

# Closing the gap between statistical and scientific workflows for improved forecasts in ecology

Victor Van der Meersch<sup>1\*</sup>, James Regetz<sup>2</sup>, T. Jonathan Davies<sup>1,3</sup> & EM Wolkovich<sup>1</sup>

November 19, 2025

<sup>1</sup> Forest and Conservation Sciences, University of British Columbia, Vancouver, BC V6T 1Z4, Canada

<sup>2</sup> National Center for Ecological Analysis and Synthesis, 1021 Anacapa St, Santa Barbara, CA 93101, United States

<sup>3</sup> Botany, University of British Columbia, Vancouver, BC V6T 1Z4, Canada

\* <mailto:victor.vandermeersch@ubc.ca>

For: Workflow for Applied Data Analysis theme issue for *Phil Trans A* as an *Opinion*

## Abstract

Concerns about biodiversity loss and climate change have led to greater demands for ecological models. Datasets for developing these models have increased in size and complexity, including in their geographical, temporal and phylogenetic dimensions. New research often suggests that models accounting for these complexities can yield more accurate trends and predictions. We argue, however, that the usual workflows for model fitting in ecology make it difficult to evaluate and compare current models. First, the research community is split between two spheres that prevent uniting trend estimation and forecasting. One research sphere focuses on using data to fit simple, trend-like models with few parameters, which is separated from research developing forecasting models, often including complex, mechanistic sub-models indirectly informed by data. Second, in both cases, models tend to be developed without a coherent framework for linking scientific questions and understanding to statistical and modeling decisions. To address these challenges we propose a workflow that integrates statistical and scientific practices through clear steps, many of which rely on data simulation to inform decisions in the process, and where forecasting is a natural output. We show how this approach, coupled with a shift toward universal training, more open model sharing, and alignment on common datasets, could harmonize currently divided efforts at trend estimation and forecasting to better inform sustainable policies.

## <sup>1</sup> 1 Introduction

- <sup>2</sup> Anthropogenic drivers are reshaping natural systems (Díaz *et al.*, 2019). Impacts are projected  
<sup>3</sup> to increase in coming decades, as climate change accelerates biodiversity loss, altering ecosystem  
<sup>4</sup> services and human well-being (IPBES, 2019). Implementing sustainable policies to mitigate these  
<sup>5</sup> impacts is thus a global priority, but designing the best policies requires estimating and under-  
<sup>6</sup> standing biodiversity and ecosystem trends to date, alongside the skill to forecast future dynamics.  
<sup>7</sup> Meeting these global policy needs has led often to two separate paths: one focused on estimating  
<sup>8</sup> trends from new global datasets, and another focused on forecasting from generally distinct datasets

9 or mechanistic models based on fewer data. Newly available large-scale, long-term datasets have  
10 provided our first ‘global’ estimates of biodiversity trends (e.g. Loh *et al.*, 2005; Dornelas *et al.*,  
11 2018), but these data—gathered opportunistically from multiple sources—are unbalanced and suffer  
12 from large geographic, temporal and taxonomic sampling biases. Models to date have failed to fully  
13 address these challenges and, perhaps because of these limitations, are rarely if ever used for fore-  
14 casting. Instead, forecasting—under different plausible scenarios—has generally relied on entirely  
15 different datasets combined with either correlative or process-based models (IPBES, 2019), with  
16 process-based models often promoted as the most realistic approach (Urban *et al.*, 2016; Pilowsky  
17 *et al.*, 2022) because they focus on mechanistic representations of ecosystem functioning. These  
18 approaches have failed to yield agreement on current species trends, leading to ongoing debates  
19 about the magnitude and even direction (Dornelas *et al.*, 2014; Leung *et al.*, 2020; Buschke *et al.*,  
20 2021; Johnson *et al.*, 2024), and producing forecasts that diverge due to high model uncertainty at  
21 the ecological level (Cheaib *et al.*, 2012; Thuiller *et al.*, 2019).

22 These two modeling approaches may appear to pursue independent inferential goals—explanation  
23 vs. prediction—but in reality this distinction is blurred. Trend estimation may be nominally fo-  
24 cused on explanatory outcomes, yet it rarely links clearly to theories that could provide causal  
25 inference, usually because it tends to be carried out using simpler models. Moreover, estimated  
26 trends are frequently treated—implicitly and explicitly—as quantities that project forward into the  
27 future, taking on a forecasting role. In contrast, approaches using complex forecasting models are  
28 certainly built for predictive purposes, yet these also have an additional agenda. Developing and  
29 using mechanistic, process-based models is often justified by the assumption that “we must under-  
30 stand to predict”, and such models are often judged by how faithfully they mimic the real-world  
31 processes they represent, which conflates explanation with prediction (Shmueli, 2010).

32 We argue that many current debates and diverging forecasts are driven by the incoherent and  
33 disconnected workflows used today in ecology (Loreau *et al.*, 2022; Talis & Lynch, 2023; Johnson  
34 *et al.*, 2024). Research estimating biodiversity trends has become focused on methodological aspects  
35 because the current workflow fails to examine the gap between ideal and available data, and rarely  
36 tests for predictive accuracy that could scale up to allow forecasting. At the same time, process-  
37 based models developed for forecasting often evolve through the addition of new separate layers or  
38 components because the current workflow rarely examines the model as a functioning whole and  
39 thus ignores major problems (e.g. non-identifiability, discussed below). Thus, it encourages new  
40 parts that are often disconnected from the original research aim, its data stream, and the previous  
41 scientific insights.

42 Workflows that fully integrate all the steps required to build a model from an ecological question,  
43 with evaluation of limitations and potential problems before estimating its parameters and making  
44 projections, could reduce many of these problems. In particular, we argue that workflows that  
45 incorporate data simulation at multiple steps can quickly identify flaws in model structure and  
46 constraints in data, and allow us to understand when, where, and why different models diverge  
47 (McElreath, 2018; Betancourt, 2020; Gelman *et al.*, 2020; Schad *et al.*, 2020; Grinsztajn *et al.*,  
48 2021; van de Schoot *et al.*, 2021; Wolkovich *et al.*, 2024). Towards this aim, we outline the steps of  
49 a universal workflow that could harmonize both trend estimation and forecasting.

## 50 2 Scientific method and workflows

51 Quantitative science relies on a model-based framework to confront hypotheses with data (Chamber-  
52 lin, 1965). In an idealized scientific method, we would formulate a research question and hypotheses,

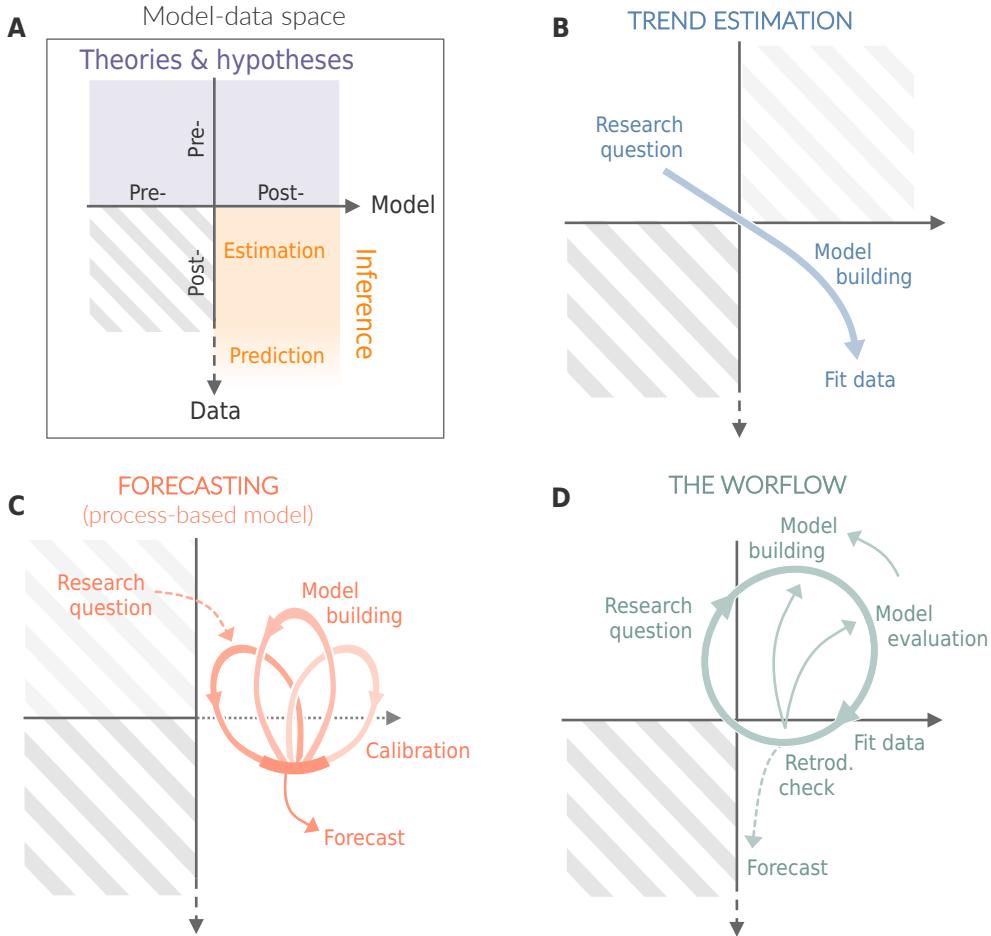


Figure 1: Different trajectories of current (b-c) and proposed (d) workflows through model-data space during model development, from pre-model/pre-data to post-model/post-data quadrants. Panel A serves as a legend, showing where model development should begin (carefully thinking about the hypotheses to test) and when inference should be made, for either explanatory purpose (estimation) or forecasting (prediction). Panel B illustrates that, in current trend estimation approaches, most time is spent in the post-model/post-data quadrant, where models are directly fitted to empirical data—often with no prior evaluation of the model. Panel C illustrates the typical process-based model development where a lot of time is spent building and calibrating (fitting) separate submodels (represented by the separated ovals) without clear distinction between model building and model calibration and without evaluating the full model structure *a priori*. Additionally, the specific hypotheses the model is designed to test are rarely clearly stated. Panel D illustrates the workflow highlighted in this paper (see main text and Figure 2 for details). Ideally, it begins in the pre-model/pre-data quadrant, where the research question is defined. The next step moves to the post-model/pre-data quadrant, where a model is built—*independently* of the data. This is where we should spend a good deal of time evaluating model behavior using simulated data. Once we are satisfied with our model, we can move to the post-model/post-data quadrant, where the model is fitted to real data. Then, we perform retrodictive checks to compare model predictions to observations, which likely give us some feedback to refine our model.

53 design an experiment accordingly, build a model, collect data, and use this data to inform our model  
54 and differentiate between hypotheses. This method underlies much of the recent pre-registration  
55 movement, where hypotheses and methodology are defined prior to data collection (Nosek *et al.*,  
56 2018). But this idealized method often does not apply to the reality of ecological research. Many  
57 important questions cannot be addressed through controlled experiments and replications. In such  
58 cases, we must rely on existing, heterogeneous datasets alongside uncertain and incomplete the-  
59 ory to provide a large-scale and long-term perspective (Hilborn & Mangel, 1997). Indeed, most  
60 macroecological insights have emerged from exploring patterns in these datasets (exploratory data  
61 analysis).

62 This reality should drive researchers to use more coherent methods that remain robust for  
63 the intended inferential goals, even with imperfect data and knowledge gaps. But the current  
64 workflows combined with the challenges ecologists are facing—both in terms of data complexity and  
65 societal needs—instead may lead to persistent problems. Trend estimation has focused mostly on  
66 fitting a model to empirical data (i.e. post-model/post-data, Figure 1b)—without the checks (post-  
67 model/pre-data) and likely feedbacks that often highlight uncertainty and related limitations in the  
68 model and/or data (Figure 1b). For forecasting, researchers have focused on making predictions  
69 with increasingly complex mechanistic models (Figure 1c), frequently obscuring the steps underlying  
70 model building and parameterization (and without a clear distinction between pre- and post-data).  
71 Researchers often calibrate the different parts of these models separately, and fix some parameter  
72 values based on experiments and expert knowledge, to avoid problems when trying to fit the model  
73 as a whole. Addressing these problems while accounting for the realities of working with ecological  
74 data requires a more comprehensive workflow.

75 We argue a workflow that moves along the data-model space in a coherent sequence of steps  
76 (Figure 1d) could reduce many of these problems and thus improve ecological science. The first  
77 step of this workflow is to define an explicit research question and formulate hypotheses (step 1,  
78 Figure 2). This involves making clear assumptions about the most influential drivers, within the  
79 specific context of our study. This should guide the construction of a narrative model of how we  
80 believe the system works, focusing on the mechanisms that could generate the data we observe,  
81 including the observational error (pre-model/pre-data, Figure 1d). This step of carefully formulating  
82 hypotheses has gained increasing attention in the ecological literature (Grace & Irvine, 2020).  
83 From this narrative, we can then develop a mathematical model—an ensemble of equations that  
84 encapsulates our knowledge and is designed to answer our research question (step 2, Figure 2).  
85 Generally, starting with a relatively simple model that we could refine later makes understanding  
86 the model and how it interacts with empirical data easier (see example workflow we provide as  
87 a supplementary file). At this stage, prioritizing biologically meaningful parameters is crucial, as  
88 it allows us to have a sense of plausible parameter values. This means choosing a model formu-  
89 lation where each parameter corresponds to an interpretable behavior (which sometimes requires  
90 considering alternative parameterization).

91 With a model in place, the next step focuses on testing and understanding it via data simulation  
92 (step 3, Figure 2). ‘Fake’ or ‘test’ data are generated directly from the model by fixing parameters  
93 to some reasonable values, which is straightforward if the parameters are interpretable, and from  
94 ‘fake’ (simulated) predictor data. We then fit our model to this simulated dataset and evaluate  
95 its ability to recover the prescribed values (post-model/pre-data, Figure 1d). At this stage, the  
96 focus is on understanding the model, so we may need to spend time thinking about whether each  
97 parameter is realistic or not. This is also a step for making sure the model is working as expected  
98 (see example workflow). Ideally, this data simulation step should be repeated several times with

99 different parameter values, sampled within a reasonable range. In a Bayesian framework, simulated  
 100 parameters can be sampled from the prior distribution (allowing us to check the implications of  
 101 our priors Gelman *et al.*, 2020, and to validate model inferences using simulation-based calibration  
 102 Talts *et al.*, 2018). In other frameworks, they can be sampled from a range of biologically reasonable  
 103 values (which is very similar to the concept of a prior).

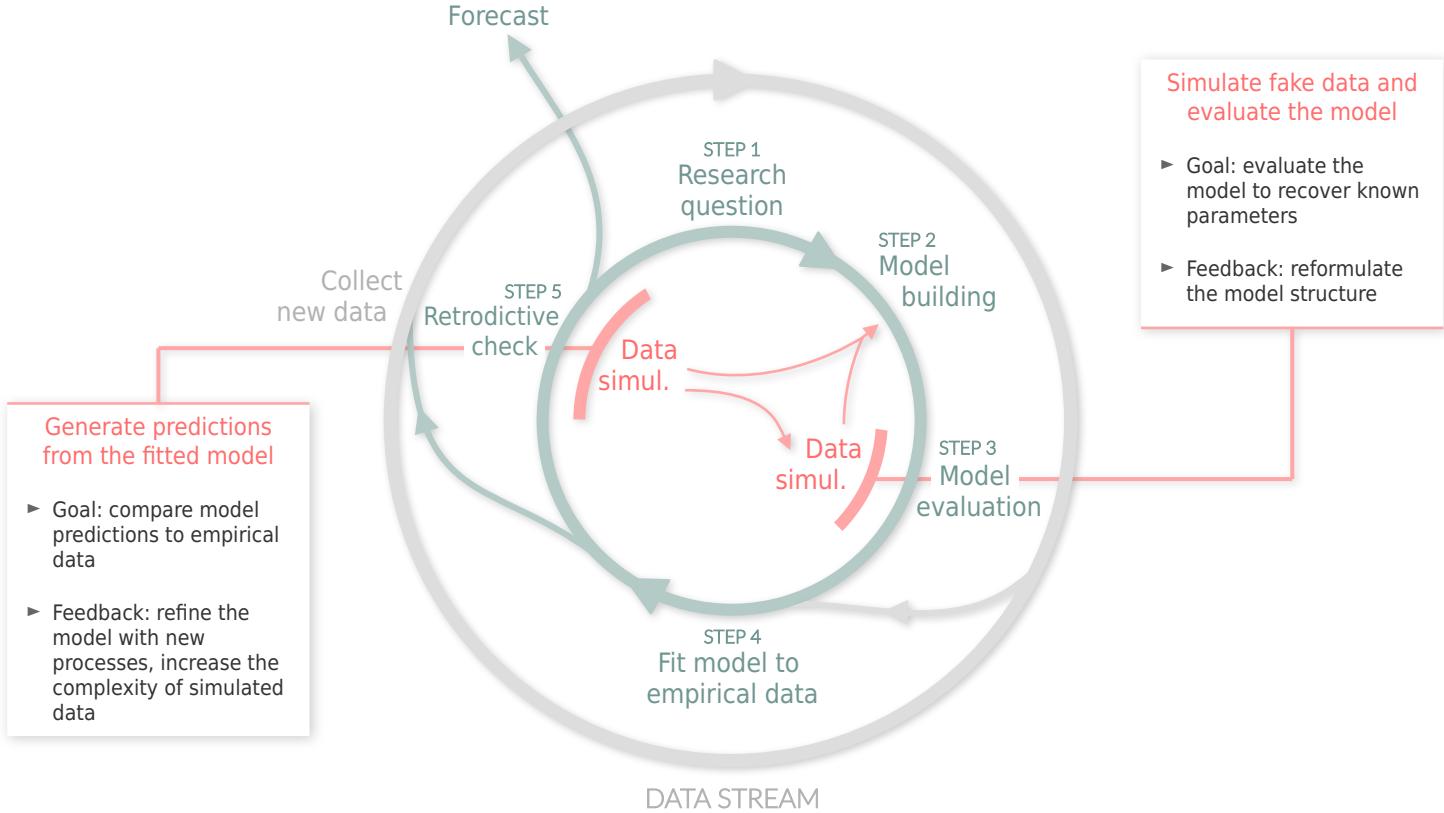


Figure 2: The workflow we propose here, which builds from recent advances in workflows (Betancourt, 2020; Gelman *et al.*, 2020; Schad *et al.*, 2020; Grinsztajn *et al.*, 2021; van de Schoot *et al.*, 2021; Wolkovich *et al.*, 2024), focuses on iterative feedbacks between the research question, model and data. Most research should start at Step 1, with the research question, followed by extensive model building and evaluation using simulated data (Steps 2 and 3) before proceeding to fitting the model on empirical data and examining it through retrodictive checks (Steps 4 and 5). Within this workflow, forecasting is a natural output of the process and not a separate process or one available for only certain modeling approaches. The integration of observations (the data stream) occurs at Step 4—only after the model has been thoroughly evaluated—and can also highlight opportunities to collect new data and enrich the data stream. This figure is expanded from Figure 1d.

104 Once we are confident about our model structure, we can introduce real data as part of an  
 105 initial model fitting step (step 4, Figure 2). This way, we obtain parameter estimates constrained  
 106 by observations (post-model/post-data, Figure 1d). These parameter estimates lead to the second  
 107 data simulation step, this time using our fitted model parameters to generate predictions (step  
 108 5, Figure 2). This—which we call a retrodictive check (Betancourt, 2020, also called a posterior  
 109 predictive check in a Bayesian workflow, Gelman *et al.*, 2020)—allows model output to be compared  
 110 to observations (see Supplementary Figure 1). This is a powerful approach, in part because checks  
 111 should be tailored to assess key features of the data and model output together in regard to our  
 112 research question, but this also means there is no standard approach (Gelman *et al.*, 2020). It is  
 113 only once all steps have been completed that we can interpret parameter values with respect to  
 114 our research question. The workflow encourages a focus on the full model, where any parameter

115 (such as a trend estimate) must be carefully interpreted alongside others, as all are fundamental  
116 components that shape both inference and forecasting.

117 Within such a workflow, forecasting emerges as a natural outcome. Rather than being a fi-  
118 nal goal, forecasting only involves jointly modeling new circumstances along with the original  
119 data. This workflow could also bridge gaps in certain areas between exploratory analyses and  
120 developing research questions. For example, in macroecological studies model building is often  
121 informed by patterns in the data. The adoption of this workflow would make the exploratory stage  
122 more transparent—as an explicit preliminary step for entering the workflow—and would compel  
123 researchers to more clearly develop a research question before extensive model fitting (Figure 1).

124 A key feature of this workflow is the central role of data simulation, which introduces two feed-  
125 back loops. The first feedback arises when we evaluate the model on simulated data. The failure  
126 of the model to recover known parameter values and handle the complexity of the simulated data  
127 should prompt reconsidering the model, or even reformulating the research question. Further, this  
128 step might reveal that some parameters are highly non-identifiable (meaning the parameter(s) can-  
129 not be uniquely estimated), flagging the need to change the model structure—before incorporating  
130 empirical observations. The second feedback loop comes from the retrodictive check. Discrepancies  
131 here may indicate a missing key driver, and suggest the current model is too simplistic. We can  
132 refine the model to integrate the missing process(es)—if we can identify them—and return to the  
133 start of the workflow. Insights from the retrodictive check can also lead us to introduce additional  
134 complexity when simulating fake data, such as phylogenetic structure (see Supplementary Figure 1)  
135 or observational biases (e.g. unbalanced data). For example, if a researcher realizes their empirical  
136 data is geographically biased (for example, more intensive sampling in Europe), this bias should  
137 be built into the model and thus into this data simulation step. This iterative evaluation of the  
138 model moves beyond a simple reliance on goodness-of-fit metrics. At each iteration, we are able  
139 to evaluate the model behavior, both with simulated and real data, taking into account our expert  
140 knowledge of the ecological processes. These feedback loops are applied currently only in Bayesian  
141 frameworks (to our knowledge), but could and should extend across other modeling approaches  
142 given their power to improve models and, in turn, scientific understanding.

### 143 3 The workflow in practice

144 Across the different fields of ecology—for both parameter estimation and forecasting—a systematic  
145 application of a coherent workflow could highlight the best opportunities to accurately understand  
146 and manage uncertainties and yield new scientific insights. This will help refocus the debate on  
147 designing new hypotheses, formulating new questions—and guiding efforts to collect new data.  
148 Here, we illustrate how such a workflow could lead to significant improvements in two related  
149 areas: (i) estimating global biodiversity trends and (ii) forecasting species and ecosystem dynamics  
150 using process-based models.

#### 151 3.1 Trends

152 Ecologists today have amassed data on populations and species across the globe; they have also  
153 engaged in an increasing number of debates on regional and global trends over time, with arguments  
154 over the magnitude and even direction of population and biodiversity metrics (Dornelas *et al.*, 2014;  
155 Leung *et al.*, 2020; Terry *et al.*, 2022; Müller *et al.*, 2024). While shifting estimates are part of the  
156 process of science—refining our approaches and thus estimates over time—we believe these debates  
157 would be fewer and they would be more rapidly resolved through use of an improved workflow.

158 We argue that an improved workflow that required data simulation and retrodictive checks  
159 would lead to larger model advances and a greater recognition of uncertainty—thus highlighting  
160 likely consistency in estimates across models—that could better aid policy. Using the workflow  
161 would make it more obvious that what now appear as major discrepancies are shifts in point  
162 estimates that are generally all in the same uncertainty space (Johnson *et al.*, 2024)—and would  
163 challenge modelers to show major predictive advances, which is not currently part of the process.  
164 Explanatory power in most models of observational data is usually very low (Low-Décarie *et al.*,  
165 2014; Møller & Jennions, 2002) and thus tests of models' predictions rarely expected. But the  
166 workflow highlights that predictions from the model—what we call retrodictive checks—are part of  
167 the process of science, and critical to testing for what may be missing in a model (see Supplementary  
168 Figure 1).

169 We expect retrodictive checks on most published trend analyses would highlight major missing  
170 components in these models, and drive changes both in the models themselves and in the simulated  
171 data to check the models. This step builds somewhat on the skills needed for null models (Gotelli  
172 & Ulrich, 2012), but with a shift in focus towards the specific bespoke model at hand. Ecologists  
173 have started to use simulated data more to understand potential limitations of their models and  
174 data combined (Hilborn & Mangel, 1997), but this is still extremely rare, and efforts to date often  
175 treat simulations as separate from the statistical model (Buschke *et al.*, 2021; Dove *et al.*, 2023),  
176 short-circuiting their full utility when used in an iterative workflow.

177 Applying the workflow to current trend estimates could importantly highlight the best way to  
178 improve data collection for more reliable estimates. Returning to the example of a global estimate of  
179 trends in vertebrate populations of species over time (see Box) and applying our proposed workflow  
180 would mean more efforts to define the goal and question—is it a simple global estimate? Or a  
181 need to also find which species are declining most, including those that may have poor or no data?  
182 From there a generative model using simulated data for testing could incorporate many aspects  
183 of the populations, and data, that are often only included in ‘null’ or ‘synthetic data generation’  
184 currently (Buschke *et al.*, 2021; McRae *et al.*, 2025), but could be built into the models fit to the  
185 empirical data. Eventually fitting the empirical data and performing retrodictive checks would  
186 likely highlight major missing components of the generative model (see Supplementary Figure 1)  
187 and, ultimately, this would help inform our global estimates of mean trends (see example workflow  
188 we provide as a supplement file). For example, certain populations are recovering for very specific  
189 reasons (e.g. elephants in regions where the ivory trade drove declines in the past) that perhaps  
190 should be modeled. From this model, what data are most critically needed to address the updated  
191 aims would become clearer and could drive new data collection (Toszogyova *et al.*, 2024).

## 192 3.2 Forecasting from process-based models

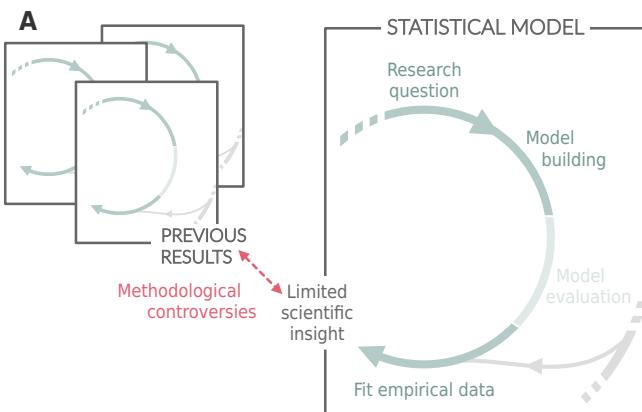
193 Ecological forecasting is a broad field with a diverse range of methods. Across these methods,  
194 process-based modeling is often considered the gold standard for forecasting in ecology (Urban  
195 *et al.*, 2016; Pilowsky *et al.*, 2022) and beyond because it is based on mechanistic understanding  
196 that should drive accurate out-of-sample predictions. This focus on a mechanistic basis, however,  
197 generally drives newer models to incorporate greater complexity—and an ever-growing number of  
198 parameters. This can make it difficult to increase scientific understanding (Franklin *et al.*, 2020)  
199 and suggest or model potential policies. In principle, increasing model complexity can be benefi-  
200 cial by enhancing mechanistic realism, better representing more complex dynamics, and reducing  
201 uncertainty by restricting the effective parameter space. In practice, however, this is not always  
202 the outcome. In process-based modeling for climate forecasts, the uncertainty range on the effect

of increasing CO<sub>2</sub> concentration on temperature have remained largely unchanged over decades of increasing model complexity (Zelinka *et al.*, 2020). This has driven calls for more rigorous and transparent calibration processes (Balaji *et al.*, 2022). Similar concerns arise in ecology, where strong disagreements persist about the effect of climate change on future species distributions (Cheaib *et al.*, 2012) and ecosystem dynamics (Lovenduski & Bonan, 2017) after decades of modeling work. These uncertainties have large implications beyond ecology, as they influence simulations of biosphere-atmosphere interactions and, ultimately, future climate projections (Bonan & Doney, 2018; Simpson *et al.*, 2025). Some researchers now advocate for simplifying models, to avoid over-parametrization when the data provide little information to constrain some parameters (Wang *et al.*, 2017; Harrison *et al.*, 2021). These arguments stress that the strength of process-based models is their interpretability, and thus their parameters should represent biological processes, and the values of these parameters are of interest. If a model becomes too complex, however, it may become a black box, where many parameters are effectively hidden and can take on unreasonable values. Further, with so many parameters, understanding the sources of uncertainty and how they propagate through the model may become nearly impossible (see Box). Each additional process and parameter can increase overall uncertainty to the point where model projections lose their usefulness for decision makers (Saltelli *et al.*, 2020).

Process-based models used to project species and ecosystem distributions are some of the most important for informing policy, and they highlight many of these problems. Most of the focus is on the model projections—often represented as values on maps, presented without uncertainties. Model evaluation generally focuses on how well these projections match observed distributions, sometimes under different climatic conditions to challenge the models (Van der Meersch *et al.*, 2025)—most of the time evaluating only one of the many output variables of the model. The complexity of these models can make it difficult to assess how well the potential parameter space was searched, and whether there was any potential non-identifiability. Studies of such underlying problems are generally separate; thus potential model problems are usually exposed only later (Van der Meersch & Chuine, 2025), as opposed to being discovered in preliminary steps before generating forecasts.

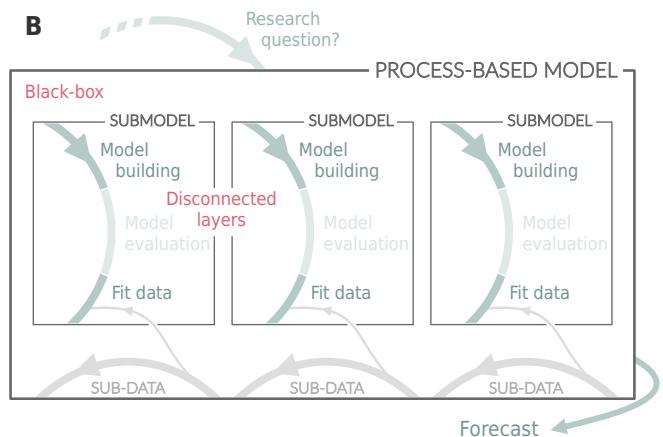
Applying the workflow to process-based models would help open the black box and thus could identify and fix model problems before forecasting. Each successive step of model development in the proposed workflow may highlight problems and a path to solutions. Incorporating data simulation would introduce a crucial step between model building and data fitting (also called calibration), ensuring a clear delineation between the two, and help expose potential parameter identifiability issues earlier in the model design. Uncovering identifiability issues would likely force researchers to begin with a simpler version of the model, which they could build on iteratively, testing for support—or lack thereof—when adding model complexity. The workflow may also highlight model problems by requiring more explicit model calibration (i.e. data fitting), which is currently hidden within opaque ‘model building’, making it easy to hide non-identifiability. Once found, non-identifiable parts of models could be addressed by reformulating the mathematical structure of certain processes, or finding ways to apply additional constraints (e.g. narrower ranges for certain parameters or developing new hypotheses that target the appropriate level of complexity). The resulting process-based models would likely be simpler and thus more tractable for quantifying parameter uncertainty and propagating uncertainty through to projections.

## Trend estimation



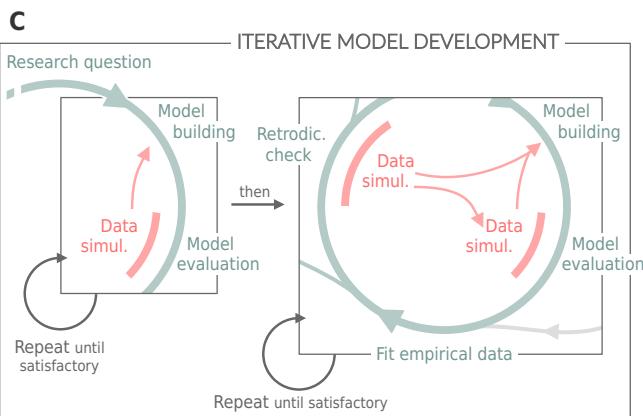
In the current workflow for estimating trends over time, a model is typically chosen *a priori* to fit to data, yielding parameter estimates that are treated as true and often translated directly into published findings and conclusions, without interrogating the model using simulated data and carefully evaluating its performance (see example workflow we provide as a supplementary file). Any such analysis must be treated with caution, because different model variants can yield very different estimates (hence different conclusions), and published results may not prove robust when confronted with future reanalysis of the same data (see Figure A above). The Living Planet Index (LPI, [www.livingplanetindex.org](http://www.livingplanetindex.org)), which aims to include long-term data on vertebrate populations of species across the globe, is emblematic of these conflicting results. A growing number of high-profile papers have challenged how strong the evidence is for population decline (Dornelas *et al.*, 2014; Gonzalez *et al.*, 2016; Wagner *et al.*, 2021; Müller *et al.*, 2024), with each paper taking a slightly different analytical approach. For example, using LPI data, Leung *et al.* (2020) published a mixture model that suggested most populations were not significantly declining, followed by other alternative modeling approaches (Buschke *et al.*, 2021; Puurinen *et al.*, 2022) including a recent one suggesting a basic analysis of the dataset should always include three sources of autocorrelation, finding trends that encompassed many previous results (Johnson *et al.*, 2024).

## Mechanistic forecasting



Model development is the central step of the process-based workflow, typically requiring several years, yet it often remains opaque for anyone who has not worked the model itself. The step of designing the model—translating knowledge and hypotheses into mathematical equations and parameters—is often blurred with the step of model calibration (or tuning), where parameter values are inferred. Models are often treated as an accumulation of multiple submodels, each governing one or several ecological processes (see Figure B above). Rather than being fitted as a whole, submodels are calibrated separately against specific subsets of data, and some parameters are simply prescribed (i.e., fixed to a value found in the literature) or tuned to reproduce certain observations or theory. The way models are currently calibrated is likely not a coincidence, but rather a workaround to avoid confronting the full complexity of the model. By calibrating submodels separately researchers are less likely to confront structural degeneracies in models (often because many parameters can compensate for others); in contrast, fitting submodels together (as a whole) would reveal such issues at a point when they can be addressed.

## A common workflow to bridge trend estimation and forecasting



A universal workflow offers an opportunity to bridge statistical and process-based frameworks, integrating mechanistic knowledge and leveraging robust statistical approaches (e.g. Rounce *et al.*, 2020). Process-based models would no longer be perceived as deterministic black boxes by other researchers but rather as robust statistical frameworks encapsulating both data structure and mechanistic knowledge—and where the full model is fitted jointly. It would be an opportunity to incorporate mechanistic assumptions beyond the process-based modeling community, potentially improving trend estimates. For both trend estimation and forecasting, the workflow would refocus attention on the research question, highlighting the ecological hypotheses that justify the use and design of the model.

247 **4 Barriers and opportunities**

248 We believe our workflow could help advance ecological science and its applications, but widespread  
249 use of it requires overcoming major hurdles that pervade science. The first is pressure to publish  
250 quickly, which can be at odds with the reality that good model fitting is inherently iterative and  
251 takes time. The second is reluctance to embrace adoption of open science practices that ensure  
252 modeling efforts are fully transparent and reproducible. We believe adopting a workflow such as  
253 the one we propose may change this reluctance, and aligns with ongoing efforts to place increasing  
254 value on research that is carefully developed, openly collaborative (including both data and code),  
255 and transparent about areas of uncertainty.

256 **4.1 Adopting the workflow**

257 Advancing ecology to where most researchers use models built more flexibly from ecological theory  
258 and insights applied to their ecological systems will not happen rapidly without a major shift in  
259 training. Much of ecology still divides the world into training for those who gather data and learn  
260 a limited set of pre-built models versus those who develop more complex models. In ecological  
261 training today, researchers who conduct field and lab studies often learn a limited set of particular  
262 statistical tests matched to particular experiment designs and simple information on their variable  
263 types (e.g. categorical  $x$  and  $y$  leads to using a chi-squared test).

264 When ecologists trained in a limited set of tests require more complex models, they are ex-  
265 pected to collaborate with other ecologists trained more in model development (though often for  
266 highly specific applications, such as wildlife population estimates, where generative models are of-  
267 ten predefined). These two groups further differ from process-based modelers, who often train in  
268 physical and ecophysiological processes and how to abstract them into mainly deterministic models.  
269 None of these groups have fully integrated data simulation into their statistical or scientific work-  
270 flows. Simulation is generally reserved as a form of training needed mainly by those specializing in  
271 theoretical ecology, who often solve analytical equations but rarely link to empirical data. While  
272 specialization is valuable, we argue the fundamental separation in ecology has overly-siloed these  
273 groups and prevented more rapid progress.

274 We recommend that scientists who regularly engage in model-driven research efforts would  
275 benefit from unified training about how to generate well-formed questions and appropriate models,  
276 and then how to simulate data from them. Through this and the use retrodictive checks, most  
277 ecologists would be better equipped to think through what parameters are most critical to their  
278 question and/or aim (e.g. management), and also gain a much stronger connection to the level  
279 of uncertainty in many of ecological estimates. Empiricists would be more likely to recognize  
280 critical gaps in current models fit by those specializing in ecological modeling and help advance  
281 those models. Process-based modelers may start a new generation of simpler models that are more  
282 tractable to theoretical ecologists, who may see new bridges from their work to empirical data  
283 and forecasting. Such progress could be accelerated through collaboration with statisticians who  
284 are already using or otherwise well-equipped to adopt our proposed workflow (Betancourt, 2020;  
285 Gelman *et al.*, 2020; Grinsztajn *et al.*, 2021; van de Schoot *et al.*, 2021).

286 Beyond routine application of the workflow and universal training to support it, the full transfor-  
287 mative potential of the workflow hinges on additional broader systemic changes within the research  
288 community. First, fostering more open model sharing through standardized repositories and col-  
289 laborative platforms would accelerate scientific discovery by allowing researchers to build upon,  
290 validate, and refine existing models more efficiently. Second, open sharing of more comprehen-

291 sive study and sampling design details associated with datasets would enable more appropriate  
292 data integration and model design decisions, and independent validation of these decisions by the  
293 community. Third, where feasible, alignment on common datasets would provide a standardized  
294 basis for model development and comparison, reducing the fragmentation of efforts and facilitating  
295 more direct and meaningful evaluations of different modeling approaches. Coupled with universal  
296 training, these shifts in the sharing and standardization of data and models would create a more  
297 collaborative, efficient, and rigorous environment for ecological modeling, ultimately leading to  
298 more accurate forecasts and better understanding of complex environmental systems.

299 *Conclusions:*

300 With rapid advances in machine learning, improving current methods to gain greater scientific  
301 insights to drive better forecasting seems increasingly important. A careful and coherent workflow is  
302 essential to preserve the interpretability of non-machine-learning models—their primary advantage.  
303 Machine learning will likely surpass process-based models for forecasting accuracy, especially if the  
304 latter lack robust estimation of their parameters and fall into a complexity trap—a trap with  
305 additional costs to interpretability of process-based models. Similarly, estimates of trends from  
306 empirical data using models without clear mechanistic drivers may soon offer fewer advantages  
307 over machine learning.

308 Today model development in ecology is rarely transparent, which limits how easily the research  
309 community can understand models, and thus identify potential issues. Instead of broad inclusive  
310 conversations about how to improve models to advance our ecological understanding, a significant  
311 portion of scientific debate has become mired in methodological considerations. However, we believe  
312 our workflow provides a tractable step to fixing this. By focusing on model development more tightly  
313 tied to ecological expertise, we argue this workflow would broaden the community that contributes  
314 to model development. It may also help resolve apparent conflicts by identifying where divergences  
315 in model predictions emerge, whether from differences in assumptions, model structures, or other  
316 aspects of the modeling process. As ecologists are increasingly expanding their computational  
317 toolkits, many field, and lab, and other forms of ‘empirical’ ecologists have the basic tools to follow  
318 this workflow to build models that better represent their ecological domains of interest, and—most  
319 importantly—to interrogate those models.

320 **References**

- 321 Balaji, V., Couvreux, F., Deshayes, J., Gautrais, J., Hourdin, F. & Rio, C. (2022) Are general  
322 circulation models obsolete? *Proceedings of the National Academy of Sciences* **119**, e2202075119.
- 323 Betancourt, M. (2020) Towards A Principled Bayesian Workflow. [https://betanalpha.github.io/assets/case\\_studies/principled\\_bayesian\\_workflow.html](https://betanalpha.github.io/assets/case_studies/principled_bayesian_workflow.html).
- 325 Bonan, G.B. & Doney, S.C. (2018) Climate, ecosystems, and planetary futures: The challenge to  
326 predict life in earth system models. *Science* **359**.
- 327 Buschke, F.T., Hagan, J.G., Santini, L. & Coetzee, B.W.T. (2021) Random population fluctuations  
328 bias the living planet index. *Nature Ecology & Evolution* **5**, 1145–1152.
- 329 Chamberlin, T.C. (1965) Method of multiple working hypotheses. *Science* **148**, 754.
- 330 Cheaib, A., Badeau, V., Boe, J., Chuine, I., Delire, C., Dufrêne, E., François, C., Gritti, E.S.,  
331 Legay, M., Pagé, C., Thuiller, W., Viovy, N. & Leadley, P. (2012) Climate change impacts on  
332 tree ranges: model intercomparison facilitates understanding and quantification of uncertainty.  
333 *Ecology Letters* **15**, 533–544.
- 334 Díaz, S., Settele, J., Brondízio, E.S., Ngo, H.T., Agard, J., Arneth, A., Balvanera, P., Brauman,  
335 K.A., Butchart, S.H.M., Chan, K.M.A., Garibaldi, L.A., Ichii, K., Liu, J., Subramanian, S.M.,  
336 Midgley, G.F., Miloslavich, P., Molnár, Z., Obura, D., Pfaff, A., Polasky, S., Purvis, A., Razzaque,  
337 J., Reyers, B., Chowdhury, R.R., Shin, Y.J., Visseren-Hamakers, I., Willis, K.J. & Zayas, C.N.  
338 (2019) Pervasive human-driven decline of life on earth points to the need for transformative  
339 change. *Science* **366**.
- 340 Dornelas, M., Antão, L.H., Moyes, F., Bates, A.E., Magurran, A.E., Adam, D., Akhmetzhanova,  
341 A.A., Appeltans, W., Arcos, J.M., Arnold, H., Ayyappan, N., Badihi, G., Baird, A.H., Barbosa,  
342 M., Barreto, T.E., Bässler, C., Bellgrove, A., Belmaker, J., Benedetti-Cecchi, L., Bett, B.J.,  
343 Bjorkman, A.D., Błażewicz, M., Blowes, S.A., Bloch, C.P., Bonebrake, T.C., Boyd, S., Bradford,  
344 M., Brooks, A.J., Brown, J.H., Bruelheide, H., Budy, P., Carvalho, F., Castañeda-Moya, E.,  
345 Chen, C.A., Chamblee, J.F., Chase, T.J., Siegwart Collier, L., Collinge, S.K., Condit, R., Cooper,  
346 E.J., Cornelissen, J.H.C., Cotano, U., Kyle Crow, S., Damasceno, G., Davies, C.H., Davis, R.A.,  
347 Day, F.P., Degraer, S., Doherty, T.S., Dunn, T.E., Durigan, G., Duffy, J.E., Edelist, D., Edgar,  
348 G.J., Elahi, R., Elmendorf, S.C., Enemar, A., Ernest, S.K.M., Escribano, R., Estiarte, M., Evans,  
349 B.S., Fan, T., Turini Farah, F., Loureiro Fernandes, L., Farneda, F.Z., Fidelis, A., Fitt, R., Fosaa,  
350 A.M., Daher Correa Franco, G.A., Frank, G.E., Fraser, W.R., García, H., Cazzolla Gatti, R.,  
351 Givan, O., Gorgone-Barbosa, E., Gould, W.A., Gries, C., Grossman, G.D., Gutiérrez, J.R., Hale,  
352 S., Harmon, M.E., Harte, J., Haskins, G., Henshaw, D.L., Hermanutz, L., Hidalgo, P., Higuchi, P.,  
353 Hoey, A., Van Hoey, G., Hofgaard, A., Holeck, K., Hollister, R.D., Holmes, R., Hoogenboom, M.,  
354 Hsieh, C., Hubbell, S.P., Huettmann, F., Huffard, C.L., Hurlbert, A.H., Macedo Ivanauskas, N.,  
355 Janík, D., Jandt, U., Jaźdewska, A., Johannessen, T., Johnstone, J., Jones, J., Jones, F.A.M.,  
356 Kang, J., Kartawijaya, T., Keeley, E.C., Kelt, D.A., Kinnear, R., Klanderud, K., Knutson, H.,  
357 Koenig, C.C., Kortz, A.R., Král, K., Kuhn, L.A., Kuo, C., Kushner, D.J., Laguionie-Marchais,  
358 C., Lancaster, L.T., Min Lee, C., Lefcheck, J.S., Lévesque, E., Lightfoot, D., Lloret, F., Lloyd,  
359 J.D., López-Baucells, A., Louzao, M., Madin, J.S., Magnússon, B., Malamud, S., Matthews,  
360 I., McFarland, K.P., McGill, B., McKnight, D., McLarney, W.O., Meador, J., Meserve, P.L.,  
361 Metcalfe, D.J., Meyer, C.F.J., Michelsen, A., Milchakova, N., Moens, T., Moland, E., Moore, J.,

- 362 Mathias Moreira, C., Müller, J., Murphy, G., Myers-Smith, I.H., Myster, R.W., Naumov, A.,  
363 Neat, F., Nelson, J.A., Paul Nelson, M., Newton, S.F., Norden, N., Oliver, J.C., Olsen, E.M.,  
364 Onipchenko, V.G., Pabis, K., Pabst, R.J., Paquette, A., Pardede, S., Paterson, D.M., Pélassier,  
365 R., Peñuelas, J., Pérez-Matus, A., Pizarro, O., Pomati, F., Post, E., Prins, H.H.T., Priscu, J.C.,  
366 Provoost, P., Prudic, K.L., Pulliaisen, E., Ramesh, B.R., Mendivil Ramos, O., Rassweiler, A.,  
367 Rebelo, J.E., Reed, D.C., Reich, P.B., Remillard, S.M., Richardson, A.J., Richardson, J.P., van  
368 Rijn, I., Rocha, R., Rivera-Monroy, V.H., Rixen, C., Robinson, K.P., Ribeiro Rodrigues, R.,  
369 de Cerqueira Rossa-Feres, D., Rudstam, L., Ruhl, H., Ruz, C.S., Sampaio, E.M., Rybicki, N.,  
370 Rypel, A., Sal, S., Salgado, B., Santos, F.A.M., Savassi-Coutinho, A.P., Scanga, S., Schmidt,  
371 J., Schooley, R., Setiawan, F., Shao, K., Shaver, G.R., Sherman, S., Sherry, T.W., Siciński, J.,  
372 Sievers, C., da Silva, A.C., Rodrigues da Silva, F., Silveira, F.L., Slingsby, J., Smart, T., Snell,  
373 S.J., Soudzilovskaia, N.A., Souza, G.B.G., Maluf Souza, F., Castro Souza, V., Stallings, C.D.,  
374 Stanforth, R., Stanley, E.H., Mauro Sterza, J., Stevens, M., Stuart-Smith, R., Rondon Suarez,  
375 Y., Supp, S., Yoshio Tamashiro, J., Tarigan, S., Thiede, G.P., Thorn, S., Tolvanen, A., Teresa  
376 Zugliani Toniato, M., Totland, Ø., Twilley, R.R., Vaitkus, G., Valdivia, N., Vallejo, M.I., Valone,  
377 T.J., Van Colen, C., Vanaverbeke, J., Venturoli, F., Verheyen, H.M., Vianna, M., Vieira, R.P.,  
378 Vrška, T., Quang Vu, C., Van Vu, L., Waide, R.B., Waldock, C., Watts, D., Webb, S., Wesolowski,  
379 T., White, E.P., Widdicombe, C.E., Wilgers, D., Williams, R., Williams, S.B., Williamson, M.,  
380 Willig, M.R., Willis, T.J., Wipf, S., Woods, K.D., Woehler, E.J., Zawada, K. & Zettler, M.L.  
381 (2018) Biotime: A database of biodiversity time series for the anthropocene. *Global Ecology and*  
382 *Biogeography* **27**, 760–786.
- 383 Dornelas, M., Gotelli, N.J., McGill, B., Shimadzu, H., Moyes, F., Sievers, C. & Magurran, A.E.  
384 (2014) Assemblage time series reveal biodiversity change but not systematic loss. *Science* **344**,  
385 296–299.
- 386 Dove, S., Böhm, M., Freeman, R., McRae, L. & Murrell, D.J. (2023) Quantifying reliability and data  
387 deficiency in global vertebrate population trends using the living planet index. *Global Change*  
388 *Biology* **29**, 4966–4982.
- 389 Franklin, O., Harrison, S.P., Dewar, R., Farrior, C.E., Brännström, A., Dieckmann, U., Pietsch, S.,  
390 Falster, D., Cramer, W., Loreau, M., Wang, H., Mäkelä, A., Rebel, K.T., Meron, E., Schymanski,  
391 S.J., Rovenskaya, E., Stocker, B.D., Zaehle, S., Manzoni, S., van Oijen, M., Wright, I.J., Ciais,  
392 P., van Bodegom, P.M., Peñuelas, J., Hofhansl, F., Terrer, C., Soudzilovskaia, N.A., Midgley, G.  
393 & Prentice, I.C. (2020) Organizing principles for vegetation dynamics. *Nature Plants* **6**, 444–453.
- 394 Gelman, A., Vehtari, A., Simpson, D., Margossian, C.C., Carpenter, B., Yao, Y.,  
395 Kennedy, L., Gabry, J., Bürkner, P.C. & Modrák, M. (2020) Bayesian workflow.  
396 <https://doi.org/10.48550/arXiv.2011.01808>.
- 397 Gonzalez, A., Cardinale, B.J., Allington, G.R., Byrnes, J., Arthur Endsley, K., Brown, D.G.,  
398 Hooper, D.U., Isbell, F., O'Connor, M.I. & Loreau, M. (2016) Estimating local biodiversity  
399 change: a critique of papers claiming no net loss of local diversity. *Ecology* **97**, 1949–1960.
- 400 Gotelli, N.J. & Ulrich, W. (2012) Statistical challenges in null model analysis. *Oikos* **121**, 171–180,  
401 gotelli, Nicholas J. Ulrich, Werner.
- 402 Grace, J.B. & Irvine, K.M. (2020) Scientist's guide to developing explanatory statistical models  
403 using causal analysis principles. *Ecology* **101**.

- 404 Grinsztajn, L., Semenova, E., Margossian, C.C. & Riou, J. (2021) Bayesian workflow for disease  
405 transmission modeling in stan. *Statistics in Medicine* **40**, 6209–6234.
- 406 Harrison, S.P., Cramer, W., Franklin, O., Prentice, I.C., Wang, H., Brännström, A., de Boer, H.,  
407 Dieckmann, U., Joshi, J., Keenan, T.F., Lavergne, A., Manzoni, S., Mengoli, G., Morfopoulos,  
408 C., Peñuelas, J., Pietsch, S., Rebel, K.T., Ryu, Y., Smith, N.G., Stocker, B.D. & Wright, I.J.  
409 (2021) Eco-evolutionary optimality as a means to improve vegetation and land-surface models.  
410 *New Phytologist* **231**, 2125–2141.
- 411 Hilborn, R. & Mangel, M. (1997) *The Ecological Detective: Confronting Models with Data*. Prince-  
412 ton University Press.
- 413 IPBES (2019) Global assessment report on biodiversity and ecosystem services of the intergovern-  
414 mental science-policy platform on biodiversity and ecosystem services. Tech. rep.
- 415 Johnson, T.F., Beckerman, A.P., Childs, D.Z., Webb, T.J., Evans, K.L., Griffiths, C.A., Capdevila,  
416 P., Clements, C.F., Besson, M., Gregory, R.D., Thomas, G.H., Delmas, E. & Freckleton, R.P.  
417 (2024) Revealing uncertainty in the status of biodiversity change. *Nature* **628**, 788–794.
- 418 Leung, B., Hargreaves, A.L., Greenberg, D.A., McGill, B., Dornelas, M. & Freeman, R. (2020)  
419 Clustered versus catastrophic global vertebrate declines. *Nature* **588**, 267–271.
- 420 Loh, J., Green, R.E., Ricketts, T., Lamoreux, J., Jenkins, M., Kapos, V. & Randers, J. (2005)  
421 The living planet index: using species population time series to track trends in biodiversity.  
422 *Philosophical Transactions of the Royal Society B: Biological Sciences* **360**, 289–295.
- 423 Loreau, M., Cardinale, B.J., Isbell, F., Newbold, T., O'Connor, M.I. & de Mazancourt, C. (2022)  
424 Do not downplay biodiversity loss. *Nature* **601**, E27–E28.
- 425 Lovenduski, N.S. & Bonan, G.B. (2017) Reducing uncertainty in projections of terrestrial carbon  
426 uptake. *Environmental Research Letters* **12**, 044020.
- 427 Low-Décarie, E., Chivers, C. & Granados, M. (2014) Rising complexity and falling explanatory  
428 power in ecology. *Frontiers in Ecology and the Environment* **12**, 412–418.
- 429 McElreath, R. (2018) *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*.  
430 Chapman and Hall/CRC.
- 431 McRae, L., Cornford, R., Marconi, V., Puleston, H., Ledger, S.E., Deinet, S., Oppenheimer, P.,  
432 Hoffmann, M. & Freeman, R. (2025) The utility of the living planet index as a policy tool and  
433 for measuring nature recovery. *Philosophical Transactions B* **380**, 20230207.
- 434 Møller, A. & Jennions, M.D. (2002) How much variance can be explained by ecologists and evolu-  
435 tionary biologists? *Oecologia* **132**, 492–500.
- 436 Müller, J., Hothorn, T., Yuan, Y., Seibold, S., Mitesser, O., Rothacher, J., Freund, J., Wild, C.,  
437 Wolz, M. & Menzel, A. (2024) Weather explains the decline and rise of insect biomass over 34  
438 years. *Nature* **628**, 349–354.
- 439 Nosek, B.A., Ebersole, C.R., DeHaven, A.C. & Mellor, D.T. (2018) The preregistration revolution.  
440 *Proceedings of the National Academy of Sciences* **115**, 2600–2606.

- 441 Pilowsky, J.A., Colwell, R.K., Rahbek, C. & Fordham, D.A. (2022) Process-explicit models reveal  
442 the structure and dynamics of biodiversity patterns. *Science Advances* **8**, eabj2271.
- 443 Puurtinen, M., Elo, M. & Kotiaho, J.S. (2022) The living planet index does not measure abundance.  
444 *Nature* **601**, E14–E15.
- 445 Rounce, D.R., Khurana, T., Short, M.B., Hock, R., Shean, D.E. & Brinkerhoff, D.J. (2020) Quantifying  
446 parameter uncertainty in a large-scale glacier evolution model using bayesian inference:  
447 application to high mountain asia. *Journal of Glaciology* **66**, 175–187.
- 448 Saltelli, A., Bammer, G., Bruno, I., Charters, E., Di Fiore, M., Didier, E., Nelson Espeland, W.,  
449 Kay, J., Lo Piano, S., Mayo, D., Pielke Jr, R., Portaluri, T., Porter, T.M., Puy, A., Rafols, I.,  
450 Ravetz, J.R., Reinert, E., Sarewitz, D., Stark, P.B., Stirling, A., van der Sluijs, J. & Vineis, P.  
451 (2020) Five ways to ensure that models serve society: a manifesto. *Nature* **582**, 482–484.
- 452 Schad, D.J., Betancourt, M. & Vasishth, S. (2020) Toward a principled bayesian workflow in cog-  
453 nitive science.
- 454 Shmueli, G. (2010) To explain or to predict? *Statistical Science* **25**.
- 455 Simpson, I.R., Shaw, T.A., Ceppi, P., Clement, A.C., Fischer, E., Grise, K.M., Pendergrass, A.G.,  
456 Screen, J.A., Wills, R.C., Woollings, T. *et al.* (2025) Confronting earth system model trends with  
457 observations. *Science advances* **11**, eadt8035.
- 458 Talis, E.J. & Lynch, H.J. (2023) Capturing stochasticity properly is key to understanding the  
459 nuances of the living planet index. *Nature Ecology & Evolution* **7**, 1194–1195.
- 460 Talts, S., Betancourt, M., Simpson, D., Vehtari, A. & Gelman, A. (2018) Validating bayesian infer-  
461 ence algorithms with simulation-based calibration. <https://doi.org/10.48550/arXiv.1804.06788>.
- 462 Terry, J.C.D., O’Sullivan, J.D. & Rossberg, A.G. (2022) No pervasive relationship between species  
463 size and local abundance trends. *Nature Ecology & Evolution* **6**, 140–144.
- 464 Thuiller, W., Guéguen, M., Renaud, J., Karger, D.N. & Zimmermann, N.E. (2019) Uncertainty in  
465 ensembles of global biodiversity scenarios. *Nature Communications* **10**.
- 466 Toszogyova, A., Smyčka, J. & Storch, D. (2024) Mathematical biases in the calculation of the living  
467 planet index lead to overestimation of vertebrate population decline. *Nature Communications* **15**,  
468 5295.
- 469 Urban, M.C., Bocedi, G., Hendry, A.P., Mihoub, J.B., Pe’er, G., Singer, A., Bridle, J.R., Crozier,  
470 L.G., De Meester, L., Godsoe, W., Gonzalez, A., Hellmann, J.J., Holt, R.D., Huth, A., Johst,  
471 K., Krug, C.B., Leadley, P.W., Palmer, S.C.F., Pantel, J.H., Schmitz, A., Zollner, P.A. & Travis,  
472 J.M.J. (2016) Improving the forecast for biodiversity under climate change. *Science* **353**, aad8466.
- 473 van de Schoot, R., Depaoli, S., King, R., Kramer, B., Maertens, K., Tadesse, M.C., Vannucci, M.,  
474 Gelman, A., Veen, D., Willemsen, J. & Yau, C. (2021) Bayesian statistics and modelling. *Nature*  
475 *Reviews Methods Primers* **1**.
- 476 Van der Meersch, V., Armstrong, E., Mouillot, F., Duputié, A., Davi, H., Saltré, F. & Chuine, I.  
477 (2025) Paleorecords reveal biological mechanisms crucial for reliable species range shift projec-  
478 tions amid rapid climate change. *Ecology Letters* **28**.

- 479 Van der Meersch, V. & Chuine, I. (2025) Can inverse calibration help improving process-explicit  
480 species distribution models? *Ecological Modelling* **506**, 111132.
- 481 Wagner, D.L., Grames, E.M., Forister, M.L., Berenbaum, M.R. & Stopak, D. (2021) Insect decline  
482 in the anthropocene: Death by a thousand cuts. *Proceedings of the National Academy of Sciences*  
483 **118**, e2023989118.
- 484 Wang, H., Prentice, I.C., Keenan, T.F., Davis, T.W., Wright, I.J., Cornwell, W.K., Evans, B.J. &  
485 Peng, C. (2017) Towards a universal model for carbon dioxide uptake by plants. *Nature Plants*  
486 **3**, 734–741.
- 487 Wolkovich, E., Davies, T.J., Pearse, W.D. & Betancourt, M. (2024) A four-step bayesian workflow  
488 for improving ecological science.
- 489 Zelinka, M.D., Myers, T.A., McCoy, D.T., Po-Chedley, S., Caldwell, P.M., Ceppi, P., Klein, S.A. &  
490 Taylor, K.E. (2020) Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research  
491 Letters* **47**.