

# A universal thermal performance curve arises in biology and ecology

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This manuscript was compiled on September 10, 2025

Temperature has strong impacts on all biological and ecological processes, and thermal performance curves (TPCs) have been employed recurrently to assess them. TPCs almost always take a particular asymmetric shape across the biological hierarchy, with many different competing mechanisms and models doing a similarly good job of trying to explain the TPC phenomenon. Here, we reveal that the ubiquitous exponential scaling of biological processes with temperature creates a mechanistic tendency for TPC data and models to collapse onto a single curve (which we call the Universal TPC, UTPC), explaining mathematically why biological systems respond to temperature in such a consistent way. We illustrate that many seemingly different TPCs actually approximate rescaled versions of the same curve, even when thermal performance estimates vary widely across organisms, systems, and contexts. We demonstrate remarkable UTPC collapse across the tree of life, with diverse datasets spanning microbes to vertebrates, and individual physiology to population growth. UTPC phenomena also provide a strong new theoretical basis for predicting performance of warm-adapted organisms will be more sensitive to- and less tolerant of- temperature fluctuations; an important consideration in the context of climate change.

Thermal Performance Curves | Metabolic Theory of Ecology | activation energy | critical temperature |

Thermal performance curves (TPCs) have wide-reaching applicability in biology, providing a general framework to assess the thermal response of life, from biochemical rates up to ecologically relevant processes, such as population growth (1–6). In essence, these curves describe how rates of performance or fitness traits change as a function of temperature, indicating the range of temperatures in which performance can be sustained and the optimal temperature at which performance is maximized, among many other descriptors (6–8). Across a wide range of biological systems, empirically derived TPCs tend to follow a similar unimodal and asymmetric pattern, exhibiting an optimal temperature with an exponential-like increase of performance in the cooler side and a steep descent to zero performance (often complete failure or death) in the warmer side (Figure 1) (1, 3, 6, 9, 10). Although some traits (such as those indexing mortality rates) deviate from this general shape, the overall ubiquity of the TPC shape across the biological hierarchy is striking. However, a comprehensive explanation for the common TPC shape remains elusive.

The general unimodal and asymmetric shape of such TPCs across traits (11) and levels of biological organization (6), suggests that the thermal dependency of biological processes arises from a universal law, and an increasing number of competing models are now integrating TPCs to describe performance data and in the search for universal principles (12–14). Many of these models take a semi- or fully mechanistic view based on exponential or Arrhenius scaling of biochemical reactions coupled with processes of protein degradation, enzyme chemical kinetics (15) (Figure 2a) or supply-demand mismatches (6) (Figure 2b) to explain the decline phase of the curve. These models have been used to identify key properties such as species’ optimal temperatures, their thermal range, as well as the prediction of thermal responses of natural populations from laboratory trials (i.e. (10, 16–19).

## Significance Statement

Temperature impacts the performance of systems in a strangely consistent way from the level of cells to individuals, populations and ecosystems: performance increases exponentially with temperature to an optimum, and then abruptly declines. What causes this ubiquitous asymmetric shape across the biological hierarchy has attracted much debate, with many different mechanisms proposed to explain the classic form of ‘thermal performance curves (TPC)’. Here we reveal, mathematically, the mechanism which causes the TPC shape, and explains why it is so common across biology. These findings explain why so many different systems respond to temperature in a similar fashion, regardless of the underlying chemical, biological or ecological processes at play. This new mechanistic insight should help us understand how biological systems adapt to temperature variation, and especially for predicting future responses to changing climates.

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Authors contribution: J-FA, ALJ and NP conceived the study. J-FA prepared the mathematical demonstration of the UTPC. J-FA, ALJ and IP-M performed the analysis and the graphical representation of the results. NP and ALJ shared senior authorship roles. All authors participate during preparation of the first draft and contributed to the final manuscript.

Competing interests: The authors declare no competing interests.

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Nevertheless, since most existing models – after more or less effort to locate optimal parameters – seem capable of fitting empirical TPCs (Figure 2c), with a similar shape, it is difficult to discriminate between competing theoretical mechanisms. Additionally, multiple models can even be fitted to the same curve and often several fail to converge (14). Thus, while mechanistic models have successfully described various aspects of thermal performance, the broader challenge lies in reconciling their diverse approaches into a unified theoretical framework (20). Many existing models focus on different proximate mechanisms, but it remains unclear which of them play the most fundamental role in shaping TPCs across biological systems. A recent paper (15) proposed a promising first-principles general model of diverse biological responses, but produces a Gaussian curve (see the Supplementary Material). Accordingly, the consistent left-skewed shape characterising most TPCs remains unexplained by a unifying mechanism, despite being widely observed across almost all fields of biology.

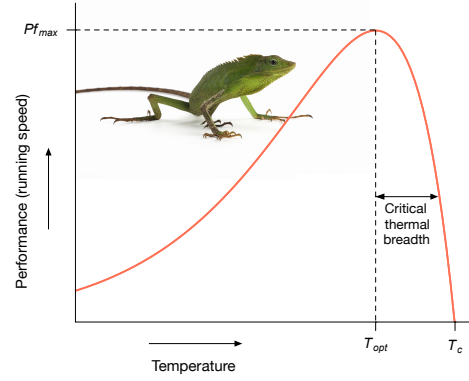
Here we reveal the mathematical mechanism that explains why TPCs have such a similar shape across the biological hierarchy, and why so many different phenomenological models can fit empirical TPC data: exponential scaling of any biological process with temperature causes a strong attraction (?) to a single TPC shape, which we call the Universal Thermal Performance Curve (UTPC). Our analysis shows a different set of tested TPC models can be expressed as shifted and scaled versions of a UTPC. We illustrate convergence to the UTPC by starting from first principles of the Metabolic Theory of Ecology and introduce a generic performance process that causes a decline in performance at higher than optimal temperatures. We show that within the limits of biological temperatures, there exists an attractor towards a very simple UTPC equation  $y(x) = e^x(1-x)$  where  $x$  is a simple rescaling of temperature, regardless of the myriad different processes or mechanisms that might be causing performance to decline at high temperature (21). In doing so, we identify why most common models of TPCs collapse onto the UTPC (and each other) and when we might expect them to diverge. We further investigate the properties of this general curve and show that the activation energy familiar from the Arrhenius equation is positively correlated with the optimal temperature and inversely correlated with thermal breadth; mathematical dependencies that could explain several long-observed macroecological patterns. We illustrate the universality of the UTPC by applying it to a large dataset spanning seven kingdoms, 39 phyla, and a broad range of performance metrics from individual- to population-levels.

## Description of the Universal Temperature-Performance Curve (UTPC)

Metabolic Theory of Ecology is partly (along with allometric scaling with body mass) grounded on the Arrhenius scaling function. This phenomenological function describes the accelerating pace of biochemical reactions with temperature  $T$  (expressed here in Kelvin) as an exponential function of *inverse temperature*:

$$\text{Arrhenius}(T) \propto e^{-\frac{E_a}{k_B T}} \quad [1]$$

Here  $E_a$  is the activation energy of the studied metabolic process (found to be roughly between 0.3 and 0.8 eV in



**Fig. 1.** Empirically derived thermal performance curves (TPCs) typically exhibit a unimodal and asymmetric pattern. We represent a hypothetical generalized thermal performance curve (TPC), illustrating how performance traits — such as running speed in lizards — exponentially increase with temperature until reaching a maximum performance ( $Pf_{max}$ ) at the optimal temperature ( $T_{opt}$ ). Beyond this peak, performance declines sharply as temperature continues to rise, eventually reaching a minimum or collapsing at the critical temperature ( $T_c$ ). Another widely used parameter in TPC studies is the thermal breadth ( $T_{breadth}$ ), which quantifies the range of temperatures over which performance is above a given threshold. Here we show the critical thermal breadth, which spans  $T_{opt}$  to  $T_c$ .

biological systems(22)) and  $k_B$  the Boltzmann constant  $k_B = 8.6 \times 10^{-5}$  eV/K.

### Step 1: Simplification of the Arrhenius Function.

When considering the range of temperatures in which most life is sustained – from approx.  $-40$  to  $+80$  degrees Celsius ( $^{\circ}\text{C}$ ) (23), the Arrhenius function is effectively indistinguishable from a standard exponential function of temperature but now expressed in Celsius ( $T^{\circ} = T - T_0$ , where  $T_0 \approx 273$  K). We refer to the Supplementary Materials where we explain in detail why this seemingly trivial unit shift allows a drastic simplification of the Arrhenius function. To best reveal this simple form, we first introduce a non-dimensional temperature variable, defined as  $\tau = (T - T_0)/T_0 = T^{\circ}/T_0$ .

We then introduce a *small* non-dimensional parameter  $\epsilon$ , inversely related to activation energy:

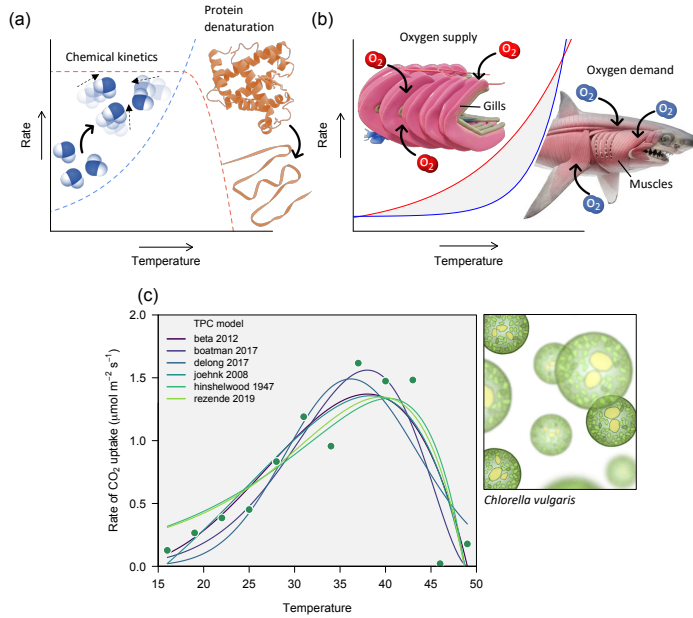
$$3 \times 10^{-2} \lesssim \epsilon = \frac{k_B T_0}{E_a} \lesssim 7 \times 10^{-2} \quad [2]$$

This crucial parameter is the characteristic, non-dimensional, scale of variation of the Arrhenius function (introduced by (24)), in the sense that for biologically relevant temperatures the latter simply reads

$$\text{Arrhenius}(T) \propto e^{\tau/\epsilon} \quad [3]$$

### Step 2: Enforcing an optimal performance.

Rates of biological performance such as running speed, photosynthesis rates, or population growth rates, cannot be modelled as a simple increasing exponential reaction rate. Although biological performance traits typically manifest an exponential increase with temperature up to a point, they will necessarily decline thereafter (as commented in the introduction, this decline is often observed to be abrupt). A phenomenological way to account for this when modelling performance is to define a factor function  $g(\tau)$  that is zero or very small at high temperatures and is otherwise bounded or



**Fig. 2.** Numerous Thermal Performance Curve (TPC) models have been proposed to explain the unimodal temperature-response of performance rates in biological systems using semi- or fully mechanistic approaches. For example, **(a)** a phase of positive exponential increase followed by a negative exponential decrease, typically attributed to scaling of biochemical reactions and protein degradation processes, or **(b)** differences between supply and demand to tissues of energy or molecules such as oxygen. **(c)** Regardless of the different proposed mechanisms, TPCs tend to take the same shape. For instance, fitting various TPC models to the photosynthetic rate data of *Chlorella vulgaris*, an aquatic algae, reveals that all models, despite their differences, align well with the empirical data. This analysis employed empirical data and six mechanistic models from the R package rTPC (39), showcasing their ability to accurately represent observed data points.

sub-exponential so as to not completely mask the exponential component. This factor function may have various mechanistic underpinnings (see Supplementary Materials for three distinct models), but will generically ensure that the exponential dominates at low temperatures before being dominated by  $g(\tau)$  at high temperatures. For simplicity we assume  $g$  to be a smooth function. Thus the performance measured, noted  $P_f$ , is modelled as

$$P_f(\tau) \propto e^{\tau/\epsilon} g(\tau) \quad [4]$$

which is very small or zero at both high (owing to  $g(\tau) \rightarrow 0$ ) and low (owing to  $e^{\tau/\epsilon} \rightarrow 0$ ) temperatures. To locate the predicted optimum temperature  $\tau_{opt}$ , which occurs when the slope of performance changes direction, we take the first derivative of this function:

$$P'_f(\tau) \propto e^{\tau/\epsilon} (g'(\tau) + g(\tau)/\epsilon) \quad [5]$$

This expression is zero at the optimal value  $\tau_{opt}$ . Since  $e^{\tau/\epsilon}$  must be strictly positive for any value of  $\tau$ , the only way for  $P'_f(\tau_{opt})$  to vanish is if the term in parentheses equals 0. This gives us the defining equation of optimal temperature

$$P'_f(\tau_{opt}) = 0 \Leftrightarrow \frac{g'(\tau_{opt})}{g(\tau_{opt})} = -1/\epsilon \quad [6]$$

This turning point in performance occurs when the rate of decline in performance arising from the factor function  $g(\tau)$  balances out exactly the rate of increase caused by the exponential component. We will make use of this crucial property in what follows, where the UTPC is revealed.

### Step 3: Rescaling and convergence towards the UTPC.

We now rescale both performance and temperature with respect to their optimal values. We first define *relative* performance  $RP_f(\tau)$ , taking values between 0 and 1. Its expression reads

$$RP_f(\tau) = \frac{P_f(\tau)}{P_f(\tau_{opt})} = e^{(\tau - \tau_{opt})/\epsilon} \frac{g(\tau)}{g(\tau_{opt})}. \quad [7]$$

Next, we introduce  $x = (\tau - \tau_{opt})/\epsilon$  which represents the departure from optimal temperature, *relative to the thermal scale*  $\epsilon$ . Having rescaled and recentered both performance and temperature, we finally define  $y(x) = RP_f(\tau(x))$ , which reads

$$y(x) = RP_f(\tau(x)) = RP_f(\tau_{opt} + \epsilon x) = e^x \frac{g(\tau_{opt} + \epsilon x)}{g(\tau_{opt})}. \quad [8]$$

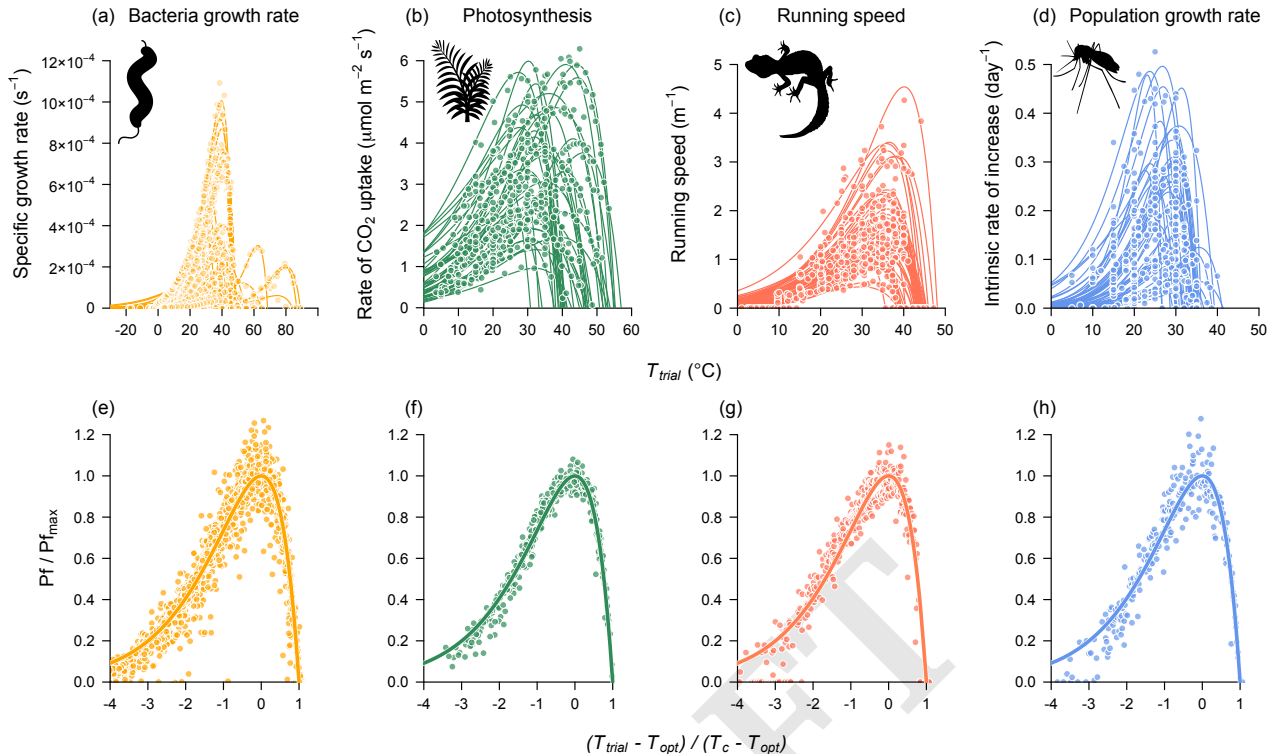
We then use a Taylor expansion of  $g(\tau_{opt} + \epsilon x)$  to recognize the properties of the optimum temperature given by eq. (6). At leading order in  $\epsilon$  (recall from Eq. 18 in Supplementary Material that  $\epsilon$  is much smaller than 1) we have:

$$y(x) \approx e^x \left( \frac{g(\tau_{opt}) + g'(\tau_{opt})\epsilon x}{g(\tau_{opt})} \right) \approx e^x \left( 1 + \frac{g'(\tau_{opt})}{g(\tau_{opt})} \epsilon x \right) \quad [9]$$

Using eq. 6, we recognize in  $y(x)$  the elementary function:

$$y(x) \approx e^x (1 - x) \quad [10]$$

whose graph defines the UTPC. Higher order terms of the Taylor expansion can be used to give a criterion for convergence towards this limit form (see Supplementary Material). Such an analysis shows that if the characteristic scale of variation of  $g$  is larger than  $\epsilon$ , then the associated TPC will automatically converge on the UTPC, independently of the precise form of the factor function  $g$  and the biological mechanisms on which it is based. Applying this framework to available empirical data (see Material and Methods), we demonstrate that thermal performance phenomena, once properly rescaled, tend to collapse on the predicted universal curve (UTPC). We re-analyzed the large datasets from Kontopoulou et al. (20) and Rezende and Bozinovic (6) comprising more than 2700 empirical datasets of thermal performance from seven kingdoms and 39 phyla, and a broad range of performance metrics spanning individual physiology (e.g. respiration rate) to population growth. With this approach, we show that the UTPC fits a remarkably accurate prediction on the rescaled empirical data, regardless of the organism or performance trait



**Fig. 3.** Data collapse, and models converge, onto a Universal Thermal Performance Curve (UTPC), which only requires optimal and critical temperatures as parameters. Top panels show empirical data on thermal performance encompassing (a) specific growth rate of proteobacteria ( $n = 131$ ), (b) biochemical rates of photosynthesis in plants ( $n = 43$ ), (c) running speeds of lizards ( $n = 51$ ), and (d) population growth in insects ( $n = 47$ ). Lower panels (e–h) showcase the rescaled data from the processes exposed on top, along with their corresponding alignment to the Universal Thermal Performance Curve (UTPC) equation. Datasets are from Kontopoulos et al. (20) for proteobacteria and from Rezende and Bozinovic (6) for other groups.

(Figure 3, 4). This rescaling exercise ensures that data from different systems are standardized within the same analytical framework, allowing for direct comparisons across datasets. On the other hand, the UTPC precisely identifies the relevant parameters that can be tuned to fit empirical data. Since the UTPC takes only  $T_{opt}$  and  $\mathcal{E}$  (or equivalently  $T_c$ ) as parameters, in the UTPC limit, any combination of additional parameters that do not change  $T_c$  and/or  $T_{opt}$  will be impossible to infer.

In the attached Supplementary Material we elaborate on the UTPC convergence phenomenon of three TPC models. These include the classic *Protein Denaturation Model*, the *Trade-Off Model between Resource Acquisition and Maintenance Costs*, and a model Based on the *Kinetic Theory*, each model providing a distinct perspective on thermal adaptation in biological systems. Notably, we show that the only purely mechanistic model that we know of, namely the one based on first principle of Kinetic Theory (15), is the only one that can never converge towards UTPC. But, as we show, this model predicts a Gaussian TPC, which is symmetrical unlike most thermal performance data. This unforeseen, perhaps unfortunate finding undermines the claim of (15) that TPCs can be universally predicted from first principles of thermodynamics.

Lastly, while the UTPC formulation inherently assumes strictly positive performance values, it can easily adapted for dataset where performance include negative values. For

example, this is the case in studies of population growth rate across thermal gradients, where negative performance indicate population decline. In such cases, a straightforward approach is to shift all performance values by adding a constant, ensuring all data are positive before fitting the UTPC model. After fitting, both data and UTPC can be adjusted back by subtracting the same constant, without affecting the curve's shape. We provide a detailed implementation in the Supplementary Material. Thus, the UTPC framework remain broadly applicable across diverse performance dataset, including those where performance extend to negative ranges.

### Activation Energy is inversely proportional to thermal breadth

We see in the UTPC expression eq. (10) that the critical temperature ought to correspond to  $x = 1$ , at which point the exponential is multiplied by 0. Thus that  $\tau_c - \tau_{opt} = \epsilon$ . This means that rescaled temperatures can be seen as rescaled with respect to the critical thermal breath  $T_c - T_{opt}$ , in the sense that:

$$x = \frac{\tau - \tau_{opt}}{\epsilon} = \frac{\tau - \tau_{opt}}{\tau_c - \tau_{opt}} = \frac{T - T_{opt}}{T_c - T_{opt}} \quad [11]$$

This comes from the fact that in the UTPC limit, there is a unique thermal range  $\mathcal{E}$  characterizing the relationship between performance and temperature. This range coincides with the



critical thermal breadth since we just saw that  $\mathcal{E} = T_c - T_{opt}$ , but also with the scale associated with the Arrhenius function. Indeed, as a corollary of eq. (11), if a model is indistinguishable from the UTPC, then this means that there exists a direct link between the critical thermal range  $T_c - T_{opt}$  and the activation energy  $E_a$  coming from the Arrhenius factor. To see this we simply unpack the non dimensional expression  $\epsilon = T_c - T_{opt}$  to see that

$$\tau_c - \tau_{opt} = \epsilon \Leftrightarrow T_c - T_{opt} = \epsilon T_0 \Leftrightarrow \mathcal{E} = T_c - T_{opt} = \frac{k_B T_0^2}{E_a} [12]$$

In other words, for any model indistinguishable from UTPC, the difference between  $T_c$  and  $T_{opt}$  is inversely proportional to activation energy  $E_a$ , as the latter fully controls the (unique) scale of variations of the TPC under study.

## 1. Activation Energy increases optimal temperature

We now focus on the expected relationship, in the UTPC limit, between the thermal optimum  $T_{opt}$  and activation energy  $E_a$ . If we differentiate the defining equation of thermal optimum eq. (6) with respect to  $\epsilon$  we get to  $\frac{\partial T_{opt}}{\partial \epsilon} \approx -1$ , where the approximation precisely holds when the criteria for convergence towards UTPC is met (see Supplementary Material). Unpacking the non-dimensional terms yields

$$\frac{\partial T_{opt}}{\partial E_a} \approx \frac{k_B T_0^2}{E_a^2} [13]$$

meaning that thermal optimum ought to predictably increase with activation energy. Note that there are diminishing returns to this dependency (activation energy appears in the denominator of the right hand side of the above equation), so that the higher activation energy is, the less it would increase the thermal optimum. Given the results of the previous section, we have arrived at quantitative predictions showing that as activation energy increases, thermal optimum increases but thermal breadth is reduced. In other words, increasing the rate of the exponential increase in performance with temperature will tend to increase a system's  $T_{opt}$ , but will simultaneously narrow the range of temperatures over which it can perform.

It should be noted however, that although in the UTPC limit  $T_c - T_{opt}$  only depends on activation energy,  $T_{opt}$  itself (and thus also  $T_c$ ) can depend on other parameters (In the attached Supplementary Material we compute  $T_{opt}$  for three different models; other model-specific parameters do play a role). Thus, one should not necessarily expect to have  $T_{opt}$  and  $E_a$  correlate across populations of a given species, and even less so across species. The claim that we can make is that, if adaptation occurs via a change in activation energy, in the UTPC limit there will be a trade-off between increasing  $T_{opt}$  and widening the critical thermal range  $T_c - T_{opt}$ .

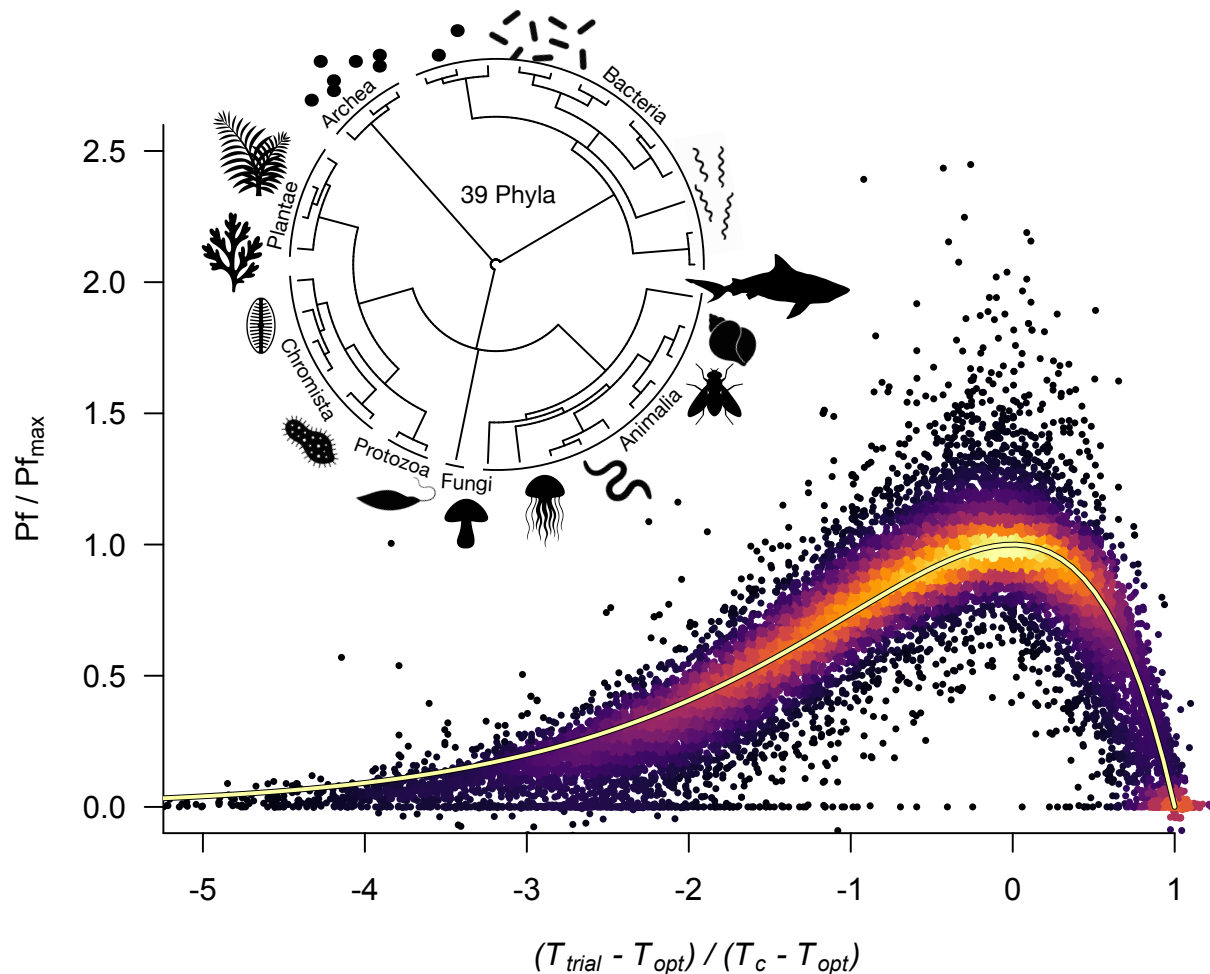
## Discussion

The UTPC framework provides a unifying perspective on why many biological systems and mathematical models converge on a similar shape when describing thermal performance responses. Since so many (but not all; e.g. some TPCs take a Gaussian shape; (15)) different interacting processes and mechanisms with exponential components will approximate each other closely in the form of a UTPC, it may be less satisfying to seek proximate mechanisms underlying the

shape of different TPCs compared to understanding why concepts such as thermodynamics and kinetics drive such repeatable responses in phenomena like the ATP required by cells, oxygen required by tissues, and the energy fluxes of ecosystems. This issue remains controversial (12, 20, 25–27), but it dictates formation of the UTPC, and so sets the form of how performance varies across the diversity of life.

Different organisms and processes exhibit specificities in their rates of performance increase (expansion), decrease (contraction), and optimal temperatures ( $T_{opt}$ ), necessitating our normalization procedure to translate unique thermal responses of different biological entities into a common normalized curve (akin to how z-score transformation provides a standard for diverse data points). By removing differences of scale, the normalized curve could represent a new null model through which to explore mechanisms facilitating deviation from the UTPC shape (e.g. symmetrical or right-skewed TPCs; (3, 6, 28, 29)), as well as rescaling of the UTPC (adjusting  $T_{opt}$ , height and breadth of TPCs) via acclimation and adaptation. Ectotherms have a limited but measurable capacity to reduce the thermodynamic influence of temperature on biological rates (30), so it could be fruitful to explore the general capacity of biological systems to deviate from the UTPC constraint. Data from a very diverse set of organisms and performance metrics shows general convergence to the UTPC (Figure 3e-h; Figure 4, and Supplementary Material where collapse of data to UTPC is seen across phyla and performance metric), but residual variation around UTPC could reflect acclimation capacity that is worthy of future study. While several studies have reported evolutionary variation in the TPCs (e.g., (14, 31)), our analysis does not account for potential evolutionary shifts in thermal performance. Thus, whether ancestral of evolved TPCs align with the UTPC framework or exhibit significant deviations remains an open question that warrants further research.

We illustrate an intrinsic dependency between the activation energy  $E_a$  and  $T_{opt}$ , as well as between the range spanning  $T_c$  and  $T_{opt}$ . The former could hint toward the molecular mechanisms by which systems rescale the UTPC to increase or decrease  $T_{opt}$ , since it is well accepted that activation energy can be adjusted via acclimation processes (i.e. (32–34)), and the latter reveals a mechanistic link between the rate of the exponential rise and the thermal range over which a system can perform. The dependencies of  $E_a$  on  $T_{opt}$  and on thermal breadth should be explored further because they might partly or fully explain long-studied macro-physiological patterns such as narrowing of thermal breadth for warmer-adapted species and populations (35, 36). Indeed, the tendency of UTPC to create higher  $T_{opt}$  for higher  $E_a$  (and in turn, smaller  $T_c - T_{opt}$ ) can explain why warmer-adapted species tend to have narrower thermal breadths; this long-observed global pattern may arise from constraints of exponential scaling (36), not adaptation to thermally stable environments (35). Further exploring these UTPC interactions could also provide useful tools for predicting key aspects of TPCs by only measuring some of their components; a potentially powerful outcome of the UTPC framework is that it enables estimating the decline phase of performance beyond  $T_{opt}$  by just measuring the exponential rise of a TPC (below  $T_{opt}$ ), or reconstructing a full TPC simply by measuring the distance between  $T_{opt}$  and  $T_c$ . These UTPC characteristics could facilitate broader TPC understanding from less data.



**Fig. 4.** Biological performance across the tree of life collapses onto the Universal Thermal Performance Curve (UTPC). Shown are approx. 30,000 performance measurements derived from seven kingdoms, 39 phyla and 2710 experiments. Performance is represented by diverse rates including metabolism, individual growth, foraging intensity, voluntary activity, and population growth (see Supplementary Material for data grouped by phylum and performance metric). Data are presented on both axes relative to the parameters ( $T_{opt}$ ,  $T_c$  and  $Pf_{max}$ ) estimated by fitting the UTPC equation to each of the 2710 experiments; the UTPC is overlaid as a yellow line. Data are coloured by the relative density of neighbouring points.

Finally, a potentially concerning implication of this work is that for an organism or system to adjust to warmer temperature by increasing its  $T_{opt}$ , it will tend to come with increased thermal sensitivity (elevated  $E_a$ ), and also a reduced range of temperatures over which it can perform (narrower breadth). A steeper increase in physiological performance with warming is thought to reduce resilience of organisms to climate change (30), as is a narrower thermal breadth, particularly for species adapted to warmer environments (37). These dependencies, as described within the UTPC framework, could represent additional challenges for organisms in the context of climate change, particularly since future environments are expected to experience both rising temperatures and greater thermal variability. However, we acknowledge that species differ in their capacity to adjust to changing climates, so more work is needed to assess how the UTPC dependencies interact with acclimation and evolutionary responses. Better understanding how organisms can physiologically adjust by rescaling the UTPC and departing from its limits might help

predict overall resilience and separate likely winners from losers in this era of climate change.

**Data accessibility statement.** The R script used to conduct the data analysis and the datasets are available at the GitHub repository <https://github.com/AndrewLJackson/UTPC-paper>.

## Materials and Methods

### Empirical data show convergence towards UTPC

Here we demonstrate with empirical data that thermal performance phenomena, once properly rescaled, tend to collapse on the predicted universal curve (UTPC). We re-analyzed two datasets; firstly, the full dataset from Rezende and Bozinovic (6) comprising a total of 141 empirical datasets of thermal performance over three broad biological levels of organization, describing biochemical rates of photosynthesis in plants ( $n = 43$ ), population growth in insects ( $n = 47$ ), and running speeds of lizards ( $n = 51$ ). Second, we used the full 'thermal performance dataset' from Kontopoulos (20) comprising 30970 measurements of thermal performance from seven kingdoms and 39 phyla, and including 152 unique measures of 'performance' such as specific growth rate of bacteria, radial

growth rate of fungi, respiration and photosynthesis rates of animals and plants, foraging velocity and body acceleration in insects and sharks (respectively), and population growth rates of seven kingdoms. For each taxa, data comprised of a sequence of temperatures  $\{T_i\}_{i=1,2,\dots}$ ; and associated performances  $\{P_{f,i}\}_{i=1,2,\dots}$ ; whose units depends on the kind of experiments and organisms considered. It is important to note that the definition of upper critical temperature ( $T_c$ ) tend to vary across performance metrics, particularly for those that do not reach zero, making its identification inherently challenging. Here, as we now explain, we inferred a scale of variation  $\mathcal{E}$  through parameter optimization rather than directly from empirical data. This scale, under UTPC convergence, can be then used to infer  $T_c$  (as in eq. 11). Concretely, three parameters were estimated for each empirically observed TPC: Maximum performance ( $P_{fmax}$ ), optimum temperature ( $T_{opt}$ ), and the characteristic thermal range ( $\mathcal{E}$ ), interpreted in the UTPC limit as the critical thermal range  $\mathcal{E} = T_c - T_{opt}$  (as in eq. 11). Parameter estimation was performed using the least squares method on the target function:

$$S = \sum_i \left( P_{f,i} - \widehat{P}_f(T_i) \right)^2, \quad [14]$$

where

$$\widehat{P}_f(T_i) = e^{\frac{T_i - T_{opt}}{\mathcal{E}}} \left( 1 - \frac{T_i - T_{opt}}{\mathcal{E}} \right) P_{fmax}, \quad [15]$$

using the box-constrained method L-BFGS-B within the R function stats::optim (38). Note eq. (15) takes the general form of the UTPC. The L-BFGS-B method finds the parameters that minimize the sum of squared residuals  $S$ . The optimization process was initialized by setting  $P_{fmax}$  to the maximum performance recorded,  $T_{opt}$  to the associated temperature, while the expected expression  $\mathcal{E} = T_c - T_{opt}$  was used to set a starting point using the highest recorded temperature in the data set. Then, estimated parameters  $P_{fmax}$ ,  $T_{opt}$ , and the thermal range  $\mathcal{E}$  were used to rescale the empirical data. All analytical protocols, including parameter optimization via the L-BFGS-B method, are available along with the data and the code to replicate the analyses in this study (see Data Accessibility Statement).

**ACKNOWLEDGMENTS.** This work was partly funded by a Science Foundation Ireland Grant (18/SIRG/5549) awarded to NLP; an Irish Research Council Laureate award (IRCLA/2017/186) to ALJ; and a Marie Skłodowska-Curie postdoctoral fellowship 2022 awarded to IPM (as part of eWARM project; number 101110111) J-FA was supported by the TULIP Laboratory of Excellence (ANR-10-LABX-41). We are very grateful to two reviewers and the handling editor for very thoughtful and helpful comments. Special thanks to reviewer Samraat Pawar who pushed us to explore the applicability of our model to the very large dataset and prompted the generation of Figure 4.

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