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 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., McLaughlin 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 (Villarreal 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.

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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.

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**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

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