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

Mary E. Lofton[1], Tadhg N. Moore[1], Whitney M. Woelmer[1], R. Quinn Thomas[1], and Cayelan C. Carey[1]

[1]Affiliation not available

April 09, 2024

Mary Lofton[1,2a], Tadhg Moore[1b], Whitney Woelmer[1c], Quinn Thomas[1,2,3d], Cayelan Carey[1,2e]

[1]Department of Biological Sciences, Virginia Tech. 926 West Campus Drive, Blacksburg, Virginia, 24061, United States

[2]Center for Ecosystem Forecasting, Virginia Tech. 1015 Life Science Circle, Blacksburg, VA 24061, United States

[3]Department of Forest Resources and Environmental Conservation, Virginia Tech. 310 West Campus Drive, Blacksburg, Virginia, 24061, United States

[a] Postdoctoral Research Associate; melofton@vt.edu

[b] Postdoctoral Research Associate; tadhg.moore6@gmail.com

[c] Ph.D. Candidate; wwoelmer@vt.edu

[d] Associate Professor; rqthomas@vt.edu

[e] Professor; cayelan@vt.edu

Abstract

Data science skills (e.g., analyzing, modeling, and visualizing large datasets) are increasingly needed by undergraduates in environmental science. 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 (Environmental Data-Driven Inquiry & Exploration) program to introduce undergraduate students and instructors to ecological forecasting, an emerging subdiscipline which integrates multiple data science skills. Ecological forecasting aims to improve natural resource management by providing future predictions of ecosystems with uncertainty. We assessed the efficacy of the modules with 596 students and 26 instructors over three 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: active learning, ecosystem modeling, National Ecological Observatory Network (NEON), training program, undergraduate education

Introduction

Data science skills, such as visualizing, analyzing, and modeling large datasets, are increasingly needed by ecology and environmental science undergraduate students (Farrell and Carey 2018, Auker and Barthelmess 2020, Feng et al. 2020, Cooke et al. 2021). 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). As a result, analysis of large datasets is now required across a variety of environmental science and ecology careers, necessitating new approaches to training researchers, instructors, and students in data science skills (Hampton et al. 2017, National Academies of Sciences 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). Consequently, 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.

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 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 active learning, in which students learn by doing rather than passively listening or watching (Bonwell and Eison 1991). Active learning has been shown to enhance student outcomes (Freeman et al. 2014), especially for underrepresented groups (Theobald et al. 2020). Key components of active learning that can be easily embedded within ecological forecasting curricula include: authentic assessments that engage students in real-world, relevant 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 problem-solve (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 active learning *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 active learning (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 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 multi-year, multi-institutional 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, as lack of time is often cited as a barrier to instructor professional development (Williams et al. 2019), instructional materials associated with active learning activities 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 (Environmental Data-Driven Inquiry and Exploration) program (Carey et al. 2020, Hounshell et al. 2021, Moore et al. 2022, Woelmer et al. 2023a) that uses active learning techniques to teach data science skills in the context of ecological forecasting. While 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 to undergraduates (Willson et al. 2023). In addition, all materials are designed to be approachable to both instructors and students, as 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 U.S.'s National Ecological Observatory Network (NEON) to address relevant societal challenges such as predicting freshwater quality impairment.

Here, 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: (1) How does completion of Macrosystems EDDIE ecological forecasting modules affect student confidence and understanding of data science and ecological forecasting skills? (2) 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, as previous work has shown that two major barriers to integrating data science active learning activities into existing curricula are a lack of instructor training (Williams et al. 2019, Emery et al. 2021) and student confidence (Williams et al. 2019, Cuddington et al. 2023).

Overview of the Macrosystems EDDIE curriculum

The Macrosystems EDDIE ecological forecasting curriculum for undergraduates comprises four standalone modules: Introduction to Ecological Forecasting, Understanding Uncertainty in Ecological Forecasts, Using Data to Improve Ecological Forecasts, and Using Ecological Forecasts to Guide Decision-Making (Fig. 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 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, as instructors can choose whether to complete just Activity A, Activities A and B, or all three activities in one to three-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.

The modules in the Macrosystems EDDIE ecological forecasting curriculum are designed to both 1) introduce ecological forecasting concepts and 2) develop data science skills (Fig. 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 datasets requires students to evaluate the quality of the data (e.g., gaps, outliers, biases) and confront how inherent variability and error in environmental datasets may affect their analyses. In addition, each module asks students to interpret data visualized using various methods, ranging from time series and scatterplots to probabilistic forecasts and histograms. Finally, each module focuses 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.

Macrosystems EDDIE modules include a comprehensive set of instruction materials and are suitable for implementation in a variety of class contexts (Fig. 1). All 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, as 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 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 (~30 minute) Microsoft PowerPoint presentation with slide notes; a Microsoft Word student handout with pre-class 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, one-hour class sessions vs. one, three-hour lab period) and modalities (e.g., virtual, face-to-face, hybrid).

All 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, 2024b, Woelmer et al. 2023b, Lofton et al. 2024c), and all module code is published in the Zenodo repository (Moore et al. 2023b, 2023c, 2024a, Woelmer et al. 2022, Lofton et al. 2024a, 2024b). In addition, all module code is maintained and updated at the Macrosystems EDDIE GitHub organization (https://github.com/MacrosystemsEDDIE). We encourage and welcome instructors and students to adapt and modify these materials for their classrooms, projects, and research.

Module descriptions

Introduction to Ecological Forecasting (Intro to Forecasting)

This module introduces students to 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). 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 et al. (2022a) and Moore et al. (2022b), respectively.

Understanding Uncertainty in Ecological Forecasts (Forecasts & Uncertainty)

This module introduces students to concepts and methods for quantifying forecast uncertainty, which entails identifying the range of possible future model outcomes (Dietze 2017b). 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 et al. (2023b), Moore et al. (2023c), and Moore et al. (2023a), respectively.

Using Data to Improve Ecological Forecasts (Forecasts & Data)

This module introduces students to 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 vs. once a day) and with low vs. 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 as well as instructor materials are also published with DOIs in Lofton et al. (2024a), Lofton et al. (2024b), and Lofton et al. (2024c), respectively.

Using Ecological Forecasts to Guide Decision Making (Forecasts & 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 et al. (2022) and Woelmer et al. (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 (Table S1; Carey et al. 2020, Hounshell et al. 2021). Notably, as 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 Fig. 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 & Decisions in R Shiny

Ecology is a third-year lecture/laboratory undergraduate course of ~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 ~24 students each by a team of teaching assistants in a single, 3-hour laboratory period.

Freshman Ecology and Evolution Seminar: Forecasts & Uncertainty in R Shiny

Freshman Seminar: Ecology and Evolution is a first-year course designed for ~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 ~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 upon enrollment in the course. The instructor designed a two-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 emerging 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, students 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-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-assessments for the *Introduction to Ecological Forecasting* module to avoid survey fatigue. 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/long-term data and data from sensor networks after teaching a module, and any other feedback the instructor wished to provide.

Modules were assessed from January 2021 through May 2023 in 32 courses across 22 institutions (Table S1), with a total of 596 students completing one or more questions for both the pre- and post-assessment and 26 instructors completing a feedback survey. We compared pre- and post-module responses with paired Wilcoxon signed rank tests to evaluate student growth. Due to widely varying numbers of students across experience levels and courses (Table S1), we aggregated all 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 (Text S1, Tables S2-S7). All assessment was conducted following approved Institutional Review Board (IRB) 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 et al. (2024d).

Curriculum assessment results

Q1: How does completion of Macrosystems EDDIE ecological forecasting modules affect student perceptions and knowledge of data science and ecological forecasting skills?

Completing one or more Macrosystems EDDIE ecological forecasting modules improved student confidence in both their ecological forecasting and data science skills (Fig. 2a, Fig. S1). Students gained the most confidence from pre-module to post-module 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 (Fig. 2a).

Module completion similarly improved student understanding of ecological forecasting concepts, regardless of which module was completed (Fig. 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 modules, 31% of students could define an ecological forecast before module completion, while 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 (Fig. S2, S3).

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 (Fig. 3a). Importantly, this increase in skills translated into gains outside of the classroom, as most 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 (Fig. 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 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 'very easy' to teach (Fig. 3a).

Most instructors reported that they would use the modules again (Fig. 3b). Seven of the 26 instructors who filled out the feedback survey were teaching assistants who were not responsible for course curriculum design and might not teach the class in future years, and the rest were faculty instructors of record for the course with the ability to make future decisions regarding course curriculum. For a summary of instructor qualitative feedback on the modules, see Text S2.

Discussion

Through formal assessment of the Macrosystems EDDIE ecological forecasting curriculum for undergraduates, we found that modules were successful in increasing student confidence and knowledge of ecological forecasting and data science (Fig. 2) and lowered the barrier of entry to these fields for instructors (Fig. 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 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.

Our results indicate that flexible, short, and easy-to-use modules increase student confidence in data science and ecological forecasting skills. In particular, students showed the greatest gains in confidence in ecological forecasting skills (Fig. 2a), likely because they had lower initial confidence in ecological forecasting skills (e.g., generating forecasts, for which students reported a median pre-module Likert score of 2, or 'slightly confident'). In comparison, student confidence in their data science skills was relatively higher prior to completing the module (e.g., graphing data, with a median pre-module score of 4, or 'very confident'; Fig. 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 (Fig. S1). Ultimately, increased student confidence and knowledge of data science and forecasting are relevant beyond the life sciences, as workers with data science and predictive modeling skills are sought across multiple sectors (Stanton and Stanton 2019).

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 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 Macrosystems EDDIE modules were easy to use and very to extremely effective in teaching ecological forecasting and data science concepts (Fig. 3).

Qualitative responses to our instructor survey indicated that a 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 (Text S2). 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. Finally, most 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 (Fig. 3b), indicating that the modules build skills and data science familiarity with instructors as well as students. 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 students (Beyer et al. 2009, Emery et al. 2021).

Modules were iteratively revised in response to student and faculty feedback. 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, RMarkdown versions of the *Forecasts & Uncertainty* and *Forecasts & Data* modules were developed based on requests from 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 teaching the module to their own research projects, as they can modify the code for their own datasets and research questions.

Macrosystems EDDIE ecological forecasting modules may facilitate the use and analysis of large datasets, including NEON data, by instructors who have not had extensive data science training. While interdisciplinary collaborations with, e.g., 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 sum, 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.

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 datasets for addressing environmental challenges.

Acknowledgements

We thank the students and instructors who tested Macrosystems EDDIE ecological forecasting modules, especially Kait Farrell, Matt Hipsey, Leah Johnson, Nick Record, and Kiyoko Yokota. We also thank the Virginia Tech Reservoir Group and our undergraduate focus groups for their feedback, especially Caroline Bryant, Arpita Das, George Haynie, Ryan Keverline, Michael Kricheldorf, Rose Thai, Evelyn Tipper, and Jacob Wynne. We thank Monica Bruckner, Ashley Carlson, Kristin O'Connell, and Cailin Huyck Orr at the Science Education Resource Center at Carleton College for administrative assistance with module testing.

All module testing and assessment was conducted following approved Institutional Review Board (IRB) protocols (Virginia Tech IRB 19-669 and Carleton College IRB 19-20 065). This work was funded by NSF DEB-1926050, DBI-1933016, and EF-2318861.

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 et al. (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 (IRB) protocols (Virginia Tech IRB 19-669 and Carleton College IRB 19-20 065). The published data have been pre-processed to remove any sensitive or personally identifying information.

References

Andrews TC, Auerbach AJJ, Grant EF. 2019. Exploring the relationship between teacher knowledge and active-learning implementation in large college biology courses. CBE—Life Sciences Education 18: ar48.

Auerbach AJJ, Andrews TC. 2018. Pedagogical knowledge for active-learning instruction in large undergraduate biology courses: a large-scale qualitative investigation of instructor thinking. International Journal of STEM Education 5: 19.

Auker LA, Barthelmess EL. 2020. Teaching R in the undergraduate ecology classroom: approaches, lessons learned, and recommendations. Ecosphere 11: e03060.

Belland BR. 2014. Scaffolding: Definition, Current Debates, and Future Directions. Pages 505–518 in Spector JM, Merrill MD, Elen J, and Bishop MJ, eds. Handbook of Research on Educational Communications and Technology. Springer New York.

Beyer CJ, Delgado C, Davis EA, Krajcik J. 2009. Investigating teacher learning supports in high school biology curricular programs to inform the design of educative curriculum materials. Journal of Research in Science Teaching 46: 977–998.

Bodner K, Rauen Firkowski C, Bennett JR, Brookson C, Dietze M, Green S, Hughes J, Kerr J, Kunegel-Lion M, Leroux SJ, McIntire E, Molnár PK, Simpkins C, Tekwa E, Watts A, Fortin M. 2021. Bridging the divide between ecological forecasts and environmental decision making. Ecosphere 12: e03869.

Bonwell CC, Eison JA. 1991. Active learning: Creating excitement in the classroom. 1991 Association for the Study of Higher Education-Education Resources Information Center (ASHE-ERIC) higher education report. ERIC.

Bowser G, Cid CR. 2021. Developing the ecological scientist mindset among underrepresented students in ecology fields. Ecological Applications 31: e02348.

Bradford JB, Weltzin J, McCormick ML, Baron J, Bowen Z, Bristol S, Carlisle D, Crimmins T, Cross PC, DeVivo J, Dietze M, Freeman M, Goldberg J, Hooten M, Hsu L, Jenni K, Keisman JL, Kennen J, Lee K, Lesmes DP, Loftin K, Miller BW, Murdoch PS, Newman J, Prentice KL, Rangwala I, Read J, Sieracki J, Sofaer H, Thur S, Toevs G, Werner F, White CL, White T, Wiltermuth MT. 2020. Ecological forecasting—21st century science for 21st century management. U.S. Geological Survey. Open-File Report 2020–1073.

Bybee RW, Taylor JA, Gardner A, Van Scotter P, Powell JC, Westbrook A, Landes N. 2006. The BSCS 5E instructional model: Origins and effectiveness. Colorado Springs, Co: BSCS Science Learning.

Carey CC, Darner Gougis R, Klug JL, O'Reilly CM, Richardson DC. 2015. A model for using environmental data-driven Inquiry and exploration to teach limnology to undergraduates. Limnology and Oceanography Bulletin 24: 32–35.

Carey CC, Farrell KJ, Hounshell AG, O'Connell K. 2020. Macrosystems EDDIE teaching modules significantly increase ecology students' proficiency and confidence working with ecosystem models and use of systems thinking. Ecology and Evolution 10: 12515–12527.

Carey CC, Ward NK, Farrell KJ, Lofton ME, Krinos AI, McClure RP, Subratie KC, Figueiredo RJ, Doubek JP, Hanson PC, Papadopoulos P, Arzberger P. 2019. Enhancing collaboration between ecologists and computer scientists: lessons learned and recommendations forward. Ecosphere 10: e02753.

Carrillo CM, Ault TR, Wilks DS. 2018. Spring onset predictability in the North American multimodel ensemble. Journal of Geophysical Research: Atmospheres 123: 5913–5926.

Chang W, Cheng J, Allaire JJ, Sievert C, Schloerke B, Xie Y, Allen J, McPherson J, Dipert A, Borges B. 2023. Shiny: Web Application Framework for R.

Cheruvelil KS, Soranno PA. 2018. Data-intensive ecological research is catalyzed by open science and team science. BioScience 68: 813–822.

Cheruvelil KS, Soranno PA, Weathers KC, Hanson PC, Goring SJ, Filstrup CT, Read EK. 2014. Creating and maintaining high-performing collaborative research teams: the importance of diversity and interpersonal skills. Frontiers in Ecology and the Environment 12: 31–38.

Cleverly J, Eamus D, Edwards W, Grant M, Grundy MJ, Held A, Karan M, Lowe AJ, Prober SM, Sparrow B, Morris B. 2019. TERN, Australia's land observatory: addressing the global challenge of forecasting ecosystem responses to climate variability and change. Environmental Research Letters 14: 095004.

Cooke J, Araya Y, Bacon KL, Bagniewska JM, Batty LC, Bishop TR, Burns M, Charalambous M, Daversa DR, Dougherty LR, Dyson M, Fisher AM, Forman D, Garcia C, Harney E, Hesselberg T, John EA, Knell RJ, Maseyk K, Mauchline AL, Peacock J, Pernetta AP, Pritchard J, Sutherland WJ, Thomas RL, Tigar B, Wheeler P, White RL, Worsfold NT, Lewis Z. 2021. Teaching and learning in ecology: a horizon scan of emerging challenges and solutions. Oikos 130: 15–28.

Cuddington K, Abbott KC, Adler FR, Aydeniz M, Dale R, Gross LJ, Hastings A, Hobson EA, Karatayev VA, Killion A, Madamanchi A, Marraffini ML, McCombs AL, Samyono W, Shiu S-H, Watanabe KH, White ER. 2023. Challenges and opportunities to build quantitative self-confidence in biologists. BioScience 73: 364–375.

Dauphin B, Rellstab C, Wuest RO, Karger DN, Holderegger R, Gugerli F, Manel S. 2023. Re-thinking the environment in landscape genomics. Trends in Ecology & Evolution 38: 261–274.

D'Avanzo C, Anderson CW, Hartley LM, Pelaez N. 2012. A faculty-development model for transforming introductory biology and ecology courses. BioScience 62: 416–427.

Derting TL, Ebert-May D, Henkel TP, Maher JM, Arnold B, Passmore HA. 2016. Assessing faculty professional development in STEM higher education: Sustainability of outcomes. Science Advances 2: e1501422.

Dietze M. 2017a. Ecological Forecasting. Princeton University Press.

Dietze MC. 2017b. Prediction in ecology: a first-principles framework. Ecological Applications 27: 2048–2060.

Dietze MC, Fox A, Beck-Johnson LM, Betancourt JL, Hooten MB, Jarnevich CS, Keitt TH, Kenney MA, Laney CM, Larsen LG, Loescher HW, Lunch CK, Pijanowski BC, Randerson JT, Read EK, Tredennick AT, Vargas R, Weathers KC, White EP. 2018. Iterative near-term ecological forecasting: Needs, opportunities, and challenges. Proceedings of the National Academy of Sciences 115: 1424–1432.

Ebert-May D, Derting TL, Hodder J, Momsen JL, Long TM, Jardeleza SE. 2011. What we say is not what we do: Effective evaluation of faculty professional development programs. BioScience 61: 550–558.

Emery NC, Crispo E, Supp SR, Farrell KJ, Kerkhoff AJ, Bledsoe EK, O'Donnell KL, McCall AC, Aiello-Lammens ME. 2021. Data science in undergraduate life science education: A need for instructor skills training. BioScience 71: 1274–1287.

Ernest SKM, Ye H, White EP. 2023. Ecological Forecasting and Dynamics: A graduate course on the fundamentals of time series and forecasting in ecology. Journal of Open Source Education 6: 198.

Farley SS, Dawson A, Goring SJ, Williams JW. 2018. Situating ecology as a big-data science: Current advances, challenges, and solutions. BioScience 68: 563–576.

Farrell KJ, Carey CC. 2018. Power, pitfalls, and potential for integrating computational literacy into undergraduate ecology courses. Ecology and Evolution 8: 7744–7751.

Feng X, Qiao H, Enquist BJ. 2020. Doubling demands in programming skills call for ecoinformatics education. Frontiers in Ecology and the Environment 18: 123–124.

Freeman S, Eddy SL, McDonough M, Smith MK, Okoroafor N, Jordt H, Wenderoth MP. 2014. Active learning increases student performance in science, engineering, and mathematics. Proceedings of the National Academy of Sciences 111: 8410–8415.

Goodman KJ, Parker SM, Edmonds JW, Zeglin LH. 2015. Expanding the scale of aquatic sciences: the role of the National Ecological Observatory Network (NEON). Freshwater Science 34: 377–385.

Hampton SE, Jones MB, Wasser LA, Schildhauer MP, Supp SR, Brun J, Hernandez RR, Boettiger C, Collins SL, Gross LJ, Fernandez DS, Budden A, White EP, Teal TK, Labou SG, Aukema JE. 2017. Skills and knowledge for data-intensive environmental research. BioScience 67: 546–557.

Hampton SE, Strasser CA, Tewksbury JJ, Gram WK, Budden AE, Batcheller AL, Duke CS, Porter JH. 2013. Big data and the future of ecology. Frontiers in Ecology and the Environment 11: 156–162.

Hazen EL, Scales KL, Maxwell SM, Briscoe DK, Welch H, Bograd SJ, Bailey H, Benson SR, Eguchi T, Dewar H, Kohin S, Costa DP, Crowder LB, Lewison RL. 2018. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. Science Advances 4: eaar3001.

Heilman KA, Dietze MC, Arizpe AA, Aragon J, Gray A, Shaw JD, Finley AO, Klesse S, DeRose RJ, Evans MEK. 2022. Ecological forecasting of tree growth: Regional fusion of tree-ring and forest inventory data to quantify drivers and characterize uncertainty. Global Change Biology 28: 2442–2460.

Heim AB, Holt EA. 2018. Comparing student, instructor, and expert perceptions of learner-centeredness in post-secondary biology classrooms. PLOS ONE 13: e0200524.

Hounshell AG, Farrell KJ, Carey CC. 2021. Macrosystems EDDIE teaching modules increase students' ability to define, interpret, and apply concepts in macrosystems ecology. Education Sciences 11: 382.

Hughes PW, Ellefson MR. 2013. Inquiry-based training improves teaching effectiveness of biology teaching assistants. PLoS ONE 8: e78540.

Johnson LR, Gramacy RB, Cohen J, Mordecai E, Murdock C, Rohr J, Ryan SJ, Stewart-Ibarra AM, Weikel D. 2018. Phenomenological forecasting of disease incidence using heteroskedastic Gaussian processes: A dengue case study. The Annals of Applied Statistics 12: 27–66.

Keller M, Schimel DS, Hargrove WW, Hoffman FM. 2008. A continental strategy for the National Ecological Observatory Network. The Ecological Society of America: 282-284.

Kruger J, Dunning D. 1999. Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. Journal of Personality and Social Psychology 77: 1121–1134.

LaDeau SL, Han BA, Rosi-Marshall EJ, Weathers KC. 2017. The next decade of big data in ecosystem science. Ecosystems 20: 274–283.

Lewis ASL, Rollinson CR, Allyn AJ, Ashander J, Brodie S, Brookson CB, Collins E, Dietze MC, Gallinat AS, Juvigny-Khenafou N, Koren G, McGlinn DJ, Moustahfid H, Peters JA, Record NR, Robbins CJ, Tonkin J, Wardle GM. 2023. The power of forecasts to advance ecological theory. Methods in Ecology and Evolution 14: 746–756.

Lewis ASL, Woelmer WM, Wander HL, Howard DW, Smith JW, McClure RP, Lofton ME, Hammond NW, Corrigan RS, Thomas RQ, Carey CC. 2022. Increased adoption of best practices in ecological forecasting enables comparisons of forecastability. Ecological Applications 32: e02500.

Liu Q, Rowe MD, Anderson EJ, Stow CA, Stumpf RP, Johengen TH. 2020. Probabilistic forecast of microcystin toxin using satellite remote sensing, in situ observations and numerical modeling. Environmental Modelling & Software 128: 104705.

Lofton ME, Moore TN, Thomas RQ, Carey CC. 2024a. Macrosystems EDDIE Module 7: Using Data to Improve Ecological Forecasts, R Shiny version 1. https://doi.org/10.5281/zenodo.10903839

Lofton ME, Moore TN, Thomas RQ, Carey CC. 2024b. Macrosystems EDDIE Module 7: Using Data to Improve Ecological Forecasts, RMarkdown version 1. https://doi.org/10.5281/zenodo.10909589

Lofton ME, Moore TN, Thomas RQ, Carey CC. 2024c. Macrosystems EDDIE Module 7: Using Data to Improve Ecological Forecasts (Instructor Materials). https://doi.org/10.6073/pasta/6c8478d9aa04eeab55646ffa8e62b278

Lofton ME, Moore TN, Woelmer WM, Thomas RQ, Carey CC. 2024d. A modular curriculum to teach undergraduates ecological forecasting improves student and instructor confidence in their data science skills (Code Repository). https://doi.org/10.5281/zenodo.10932209

Luo Y, Ogle K, Tucker C, Fei S, Gao C, LaDeau S, Clark JS, Schimel DS. 2011. Ecological forecasting and data assimilation in a data-rich era. Ecological Applications 21: 1429–1442.

Mcloughlin MP, Stewart R, McElligott AG. 2019. Automated bioacoustics: methods in ecology and conservation and their potential for animal welfare monitoring. Journal of The Royal Society Interface 16: 20190225.

Moore TN, Lofton ME, Carey CC, Thomas RQ. 2023a. Macrosystems EDDIE Module 6: Understanding Uncertainty in Ecological Forecasts (Instructor Materials). https://doi.org/10.6073/pasta/1ce758925388a9273083c24ed0ee0c05

Moore TN, Lofton ME, Carey CC, Thomas RQ. 2023b. Macrosystems EDDIE Module 6: Understanding Uncertainty in Ecological Forecasts, R Shiny version 2. https://doi.org/10.5281/zenodo.10380760

Moore TN, Lofton ME, Carey CC, Thomas RQ. 2023c. Macrosystems EDDIE Module 6: Understanding Uncertainty in Ecological Forecasts, RMarkdown version 1. https://doi.org/10.5281/zenodo.10380340

Moore TN, Lofton, ME, Carey CC, Thomas RQ. 2024a. Macrosystems EDDIE Module 5: Introduction to Ecological Forecasting, R Shiny version 2. https://doi.org/10.5281/zenodo.10733117

Moore TN, Lofton, ME, Carey CC, Thomas RQ. 2024b. Macrosystems EDDIE Module 5 version 2: Introduction to Ecological Forecasting (Instructor Materials). https://doi.org/10.6073/pasta/b3953d81b3b4158e0ec5375c04774bd2

Moore TN, Thomas RQ, Woelmer WM, Carey CC. 2022. Integrating ecological forecasting into undergraduate ecology curricula with an R Shiny application-based teaching module. Forecasting 4: 604–633.

Naithani K, Jones M, Grayson KL. 2022. Building communities of teaching practice and data-driven open education resources with NEON faculty mentoring networks. Ecosphere 13: e4210.

Nathan R, Monk CT, Arlinghaus R, Adam T, Alos J, Assaf M, Baktoft H, Beardsworth CE, Bertram MG, Bijleveld AI, Brodin T, Brooks JL, Campos-Candela A, Cooke SJ, Gjelland KO, Gupte PR, Harel R, Hellstrom G, Jeltsch F, Killen SS, Klefoth T, Langrock R, Lennox RJ, Lourie E, Madden JR, Orchan Y, Pauwels IS, Říha M, Roeleke M, Schlägel UE, Shohami D, Signer J, Toledo S, Vilk O, Westrelin S, Whiteside MA, Jarić I. 2022. Big-data approaches lead to an increased understanding of the ecology of animal movement. Science 375: eabg1780.

National Academies of Sciences E. 2018. Data science for undergraduates: Opportunities and options. National Academies Press.

Niu S, Luo Y, Dietze MC, Keenan TF, Shi Z, Li J, Iii FSC. 2014. The role of data assimilation in predictive ecology. Ecosphere 5: 1–16.

Novak GM, Patterson ET, Gavrin AD, Christian W. 1999. Just in time teaching. American Association of Physics Teachers.

O'Brien LT, Bart HL, Garcia DM. 2020. Why are there so few ethnic minorities in ecology and evolutionary biology? Challenges to inclusion and the role of sense of belonging. Social Psychology of Education 23: 449–477.

O'Connell K, Altermatt E, Darner R, Iverson E, Meixner T, O'Reilly C, Orr CH, Soule D. 2024. Project EDDIE Module Development Rubric.

O'Reilly CM, Gougis RD, Klug JL, Carey CC, Richardson DC, Bader NE, Soule DC, Castendyk D, Meixner T, Stomberg J, Weathers KC, Hunter W. 2017. Using Large Data Sets for Open-Ended Inquiry in Undergraduate Science Classrooms. BioScience 67: 1052–1061.

Ouellet-Proulx S, St-Hilaire A, Boucher M-A. 2017. Water Temperature Ensemble Forecasts: Implementation Using the CEQUEAU Model on Two Contrasted River Systems. Water 9: 457.

Owens MT, Trujillo G, Seidel SB, Harrison CD, Farrar KM, Benton HP, Blair JR, Boyer KE, Breckler JL, Burrus LW, Byrd DT, Caporale N, Carpenter EJ, Chan Y-HM, Chen JC, Chen L, Chen LH, Chu DS, Cochlan WP, Crook RJ, Crow KD, De La Torre JR, Denetclaw WF, Dowdy LM, Franklin D, Fuse M, Goldman MA, Govindan B, Green M, Harris HE, He Z-H, Ingalls SB, Ingmire P, Johnson ARB, Knight JD, LeBuhn G, Light TL, Low C, Lund L, Márquez-Magaña LM, Miller-Sims VC, Moffatt CA, Murdock H, Nusse GL, Parker VT, Pasion SG, Patterson R, Pennings PS, Ramirez JC, Ramirez RM, Riggs B, Rohlfs RV, Romeo JM, Rothman BS, Roy SW, Russo-Tait T, Sehgal RNM, Simonin KA, Spicer GS, Stillman JH, Swei A, Tempe LC, Vredenburg VT, Weinstein SL, Zink AG, Kelley LA, Domingo CR, Tanner KD. 2018. Collectively improving our teaching: Attempting biology department–wide professional development in scientific teaching. CBE—Life Sciences Education 17: ar2.

Petchey OL, Pontarp M, Massie TM, Kéfi S, Ozgul A, Weilenmann M, Palamara GM, Altermatt F, Matthews B, Levine JM, Childs DZ, McGill BJ, Schaepman ME, Schmid B, Spaak P, Beckerman AP, Pennekamp F, Pearse IS. 2015. The ecological forecast horizon, and examples of its uses and determinants. Ecology Letters 18: 597–611.

Schussler EE, Read Q, Marbach-Ad G, Miller K, Ferzli M. 2015. Preparing biology braduate teaching assistants for their roles as instructors: An assessment of institutional approaches. CBE—Life Sciences Education 14: ar31.

Stanton AD, Stanton WW. 2019. Closing the skills gap: Finding skilled analytics professionals for a dynamically changing data-driven environment. Applied Marketing Analytics 5: 170–184.

Stets JE, Brenner PS, Burke PJ, Serpe RT. 2017. The science identity and entering a science occupation. Social Science Research 64: 1–14.

Theobald EJ, Hill MJ, Tran E, Agrawal S, Arroyo EN, Behling S, Chambwe N, Cintrón DL, Cooper JD, Dunster G, Grummer JA, Hennessey K, Hsiao J, Iranon N, Jones L, Jordt H, Keller M, Lacey ME, Littlefield

CE, Lowe A, Newman S, Okolo V, Olroyd S, Peecook BR, Pickett SB, Slager DL, Caviedes-Solis IW, Stanchak KE, Sundaravardan V, Valdebenito C, Williams CR, Zinsli K, Freeman S. 2020. Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. Proceedings of the National Academy of Sciences 117: 6476–6483.

Villarroel V, Bloxham S, Bruna D, Bruna C, Herrera-Seda C. 2018. Authentic assessment: creating a blueprint for course design. Assessment & Evaluation in Higher Education 43: 840–854.

Vincent-Ruz P, Schunn CD. 2018. The nature of science identity and its role as the driver of student choices. International Journal of STEM Education 5: 48.

Weathers KC, Hanson PC, Arzberger P, Brentrup J, Brookes J, Carey CC, Gaiser E, Gaiser E, Hamilton DP, Hong GS, Ibelings B, Istvánovics V, Jennings E, Kim B, Kratz T, Lin F, Muraoka K, O'Reilly C, Rose KC, Ryder E, Zhu G. 2013. The Global Lake Ecological Observatory Network (GLEON): The evolution of grassroots network science. Limnology and Oceanography Bulletin 22: 71–73.

Wiliam D. 2011. What is assessment for learning? Studies in Educational Evaluation 37: 3–14.

Williams JJ, Drew JC, Galindo-Gonzalez S, Robic S, Dinsdale E, Morgan WR, Triplett EW, Burnette JM, Donovan SS, Fowlks ER, Goodman AL, Grandgenett NF, Goller CC, Hauser C, Jungck JR, Newman JD, Pearson WR, Ryder EF, Sierk M, Smith TM, Tosado-Acevedo R, Tapprich W, Tobin TC, Toro-Martínez A, Welch LR, Wilson MA, Ebenbach D, McWilliams M, Rosenwald AG, Pauley MA. 2019. Barriers to integration of bioinformatics into undergraduate life sciences education: A national study of US life sciences faculty uncover significant barriers to integrating bioinformatics into undergraduate instruction. PLOS ONE 14: e0224288.

Willson AM, Gallo H, Peters JA, Abeyta A, Bueno Watts N, Carey CC, Moore TN, Smies G, Thomas RQ, Woelmer WM, McLachlan JS. 2023. Assessing opportunities and inequities in undergraduate ecological forecasting education. Ecology and Evolution 13: e10001.

Woelmer W, Moore T, Thomas Q, Carey. 2022. Macrosystems EDDIE Module 8: Using Ecological Forecasts to Guide Decision-Making (R Shiny application). https://doi.org/10.5281/zenodo.7074674

Woelmer WM, Moore TN, Lofton ME, Thomas RQ, Carey CC. 2023a. Embedding communication concepts in forecasting training increases students' understanding of ecological uncertainty. Ecosphere 14: e4628.

Woelmer WM, Thomas RQ, Moore TN, Carey CC. 2023b. Macrosystems EDDIE Module 8: Using Ecological Forecasts to Guide Decision-Making (Instructor Materials). https://doi.org/10.6073/pasta/8bf4a076433f0e9f74f1d764d5bd4c3f

Xie Y, Allaire JJ, Grolemund G. 2018. R markdown: The definitive guide. CRC Press.

Biographical information

Mary Lofton is a postdoctoral research associate in the Virginia Tech Center for Ecosystem Forecasting. Her research interests are modeling and forecasting of freshwater ecosystems and development of educational resources to help students gain data science and systems thinking skills.

Tadhg Moore is currently a lake scientist at Limnotrack in Hamilton, New Zealand. He develops and delivers online platforms for water quality monitoring and modelling data for water resource managers.

Whitney Woelmer is currently a postdoctoral researcher at the University of Waikato in Hamilton, New Zealand. She is a quantitative limnologist interested in understanding and predicting freshwater ecosystem dynamics.

R. Quinn Thomas is an associate professor and co-director of the Virginia Tech Center for Ecosystem Forecasting. His research interests are modeling and forecasting of forest and freshwater ecosystem dynamics.

Cayelan Carey is a professor and co-director of the Virginia Tech Center for Ecosystem Forecasting. Her research integrates field studies, modeling, and forecasting to understand freshwater ecosystem dynamics.

Figures

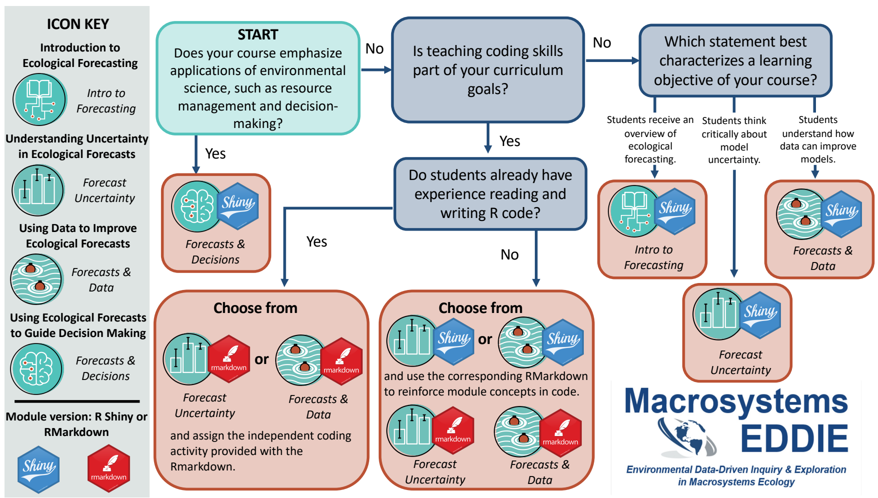

Figure 1: Conceptual diagram of Macrosystems EDDIE ecological forecasting curriculum content and workflow to guide instructors on potential ways the modules could be implemented into their courses, depending on learning objectives and student experience level.

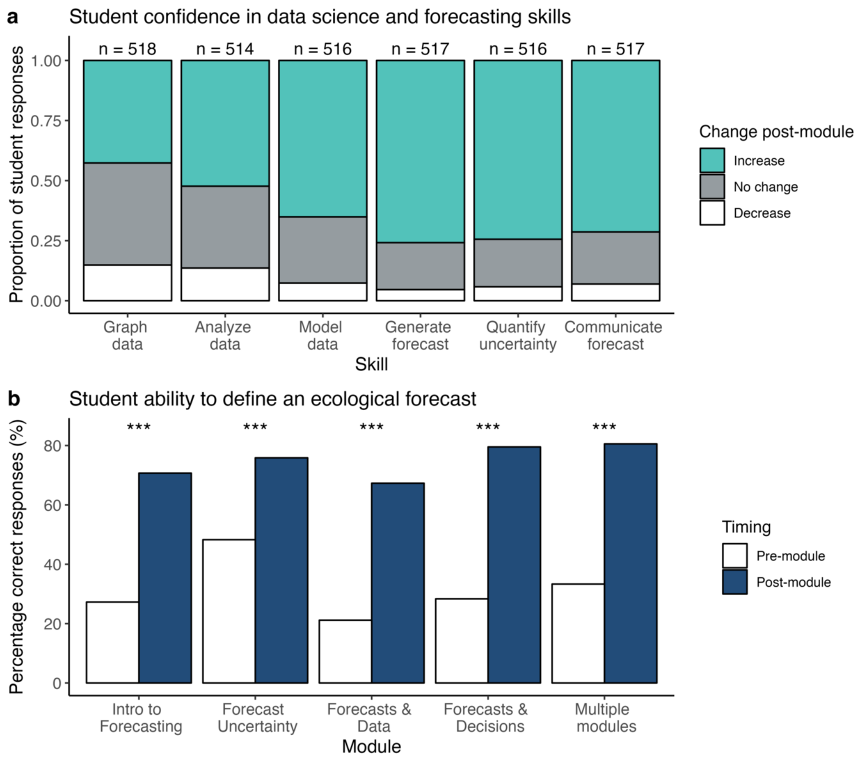

Figure 2: Effect of module completion on (a) student confidence in data science (graph data, analyze data, model data) and forecasting (generate forecast, quantify uncertainty, communicate forecast) skills and (b) knowledge of ecological forecasting. (a) Student confidence was assessed via Likert scores, where 1 was "not confident at all" and 5 was "extremely confident". Changes in student confidence were calculated by subtracting each student's pre-module score from the post-module score. Numbers above each bar indicate the number of student responses obtained for each assessment question. (b) 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; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

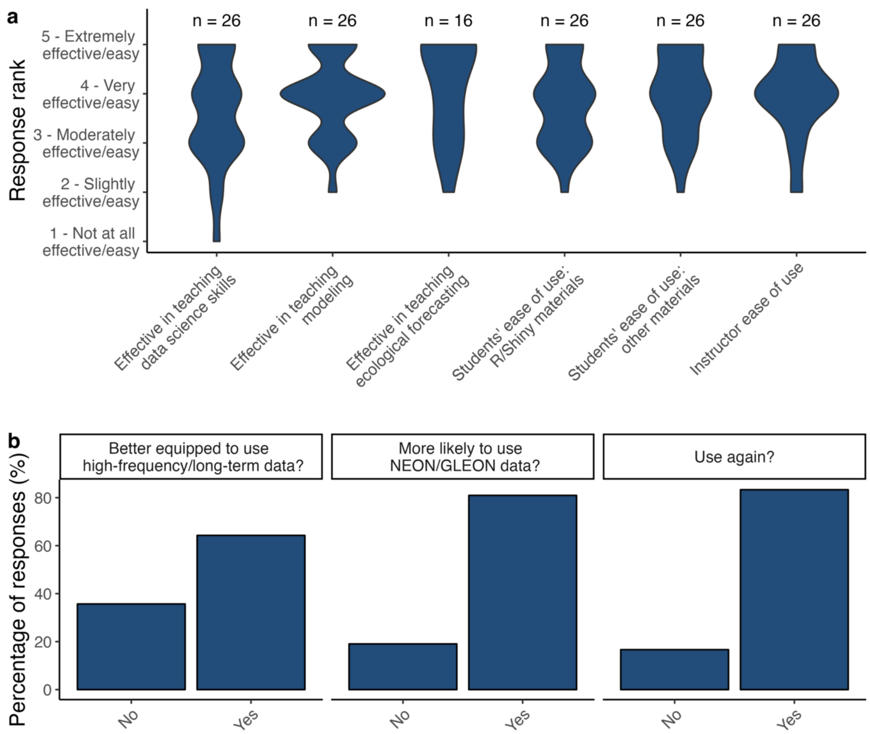

Figure 3: Instructor perceptions of module ease of use and efficacy in teaching data science and ecological forecasting skills (a) and the number of instructors who reported they would use the module again, were better equipped to use high-frequency/long-term data, and were more likely to use sensor network data (b). (a) Numbers above each violin plot indicate the number of instructor responses received for each question. (b) NEON = National Ecological Observatory Network; GLEON = Global Lake Ecological Observatory Network.

Supplemental Information

Hosted file

`supplement.docx` available at https://authorea.com/users/540012/articles/741831-a-modular-curriculum-to-teach-undergraduates-ecological-forecasting-improves-student-and-instructor-confidence-in-their-data-science-skills