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Education

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A modular curriculum to teach undergraduates ecological forecasting improves student and instructor confidence in their data science skills

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Abstract

Data science skills (e.g., analyzing, modeling, and visualizing large data sets) are increasingly needed by undergraduates in the life sciences. However, a lack of both student and instructor confidence in data science skills presents a barrier to their inclusion in undergraduate curricula. To reduce this barrier, we developed four teaching modules in the Macrosystems EDDIE (for *environmental data-driven inquiry and exploration*) program to introduce undergraduate students and instructors to ecological forecasting, an emerging subdiscipline that integrates multiple data science skills. Ecological forecasting aims to improve natural resource management by providing future predictions of ecosystems with uncertainty. We assessed module efficacy with 596 students and 26 instructors over 3 years and found that module completion increased students' confidence in their understanding of ecological forecasting and instructors' likelihood to work with long-term, high-frequency sensor network data. Our modules constitute one of the first formalized data science curricula on ecological forecasting for undergraduates.

Keywords: ecosystem modeling, National Ecological Observatory Network (NEON), student engagement, training program, undergraduate education

Data science skills, such as visualizing, analyzing, and modeling large data sets, are increasingly needed by undergraduate students across biological subdisciplines (Barone et al. 2017), ranging from ecology and environmental science (Farrell and Carey 2018, Auker and Barthelmess 2020, Feng et al. 2020, Cooke et al. 2021) to evolutionary biology (Muñoz and Price 2019) and neuroscience (Goldman and Fee 2017, Juavinett 2022). For example, recent advancements in environmental monitoring technology (e.g., Mcloughlin et al. 2019, Nathan et al. 2022, Dauphin et al. 2023) and the rise of environmental observatory networks (Keller et al. 2008, Weathers et al. 2013, Cleverly et al. 2019) have resulted in a deluge of big data in ecology (Hampton et al. 2013, LaDeau et al. 2017, Farley et al. 2018). Technological breakthroughs, such as the widespread digitization of biological museum collections (Muñoz and Price 2019) and the ability to record the activity of thousands of neurons simultaneously (Goldman and Fee 2017), have similarly resulted in accumulation of big data in other biological subdisciplines. As a result, analysis of large data sets is now emphasized across a variety of life science careers, necessitating new approaches to training researchers, instructors, and students in data science skills (Hampton et al. 2017, National Academies of Sciences, Engineering, and Medicine 2018, Wilson Sayres et al. 2018, Feng et al. 2020, Emery et al. 2021).

Currently, a lack of both student and instructor familiarity with data science concepts, methods, and tools presents a major barrier to incorporation of data science into undergraduate life science curricula (Williams et al. 2019, Emery et al. 2021, Naithani et al. 2022, Cuddington et al. 2023). This gap often exists because instructors themselves have not received training in data science skills (Williams et al. 2019, Emery et al. 2021), and students do not have the requisite background skills and confidence to effectively engage in data science training (Williams et al. 2019, Cuddington et al. 2023). In some cases, students may lack requisite skills due to an opportunity gap, in which students from underrepresented backgrounds have not had the same opportunities to learn quantitative skills as their classmates (Shukla et al. 2022). Consequently, the development of educational materials approachable to both instructors and students is needed to lower the barrier to data science education in ecology and environmental science and help reduce losses of underrepresented groups in STEM (science, technology, engineering, and mathematics; Seymore and Hunter 2019).

Ecological forecasting is an ideal topic for engaging instructors and students in data science training (Willson et al. 2023). First, ecological forecasting has the potential to guide environmental management decisions (Johnson et al. 2018, Liu et al. 2020, Bodner et al. 2021, Heilman et al. 2022), thereby engaging students in real-world problem-solving. Ecological forecasts, which provide predictions of the future state of ecosystems with uncertainty (Luo et al. 2011, Petchey et al. 2015), are critically needed to help manage natural resources increasingly threatened by climate and land-use change (Bradford et al. 2020). Examples of

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societally important forecasts exist for many ecological systems, including river temperature forecasts to guide reservoir water release decisions and protect fish species (Ouellet-Proulx et al. 2017), temperature-based spring onset forecasts to inform agricultural decision-making (Carrillo et al. 2018), and forecasts of endangered ocean species to avoid bycatch (Hazen et al. 2018).

Second, generating ecological forecasts requires students to step through the scientific method (Moore et al. 2022, Lewis et al. 2023), providing critical skills in developing and testing hypotheses, which are transferable across scientific disciplines. In the iterative forecast cycle, similar to the scientific method, researchers develop hypotheses about how ecosystems function, instantiate hypotheses into a predictive model, use the model to generate forecasts into the future, evaluate forecasts with observations once the future arrives and new data are available, and use evaluation results to iteratively update and improve hypotheses, models, and predictions (Dietze et al. 2018).

Third, ecological forecasting problems are particularly well suited for actively engaging students in learning, because they explore relevant, real-world challenges (Taylor and Parsons 2011). Student engagement has been shown to enhance student outcomes (Carini et al. 2006), especially for underrepresented groups (Theobald et al. 2020). Key strategies to engage students that can be easily embedded within ecological forecasting curricula include authentic assessments that engage students in solving problems similar to what they will encounter in their future careers (Villarroel et al. 2018), scaffolding to help students progressively build more complex skills and solve problems (Belland 2014), and formative assessments that provide students with specific, actionable guidance on their progress, with opportunities to apply that guidance moving forward (Wiliam 2011).

To effectively use ecological forecasting as a platform for teaching data science in undergraduate classrooms, instructors must have both pedagogical knowledge of student engagement strategies and disciplinary knowledge of data science and ecological forecasting (Auerbach and Andrews 2018, Andrews et al. 2019). However, research has demonstrated substantial gaps in instructor knowledge in both effective engagement of students (Auerbach and Andrews 2018, Andrews et al. 2019) and data science (Williams et al. 2019, Emery et al. 2021). Given that ecological forecasting is an emerging field (Lewis et al. 2022) and that educational resources in ecological forecasting remain rare (Willson et al. 2023), it is unlikely that many instructors have training in this area.

To address gaps in instructor knowledge in the life sciences, multiple models of instructor professional development have been trialed, including short, intensive trainings for teaching assistants (Hughes and Ellefson 2013, Schussler et al. 2015); department-wide training programs for faculty (Owens et al. 2018); and multiyear, multiinstitutional programs for postdoctoral researchers (Ebert-May et al. 2011, D'Avanzo et al. 2012, Derting et al. 2016). Outcomes of these professional development activities frequently rely solely on instructor feedback (Ebert-May et al. 2011). However, instructor and student perceptions of the effectiveness of teaching practices in the classroom can differ from each other (Heim and Holt 2018). Consequently, the effectiveness of instructor professional development should be evaluated using multiple methods (e.g., reflection and feedback, observing teaching practices, student assessments; Ebert-May et al. 2011, Heim and Holt 2018) and incorporate input from both students and faculty. Moreover, because a lack of time is often cited as a barrier to instructor professional development (Williams et al. 2019), instructional materials should include short, accessible definitions and examples of key concepts to provide just in time (*sensu* Novak et al. 1999) pedagogical, data science, and ecological forecasting training for instructors as well as students.

To lower the barrier of entry to data science for both undergraduate students and instructors in ecology and environmental science, we developed and assessed a modular curriculum within the Macrosystems EDDIE (for *environmental data-driven inquiry and exploration*) program (Carey et al. 2020, Hounshell et al. 2021, Moore et al. 2022, Woelmer et al. 2023a), which uses student engagement techniques to teach data science skills in the context of ecological forecasting. Although previous educational materials on ecological forecasting have been developed for advanced students, primarily at the graduate level (e.g., Dietze 2017a, Ernest et al. 2023), our curriculum is one of the first that is specifically targeted at undergraduates (Willson et al. 2023). In addition, all materials are designed to be approachable to both instructors and students, because coding experience is not a necessary prerequisite and each module is accompanied by substantial introductory and supporting materials for instructors. Moreover, students work with data from the US National Ecological Observatory Network (NEON) to address relevant societal challenges such as predicting freshwater quality impairment.

In the present article, we present an overview of the Macrosystems EDDIE ecological forecasting curriculum and examples of how it has been implemented in various course contexts. We also analyze student and instructor assessment data to address the following questions: (Q1) How does student confidence and understanding of data science and ecological forecasting skills change after completion of Macrosystems EDDIE ecological forecasting modules? and (Q2) What are instructor perceptions of module ease of use and efficacy in teaching data science and ecological forecasting concepts? We were specifically focused on student confidence and instructor perceptions, because previous work has shown that two major barriers to integrating data science activities into existing curricula are a lack of student confidence (Williams et al. 2019, Cuddington et al. 2023) and a lack of instructor training (Williams et al. 2019, Emery et al. 2021).

Overview of the Macrosystems EDDIE curriculum

The Macrosystems EDDIE ecological forecasting curriculum for undergraduates includes four stand-alone modules: Introduction to Ecological Forecasting, Understanding Uncertainty in Ecological Forecasts, Using Data to Improve Ecological Forecasts, and Using Ecological Forecasts to Guide Decision-Making (figure 1). Like all EDDIE modules, Macrosystems EDDIE ecological forecasting modules are designed using the 5E (engagement, exploration, explanation, expansion, evaluation) instructional model (Bybee et al. 2006), which is implemented through a scaffolded A–B–C structure (O'Connell et al. 2024). In all modules, activity A engages the students and asks them to explore the module's focal topic, activity B further explains and asks students to expand on that topic, and activity C evaluates students' understanding of the topic (Carey et al. 2015, O'Reilly et al. 2017). The three-part scaffolded structure also maximizes the adaptability of Macrosystems EDDIE modules to various classroom contexts, because the instructors can choose whether to complete just activity A, activities A and B, or all three activities in 1–3-hour course periods. Each module can be taught individually, or instructors may choose to implement multiple modules throughout their curriculum; example use cases are detailed in the "Course implementation" section below.

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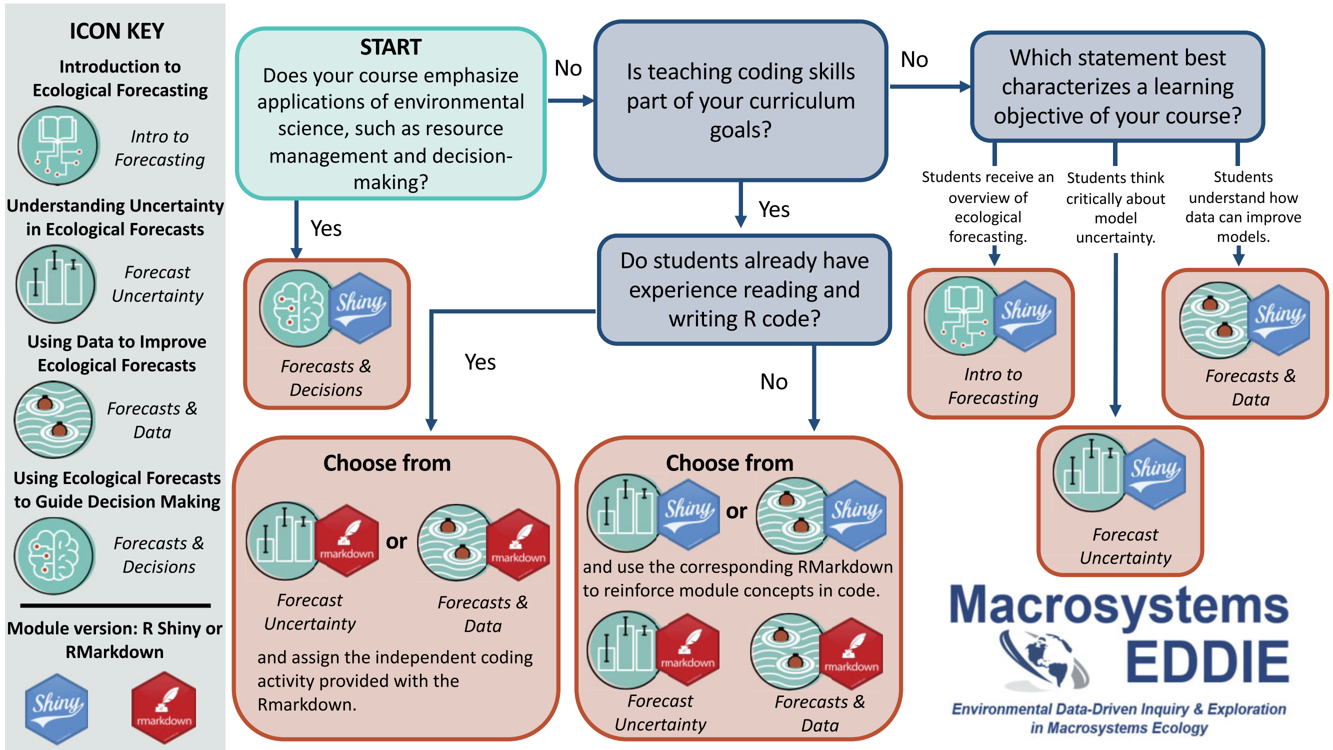

Figure 1. Conceptual diagram of Macrosystems EDDIE ecological forecasting curriculum content and workflow to guide instructors on potential ways the modules could be implemented into their courses, depending on learning objectives and student experience level.

The modules in the Macrosystems EDDIE ecological forecasting curriculum are designed to both introduce ecological forecasting concepts and develop data science skills (figure 1). To accomplish the first goal, each module covers a foundational concept in ecological forecasting, and students then apply the forecasting concept to a NEON lake site of their choice. To develop data science skills, students use environmental data collected by NEON (Keller et al. 2008, Goodman et al. 2015) as the basis for their forecasting analyses. Working with NEON data sets requires students to evaluate the quality of the data (e.g., gaps, outliers, biases) and to confront how inherent variability and error in environmental data sets may affect their analyses. In addition, each module asks the students to interpret data visualized using various methods, ranging from time series and scatterplots to probabilistic forecasts and histograms. Finally, each module is focused on one or more foundational quantitative skills in ecological forecasting, including building and calibrating ecological models, generating forecasts, quantifying the uncertainty associated with predictions, using new observations to update forecast models, and designing forecast visualizations to effectively communicate forecast output. To enable students without prior exposure to formal instruction on quantitative reasoning skills to complete the module, no previous knowledge of the data science and ecological forecasting concepts in the module are needed; all instruction is provided within the module itself.

The Macrosystems EDDIE modules include a comprehensive set of instruction materials and are suitable for implementation in a variety of class contexts (figure 1). All of the modules are delivered through an R Shiny interface, where R code is used to render a website that students can access in their Internet browser (Chang et al. 2023). This permits a user-friendly, point-and-click interface for introductory students and aims to lower the intimidation barrier to ecological forecasting, because students do not need to have any coding skills to generate a forecast. For classrooms where gaining R coding skills is a learning objective, two of the modules (Understanding Uncertainty in Ecological Forecasts and Using Data to Improve Ecological Forecasts) have RMarkdown activities in addition to R Shiny materials. The RMarkdown activities enable students to access and modify the code underlying the R Shiny app and complete module activities in the R programming environment (Xie et al. 2018).

All of the Macrosystems EDDIE ecological forecasting materials are designed to provide instructors with just in time training (*sensu* Novak et al. 1999) on data science skills as they prepare to teach the modules in their classrooms. In addition to the R Shiny application (and RMarkdown file if applicable), each module includes an introductory (approximately 30 minute) Microsoft PowerPoint presentation with slide notes; a Microsoft Word student handout with preclass readings, activities, and questions associated with the module; a comprehensive instructor manual with learning objectives; detailed guidelines for module implementation and answer keys; and a quick start guide to the R Shiny applications. Notably, instructor manuals include strategies for teaching and recommendations for implementing the modules across a variety of course schedules (e.g., three 1-hour class sessions versus one 3-hour lab period) and modalities (e.g., virtual, face-to-face, hybrid).

All of the module teaching materials are licensed under the CC BY-NC-SA 3.0 license, allowing modification for classroom use, and are published in the Environmental Data Initiative repository (Moore et al. 2023a, Woelmer et al. 2023b, 2024b, Lofton et al. 2024c), and all module code is published in the Zenodo repository (Woelmer et al. 2022, Moore et al. 2023b, 2023c, Lofton et al. 2024a, 2024a, 2024b). In addition, all module code is maintained and updated at the Macrosystems EDDIE GitHub organization (https://github.com/MacrosystemsEDDIE). We encourage and

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welcome instructors and students to adapt and modify these materials for their classrooms, projects, and research.

Module descriptions

Below we provide brief descriptions of each of the four modules within the Macrosystems EDDIE ecological forecasting curriculum.

Introduction to ecological forecasting (intro to forecasting)

This module provides an overview of the ecological forecasting cycle, which includes the following steps: create a hypothesis, build a model, quantify model uncertainty, generate a forecast, communicate the forecast, assess the forecast, and update the model as new data become available (Dietze et al. 2018). The students complete each step in the cycle as they generate water quality forecasts for various NEON lake sites. See http://module5.macrosystemseddie.org for a detailed description of the module; module code and instructor materials are also published with DOIs in Moore and colleagues (2022a, 2022b, respectively).

Understanding uncertainty in ecological forecasts (forecasts and uncertainty)

This module introduces concepts and methods for quantifying forecast uncertainty, which entails identifying the range of possible future model outcomes (Dietze 2017b). The students build simple linear models to forecast water temperature at a NEON lake site of their choice and calculate the uncertainty associated with the forecasts. See http://module6.macrosystemseddie.org for a detailed description of the module; module code for the R Shiny application and RMarkdown, as well as instructor materials, are also published with DOIs in Moore and colleagues (2023b, 2023c, 2023a, respectively).

Using data to improve ecological forecasts (forecasts and data)

This module introduces concepts and methods for data assimilation, or the process of updating forecast models to incorporate new data as they become available (Niu et al. 2014). Students fit an autoregressive time series model to predict chlorophyll-a at a NEON lake site of their choice and examine the effect of updating the initial (starting) conditions of the model with chlorophyll-a data at different temporal frequencies (e.g., updating the model once a week versus once a day) and with low versus high observation uncertainty. See http://module7.macrosystemseddie.org for a detailed description of all module materials; module code for the R Shiny application and RMarkdown and instructor materials are also published with DOIs in Lofton and colleagues (2024a, 2024b, and 2024c, respectively).

Using ecological forecasts to guide decision-making (forecasts and decisions)

This module explores how different methods of visualizing and communicating forecasts can affect decision-making. Students are asked to critically evaluate, interpret, and design different ecological forecast visualizations for water quality management. See http://module8.macrosystemseddie.org for a detailed description of the module; module code and instructor materials are also published with DOIs in Woelmer and colleagues (2022, 2023b, respectively).

Course implementation

To date, Macrosystems EDDIE modules have been implemented and assessed in life science courses at a wide range of higher education institutions, ranging from small, primarily undergraduate institutions to large, research-focused universities (supplemental table S1; Carey et al. 2020, Hounshell et al. 2021). Notably, because all materials are publicly available, instructors can integrate modules into their curricula independently of module developers. Below, we provide three examples of courses in which Macrosystems EDDIE ecological forecasting modules have been implemented (following figure 1). These examples were selected to illustrate both the breadth of courses across which the modules have been applied, as well as the various ways in which instructors choose to adapt Macrosystems EDDIE ecological forecasting materials for their classes. Institutional designations are provided following the Carnegie Classification of Institutions of Higher Education (https://carnegieclassifications.acenet.edu).

Ecology: Forecasts and decisions in R Shiny

Ecology is a third-year lecture and laboratory undergraduate course of approximately 250 students at a public R1 state university. Key learning outcomes of the laboratory curriculum include communicating scientific knowledge in writing, designing and implementing ecological studies and data analyses, and conducting collaborative team science, with an emphasis on inquiry-based learning. The instructor taught Using Ecological Forecasts to Guide Decision-Making in the R Shiny interface to introduce students to the emerging field of ecological forecasting, as well as encourage them to consider connections between sociological and ecological systems, such as how communication of forecasts can affect resource management and therefore water quality. For this course, the module was taught across 11 lab sections of approximately 24 students each by a team of teaching assistants in a single, 3-hour laboratory period.

Freshman ecology and evolution seminar: Forecasts and uncertainty in R Shiny

Freshman Seminar: Ecology and Evolution is a first-year course designed for approximately 20 students to introduce them to the biology major at a public master's 2 state institution. Key learning outcomes of the course include explaining patterns of energy and matter flow through ecosystems, understanding ecological relationships among organisms and their environment, and explaining how humans interact with the environment via ecosystem functions and services. The instructor taught Understanding Uncertainty in Ecological Forecasts in R Shiny over three, 90-minute class periods to introduce students to ecological forecasting and explore contributions to uncertainty in models.

Environmental data science: Two modules in R Shiny and RMarkdown

Environmental Data Science is a third-year undergraduate course of approximately 20 students within the environmental data science major at a public R1 state university. Key skills developed in this course include advanced R coding, environmental data wrangling, visualization, and interpretation, and data-driven modeling. Students are expected to have basic to intermediate R coding skills on enrollment in the course. The instructor designed a 2-week unit (four 75-minute class periods) using Macrosystems EDDIE ecological forecasting materials. The dual goals of the unit were to introduce students to the emerg-

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ing field of ecological forecasting, as well as to better understand model uncertainty and how to calculate it. During the first week, students completed Introduction to Ecological Forecasting using the R Shiny app. During the second week, they completed Understanding Uncertainty in Ecological Forecasts using RMarkdown. This format permitted students to be introduced to a new concept (ecological forecasting) in a user-friendly interface (R Shiny) and then subsequently apply this new knowledge to a more in-depth task (uncertainty quantification) while reinforcing and developing coding skills (in RMarkdown).

Curriculum assessment methods

Independent assessment of the effectiveness of each Macrosystems EDDIE ecological forecasting module was administered by the Science Education Resource Center (SERC) at Carleton College. Through SERC's secure, online portal, we delivered pre- and post-treatment assessments of students who completed one or more modules and also collected instructor feedback after module completion. Each module's student assessment included Likert scale ranking and multiple choice questions that were consistent across all modules, as well as multiple choice and short answer questions that were specific to the individual module. Students who completed multiple modules, regardless of which modules they completed, were given the pre- and post-treatment assessments for the Introduction to Ecological Forecasting module to avoid survey fatigue. The instructor feedback surveys included Likert scale ranking questions about module ease of use and efficacy in meeting learning objectives, as well as multiple choice and short answer questions about the delivery of the module, how likely the instructor was to use high-frequency or long-term data and data from sensor networks after teaching a module and any other feedback the instructor wished to provide.

The modules were assessed from January 2021 through May 2023 in 32 courses across 22 institutions (table S1). Although our institutional review board protocol did not permit collection of demographic data for students who completed modules, we obtained demographic summaries of undergraduate enrollment by race and ethnicity in 2022 for participating institutions located in the United States (20 of 22 total institutions) as an approximate representation of the individual students who completed the modules (supplemental table S2). Most US institutions that participated in the module testing enrolled a majority (more than 50%) of White students in 2022 (15 of 20 institutions). Four module testing institutions were classified as minority serving by the US Department of Education using 2021–2022 enrollment data (US Department of Education 2024), with one institution classified as a Native American–serving nontribal institution and three institutions classified as Asian American and Native American Pacific Islander–serving institutions, with one of those also classified as a Hispanic-serving institution.

A total of 596 students completed one or more questions for both the pre- and the post-assessment and 26 instructors completed a feedback survey (previous instructor experience teaching the course and instructor career stage are reported in supplemental table S3). To evaluate student growth after completing a module, we compared the pre- and post-module responses with paired Wilcoxon signed rank tests. Due to widely varying numbers of students across experience levels and courses (table S1), we aggregated all of the students' responses together for statistical analysis. All module assessment and instructor survey questions, as well as details regarding the analysis of assessment responses, can be found in the supplemental material (supplemental text S1, supplemental tables S4–S9). All assessment was conducted following approved institutional review board protocols (Virginia Tech IRB 19–669 and Carleton College IRB 19–20 065). Anonymized, aggregated student assessment and instructor feedback data and code to reproduce figures and statistics are published in Lofton and colleagues (2024d).

Curriculum assessment results

Below, we present results for each of our research questions, obtained from analysis of student assessment data (Q1) and instructor feedback data (Q2).

Q1: How do student confidence and understanding of data science and ecological forecasting skills change after completion of Macrosystems EDDIE ecological forecasting modules?

Completing one or more Macrosystems EDDIE ecological forecasting modules improved student confidence in both their ecological forecasting and data science skills (figure 2a, supplemental figure S1). Students gained the most confidence from premodule to postmodule in their ecological forecasting skills, such as generating a forecast (with 76% of students reporting an increase in confidence), quantifying uncertainty (74%), and communicating a forecast (71%). Among data science skills, the largest percentage of students gained confidence in modeling data (65%), followed by analyzing (52%) and graphing data (43%). Of the students who did not exhibit a gain in confidence in their ecological forecasting and data science skills, most (71%–81%) reported no change in confidence rather than a decrease in confidence (figure 2a). Although uneven sample sizes across course levels (introductory undergraduate, upper level undergraduate, graduate) and small sample sizes for introductory undergraduate (n = 22) and graduate (n = 38) courses precluded a statistical comparison of student outcomes across course levels, our data indicate that undergraduate students may have been more likely to experience a change in confidence than were graduate students (supplemental figure S2).

Module completion similarly improved student understanding of ecological forecasting concepts, regardless of which module was completed (figure 2b). We observed a significant increase in students' ability to correctly define an ecological forecast after completing any one of the modules or multiple modules across course levels (figure 2b). We also observed increases among students within a course level (supplemental figure S3), although uneven sample sizes prevented statistical comparison across course levels. Across the modules, 31% of students could define an ecological forecast before module completion, whereas 76% of students could correctly complete this task after module completion. Students also improved in their ability to define and describe other ecological forecasting concepts, such as data assimilation and uncertainty propagation; however, gains in student understanding in these areas were uneven (supplemental figures S4 and S5).

Q2: What are instructor perceptions of module ease of use and efficacy in teaching data science and ecological forecasting concepts?

Instructors reported that modules were usable and effective in teaching data science skills and ecological forecasting (figure 3a). Importantly, this increase in skills translated into gains

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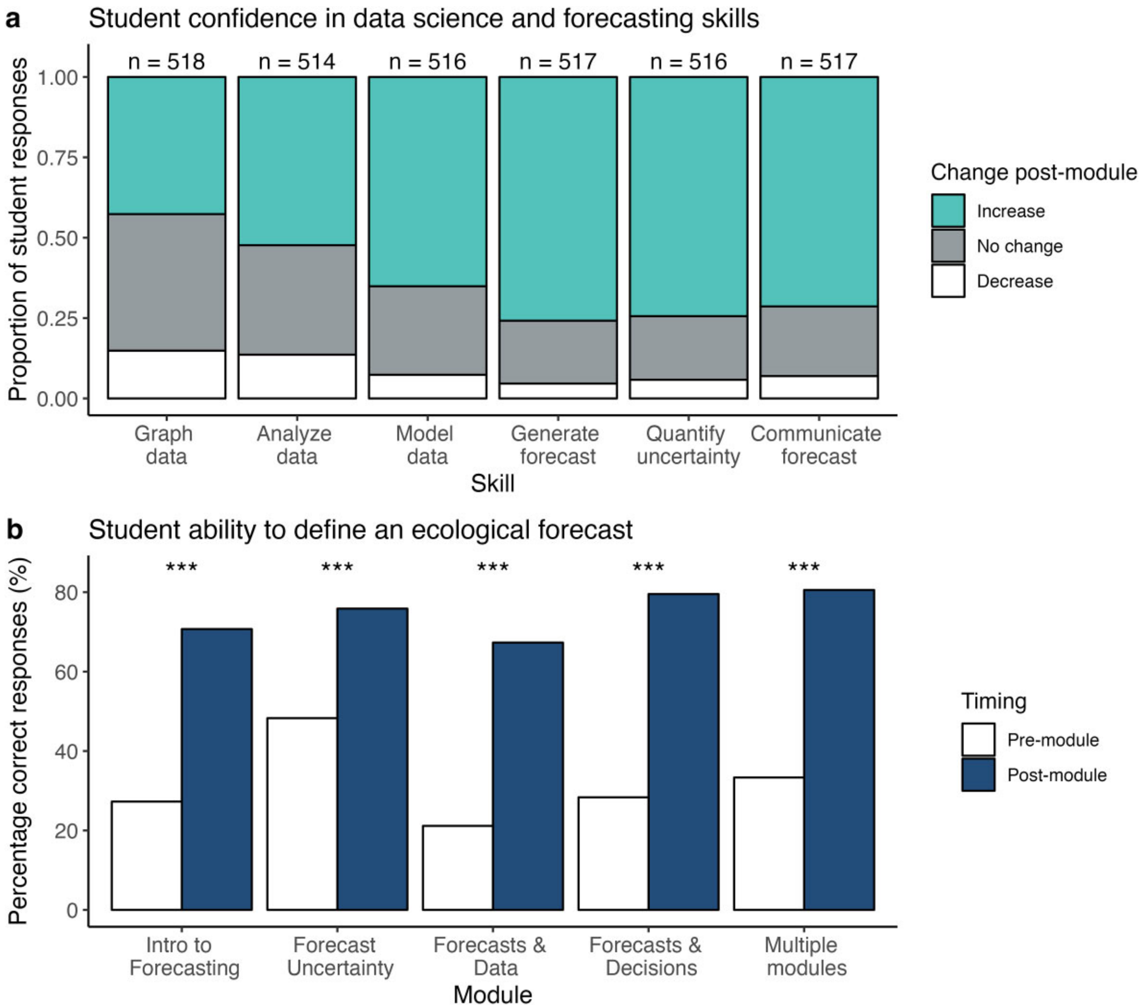

Figure 2. Effect of module completion on (a) student confidence in data science (graph data, analyze data, model data) and forecasting (generate forecast, quantify uncertainty, communicate forecast) skills and (b) knowledge of ecological forecasting. (a) Student confidence was assessed via Likert scores, where 1 was "not confident at all" and 5 was "extremely confident." Changes in student confidence were calculated by subtracting each student's premodule score from the postmodule score. The numbers above each bar indicate the number of student responses obtained for each assessment question. (b) The differences in students' ability to identify the definition of an ecological forecast before and after module completion were assessed via paired, two-sided Wilcoxon signed rank tests. *$p < .05$. **$p < .01$. ***$p < .001$.

outside of the classroom, because most of the instructors reported that they were more likely to use high-frequency, long-term data, as well as data from established ecological observatory sensor networks (e.g., NEON, GLEON) in their research after teaching a module (figure 3b). Instructor responses to module feedback surveys indicated that modules were "very effective" in teaching data science skills and modeling, and "very effective" to "extremely effective" in teaching ecological forecasting. In addition, instructors reported that the modules were "very easy" for students to use across both the R Shiny materials and other materials (e.g., instructor manual and introductory presentation) and were "very easy" to teach (figure 3a).

Most instructors reported that they would use the modules again (figure 3b). Seven of the 26 instructors who filled out the feedback survey were part-time teaching assistants who were not responsible for course curriculum design and teaching the class in future years (table S3), and the rest were faculty instructors of record for the course with the ability to make future decisions regarding course curriculum. Eleven instructors were early career, defined as being either a graduate student or within 8 years of having received their PhD. For a summary of instructor qualitative feedback on the modules, see supplemental text S2.

Implications of Macrosystems EDDIE curriculum assessment results for biological data science education

Through formal assessment of the Macrosystems EDDIE ecological forecasting curriculum for undergraduates, we found that the modules were successful in increasing student confidence and knowledge of ecological forecasting and data science (figure 2) and lowered the barrier of entry to these fields for instructors (figure 3). In an era when data science and ecological forecasting skills are increasingly needed to tackle pressing biological and environmental science problems (Hampton et al. 2017, National Academies of Sciences, Engineering, and Medicine 2018, Feng et al. 2020, Emery et al. 2021), the Macrosystems EDDIE curriculum provides one pathway to introducing these skills to both students and instructors.

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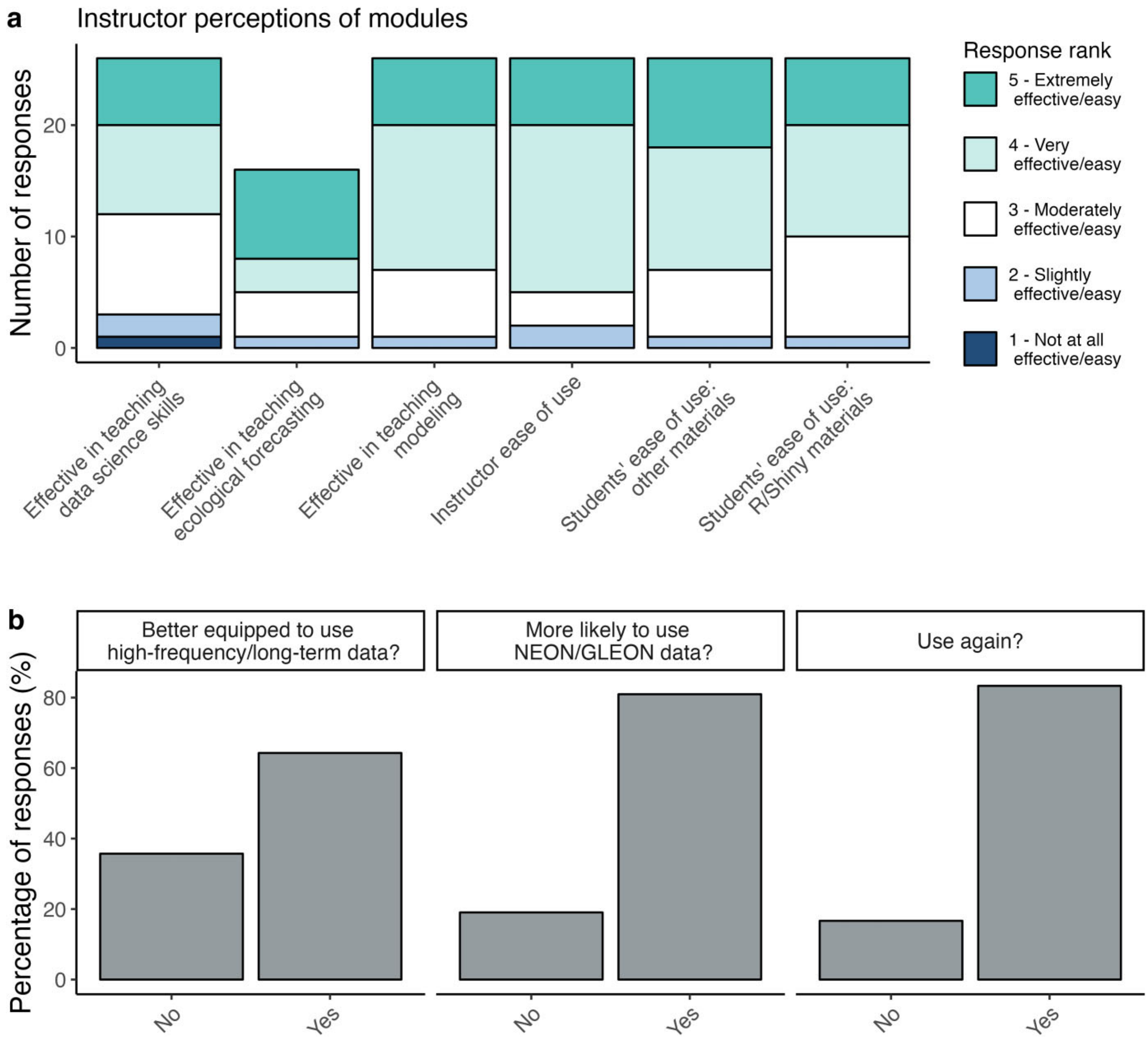

Figure 3. Instructor perceptions of module ease of use and efficacy in teaching data science and ecological forecasting skills (a) and the number of instructors who reported they would use the module again, were better equipped to use high-frequency or long-term data and were more likely to use sensor network data (b). (a) Abbreviations: NEON, National Ecological Observatory Network; GLEON, Global Lake Ecological Observatory Network.

Our results indicate that flexible, short, and easy-to-use modules increased student confidence in their data science and ecological forecasting skills. In particular, students showed the greatest gains in confidence in ecological forecasting skills (figure 2a), likely because they had lower initial confidence in their ecological forecasting skills (e.g., generating forecasts, for which the students reported a median premodule Likert score of 2, or "slightly confident"). In comparison, students' confidence in their data science skills was relatively higher prior to completing the module (e.g., graphing data, with a median premodule score of 4, or "very confident"; figure S1). The Dunning–Kruger effect (Kruger and Dunning 1999) may explain the few students that exhibited decreases in confidence (ranging from $n = 24$ students for the skill of generating a forecast to $n = 77$ students for the skill of graphing data), in which novice students overestimate their abilities and, as they progress, are much better able to estimate their abilities, which are less than they previously thought (figure S1). Ultimately, increased student confidence and knowledge of data science and forecasting are relevant beyond the life sciences, because workers with data science and predictive modeling skills are sought across multiple sectors (Stanton and Stanton 2019).

The modular design and student engagement strategies of the Macrosystems EDDIE curriculum follow inclusive teaching guidelines and may help reduce opportunity gaps for underrepresented students in STEM. Each module applies the key inclusive teaching practices of providing adequate course structure (*sensu* Freeman et al. 2011, Eddy and Hogan 2014) and differentiated instruction (*sensu* Hall et al. 2004). To facilitate structured learner–learner interactions that support equitable participation in learning (Eddy and Hogan 2014), the Macrosystems EDDIE module instructions specify that students work together in pairs or small groups, with well-defined group tasks and recommendations for the instructor

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about the timing of group check-ins and full-class discussions. In addition, the flexible A–B–C structure of the Macrosystems EDDIE modules encourages differentiated instruction among and within classrooms, so that students' diverse needs are acknowledged and the instructor can respond to new needs as they arise.

In particular, the Macrosystems EDDIE modules may help reduce the opportunity gap for underrepresented students in STEM (*sensu* Shukla et al. 2022) by providing "just in time" instruction (*sensu* Novak et al. 1999) on quantitative skills and encouraging place-based learning (*sensu* Semken and Freeman 2008). Macrosystems EDDIE modules stand alone and do not assume that the students have had prior instruction in quantitative methods such as fitting a linear regression or interpreting the output of an ecosystem model. All of the instruction needed to complete the module activities is provided within the module itself (as "just in time" instruction), decreasing the potential adverse effects of an opportunity gap among students. Moreover, the ability of students to choose a lake site within each module may facilitate place-based learning, in which students focus on local and regional environments as the context for their science learning (Semken and Freeman 2008). Place-based learning has been shown to enhance students' feeling of belonging and reduce equity gaps among underrepresented students in undergraduate STEM classrooms (Johnson et al. 2020).

Instructor feedback after teaching a module indicates that the Macrosystems EDDIE approach of "just in time" background skills training (*sensu* Novak et al. 1999) and robust instructional supporting material may be successful strategies for instructor professional development in data science. We received positive feedback regarding the effect of the Macrosystems EDDIE modules on both the growth of instructor pedagogical (e.g., active learning) and disciplinary (e.g., data science and ecological forecasting) knowledge (Auerbach and Andrews 2018, Andrews et al. 2019). Most instructors said that the Macrosystems EDDIE modules were easy to use and very to extremely effective in teaching ecological forecasting and data science concepts (figure 3).

The qualitative responses to our instructor survey indicated that the comprehensive instructional support materials associated with each module increased the ease of module use for both students and instructors (text S2). The comprehensive introduction to the structure, development, and interpretation of the forecasting models used in each module (e.g., reviewing the structure of a simple ecosystem primary productivity model in the Intro to Forecasting module) was helpful to both students and instructors. In addition, instructors reported that the accompanying instructor manual with detailed talking points for each slide in the introductory presentation and suggested timing for each activity within the module were helpful for classroom implementation. Moreover, most of the instructors reported that they were better equipped to use long-term and high-frequency data and more likely to use sensor network data after teaching a module (figure 3b), indicating that the modules build skills and data science familiarity with instructors as well as students. Finally, the relatively short duration (1–3 hours) and flexible A–B–C structure of the modules allowed instructors to introduce data science and ecological forecasting skills into their classrooms without substantially reworking their existing course curricula, potentially facilitating the use of the modules by instructors at primarily undergraduate, minority-serving institutions, who may bear substantial course loads with limited time to restructure curricula. Overall, an important achievement of this adaptable, accessible curriculum is training the trainers, in which an instructor gains skills and knowledge in a new area, which are then transferred to their students (Beyer et al. 2009, Emery et al. 2021).

The modules were iteratively revised in response to student and faculty feedback (text S2). For example, we revised early versions of the modules to provide a more in-depth introduction in activity A to the modeling approaches used for forecasting as a method of "just in time" training for both students and instructors. In addition, the RMarkdown versions of the Forecasts and Uncertainty and Forecasts and Data modules were developed based on requests from both upper level undergraduate and graduate instructors. The RMarkdown files provide scaffolding for both students and instructors, who can start by working through materials in the point-and-click R Shiny interface and then move to the code under the hood of the Shiny application if they wish. Importantly, this scaffolding may enable students and instructors to transfer skills learned from the module to their own research projects, because they can modify the code for their own data sets and research questions. Finally, in response to feedback that early versions of the complete module activities (A, B, and C) were taking some introductory undergraduate students more than 3 hours to complete, we focused and rebalanced module content to reduce completion time.

Macrosystems EDDIE ecological forecasting modules may facilitate the use and analysis of large data sets, including NEON data, by instructors who have not had extensive data science training. Although interdisciplinary collaborations with, for example, computer scientists can facilitate analyses with large computational demands, ecologists must still possess basic data science skills, such as coding and data wrangling, modeling, and visualization, to make these collaborations a success (Cheruvelil et al. 2014, Cheruvelil and Soranno 2018, Carey et al. 2019). In summary, we found that the development of comprehensive supporting materials aimed to provide background skills and pedagogical training for instructors is critical for the effective implementation of new data science material into existing undergraduate curricula and may also facilitate new research efforts for instructors. Up-to-date versions of the modules are available on GitHub (https://github.com/MacrosystemsEDDIE), and feedback on module content and ease of use is welcome and can be submitted at MacrosystemsEDDIE.org.

Our study presents some limitations that should be considered when interpreting our findings and may help inform future curriculum assessment efforts. First, small class sizes ($n < 20$) in several of our test courses precluded the use of a control group, and we were neither able to control for differences in student learning environments nor assess possible instructor effects, which likely ranged widely across courses (listed in table S1). Although these limitations may explain some of our nonsignificant findings (e.g., figures S4b and S5a), the fact that we still observed improvements in student confidence and knowledge of ecological forecasting across institutions and instructors is promising. In addition, we did not collect individualized demographic data as part of our student assessment, and the number of first-year students who completed our modules was relatively small. As a result, we cannot quantitatively assess whether Macrosystems EDDIE modules are able to reduce opportunity gaps for underrepresented student groups in STEM or whether there are differences in module effectiveness across first-year undergraduate, upper-level undergraduate, and graduate students.

Importantly, our findings can inform new and ongoing development of modular curricula in multiple life science subdisciplines (e.g., evolutionary biology, Griffith et al. 2024; microbiology, Dill-McFarland et al. 2021). Specifically, we would recommend that

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developers of open-access, modular curricula in the life sciences provide comprehensive instructional support materials (e.g., instructor manuals), consider that "just in time" teaching of data science skills benefits both students and instructors, and plan for ongoing maintenance and iterative revisions of modules using student and instructor feedback.

To train ecological and environmental scientists in data science and ecological forecasting concepts and skills, these topics need to be presented in a relevant, approachable way for both students and instructors. Our data indicate that the Macrosystems EDDIE approach is effective in engaging both instructors and students in data science and ecological forecasting, and our observed increases in student confidence may foster greater student science identity and retention in STEM (Stets et al. 2017, Vincent-Ruz and Schunn 2018, O'Brien et al. 2020, Bowser and Cid 2021). Ultimately, increased data science confidence and proficiency by both undergraduate students and instructors unleashes tremendous potential to leverage large data sets for addressing environmental challenges.

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Author contributions

Mary E. Lofton (Formal analysis, Investigation, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing), Tadhg N. Moore (Investigation, Methodology, Project administration, Software, Writing – review & editing), Whitney M. Woelmer (Formal analysis, Investigation, Methodology, Software, Writing – review & editing), R. Quinn Thomas (Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing), and Cayelan C. Carey (Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing)

Supplemental material

Supplemental data are available at *BIOSCI* online.

Data availability statement

Anonymized, aggregated student assessment and instructor feedback data as well as code to recreate figures and statistics associated with the manuscript are published with a DOI in the Zenodo repository in Lofton and colleagues (2024d); access at https://doi.org/10.5281/zenodo.10932209. All students and faculty consented to participate in the study per our institutional review board protocols (Virginia Tech IRB 19-669 and Carleton College IRB 19-20 065). The published data have been preprocessed to remove any sensitive or personally identifying information.

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