CAREER: What's next? Developing novel quantitative tools to address conflicting evidence in temporal ecology

Ecological systems are shaped, fundamentally, by processes that occur over broad scales of space and time. The ever-increasing availability of ecological data has afforded ecologists the ability to scale up their understanding of systems through synthetic datasets: that is, databases that bring together observations from many studies, enabling scientists to examine patterns at the macroecological level [1]. Yet, the opportunity presented by new, synthetic approaches to ecology requires innovation in training, analytical methods, and outreach to ensure these novel approaches can be meaningfully understood and incorporated into management of our ecological systems [2]. Bringing ecology into the data revolution is filled with both opportunities and challenges. As ecology moves from a field primarily based on smaller scale trials producing data based on experimental manipulations to one incorporating large scale, primarily observational and integrative datasets, it is vital that practicing scientists and students alike are trained not just to process more data, but be able to critically integrate it [3]. While the opportunities presented by broad scale observational networked science such as the National Ecological Observatory Network (NEON), and long-term experimental trials such as those produced by the US Long-Term Ecological Research (LTER) network cannot be overstated [4, 5], it is essential that biologists-in-training understand the nuances of interpreting observational versus confirmatory experiments, such as how statistical tools built for more traditionally obtained data can break down when applied to observational systems [3, 6–9]. Furthermore, broad scale ecological synthesis relies on both quality data and quality documentation, because integrating the context in which data is taken is crucial to its interpretation [10].

The era of synthetic and big data ecology has enabled ecologists to examine problems at a much greater scale than previously imagined. However, because these more synthetic approaches often involve bringing together data collected at different spatial scales or temporal intervals, analytical approaches to moving between scales, from short-term plot-based studies to long-term, remotely sensed data that integrates information from a distance, are essential [11, 12]. Spatial ecology has long recognized these challenges and was quick to develop tools and guidelines to help scientists move information through spatial scales while minimizing analytical biases [13]. However, temporal ecology has lagged behind spatial ecology in its development of tools, theory and frameworks for evaluating and understanding issues of temporal scale and the responses of ecological processes [14]. Studies examining longer-term data often find that population patterns don't match those predicted by shorter-term observations [15, 16]. Interaction networks between organisms change completely depending on the temporal scale at which they are examined [17]. Temporal ecology differs from spatial ecology in two important ways: first, time cannot be manipulated, and secondly, it is unidirectional, and thus, requires specialized tools and frameworks for interpretation [14]. Processes occurring at one temporal scale may interact with those occurring at another scale, producing hierarchical effects [18]. Furthermore, driver-response relationships are not necessarily constant through time and may interact with recent and historical conditions [19]. However, an understanding of temporal dynamics is essential to the interpretation of practically all ecological processes, and most, if not all ecological questions contain at least an implicit temporal element.

The problem with our unresolved understanding of temporal processes in ecology can be well illustrated by a case study of what is a seemingly simple question: *are insect populations in decline*? Insect decline is a widely publicized, potentially catastrophic phenomenon, but is subject to controversy and scientific debate. The controversy has roots in the publication of several recent high-profile papers which, through various methodologies, found that insects, as a group, were declining in numbers over recent decades, sometimes dramatically [20–22]. A lively scientific discussion surrounding the insect decline phenomenon has ensued, with many authors arguing that several of these studies used biased or non-transparent protocol when synthesizing data [23], inappropriate measurements and models for measuring the phenomena [24], extrapolation of small scale data to inappropriately large spatial and temporal scales [25, 26], and as a result of these issues, misdirected public attention and resources [27].

Despite the ongoing debate, there is strong evidence that many insect populations are responding negatively to human activities and global change [28]. However, it is unlikely to be as simple as a consistent pattern of decline among all insects. For example, a recent meta-analysis which only included long-term surveys of insect abundance found that there was an overall trend of decline amongst terrestrial insects, but an increase in the abundance of insects associated with freshwater sites [29]. The authors also noted considerable variation in the observed trends within each grouping, even among closely adjacent sites, and noted geographical and site selection biases present in the available data, likely impacting observed trends. Yet, this study incorporated several data quality advantages over previous work; specifically it only included long-term (>10y) data produced by standardized sampling methods [29].

Understanding the insect decline phenomenon, like many problems in ecology, is complex and multifaceted, and is unlikely to be solved without careful consideration of many covariates and irregular responses. Insects as a group are extremely diverse in life history, habitat, and behavior, and are present in practically all terrestrial and freshwater ecosystems worldwide: differential responses to change are assumed to be the rule [28]. It is expected that insects will respond to anthropogenic change in geographically, temporally and phylogenetically unequal ways [30]: even if simple patterns exist, these patterns would likely be the manifestation of a multitude of differing drivers and processes, interacting in variable ways over space and time. For instance, we may observe a simple decline in the number or density of a given taxon (or multiple taxa) in response to land use or environmental change over time [20]. However, in the case of manipulations or interventions in land use, management, or invasions of adventive species, pulsed changes in underlying population regulatory dynamics can be observed [31, 32]. Shifting dynamics may occur over both pulsed and smooth disturbances, and lags between disturbance and response may occur [33]. Furthermore, 'insect decline' could manifest not as an overall reduction in numbers, but as community turnover towards invasive species or a more simplified community [34–36]. Instead of a single, unified hypothesis of 'insect decline', it is very likely that these processes (and others) all contribute to these observations simultaneously in interacting and unequal ways [37].

Yet, simply establishing reliable trends with insect population data is fraught with challenges, even where longer-term data exist [38]. Under situations of minimal disturbance, insect population regulation is complex and prone to large fluctuations [28]. A number of biases affect the collection of time series data, making the likelihood of detecting spurious trends high particularly when evaluated using simple statistical tools that ignore the temporal structure of the data [7, 8, 39]. Numerous common issues associated with quantitative reasoning applied to insect time series data may ultimately lead those evaluating these types of data to reach spurious or inaccurate conclusions [38]. Furthermore, examining a problem of macroecological scale is inherently synthetic and involves bringing together data produced by different methods, in different places, and thus has the potential to magnify all the issues of time series interpretation, synthetic data, and scaling [2].

The proposed program will use an information and data science approach to develop quantitative tools and frameworks for examining population and community time series data, with a focus on the insect decline controversy. I will use this framework to develop novel constructs for interpreting temporal processes in ecological systems, build new computational tools to support the scientific community, and deploy an education and outreach program targeted at developing critical quantitative and numeracy skills in both trainees and the broader community. My proposed research program examines:

Metrics and data quality: Are we measuring or computing ecological parameters that are most relevant to the process being described? What conditions compromise the validity of the metric? Is the scale the measurement is taken at relevant to the process?

Trajectory: Are we using the correct tools to characterize directionality in a system? How long do we need to watch a system to characterize its trajectory?

Change: When we characterize change in driving processes, how do we characterize uncertainty around changepoints and magnitude of change?

To advance this research program, in this proposal, my specific aims are to:

1. Develop and evaluate improved approaches to selecting metrics, examining trajectory, and measuring changepoints in ecological systems, and testing these tools in the context of temporal ecology in general and insect decline as a specific motivating case study.

2. Develop educational approaches to improve numerical literacy and quantitative/computational critical thinking skills among students in biology that can be deployed at scale.
3. Develop an outreach program that makes critical numeracy publicly accessible while highlighting the work of women and underrepresented minority scholars.

INTEGRATION OF PROPOSED RESEARCH AND EDUCATION WITH CAREER GOALS

I am deeply interested in ecological data synthesis as a field in general, but the work in my lab generally involves some synthetic or information science component, as interpreted through a lens of biodiversity science. I have a strong history of integrating transdisciplinary thinking into addressing complex issues, particularly where data and environmental science intersects with issues of learning, information, management, equity and justice. My experience in pure and applied ecology, data science, and in the tech industry through my Mozilla Fellowship uniquely positions me to address the research, education and outreach goals I have described in this proposal. As an insect ecologist with experience working in both invasive pest management and species of conservation concern, I have always had a strong interest in how the dynamics of species interact with human problem-solving needs. As a graduate student, my work focused on several invasive insects, identifying information gaps, and developing practical solutions to information-intensive problems through physiological, behavioral, and modeling approaches that integrated population ecology and economics [40–44]. During my doctorate, I also learned how I could use quantitative techniques to both mentor students and help them solve vexing 'data mysteries' [45, 46], and worked with land managers to integrate (often sparse, sometimes contradictory) information into management plans for species-at-risk [47, 48]. During my postdoctoral training, I was first introduced to the unique challenges of long-term ecology through my work with the US LTER network [31, 36, 49]. During this time, I also came to appreciate data science as a field in itself, and as an opportunity to teach biology students to think more deeply about information, experimental design and how we fundamentally understand our systems [50–54]. Now, as an Assistant Professor, I have created a lab that focuses on this integration of data science, computation, and population ecology, situating me to address questions about how our approaches to data and information shape our understanding of ecological systems, and to build information tools to address gaps in our understanding. The work proposed here will serve to not just propel my research program forward, but advance student training in biological and ecological synthesis, and provide practicable analytical solutions to tackling tough problems at the nexus of data, the environment, and human needs.

Ecological research is undergoing a cultural shift towards information integration and synthesis, driven, at least in part, by the open science movement [3]. Cultural shifts within a discipline also present an opportunity to be intentional about values supported by the new practices under development. In my program, education, research and outreach goals are aligned with a focus on quantitative critical thinking, as interpreted through the values of transparency and openness, plurality (i.e. incorporating *other ways of knowing* into scientific approaches; [55, 56]), and diversity and equity for all. My education and outreach program feeds naturally into my research (and vice versa) because at the core of each is examining how information is synthesized into knowledge, from '*what data should we collect to examine this phenomenon?*' to '*how do we know that this phenomenon is occurring?*' to '*what should we do to manage this phenomenon?*' I see this connection as an opportunity to train undergraduate and graduate students while asking big, multi-modal questions, and as a way of creating a program that offers opportunities for genuine connection with data, information and environmental issues amongst my trainees. This project will, over the next decade, establish my lab as a destination for ecological synthesis, tool building and environmental problem solving while building its culture of openness, inclusion, and interdisciplinary thinking.

CONCEPTUAL APPROACH: *An information science framework for evidence synthesis in ecology*

There are many facets to the insect decline controversy, like many complex ecological problems. These problems can generally be grouped into four categories:

- A lack of appropriate data.
- A lack of appropriate tools for filtering and analyzing the data.
- A lack of appropriate frameworks for interpreting the analysis and integrating results.

- A lack of framework for integrating knowledge with our goals and values to guide action.

The facets of this conflict can largely be classified using a well-established construct from the information sciences described as the “Data-Information-Knowledge-Wisdom” hierarchy or simply, the information hierarchy, originally articulated in the late 1980s [57]. The information hierarchy concept is both widely used and widely criticized by information scientists [58, 59], at least in part for the weakly articulated concept of ‘wisdom’ and the hierarchical nature of the elements [60, 61]. Indeed, the pinnacle of this hierarchy has been described in various forms, including wisdom, ‘truth’ and even ‘enlightenment’ [58]. Furthermore, conceptualization of the more basal levels of the information hierarchy are both modulated by epistemic belief and culture [62]. As this relates to scientific discovery, the path from data to knowledge is ultimately steeped in the constructs of its practitioners. It has long been asserted that although statistical, quantitative and computational methods are used to create a patina of objectivity in this hierarchy, each level of reasoning nevertheless incorporates at least some level of subjectivity, from decisions about how and what data to collect, what hypotheses or models to test, and how the results are ultimately interpreted [63, 64]. Although problematic in its original structure, the information hierarchy is a conceptually useful construct for reconciling difficult problems, especially where stepwise transparency of the decision-making process is vital. With explicit acknowledgement and transparency of the subjectivity throughout the information hierarchy, we can reimagine this construct as instead a **knowledge creation cycle**, with all components modulated by epistemic belief [58, 65, 66] (Figure 1). When data, information and knowledge (and the transitions between these states) are explicitly and transparently acknowledged as outputs of processes, modulated by culture and belief, a more holistic and equitable understanding of complex problems can be realized [67].

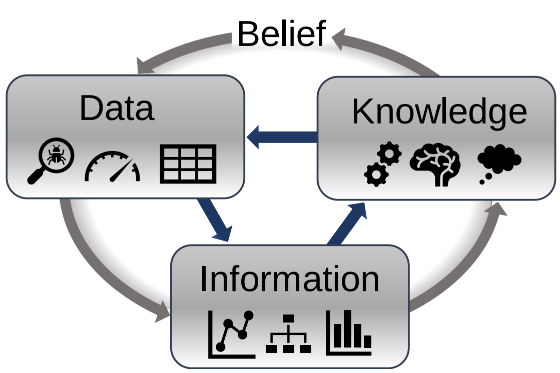

Figure 1: The Knowledge Creation Cycle is a re-imagining of the Information Hierarchy. In this conceptualization we explicitly acknowledge the role that subjective decisions, conventions and culture (i.e. existing belief) play into and create feedbacks with each step of knowledge creation, from choosing what to measure and how to measure it (Data), selecting models and analysis approaches (Information), to integration, interpretation, and making predictions (Knowledge), to explanations of phenomena and making recommendations for actions (Belief).

The reality of data, methodological and analytical biases in qualitative research is widely acknowledged [68, 69], but the role of these personal frames of reference in the scientific knowledge produced has historically been less well-articulated in quantitative research [70]. In ecology and evolutionary biology, lack of reproducibility in findings is often attributed to strong spatial and temporal dependencies in the processes being measured, leading ecologists to advocate for ‘metaresearch’ approaches where generalities are sought beyond the site-level [71]. An increasing emphasis on computational reproducibility and increased reporting of analytical methods allows “reviewers and other readers to follow the decision-making processes of authors” and thus implicitly serves as a means of evaluating quantitative biases [72]. Yet, recent studies examining biases in analytical approaches in ecology have focused on deliberate misconduct or resource limitations preventing an experiment from being authentically repeated [73, 74], and **few explicitly examine the impact of subtle choices (such as when to begin a study) on analytical outputs** [9]. Although some authors have gone so far as to claim that the majority of research findings are ‘false’ [75], proponents of the open science movement have offered open, reproducible practices, often heavily relying on technological applications as a panacea to weeding out ‘false’ results [76]. Within environmental sciences, increasing standardization, enhanced metadata and reproducible workflow documentation would certainly enhance our ability to bring multiple data sources together [77]. Yet, this framing of the reproducibility crisis falls into a familiar problem of scientific absolutism: truth is a specific thing that can be found if one applies the right tools. The ‘open’ extension of the scientific method can introduce, and in fact, exacerbate the inequities and biases of ‘classical’ science when not applied thoughtfully [79]. Even in sources advocating for large-scale data integration, authors acknowledge that challenges to large-scale data integration are largely socio-cultural: between issues of tool usability and uptake and critical information literacy issues, massive barriers to ecological synthesis persist [2].

Using the modified knowledge creation cycle (Figure 1), it becomes possible to explicitly examine data, methodological and interpretation biases in the development of syntheses, but also to guide our application of these principles to other fields. In this proposal, I will use this framework to guide the development of novel methodologies and data syntheses to incorporate broader perspectives, and to explicitly inform the structuring of education and outreach materials designed to improve critical quantitative skills in scientists, trainees and the public.

OUTLINE OF PROPOSED RESEARCH AND EDUCATION ACTIVITIES

Aim 1: Develop and evaluate improved approaches to selecting metrics, examining trajectory, and measuring changepoints in ecological systems, and testing these tools in the context of temporal ecology in general and insect decline as a specific motivating case study.

Aim 1a: Improve Metrics: Evaluate information quality in data produced by common methods of insect surveillance.

Background: Understanding large-scale patterns in insect populations, like many environmental problems, requires bringing together data collected across a variety of modalities. In insect ecology, monitoring programs often use varied sampling methods, varied spatial and temporal extents, and collect information on varied life history traits: in short, data integration is fraught by significant heterogeneities [79]. Furthermore, because the vast majority of insect surveys are collected with a particular entomological question in mind, insect data are largely context specific, and interpreted within the frame of reference of the study itself. The notable exception to the more piecemeal data are those produced by wide scale observation networks, such as the scientist-run European suction trap network [80, 81], and public-science powered databases such as *iNaturalist*. Even with wide-scale availability of data from a variety of sources, this context-dependence becomes a barrier to data integration among studies [2].

Context-dependence often manifests as biases in data. The act of measuring something is often an abstraction or 'snapshotting' of a natural process, and the measurement taken is inevitably modulated by its context, creating bias. Although bias itself is often framed somewhat nefariously, in the context of misconduct or carelessness, biases in data can be the result of any number of cognitive, structural, or sampling processes [82]. These biases interact with the ecology of the phenomenon under study: for instance, in insects, because behavior and body size varies between different life stages, monitoring plans for invasive insects are likely to sample different stages unequally [83]. Even subtle differences in the deployment of measuring devices can affect what is measured, such as placement of a trap in the shade [84]. Furthermore, indirect effects such as changing environmental conditions can alter insect behavior and thus change trap efficiency, biasing patterns measured even when population numbers themselves do not change [85]. Because insect trapping efficiency is widely known by practitioners to vary so dramatically, entire books have been devoted to guiding scientists how to sample populations of insects occurring on single plant species [e.g. 86]. Despite this, bias in data produced by scientists is rarely explicitly considered in ecology and evolution [82], with the apparent exception of geographical biases [87, 88], possibly due to their stark visibility. For example, geographical biases in observation intensity create clear patterns in records submitted to the *iNaturalist* app (Figure 2), both with respect to natural patterns human activity (Figure 2A) and the effect of specific human interventions on observation frequency (Figure 2B).

In recent years, the rise in popularity in distributed monitoring of environmental phenomena using public (citizen) science approaches has been met with both enthusiasm and skepticism by practicing scientists [89]. Although public science approaches offer unprecedented breadth of data for biodiversity monitoring, concerns about data quality and bias have been similarly levied, leading to numerous studies comparatively examining 'data quality' between public and scientific data sources [90, 91]. **I would argue that this comparative approach is essential not just for integrating data produced by public and**

scientific observations, but also when integrating data produced within the bounds of traditional scientific studies in order to examine bias and context.

When bringing data together for synthesis regardless of its source, it may be impossible to eliminate bias. However, it is possible to reconcile apparent discrepancies in data sources using a variety of analytical approaches [53]. **Relatively simple comparative approaches can offer insights which may be particularly useful for training purposes, to illustrate how methodological differences in data collection may ultimately yield different results** [92]. Furthermore, when it is found that results and conclusions are relatively insensitive to varying methodologies, it allows us to be more confident in our understanding and beliefs about a system's function [93]. **These insights will be particularly important to understanding the insect decline phenomenon in the context of community turnover.**

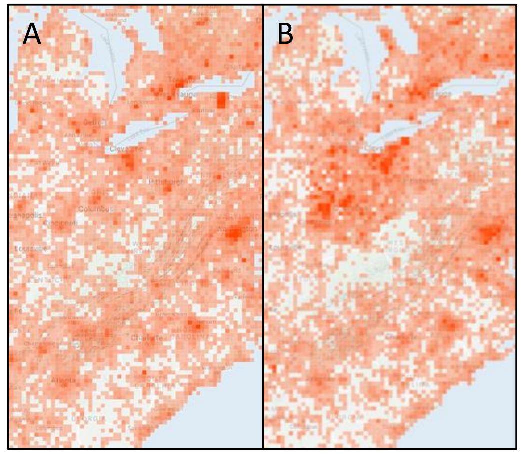

Figure 2: We can observe human influence on patterns in natural history data when we visualize the distributions of observations of different taxa plotted on a map. Both panels display records for a portion of east-central North America, as reported to *iNaturalist*, using a 'heatmap' scale, where darker colors indicate more records for a given location. The maps have the lower peninsula of Michigan in the upper left of both panels and the Atlantic Ocean in the lower right. Panel A reports observations of mammals (~1M records in the database), panel B reports observations of Odonata (dragonflies and damselflies, ~0.85M records). While geographical biases in number of records roughly follow patterns of human density in both maps (i.e. there are darker pixels near many urban areas), the political boundaries of the state of Ohio are distinctly visible in panel B, the result of the many records produced by the Ohio Dragonfly Survey, a highly successful public outreach program run out of Ohio State University.

1ai: How does the design of observation methods affect our observations of insect communities?

Proposed work: The 'best' trapping methods for insect ecology are a source of ongoing debate in the entomological literature, and the recommendations generally suggest selecting the method optimized for the ecological question at hand [94]. However, this practice does little to ensure inter-operability of data produced and limits the context in which data produced by an individual study may be interpreted. For example, in a 2019 preliminary trial, my research group sought to examine the functional dynamics of insects in green roofs in the context of the habitat template hypothesis, which predicts that human built environments will function in ecologically similar ways to structurally analogous natural habitats [95]. Because of the physical constraints of the environment being sampled, we used insect traps adapted to deployment on hard surfaces, where underlying substrate could not be disturbed [96]. We placed 369 traps on green roofs and in thin soil environments (alvars, rock prairies) and captured approximately 32,000 insects over the summer. However, we only captured 10 carabid beetles, a taxon that is considered an important ecological indicator [97], across the whole sampling effort. Was this observation the result of a trapping bias or a genuine rarity of this taxon at our sites? In either case, how would we advise future users of these data integrate them into a larger study of biodiversity?

In order to address this lack of contextualization in biodiversity surveys, it is critical to perform direct, comparative methodological studies. Thus, I propose a highly multi-modal, two-pronged trap design study to help create context for integration of insect survey data. The first component involves a field study: we will create trapping arrays using a variety of standard insect trapping techniques: sticky cards, bowl arrays, pitfalls, ramp traps, flight intercept traps, photo traps deployed at easily accessible research properties owned by Kent State. Insects will be collected at weekly intervals and compiled by undergraduate and graduate students, recording identity, abundance, location and trap type, and these data will be subjected to multivariate analyses to compare how insect communities captured vary by trapping methodology. Although the geographic scope of this work is relatively small, this research serves several important purposes in building my research program: first, it will help to contextualize trapping biases associated with fieldwork techniques common to students in my lab. Secondly, it provides a highly tactile, ongoing research project with local accessibility and relevance that will provide data and specimens for a number of entry-level investigations over the course of the project, supporting the recruitment of undergraduates. The second facet of this trap design study is meta-analytic in nature and will serve to tie the field component to the broader context of insect population studies in general: we will conduct a literature and web survey and compile and mine insect survey data from studies, natural history collections and public science projects, including taxonomic identity, trapping methodology, location and habitat. These data will be subjected to a comparative biodiversity analysis using classical techniques and metrics (such as nonmetric multi-dimensional scaling) and more modern, machine learning based approaches [98, 99], and then using these outputs in a meta-analytic framework to understand how trapping methodology interacts with other environmental variables to ultimately affect the patterns in biodiversity observed. This study will improve our understanding of trapping and taxonomic biases in monitoring insects and will provide researchers guidance on how to integrate multi-modal insect survey data and has the potential for helping to guide the design of more efficient sampling methodologies for future researchers. Furthermore, findings can be used to examine existing insect community survey data for evidence of change from the context of community composition and turnover over time.

1aii: How do we integrate multiple imperfect data sources into a more holistic understanding of a species' dynamics in space and time?

Proposed work: To effectively monitor if a species is changing in space and (or) time, it is necessary to establish a baseline not just of its abundance, but its distribution and phenology. However, because many species of interest are monitored using several different methods that may capture different aspects of their life history, contradictory or incomplete data are common [53, 100]. Reconciling these data sources presents a challenge, particularly for species of conservation concern, where observations are scarce. To examine this data integration problem, Odonata (the dragonflies and damselflies) present an ideal model system: they are a ubiquitous, sensitive taxon, and tend to be large, showy insects, making them of interest to collectors and nature photographers [101], and are thus often recorded in scientific insect surveys, natural history collections and in public science databases (Figure 2). To establish a detailed, multi-modal, database, we will compile records of Odonata from literature, museum and public science collections, focusing on eastern North America. We will use these data to create species distribution models and phenological models for each data source [50, 102] at differing taxonomic resolutions (i.e. all records, by family, and then for target species). We will then use a model-stacking approach [sensu 103] to examine commonalities, and importantly, discrepancies between model predictions, and identify biasing factors from each sampling modality. The results will be used to reconcile differences in model predictions and identify sampling methodologies where range or phenological change are more likely to be captured, enhancing monitoring programs, and provide a framework for relating phenological and spatial occurrence data to longer-term population trends.

Aim1b: Understand Trajectory: how much information is needed about a system to be able to comment on where it is going?

Background: The question of trajectory over time is central in ecology, particularly as related to how ecological systems are responding to disturbance or will behave under future climate or environmental conditions [104]. Furthermore, short-term dynamics observed in an ecological system are not always indicative of the long-term trajectory of that system [11]. In population processes, for example, density-dependent deterministic mechanisms couple with environmental perturbations to produce highly variable population numbers during any given time slice [105]. With insect populations, this is especially true, because their population numbers may naturally vary by many orders of magnitude, making the likelihood of capturing spurious trends with conventional statistical approaches high [28]. **A fundamental problem arises when shorter-term studies apply statistical tools at time scales that are not matched with the underlying processes to make inferences about trajectory: not only may spurious trends be observed, but because only a portion of the underlying process variability is captured, a higher degree of statistical confidence in the result will be found**. Misleading or spurious shorter-term trends are common in ecological systems, and being able to identify them depends highly on the time of observation [14]. The application of simple linear models to these spurious trends will give a

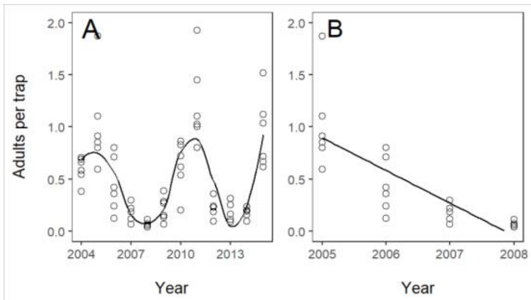

Figure 3: A real world demonstration of a temporal scaling problem. Captures of fireflies (primarily *Photinus pyralis*) observed at Kellogg Biological Station's Early Successional plots, Hickory Corners, MI, from 2004-2015 (data adapted from Hermann et al 2016 and discussed in Bahlai, White et al 2020). Panel A presents all 12 years of observations, and the black line represents a LOESS smoother giving a moving average, suggesting a cyclical dynamic may be occurring. A simple linear regression was not significant (slope -0.006±0.015, p=0.71, R^2=0.002). However, if the study had been limited to 4 years from 2005-2008 (Panel B), dramatically different conclusions would have been observed. A simple linear regression of these data would very likely have been interpreted as 'strong evidence' that a decline was occurring in this population ((slope -0.31±0.05, p=0.000003, R^2=0.633)

researcher a false sense of confidence in the relationship between the response being measured and time, and thus more likely to make errors in prediction [106] (Figure 3).

It would seem that to study trajectory, 'more data are better' would be the guiding philosophy, but care must be taken to optimize a balance between genuine information needs and cost, effort and time [107]. In one study, short-term population trends were generally reflective of longer-termed patterns, but reliability of this relationship varied by the generation length of the organism under study [108]. However, it would require two decades of observations to reliably detect a change of 1% per year across a variety of vertebrate taxa [8, 108]. For some invertebrates, although longer time series were generally better for establishing the population's trajectory, diminishing returns in precision were observed after about 10-15 years of data were collected [109].

To standardize our approach to understanding trajectory, I developed a data mining tool that allows us to mine existing long-term data to determine the frequency of 'misleading' trends present in a given time series (and conversely, the length of observation period necessary to minimize risk of capturing a misleading trend) [9]. The tool, known as the 'bad breakup algorithm', takes time series data and breaks it into all possible sequential subsets of data, and fits a simple (ordinary least squares) linear model to the response over time in each of the sequential subsets, then compiles common statistics. Although R^2 and p are not measures of statistical confidence *per se,* they are often used by ecologists in this way [110, 111], and thus are used by the algorithm as a means to approximate 'conclusions' that a researcher might make of the data. These conclusions are compared to those produced by the same model fit to all the data, allowing us to quantify the frequency of dissimilar conclusions and the range of possible numerical estimates for relevant statistical parameters. In the first application of this algorithm, Cusser et al [112] examined a thirty-year experiment comparing the sustainability and productivity attributes of an agricultural cropping system under several management regimes. In this system, due to high variability between treatments, 15-year observation periods were needed to detect consistent between-treatment differences in yield and soil water availability, and at least 1/5 of all windows examined resulted in spurious, statistically misleading trends (i.e. suggest the opposite relationship between management treatments). I am currently expanding this work to use the algorithm to conduct a quantitative synthesis of patterns in data produced by the LTER network. My colleagues and I are specifically examining how various biotic and abiotic factors affect our likelihood of observing misleading trends, and this work has laid the foundation for, and highlighted the need to, expand this research in two novel directions: one to expand the functionality of the tool, and the second to apply the tool to insect survey data, to assess its reliability when used in global synthesis.

1bi: What is the rate of spurious trends in systems that are governed by non-linear processes? Proposed work: In order to understand trends more broadly in ecological systems, it is necessary to develop a tool that can handle non-linear processes. This tool will have broad applicability in ecology and potentially a wide variety of other fields: essentially it could be applied to any process that incorporates a directional response to some underlying driver. The tool would allow scientists to assess how much data are needed in order to confidently make a projection about their system in the context of the natural variability of the data, rather than by more arbitrary standards (such as fit statistics considered in isolation). The tool will build on the original 'bad breakup' prototype, but will be designed to handle irregular sampling intervals and missing data, and will allow a user to choose from a suite of pre-programed nonlinear functions (i.e. polynomial, sinusoidal, exponential, logistic) and allow for user-specified models and fit statistics. This will be implemented as an R package and will include several vignettes which demonstrate package functionality and applications. I will also develop detailed tutorials to include in addition to the fundamental package documentation required. The package will be submitted to CRAN and disseminated via my professional networks, and a manuscript documenting the package, its functionality and several case studies will be submitted to an appropriate venue such as *Methods in Ecology and Evolution* or *PLOS Computational Biology*.

1bii: How often are insect population trend data misleading? Can we characterize which data show genuine trends and which trends are spurious, biased or contain insufficient information?
Proposed work: To date, many of the attempts to synthesize insect surveys into information about population trajectories have suffered from mischaracterization of data, inappropriate approaches to meta-analysis, or over-extension of claims [38]. Yet, despite varied methods, numerous sources have converged on a similar set of conclusions, including both studies which have been subjected to considerable scrutiny for their methodology [20–22], and several studies which specifically sought to correct biases and data quality issues in their analyses [29, 113]. Are these signals representative of a true broader trend or caused by problematic data, analysis approaches, or some combination thereof? An effort to create a global database of insect biodiversity data, EntoGEM, is underway: the project coordinators envision using this data to create a global systemic map of insect declines [114]. However, the EntoGEM project will also create an open data product that will serve as the ideal test case for the trajectory tool developed in Aim 1bi: using this tool, I will characterize not just the apparent trajectory of each observed population in the EntoGEM database, but also identify (spatial, taxonomic, methodological) patterns in spurious trends. The outputs of this study will help inform future monitoring strategies and provide important contextualization of data produced by existing monitoring networks.

Aim 1c: Pinpointing Change: when processes governing dynamic ecological systems change, can we quantify uncertainty around the timing and magnitude of these changes?

Background: An important facet of understanding the trajectories of ecological systems is understanding how, and when, these processes will undergo abrupt changes [115, 116]. Understanding discontinuities, change points or regime shifts has highly interdisciplinary applications, and has been examined for a variety of processes related to climate [117, 118], ecology [119], and economic and social systems [120, 121]. However, population dynamics are of particular interest for these tools: because population dynamics are determined by internal, biotic rules and also external abiotic factors, it is desirable to build tools which can help decouple these processes [122]. External perturbations can lead to shifts in population dynamics, such that the parameters governing population abundance transition to other values [123, 124]. **Identifying dynamic shifts in noisy ecological systems is challenging using real-world data due to a lack of systematic, adaptable tools** [116]. **Current tools for detecting abrupt change in systems tend to characterize uncertainty in breakpoints poorly (if at all) and most tools do not use specific deterministic processes in identifying these changes.** Historically, break points in ecological systems have largely been examined through the use of segmented regressions, using models that do not account for non-linearities, nor uncertainty in break point location [115, 116, 123, 125, 126]. Furthermore, break points are often applied to time series data based on specific hypotheses surrounding factors affecting population changes or visualizations [4, 123, 125–127], creating the potential for biases in break point selection. Additionally, break point detection methods employing null-hypothesis significance testing have relatively low sensitivity in situations where statistical power is limited: in a 2009 review, common break point methods were tested on typical contemporary ecological time series with 20-40 time steps, and authors found that only the most extreme transitions occurring near the midpoint of the time series were detected [115]. In response to these issues, I developed the “Dynamic Shift Detector,” a break point analysis tool that uses an information-theory based model selection to create a sensitive, parsimonious tool that provides both estimates of how parameters shift, and also a measurement of ‘confidence’ in each individual break point in a time series [32]. The tool uses the Ricker model, a simple dynamic model which has relatively good performance describing dynamics of insect populations near their carrying capacity, and it outputs ecologically meaningful parameters [128]. In its original implementation, my co-author and I applied the model to dynamics of two important insect species, and the algorithm was able to detect the timing (and magnitude of impact) of several environmental and human management changes on the dynamics of both species [32]. These insights are important for understanding how human actions ultimately impact a species dynamics: for instance, in our monarch butterfly case study (Figure 4) we found that shifts, primarily manifesting as carrying capacity loss, corresponded to dramatic increases in the use of the herbicide glyphosate in midwestern soybean, and then corn, in 2003 and 2008 respectively, supporting that a previously proposed mechanism of decline of this insect was observable at the population level [129].

The Dynamic Shift Detector has several unique advantages among changepoint methods in the mechanics of how it computes uncertainty, however it is limited to population processes by its underlying Ricker structure. Recognizing these limitations, I have partnered with several colleagues involved in developing changepoint methodologies [130–134] to standardize inputs, outputs and conduct direct comparisons of the performance of each approach on standardized test datasets. We have received funding for our working group from the Canadian Institute for Ecology and Evolution and work is underway to develop an R package ('abrupt') for detecting abrupt shifts in a variety of processes. Insights from this working group have helped to frame how the Dynamic Shift Detector can be revised to broaden its scope and applicability to a wider variety of systems.

1c: Can we build a model-agnostic tool that locates breakpoints and quantifies change in a variety of systems? Proposed work: Understanding both the timing of and uncertainty surrounding these changes is an important element in making future predictions in dynamical systems, but especially for population and community processes. In addition to understanding what trends are occurring, in order to understand the trajectory of a system, it is essential to understand when and how trends change. Building on my approach with the bad breakup algorithm, I will use the Dynamic Shift Detector, integrated with output standards determined by the abrupt change working group, to build a model-agnostic change detection tool that uses the underlying model-selection structure of the Dynamic Shift Detector, but allows user customizability in underlying process model. Similar to outputs of Aim 1bi, although the intended structure of the tool is for temporal processes in ecological systems, conceivably, this could be applied to spatial processes, or other systems where there exists a model for the unperturbed state. The tool would allow users to fit data series to assess the location, magnitude, and associated uncertainly around deviation from an underlying pattern, and allow users to discern between abrupt and gradual shifts between underlying model parameter values. Additionally, this tool will be designed to handle irregular sampling intervals and missing data. As in Aim 1bi, the tool will be implemented as an R package, and will include several vignettes (based on data compiled for the 'abrupt' package) which will demonstrate applications and follow a similar documentation and dissemination plan.

To examine the prevalence of dynamical shifts in insect systems, I will use this tool to mine existing long-term databases of insect abundance [sensu 29] and those identified by EntoGEM (see Aim 1bii). Outputs of this analysis will be synthesized with those produced in Aims 1a and 1b to evaluate the broader quantitative evidence surrounding the global insect decline phenomenon.

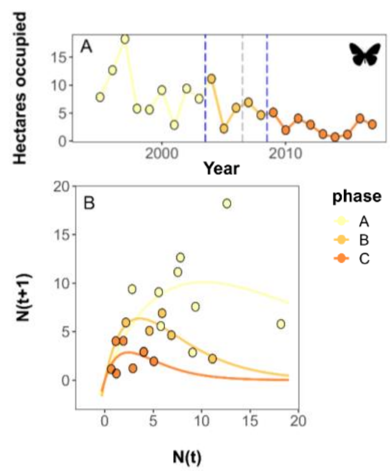

Figure 4: Population data documenting the area occupied by monarch butterflies in their winter habitat in central Mexico from 1994-2016. A) Time series data showing the total area occupied by overwintering monarchs each year in December. Vertical blue lines indicate years in which dynamic shifts occurred, as estimated by the Dynamic Shift Detector algorithm. Break weights, a measure of confidence in the break points (scale 0-1), were estimated at 0.49, and 0.26, for 2003 and 2008 respectively. An additional minor break with a weight of 0.14 was found at 2006 (grey dashed line). B) Ricker fits of time series data segments, with populations at time t+1 described as a function of populations observed at time t. Butterfly art by D. Descouens and T.M. Seesey, used under a CC-BY 3.0 license. Figure adapted from Bahlai and Zipkin (2020).

Aim 2: Develop educational approaches to improve numerical literacy and quantitative/ computational critical thinking skills among students in biology that can be deployed at scale.

Background: Quantitative and mathematical skills, including statistics, modelling and programming have been acknowledged as part of a biologist's essential toolkit for some time [135]. Yet, traditional quantitative training for biologists tends to focus just on statistics, and not, more broadly, on these data-science-type skills, leaving students less able to handle data-intensive problems [136]. Despite the central role critical numeracy plays in solving complex problems in biology, biology students are generally reputed to have negative attitudes towards quantitative subjects when compared to students from other sciences [137]. When measured, however, the emotional effect of this apparent mathematical hesitancy is often minor or inconsistent [138], suggesting a strong context-dependence in the observed effect and opportunities for these attitudes to be addressed by pedagogical insights. Improved motivation, achievement and emotional satisfaction is observed when educational content is adaptive and relevant to students' interests, needs and goals [139]. When statistics classes use real-life data, students additionally gain better understanding of the subject matter and increased retention [140]. Using realistic examples, problem solving and active learning all play an important role in improving student retention of quantitative subject matter [141]. Computer scientists highlight the importance of modelling mistakes through active, live-coding, breaking down barriers of perfectionism and giving students real-time 'debugging' experience [142]. Hands-on programming experience decreases student 'fear' of data science and is thought to deepen their understanding of quantitative issues in their own research [143]. The act of data collection itself, although an important part of any scientist's workflow, has limited impact on student attitudes and confidence in applying quantitative knowledge, so simply working with data may be enough for students to gain an appreciation for quantitative methods [144]. Yet, studies of these approaches rarely highlight what **I perceive as the most critical benefit of active learning approaches: active, real world case study-based learning allows a student to understand the role of context, information quality and subjectivity in quantitative reasoning.** The lack of nuance in traditional approaches to quantitative training directly leads to practicing scientists who are unable to synthesize information in an effective way, as we have observed in the rush to examine global insect declines and ensuing controversy [38]. Furthermore, this lack of critical information training leaves students ill-equipped to effectively analyze their own authentic, noisy data or more likely to inappropriately wedge incremental processes into tools designed to test binaries [145, 146], and when data do not fit the statistical paradigm applied to them, be filed away, reinforcing patterns of publication bias [147].

Proposed work: Integrate information science and critical quantitative approaches into graduate training programs in biology. It has been my observation, through collaboration with and mentorship of graduate students, that many students struggle with a "now what?" moment at the point in their program when they have collected some data and are now tasked with analysis. They have been primed for this confusion by their previous experiences with classes where the problems have been designed with a clear 'right answer' for a simplified problem, and tend to view variability as a problem or 'error' rather than an authentic manifestation of a natural process. Further, as open and reproducible workflows are increasingly valued in ecology and biology, a training gap exists [148], leaving students frustrated by not just inadequate insight, but increasing documentation requirements and an accompanying self-consciousness about having to show their work. In response to these observations, I developed the Reproducible Quantitative Methods (RQM) course as an immersive, technology driven and open-ended project-based learning course [54]. Conceptually, RQM is designed to use an authentic 'donated' or public dataset, and lead the students through documentation, data cleaning, analysis, write up and publication through specific exercises and discussions. The course is divided into four units: data management, reproducible analytics, effective visualization, and the scientific publication process, with activities that push the major project forward through each, and guided readings and class debates to contextualize larger issues arising from the subject matter. Over the four offerings of this course, three student projects have ultimately been published in the scientific literature at this time [50, 53, 149] and student response has generally been very positive. However, each offering is an extreme time commitment for both the students and the instructor, and class size must be limited in order to make project groups manageable and division of labor equitable among students. Furthermore, to take a project to the depth required for publication, the projects are generally limited by the instructor's disciplinary expertise, and thus the course does not typically serve students outside of the environmental sciences.

Like many learning experiences designed to be deeply immersive, RQM is generally effective and appreciated, while also being extremely limited in its scalability [150]. With a growing list of skills now effectively required for a career in biology [151], finding an efficient, scalable way to address the 'now what?' problem associated with the application of these skills becomes all the more essential for a wide swath of biologists-in-training.

This is no less true at Kent State Biological Sciences, where our department graduate program offers M.S. and Ph.D. degrees in three diverse areas: Cell Biology and Molecular Genetics; Integrative Physiology and Neurobiology; and Ecology and Evolutionary Biology. Currently, a relatively limited set of offerings are available to graduate students wishing to develop advanced skills in quantitative reasoning in the Department of Biological Sciences. These courses include RQM, with its limited enrollment, and offerings in skill-based courses such as Biological Statistics (a statistics course that is taught from a classical frequentist perspective) and Bioinformatics. Thus, **I propose to develop a novel, modularized course, "Critical Data Science for Biologists" which focusses on developing higher-order quantitative reasoning in biology graduate students, at scale**. The course will initially be offered as a single, semester-long course, divided into 3-6 hour 'workshop' modules focusing on a particular problem. Like RQM, the course will focus on authentic data and problems, but unlike RQM, the data itself will not be the common element through the duration of the course. Instead, I will introduce the modified knowledge creation cycle (Figure 1) at the beginning of the course, and we will use this construct as a framework for critically examining how data is interpreted in the context of real-world problems. Modules will be based on a variety of case studies (such as papers published with open data), news stories, and historical examples, and students will be tasked with dissecting a finding, from identifying the fundamental unit of data used in the study to identifying sources of potential bias and how the authors dealt with any information that did not fit their conclusions. Because the course will be designed to be module-based, the course content can be more easily customized to meet the disciplinary needs of a diverse student population, elements can be relatively easily updated and, if created as open curriculum materials (i.e. published on the web and made available under an open license) as RQM has been, relatively easily adapted, as a whole or in part, by other instructors, either in its entirety or as a module within existing coursework. The workshop module model has been successfully used by organizations such as The Carpentries to disseminate curriculum materials beyond a single institution [152, 153]. Materials will be distributed through the Environmental Data Science Inclusion Network (EDSIN; an NSF INCLUDES project) hub on QUBES (a community portal for math and biology educators).

Assessment plan. A critical question arises when we identify new elements that we believe will improve the success of our students: *How will this fit?* That is, what is the most efficient way to tackle this apparent deficit without over-extending our students? Thus, it is necessary to collect information on how each training approach affects student attitudes towards quantitative methods in biology. I will work with a science education specialist (Senior Personnel Bridget Mulvey) to develop a comprehensive survey-based pre/post and comparative assessment plan for student competencies in data analytics [154], examining student responses along several quantitative and qualitative assessment measures, including satisfaction, perceived competency in the subject matter, and scientific self-identity, in student populations taking Biological Statistics (classic approach), RQM (immersive project-based approach), and Critical Data Science for Biologists (modularized problem-based approach).

Aim 3: Develop an outreach program that makes critical numeracy publicly accessible while highlighting the work of women and underrepresented minority scholars.

Background: Public trust in and understanding of science is critical to human quality of life. Both public and scientists attitudes towards scientific concepts are dramatically shaped by culture, national identity, and individual identity [155]. These attitudes not only shape public opinion but policy and regulatory decisions on important socio-ecological and socio-biological issues [156, 157]. Yet, exposure to apparently contradictory information from scientific studies can adversely impact public understanding of, and compliance with, expert recommendations [158]. While it is unlikely (and undesirable) that the communication of apparently contradictory information to the public can be controlled, public understanding of complex scientific concepts can be fostered through better communication of information credibility and context [159]. Fostering informal understanding of quantitative and statistical concepts, such as 'data as evidence' and 'probabilistic thinking,' is associated with deeper understanding and appreciation of scientific concepts in learners as young as primary school age [160]. In addition to trust and understanding, however, is the manifestation of how individuals *identify with* science, that is, how a person's conception of science contributes to their moral positioning, beliefs and sense of self-worth [161]. Teaching science as a process-based enterprise not only positions learners for higher achievement in STEM classes, it helps these students find meaning and position in science [162]. The overall effect and retention of nature-of-science training may be more pronounced when delivered by relatable messengers [163]. Relatability of culture and belief of the person delivering the message can play a critical role in the learning difficult or controversial concepts [164]. Furthermore, informal engagement in STEM outreach programs prior to participation in formal, university level STEM programs was associated with prolonged interest and engagement with a student's field [165]. Broader public understanding of science thus requires accessible, diverse, and critical engagement.

Proposed work: Develop a podcast incorporating transdisciplinary perspectives on the nature of information. Podcasts are an increasingly popular 'edutainment' medium which are widely applicable across education and outreach contexts [166]. When used in undergraduate training, students generally respond favorably to their efficiency as a learning tool, citing their ability to listen to a podcast while doing other activities such as driving or chores [167]. A particular advantage of this medium is it conveys a sense of intimacy among listeners, enabling connection with subject matter [168], making podcasting an ideal medium for tackling discussion of complex issues requiring examination and context. My objective is to create a palatable, easy to listen to podcast that takes a multi-faceted view of the data > information > knowledge > belief pipeline across fields. The podcast will take a unique interdisciplinary format: it will take a data science perspective, supported by co-hosts who are disciplinary experts from science education research (Senior Person Bridget Mulvey) and sociology of scientific belief (Senior Person Rebecca Catto). The working title of the podcast is: **How do you know? A podcast exploring the numbers behind our beliefs, and everything in between.** We will use a semi-structured interview format to call upon experts across disciplines to join us in discussions, exploring what data means in different professions and from different perspectives. We will discuss the checks and balances each field uses in turning data and information into knowledge, and the mechanisms by which fields self-correct. We will recruit practicing scientists and academics from a variety of disciplines, with emphasis on scholars from minoritized or historically excluded groups, to provide a means of authentic connection between listeners and diversified role models. These experts will be recruited through our personal networks and through databases of diverse experts, such as EDSIN and DiversifyEEB. Because we envision both an 'open web' audience and a classroom end use, we will approach each 40 minute podcast episode in three to four 10-15 minute segments to increase potential modularity [166]. We envision generating two six-episode 'seasons' of the podcast, with each episode centering around a given theme, such as "Finding consensus: what do we do when our data contradicts itself?" and "Causation from correlation: can we find out what's going on in systems we can't experiment on?" For each episode, we will develop companion curriculum materials targeted at students in high school and undergraduate science programs. We will make podcast episodes and companion materials freely available on the web via standard platforms (e.g. Captivate.fm, Buzzsprout) and promote it via social media and via our established professional networks, and like the products developed for Aim 2, curriculum materials will be distributed via EDSIN/QUBES. All podcasts will be transcribed at the time of production to ensure compatibility with education materials guidelines in accordance with the Americans with Disabilities Act of 1990. **Immediately prior to submission to this proposal, we learned that we had been awarded seed funds from the Mozilla Foundation to begin work on a 4 episode 'prototype' season in Fall 2020, so this proposal will serve to expand on that work.**

Assessment plan. This outreach strategy involves reaching both a classroom and a more informal public audience. The reception of the podcast with a public audience will be assessed through the collection of listenership statistics (i.e. downloads) and through audience responses (i.e. comments and engagement via social media). Once curriculum materials are deployed and there is evidence of their use, we will conduct a survey-based assessment similar to that used in Aim 2 to determine student responses to modular, podcast-based curricular activities used in high school and undergraduate classrooms.

BROADER IMPACTS

This research, education and outreach program brings together a highly interdisciplinary perspective and set of resources designed for tackling complex ecological problems. Furthermore, **the proposed program places itself in a broader, transdisciplinary context of science education and sociology through direct collaboration with academics who are leaders in those fields, fostering meaningful transdisciplinary synthesis**. It will create new analytical tools that can be applied to complex systems and data science problems in other fields, train undergraduate and graduate students and post-doctoral scholars, and reach out to younger learners and the public. The research components will utilize public datasets, and draw connections between short- and long-term studies, demonstrating pathways to broader use of archival data, increasing the impact of public investments in research. The proposed work will particularly respond to these targeted areas:

Enhanced infrastructure for research and education. Although community acceptance for incorporating open scientific approaches into research is increasing in recent years, in many cases this incorporation remains perfunctory or superficial. My goal, with the proposed work, is to provide a framework for downstream use of the tools and curriculum I build, so that my research and teaching can meaningfully be used as a starting point for other scientists and educators. My commitment to 'radical openness' of data, intermediate data products, analysis code and curriculum not only will ensure reproducibility of the present work, but will provide future scientists with both clear entry points, and a model for building their own open work with this communal resource.

Broaden dissemination to enhance scientific and technological understanding. I am a vocal proponent of open science approaches with specific interests in diversifying accessibility [51, 52]. Through this work, I will demonstrate the use of open analytical workflows (i.e. reproducible coding, open data, open note-booking) to mainstream academic biologists, but also perform specific outreach on diversifying access within open science itself (i.e. developing materials that are both 'open access' and compatible with regulations surrounding digital products as outlined in the Americans with Disabilities Act, for example, including captions/transcripts and ensuring materials produced are screen-reader compatible; [169]). These approaches allow biologists to more effectively connect with data scientists, engineers, and sociologists, fostering future cross-disciplinary collaborations. The podcast will allow findings, and broader scientific perspectives, to be disseminated to a wide public audience.

Undergraduate and graduate education. In addition to 2 graduate students, this project will train 1-2 undergraduate students in years 2-5 of the project. The curriculum developed will be made available so that in addition to directly reaching graduate students enrolled in the new course (likely ~10 per year), material from the class as well as the podcast can be used in classrooms from the high school through graduate level, reaching many more students.

*Broaden participation of under-represented groups***.** The podcast and curriculum materials will help reach students and interested people across a broad audience. Furthermore, the podcast will preferentially recruit interviewees from marginalized and historically excluded groups, helping to provide a pool of visible role models to listeners while providing a platform for sharing and promoting their work to interviewees, an important facet to improving retention of marginalized people in the sciences [170]. I have a strong history of recruiting students from historically excluded groups, from diverse economic backgrounds, and from the LGBTQ+ community (through outreach, teaching, recruitment through the Ecological Society of America's SEEDs program, and more locally through Kent State's Summer Undergraduate Research Experience program) and will continue to seek out and actively encourage applicants from the widest possible pool of backgrounds, and will continue to incorporate a transparent, supportive lab culture to foster retention of students once they enroll.

RESULTS FROM PRIOR NSF AWARDS

I am lead PI of NSF #1838807 *EAGER: Managing our expectations: quantifying and characterizing misleading trajectories in ecological processes*, a two-year award for $175,624, 10/01/2018-09/30/2020, from the NSF Office of Advanced Cyberinfrastructure. ***Intellectual Merit:*** This project aims to mine data produced by the LTER to gain understanding of how short-term trends in ecological systems scale to long-term processes and system trajectories using a linear approach, and how scaling patterns change with ecosystem attributes, with an aim to answer the question “*how much observational data is necessary to make sound forecasts of a system’s trajectory?*” ***Broader impacts:*** My collaborators and I have trained three undergraduate students, all coming from groups underrepresented in the sciences (two students from non-binary genders, one with a visible disability, and one woman of color), and resultant work was presented at the Annual Biomedical Research Conference for Minority Students in Anaheim in 2019, and two posters will be presented (virtually) at the Ecological Society of America meeting in August 2020. Two manuscripts based on student research are currently in preparation. Students also gained experience with public outreach by sharing their ‘data wrangling’ experiences on the blog “Practical Data Management for Bug Counters.” ***Evidence of research products:*** Our initial algorithm is available at on Github [171], and a refined version is described in a manuscript currently available as a preprint [9]. In collaboration with Sarah Cusser and Nick Haddad at Michigan State we recently published a manuscript at Global Change Biology using the algorithm, where we found that no-till agricultural management is associated with long-term yield and environmental benefits, but because of system variability, particularly after extreme events, short-term studies (<5y in length) will produce misleading results >30% of the time [112].

PROJECT TIMELINE

A project timeline, with all major activities and personnel, is given in Figure 5. The timeline assumes a July 2021 start date.

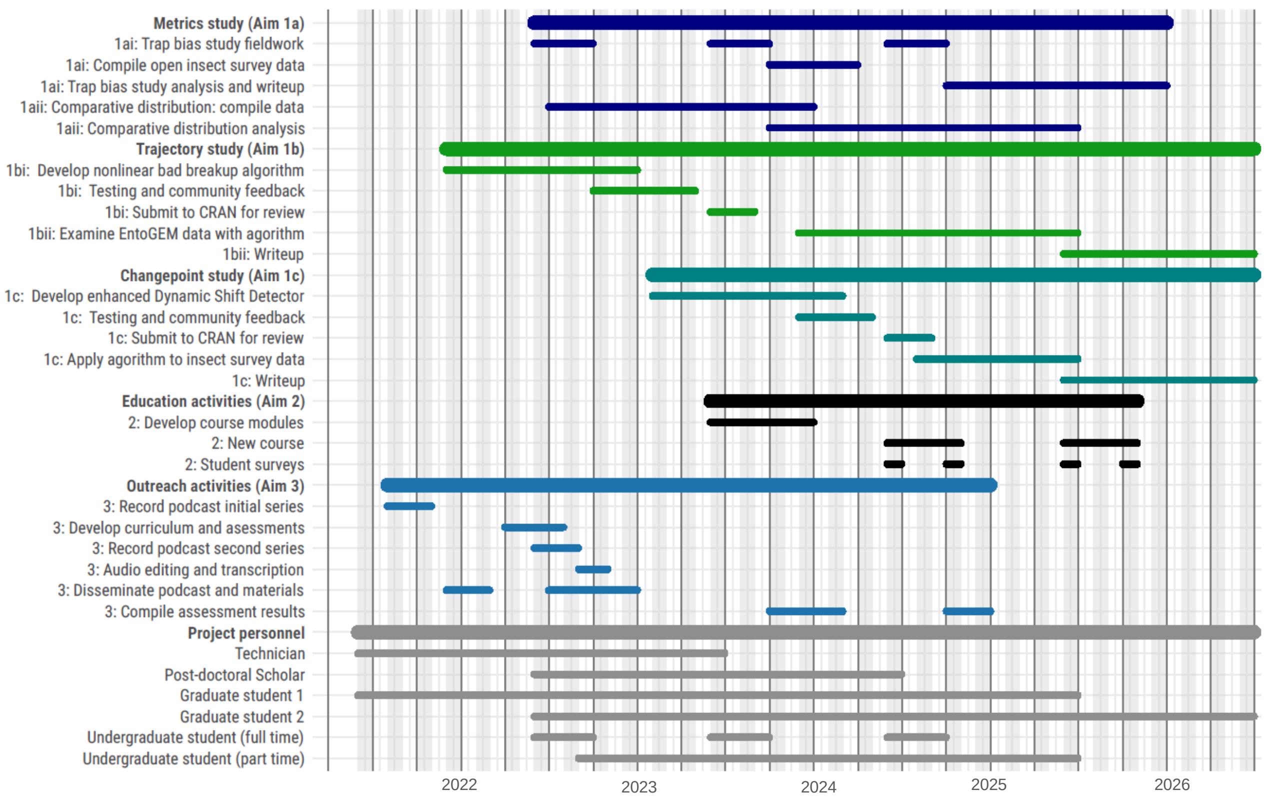

Figure 5: An approximate timeline for all major project activities.*

**Note that graduate assistant funding will be allocated to two GA lines, and students will otherwise be funded with teaching assitanceships.*

1. Poisot T, Gravel D, Leroux S, Wood SA, Fortin M-J, Baiser B, Cirtwill AR, Araújo MB, Stouffer DB (2016) Synthetic datasets and community tools for the rapid testing of ecological hypotheses. *Ecography*, 39(4):402–408. https://doi.org/10.1111/ecog.01941

2. Michener WK, Jones MB (2012) Ecoinformatics: supporting ecology as a data-intensive science. *Trends in ecology & evolution*, 27(2):85–93.

3. Nilsen EB, Bowler DE, Linnell JDC (2020) Exploratory and confirmatory research in the open science era. *Journal of Applied Ecology*, 57(4):842–847. https://doi.org/10.1111/1365-2664.13571

4. Knapp AK, Smith MD, Hobbie SE, Collins SL, Fahey TJ, Hansen GJA, Landis DA, La Pierre KJ, Melillo JM, Seastedt TR, Shaver GR, Webster JR (2012) Past, present, and future roles of long-term experiments in the LTER Network. *Bioscience*, 62(4):377–389. https://doi.org/10.1029/2008gb003336

5. SanClements M, Lee RH, Ayres ED, Goodman K, Jones M, Durden D, Thibault K, Zulueta R, Roberti J, Lunch C, Gallo A (2020) Collaborating with NEON. *BioScience*, 70(2):107–107. https://doi.org/10.1093/biosci/biaa005

6. Chatterjee S, Hadi AS (1986) Influential Observations, High Leverage Points, and Outliers in Linear Regression. *Statist. Sci.*, 1(3):379–393. https://doi.org/10.1214/ss/1177013622

7. Fournier AMV, White ER, Heard SB (2019) Site-selection bias and apparent population declines in long-term studies. *Conservation Biology*, 33(6):1370–1379. https://doi.org/10.1111/cobi.13371

8. White ER (2019) Minimum Time Required to Detect Population Trends: The Need for Long-Term Monitoring Programs. *BioScience*, :biy144–biy144. https://doi.org/10.1093/biosci/biy144

9. Bahlai CA, White ER, Perrone JD, Cusser S, Whitney KS (2020) An algorithm for quantifying and characterizing misleading trajectories in ecological processes. *bioRxiv*, :2020.07.07.192211. https://doi.org/10.1101/2020.07.07.192211

10. Ellison AM, Osterweil LJ, Clarke L, Hadley JL, Wise A, Boose E, Foster DR, Hanson A, Jensen D, Kuzeja P, Riseman E, Schultz H (2006) ANALYTIC WEBS SUPPORT THE SYNTHESIS OF ECOLOGICAL DATA SETS. *Ecology*, 87(6):1345–1358. https://doi.org/10.1890/0012-9658(2006)87[1345:AWSTSO]2.0.CO;2

11. Carey CC, Cottingham KL (2016) Cross-scale Perspectives: Integrating Long-term and High-frequency Data into Our Understanding of Communities and Ecosystems. *The Bulletin of the Ecological Society of America*, 97(1):129–132. https://doi.org/10.1002/bes2.1205

12. Chave J (2013) The problem of pattern and scale in ecology: what have we learned in 20 years? *Ecology Letters*, 16(s1):4–16. https://doi.org/10.1111/ele.12048

13. Newman EA, Kennedy MC, Falk DA, McKenzie D (2019) Scaling and Complexity in Landscape Ecology. *Frontiers in Ecology and Evolution*, 7https://doi.org/10.3389/fevo.2019.00293

14. Wolkovich EM, Cook BI, McLauchlan KK, Davies TJ (2014) Temporal ecology in the Anthropocene. *Ecology Letters*, 17(11):1365–1379. https://doi.org/10.1111/ele.12353

15. Yu H, Luedeling E, Xu J (2010) Winter and spring warming result in delayed spring phenology on the Tibetan Plateau. *Proceedings of the National Academy of Sciences*, 107(51):22151–22156.

16. Ziebarth NL, Abbott KC, Ives AR (2010) Weak population regulation in ecological time series. *Ecology letters*, 13(1):21–31.

17. Schwarz B, Vázquez DP, CaraDonna PJ, Knight TM, Benadi G, Dormann CF, Gauzens B, Motivans E, Resasco J, Blüthgen N, Burkle LA, Fang Q, Kaiser-Bunbury CN, Alarcón R, Bain JA, Chacoff NP, Huang S-Q, LeBuhn G, MacLeod M, Petanidou T, Rasmussen C, Simanonok MP, Thompson AH, Fründ J (2020) Temporal scale-dependence of plant–pollinator networks. *Oikos*, n/a(n/a)https://doi.org/10.1111/oik.07303

18. McCann NP, Zollner PA, Gilbert JH (2017) Temporal scaling in analysis of animal activity. *Ecography*, 40(12):1436–1444. https://doi.org/10.1111/ecog.02742

19. Ryo M, Aguilar-Trigueros CA, Pinek L, Muller LAH, Rillig MC (2019) Basic Principles of Temporal Dynamics. *Trends in Ecology & Evolution*, 34(8):723–733. https://doi.org/10.1016/j.tree.2019.03.007

20. Hallmann CA, Sorg M, Jongejans E, Siepel H, Hofland N, Schwan H, Stenmans W, Müller A, Sumser H, Hörren T (2017) More than 75 percent decline over 27 years in total flying insect biomass in protected areas. *PloS one*, 12(10):e0185809.

21. Lister BC, Garcia A (2018) Climate-driven declines in arthropod abundance restructure a rainforest food web. *Proceedings of the National Academy of Sciences*, 115(44):E10397. https://doi.org/10.1073/pnas.1722477115

22. Sánchez-Bayo F, Wyckhuys KA (2019) Worldwide decline of the entomofauna: A review of its drivers. *Biological conservation*, 232:8–27.

23. Grames EM, Elphick CS (2020) Use of study design principles would increase the reproducibility of reviews in conservation biology. *Biological Conservation*, 241:108385. https://doi.org/10.1016/j.biocon.2019.108385

24. Thomas C, Jones TH, Hartley SE (2019) “Insectageddon”: a call for more robust data and rigorous analyses. *Global change biology*,

25. Saunders ME, Janes JK, O’Hanlon JC (2019) Moving On from the Insect Apocalypse Narrative: Engaging with Evidence-Based Insect Conservation. *BioScience*, 70(1):80–89. https://doi.org/10.1093/biosci/biz143

26. Simmons BI, Balmford A, Bladon AJ, Christie AP, De Palma A, Dicks LV, Gallego-Zamorano J, Johnston A, Martin PA, Purvis A, Rocha R, Wauchope HS, Wordley CFR, Worthington TA, Finch T (2019) Worldwide insect declines: An important message, but interpret with caution. *Ecology and Evolution*, 9(7):3678–3680. https://doi.org/10.1002/ece3.5153

27. Komonen A, Halme P, Kotiaho JS (2019) Alarmist by bad design: Strongly popularized unsubstantiated claims undermine credibility of conservation science. *Rethinking Ecology*, 4

28. Wagner DL (2020) Insect declines in the Anthropocene. *Annual review of entomology*, 65:457–480.

29. Klink R van, Bowler DE, Gongalsky KB, Swengel AB, Gentile A, Chase JM (2020) Meta-analysis reveals declines in terrestrial but increases in freshwater insect abundances. *Science*, 368(6489):417. https://doi.org/10.1126/science.aax9931

30. Montgomery GA, Dunn RR, Fox R, Jongejans E, Leather SR, Saunders ME, Shortall CR, Tingley MW, Wagner DL (2020) Is the insect apocalypse upon us? How to find out. *Biological Conservation*, 241:108327. https://doi.org/10.1016/j.biocon.2019.108327

31. Bahlai CA, Werf W vander, O’Neal M, Hemerik L, Landis DA (2015) Shifts in dynamic regime of an invasive lady beetle are linked to the invasion and insecticidal management of its prey. *Ecological Applications*, https://doi.org/10.1890/14-2022.1

32. Bahlai CA, Zipkin EF (2020) The Dynamic Shift Detector: An algorithm to identify changes in parameter values governing populations. *PLOS Computational Biology*, 16(1):e1007542. https://doi.org/10.1371/journal.pcbi.1007542

33. Allstadt AJ, Haynes KJ, Liebhold AM, Johnson DM (2013) Long-term shifts in the cyclicity of outbreaks of a forest-defoliating insect. *Oecologia*, 172(1):141–151. https://doi.org/10.1007/s00442-012-2474-x

34. Evans EW, Soares A, Yasuda H (2011) Invasions by ladybugs, ladybirds, and other predatory beetles. *Biocontrol*, 56(4):597–611. https://doi.org/10.1007/s10526-011-9374-6

35. Henn M, Nichols H, Zhang Y, Bonner TH (2014) Effect of artificial light on the drift of aquatic insects in urban central Texas streams. *Journal of Freshwater Ecology*, 29(3):307–318.

36. Bahlai C, Colunga-Garcia M, Gage S, Landis D (2015) The role of exotic ladybeetles in the decline of native ladybeetle populations: evidence from long-term monitoring. *Biological Invasions*, 17(4):1005–1024. https://doi.org/10.1007/s10530-014-0772-4

37. Egerer MH, Arel C, Otoshi MD, Quistberg RD, Bichier P, Philpott SM (2017) Urban arthropods respond variably to changes in landscape context and spatial scale. *Journal of Urban Ecology*, 3(jux001)https://doi.org/10.1093/jue/jux001

38. Didham RK, Basset Y, Collins CM, Leather SR, Littlewood NA, Menz MHM, Müller J, Packer L, Saunders ME, Schönrogge K, Stewart AJA, Yanoviak SP, Hassall C (2020) Interpreting insect declines: seven challenges and a way forward. *Insect Conservation and Diversity*, 13(2):103–114. https://doi.org/10.1111/icad.12408

39. Brown CJ, Schoeman DS, Sydeman WJ, Brander K, Buckley LB, Burrows M, Duarte CM, Moore PJ, Pandolfi JM, Poloczanska E, Venables W, Richardson AJ (2011) Quantitative approaches in climate change ecology. *Global Change Biology*, 17(12):3697–3713. https://doi.org/10.1111/j.1365-2486.2011.02531.x

40. Bahlai CA, Welsman JA, Macleod EC, Schaafsma AW, Hallett RH, Sears MK (2008) Role of visual and olfactory cues from agricultural hedgerows in the orientation behavior of multicolored Asian lady beetle (Coleoptera: Coccinellidae). *Environmental Entomology*, 37:973–979.

41. Bahlai CA, Schaafsma AW, Lagos D, Voegtlin D, Smith JL, Welsman JA, Xue Y, DiFonzo C, Hallett RH (2014) Factors inducing migratory forms of soybean aphid and an examination of North American spatial dynamics of this species in the context of migratory behavior. *Agriculture and Forest Entomology.*, 16(3):240–250.

42. Bahlai CA, Sikkema S, Hallett RH, Newman J, Schaafsma AW (2010) Modeling distribution and abundance of soybean aphid in soybean fields using measurements from the surrounding landscape. *Environmental Entomology*, 39(1):50–56.

43. Bahlai CA, Xue Y, McCreary CM, Schaafsma AW, Hallett RH (2010) Choosing organic pesticides over synthetic pesticides may not effectively mitigate environmental risk in soybeans. *PLoS ONE*, 5(6):e11250.

44. Hallett RH, Bahlai CA, Xue Y, Schaafsma AW (2014) Incorporating natural enemy units into a dynamic action threshold for the soybean aphid, Aphis glycines (Hemiptera: Aphididae). *Pest Management Science*, 70(6):879–888. https://doi.org/10.1002/ps.3674

45. Brunke AJ, Bahlai CA, Sears MK, Hallett RH (2009) Generalist predators (Coleoptera: Carabidae, Staphylinidae) associated with millipede populations in sweet potato and carrot fields and implications for millipede management. *Environmental Entomology*, 38(4):1106–1116.

46. Brunke AJ, O'Keefe L, Bahlai CA, Sears MK, Hallett RH (2012) Guilty by association: an evaluation of millipedes as pests of carrot and sweet potato. *Journal of Applied Entomology*, :Online pre-print. DOI 10.1111/j.1439-0418.2012.01708.x. https://doi.org/10.1111/j.1439-0418.2012.01708.x

47. Farrell TC, Copeland C, Bahlai CA (2010) Recovery strategy for the Northern Barrens Tiger Beetle (Cicindela patruela) in Ontario. *Ontario Ministry of Natural Resources, Peterborough, Ontario.*, :vi + 17 pp.

48. Pulfer TL, Bahlai CA, Mousseau L (2011) Recovery Strategy for Laura's Clubtail (Stylurus laurae) in Ontario. Ontario Recovery Strategy Series. *Ontario Ministry of Natural Resources, Peterborough, Ontario.*, :v + 23 pp.

49. Bahlai CA, Colunga-Garcia M, Gage SH, Landis DA (2013) Long term functional dynamics of an aphidophagous coccinellid community are unchanged in response to repeated invasion. *PLoS One*, 8(12):e83407. https://doi.org/10.1371/journal.pone.0083407

50. Hermann SL, Xue S, Rowe L, Davidson-Lowe E, Myers A, Eshchanov B, Bahlai CA (2016) Thermally moderated firefly activity is delayed by precipitation extremes. *Royal Society open science*, 3(12):160712.

51. Teal T, Becker E, Wilson G, Pawlik A, Raniere Silva, Gatto L, Francois Michonneau, Steyn J, Cabunoc A, Bahlai C, Lapp H, White E, Jordan KL, Marwick B, Sebastian, Leonorgg, Emonet R, Banaszkiewicz P, Corpuz A, Brauning R, Nurnberger A, Anelda Van Der Walt, Bergman C, Dashnow H, Allen J, Pipitone J, Ram K, Belkin M, Hansen M, Neeb M, Young N, Brym Z, Evanwill, Konovalov A, Mills B, Martinez C, Beck D, Rodriguez-Sanchez F, Devenyi GA, Carroll I, Saunders J, Hollister JW, Duckles J, Woo K, Dreyer M, Poisot T, W. Trevor King, Rcarns (2017) Data Carpentry Spreadsheet Ecology Lesson V2017.04.0. https://doi.org/10.5281/zenodo.570047

52. Wright S, Marsh Z, Bahlai C, Robinson D (2017) Open Data Training Primers. *Mozilla Science Lab*, https://mozillascience.github.io/open-data-primers/

53. Saunders SP, Farr MT, Wright AD, Bahlai CA, Ribeiro Jr. JW, Rossman S, Sussman AL, Arnold TW, Zipkin EF (2019) Disentangling data discrepancies with integrated population models. *Ecology*, 100(6):e02714. https://doi.org/10.1002/ecy.2714

54. Bahlai C, Moser A, Braun C (2020) cbahlai/rqm-template: Reproducible Quantitative Methods- A Course Template. https://doi.org/10.5281/ZENODO.3958031

55. Walter M, Andersen C (2013) Indigenous statistics: A quantitative research methodology.

56. Harmin M, Barrett MJ, Hoessler C (2017) Stretching the boundaries of transformative sustainability learning: On the importance of decolonizing ways of knowing and relations with the more-than-human. *Environmental Education Research*, 23(10):1489–1500. https://doi.org/10.1080/13504622.2016.1263279

57. Ackoff RL (1989) From data to wisdom. *Journal of applied systems analysis*, 16(1):3–9.

58. Rowley J (2007) The wisdom hierarchy: representations of the DIKW hierarchy. *Journal of Information Science*, 33(2):163–180. https://doi.org/10.1177/0165551506070706

59. De Mauro A, Greco M, Michele G (2016) A formal definition of Big Data based on its essential features. *Library Review*, 65(3):122–135. https://doi.org/10.1108/LR-06-2015-0061

60. Frické M (2008) The knowledge pyramid: a critique of the DIKW hierarchy. *Journal of Information Science*, 35(2):131–142. https://doi.org/10.1177/0165551508094050

61. Hoppe A, Seising R, Nurnberger A, Wenzel C (2011) Wisdom - the blurry top of human cognition in the DIKW-model? *Proceedings of the 7th conference of the European Society for Fuzzy Logic and Technology (EUSFLAT-2011)*, https://doi.org/10.2991/eusflat.2011.91

62. List A, Peterson EG, Alexander PA, Loyens SMM (2018) The role of educational context in beliefs about knowledge, information, and truth: an exploratory study. *European Journal of Psychology of Education*, 33(4):685–705. https://doi.org/10.1007/s10212-017-0359-4

63. Berger JO, Berry DA (1988) Statistical Analysis and the Illusion of Objectivity. *American Scientist*, 76(2):159–165.

64. Hughes DM (1995) Significant differences: The construction of knowledge, objectivity, and dominance. *Women's Studies International Forum*, 18(4):395–406. https://doi.org/10.1016/0277-5395(95)80031-J

65. Tuomi I (1999) Data Is More than Knowledge: Implications of the Reversed Knowledge Hierarchy for Knowledge Management and Organizational Memory. *Journal of Management Information Systems*, 16(3):103–117. https://doi.org/10.1080/07421222.1999.11518258

66. Kebede G (2010) Knowledge management: An information science perspective. *International Journal of Information Management*, 30(5):416–424. https://doi.org/10.1016/j.ijinfomgt.2010.02.004

67. D'Ignazio C, Klein LF (2020) Data feminism.

68. Podsakoff PM, MacKenzie SB, Podsakoff NP (2011) Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annual Review of Psychology*, 63(1):539–569. https://doi.org/10.1146/annurev-psych-120710-100452

69. Catto R (2016) Bracketing out the Truth? Managing Bias in the Study of new Religious Movements. *Religion and Knowledge: Sociological Perspectives*, :269.

70. Freese J, Peterson D (2018) The Emergence of Statistical Objectivity: Changing Ideas of Epistemic Vice and Virtue in Science. *Sociological Theory*, 36(3):289–313. https://doi.org/10.1177/0735275118794987

71. Fidler F, Chee YE, Wintle BC, Burgman MA, McCarthy MA, Gordon A (2017) Metaresearch for Evaluating Reproducibility in Ecology and Evolution. *BioScience*, 67(3):282–289. https://doi.org/10.1093/biosci/biw159

72. Powers SM, Hampton SE (2019) Open science, reproducibility, and transparency in ecology. *Ecological Applications*, 29(1):e01822. https://doi.org/10.1002/eap.1822

73. Schnitzer SA, Carson WP (2016) Would Ecology Fail the Repeatability Test? *BioScience*, 66(2):98–99. https://doi.org/10.1093/biosci/biv176

74. Fraser H, Parker T, Nakagawa S, Barnett A, Fidler F (2018) Questionable research practices in ecology and evolution. *PLOS ONE*, 13(7):e0200303. https://doi.org/10.1371/journal.pone.0200303

75. Ioannidis JPA (2005) Why Most Published Research Findings Are False. *PLOS Medicine*, 2(8):e124. https://doi.org/10.1371/journal.pmed.0020124

76. Munafò MR, Nosek BA, Bishop DVM, Button KS, Chambers CD, Percie du Sert N, Simonsohn U, Wagenmakers E-J, Ware JJ, Ioannidis JPA (2017) A manifesto for reproducible science. *Nature Human Behaviour*, 1(1):0021. https://doi.org/10.1038/s41562-016-0021

77. Reichman OJ, Jones MB, Schildhauer MP (2011) Challenges and Opportunities of Open Data in Ecology. *Science*, 331(6018):703. https://doi.org/10.1126/science.1197962

78. Bahlai CA, Bartlett LJ, Burgio KR, Fournier AMV, Keiser CN, Poisot T, Stack Whitney K (2019) Open Science Isn't Always Open to All Scientists. *American Scientist*, 107:78–82.

79. Rosenheim JA, Gratton C (2017) Ecoinformatics (Big Data) for Agricultural Entomology: Pitfalls, Progress, and Promise. *Annual Review of Entomology*, 62(1):399–417. https://doi.org/10.1146/annurev-ento-031616-035444

80. Cocu N, Conrad K, Harrington R, Rounsevell MDA (2005) Analysis of spatial patterns at a geographical scale over north-western Europe from point-referenced aphid count data. *Bulletin of Entomological Research*, 95(01):47–56. https://doi.org/10.1079/BER2004338

81. Harrington R, Woiwod I (2007) Foresight from hindsight: the Rothamsted insect survey. *Outlooks on Pest Management*, 18:9–14.

82. Zvereva EL, Kozlov MV (2019) Biases in studies of spatial patterns in insect herbivory. *Ecological Monographs*, 89(3):e01361. https://doi.org/10.1002/ecm.1361

83. Zink AG, Rosenheim JA (2004) State-dependent sampling bias in insects: implications for monitoring western tarnished plant bugs. *Entomologia Experimentalis et Applicata*, 113(2):117–123. https://doi.org/10.1111/j.0013-8703.2004.00213.x

84. Georgitis KM (2001) Evaluating shade bias in insect trap catch and assessing the shortand long-term impacts of herbicide application in regenerating clearcuts on flowering plant communities. Master's Thesis.

85. Holyoak M, Jarosik V, Novák I (1997) Weather-induced changes in moth activity bias measurement of long-term population dynamics from light trap samples. *Entomologia Experimentalis et Applicata*, 83(3):329–335. https://doi.org/10.1046/j.1570-7458.1997.00188.x

86. (1980) Sampling Methods in Soybean Entomology.

87. Reddy S, Dávalos LM (2003) Geographical sampling bias and its implications for conservation priorities in Africa. *Journal of Biogeography*, 30(11):1719–1727. https://doi.org/10.1046/j.1365-2699.2003.00946.x

88. Kramer-Schadt S, Niedballa J, Pilgrim JD, Schröder B, Lindenborn J, Reinfelder V, Stillfried M, Heckmann I, Scharf AK, Augeri DM, Cheyne SM, Hearn AJ, Ross J, Macdonald DW, Mathai J, Eaton J, Marshall AJ, Semiadi G, Rustam R, Bernard H, Alfred R, Samejima H, Duckworth JW, Breitenmoser-Wuersten C, Belant JL, Hofer H, Wilting A (2013) The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions*, 19(11):1366–1379. https://doi.org/10.1111/ddi.12096

89. Kosmala M, Wiggins A, Swanson A, Simmons B (2016) Assessing data quality in citizen science. *Frontiers in Ecology and the Environment*, 14(10):551–560.

90. Gardiner MM, Allee LL, Brown PMJ, Losey JE, Roy HE, Smyth RR (2012) Lessons from lady beetles: accuracy of monitoring data from US and UK citizen-science programs. *Frontiers in Ecology and the Environment*, :doi: 10.1890/110185.

91. Hochmair HH, Scheffrahn RH, Basille M, Boone M (2020) Evaluating the data quality of iNaturalist termite records. *PLOS ONE*, 15(5):e0226534. https://doi.org/10.1371/journal.pone.0226534

92. Giri C, Zhu Z, Reed B (2005) A comparative analysis of the Global Land Cover 2000 and MODIS land cover data sets. *Remote Sensing of Environment*, 94(1):123–132. https://doi.org/10.1016/j.rse.2004.09.005

93. Derville S, Torres LG, Iovan C, Garrigue C (2018) Finding the right fit: Comparative cetacean distribution models using multiple data sources and statistical approaches. *Diversity and Distributions*, 24(11):1657–1673. https://doi.org/10.1111/ddi.12782

94. Yi Z, Jinchao F, Dayuan X, Weiguo S, Axmacher JC (2012) A Comparison of Terrestrial Arthropod Sampling Methods. *Journal of Resources and Ecology*, 3(2):174–182. https://doi.org/10.5814/j.issn.1674-764x.2012.02.010

95. Lundholm JT (2006) Green roofs and facades: a habitat template approach. *Urban habitats*, 4(1):87–101.

96. Bouchard P, Wheeler TA, Goulet H (2005) Ground beetles (Coleoptera: Carabidae) from alvar habitats in Ontario. *Journal of the Entomological Society of Ontario*, 136:3–23.

97. Koivula MJ (2011) Useful model organisms, indicators, or both? Ground beetles (Coleoptera, Carabidae) reflecting environmental conditions. *ZooKeys*, (100):287–317. https://doi.org/10.3897/zookeys.100.1533

98. Hart NH, Huang L (2012) Counting Insects in Flight Using Image Processing Techniques. *Proceedings of the 27th Conference on Image and Vision Computing New Zealand*, :274–278. https://doi.org/10.1145/2425836.2425891

99. Peters DPC, Havstad KM, Cushing J, Tweedie C, Fuentes O, Villanueva-Rosales N (2014) Harnessing the power of big data: infusing the scientific method with machine learning to transform ecology. *Ecosphere*, 5(6):art67. https://doi.org/10.1890/ES13-00359.1

100. Isaac NJB, Jarzyna MA, Keil P, Dambly LI, Boersch-Supan PH, Browning E, Freeman SN, Golding N, Guillera-Arroita G, Henrys PA, Jarvis S, Lahoz-Monfort J, Pagel J, Pescott OL, Schmucki R, Simmonds EG, O’Hara RB (2020) Data Integration for Large-Scale Models of Species Distributions. *Trends in Ecology & Evolution*, 35(1):56–67. https://doi.org/10.1016/j.tree.2019.08.006

101. Parr A (2010) Monitoring of Odonata in Britain and possible insights into climate change. *BioRisk*, 5:127.

102. Araújo MB, Luoto M (2007) The importance of biotic interactions for modelling species distributions under climate change. *Global Ecology and Biogeography*, 16(6):743–753.

103. Rosner-Katz H, McCune JL, Bennett JR (2020) Using stacked SDMs with accuracy and rarity weighting to optimize surveys for rare plant species. *Biodiversity and Conservation*, https://doi.org/10.1007/s10531-020-02018-1

104. Sutherland WJ, Freckleton RP, Godfray HCJ, Beissinger SR, Benton T, Cameron DD, Carmel Y, Coomes DA, Coulson T, Emmerson MC, Hails RS, Hays GC, Hodgson DJ, Hutchings MJ, Johnson D, Jones JPG, Keeling MJ, Kokko H, Kunin WE, Lambin X, Lewis OT, Malhi Y, Mieszkowska N, Milner-Gulland EJ, Norris K, Phillimore AB, Purves DW, Reid JM, Reuman DC, Thompson K, Travis JMJ, Turnbull LA, Wardle DA, Wiegand T (2013) Identification of 100 fundamental ecological questions. *Journal of Ecology*, 101(1):58–67. https://doi.org/10.1111/1365-2745.12025

105. Turchin P (2003) Complex population dynamics: a theoretical/empirical synthesis. 35

106. Boldina I, Beninger PG (2016) Strengthening statistical usage in marine ecology: Linear regression. *Journal of Experimental Marine Biology and Ecology*, 474:81–91. https://doi.org/10.1016/j.jembe.2015.09.010

107. White ER, Bahlai CA (2020) Experimenting with the past to improve environmental monitoring programs. *Frontiers in Ecology and Evolution*, https://doi.org/10.3389/fevo.2020.572979

108. Wauchope HS, Amano T, Sutherland WJ, Johnston A (2019) When can we trust population trends? A method for quantifying the effects of sampling interval and duration. *Methods in Ecology and Evolution*, 10(12):2067–2078. https://doi.org/10.1111/2041-210X.13302

109. Rueda-Cediel P, Anderson KE, Regan TJ, Franklin J, Regan HM (2015) Combined Influences of Model Choice, Data Quality, and Data Quantity When Estimating Population Trends. *PLOS ONE*, 10(7):e0132255. https://doi.org/10.1371/journal.pone.0132255

110. Yoccoz NG (1991) Use, Overuse, and Misuse of Significance Tests in Evolutionary Biology and Ecology. *Bulletin of the Ecological Society of America*, 72(2):106–111.

111. Nakagawa S, Cuthill I (2007) Effect size, confidence interval and statistical significance: a practical guide for biologists. *Biological Reviews*, 82:591–605.

112. Cusser S, Bahlai C, Swinton SM, Robertson GP, Haddad NM (2020) Long-term research avoids spurious and misleading trends in sustainability attributes of no-till. *Global Change Biology*, 26(6):3715–3725. https://doi.org/10.1111/gcb.15080

113. Wepprich T, Adrion JR, Ries L, Wiedmann J, Haddad NM (2019) Butterfly abundance declines over 20 years of systematic monitoring in Ohio, USA. *PLOS ONE*, 14(7):e0216270. https://doi.org/10.1371/journal.pone.0216270

114. Grames E, Montgomery G, Haddaway N, Dicks L, Elphick C, Matson T, Nakagawa S, Saunders M, Tingley M, White T, Woodcock P, Wagner D (2019) Trends in global insect abundance and biodiversity: A community-driven systematic map protocol. https://doi.org/10.17605/OSF.IO/Q63UY

115. Andersen T, Carstensen J, Hernández-García E, Duarte CM (2009) Ecological thresholds and regime shifts: approaches to identification. *Trends in Ecology & Evolution*, 24(1):49–57. https://doi.org/10.1016/j.tree.2008.07.014

116. Bestelmeyer BT, Ellison AM, Fraser WR, Gorman KB, Holbrook SJ, Laney CM, Ohman MD, Peters DPC, Pillsbury FC, Rassweiler A, Schmitt RJ, Sharma S (2011) Analysis of abrupt transitions in ecological systems. *Ecosphere*, 2(12):art129. https://doi.org/10.1890/es11-00216.1

117. Ducré-Robitaille J-F, Vincent LA, Boulet G (2003) Comparison of techniques for detection of discontinuities in temperature series: DETECTING DISCONTINUITIES IN TEMPERATURE SERIES. *International Journal of Climatology*, 23(9):1087–1101. https://doi.org/10.1002/joc.924

118. Rodionov SN (2004) A sequential algorithm for testing climate regime shifts: ALGORITHM FOR TESTING REGIME SHIFTS. *Geophysical Research Letters*, 31(9):n/a-n/a. https://doi.org/10.1029/2004GL019448

119. Beaugrand G, Conversi A, Chiba S, Edwards M, Fonda-Umani S, Greene C, Mantua N, Otto SA, Reid PC, Stachura MM, Stemmann L, Sugisaki H (2015) Synchronous marine pelagic regime shifts in the Northern Hemisphere. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 370(1659):20130272. https://doi.org/10.1098/rstb.2013.0272

120. Zampolli F (2006) Optimal monetary policy in a regime-switching economy: The response to abrupt shifts in exchange rate dynamics. *Computing in economics and finance*, 30(9):1527–1567. https://doi.org/10.1016/j.jedc.2005.10.013

121. Holling CS (2001) Understanding the Complexity of Economic, Ecological, and Social Systems. *Ecosystems*, 4(5):390–405. https://doi.org/10.1007/s10021-001-0101-5

122. Bjørnstad ON, Grenfell BT (2001) Noisy Clockwork: Time Series Analysis of Population Fluctuations in Animals. *Science*, 293(5530):638. https://doi.org/10.1126/science.1062226

123. Hare SR, Mantua NJ (2000) Empirical evidence for North Pacific regime shifts in 1977 and 1989. *Progress in Oceanography*, 47(2):103–145. https://doi.org/10.1016/S0079-6611(00)00033-1

124. Carpenter SR, Brock WA, Cole JJ, Kitchell JF, Pace ML (2008) Leading indicators of trophic cascades. *Ecology Letters*, 11(2):128–138. https://doi.org/10.1111/j.1461-0248.2007.01131.x

125. Weimerskirch H, Inchausti P, Guinet C, Barbraud C (2003) Trends in bird and seal populations as indicators of a system shift in the Southern Ocean. *Antarctic Science*, 15(2):249–256.

126. Berryman A, Lima M (2006) Deciphering the effects of climate on animal populations: diagnostic analysis provides new interpretation of Soay sheep dynamics. *The American Naturalist*, 168(6):784–795.

127. Toms JD, Lesperance ML (2003) Piecewise regression: a tool for identifying ecological thresholds. *Ecology*, 84(8):2034–2041. https://doi.org/10.1890/02-0472

128. Gadrich T, Katriel G (2016) A Mechanistic Stochastic Ricker Model: Analytical and Numerical Investigations. *International Journal of Bifurcation and Chaos*, 26(04):1650067. https://doi.org/10.1142/S021812741650067X

129. Pleasants JM, Oberhauser KS (2013) Milkweed loss in agricultural fields because of herbicide use: effect on the monarch butterfly population. *Insect Conservation and Diversity*, 6(2):135–144. https://doi.org/10.1111/j.1752-4598.2012.00196.x

130. Pedersen EJ, Thompson PL, Ball RA, Fortin M-J, Gouhier TC, Link H, Moritz C, Nenzen H, Stanley RR, Taranu ZE (2017) Signatures of the collapse and incipient recovery of an overexploited marine ecosystem. *Royal Society open science*, 4(7):170215.

131. Beck KK, Fletcher M-S, Gadd PS, Heijnis H, Saunders KM, Simpson GL, Zawadzki A (2018) Variance and rate-of-change as early warning signals for a critical transition in an aquatic ecosystem state: a test case from Tasmania, Australia. *Journal of Geophysical Research: Biogeosciences*, 123(2):495–508.

132. Roberts CP, Twidwell D, Burnett JL, Donovan VM, Wonkka CL, Bielski CL, Garmestani AS, Angeler DG, Eason T, Allred BW (2018) Early warnings for state transitions. *Rangeland ecology & management*, 71(6):659–670.

133. Benito X, Feitl MG, Fritz SC, Mosquera PV, Schneider T, Hampel H, Quevedo L, Steinitz-Kannan M (2019) Identifying temporal and spatial patterns of diatom community change in the tropical Andes over the last *c* . 150 years. *Journal of Biogeography*, 46(8):1889–1900. https://doi.org/10.1111/jbi.13561

134. Burnett JL (2019) Regime Detection Measures for the Practical Ecologist.

135. Hunter P (2005) Laptop biology. *EMBO reports*, 6(3):208–210. https://doi.org/10.1038/sj.embor.7400358

136. Hardin J, Hoerl R, Horton NJ, Nolan D, Baumer B, Hall-Holt O, Murrell P, Peng R, Roback P, Temple Lang D, Ward MD (2015) Data Science in Statistics Curricula: Preparing Students to “Think with Data.” *The American Statistician*, 69(4):343–353. https://doi.org/10.1080/00031305.2015.1077729

137. Salkind NJ, Frey BB (2019) Statistics for people who (think they) hate statistics.

138. Wachsmuth LP, Runyon CR, Drake JM, Dolan EL (2017) Do Biology Students Really Hate Math? Empirical Insights into Undergraduate Life Science Majors’ Emotions about Mathematics. *CBE—Life Sciences Education*, 16(3):ar49. https://doi.org/10.1187/cbe.16-08-0248

139. Walkington C, Bernacki ML (2014) Motivating students by “personalizing” learning around individual interests: A consideration of theory, design, and implementation issues. *Motivational interventions*,

140. Neumann DL, Hood M, Neumann MM (2013) Using real-life data when teaching statistics: student perceptions of this strategy in an introductory statistics course. *Statistics Education Research Journal*, 12(2)

141. Cilli-Turner E (2015) Measuring Learning Outcomes and Attitudes in a Flipped Introductory Statistics Course. *PRIMUS*, 25(9–10):833–846. https://doi.org/10.1080/10511970.2015.1046004

142. Brown NCC, Wilson G (2018) Ten quick tips for teaching programming. *PLOS Computational Biology*, 14(4):e1006023. https://doi.org/10.1371/journal.pcbi.1006023

143. Mascaró M, Sacristán AI, Rufino MM (2016) For the love of statistics: appreciating and learning to apply experimental analysis and statistics through computer programming activities 1. *Teaching Mathematics and its Applications: An International Journal of the IMA*, 35(2):74–87. https://doi.org/10.1093/teamat/hrw006

144. Carnell LJ (2008) The Effect of a Student-Designed Data Collection Project on Attitudes Toward Statistics. *Journal of Statistics Education*, 16(1):null-null. https://doi.org/10.1080/10691898.2008.11889551

145. Gelman A (2017) The Failure of Null Hypothesis Significance Testing When Studying Incremental Changes, and What to Do About It. *Personality and Social Psychology Bulletin*, 44(1):16–23. https://doi.org/10.1177/0146167217729162

146. McShane BB, Gal D (2017) Statistical Significance and the Dichotomization of Evidence. *Journal of the American Statistical Association*, 112(519):885–895. https://doi.org/10.1080/01621459.2017.1289846

147. Amrhein V, Greenland S (2018) Remove, rather than redefine, statistical significance. *Nature Human Behaviour*, 2(1):4–4. https://doi.org/10.1038/s41562-017-0224-0

148. Hampton SE, Anderson SS, Bagby SC, Gries C, Han X, Hart EM, Jones MB, Lenhardt WC, MacDonald A, Michener WK, Mudge J, Pourmokhtarian A, Schildhauer MP, Woo KH, Zimmerman N (2015) The Tao of open science for ecology. *Ecosphere*, 6(7):art120. https://doi.org/10.1890/es14-00402.1

149. Stachelek J, Ford C, Kincaid D, King K, Miller H, Nagelkirk R (2018) The National Eutrophication Survey: lake characteristics and historical nutrient concentrations. *Earth System Science Data*, 10(1)

150. Wei CA, Woodin T (2011) Undergraduate Research Experiences in Biology: Alternatives to the Apprenticeship Model. *CBE—Life Sciences Education*, 10(2):123–131. https://doi.org/10.1187/cbe.11-03-0028

151. National Research Council (2009) A new biology for the 21st century.

152. Goldman J (2019) Data Science Training for the Future: Building a Carpentries Consortium. https://doi.org/10.13028/Q2BX-Q484

153. Michonneau F, Paul D (2019) Scaling Up Data Literacy and Computing Skills Training in Biodiversity Science, Lessons Learned from The Carpentries. *Biodiversity Information Science and Standards*, 3https://doi.org/10.3897/biss.3.35108

154. Hoffman K, Leupen S, Dowell K, Kephart K, Leips J (2016) Development and Assessment of Modules to Integrate Quantitative Skills in Introductory Biology Courses. *CBE—Life Sciences Education*, 15(2):ar14. https://doi.org/10.1187/cbe.15-09-0186

155. Catto RA, Jones S, Kaden T, Elsdon-Baker F (2019) Diversification and internationalization in the sociological study of science and religion. *Sociology Compass*, 13(8):e12721. https://doi.org/10.1111/soc4.12721

156. De Witt A, Osseweijer P, Pierce R (2015) Understanding public perceptions of biotechnology through the "Integrative Worldview Framework." *Public Understanding of Science*, 26(1):70–88. https://doi.org/10.1177/0963662515592364

157. Ho SS, Leong AD, Looi J, Chen L, Pang N, Tandoc E (2019) Science Literacy or Value Predisposition? A Meta-Analysis of Factors Predicting Public Perceptions of Benefits, Risks, and Acceptance of Nuclear Energy. *Environmental Communication*, 13(4):457–471. https://doi.org/10.1080/17524032.2017.1394891

158. Clark D, Nagler RH, Niederdeppe J (2019) Confusion and nutritional backlash from news media exposure to contradictory information about carbohydrates and dietary fats. *Public Health Nutrition*, 22(18):3336–3348. https://doi.org/10.1017/S1368980019002866

159. Asplund T (2018) Communicating Climate Science: A Matter of Credibility—Swedish Farmers' Perceptions of Climate-Change Information. *The International Journal of Climate Change: Impacts and Responses*, 10(1):23–38. https://doi.org/10.18848/1835-7156/CGP/v10i01/23-38

160. Makar K, Rubin A (2009) A framework for thinking about informal statistical inference. *Statistics Education Research Journal*, 8(1)

161. Jones SH, Elsdon-Baker F, Catto R, Kaden T (2020) What science means to me: Understanding personal identification with (evolutionary) science using the sociology of (non)religion. *Public Understanding of Science*, :0963662520923110. https://doi.org/10.1177/0963662520923110

162. Bell RL, Mulvey BK, Maeng JL (2012) Beyond Understanding: Process Skills as a Context for Nature of Science Instruction. *Advances in Nature of Science Research*, :225–245. https://doi.org/10.1007/978-94-007-2457-0_11

163. Wheeler LB, Mulvey BK, Maeng JL, Librea-Carden MR, Bell RL (2019) Teaching the teacher: exploring STEM graduate students' nature of science conceptions in a teaching methods course. *International Journal of Science Education*, 41(14):1905–1925. https://doi.org/10.1080/09500693.2019.1647473

164. Holt EA, Ogden TH, Durham SL (2018) The positive effect of role models in evolution instruction. *Evolution: Education and Outreach*, 11(1):11. https://doi.org/10.1186/s12052-018-0086-6

165. Goff EE, Mulvey KL, Irvin MJ, Hartstone-Rose A (2019) The effects of prior informal science and math experiences on undergraduate STEM identity. *Research in Science & Technological Education*, :1–17. https://doi.org/10.1080/02635143.2019.1627307

166. Drew C (2017) Edutaining audio: an exploration of education podcast design possibilities. *Educational Media International*, 54(1):48–62. https://doi.org/10.1080/09523987.2017.1324360

167. Chin A, Helman A, Chan TM (2017) Podcast Use in Undergraduate Medical Education. *Cureus*, 9(12):e1930–e1930. https://doi.org/10.7759/cureus.1930

168. Swiatek L (2018) The Podcast as an Intimate Bridging Medium. *Podcasting: New Aural Cultures and Digital Media*, :173–187. https://doi.org/10.1007/978-3-319-90056-8_9

169. Goring SJ, Whitney KS, Jacob AL (2018) Accessibility is imperative for inclusion. *Frontiers in Ecology and the Environment*, 16(2):63–63. https://doi.org/10.1002/fee.1771

170. Miriti MN, Bailey K, Halsey SJ, Harris NC (2020) Hidden figures in ecology and evolution. *Nature Ecology & Evolution*, https://doi.org/10.1038/s41559-020-1270-y

171. Bahlai C (2019) cbahlai/bad_breakup: The bad breakup Algorithm. https://doi.org/10.5281/zenodo.2561051