

~~A biomechanical approach to i~~Inferring size-based functional responses in
aquatic and terrestrial systems~~from the physical properties of the medium~~

Portalier S.M.J.¹, ~~Cherif M.~~², Fussmann G.F.^{3,2}, Loreau M.^{3,4} Cherif M.⁴

¹: Department of Mathematics and Statistics, University of Ottawa, Ottawa, ON, Canada

²: ~~French National Institute for Agriculture, Food, and Environment (INRAE), Aquatic
Ecosystems and Global Change Research Unit, Cestas, France~~ Department of Biology, McGill
University, Montreal, QC, Canada

³: ~~Department of Biology, McGill University, Montreal, QC, Canada~~ Centre for Biodiversity
Theory and Modelling, Theoretical and Experimental Ecology Station, CNRS, Moulis, France

⁴: ~~Centre for Biodiversity Theory and Modelling, Theoretical and Experimental Ecology Station,
CNRS, Moulis, France~~ French National Institute for Agriculture, Food, and Environment
(INRAE), Aquatic Ecosystems and Global Change Research Unit, Cestas, France

Correspondance:

Corresponding author: Portalier Sebastien M.J.

Email: sebastien.portalier@mail.mcgill.ca

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Abstract

First derivations of ~~the~~predators' functional response were mechanistic, but subsequent uses of these ~~mechanistically derived~~ functions tended to be ~~mostly~~ phenomenological. ~~Further~~A better understanding of ~~the~~ mechanisms underpinning ~~predator-prey relationships~~the functional response might lead to novel insights into ~~functional response~~ predator-prey relationships in natural systems. ~~Because recent consideration of the physical properties of the environment has improved our understanding of predator-prey interactions, we advocate the use of physics-based approaches for the derivation of the functional response from first principles. Several experiments already demonstrated the dependence of the functional response on such physical factors as temperature, turbidity and viscosity. Here we use a novel mechanistic approach that makes explicit consideration of the movement of organisms. Living organisms are constrained by the physical properties of their surrounding medium. First principles suggest that~~ In particular, these physical- ~~factors~~properties affect the functional response, ~~mediated by body size, by~~ constraining the ability of both predators and prey to move, ~~and thus affect the functional response. Effects on movement are often mediated by the body sizes of the predator and its prey. A physics-based derivation of the functional response should thus consider the movement of organisms in relation to their physical environment as they are engaged in predation. One recent article presents a model along these criteria. As an initial validation of our claim, we use a slightly-modified version of this model in order to derive the classical parameters of the functional response (i.e., attack rate and handling time) of aquatic organisms, as affected by body size, buoyancy, water density and viscosity. We compared the predictions of this first model to relevant data collected mostly from recent meta-analyses. Our model provided good fit for most parameters of the functional response, but failed to predict handling time. Remarkably, this is the only parameter~~

~~from the original model whose derivation did not rely on physical principles. Parameters in the model were not estimated from observational data. Hence, systematic discrepancies between predictions and real data point immediately to errors in the model. An added benefit to functional response derivation from physical principles is thus As an example of this approach, we build a model that derives classical parameters of the functional response (i.e., attack rate and handling time) from body size and physical factors. The novelty of this approach is that parameters are not estimated from observational data. The model only needs data on body size and physical properties of the medium, which can be easily measured. Our approach also to provides easy ways to validate or falsify hypotheses about predator-prey relationships, because discrepancies between predictions and real data point immediately to either errors in the model or missing mechanisms.~~

Keywords: functional response, predator, prey, medium, body size, mechanics

Introduction

The study of prey consumption by a predator (i.e., the functional response) began several decades ago (Gause, 1934; Gause et al., 1936) and was accompanied by the development of a theoretical framework based on mechanistic principles (Lotka, 1923; Volterra, 1926; Beverton and Holt, 1957; Watt, 1959). The model proposed by Holling ([1959](#); 1961; 1966) is one of the best known. This mechanistic model defines fundamental parameters such as attack rate (the rate at which a predator encounters and captures prey) and handling time (the time needed by the predator to subdue, ingest and digest the captured prey, and during which the predator cannot attack another prey). These parameters can be measured concomitantly, and they give information about factors that constrain predation on a given prey, which is a strength of this mechanistic approach.

Holling's type-I, II and III models and subsequently derived models (e.g., Rogers (1972)) are still widely used as a framework to derive the values of attack rate and handling time from empirical data (e.g., Andresen and van der Meer, 2010; Farhadi et al., 2010; Papanikolaou et al., 2011)). These approaches give valuable information on the studied systems, and they allow hypothesis testing, such as the effects of temperature (Archer et al., 2019) and predator satiation (Li et al., 2018) on the functional response. However, these studies have been mostly carried out in the laboratory, where many external factors do not play a role (Abrams, 1982). Hence, the results are hard to generalise and transpose to natural situations. Nonetheless, Holling's model has been a very successful approach founded on mechanistic principles.

Several studies have investigated the role played by specific factors known to affect the functional response. ~~These models have emphasized different features of predator-prey relationships~~, such as feeding saturation (DeAngelis et al., 1975) and interactions between predators (Beddington, 1975; Sih, 1979). In particular, the body size of both predator and prey are known to strongly affect the functional response (Aljetlawi et al., 2004; Vucic-Pestic et al., 2010). Body size is a good predictor of trophic position (Miller et al., 1992; Williams et al., 2010) and affects the overall dynamics of the interaction (Yodzis and Innes, 1992). Strikingly, the surrounding physical medium remains absent or, at least, only implicit in most studies, despite the tight relationship between body size and the physical environment as experienced by the organism (Purcell 1977, Bonner 2006). Although, in his pioneer work, Tansley (1935) stated that organisms should not be separated from their "special environment, with which they form one physical system", the role played by the physical medium in constraining the functional response remains largely unexplored. In the present paper, we argue that including physical features into predator-prey models is likely to lead to novel insights about species interactions.

However, the surrounding physical medium remains absent or, at least, only implicit in most models, despite its ubiquity in real ecosystems. Although, in his pioneer work, Tansley (1935) stated that organisms should not be separated from their “special environment, with which they form one physical system”, the role played by the physical medium in constraining the functional response remains largely unexplored. Including physical features into predator-prey models is likely to lead to novel insights about species interactions.

Empirical evidence of the impact of the physical properties of the medium on the functional response

Early developments of the functional response theory considered physical factors, notably spatial heterogeneity, only implicitly (Hardman and Turnbull 1974), with the notable exception of temperature (Mack et al., 1981). However, experimental investigation of the effect of one or the other physical property of the environment can be found here and there in the literature.

Temperature, the most thoroughly investigated factor, has been found to affect both attack rate and handling time, although its effects may vary according to the taxonomic group of the consumer, and the dimensionality of the interaction (Uiterwaal and DeLong, 2020). Turbulence, another reasonably well-studied factor in aquatic habitats, was found to affect predator attack rate of small aquatic predators, especially when prey abundance is low (MacKenzie and Kjørboe, 1995), although this effect seems to vary with feeding modes (Saiz et al., 2003). Medium viscosity is another factor that is known to affect feeding efficiency of planktonic predators by modifying their mobility, which in turn affects predator-prey encounter rate (Luckinbill, 1973; Tyrell and Fisher, 2019). Last, turbidity is an important factor for predators relying on visual cues

to detect their prey, as it is likely to affect predator-prey encounter rate (Turesson and Brönmark, 2007).

This short overview shows that experimental investigation of the physical dimension of functional responses is far from being exhaustive, or even well advanced, with the notable exceptions of temperature, and to a lesser extent, turbulence. Perhaps lacking is a comprehensive theoretical framework that would provide the impetus for empirical studies that would reach beyond the specific interest of the various investigators of the functional response.

Theoretical approaches to the role of physical features of the environment in predation

~~Physical features of the medium and size-related constraints~~

Previous studies that have considered the surrounding medium have usually focused on specific aspects of predation or on specific taxa (Domenici et al., 2011), or have investigated one specific aspect of the medium such as dimensionality (Pawar et al., 2012; 2015) or habitat complexity (Barrios-O'Neill et al., 2016), more rarely two factors simultaneously (Wasserman et al., 2016). But the overall role played by the surrounding medium acting on the predator-prey relationship, which drives the functional response, remains to be explored.

Clearly, living organisms are constrained by the physical properties of the surrounding medium (Denny, 1993; Denny, 2016; Vogel, 1996). These properties affect the way organisms move and/or interact with each other in different ways. For example, we already reviewed some of the evidence in aquatic systems showing that, turbidity is an essential factor for predator or prey that rely on visual cues to detect each other (Martens et al., 2015). Another example iwas

turbulence, which controls many planktonic organisms' suspension within the water column (Rodríguez et al., 2001) and affects contact rate between predators and prey (Kiørboe and Saiz, 1995).

More fundamental are ~~An important aspect of those factors that are typically~~ mechanical factors (i.e., gravity, density and viscosity) ~~is that they constrain motion.~~ These mechanical factors are ubiquitous, affect small (Kiørboe and Saiz, 1995) as well as large predators (Howland, 1974; Domenici et al., 2007) and are usually size-dependent. Since predation usually implies motion, these factors create mechanical constraints acting differently on predators in different physical environments (Cloyed et al., 2021). Clearly, A aquatic organisms do not experience the effects of gravity as terrestrial organisms usually do because the medium density is much higher in water than in air, which creates higher buoyancy. ~~Since predation usually implies motion, these factors create mechanical constraints acting differently on predators in different physical environments. These mechanical factors are ubiquitous, affect small (Kiørboe and Saiz, 1995) as well as large predators (Howland, 1974; Domenici et al., 2007) and are usually size-dependent. In particular, Moreover,~~ medium viscosity and density affect species' motion according to body size through drag (Beveridge et al., 2010a, b), which is why the motion of planktonic organisms has very different features than that of larger organisms. Metrics such as the Reynolds number are commonly used to discriminate between organisms that experience viscous drag (low Reynolds number) and those that experience high inertia (high Reynolds number). These features affect species according to their size and shape (Koehl and Strickier, 1981; Koehl, 1996). Thus, incorporating mechanical constraints into models could lead to a better understanding of the size-based relationship between predators and prey, and hence of the size structure of food webs.

Due to this size dependence, models incorporating physical (including mechanical) factors into predation merge size-related biological and mechanical constraints in classical predator-prey systems. Several studies have begun to investigate this promising avenue. For example, the dimensionality of the physical medium was shown to constrain predator-prey interactions since predators are expected to capture pelagic and flying prey more efficiently than benthic and terrestrial prey (Pawar et al., 2012). Extending this framework to predict pairwise trophic interactions in natural situations, Pawar et al. (2019) fall short of deriving the parameters of their functional response model from physical factors other than dimensionality. Despite this narrow scope, their model successfully reproduces some important differences in the consumer-resource size structure of 2D versus 3D communities. However, dimensionality is only one feature of the physical medium. Some studies coupled several physical properties of the medium simultaneously in a plankton model (Baird and Emsley, 1999), including their effects on different resource-use strategies, such as photosynthesis, nutrient uptake and predation (Baird et al., 2006). Addition of these biomechanical mechanisms correctly predicted emergent ecosystem properties, such as deep chlorophyll maxima, where non-biomechanical models were unable to do so (Baird et al., 2004). This additional realism was due specifically to the inclusion of effects of hydromechanical processes such as advection and turbulent dissipation on planktonic organisms (Baird et al., 2004, 2006). This kind of approach was later extended to marine food webs using an oceanographic model, which proved interesting in its capacity to generate realistic food webs with relatively few generic rules (Baird and Suthers, 2007). But the validation of the model assumptions at a scale smaller than the ecosystem was less successful, due to the discrepancy between the small size of planktonic organisms, and the scale at which the model was applied (ocean basins and currents). Similarly, a framework for predicting the optimal motion of larger organisms as a function of size and internal and external factors is under development (Wilson et

al., 2015, 2013). The importance of physical factors in determining motion has been acknowledged (Wilson et al., 2015), but their explicit and quantitative inclusion in this framework has started only very recently (Portalier et al., 2019). As successful as these milestone models have been, they did not provide for a mechanistically-derived functional response, applicable over a wide range of different organisms and of well-defined physical conditions. However, we feel that their contributions bring the field to the brink of such a realisation.

As an illustration to how the functional response can be derived from such models that consider physical factors explicitly, we present in the next section our own derivation of the functional response, that results from just a slight modification of Portalier et al.'s model (2019). We see this derivation only as a first step, since only a handful of physical factors are considered (gravity, viscosity and medium density). More work will be needed in order to integrate the other important factors, such as dimensionality and turbulence. Meanwhile, we conducted a comparison of the model predictions with actual data for aquatic organisms, with the hope that systematic deviations between observed and predicted data would reveal shortcomings of the model and thus point out to the next advances to pursue.

~~The main advantage of many models coupling physical and general biological laws is that parameters in the models are mostly related to the body size of predators and prey, a trait that is commonly measured, which makes predictions from the models easily testable. Applying this approach to the study of the functional response would allow for a real novelty since the parameters of the functional response would no longer be measured at the community level, but would be derived from the individual (or species) level. Classical parameters such as attack rate and handling time would become emerging properties of the model. Another strength of this~~

approach is that it allows hypothesis testing, since discrepancies between predicted and observed patterns would point to incomplete or erroneous hypotheses.

In order to illustrate this novel approach, we propose to include some of the mechanical factors related to body size in a theoretical model that predicts the functional response of a given predator consuming a given prey.

A first case of an inferring of the functional response from the physical properties of the medium

A case study as an example of new mechanistic approaches

In a recent study, Portalier et al. (2019) provided a biomechanical model that uses general laws of mechanics and well-known biological laws, all related to body size, to predict predator-prey interactions. This model predicts the occurrence of trophic links fits data remarkably well (e.g., the model predicts more than 80% of the predator-prey interactions in pelagic systems Portalier et al., 2019). It also ~~The model~~ provides a detailed mechanism for predation, where predators have to move around for searching, capturing and handling their prey. All these aspects depend on the body masses of both the predator and its prey. The model therefore provides values for encounter rate, capture time, and handling time, as well as energetic expenditure for the predator, but only at one nominal population density of the prey. In the present model, we apply the model to a range of prey abundance, and we focus on the time expenditure only (not energetic expenditure). The parameters of the functional response can be immediately computed from ~~the~~ this biomechanical model. Hence, this model provides a novel method to parameterize a functional response based on individual traits, and on using mechanical laws. The biomechanical model

assumes that both the predator and the prey can detect each other without any interference. This is why ~~According to the biomechanical model assumptions,~~ it is well suited for pelagic organisms. Benthic organisms living in two dimensions experience a more complex environment and would require additional features to be modelled.

Main framework

~~The~~ original model ~~uses body size and physical features of the medium to predict~~ the potential of predation to take place successfully. ~~predator-prey interactions. Hence, the model requires the body masses of both the predator and its prey. It does so by including~~ the physical features of the medium: parameters are acceleration due to gravity, body density, medium density, and medium viscosity. Then, the model computes all the necessary information to predict feasible predator-prey interactions (i.e., encounter rate, capture probability, handling time and net energy gain for the predator).

Predation is broken down into three successive sequences: a predator needs to search, capture, and then handle its prey. Each predation sequence leads to a time expenditure and requires motion. Following the idea developed by Bejan and Marden (2006), motion is modelled as an oscillatory process that is decomposed into three sequences. First, an organismal stroke leads to a thrust that propels the body upwards (following Archimedes' force, but facing gravity and drag (D) due to density and viscosity) and forwards (facing drag).

Relative speed of the predator and prey is a nexus in the model, because it determines whether the two organisms encounter and whether the one captures the other successfully. It is also the only calculated function that includes the effects of physical factors in the model because ~~It~~ is possible to numerically derive vertical speed from simple mechanical laws:

$$\dot{v} = \frac{F_{Mv}}{M_b} + \frac{g\rho V_b}{M_b} - g - D(v, M_b, \rho_m, \mu) \quad (1)$$

where v is instantaneous vertical speed, F_{Mv} is thrust vertical force, M_b is body mass, g is acceleration due to gravity, V_b is body volume, ρ is medium density, D is drag that varies with speed, body mass, density, and medium viscosity (μ). Second, when stroke ends, the body continues its ascending movement by inertia until it stops.

$$\dot{v} = \frac{g\rho V_b}{M_b} - g - D(v, M_b, \rho_m, \mu) \quad (2)$$

Third, the body returns by inertia to its original vertical position.

$$\dot{v} = -\frac{g\rho V_b}{M_b} + g - D(v, M_b, \rho_m, \mu) \quad (3)$$

During this vertical oscillation, the body moves forward compared to its original horizontal position over a distance that depends on the forward component of thrust. The instantaneous horizontal speed can be derived using a method similar to vertical speed, but it considers only thrust and drag (see supplementary material for more details). Then, another sequence begins. The model computes the thrust force needed to propel the body (which is constrained by body size), the horizontal distance covered, the speed and the associated energetic cost that maximizes the probability to capture a prey, and the net energy gain from its consumption. We tested the model's goodness of fit by computing the root mean squared deviation (RMSD) that represents the mean deviation of the predicted versus observed data. In addition, we checked for model bias by testing whether the slope and intercept of the regression of Observed versus Predicted data (OP) do not significantly differ from 1 and 0 respectively, and added body size as a cofactor. Predicted speeds fit data well (Fig 1, RMSD = 7.65). The model does not show any significant bias (i.e., OP slope and intercept do not significantly differ from 1

($p = 0.707$) and 0 ($p = 0.283$) respectively, with no significant bias due to body size ($p > 0.19$, see Supplementary material). Notice that the model did not include a constraint due to limitations of quickly available energy for the speed of large animals in our model (as Hirt et al. (2017) did). However, it will be an interesting aspect to consider in the future. Both predator and prey follow the same rules, with the difference that the prey only maximizes its probability to escape predation.

Predation on a given prey requires first its encounter, followed by capture and finally handling. Encounter rate is determined by the speeds of the predator and prey calculated in the model (see above), and then used in a formula according to (Rothschild and Osborn, (1988). The relative speed between the predator and the prey calculated at the time of capture also determines the probability of capture (and therefore the total time for searching a prey that leads to a successful capture), and time for capture. Both predator and prey follow the same rules, with the difference that the prey only maximizes its probability to escape predation. Search time (t_s) represents the time needed by a predator to contact a prey that leads to a successful capture (e.g., if the capture probability is 0.5, then the predator needs to contact a prey twice on average to successfully capture it). Capture time (t_c) is the time needed to move towards a prey once detected and seize it. Last, handling time (t_h) is the time needed to consume and digest the prey. Handling time is the only component in the model of the functional response that is independent of speed and thus the physical/mechanical factors mentioned above, although effects in reality cannot be totally brushed aside. It is also known to vary with other physical factors such as temperature (Rall et al., 2012). The functional response ($f(N)$) is defined as the inverse of the time needed for searching, capturing and handling one unit of prey of abundance N . The function may be written as follows (see supplementary material)

$$f(N) = \frac{N\beta P_c}{1 + N\beta P_c(t_c + t_h)} \quad (4)$$

βP_c represents the attack rate, where β is the encounter rate (constrained by predator and prey speeds), and P_c is the capture probability. Capture time and handling time are taken into account instead of handling time only. Under this form, one can recognize a modified version of Holling's disk equation (1961).

Given the assumptions made on the encounter rate (see Supplementary Material), the functional response behaves as a type-II response. However, equation 4 is flexible enough to allow for a type-III response, but it would require the addition of mechanisms to make the encounter rate dependent on the population density of the prey. All parameter values change according to both predator and prey sizes, while attack rate, capture probability and capture time also vary with the mechanical ~~properties~~features of the medium.

Case study: validation of the model and interpretation

Data were collected ~~in order~~ to test predictions from the model. Most data come from two meta-analyses (Hirt et al., 2017; Li et al., 2018), as well as our own literature search ~~(cite here if only a couple of papers, or add a table with references in the supplementary material)~~. To be pertinent, data have to mention predator and prey sizes explicitly. Most data are individual-based, which means that two individuals from the same species but with different sizes are treated separately. We computed the RMSD, and we tested whether the slope and intercept of the OP regression (see above). Body size was added as a cofactor (except for capture rate as the range of predator size in the dataset was not wide enough and was unbalanced), and the source of data (i.e., the original study where the data comes from) as a random factor.

Predicted attack rate, capture probability and handling time were compared to real data coming from aquatic systems (Fig. 2). It appears that the model fits the data quite well for attack rate ($\text{RMSD} = 1.2\text{e-}4$, OP slope and intercept do not significantly differ from 1 ($p = 0.19$) and 0 ($p = 0.16$) respectively, and no significant bias in the model due to body size ($p > 0.16$), except for predators of size around 10 mg ($p = 0.01$), and no effect of the source of data, see Supplementary material) (except for very small organisms, but there is also a limited amount of data) and capture probability ($\text{RMSD} = 0.23$, OP slope and intercept do not significantly differ from 1 ($p = 0.775$) and 0 ($p = 0.49$) respectively). Linking mechanical features from the medium and body size allows a good estimate of attack rate and capture probability for pelagic predators, without the need to extrapolate from data already collected. However, handling time is usually underestimated poorly estimated by the model, especially for small predators, while the model is more accurate for larger predators ($\text{RMSD} = 559315.8$, OP slope and intercept are significantly different from 1 ($p < 2\text{e-}16$) and 0 ($p = 1.16\text{e-}7$) respectively, body size has also a significant effect ($p < 0.05$), but not the source of data). These discrepancies among for small predators sizes opens the door to many hypotheses that remain to be tested. Note that handling time this parameter is not dependent on mechanical features of the medium in Portalier et al., but is determined only by physiological arguments and allometric laws. Thus, the results suggest that the relationship between predator size, prey size and handling time is driven by a more complex set of allometric laws that differ between small and large predators (Emerson et al., 1994), or that other factors affect increase handling time according to the size of the for small predators. Some studies also suggested that handling time may not be static for a given predator, but vary with prey abundance (Okuyama, 2010). These are examples of potential mechanisms that could be added to the model in the future. hypotheses that can be inferred from the analysis of such a model.

Conclusions and future directions

Although theoretical considerations of the physical properties of the medium in the study of predator-prey interactions are still in their early stages of development, they provide novel understanding and good fit to various aspects of the interaction.

Here, we applied one of the models to generate quantitative predictions for the parameters of the functional response of aquatic metazoans. The model ~~we chose~~proposed here ~~uses~~ fundamental~~the~~ mechanical properties of the medium to develop a mechanistic approach to the functional response. However, it considers only a limited set of physical factors. The model could be improved in several ways. Future studies could include ~~additional~~more physical factors such as dimensionality, hydrodynamics and temperature, which affects the physical properties of the medium (MacKenzie and Kjørboe, 1995; Larsen and Riisgård, 2009; Uiterwaal and DeLong, 2020), and organisms' metabolism (Brown et al., 2004). They could also consider factors that affect prey detection such as light and chemical cues. These factors diffuse differently in air and water, and the perception ability of predators seems to be related to size (Martens et al., 2015). This novel framework is promising because it provides easy ways to validate or falsify hypotheses. Hence, any discrepancy between predictions and real data points immediately towards an error in the model, or it means that important mechanisms are missing (as shown for handling time in our case study). It can also suggest novel hypotheses to be empirically or theoretically tested.

In our model, the processes based on mechanical factors (i.e., speed, attack rate, capture probability) fit data well, although discrepancies occur at low predator sizes, which suggests that further refinements are needed. Handling time shows ~~at~~the lowest ~~str~~ goodness of fit, and it is the only one that does not include any ~~physical-mechanical~~ factors. A better mechanism for handling

is thus needed. Ingestion has received some attention in the existing literature, especially for aquatic organisms (Holzman et al., 2012). Mechanisms driving digestion have also received some attention. For example, there are models of gut motility according to prey size and gut volume (Salvanes et al., 1995), although they usually do not include physical factors from the medium that may affect the process (e.g., temperature, pressure). However, both ingestion and digestion models might be difficult to generalize to a large variety of species (and sizes). Moreover, other aspects of handling time are likely to play a role. For instance, prey subjugation before ingestion is an essential aspect. Unfortunately, studies on this topic seem to focus either on dangerous (e.g., poisonous) prey (Mukherjee and Heithaus, 2013), or on specific species (Schatz et al., 1997), which makes them difficult to generalize. Last, predator satiation or hunger remains a fundamental aspect of predator activity (Jeschke et al., 2002; [Jeschke, 2007](#)). While it has been included in several studies, its underpinning processes remain to be modelled. Therefore, a generic mechanical description of handling that would cover its different components and be valid across a wide range of sizes would represent a significant improvement.

Similarly, the foraging mode of predators is also an important topic. Portalier et al.'s model assumes that both the predator and the prey are active and can detect each other without any interference. However, these assumptions are not valid for sit-and-wait predators (Kjørboe, 2011; Twardochleb et al., 2020). Indeed, the model can compute encounter rate between a moving prey and a non-moving predator by setting the speed of the predator to zero. But additional behavioral aspects (such as camouflage) would require additional features to the model. Moreover, these behavioral aspects are not related to size. But it can be a way to explore to improve the model.

More generally, the strength of this kind of approach is to derive patterns at the community level from ~~rules~~~~measures~~ ~~acting~~~~done~~ at the individual level within physical context of their environment~~er species-level~~. Thus, the functional response predicted is an emerging property of the ecosystem. One could even go further by including other aspects associated to predation such as behavioral features (e.g., predator avoidance, interference between predators, social aspects) that were already considered by Holling (1966). This approach opens up a promising avenue for new studies that would merge the biological ~~part~~ and the physical ~~component~~~~part~~ of the ecosystem~~medium~~.

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Contribution of authors

S.P. led the writing of the manuscript, implemented the model, gathered data, and performed simulations and analysis. S.P. and M.C. led the revision of the manuscript. M.C., G.F. and M.L. provided conceptual advices and guidance. All authors discussed the results and contributed equally to earlier drafts.

Data accessibility

Data and the MATLAB code used to implement the model will be stored in a public depository should the manuscript be accepted. During the review process, data and code will be made available in a temporary archive on GitHub:
https://github.com/sportalier/Code_Data_Frontiers_In_Ecology_And_Evolution.git.

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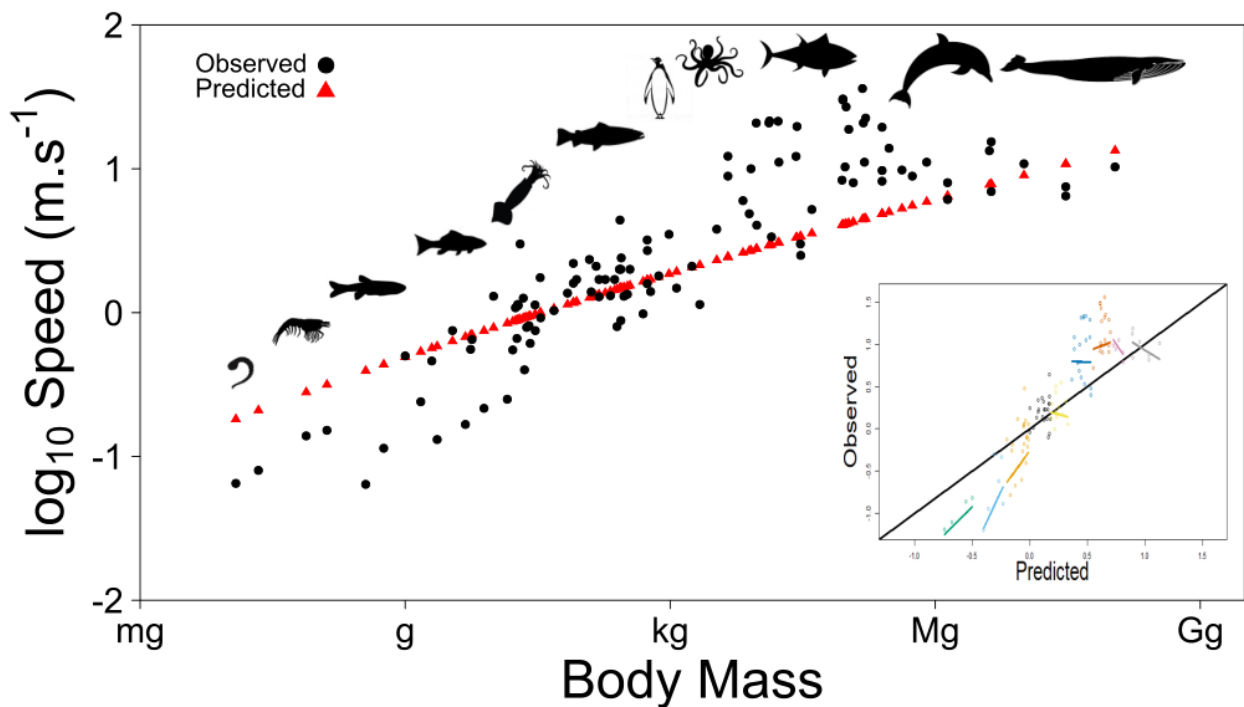
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586



587

588 **Figure 1:** Species-specific speed according to body size for organisms moving in aquatic

589 systems. Speed increases with body size, since overall muscular power generating thrust

590 increases with size. Despite variation among species, the predicted speed fits data well (data from

591 (Hirt et al., 2017)). ~~However, the model does not predict the relative reduction of speed for very~~

592 ~~large animals since it does not include any specific mechanism to do so.~~ The plot in the bottom-

593 right corner is the observed versus predicted data. Black line has a slope of 1 and intercept of 0.

594 Color points represent the different size ranges. Colored lines are (non-significant) regression

595 lines of the corresponding points.

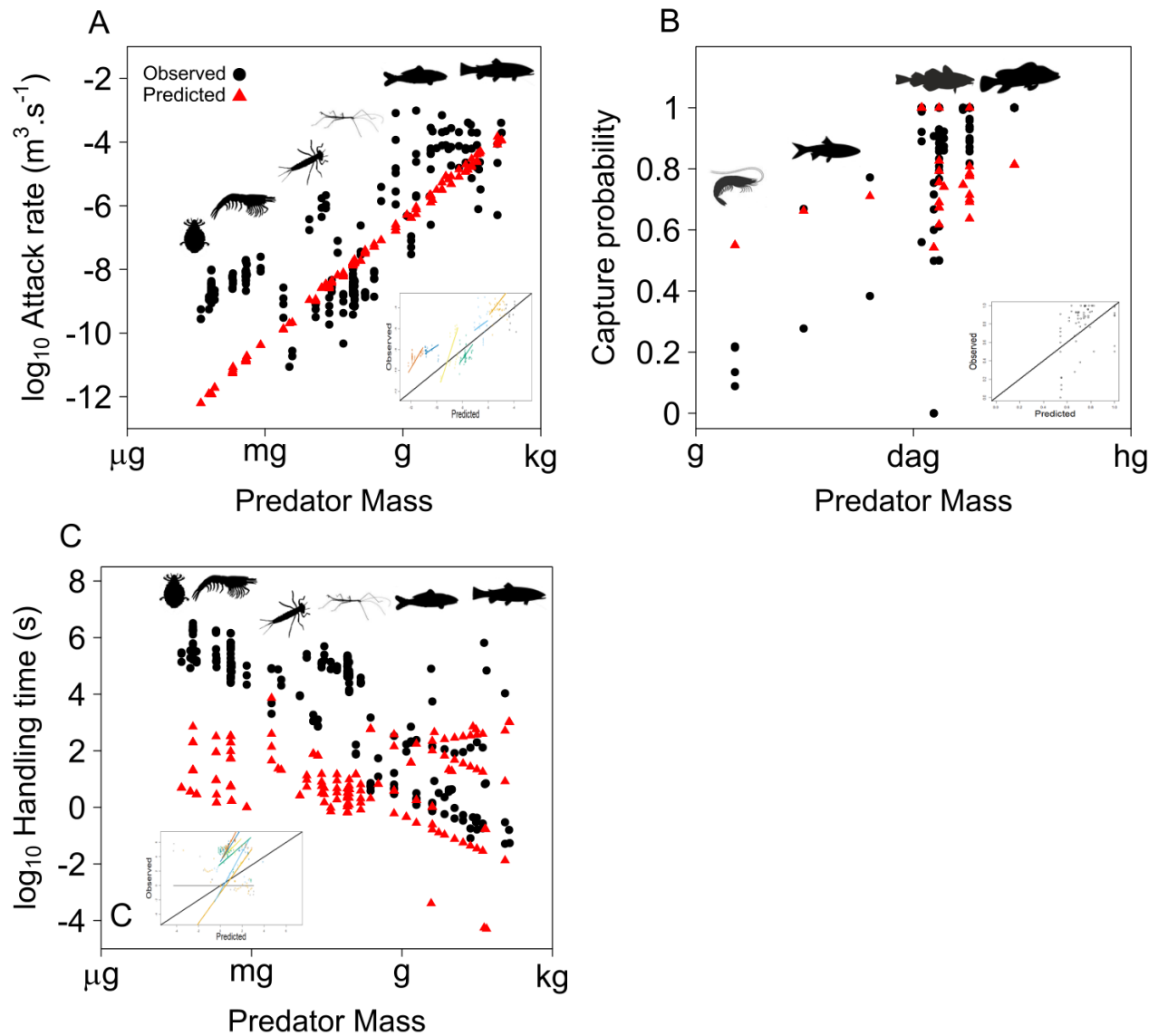


Figure 2: Predator attack rate (A), capture probability (B) and handling time (C) according to predator mass in aquatic systems. The model fits the data quite well for attack rate (except for very small organisms) and capture probability. However, data show some variability. Predictions for handling time are more accurate for relatively large predators than for smaller predators. This suggests that more investigations are needed in order to understand how mechanical factors constrain handling time for predators according to predator and prey sizes. [The plot at the bottom](#)

603 of each panel is the observed versus predicted data (same as Fig. 1). The colored regression lines
604 are non-significant in A, but significant in C.

Supplementary Material

Inferring size-based functional responses from the physical properties of the medium

Portalier S.M.J., Fussmann G.F., Loreau M., Cherif M.

1 MAIN FRAMEWORK

Our approach is based on the recently published biomechanical model (Portalier et al., 2019). This model uses body size and physical features of the medium, to predict predator to prey interactions.

Hence, the model requires body masses of both the predator and its prey. The physical parameters are acceleration due to gravity, body density, medium density, and medium viscosity. Then, the model computes all necessary information to predict feasible predator-prey interactions.

In the present article, only elements required for the computation of a functional response will be described. A full description of the model can be found in the original study (Portalier et al., 2019). A list of parameters computed from the biomechanical model and used in the present study can be found in table S1.

Predation implies motion, and motion is constrained by the mechanical properties of the medium. Following the idea developed by Bejan and Marden (2006), motion can be modelled as an oscillatory movement. Animal stroke propels its body upwards and forwards, then the body returns to its original vertical position, but it has moved forward. We decompose motion into two components: a vertical one and a horizontal one. Mechanical factors affect the body in different ways during the whole process (see Fig. S1).

1.1 Vertical component of motion

During stroke, the organism applies a thrust force (e.g., muscles, flagella). Part of this force is dedicated to a vertical lift. This upward motion follows Archimedes force (due to the difference between medium and body densities), but is opposed to weight (due to gravity) and drag (due to medium density and viscosity). When thrust stops, the body pursues its movement upwards by inertia, until it stops. Then, the body returns to its original vertical position by inertia, following weight, but in opposition to Archimedes' force and drag.

1.2 Horizontal component of motion

The other part of the thrust is allocated to the horizontal component of motion. The body is pushed forwards, facing drag. When thrust stops, the body pursues its motion by inertia, until drag stops it. Both vertical and horizontal components are essential: the horizontal component determines the distance travelled between two points, but it requires that the vertical component either lifts the body or the surrounding medium, allowing motion (Bejan and Marden, 2006).

1.3 Animal speed

Using this framework, the model can compute animal speed. The maximal muscular output that an organism can develop is related to its size (Marden Allen, 2002). Then, the model computes the energetic cost associated to a given motion sequence according to the initial thrust force developed in the vertical

(F_{Mv}) and horizontal planes (F_{Mh}), and the distance covered during the active phase in the vertical (x_v) and horizontal planes (x_h).

$$Work = \int_{t_0}^{t_{force}} F_{Mv} x_v dx + \int_{t_0}^{t_{force}} F_{Mh} x_h dx \quad (S1)$$

The work can then be divided by the total duration of the sequence (from t_0 to t_3) to yield a cost *per time* ($Cost_{pt}$).

$$Cost_{pt} = \frac{Work}{t_3} \quad (S2)$$

The model can then compute a species-specific speed (\bar{v}) that leads to a maximal speed to a minimal cost.

$$(F_{Mv}, F_{Mh}) \Rightarrow \text{Min} \left(\frac{Work}{\bar{v}} \right) \quad (S3)$$

The computed species-specific speed fits existing data remarkably well (Fig. 1 main text).

2 PREDATION

Predation is broken up into three successive sequences: a predator needs to search, capture and then handle its prey. Each predation sequence leads to time expenditures. Thus, predation on a given prey requires time for searching (t_s), time for capturing (t_c) and time for handling (t_h) this prey. Each predatory activity implies motion, and motion is constrained by physical factors (mentioned above).

2.1 Search sequence

During searching time, both predator and prey move at a species-specific speed (v_p for predator and v_n for prey) that scales with body size. A given predator will encounter an individual from the prey population at a rate E_r (Rothschild and Osborn, 1988) depending on prey abundance (N), and predator detection distance (D_p). Predator detection distance scales with its size (Pawar et al., 2012).

$$E_r = \frac{\pi D_p^2 (v_N^2 + 3v_P^2)}{3v_P} N \quad (S4)$$

For a given predator and a given prey, all parameters are constant except prey abundance (N). Thus, encounter rate (Eq. S4) can write

$$E_r = \beta N \quad (S5)$$

2.2 Capture sequence

Once a prey is detected, the capture sequence begins. The predator jumps and tries to seize its prey, while the prey tries to escape, the distance between the predator and the prey is assumed to be the detection distance of the prey (that scales with prey size). Relative speed at time when predator reaches the prey leads to a capture probability (P_C) using a logistic function.

$$P_c = \frac{1}{1 + \frac{v_N}{v_P}} \quad (S6)$$

If the predator cannot reach the prey, then $P_C = 0$.

2.3 Handling sequence

Last, the predator is kept busy during the time needed to consume the prey: the handling time (t_h).

$$t_h = t_{cons} + t_{dig} \quad (S7)$$

where t_{cons} is consumption time, and t_{dig} is digestion time.

$$t_{cons} = B_t \frac{M_N}{B_s} \quad (S8)$$

where B_t is bite time, B_s is bite size, M_N is prey mass. Bite size scales with predator size (Wilson and Kerley, 2003).

$$B_s = \rho_b \frac{4}{3} \pi \left(\frac{B_0}{2} \left(\frac{M_P}{M_{Ob}} \right)^{0.32} \right)^3 \quad (S9)$$

where B_0 is bite diameter at reference size, M_P is predator mass, M_{Ob} is reference size, and ρ_b is body density. Bite time depends on bite size (Laca et al., 1994).

$$B_t = 0.1 B_s^2 \quad (S10)$$

Digestion time writes (Hendriks, 1999)

$$t_{dig} = t_{dig0} \frac{M_P}{B_s} M_N^{0.25} \quad (S11)$$

where t_{dig0} is digestion time for 1 kg of organism.

2.4 Time computation

Overall, the biomechanical model gives the total time that a predator needs to feed on a prey (for searching, capturing and handling the prey). Searching time is assumed to be the inverse of encounter rate times the probability of capture (i.e., the time needed to contact one prey that would lead to a successful capture).

$$t_s = \frac{1}{E_r P_c} \quad (S12)$$

Capture time (t_c) is the time needed for the predator to reach the prey during that jump. Last, handling time (t_h) is the time needed to consume and digest the prey.

2.5 Functional response

The functional response is defined as the inverse of the time needed for searching, capturing and handling one unit of prey.

$$f(N) = \frac{1}{t_s + t_c + t_h} \quad (S13)$$

Using equations (Eq. S5) and (Eq. S12) to replace search time, equation (Eq. S13) writes

$$f(N) = \frac{1}{\frac{1}{E_r P_c} + t_c + t_h} = \frac{1}{\frac{1}{N \beta P_c} + t_c + t_h} \quad (S14)$$

And rearranging

$$f(N) = \frac{N\beta P_c}{1 + N\beta P_c(t_c + t_h)} \quad (\text{S15})$$

Under this form, one can recognize a modified version of Hollings disk equation (Holling, 1961), where βP_c represents attack rate, and where capture and handling times are taken into account instead of handling time only.

Given the assumptions made on the encounter rate (Eq. S4), it is a type II functional response. In addition to prey abundance (N), its value changes according to both predator size, prey size and the medium (i.e., aquatic versus terrestrial).

2.6 Predicted attack rate and handling time according to body size

The model predicts attack rate and handling time according to predator and prey body masses. It allows investigating the overall trends for these parameters across a wide range of sizes. It appears that attack rate mostly varies with predator size (i.e., a larger predator attacks prey more efficiently). For a given predator, attack rate slightly decreases with increasing prey size (Fig. S2A). Predator size is bounded for very small predators since they do not move fast enough to contact and/or capture any prey. There is an upper prey size limit for all predators: due to the model assumptions, a predator cannot capture a prey larger than itself.

Handling and capture times mostly vary with prey size (a larger prey requires more time to be reached and consumed). But a larger predator will be capture and consume a given prey faster than a smaller predator (Fig S2B). There is an upper prey size limit and a lower predator size limit for similar reasons as attack rate.

3 GOODNESS OF FIT

Predicted speed, attack rate, capture probability and handling time were tested against the corresponding observed data. For each parameter, we tested whether the slope of the observed (y_i) versus predicted (\hat{y}_i) data was significantly different from 1, and the intercept from 0. Thus, for each parameter, the following linear regression was computed

$$\hat{y}_i - y_i = \beta_0 + \beta_1 \hat{y}_i + \epsilon_i \quad (\text{S16})$$

and we tested for β_0 and β_1 significantly differing from 0 (i.e., if both the slope and the intercept are non-significant, then the model is unbiased).

Body mass was added as a cofactor. It was divided into size classes that are the $\log_{10}(\text{mass})$. Last, the source of observed data (i.e., the original study where the data comes from) was added as a random variable. Tests were done using R software (R Core Team, 2021). Linear mixed effects models were computed using the function *lmer()* from package *lme4*.

3.1 Speed

```
##
## Call:
## lm(formula = (log10(Predicted)-log10(Observed)) ~ log10(Predicted) * Log10(Size),
##     data = speed)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.5712 -0.1411  0.0000  0.1381  0.5491
##
```

```
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -0.13088    0.12118  -1.080    0.283
## log10(Predicted)  0.36150    0.95794   0.377    0.707
## LogSize-2       0.12697    0.15296   0.830    0.409
## LogSize-3      -0.12742    0.52894  -0.241    0.810
## LogSize-4       0.58145    3.51993   0.165    0.869
## LogSize-5       0.23279    4.07143   0.057    0.955
## LogSize0       -0.14421    0.42123  -0.342    0.733
## LogSize1       -0.69258    0.56921  -1.217    0.227
## LogSize2       -0.53174    1.07194  -0.496    0.621
## LogSize3       -2.09452    2.46887  -0.848    0.399
## LogSize4       -1.43048    1.08560  -1.318    0.191
## log10(Predicted):LogSize-2 -1.50430    1.39239  -1.080    0.283
## log10(Predicted):LogSize-3 -2.55287    1.91555  -1.333    0.186
## log10(Predicted):LogSize-4 -0.09561    6.73315  -0.014    0.989
## log10(Predicted):LogSize-5 -0.82634    5.80581  -0.142    0.887
## log10(Predicted):LogSize0  0.72312    1.88294   0.384    0.702
## log10(Predicted):LogSize1  0.40507    1.54120   0.263    0.793
## log10(Predicted):LogSize2 -0.16581    1.91953  -0.086    0.931
## log10(Predicted):LogSize3  2.31063    3.33277   0.693    0.490
## log10(Predicted):LogSize4  1.23069    1.46035   0.843    0.402
##
## Residual standard error: 0.2493 on 89 degrees of freedom
## Multiple R-squared:  0.6205, Adjusted R-squared:  0.5394
## F-statistic: 7.658 on 19 and 89 DF,  p-value: 7.429e-12
```

The slope of the observed versus predicted data does not significantly differ from 1 and the intercept from 0. Moreover, the model does not show any significant effect of size.

3.2 Attack rate

3.2.1 Linear model of observed versus predicted data (with size as cofactor)

```
##
## Call:
## lm(formula = (log10(Predicted)-log10(Observed)) ~ log10(Predicted) * Log10(Size),
##     data = attack)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.59657 -0.30210  0.01373  0.31154  2.30214
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)     5.5224     3.9276   1.406 0.161422
## log10(Predicted)  1.2065     0.9273   1.301 0.194855
## LogSize-2      -2.2576     4.3906  -0.514 0.607753
```

```
## LogSize-3          3.2369      5.5478    0.583 0.560315
## LogSize-4          0.4997      5.3512    0.093 0.925702
## LogSize-5         -18.9658      5.3977   -3.514 0.000557 ***
## LogSize-6          9.1254      6.5522    1.393 0.165404
## LogSize-7         -4.8014      6.1781   -0.777 0.438071
## log10(Predicted):LogSize-2 -0.3884      0.9991   -0.389 0.697921
## log10(Predicted):LogSize-3  0.2965      1.1067    0.268 0.789046
## log10(Predicted):LogSize-4 -0.5330      1.0386   -0.513 0.608422
## log10(Predicted):LogSize-5 -2.6704      1.0184   -2.622 0.009482 **
## log10(Predicted):LogSize-6  0.4009      1.0493    0.382 0.702879
## log10(Predicted):LogSize-7 -0.8830      1.0125   -0.872 0.384316
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8106 on 182 degrees of freedom
## Multiple R-squared:  0.7808, Adjusted R-squared:  0.7651
## F-statistic: 49.87 on 13 and 182 DF,  p-value: < 2.2e-16
```

The slope does not significantly differ from 1 and the intercept from 0. The model does not show any significant effect of size, except for 10e-5 kg size range (i.e., 10 mg).

3.2.2 Linear mixed model of observed versus predicted data (with size as cofactor, and study as random effect)

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: (log10(Predicted)-log10(Observed)) ~ log10(Predicted) * Log10(Size)
##              + (1 | Study)
## Data: attack
##
## REML criterion at convergence: 432.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.6225 -0.3733 -0.0262  0.4750  3.0506
##
## Random effects:
## Groups   Name                Variance Std.Dev.
## Study    (Intercept)  0.2539     0.5038
## Residual                  0.4634     0.6808
## Number of obs: 196, groups: Study, 22
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)    6.045933   3.338687   1.811
## log10(Predicted)  1.401013   0.788133   1.778
## LogSize-2     -2.614779   3.745209  -0.698
## LogSize-3      2.074737   4.746497   0.437
```

```
## LogSize-4          0.547057    4.595479    0.119
## LogSize-5        -22.430350    4.685605   -4.787
## LogSize-6         6.213170    6.018440    1.032
## LogSize-7        -4.114449    5.265914   -0.781
## log10(Predicted):LogSize-2 -0.548337    0.850189   -0.645
## log10(Predicted):LogSize-3 -0.008768    0.942267   -0.009
## log10(Predicted):LogSize-4 -0.594082    0.887151   -0.670
## log10(Predicted):LogSize-5 -3.191426    0.875149   -3.647
## log10(Predicted):LogSize-6 -0.017784    0.920731   -0.019
## log10(Predicted):LogSize-7 -0.972464    0.862212   -1.128
```

```
##
## Correlation matrix not shown by default, as p = 14 > 12.
## Use print(x, correlation=TRUE) or
##      vcov(x)      if you need it
```

The source of data (study) does not have a significant effect.

3.3 Capture probability

```
##
## Call:
## lm(formula = (Predicted - Observed) ~ Predicted, data = capture)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.29572 -0.14188 -0.07843  0.05957  0.61391
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.10174    0.14516  -0.701    0.486
## Predicted    0.05461    0.19004   0.287    0.775
##
## Residual standard error: 0.2282 on 74 degrees of freedom
## Multiple R-squared:  0.001114,    Adjusted R-squared:  -0.01238
## F-statistic: 0.08256 on 1 and 74 DF,  p-value: 0.7747
```

The slope does not significantly differ from 1 and the intercept from 0. Size was not included as a cofactor, since size range in the dataset is narrow and unbalanced.

3.4 Handling time

3.4.1 Linear model of observed versus predicted data (with size as cofactor)

```
##
## Call:
## lm(formula = (log10(Predicted)-log10(Observed)) ~ log10(Predicted) * Log10(Size),
##      data = handling)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.09628 -0.50813  0.02634  0.46408  1.62628
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -1.10762     0.20102   -5.510 1.16e-07 ***
## log10(Predicted)  1.89974     0.07871  24.134 < 2e-16 ***
## LogSize-2      -0.12385     0.24569   -0.504 0.614777
## LogSize-3      -0.35114     0.29590   -1.187 0.236842
## LogSize-4      -4.09251     0.23644  -17.309 < 2e-16 ***
## LogSize-5      -4.72817     0.39279  -12.037 < 2e-16 ***
## LogSize-6      -4.45299     0.29261  -15.218 < 2e-16 ***
## LogSize-7      -4.46268     0.31104  -14.348 < 2e-16 ***
## log10(Predicted):LogSize-2 -0.21511     0.11032   -1.950 0.052662 .
## log10(Predicted):LogSize-3 -0.83831     0.19120   -4.385 1.93e-05 ***
## log10(Predicted):LogSize-4  0.56844     0.15427    3.685 0.000299 ***
## log10(Predicted):LogSize-5  0.38778     0.28084    1.381 0.168975
## log10(Predicted):LogSize-6 -0.50987     0.14760   -3.454 0.000681 ***
## log10(Predicted):LogSize-7 -1.00875     0.18156   -5.556 9.28e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6964 on 189 degrees of freedom
## Multiple R-squared:  0.9377, Adjusted R-squared:  0.9334
## F-statistic: 218.9 on 13 and 189 DF, p-value: < 2.2e-16
```

The slope and the intercept significantly differ from 1 and 0 respectively. Almost all size ranges show a significant effect.

3.4.2 Linear mixed model of observed versus predicted data (with size as cofactor, and study as random effect)

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: (log10(Predicted)-log10(Observed)) ~ log10(Predicted) * Log10(Size)
##              + (1 | Study)
##      Data: handling
##
## REML criterion at convergence: 425.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.33381 -0.61776  0.03915  0.57076  2.65191
##
## Random effects:
##   Groups   Name      Variance Std.Dev.
##   Study    (Intercept) 0.1184   0.3440
```

```

## Residual          0.3930    0.6269
## Number of obs: 203, groups: Study, 18
##
## Fixed effects:
##
##              Estimate Std. Error t value
## (Intercept)    -1.07941    0.21463  -5.029
## log10(Predicted)  1.93269    0.07375  26.207
## LogSize-2      -0.23967    0.22764  -1.053
## LogSize-3      -0.36371    0.27526  -1.321
## LogSize-4      -4.00426    0.24489 -16.351
## LogSize-5      -4.37261    0.37217 -11.749
## LogSize-6      -4.31498    0.28026 -15.396
## LogSize-7      -4.58369    0.30603 -14.978
## log10(Predicted):LogSize-2 -0.23458    0.10131  -2.316
## log10(Predicted):LogSize-3 -0.84818    0.18001  -4.712
## log10(Predicted):LogSize-4  0.47869    0.14850   3.224
## log10(Predicted):LogSize-5  0.01514    0.28520   0.053
## log10(Predicted):LogSize-6 -0.63508    0.14765  -4.301
## log10(Predicted):LogSize-7 -0.88273    0.18758  -4.706
##
## Correlation matrix not shown by default, as p = 14 > 12.
## Use print(x, correlation=TRUE) or
##      vcov(x)      if you need it

```

The source of data (study) does not have a significant effect.

Table S1. List of symbols used throughout the article

Symbol	Meaning	Value	Unit
$f(N)$	Functional response		ind.s^{-1}
N	Prey abundance		ind.m^{-3}
t_s	Search time		s
t_c	Capture time		s
t_h	Handling time		s
t_{cons}	Consumption time		s
t_{dig}	Digestion time		s
E_r	Encounter rate		ind.s^{-1}
D_P	Predator detection distance		m
v_n	Prey speed		m.s^{-1}
v_p	Predator speed		m.s^{-1}
P_c	Capture probability		dimensionless
B_s	Bite size		kg
B_t	Bite time		s
M_P	Predator size		kg
M_N	Prey size		kg
B_0	Bite diameter at reference size	0.26	mm
M_{0b}	Reference size for bite diameter	2.9	kg
ρ_b	Body density	1080	kg.m^{-3}
t_{dig0}	Reference digestion time	$2.3 * 10^4$	s.kg^{-1}

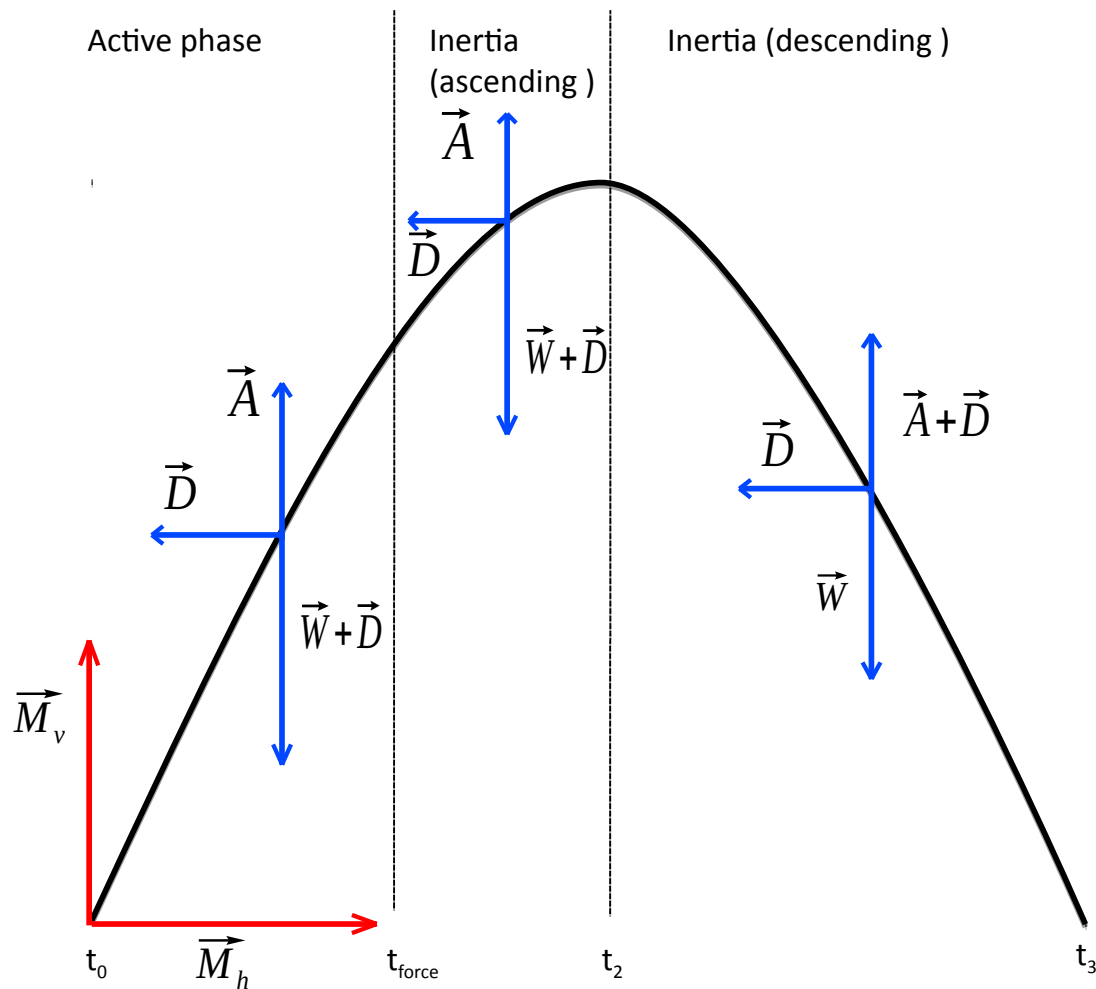


Figure S1. Framework for the computation of animal motion, represented as an oscillation. Red arrows represent thrust force due to animal stroke, and split between a vertical (M_v) and a horizontal component (M_h). Blue arrows represent forces due to mechanical factors of the medium. The sequence is decomposed into three phases. During the active phase, thrust force is applied. The body moves upwards, facing weight (W) and drag (D), but following Archimedes force (A) and forwards, facing drag, then stroke ends, the body pursue its motion by inertia. Then, the body returns to its original vertical position (descending) by inertia facing Archimedes force and drag, but following weight.

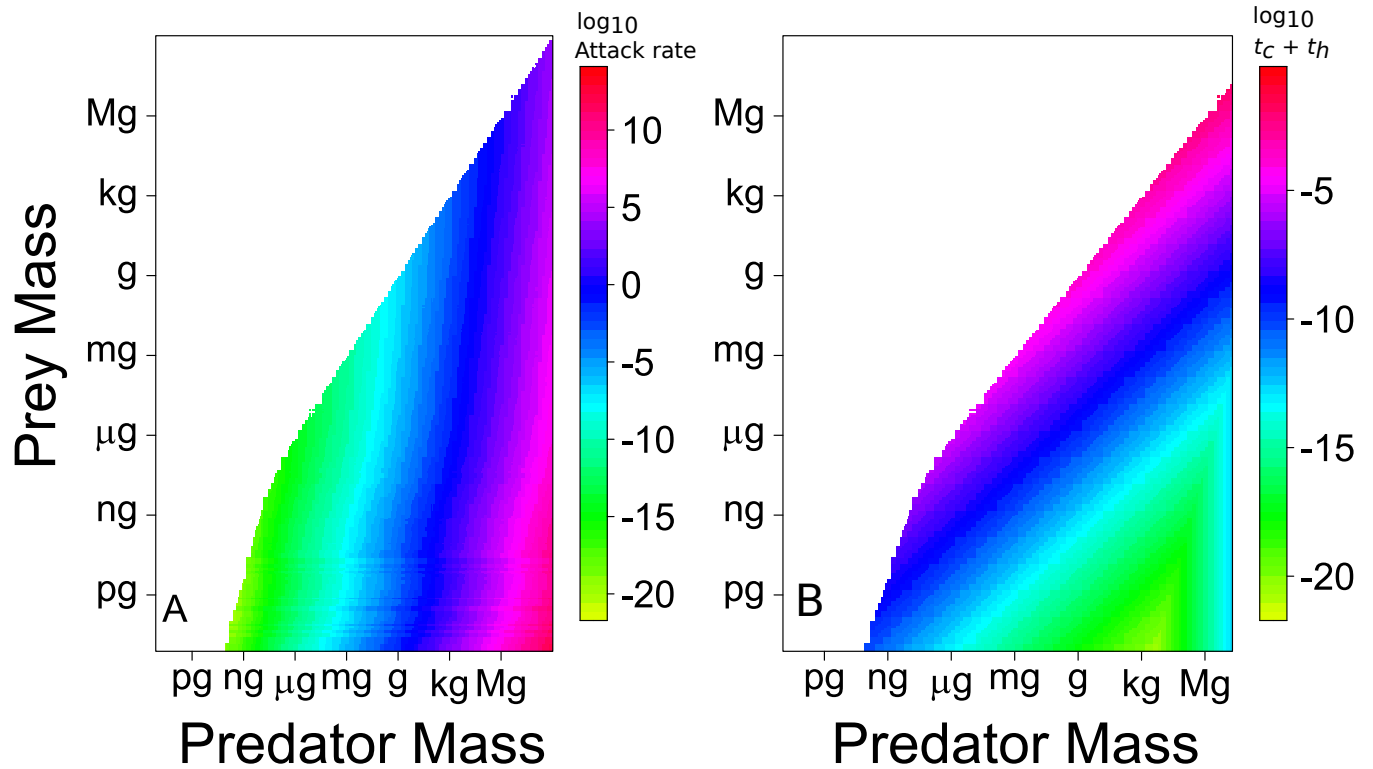


Figure S2. Predicted attack rate (A) and capture + handling times (B) according to predator and prey sizes. The white area represents cases where a predator is unable to find, capture or handle the prey, which means that the interaction is not feasible. There is a lower predator size that occurs when the predator do not move fast enough to contact and/or capture any prey. The upper prey size occurs when the predator is unable to capture the prey (due to model assumptions). Attack rate mostly varies with predator size. Capture and handling times mostly vary with prey size for a given predator.

4 REFERENCES FOR THE DATA

This section gives the full references to the data used to test the model.

For animal speed, we used the database provided in [Hirt et al. \(2017\)](#).

Attack rate and capture probability come from a database provided in [Li et al. \(2018\)](#), but you can find here the references of the original studies.

Handling time data comes from several studies including the database provided in [Li et al. \(2018\)](#). You can find all the references below.

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