficult to  
456 extrapolate broadly in space, time, or across species.

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458 *Can we predict future  $p(T_b)$ ?*

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3 459 Global-scale predictions of responses to climate change require prediction of future  $p(T_b)$ . This  
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6 460 is theoretically possible via biophysical models (Kearney *et al.* 2009), but changes in cloud-,  
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8 461 plant-, and snow-cover could easily modify thermal environments, and thus  $p(T_b)$ , even without  
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10 462 changes in climatic temperature. One approach to understanding how  $p(T_b)$  may change is to  
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12 463 observe how  $p(T_b)$  changes in response to latitudinal or altitudinal gradients as an analogue to  
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14 464 changes in time (space for time substitution) (Halbritter *et al.* 2013). However, such  
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16 465 extrapolation is inherently problematic, because  $p(T_b)$  may not change in time in the same way it  
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18 466 does in space at present, and confounding factors, such as variation in cloud or vegetation cover  
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20 467 or in radiation loads, are unaccounted for in a space-to-time substitution. In fact, empirical data  
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22 468 show that geographic and altitudinal patterns do not always conform to simple gradients due to  
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24 469 the over-riding importance of local environmental conditions. Thus, elevation and latitude can be  
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26 470 misleading metrics of thermal stress in the future (Helmuth *et al.* 2002; Pearson *et al.* 2009), and  
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28 471 they should be used as proxies only with appropriate caution.  
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36 473 A simplistic (but common) approach is to use predicted changes in average air temperature (e.g.  
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38 474 “+2 °C” for a given site) to predict future  $T_b$  and thus physiological responses and organismal  
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40 475 vulnerabilities (Helmuth *et al.* 2014). However, such an approach ignores regional and temporal  
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42 476 variation, the importance of extremes (weather events), or changes in variability regimes  
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44 477 embedded within large-scale climate (Denny *et al.* 2009). In many cases, ecosystems are already  
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46 478 experiencing local and short-term increases in temperature that exceed the projected changes in  
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48 479 global averages over the next century. For example, sea surface temperatures in the Gulf of  
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50 480 Maine are increasing faster than in the global ocean (Mills *et al.* 2013), and terrestrial  
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52 481 temperatures are increasing significantly faster in the Arctic and Antarctic than in other biomes  
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(Nielsen & Wall 2013). Thus, any TPC-based predictions of the responses of ectotherms to climate change are only as good as the assumptions underlying the ‘future climate’ data input into the model – an issue that has, in itself, received extensive discussion (see, e.g., Helmuth *et al.* 2014; Pacifici *et al.* 2015).

Thus, although  $p(T_b)$  has been explored, the temporal and spatial scale best used in ecological models remains subject to debate (Sears *et al.* 2011; Potter *et al.* 2013). Predicting  $p(T_b)$  at a global scale will likely require a combination of actual measurements, biomimetic data and biophysical models that incorporate seasonal and ontogenetic variation with behavioral and microclimate modification (e.g. Levy *et al.* 2015). Crucially, these global-scale corrections of  $p(T_b)$  will be needed to generate predictions by region or species. One way to generalise such predictions may be to develop models for particular combinations of animal and microclimate characteristics, and then conduct additional analyses to apply these models to appropriate location/species combinations.

### Putting Humpty Dumpty back together again

In any science, a general theoretical approach to a problem can be destroyed by piling up multiple objections to its implicit and explicit assumptions, or by enumerating counter examples. With respect to TPCs and the modelling approach exemplified in eqn. 1, we could allow thousands of cuts – some are discussed above – to kill this idea. However, we currently do not see an obvious substitute for the TPC approach. Consequently, we suggest that the best way forward is to modify eqn. 1 to make it more robust, functional, and sensitive to real world issues.



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3 504 Thus, our goal now is to put the Humpty-Dumpty of TPCs (which we and others have now  
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5 505 gently smashed) back together again.  
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10 507 First, Table 1 demonstrates many challenges with measuring and interpreting  $w(T_b)$ , particularly  
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12 508 in integrating across multiple levels of biological organization. These need to be resolved  
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14 509 through laboratory investigations (e.g. using *Drosophila* or other models) to better understand  
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16 510 the sources and consequences of inter-individual variation in TPCs, coupled with field-based  
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18 511 studies to better understand TPCs in nature. A key goal will be to determine how best to  
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20 512 incorporate and predict plastic and evolutionary capacities as well as within- and among-  
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22 513 population variation in TPCs. Also, we need to better understand the relationship between  
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24 514 instantaneous performance (the subject of most TPCs) and long-term fitness, for example via  
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26 515 longitudinal studies in nature, or via molecular or physiological markers of performance  
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28 516 characteristics of wild-caught animals. Such an approach will need to recognize that  
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30 517 generalizations will not apply to all species and traits. In addition to existing "model systems"  
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32 518 (for which we have considerable knowledge of their genetics, physiology, phylogeny and  
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34 519 ecology), additional foci should include: ecologically important species that have a  
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36 520 disproportionate impact in communities (such as keystone predators and habitat-forming  
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38 521 species); invasive species and disease vectors; and species that provide important ecosystem  
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40 522 services. Second, temperature is an effective master regulator, and is a good place to start, but we  
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42 523 need to evaluate the impacts of multiple interacting stressors plus interactions with the  
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44 524 microbiome, all of which modify predictions derived from TPCs. Third, we need to evaluate our  
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46 525 estimates of contemporary  $p(T_b)$ , and consider how this affects our ability to predict future  $p(T_b)$ .  
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48 526 For example, thermal microrefugia may prevent local extinctions (Potter *et al.* 2013), if those  
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refugia persist under climate change (Lima *et al.* 2016). Likewise, we need a better understanding of how anthropogenic activities will affect key modifiers of microhabitat, such as shading, air and water flow or quality, and precipitation.

Many opportunities exist for modifying our existing TPC models when making global-scale predictions (Table 1). Mechanistic models of species' distributions are already emerging that account for some of the assumptions we have identified (see Maino *et al.* 2016 for a recent summary). In terms of predicting  $w(T_b)$  some cases (e.g. fluctuating temperatures, multiple stressors, biotic interactions) will require more empirical data to determine the extent to which TPCs are predictable and generalizable. In many cases, however, models can and should be adjusted to better account for assumptions we already know to be invalid, such as ontogenetic variation (Kingsolver *et al.* 2011; Levy *et al.* 2015). Earth System Models in the plant sciences, which predict photosynthetic responses to climate change on a global scale, demonstrate that large, complex, trait-based approaches are possible and can be (broadly) successful (Rogers 2014). In the long term, we may realise that the current TPC model, which is based on instantaneous performance  $p(T_b)$ , is flawed, but we do not yet know whether its flaws are fatal and require us to move to a temperature-plus-time-series (and possibly -plus-energetics) approach to account for the complex temporal nature of thermal biology. However, for now, we believe that TPCs offer us at least an opportunity to explore climate change with broad strokes.

Ultimately, the TPC-based approach is an heuristic starting point for evaluating the biological impacts of environment and environmental change. Understanding  $w(T_b)$  is clearly important, but relating fitness to temperature will be difficult. Similarly, predicting  $p(T_b)$  is essential, but

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currently flawed. Even so, the distribution of body temperatures is not the only physiological variable that matters. Moreover,  $w(T_b)$  and  $p(T_b)$  aren't independent: the  $T_b$  history can modify  $w(T_b)$ . This is biology. The way forward is thus either to embrace such complications into our theoretical models, or to find whether the biological signal of climate change is sufficiently strong to overpower these complications. Each of the assumptions explored here can be converted into testable hypotheses and then explored in empirical sensitivity analyses, which will provide insights into how much detail is needed and what can be ignored, reducing the uncertainty in the TPC-based approach to predicting the biological impacts of climate change. Simple models like TPCs may therefore have a future, provided we acknowledge the inherent assumptions.

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**Table 1.** A summary of assumptions often made in evaluations of the relationship among the environment, body temperature, and fitness, and on their consequent hypotheses and predictions. Many of these have already been shown to be false as general rules; see text for discussion.

| Assumption  | Hypothesis  | Prediction(s)   |
|---|---|---|
| <i>Relationship between trait and fitness</i>                           |   |   |
| 1 The trait $x$ measured reflects fitness                               | Performance of trait $x$ is directly correlated with $W$                                      | Individuals with a greater value of $x$ have greater lifetime reproductive output.  |
| <i>Variation in developmental and evolutionary contexts</i>             |   |   |
| 2 Thermal performance does not change with development and reproduction | The form of the $TPC$ is static through an individual's lifetime if the environment is static | Measured $TPCs$ will not change during development/ maturation in a predictable manner for a given species  |
| 3 Thermal performance does not vary across a species' geographic range  | $w(T_b)$ is invariant within a species  | No local adaptation of $TPCs$   |
| 4 $TPCs$ will not change with climate change in the short term          | $w(T_b)$ does not evolve rapidly  | No rapid evolution of $TPCs$  |
| 5 $TPCs$ can be extrapolated to higher taxonomic levels                 | $w(T_b)$ is phylogenetically constrained  | Hierarchical taxonomic structuring of $TPC$ properties  |
| <i>Physiological variation</i>  |   |   |
| 6 Prior thermal experience does not matter                              | $w(T_b)$ is invariant with respect to prior temperature exposure                              | 1. $TPCs$ are independent of the order of temperature exposure<br>2. $TPCs$ do not change with repeated exposures   |
| 7 Extreme exposures do not matter                                       | $w(T_b)$ does not change if temperature cycles cross physiological thresholds                 | 1. $TPCs$ will not change after pre-exposure to temperatures above the $T_{opt}$ or close to the $CT_{max}$ and $CT_{min}$<br>2. $TPCs$ will not vary even with multiple exposures to a thermal cycle |
| 8 Rate of temperature change does not matter                            | $w(T_b)$ is invariant with respect to rate of temperature change                              | $TPCs$ will not differ between rapid or slow temperature transitions  |
| 9 Duration of temperature exposure does                                 | $w(T_b)$ estimates are robust to the  | $TPCs$ will not differ when calculated from long or short   |

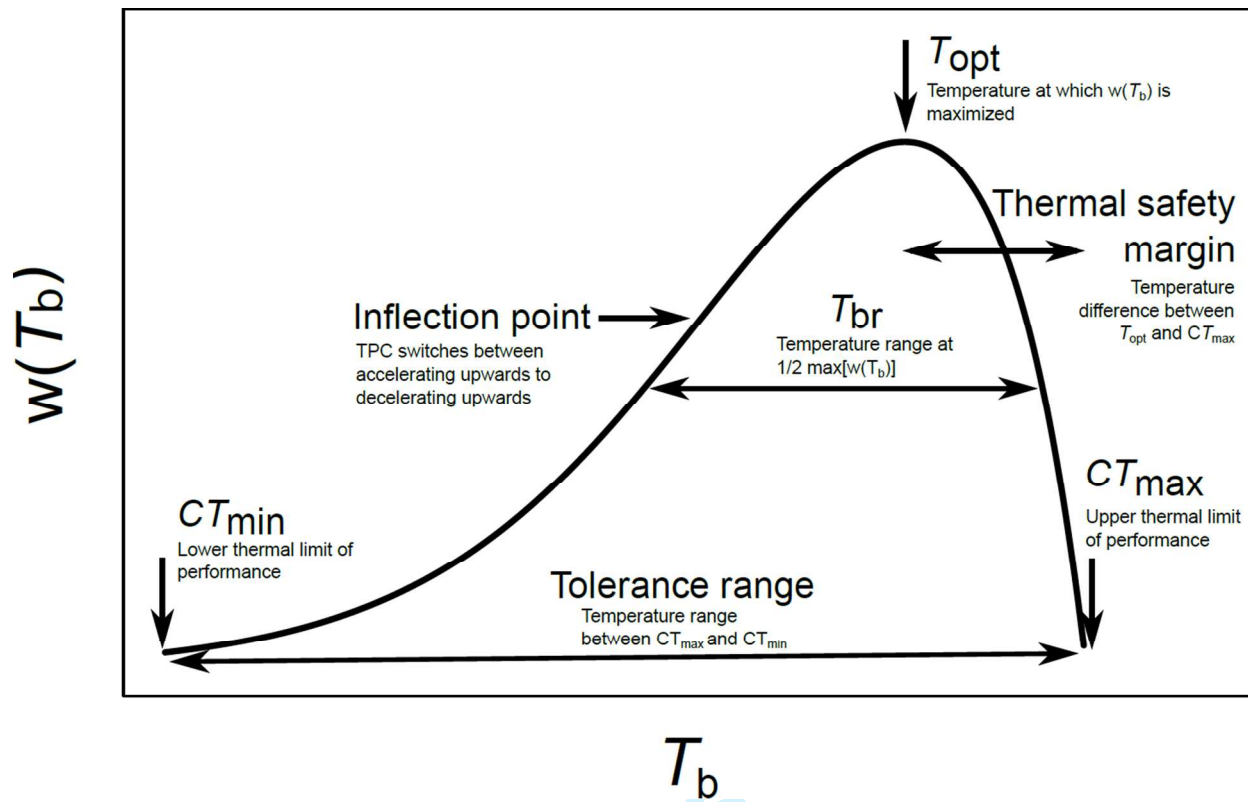
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|----|---|--|---|
| 1  | not matter  | duration of thermal exposure           | exposure to each temperature                                      |
| 2  |   |  |   |
| 3  | <i>Temperature as the primary driver of fitness</i> |  |   |
| 4  | 10 Variation in thermal performance due             | The majority of inter-individual       | 1. Heritable variation in <i>TPCs</i> exceeds plasticity          |
| 5  | to stochastic variation or biotic impacts           | variation in $w(T_b)$ is heritable     | 2. <i>TPCs</i> and $p(T_b)$ are not affected by inter- and intra- |
| 6  | (e.g. in parasitism, microbiota, and                |  | specific interactions   |
| 7  | nutrition) can be ignored                           |  |   |
| 8  |   |  |   |
| 9  | 11 Temperature is the only environmental            | $w(T_b)$ is invariant across gradients | The <i>TPC</i> will not change with variation in non-thermal      |
| 10 | parameter whose changes affect fitness              | of additional abiotic factors          | environmental parameters.   |
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**Text Box 1: A Glossary of Thermal Biology Terms**

- $CT_{\max}$  – critical thermal maximum, upper thermal limit of performance.
- $CT_{\min}$  – critical thermal minimum, lower thermal limit of performance.
- OCLTT – oxygen- and capacity-limited thermal tolerance; hypothesis that thermal performance at high and low  $T_b$  is limited by oxygen availability.
- $T_a$  – ambient temperature, an imprecise term often used as a synonym for air temperature, but can also reflect microhabitat temperature or the (measured) temperature of an animal’s immediate surroundings.
- $T_b$  – body temperature (usually core).
- $T_{br}$  – breadth of thermal performance.
- $T_e$  – operative temperature – equilibrium  $T_b$  of a specific organism in a specific microenvironment, assuming no metabolic heat increment or evaporative cooling.
- $T_{opt}$  – optimum body temperature, at which performance is maximal.
- TPC – thermal performance curve; depicting performance as a function of  $T_b$
- $T_p$  – preferred (selected) body temperature, often measured in a laboratory thermal gradient.
- TSM – thermal safety margin; various definitions are in use, but  $TSM$  is generally inversely proportional to the risk of an animal experiencing temperatures above  $CT_{\max}$ . Here we define it as the difference between  $T_{opt}$  (or maximum  $T_b$  in the field) and  $CT_{\max}$ .
- $p(T_b)$  – frequency distribution of body temperatures.
- $p(T_e)$  – frequency distribution of operative temperatures.
- $W$  – total fitness integrated over some time interval.
- $w$  – fitness.
- $w(T_b)$  – relationship between fitness with body temperature.

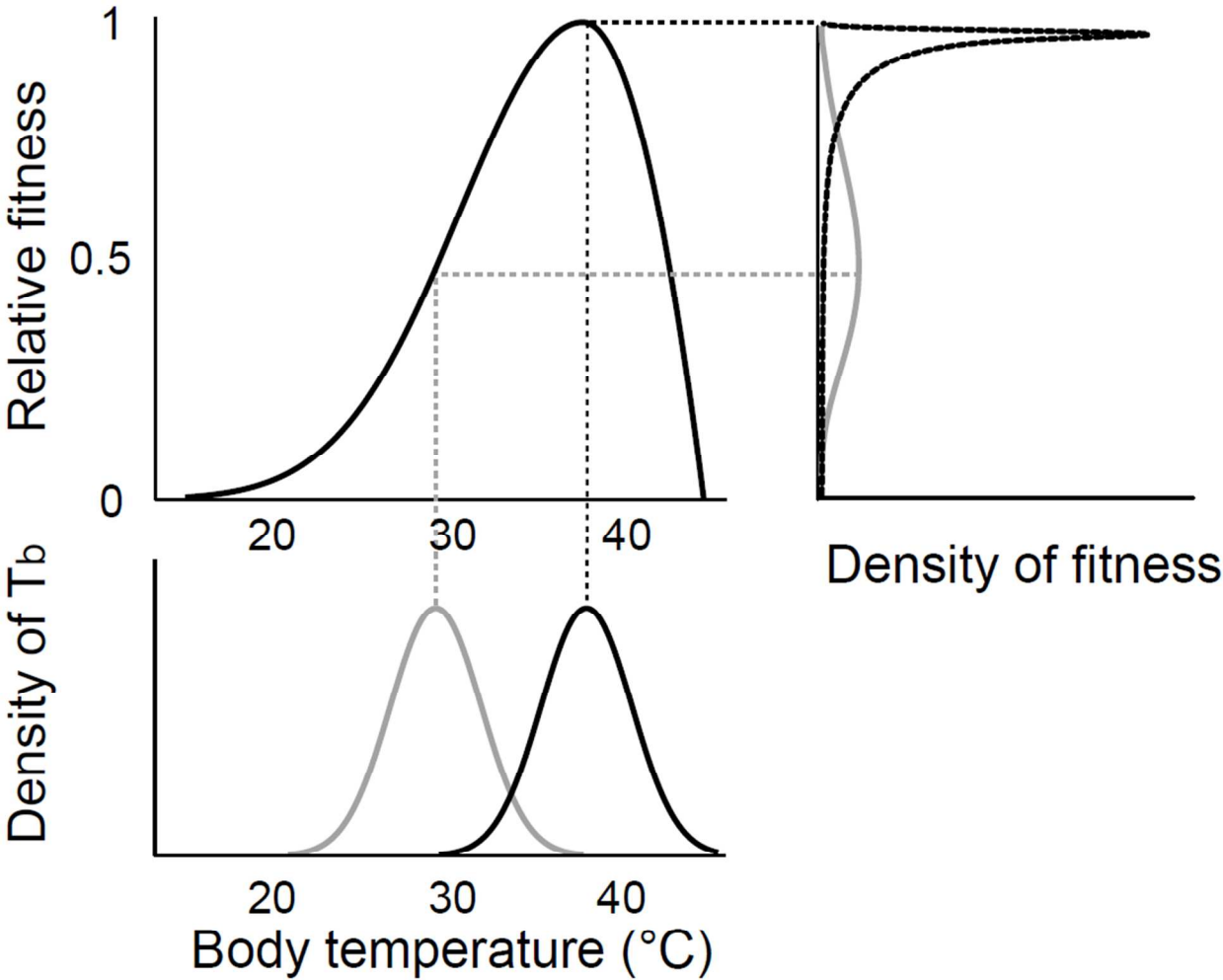
Figure 1



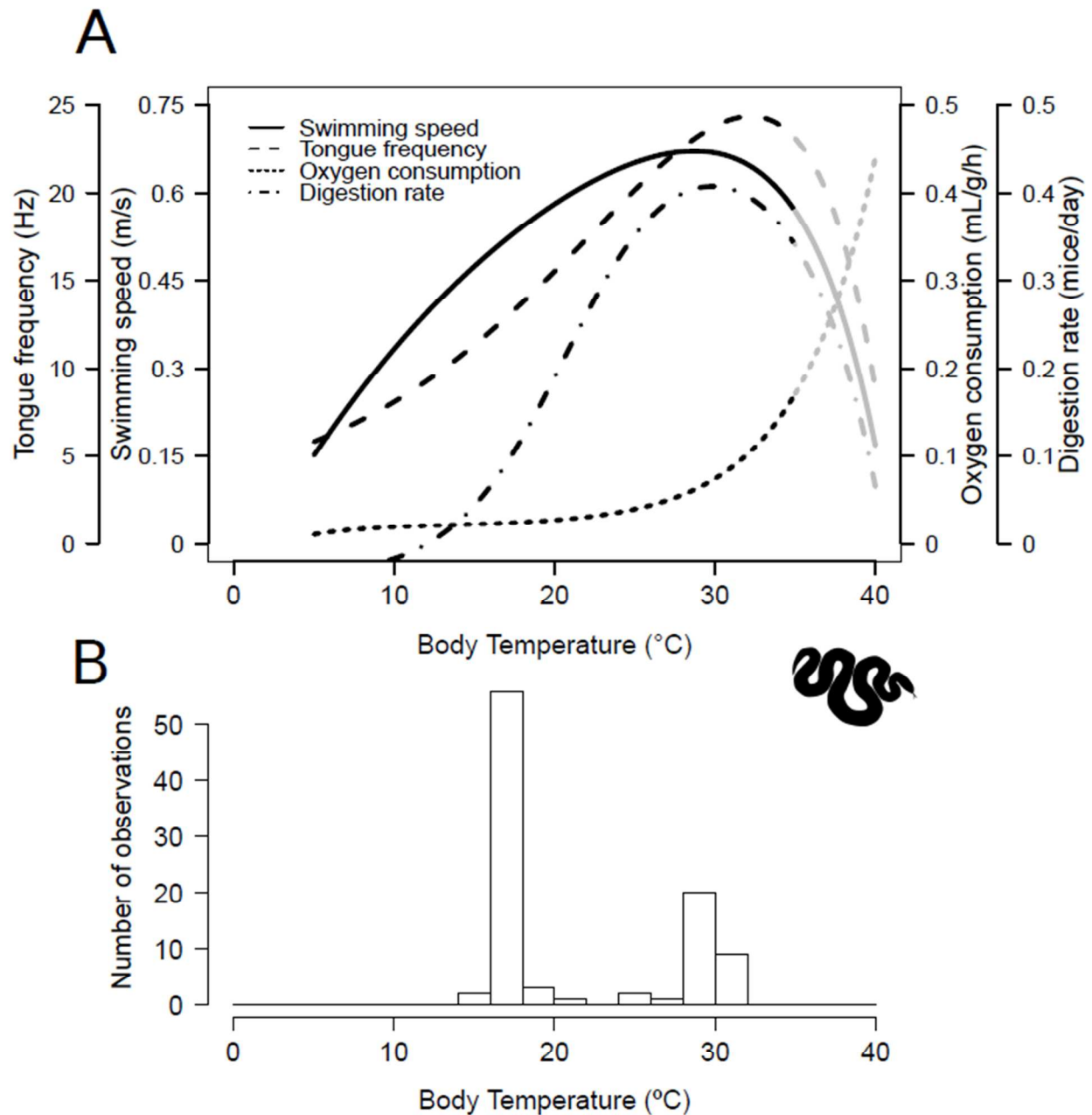
**Figure 1.** A typical thermal performance curve relating body temperature,  $T_b$  to fitness  $w(T_b)$ , with critical features highlighted (based on Huey & Stevenson 1979).  $CT_{min}$  and  $CT_{max}$ : Critical thermal minimum and maximum, respectively;  $T_{opt}$ : thermal optimum;  $T_{br}$ : Thermal breadth. This curve is based on the digestion equation from Stevenson et al. (1985).



Figure 2

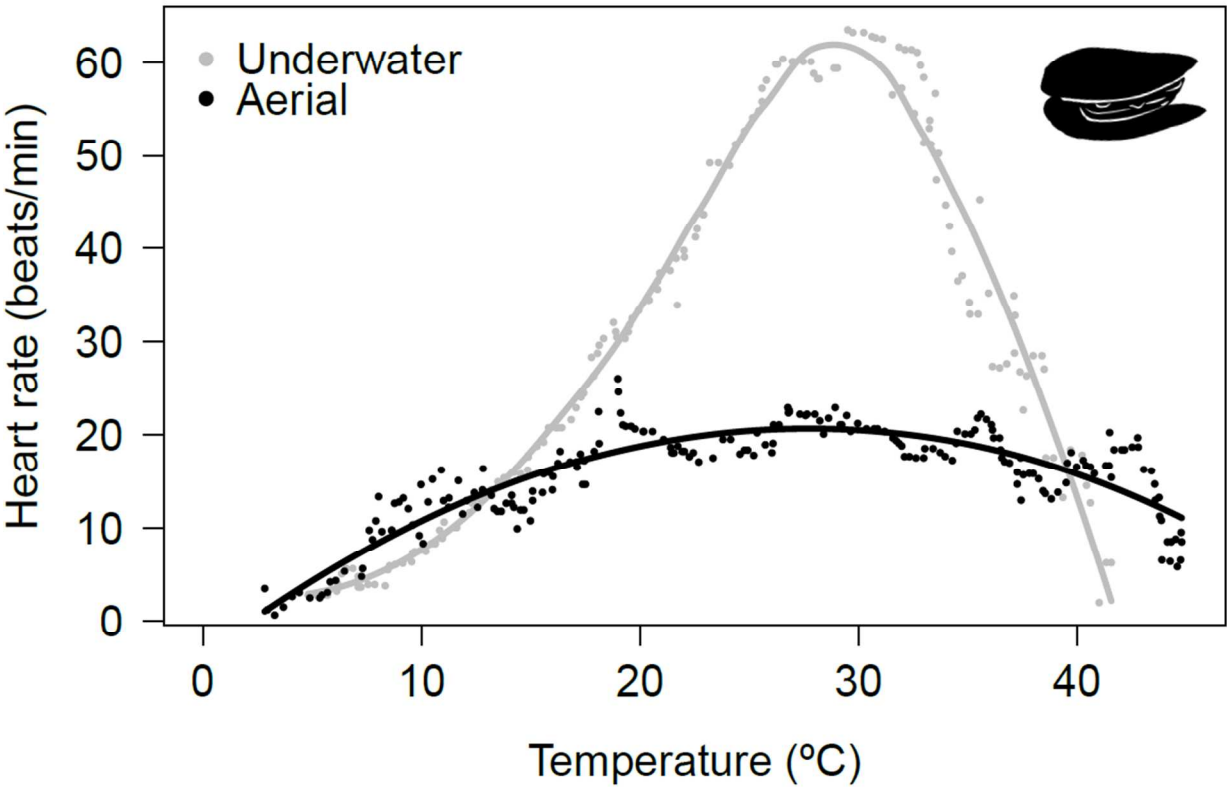


**Figure 2.** a) An hypothetical *TPC* showing relative fitness (0 to 1) as a function of body temperature (see also Fig. 1). b) Two representative distributions of body temperatures (grey = low  $T_b$ , black = high  $T_b$ ). c) Density of relative fitness for the two  $T_b$  distributions in b), calculated from Eqn. 1. The average fitness is much higher for the ectotherm with the higher  $T_b$  distribution. Based on Vasseur et al. (2014).

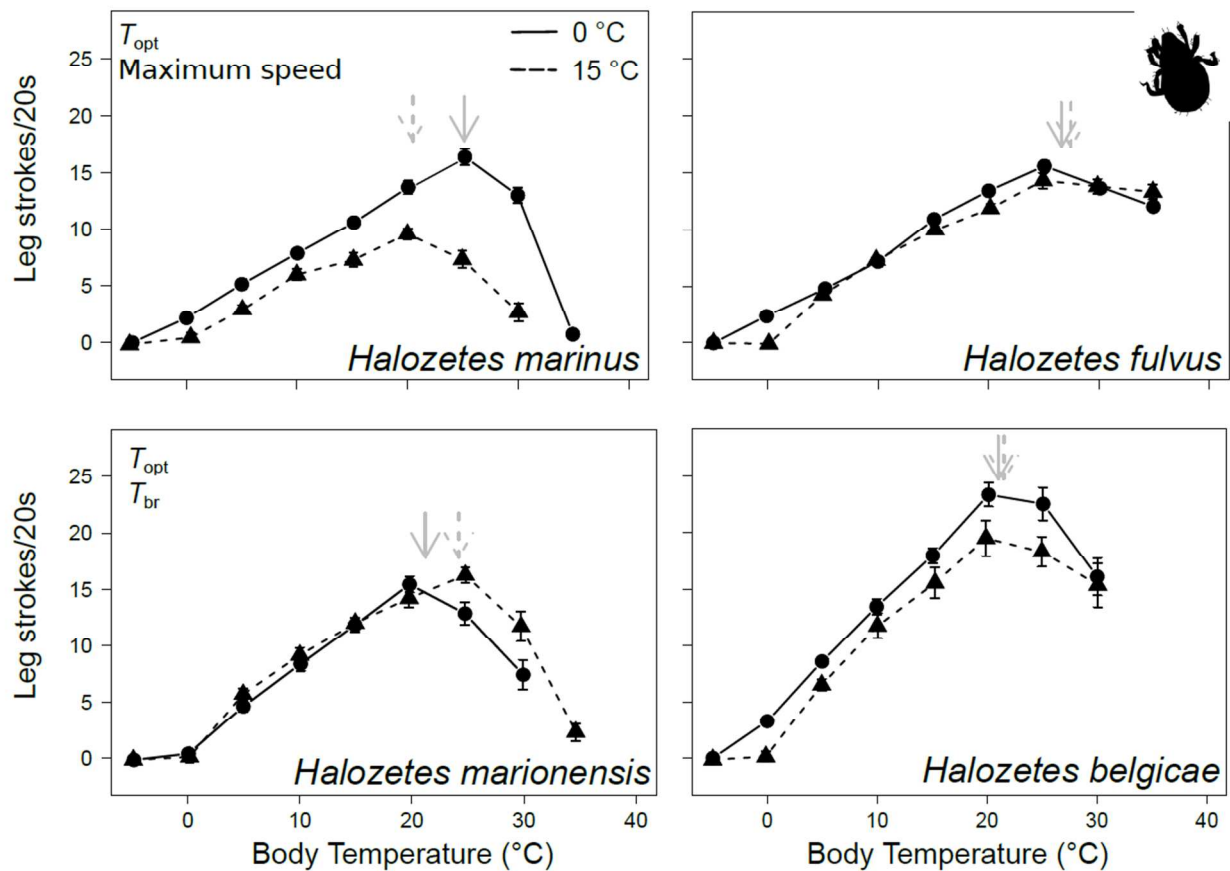
843 **Figure 3**

**Figure 3.** A) Variation in thermal performance curves for four different traits measured in the western garter snake *Thamnophis elegans*. Grey lines indicate parts of the curve that were extrapolated beyond the range of empirical data. B) The distribution of *T. elegans* field body temperatures as measured by radiotelemetry at 15 min intervals over the course of 24 h. Note the significant difference between the distribution of body temperatures and the TPC. Data from Stevenson *et al.* (1985).

Figure 4

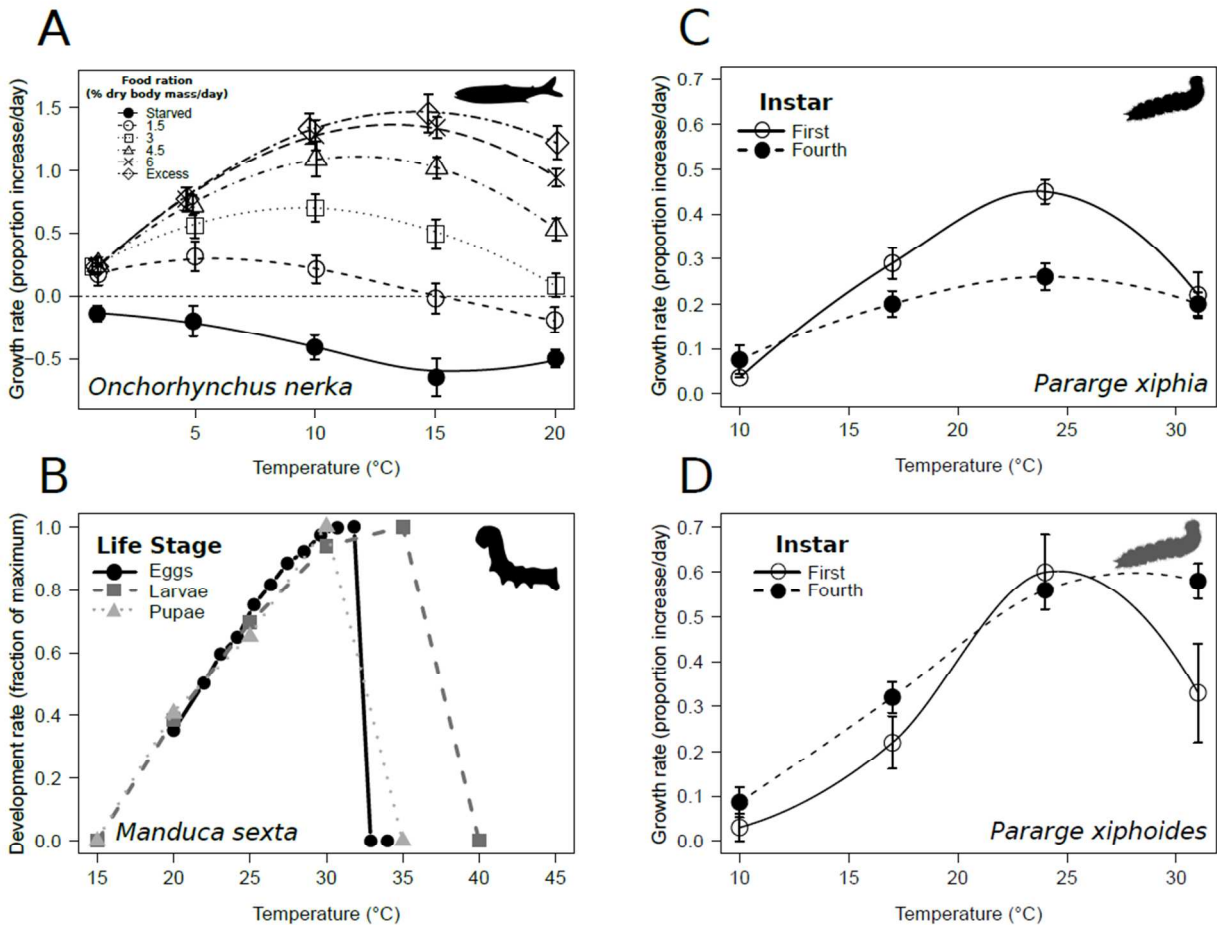


**Figure 4.** Sensitivity of thermal performance of heart rate to immediate conditions in the brown mussel *Perna perna*. Black lines and points are for emerged mussels, grey lines and points for immersed. Data from Tagliarolo and McQuaid (2015). Lines of best fit are plotted using a locally-weighted polynomial regression implemented by the loess function in R.

862 **Figure 5**

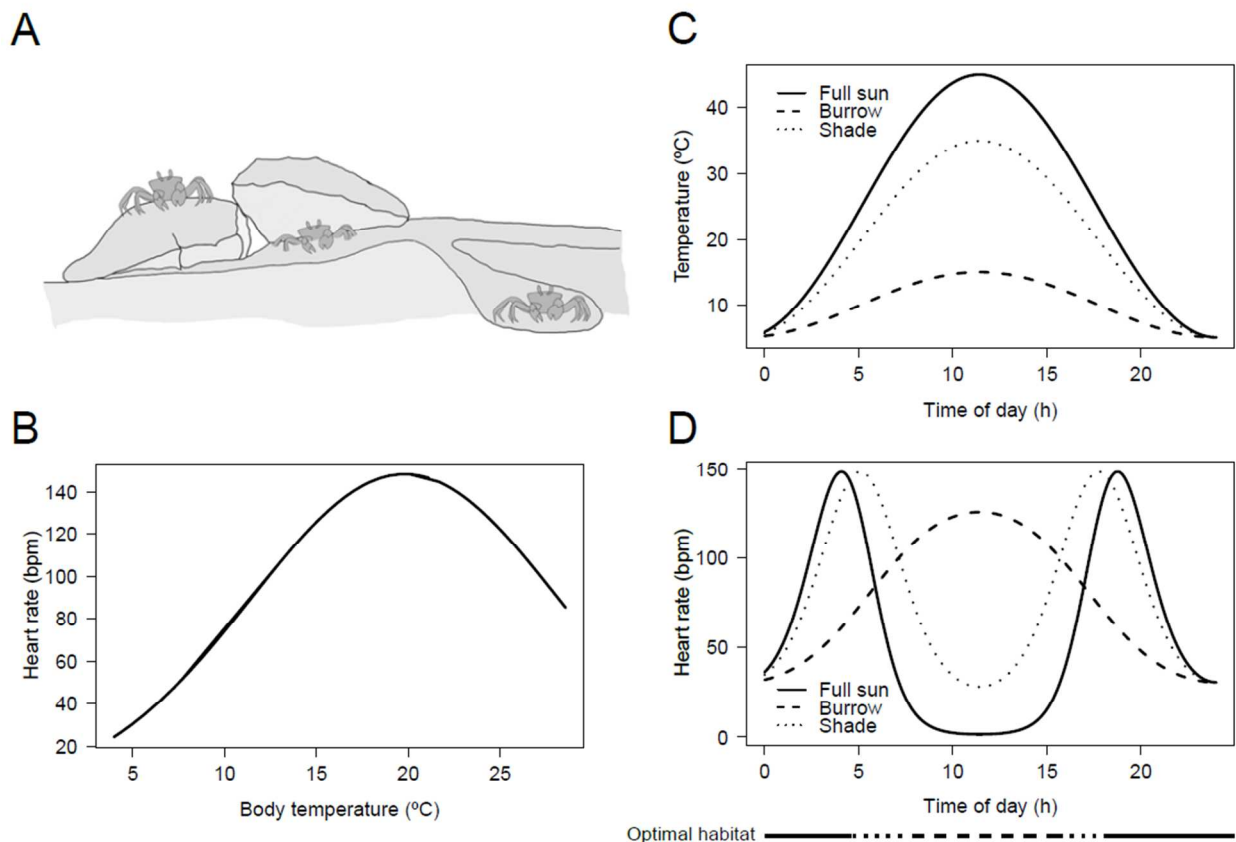
**Figure 5.** Variation in form and phenotypic plasticity of thermal performance curves of locomotor activity for four congeneric species of sub-Antarctic oribatid mites after acclimation at warm (15 °C, triangles, dashed lines and arrows) and cool (0 °C, circles, solid lines and arrows) temperatures for 7 d. Arrows indicate  $T_{opt}$ . Parameters that differ significantly between acclimation treatments are listed in the top left of each plot. Data from Deere and Chown (2006).

Figure 6



**Figure 6.** Both nutritional state and ontogenetic stage can affect *TPCs*. **(A)** Varying food ration substantially changes the *TPC* position and magnitude of  $T_{opt}$  or growth rate in juvenile sockeye salmon (*Oncorhynchus nerka*). Data from Brett et al. (1969). **(B)** *TPC* shape is determined by developmental stage (eggs, larvae, or pupae) in the sphinx moth *Manduca sexta*. Data from Kingsolver et al. (2011). **(C, D)** Species  $\times$  development interaction in *TPCs* for growth rate of nymphalid caterpillars in the genus *Pararge*. The among-species shift likely reflects behavioral differences: *P. xiphia* becoming increasingly nocturnal and *P. xiphoides* increasingly diurnal over the course of development. Data from Berger et al. (2011).

Figure 7



**Figure 7.** Behavioral thermoregulation can decouple environmental temperature and body temperature. In this example, crabs may choose between full sun, shade, and burrow habitats (A). The TPC of heart rate in the porcelain crab *Petrolisthes violaceus* (B) is based on data from Gaitán-Espitia et al. (2014). Environmental temperature varies across habitats through the day (C), data from Schneider and Helmuth (2007), and so heart rate in *P. violaceus* (modelled from B and C) will depend on which habitat it is occupying at which time of day (D), with the optimal habitat (where heart rate is maximized) varying through the course of the day.