Cracking the code: An evidence-based approach to teaching Python in an undergraduate earth science setting

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Abstract

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Abstract

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Introduction

Data programming has become the foundation of research in today’s geoscientific disciplines. As the volume and size of data sets have steadily increased, so have the complexity and ubiquity of the computational techniques used for analysis and visualization. Some argue that innovation in earth science research will increasingly be driven by one’s competency in translating ideas into computer code (Jacobs et al., 2016).

The field of oceanography is no exception to this “data tsunami,” with more hydrographic casts collected in the past two decades than over the previous 100 years (Brett et al., 2020). Unprecedented collaborative initiatives such as the Argo profiling float array (Wong et al., 2020), the National Science Foundation’s Ocean Observatories Initiative (OOI; Greengrove et al., 2020), and remote sensing platforms such as satellite altimeters (Scheick et al., 2023) are continuously adding to expansive, publicly available data sets. In addition to these observational programs, hard drives at institutions across the world are being filled with terabytes of data generated by numerical simulations. From highly resolved ocean general circulation models to the lower-resolution global climate models assessed in the Intergovernmental Panel on Climate Change (IPCC) reports, the natural ocean is being reproduced with ever-increasing fidelity (Haine et al., 2021). The resulting challenges in accessing and analyzing these data require new computational tools that enable truly open science, further motivated by the notion that “research conducted openly and transparently leads to better science” (National Academies of Sciences, Engineering, and Medicine, 2018). At the same time, modeling and observation-focused oceanographers use highly unstandardized computational methods that may deviate from best practices in software engineering, as highlighted in an ethnography of oceanographers’ programming practices (Kuksenok et al., 2017).

Discipline-specific computational coursework and data literacy are thus a critical part of a modern oceanographic undergraduate curriculum, and we infer the same applies across many geoscience disciplines. While students can collect and analyze small-scale data sets through hands-on fieldwork and labs that are common elements of undergraduate earth science curricula, working with larger, professionally collected data sets may require
familiarity with a programming language (Kastens et al., 2015). Historically, introductory programming education has been the responsibility of computer science departments, with a focus on data structures and algorithms. Geoscience-specific programming instruction will necessarily reflect distinct goals and tools compared to computer science (Grapenthin, 2011) or data science (Anderson et al., 2015; Lasser et al., 2021), namely, the use of coding to derive insight into natural systems through mathematical manipulation, visualization, and interpretation of idiosyncratic data, often in the time and space domains. Yet formal scientific computing instruction is often absent in earth science curricula, including oceanography (Old, 2019), except for highly scaffolded modules that employ coding in courses where programming is not the primary focus (e.g., Rowe et al., 2021). Even in courses that more extensively utilize programming within activity modules, such as those distributed by Project EDDIE (Environmental Data-Driven Inquiry and Exploration), pre-written code is usually provided to students (O’Reilly et al., 2022). In this void, brief but intensive hands-on workshops like those offered by Software Carpentry (https://software-carpentry.org; Wilson, 2016), Data Carpentry (https://datacarpentry.org/; Irving, 2019), and scientific societies (e.g., Arms et al., 2020) have provided crucial training to young scientists. These short workshops, however, give learners limited opportunities to apply new coding skills to their own research in a supervised setting. In lieu of formalized instruction, many earth science students teach themselves programming during research experiences or in graduate programs, which can lead to the propagation of ad hoc, inefficient, and outdated practices.

Incorporating programming into an earth science curriculum additionally opens the door to a constructivist approach to teaching scientific concepts—one that encourages students to use experimentation and self-guided inquiry to build on previous learning, construct new knowledge, and engage in critical reflection (Bada, 2015; Hadjerrouit, 2008). The iterative, reflective process of writing and refining scientific code makes it naturally suited to this individualized model of learning. In practice, a constructivist pedagogy often involves active techniques such as project-based investigation, cooperative learning, and inquiry-based activities. These have been shown to improve student competencies in information recall, analysis, and quantitative reasoning in a large-enrollment introductory oceanography course (Yuretich et al., 2001).
Throughout higher education, there is an increasing recognition that effective teaching requires a focus on active learning, which can be described broadly as students engaged in their learning due to the use of intentional teaching practices (Prince, 2004). Active modalities – including those designated as “high-impact educational practices” (Kuh et al., 2017) – stand in contrast to traditional lecturing, which represents about three-quarters of class time across STEM undergraduate and graduate courses today (Stains et al., 2018). In a survey of almost 200 undergraduate oceanography professors, for example, three-quarters indicated that they use data in their instruction but are most likely to teach using lectures, rather than creating opportunities for active inquiry (McDonnell et al., 2015). There is strong evidence that using active learning techniques increases students’ understanding and retention of material in STEM courses, with disproportionate benefits for underrepresented students and students who learn in different ways (Freeman et al., 2014; Haak et al., 2011; Theobald et al., 2020).

One reason these strategies appear to be effective is that they often require an instructor to implement more structure in their course through, for example, regular and intensive practice using scaffolded activities (Haak et al., 2011). Evidence supports the efficacy of active learning strategies in geoscience classrooms – particularly peer instruction, case studies, and problem-based activities (McConnell et al., 2017).

Embedding computing skills into a geoscience curriculum faces the challenge of introducing students to unfamiliar skills such as algorithmic thinking and overcoming a steep learning curve, similar to teaching a foreign language (Jacobs et al., 2016). Perhaps for this reason – as well as a lack of accessible software tools and insufficient computational power in previous decades (Hays et al., 2000) – existing examples of courses using geoscience data have often focused on interactive online modules, portals, or widgets that are constrained in their data sets and capabilities (e.g., Ellwein et al., 2014; Greengrove et al., 2020; Klug et al., 2017). Software such as Microsoft Excel or specialized tools like Ocean Data View face similar limitations. In comparison, programming skills are more versatile, enabling the analysis of virtually any data set from any domain and empowering students to conduct independent or mentored research projects.

Our study reports on an evidence-based redesign of an undergraduate oceanography course that teaches introductory Python programming and data analysis techniques. In subsequent sections, we highlight key course
elements (summarized schematically in Fig. 1) and assess the efficacy of the redesign from the standpoint of student engagement and learning.

Implementation

Course history and development

“Methods of oceanographic data analysis” (OCEAN 215) has been taught annually in the School of Oceanography at the University of Washington since its establishment in 2015. It was the first introductory Python course offered by the department and met in person two times each week in two-hour sessions that featured a mix of traditional lecturing and dedicated homework time. Over a ten-week quarter, students completed four assignments using programming techniques taught in lectures. The course was well-received by students, who rated it as “very good” (4 on a scale from 1-5) across a variety of metrics in end-of-quarter evaluations from 2015, 2016, 2017, and 2019 (Fig. 2), and has been perceived as demanding relative to other courses in students’ curricula (see Fig. S1 in Supplemental Materials).

However, faculty teaching other courses in the department’s curriculum reported that many students who completed OCEAN 215 later had difficulty with core Python programming tasks. A review of past senior theses – projects in which students formulate and execute original research – revealed that students often used minimal scientific code and reverted to less versatile, non-coding solutions like Microsoft Excel and Google Earth. Given that students had recognized the usefulness of the course content after completing the course (see Fig. S1 in Supplemental Materials), we speculate that their subsequent hesitancy and lack of confidence in applying Python skills was due to a lack of recurrent exposure to Python in the curriculum (see Conclusions section “Impact” for more discussion) as well as weaknesses in the course design. Possible shortcomings include an overreliance on non-interactive lectures, a lack of student-driven inquiry, assignments’ use of unrealistically clean scientific data, and course elements that were unnecessarily limiting or not reflective of current scientific Python practices.
The course was restructured (Fig. 1, Table 1) and subsequently co-taught during a 10-week quarter in 2020 by two graduate students, both of whom had served as TAs in past years. Twenty-five undergraduate students completed the course, a typical class size (Fig. 2). The plurality were third-year oceanography majors. No prior knowledge of computing or upper-level math was required or assumed. Elements retained from previous iterations included the basic format of four structured programming assignments as well as twice-weekly classes and office hours; however, the latter were conducted virtually rather than in a physical classroom.

In 2020, the COVID-19 pandemic forced a swift transition to virtual instruction. The timing of this course in Autumn 2020, however, allowed for careful planning of an online learning framework, rather than the forced adoption of emergency remote instruction necessary in the first half of 2020 (Donham et al., 2022; Hodges et al., 2020). Nonetheless, disruptions outside of the classroom were still present: students were isolated on campus or sequestered at home with family, mental health declined, and some became sick or had loved ones fall ill (Furman & Moldwin, 2021). With these realities in mind, the course redesign paid special attention to the need for a supportive and accommodating learning environment (Shay & Pohan, 2021).

The updates to the course were guided by past experience as TAs, consultation with previous teaching teams and department faculty, the need for fully virtual instruction during the pandemic, and a desire to infuse the course with active learning strategies. Changes included content that reflected the current scientific Python ecosystem (Table 1), cloud-based coding notebooks, flipped video lessons, discussions on an online question-and-answer (Q&A) forum, use of data from a wider range of earth science domains, an individually-driven final research project, encouragement of pair collaboration and use of external resources, and a syllabus with explicit policies, expectations, and the following end-of-quarter student learning objectives (SLOs):

1. Understand why the Python programming language is ideal for data analysis.
2. Write, execute, and debug Python code.
3. Access, read, transform, visualize, and interpret oceanographic data with confidence using Python.
4. Explore the ever-expanding universe of packages and tools available for creating and sharing code.
5. Formulate and investigate scientific research questions using programming and data analysis skills.

6. Adopt best practices in programming and data visualization that facilitate collaboration and information-sharing, both within the classroom and the broader scientific community.

All course materials were original, created by the graduate instructors, and are available for free reuse and adaptation under a CC-BY-4.0 license at https://ethan-campbell.github.io/OCEAN_215/.

Course content

In an introductory classroom setting, the choice of programming language matters. Python is an ideal candidate, as it is easy to learn, versatile, and free to use. First released three decades ago, Python is increasingly ubiquitous within earth science (Lin, 2012) and is widely used outside the scientific community, particularly in industry, making it valuable for students seeking a career outside of academia (Srinath, 2017). The language features concise, easily read, higher-level syntax that allows one to focus on data exploration, enabling more efficient science, while streamlining workflows starting from remote data access through to analysis and visualization (Ayer et al., 2014; Jacobs et al., 2016; Lin, 2012). For those learning programming for the first time, a primary challenge is thinking algorithmically, that is, developing structured code to solve a problem. Compared to Python, lower-level programming languages commonly taught in introductory computer science courses (such as Java and C++) require substantial syntactical overhead that can distract from achieving that pedagogical goal (Pears et al., 2007; Srinath, 2017).

Python offers other advantages. Its open-source nature has fostered a large active developer community, which has contributed to its stability and the dissemination of numerous multipurpose packages that extend its functionality. The fact that Python is free prevents a reliance on expensive commercial solutions that can render analysis code inaccessible to scientists outside of well-resourced university environments (Gentemann et al., 2021). These qualities stand in contrast to MATLAB, a scientific programming language also popular in geoscientific research. Despite the clear benefits of teaching Python in an earth science context, we find only one
documented example of an instructional approach for a conventional (quarter- or semester-long) course in the existing literature (Jacobs et al., 2016).

The updated OCEAN 215 covered scientific Python skills needed for oceanographic data analysis, starting with fundamental Python syntax, as well as data management and research practices (Table 1). Students learned core functions (see Table S1 in Supplemental Materials) from versatile, interoperable, and open-source software libraries widely used in climate-related disciplines: NumPy, a fundamental library for multidimensional array computing (Harris et al., 2020); Matplotlib, a visualization library (Hunter, 2007); Cartopy, a mapping toolbox (Met Office, 2022); SciPy, a scientific and statistical analysis library (Virtanen et al., 2020); Pandas, a toolkit for working with 1-D and 2-D data (McKinney, 2010); and Xarray, a toolkit for label-based, coordinate-aligned manipulation of multidimensional netCDF files (Hoyer & Hamman, 2017). Students were encouraged to reference online documentation and use their knowledge of general function syntax to expand their Python capabilities beyond the course content. Lessons also addressed programming best practices, such as modularizing code, adhering to variable naming conventions, writing comments, and applying consistent style and formatting (Wilson et al., 2014), as well as effective visualization principles, including legibility and labeling (Hepworth et al., 2020) and considerations of accuracy and accessibility when choosing colormaps for visualizations (Thyng et al., 2016). These concepts were introduced with examples and data from oceanographic disciplines (physics, chemistry, biology, and marine geology) and other domains (e.g., cryosphere, atmosphere, and climate) using scaffolding to familiarize students with new topics.

Course elements

Programming platform

Google Colaboratory (Colab), a cloud-based, in-browser Python development environment modeled after Jupyter notebooks, was chosen as the coding platform for the course. Notebooks can include a mix of interactive code blocks and narrative text, allowing for easy exploration of data and documentation of scientific workflows. Jupyter notebooks are widely used and considered one of the top 10 computing advances that have transformed
science (Granger & Pérez, 2021; Perkel, 2021). In general, cloud-based computing has democratized the ability to conduct complex analyses of earth science data sets, creating new opportunities for innovation, transparency, and reproducibility (Gentemann et al., 2021).

Google Colab is an ideal teaching platform compared to alternatives like an integrated development environment (IDE) and Jupyter notebooks. Unlike IDEs, Colab requires no local installation of Python or additional software, so students can start coding immediately with minimal device-specific troubleshooting. Notebooks also avoid the cognitive overhead associated with learning command-line syntax or a professional-level IDE (Jacobs et al., 2016; Pears et al., 2007). Unlike Jupyter notebooks, Colab does not require server configuration and integrates with Google Drive, facilitating file sharing and submission of assignments. Comments can be added to notebooks for grading purposes, similar to Google Docs, and built-in edit history can confirm students’ compliance with deadlines. While constraints exist, such as a lack of transparent package management, computational limitations, and the need for an internet connection, the advantages of Google Colab outweigh its disadvantages in a classroom setting.

**Flipped structure**

A flipped classroom approach was implemented by assigning 14 recorded lessons of approximately 30 minutes each to be watched before synchronous (Zoom) classes. The lessons were divided into 41 tightly scripted segments of about 10 minutes each (see Fig. S2c in Supplemental Materials). This was done with the goal of helping students maintain focus, as some evidence suggests the average student has an attention span of 15–20 minutes during traditional lecturing (Middendorf & Kalish, 1996). In addition to segmenting videos, students were reminded to take breaks between segments. Flipped video watching and in-class participation were not graded, partially in recognition of pandemic stressors but also to accommodate individual circumstances without requiring students to disclose possibly sensitive information. The expectation was that assignment grades would be sufficiently impacted if students were not engaged in these activities.
Most lessons consisted of lectures that illustrated Python concepts using multiple representations, which has been suggested as a core pedagogical strategy for teaching programming (Hadjerrouit, 2008). For example, slides introducing a new concept would often include three distinct representations: a simplified overview of syntax and function arguments, a minimal example of the function or concept being used (e.g., Fig. 1b), and a schematic or illustrative plot. Consistent fonts, color schemes, and other design elements were used to reliably indicate relationships between concepts and distinguish examples from core syntax. Some lessons used live-coding demonstrations rather than slides. Accompanying Colab notebooks were provided with each lesson to allow students to run code while watching.

*Synchronous class sessions*

In-class sessions were conducted using the Zoom platform. Each synchronous class started with simple icebreakers asking students about their well-being and anonymous polls to gather feedback about previous video lessons. Concepts from the relevant flipped videos were then briefly reviewed, leaving ample time for students to ask lingering questions. In some class sessions, short activities were used to introduce topics not covered in lesson videos.

The majority of synchronous class time was spent conducting live coding demonstrations and facilitating tutorials that integrated concepts taught in the videos. Compared to using slides or copying and pasting blocks of existing code, live coding forces slower, more digestible instruction, allows instructors to be responsive to student questions in real-time, and inevitably allows students to see instructors’ mistakes and how they are diagnosed and fixed (Wilson, 2016). Tutorials were designed with multiple goals in mind, in alignment with core considerations for programming activities laid out by Hadjerrouit (2008): (1) to encourage students to analyze the problem at hand and develop stepwise solutions; (2) to build on concepts that students previously learned, encouraging reuse and modification of previous code; and (3) to compare and contrast different ways of achieving the same analytical or graphical result. Based on positive mid-quarter feedback, the instructors emphasized these tutorials and live coding in the second half of the course.
A Google Colab notebook was prepared for each class, presenting a tutorial with four or five related but distinct problems that applied different concepts or functions to a real-world data set from oceanographic and related disciplines (e.g., Fig. 1c). Data were curated by the instructors for their instructional potential. These exercises created opportunities to divide the classroom into 4-5 person groups that worked cooperatively within Zoom breakout rooms. A “think-pair-share” model (McConnell et al., 2017; Yuretich et al., 2001) was adopted: students first individually attempted a problem for a few minutes, then teamed up in their breakout room to discuss challenges encountered and optimal solutions, and lastly returned to the main Zoom room, at which point a designated reporter from each group reviewed their results with the full class. Instructors monitored student discussions by moving between breakout rooms and provided guidance when needed. Groups’ progress was tracked by watching a shared Google Doc configured ahead of time with templates in which each group filled in their final coding solutions. Occasionally randomizing group members allowed students to gain exposure to a variety of coding styles, social dynamics, and levels of confidence with the material.

Q&A forum

An online Q&A board, Piazza, was offered as an outlet for students to connect asynchronously with peers and instructors outside of class and office hours (see Fig. 1e; note that alternative platforms with similar functionality exist, e.g., Ed Discussions). Piazza enables students to seek help on logistical or clarifying questions as well as their problem-solving processes, thereby reducing individual emails to instructors. The platform allows students to select the audience for their questions (instructors and/or classmates), post anonymously, respond to peers in threaded discussions, and collaboratively construct answers. Instructors may endorse and comment on student answers. Four brief check-ins (including Assignment #0) required Piazza submissions, and an additional quota of five substantive posts per student (i.e., those that contribute further insight to the discussion, rather than simply “Good work” or “I agree”) was prescribed in the syllabus.
Assignments and final project

Students completed four programming assignments at two-week intervals, each consisting of approachable, multi-part problems in a Google Colab notebook that utilized real scientific data (e.g., Fig. 1d). For example, one assignment tasked students with importing data collected by an ocean observing platform (a seaglider), identifying key summary statistics, creating a visualization of the glider’s location and temperature measurements, and calculating trends in the data.

Assignments incorporated elements of both “structured inquiry” and “guided inquiry,” the second and third levels in the hierarchy of Banchi & Bell (2008). Questions were somewhat less structured compared to class activities, allowing students more flexibility to design their own solutions. This created opportunities to practice both programming skills and data literacy, creating a foundation for more sophisticated independent analysis of data sets. Without a midterm exam, assignments were instructors’ main window into student progress.

Students also completed an individually driven or collaborative final project (see Text S1 in Supplemental Materials for the project description handout). The goal was for students to write code to answer a scientific question by exploring a data set of their choice, supported by ample guidance from the instructors and peer review from classmates. Similar to the structure of an introductory data programming course described by Anderson et al. (2015), low-stakes checkpoints throughout the quarter required students to share their topic, data set, scientific questions, and hypotheses on the Piazza Q&A board, as well as offer feedback on at least three classmates’ choice of data or questions. The project culminated in the delivery of a short final presentation. A rubric was provided to clearly communicate expectations and evaluation techniques for code, figures, and presentation content and delivery (see Table S2 in Supplemental Materials). Rubrics may lead to increased student performance, and in any case, rubrics are recognized as a user-friendly tool for setting guidelines and enabling self-assessment (Brookhart & Chen, 2015).

Students were offered the option to collaborate in pairs on both the assignments and final project. When programming as a pair, one student serves as the “driver,” writing code, while the other observes, monitoring the
code for defects and helping to problem-solve. Students were also allowed to reference external resources such as online documentation sites and Stack Overflow. Citations and acknowledgment of collaboration were expected in assignments and the final project, and students confirmed their agreement with the integrity policy in the initial survey (Assignment #0).

**Evaluation**

We adopt a two-pronged approach by first evaluating student achievement of SLOs using final project assessments, then exploring instructional approaches that helped students learn by using a variety of other data. The latter includes quantitative data from standardized course evaluations, an end-of-quarter student survey, engagement and usage metrics provided by the video and Q&A platforms, and graded assessments, along with qualitative data from the evaluations and student focus group. Prior to analysis, all student-specific metrics were de-identified and coded by a coauthor who was not directly involved in quantitative analyses; identified versions were not used thereafter. This study was approved as qualifying for exempt status for institutional review by the Human Subjects Division at the University of Washington.

**Initial, mid-quarter, and end-of-quarter surveys**

To gauge initial exposure to the Python programming language and coding in general, students were asked to share their prior experiences in an introductory survey distributed in the first week of class (Assignment #0). The instructors translated students’ short-answer responses into a numeric rating (1-5) using a subjective analysis of their word choice (see rubric in Table S3 and Fig. S3 in Supplemental Materials). The factors considered were any previous coding languages learned, the reported efficacy of past learning experiences, and time since last exposure to coding. The introductory survey also encouraged students to introduce themselves to the teaching team by sharing their pronouns and any anticipated accessibility, technology, or learning needs.

We also obtained summary reports from end-of-quarter Instructional Assessment System (IAS) surveys completed by OCEAN 215 students in Autumn 2015, 2016, 2017, 2019, and 2020 (results from Spring 2015 and
Autumn 2018 were unavailable), which were administered and anonymized by the University of Washington.

Standardized questions asked students to evaluate aspects of the course quality and their engagement with the course. While most questions were consistent across years, others evolved in their wording and thus required mapping or aggregation to enable comparison between years (as shown in Table S4 in Supplemental Materials).

Questions that could not be tracked across years were excluded. Students completed surveys either in paper or online format, with the class response rate of around 70% in 2020 being somewhat higher than in past years (Fig. S1 in Supplemental Materials). As IAS summary reports correspond to specific instructors, we averaged the class median responses between the two graduate instructors for each question in 2020. Changes between 2015-2019 and 2020 were tested for a statistically significant increase using a one-sided t-test for questions where increases could objectively be viewed as a desired improvement: metrics on a 1-5 (“Very poor” to “Excellent”) scale and the metrics “Time spent that was valuable” and “Participation relative to other courses.” Remaining metrics were tested for a statistically significant change in either direction using a two-sided t-test.

Furthermore, we apply a standard qualitative approach (Creswell, 1998) to extract meaning from students’ anonymous responses to open-ended questions in two IAS surveys in 2020: a mid-quarter evaluation administered during weeks 4-5 of the course and the final evaluation. The survey prompts are listed in Table S5 in the Supplemental Materials. We identified common or unique themes mentioned by students, grouped similar themes, coded responses by noting whether a theme was mentioned in either a subjectively positive context (e.g., an appreciative or affirming comment; assigned a value of +1) or subjectively negative context (e.g., an unenthusiastic or critical comment; assigned a value of –1), and tabulated the frequency of each context for all themes (Fig. 3). We also excerpt illustrative quotes from students’ responses throughout the text.

In addition to the university-managed IAS surveys, a Google Form survey was administered during the week after the final class to measure students’ perceived success relative to the course SLOs. The response rate was 92%.

Submissions were not anonymous, but instructors guaranteed to students that their responses would not impact their final course grades. As a final self-assessment of students’ Python skills, we use responses to the question,
“How proficient do you feel in writing, executing, and debugging Python code?”, which were on a 6-point scale from “Least proficient” to “Most proficient.”

**Flipped video viewership**

Panopto, the video hosting and delivery platform used in the course, provides instructors with usage statistics, including view counts, minutes delivered, percent completed, and last view time. Those metrics – associated with individual students, individual videos (both aggregated and disaggregated by student), and distinct video viewing sessions, where applicable – were downloaded, and student identities were anonymized as described above. Usage data are presented in Fig. 4, Fig. 5a, and Fig. S2 in the Supplemental Materials. Student-specific Panopto metrics computed for Fig. 6 include total minutes watched, minutes watched before the class for which a video was assigned, and minutes watched after class for the first time (i.e., late views).

**Q&A forum engagement**

Piazza, the online Q&A platform, also makes usage statistics available to instructors. The following student-specific metrics (presented in Fig. 6) were downloaded, then anonymized as described above: days online, answers, and total contributions (which include questions, notes, answers, and comments). Additionally, a time series of engagement was constructed (Fig. 5a) based on unique users per day, as provided by Piazza. The time series was supplemented by a manual tabulation of daily Piazza activity within the following categories: student questions and notes related to programming; student scheduling, extension, or logistical requests; student answers and comments; student posts that were required for assignments; and instructor posts, answers, or comments. Where relevant, those categories were further divided by chosen audience into total posts that were public and signed, public and anonymous, or private (i.e., visible to instructors only), as shown in Fig. 5b.
We use students’ final projects as a barometer of their level of scientific reasoning, their final coding competency, and their achievement of course SLOs (Fig. 7). First, questions and hypotheses posed by students in their projects were assessed based on the seven levels of the cognitive process dimension of the revised Bloom’s taxonomy (Bloom et al., 1956; Krathwohl, 2002; see rubric in Table 2 for examples referenced in our classification), similar to the methodology of Kastens et al. (2020). Second, students’ breadth of programming skills was evaluated computationally as the fraction of Python syntax elements taught in the course—namely, functions, operators, and methods—that were employed at least once in each student’s submitted project code notebook (see Table S1 in the Supplemental Materials for search terms used in the analysis). This metric varies widely between students (see Results section “Student learning outcomes”) and thus offers significant discriminatory power, albeit limited by our exclusion of miscellaneous functions that were not taught in the course but were used by some students at higher skill levels. Third, the submitted projects were graded using a rubric that was provided to students ahead of time to delineate expectations and evaluation techniques (Table S2 in the Supplemental Materials). By mapping rubric subcategories onto four of the six corresponding SLOs (see Implementation section “Course history and development”) and combining the graded scores within each category for each student, we create aggregate metrics of each student’s final achievement of those key objectives.

To represent overall student achievement, students’ final grades are included in Fig. 6 and Fig. S3 in the Supplemental Materials. Grades were recalculated to ignore two students’ incomplete assignments (0% grades) that occurred due to personal circumstances, and the following weights were re-applied: 60% for assignments #0-#4 (weighted equally), 15% for Piazza posts, and 25% for final projects. Original and recalculated final grades averaged 95.0% and 95.9%, respectively, with standard deviations of 5.7% and 3.8%.
Student focus group

Undergraduate students who completed OCEAN 215 in Autumn 2020 were considered for a focus group based on responses to a voluntary survey asking students to rate their interest in the project and provide a short paragraph about course elements that affected their learning positively or negatively. Five students were chosen based on the thoughtfulness of their written responses and the diversity of their academic backgrounds and experiences within the course. Selection was not dependent on students’ grades in the course, and it was made clear that survey responses would not impact course grades. Three focus group sessions were held in the quarter following Autumn 2020, each lasting 1-2 hours. In the sessions, the instructors asked questions designed to provoke open and candid discussion about students’ perception of course elements and took notes by paraphrasing comments. Student participants did not have access to the anonymized student metrics described above.

The five students were additionally invited to share short testimonials detailing their unique experiences in the course and were offered coauthorship on the study (as noted below in Author Contributions). The four testimonials that were submitted are presented in Text S2 in the Supplemental Materials and excerpted throughout the text. The final testimonials were assembled from students’ responses to their selection of a subset of the guiding questions included as Table S6 in the Supplemental Materials and were edited for style and grammar and to limit redundancy of themes mentioned. Insights gleaned from the focus group or testimonials are clearly denoted in the text. We use them as supporting evidence to depict students’ perspectives about the course more holistically and accurately and to indicate areas where students felt the course could be modified to improve their experience.

Results

Student learning outcomes

Students’ final project topics spanned the oceanographic, cryosphere, and atmospheric domains (Fig. 7a). Scientific questions and hypotheses posed by students largely map onto higher levels of Bloom’s taxonomy,
exemplifying higher-order questioning and prediction (Fig. 7b, Fig. 7c). The percentage of code syntax taught in the class that was used in each final project ranged widely from 6% to 29% (Fig. 7d) and exhibits no significant correlation with the assessed cognitive level of students’ questions or hypotheses (not shown). In other words, students’ level of scientific reasoning was not predictive of the analytical complexity of their finished projects.

Overall final project grades were all above 80%, with most students scoring high marks (80% or above) on four project rubric categories representing the quality of their code, visualizations, use of data, and scientific research (Fig. 7e, 7f, 7g, 7h). These categories correspond to SLOs #2, #3, #5, and #6, with some overlap (see Table S2 in Supplemental Materials). The widest spread in grades was in the category of scientific research (Fig. 7h), in which 28% of students scored below 80%.

By calculating correlations between a variety of anonymized data sources (see Evaluation), presented in Fig. 6, we explore the impact of students’ varying backgrounds and learning strategies on their course experiences and outcomes. Significantly, neither students’ final grades nor their code usage in final projects is correlated with prior coding experience, indicating that previous exposure to Python was not predictive of success in the course. Dichotomizing the class by prior coding experience (none/little versus some/moderate/lots) also reveals no statistically significant difference in final grades (Fig. S3). That said, less prior experience was associated with higher engagement with lesson videos and the Q&A forum (Fig. 6). Additionally, the positive correlation between three key metrics – total lesson minutes watched, number of Q&A forum answers, and forum days online – with the breadth of Python skills used in final projects indicates that students who demonstrated strong coding competency had likely acquired more content knowledge, frequently shared that knowledge with peers, and were more engaged with the course. Variations in students’ demonstrated Python skills cannot fully explain differences in their final grades, but the two show a positive nonlinear correlation. Students who earned higher grades tended to monitor the Q&A forum more frequently, collaborate more often with classmates, and watch lesson videos before class.
Role of course elements in student learning

Course content

Overall, students perceived the course positively, rating its content, evaluation techniques, organization, and the course as a whole markedly higher than in past years (Fig. 2). Students’ view of the course content evolved from a critical stance expressed in mid-quarter evaluations, with comments citing its abstract or challenging nature, to an appreciative view of the data skills they had acquired by the end of the course (Fig. 3). One focus group participant who was a first-time coder wrote in their testimonial (Text S2 in Supplemental Materials):

“I have always viewed research as something that is extraordinarily complicated. This class demonstrated that knowing a few basic Python functions and packages can provide a solid foundation to start conducting research.”

Flipped structure

In total, students spent 166 hours watching lesson videos on the Panopto platform. Two-thirds of the watch time occurred before the class for which the video was assigned (Fig. 4). Most lessons were released 1.5-3 days before the Zoom class meeting, and students generally watched lessons during the 24 hours prior to class. The remaining one-third of total watch time occurred throughout the month following the relevant class, of which three-quarters were first-time views. While the total video lesson minutes watched by a student were correlated with the breadth of Python skills used in their final project, the timing of their video lesson views was not (Fig. 6).

Students in the focus group expressed that they appreciated the opportunity to watch videos at a convenient time and the ability to take breaks. Some shared that they would have viewed videos immediately before class regardless of release timing, while others said they would have taken advantage of a longer period of availability. While one student reported in their final course evaluation that “occasionally the length of the recorded lectures prevented [them] from finishing them entirely,” we find no significant correlation between video or lesson duration and fraction watched (see Fig. S2f, Fig. S2h in Supplemental Materials). Half of students watched nearly
every video, with class-wide average video completion between 80-90% in most weeks (Fig. 5a). Completion
rates dropped near the end of the course, which student focus group participants suggested was due to high end-
of-quarter demands in other courses and because the material covered didn’t appear in assignments.

Some students in the focus group reported re-watching videos to review material or using corresponding slide
decks for the same purpose; one student took notes on the videos and later referenced those notes. In final course
evaluations, students noted that having slide decks available benefitted their learning (Fig. 3), with one student
sharing, “I was able to surprise myself with how much I could figure out through review when feeling helpless at
first.” Despite the addition of watching flipped videos (as well as a final project) to the overall course workload,
students estimated in final evaluations that the amount of time they spent each week was similar to past years. Yet
out of students’ total time spent on the course, nearly 90% was seen as valuable in advancing their education – a
significant increase from past years ($p \leq 0.1$; Fig. 2).

Synchronous class sessions

Interactive tutorials involving live coding demonstrations and individual activities were the most positively
reviewed course element in students’ mid-quarter and final surveys (Fig. 3). On the other hand, the large amount
of screen time was the most frequently mentioned criticism in course evaluations (Fig. 3). Students also offered
criticism on the use of breakout groups in their evaluations, with one noting, “I didn't find the small group coding
breakout rooms very helpful for coding, but they were nice for getting to know my classmates.” Several students
wished for more time and instructor guidance in breakout rooms, which contributed to their overall negative
rating (Fig. 3). Nonetheless, one focus group participant noted in their testimonial (Text S2 in Supplemental
Materials) that breakout rooms “forced us to come well-prepared for class” and in final course evaluations,
students rated their overall participation as higher relative to other courses (6.0 on a 7-point scale, where 4.0 is
“average”; Fig. 2).
Q&A forum

Students visited Piazza once every 1-5 days on average, and engagement in the form of questions, answers, and comments closely tracked assignment deadlines and peaked while students worked on the final project (Fig. 5a). Many questions from students were simple – for example, diagnosing a coding bug or clarifying the goal of an assignment – while others were more complex – such as seeking strategies to efficiently work with large data sets for one’s final project. The forum saw 530 total student contributions, out of which two-thirds were voluntary, i.e., not required by a check-in or Assignment #0 (Fig. 5b).

Students selected the three audience options (public, either signed or anonymous, and private posts) with approximately equal frequency, depending on their needs (Fig. 5b). Student focus group participants shared that the anonymous and private posting options were useful when they were worried that a question would be perceived as obvious or simple, or when they were less sure of their answer. Final course evaluations show that students overall felt positively about having access to Piazza (Fig. 3). One student shared their appreciation for the ability to post anonymously, stating that it “alleviated some anxiety about asking questions.”

Assignments and final project

In course evaluations, most students viewed the assignments and final project as beneficial (Fig. 3). Nearly half of the class – 48% of students – took advantage of the pair programming option at some point, with 34% of students collaborating on any given assignment or the project on average. Students generally chose the same classmate as their partner throughout the course. The number of times that a student worked collaboratively is presented as the metric “Pair programming experiences” in Fig. 6. One focus group participant shared their experience in their testimonial (Text S2 in Supplemental Materials):

“... we coded in completely different ways, and it was fascinating to see those differences. We were more effective together because we learned to compromise and collaborate to find the cleanest and fastest method between the two of us.”
The opportunity to synthesize course knowledge and the option to collaborate with classmates on final projects were specifically cited in students’ evaluations as positive elements of the course. The ability to use external materials and learn beyond class topics was similarly welcomed (Fig. 3), and another student expressed in their testimonial:

“[Accessing online resources like StackOverflow] developed essential skills and gave me the confidence to apply new concepts in my final project. This meant my research could be dictated by my curiosity and questions, as it should be, and not by the limitations of what concepts we had covered in class.”

That said, one critical survey comment related to ambiguity about the rigor of science expected and the open-ended nature of project checkpoints.

Discussion

Student learning outcomes

We measured students’ achievement of key SLOs (#2, #3, #5, and #6) by assessing their final projects, with the assumption that the projects represent a holistic demonstration of students’ capabilities. Those assessments indicated clear success in achieving learning objectives. Students produced impressive and original work that reflected earnest attempts to investigate scientific questions using effective coding and visualization techniques.

Consistent with research that found a weak correlation between tutor grades and self-assessments by over 3,000 undergraduate students (Lew et al., 2010), we saw no link between students’ self-assessment of programming skills in a final survey and their final grades. A caveat is that students were asked to rate their Python competence, rather than their final grade, and the two metrics may not be entirely comparable. That said, this result could still reflect the Dunning-Kruger effect, a cognitive bias in which those with the least knowledge tend to overestimate their performance or ability because they lack the competencies required for self-assessment (Kruger & Dunning, 1999). The lack of a relationship between students’ final self-assessments and any metrics other than prior coding experience points to a persistent confidence from previous Python exposure that contributed to a perception of
competence not necessarily reflected in higher grades or course-acquired skills. In contrast, our results suggest a “level playing field” in which those who came in with less previous knowledge of programming took full advantage of class resources, like lesson videos and Piazza, to ultimately reach the same level of proficiency as their peers, as shown in final grades and project code usage.

We believe the most novel aspect of this course was neither its content nor students’ success at achieving SLOs but rather how the course was taught. An effective learning environment was intentionally created using evidence-based pedagogical elements: a mix of flipped lectures and engaging activities, a student-designed research project, opportunities for student collaboration, an online discussion forum, and efforts to center accessibility and foster classroom community.

Role of course elements in student learning

Flipped structure

Blended learning models have been shown in a systematic review to improve the learning experience of novice programmers, as they allow class time to be reserved for active learning and afford students more flexibility to plan and customize their study (Alammary, 2019). Consistent with those findings, our analysis of video watch timing, student focus group feedback, and course evaluations shows that our flipped structure enabled a diversity of strategies for content acquisition. Exposure to video content before working on related in-class activities may have helped students prepare for assignments, which comprised the majority of final grades. Nonetheless, our correlation metrics suggest that the total amount of time spent viewing lessons, not whether those lessons were watched before or after a class, was most influential in students’ application of course content within their final projects.

In line with prior research on students’ perspective of the flipped model (McCallum et al., 2015), our course structure generally received student approval in course evaluations (Fig. 3). Students’ overall positive evaluations of the course are notable given hardships related to the COVID-19 pandemic, as well as findings that show
students often prefer passive lecturing over active learning due to the additional cognitive effort required to engage actively with material (Deslauriers et al., 2019).

**Synchronous class sessions**

Course evaluations indicated that in-class activities and demonstrations were well-liked and engaging. However, the facilitation of breakout groups and large amount of screen time presented challenges for students and instructors and were met with critical reviews. Though breakout rooms can allow for more individualized attention, the instructors had difficulty with distributing their finite time across groups and eliciting participation. Both can be linked to group size, and student focus group participants indeed shared mixed views on the number of students per group. Smaller groups could have encouraged more individual accountability at the expense of increasing demands on instructors’ time as they cycle between breakout rooms. Larger groups would have enabled instructors to provide more efficient guidance and increased opportunities for peer instruction but often suffer from uneven participation. The optimal configuration may depend on individual classroom circumstances.

**Q&A forum**

The wide range of question types that we observe on Piazza are in line with previous research in an undergraduate computer science setting, which similarly showed high participation rates when students are encouraged to use the platform by teaching staff (Vellukunnel et al., 2017). Our correlation analysis of student metrics also matches the positive relationship between question-asking on a Q&A forum and final grades found in that prior study. The apparent efficacy of Piazza may reside in the fact that voluntarily asking a question on a discussion forum, by definition, constitutes a form of active learning, though posts may vary in their level of reasoning and connectedness (Vellukunnel et al., 2017). Active learning would presumably be maximized if students use Piazza to seek help after they have invested time into trying different solutions and consulting other resources, which is encouraged by the asynchronous nature of the forum. While prompt instructor engagement is vital for establishing a strong teaching presence in a remotely taught course (Prince et al., 2020), it is important that responses be somewhat delayed so that an expectation of near-instantaneous feedback is not established. Importantly, this also
allows peers an opportunity to provide input. However, the instructors found that delaying feedback – particularly when a question had a straightforward answer – often ran against their desire to help students and thus proved challenging.

Assignments and final project

In each assignment notebook, copious scaffolding around each problem (e.g., step-by-step instructions, expected intermediate results, and links to documentation websites) was provided to create an environment of “structured inquiry.” In the hierarchy of Banchi & Bell (2008), who propose a four-level continuum of inquiry, for example, structured inquiry represents the second level, followed by the more independent modes of “guided inquiry” and “open inquiry.” The assignments were designed to be challenging yet were viewed favorably by both the student focus group and the final evaluation respondents. Both, however, indicated a desire for more short, frequent, low-stakes practice opportunities to help reinforce concepts and check understanding.

In contrast to instructor-generated activities, the final project allowed for student-designed questions and procedures. This encouraged “open inquiry,” an experience that is exceedingly rare in undergraduate oceanography teaching (McDonnell et al., 2015). In general, inquiry-based learning develops cognitive skills on higher levels of Bloom’s taxonomy (Bloom et al., 1956; Krathwohl, 2002). Consistent with a constructivist approach to learning (Bada, 2015), students answered complex or potentially ill-structured questions using messy and incomplete real-world datasets (e.g., Ellwein et al., 2014; Klug et al., 2017) with instructor guidance mostly related to feasibility. In courses where undergraduate students conduct research with unknown outcomes, students have reported learning gains similar to those of dedicated summer research programs (Lopatto, 2010).

Pair programming has been known to improve student learning, performance, and satisfaction in the computer science classroom, without loss of competency on exams (e.g., McDowell et al., 2002; Williams & Upchurch, 2001). In a survey of undergraduates who conducted collaborative research, almost 80% reported that working in teams or pairs enhanced their research experience (Lopatto, 2010). We found pair programming to be readily adaptable to the virtual classroom using Zoom screen-sharing, with the caveat that Colab notebooks must be
refreshed to show updates and thus edits must be made by one user at a time rather than synchronously. One lesson learned was that some pairs will gravitate towards asynchronous collaboration (i.e., a division of labor, rather than true pair programming) unless it is specified that the coding must be done synchronously. Additionally, collaborations appeared to prove more successful when coding partners had a pre-existing working relationship; naturally, this is less likely to occur in a remotely taught introductory class setting. Nonetheless, previous work has found equal benefits to student performance and confidence for students who pair program remotely using screen-sharing and audio connectivity compared to physically collocated student pairs (Hanks, 2005).

**Accessibility and inclusivity**

Efforts were made to ensure that the course was accessible for all students and that those with varying backgrounds and needs felt welcome and accommodated. Instructional approaches focused on active learning and student engagement can help to combat inequities in the classroom (Theobald et al., 2020), but equally important are strategies that promote a culture of respect and foster a sense of belonging for students (Dewsbury & Brame, 2019). A classroom community built on mutual understanding and respect promotes engagement, especially among students with marginalized identities, by creating a supportive space to share ideas and ask questions (Barrett, 2021).

The introductory survey helped the instructors affirm students’ identities and accommodate disabilities, and students’ responses led to instructors making an effort to accurately caption all lesson videos. While no students noted in the survey that they lacked computer or internet access, we shared relevant resources (e.g., a campus service for computer rentals and a public library program that loans internet hotspots) in the syllabus and initial class session.

Admittedly, connection in the classroom can be difficult to promote in the absence of face-to-face instruction. With this in mind, community was intentionally fostered throughout the course. Community guidelines were co-created on the first day of class using an activity that asked both students and instructors to contribute their
expectations of shared norms and endorse each other’s contributions. Warm-up activities like those we used at the start of synchronous classes allay anxiety about classroom engagement, connect students with each other, and create a safer environment more conducive to active learning (Bledsoe & Baskin, 2014; Chlup & Collins, 2010).

In the context of a pandemic that saw many undergraduate students isolated from friends and support networks, the instructors cultivated connection and community by emphasizing that student physical and mental well-being were priorities throughout the course, encouraging collaboration, and being easily accessible for questions, including through Piazza. For assignments that were graded, instructors offered a one-time, two-week extension to allow flexibility while still requiring students to learn foundational material. In mid-quarter evaluations, one student noted that the “low stress environment” of the course helped them learn.

To ensure the broadest possible audience for the course, previous coding experience was not required, and a prerequisite of one quarter of calculus from previous iterations of the course was removed. Instructors offered one-on-one mentoring as needed, recognizing that some students require additional, intensive help with certain topics or specialized guidance tailored to their specific learning style in order to keep pace with the class. This tutoring was also provided for students located in remote time zones in lieu of class sessions, among other accommodations. Individualized mentoring sessions have the benefit of allowing students to form a personal connection with the instructors, which is otherwise challenging in a large virtual classroom.

No textbook was required in order to allow flexibility in the topics addressed and avoid high textbook costs that have a disproportionately negative impact on historically underserved students (Jenkins et al., 2020). Instructors could consider offering excerpts from textbooks as a supplementary resource. Some earth science-oriented Python textbooks now exist in print (e.g., Alyuruk, 2019; DeCaria & Petty, 2021; Esmaili, 2021) and online (Palomino et al., 2021; https://www.earthdatascience.org/courses/intro-to-earth-data-science/); a comprehensive text not specific to earth science is also freely available online (VanderPlas, 2016; https://jakevdp.github.io/PythonDataScienceHandbook/).
Our overall approach of providing multiple modalities for student learning was consistent with a universal design for learning (UDL) framework that prioritizes equitable and inclusive teaching (Capp, 2017; Meyer et al., 2014). UDL outlines three core principles: (1) multiple means of representation, which our course accomplished through recorded lessons with text, auditory, and visual components, live coding demonstrations, and permissive use of external resources; (2) multiple means of action and expression, facilitated through practice opportunities and assignments with varying degrees of structure; and (3) multiple means of engagement, enabled by our use of individual as well as group work, verbal as well as chat-based participation, peer instruction, office hours, and the online forum.

Virtual teaching, including adaptations such as virtual office hours, offers inherent accessibility benefits for students facing long commutes, disability-related accessibility challenges, and other barriers to attending classes on campus (Pichette et al., 2020). Virtual office hours – regarded positively by students in course evaluations – offered added benefits for students who may have perceived office hours as an unfamiliar, unsafe, or inaccessible space, with breakout rooms creating privacy for students with questions on assignments or personal matters. Recorded lessons, the asynchronous Q&A board, a flexible attendance policy, and an option to submit a recorded final project presentation enabled the participation of students located in remote time zones.

That said, virtual learning can make it harder to maintain focus and limit distractions. “Zoom fatigue” is a particular form of exhaustion that may result from the intensity of continuous, close-up eye contact and seeing oneself, reduced mobility when having to stay in a video frame, and increased cognitive load from having to exaggerate nonverbal cues (Bailenson, 2021). To mitigate these effects, regular breaks were taken during class, students were encouraged to take breaks during recorded videos, a video-optional policy was instituted on Zoom, and students were allowed to use the chat function to participate, though students’ criticisms about screen time show Zoom fatigue remained a challenge. These solutions are also imperfect—breaks take class time, teaching to students with cameras off can be disorienting, and chat messages can be difficult to monitor during instruction.
Limitations

The robustness of our conclusions is limited by the relatively small sample size (25 students) and the study’s focus on a single academic quarter. Additionally, the original course was offered a total of six times prior to Autumn 2020, but we were not able to obtain IAS survey responses from Spring 2015 and Autumn 2018. As such, these data are not included in our longitudinal comparison to previous years’ course evaluations. In this comparison, we also cannot disentangle the various influences of the COVID-19 pandemic on learning from the impact of the curriculum changes that we made. Furthermore, we cannot quantify the impact of the new teaching team’s positionality as graduate students on students’ impression of course quality. A previous study, for example, found that professors who were perceived as younger received higher evaluations than professors teaching identical content who were perceived as older (Arbuckle & Williams, 2003).

While a pre-quarter assessment of student coding competency and attitudes would have been an ideal way to assess student growth, such an assessment was not conducted as the study design was conceived after the course had concluded. Data on students’ age, race, and ethnicity were not collected for similar reasons, so we were unable to explore relationships between demographic profiles and students’ experiences or success in the course. Likewise, student achievement for two of the six course SLOs (#1 and #3) could not be explicitly measured using available data, although an assessment of final projects found that students successfully met the remaining four SLOs.

While a systematic approach is used to identify and tabulate themes in the survey responses (see Evaluation section), we do not apply the same technique to qualitative data from the student focus group or their testimonials. The small sample size (five students) and the non-representative nature of the group selected by instructors would limit the appropriateness and utility of such an approach. Furthermore, the focus group conversations were not open-ended, but rather guided by questions formulated by instructors after initial analyses of other data (e.g., survey results, student learning metrics, etc.). Focus group discussions were documented through paraphrased notes rather than an exact transcription, so direct quotes are not presented. Testimonials were edited by instructors.
(as described in the Evaluation section “Student focus group”), further restricting the possibility of a quantitative thematic analysis approach.

Conclusions

Recommendations for future teaching

We recommend without reservations adopting the key elements that we describe in this paper, particularly flipped instruction, an online coding platform and discussion board, and strong attention to accessibility. That said, we encourage others to improve on our framework and regularly seek feedback from students, preferably in a format that allows for anonymity. For example, in course evaluations, students encouraged the addition of more frequent, low-stakes practice of basic skills to reinforce fundamental concepts (see Discussion section “Assignments and final project”). New practice opportunities would ideally be coupled with immediate feedback that guides further practice, which promotes efficient learning and refinement of conceptual understanding (Ambrose et al., 2010). While we did not implement graded comprehension checks for videos, these could be useful in a situation of lower engagement (Jacobs et al., 2016). Additionally, data literacy skills could be taught through higher-level exercises asking students to scrutinize the limitations, biases, and provenance of scientific data sets and make predictions and recommendations grounded in their analysis of data (see, e.g., Kastens & Krumhansl, 2017). Instructors may consider expanding our offering into a multi-course sequence to incorporate these elements.

We acknowledge the ongoing paradigm shift in many scientific fields towards “open science,” a broadly defined set of ethics that encapsulates practices like code reproducibility, curation of data for reuse, and open journal access (Brett et al., 2020; Ramachandran et al., 2021). While these practices were not explicitly taught in this course, its emphasis on collaborative programming, well-documented code, and the scientific method as an open, transparent endeavor speak to fundamental open science principles. Explicit instruction on advanced topics like reproducibility, data archival, version control using Git and GitHub (e.g., Blischak et al., 2016), manipulation of
large data sets stored on the cloud (e.g., Gentemann et al., 2021), and command-line interfaces may be more appropriate for a separate, higher-level course.

The pandemic likely accelerated existing trends in higher education towards multi-modal instruction and more engaging teaching practices (Lockee, 2021). Though universities have transitioned back to in-person teaching, an interested and highly-engaged instructor team could still offer a fully remote version of this course, potentially with minimal penalty in student performance and satisfaction compared to in-person instruction (Ghosh et al., 2022; Ramirez et al., 2022). We believe that the framework developed for this course is also well-suited to a hybrid approach that incorporates in-person tutorial and work sessions but retains the pedagogical and accessibility benefits of recorded lesson videos, virtual office hours, and platforms that enable regular online engagement. Since 2020, this course has been offered annually in-person at the University of Washington by other graduate instructor teams with a flipped structure and most of the key curriculum elements introduced in this study.

Impact

The impact of this course extends beyond the students who enrolled in Autumn 2020. The flipped lesson videos were uploaded to a dedicated YouTube channel (https://www.youtube.com/@ocean215python), where they have been collectively viewed more than 22,000 times as of January 2024, reaching over 30 different countries. Furthermore, the graduate student instructors have benefited from the professional experience of developing a curriculum and managing a classroom. Opportunities such as this have been linked with the success of doctoral students attaining future employment in higher education (Bettinger et al., 2016). Our department plans for a rotating cast of two graduate students to continue serving as the primary teaching team, with the guidance and support of a dedicated teaching mentor to develop their pedagogical skills.

For many undergraduate students without a deeper interest in data science, multiple years may pass after completing OCEAN 215 before their next opportunity to use programming. For most, this comes in the form of their senior thesis. Students’ demonstrated loss of coding skills during past intervening years (see Implementation
section “Course history and development”) suggests not only the importance of our improved instructional design but also an urgent need to infuse an oceanographic undergraduate curriculum with regular, scaffolded opportunities to practice and apply programming skills. Barriers to enacting this change include the challenge of coalescing around a primary language of instruction while realizing the benefits of exposing students to other languages – many instructors, for example, use MATLAB for research – and a lack of curriculum mapping to communicate a standard set of programming skills that students can be expected to know and apply in courses. In addition to infusing curricula with programming, effort could be invested in creating supervised research opportunities for students that involve the use of programming and data analysis skills. More broadly, we see the need for earth science undergraduate curricula to adopt active, student-centered pedagogical practices that more frequently allow students to construct knowledge through hands-on exploration of real-world data. Infusing earth science curricula with current data programming practices will naturally facilitate the achievement of these goals.

Data and code availability

The Python code used to generate the figures in this paper is available at https://github.com/ethan-campbell/Python_teaching_paper and archived on Zenodo (Campbell & Christensen, 2024). Anonymized class data are available by reasonable request from the corresponding author (E.C.C.).

Author contributions

E.C.C. and K.M.C. designed instructional materials, taught the course, conceived the study, analyzed the data, and wrote the initial manuscript. M.N. supervised the course. S.C.R. established the original course in 2015 and acquired funding. A.A., O.B., J.L., R.M., and I.O. participated in the student focus group and/or provided testimonials detailing their course experience. All authors provided input to the final manuscript.
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Disclosure statement

The authors report that there are no competing interests to declare.

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References


Figures

Figure 1. Key course elements: (a) Python platforms and software libraries that were taught (see Table S1 in Supplemental Materials for specific functions, operators, and methods); (b) flipped video lessons, with a slide demonstrating how colors, fonts, design elements, and a minimal working example help to explain Python syntax; (c) class sessions focused on active learning, showing a completed portion of a group activity; (d) programming assignments, with an illustrative plot; (e) discussion on the Piazza Q&A forum, showing a student question and a peer answer endorsed by an instructor; (f) the final research project, represented as the sequence of assigned components; (g) underlying course elements that fostered an effective learning environment. Solid arrows indicate the progression from foundational material (a) to content delivery (b) and application (c); dashed arrows indicate the contributions of discussion forum engagement (e) to students’ work on assignments (d) and the final project (f).
Figure 2. Selected metrics from anonymous end-of-quarter student evaluations in 2015, 2016, 2017, 2019, and 2020 (see Evaluation section “Initial, mid-quarter, and end-of-quarter surveys”). Differently worded questions were mapped between years as shown in Table S4 in the Supplemental Materials. Metrics shown are class medians for 2015, 2016, 2017, and 2019 (gray crosses), except for “Total students enrolled”; 2015-2019 mean or 2020 class median (black points); and 2015-2019 standard deviation (bars). Changes from 2015-2019 to 2020 were tested for a significant increase at the 95% (solid line) or 90% (dashed line) confidence level using a one-tailed t-test for all metrics except for “Total students enrolled” and “Time spent on course,” which were tested for a significant change using a two-tailed t-test (no significant change was identified for either). For more details, see Evaluation section “Initial, mid-quarter, and end-of-quarter surveys.” An absence of a line connecting the 2015-2019 and 2020 data indicates no statistically significant improvement or difference. Note that y-axes have been truncated from the full 1-5 scale (“Very poor” to “Excellent”) or 1-7 scale (“Much lower” to “Much higher”). For the full set of survey metrics, see Fig. S1 in the Supplemental Materials.
**Figure 3.** Themes identified in anonymous, open-ended student responses to mid-quarter (hatched bars) and end-of-quarter (solid bars) surveys in 2020, ranked according to the net positivity (blue) or negativity (red) of comments regarding those themes (see Evaluation section “Initial, mid-quarter, and end-of-quarter surveys”). Totals for mid-quarter and end-of-quarter evaluations are stacked, not overlapping, within each bar. Original survey prompts are listed in Table S5 in the Supplemental Materials.
Figure 4. Timing of flipped Panopto video viewing sessions relative to the class for which each video was assigned. Viewing sessions were binned along the x-axis according to their timing before or after their corresponding class (with each viewing session weighted by its duration), then total minutes for each timing bin were summed from left to right to produce the cumulative distribution of watch timing shown here. The y-axis is the cumulative fraction of total video time delivered during the course (166.3 hours over 41 videos), with video rewatches included. The median and interquartile range (25%-75%) of video releases by instructors, relative to the corresponding class, is included for reference, indicating that videos were generally released 1.5 to 3 days before they were due. Vertical shading corresponds to days; note the compressed positive x-axis scale.
Figure 5. Student engagement with online platforms. (a) Flipped video completion rates over time from Panopto are presented as both the class-wide median (dotted black line) and average (solid black line). Note that video completion by student was allowed to exceed 100% due to repeat views. Piazza Q&A forum engagement is shown as unique users per day (purple) and posts per day, segmented by the type of post (shaded curves; see colors in legend). The timing of coursework deadlines (assignments ['A#...'] and final project checkpoints) are indicated with arrows. (b) Usage of the Piazza Q&A online forum by students and instructors, segmented by type of post (outer) and further divided by chosen audience (inner). “Required posts” were those requested from every student for Assignment #0 and final project check-ins. “Public posts” were viewable by all users, while “private posts” were visible to instructors only. “Anonymous posts” refer to those in which the author was hidden from other students, but not from instructors.
Figure 6. Correlations between student-specific anonymized metrics. Two tests were applied: Pearson’s $r$ (top values) and Spearman’s $\rho$ (lower values, italicized). Higher Pearson correlations indicate stronger positive linear relationships, while higher Spearman values indicate stronger monotonic relationships, which may not necessarily be linear. Correlations without statistical significance ($p > 0.05$) are indicated by “n.s.” Colors correspond to the larger of the two correlation coefficients by absolute value. For detailed information about each metric presented, see Evaluation section “Final grades” (for “Final grade”; column 1), Table S1 in Supplemental Materials (for “Python skills used in project”; column 2), Results section “Assignments and final project” (for “Pair programming experiences; column 3), Evaluation section “Q&A forum engagement” (for Q&A forum-related metrics; columns 4-6), Evaluation section “Flipped video viewership” (for video-related metrics; columns 7-9), Table S3 in Supplemental Materials (for “Prior coding experience”; column 10), and Evaluation section “Initial, mid-quarter and end-of-quarter surveys” (for “Final self-assessment of Python skills; column 11).
Figure 7. Assessment of students’ final projects. (a) Distribution of domains of students’ final projects. If a project topic touched multiple domains, each domain was weighted such that, for example, a project spanning three domains would contribute ⅓ of a point to each of the domains’ total count. (b-c) Distribution of cognitive level of students’ questions and hypotheses. Each student’s questions and hypotheses (up to three each per student) were assessed based on the cognitive process dimension of the revised Bloom’s taxonomy (Krathwohl, 2002) using the rubric and weighting described in Table 2, with higher levels of Bloom’s taxonomy representing higher-order questioning and prediction. (d) The fraction of code syntax taught in the course that students used in their projects (see Table S1 in Supplemental Materials for assessment methodology and search terms). (e-h) Project grades within four named categories that correspond to student learning objectives (SLOs) outlined in the text (see Table S2 in Supplemental Materials for grading rubric and mapping to SLO categories). These categories (with rubric subcategories in parentheses) are code (correctness, functionality, tidiness, perseverance), visualizations (clarity, colormaps, labels, creativity), use of data (data collection, processing, results/interpretation), and scientific research (background, questions/hypotheses, explanations). Note the x-axes are truncated to 40%-100% for readability.
### Tables

**Table 1.** Core topics and concepts taught in Ocean 215. Topics listed here are not necessarily in chronological order as taught in the course, and class time was not necessarily allocated in equal proportions to each topic.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Key concepts and skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>Why code in Python?</td>
<td>The power of programming is its versatility. Python is open source, stable, popular, free, and ideal for scientific data analysis. Google Colab offers advantages in a classroom setting compared to other programming environments.</td>
</tr>
<tr>
<td>Variables and object types</td>
<td>Variables store Python objects, which include numbers, booleans, strings, lists, tuples, dictionaries, and module-specific objects. Objects can be altered, indexed, sliced, iterated over, or used in mathematical operations. Assigning meaningful variable names makes for clearer code.</td>
</tr>
<tr>
<td>Logical operations and control flow</td>
<td>Objects can be compared using logical operations (and, or, is/equals, greater/less than, in, not). Loops and if-statements facilitate repetitive and conditional actions.</td>
</tr>
<tr>
<td>Packages and functions</td>
<td>Installing and using packages extends the capabilities of Python. Built-in, imported, and user-created functions accomplish common tasks and make for more compact, efficient code. Online documentation can be used to understand functions’ arguments and outputs.</td>
</tr>
<tr>
<td>Data files</td>
<td>Oceanographic data are often stored in CSV and netCDF files, which can be read into Python, displayed, indexed, sliced, and manipulated using functions in the NumPy, Pandas, and Xarray packages. Real-world data sets can be obtained from public repositories and frequently contain messy or missing data.</td>
</tr>
<tr>
<td>Working with data</td>
<td>Data can be stored in multi-dimensional NumPy arrays and labeled structures specific to the Pandas and Xarray packages. These packages, as well as others like SciPy, have functions that average, sort, group, correlate, resample, smooth, regress, interpolate, and perform other computations on the data. Understanding common error types and tracing errors from their line of origin allow for methodical debugging of code.</td>
</tr>
<tr>
<td>Plotting</td>
<td>Line, scatter, bar, contour, pseudocolor, and other types of plots available from the Matplotlib package can be used to visualize data. Geospatial data can be projected onto maps using Cartopy. Appropriately customizing and labeling a plot is essential for interpretability.</td>
</tr>
<tr>
<td>Scientific skills</td>
<td>The modern scientific method is driven by data exploration, but also relies on traditional research skills like formulating hypotheses, interpreting the scientific significance of visualizations, effectively communicating results, and giving and receiving feedback from peers and mentors.</td>
</tr>
</tbody>
</table>
Table 2. Rubric used to classify students’ final project questions and hypotheses based on the cognitive process dimension of the revised Bloom’s taxonomy (Krathwohl, 2002). For the analyses in Fig. 7b and Fig. 7c, multiple hypotheses and/or questions offered by students (up to three each) were assessed separately and weighted such that a student’s three hypotheses, for example, would each contribute $\frac{1}{3}$ of a point to their respective cognitive level’s total count.

<table>
<thead>
<tr>
<th>Cognitive level</th>
<th>Questions</th>
<th>Hypotheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1: Remember</td>
<td>“Can the data be visualized using my skills?” Intention to recall coding techniques taught in the course and recognize their proper use</td>
<td>Recall of course material (e.g., the data can be depicted using a scatter/line/pseudocolor plot)</td>
</tr>
<tr>
<td>Level 2: Understand</td>
<td>“What stands out in the data?” Intention to summarize the data; or “Do the data resemble what we expect the ocean to look like?” Intention to interpret the data and classify what is present by comparison to known examples</td>
<td>Factual interpretation (e.g., the data will have X, Y features; the data will resemble X, Y other ocean data)</td>
</tr>
<tr>
<td>Level 3: Apply</td>
<td>“What [happens if...]” Intention to execute or implement a specific procedure, such as calculating a correlation; or “Does [...]” Intention to answer a binary (yes/no) question</td>
<td>Specific results and relationships (e.g., the answer will be yes/no; X will show an increase over time; X and Y will show a positive correlation)</td>
</tr>
<tr>
<td>Level 4: Analyze</td>
<td>“How [does/do/is/are...]” Intention to characterize or test a straightforward or single-dimensional relationship, phenomenon, or difference</td>
<td>Contextual results and relationships (e.g., X and Y will show a positive correlation, but only under Z conditions; X and Y will vary with Z; X is characterized by Y patterns)</td>
</tr>
<tr>
<td>Level 5: Evaluate</td>
<td>“How [does/do...] affect...” “What [is/are...] the relationship between...” Intention to characterize or attribute in an open-ended or multidimensional way; or “Why [does/do/is/are...]” Intention to establish causality by integrating external ideas or models and/or connecting, contrasting, or weighing multiple sources of information</td>
<td>Explanations (e.g., X and Y will show a positive correlation because of mechanism Z; X and Y exhibit different features because of Z)</td>
</tr>
<tr>
<td>Level 6: Create</td>
<td>“What [does/do...] mean...” “How [does/do...] fit into...” Intention to evaluate the implications of findings, place findings within old or new paradigms, construct or produce new frameworks, or investigate the consequences of phenomena using an open-ended approach</td>
<td>Discovery (e.g., X is important because Y; X will differ from a past model Y, where a model is composed of two or more mechanisms; X can be explained using Y model; or a hypothesis cannot be established due to lack of prior information)</td>
</tr>
</tbody>
</table>
Supplemental Materials

“Cracking the code: An evidence-based approach to teaching Python in an undergraduate earth science setting”

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This file includes:
Figures S1-S3
Tables S1-S6
Text S1-S2
Supplemental References

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‡ Current affiliation: School of Earth & Atmospheric Sciences, Georgia Institute of Technology, Atlanta, GA 30332, USA
Figure S1. All metrics from anonymous end-of-quarter student evaluations in 2015, 2016, 2017, 2019, and 2020 (see Evaluation section “Initial, mid-quarter, and end-of-quarter surveys”). Differently worded questions, indicated with an asterisk (*), were mapped between years as shown in Table S4 in the Supplemental Materials. Metrics shown are class medians for 2015, 2016, 2017, and 2019 (gray crosses, except for those in the first row [“Responses”]); 2015-2019 mean or 2020 class median (black points); and 2015-2019 standard deviation (bars). Changes from 2015-2019 to 2020 were tested for a significant increase using a one-tailed (black line) $t$-test or a significant change using a two-tailed (gray line) $t$-test at the 95% (solid line) or 90% (dashed line) confidence level according to the methodology detailed in Evaluation section “Initial, mid-quarter, and end-of-quarter surveys.” An absence of a line connecting the 2015-2019 and 2020 data indicates no statistically significant improvement or difference. Note that y-axes have been truncated from the full 1-5 scale (“Very poor” to “Excellent”) or 1-7 scale (“Much lower” to “Much higher”). Survey questions for which a consistent mapping across years was not possible were excluded; instructor-specific questions are also not shown.
Figure S2. Additional statistics on flipped lesson videos that were posted and viewed on the Panopto platform, based on video-specific metrics obtained from Panopto. Pearson’s $r$ represents the linear correlation between two variables. Note that none of the correlations tested in panels (e)-(h) were significant at the 95% ($p \leq 0.05$) or 90% ($p \leq 0.1$) confidence level. (a) Distribution of number of videos included per lesson (as the 14 topical lessons were usually split into multiple videos). (b) Distribution of the total duration of lessons. (c) Distribution of individual video duration. (d) Distribution of fraction of each video watched for each student. Fraction watched represents the total minutes that a specific video was viewed by a specific student divided by its duration, and thus can exceed 100% due to rewinds and repeat views. (e) Videos per lesson vs. average fraction watched* (* = Lesson #16 outlier removed) (Pearson’s $r = 0.46$, $p = 0.12$) (f) Lesson duration vs. average fraction watched* (Pearson’s $r = 0.05$, $p = 0.88$) (g) Video duration vs. average completion rate* (Pearson’s $r = -0.24$, $p = 0.15$) (h) Video duration vs. average fraction watched* (Pearson’s $r = -0.20$, $p = 0.22$). Fraction watched represents the total minutes that a specific video was viewed by a specific student divided by its duration, and thus can exceed 100% due to rewinds and repeat views. (e) Videos per lesson vs. video fraction watched, averaged across all students. Note that the final video lesson (Lesson #16) was excluded as an outlier due to its lower viewership where indicated using an asterisk (*). (f) Lesson duration vs. fraction watched, averaged across all students. (g) Video duration vs. completion rate, averaged across all students. Completion rate represents the fraction of a video that was viewed at least once, and thus is capped at 100% for a specific student and video (unlike “fraction watched”). (h) Video duration vs. fraction watched, averaged across all students.
Figure S3. Final course grades dichotomized by amount of prior coding experience. Coding experience was assessed using students’ written responses to the Assignment #0 survey (see Table S3 for rubric and methodology) and is divided here into two groups with none/little experience (score of 1 or 2) and some/moderate/lots of experience (score of 3, 4, or 5) containing approximately equal numbers of students. Final grades were recalculated to ignore two students’ incomplete assignments (see Evaluation section “Final grades”) and are expressed as standard deviations from the class average (gray crosses). Error bars represent the median and interquartile range (25%-75%) of final grades for each population. No significant difference in final grades was found between the two groups using a two-sided t-test ($p = 0.89$).
Table S1. Functions, operators, and methods taught in the course that were used as search terms to assess the complexity of students’ final project code. A Python script was used to count instances of each search term in students’ project code notebooks, and the number of search terms used at least once (expressed as a percent of all search terms below) is presented as the metric “Python skills used in project” in Fig. 6.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Search terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic functions</td>
<td>'len(', 'print(', 'display(', 'range(', 'enumerate(', 'zip(', 'int(', 'float(', 'complex(', 'bool(', 'tuple(', 'type(', 'readline('</td>
</tr>
<tr>
<td>Lists</td>
<td>'list(', '.append(', '.extend(', '.insert(', '.remove(', 'del', '.pop(', '.reverse(', '.copy(', '.join(', '.sort('</td>
</tr>
<tr>
<td>Strings</td>
<td>'str(', '.lstrip(', '.rstrip(', '.upper(', '.lower(', '.count(', '.replace(', '.split(', '.format('</td>
</tr>
<tr>
<td>Time</td>
<td>'datetime.now()', '.year', '.month', '.day', '.hour', '.minute', '.second', '.microsecond', 'datetime.strptime', 'datetime.strftime', '.total_seconds()', 'timedelta', 'mdates.date2num('</td>
</tr>
<tr>
<td>Pandas</td>
<td>'.Series(', '.index', '.values', '.loc', '.iloc', '.pd.concat(', '.pd.DataFrame(', '.describe(', '.to_csv', '.read_csv(', '.read_excel('</td>
</tr>
<tr>
<td>Xarray</td>
<td>'.open_dataset(', '.open_mfdataset(', '.attrs', '.isel(', '.sel(', '.item'</td>
</tr>
<tr>
<td>SciPy</td>
<td>'.stats.linregress(', 'interpolate.interp1d(', 'interpolate.griddata('</td>
</tr>
<tr>
<td>Plot types</td>
<td>'.plot(', '.scatter(', '.hist(', '.contour(', '.contourf', '.pcolorshad'</td>
</tr>
<tr>
<td>Logic</td>
<td>' if', ' while ', ' for ', ' is ', ' in ', ' not ', ' else ', ' elif', ' and ', ' -=', ' !=', ' ==', ' &gt;=', ' &lt;='</td>
</tr>
</tbody>
</table>

Table S2. Grading rubric for students’ final research projects. In the first column, corresponding main student learning objectives (SLOs) are appended to the rubric (see Implementation section “Course history and development” for the full numbered list of SLOs). Fig. 7 depicts assessments of students’ final projects using this rubric, grouped by theme and SLOs.

<table>
<thead>
<tr>
<th>Corresponding main student learning outcome(s)</th>
<th>Limited (0-50%)</th>
<th>Good (50-75%)</th>
<th>Exceptional (75-100%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Presentation content</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SLO #5 (<em>Formulate and investigate</em></td>
<td>Background</td>
<td>Topic background is missing or severely lacking in detail.</td>
<td>Topic background is sufficient, but missing</td>
</tr>
<tr>
<td>scientific research questions”</td>
<td>Questions / hypotheses</td>
<td>Data collection</td>
<td>Results / interpretation</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>------------------------</td>
<td>----------------</td>
<td>------------------------</td>
</tr>
<tr>
<td></td>
<td>Questions are not well-defined. Hypotheses are not substantiated.</td>
<td>Information about the data collection process is missing key details or is inaccurate. The limitations of the data are missing or not realistic.</td>
<td>Results of the project do not attempt to answer the scientific questions. The data visualizations are not relevant.</td>
</tr>
<tr>
<td></td>
<td>Questions are well-defined. Hypotheses draw on prior knowledge.</td>
<td>Information about the data collection process is accurate, but missing some minor details. The limitations of the data are explained.</td>
<td>Results of the project somewhat answer the scientific questions. Data visualizations are mostly appropriate for the data.</td>
</tr>
<tr>
<td></td>
<td>Questions are well-defined and pertinent for the topic. Hypotheses draw on prior knowledge and have clear explanations for why they are expected.</td>
<td>Information about the data collection process is complete and accurate. Underlying problems and limitations of the data are explained. Use of these data to answer the project questions is justified.</td>
<td>Results of the project answer, or earnestly attempt to answer, the scientific questions. Data visualizations are entirely appropriate for the data.</td>
</tr>
<tr>
<td></td>
<td>2 points</td>
<td>3 points</td>
<td>3 points</td>
</tr>
<tr>
<td>SLO #3 (&quot;Access, read, transform... and interpret oceanographic data with confidence using Python&quot;)</td>
<td>Data processing</td>
<td>The student has made errors in processing their data. The student is missing steps.</td>
<td>The student has processed the data correctly. Steps for obtaining, loading, cleaning, and analyzing the data are well-defined.</td>
</tr>
<tr>
<td></td>
<td>3 points</td>
<td>3 points</td>
<td>3 points</td>
</tr>
<tr>
<td></td>
<td>Results / interpretation</td>
<td>Results of the project do not attempt to answer the scientific questions. The data visualizations are not relevant.</td>
<td>Results of the project somewhat answer the scientific questions. Data visualizations are mostly appropriate for the data.</td>
</tr>
<tr>
<td></td>
<td>Presentation skills</td>
<td>The presentation is not in a logical order and the student makes no effort to guide the audience.</td>
<td>The presentation is organized in a logical order and shows exceptional attention to guiding the audience.</td>
</tr>
<tr>
<td></td>
<td>Timing</td>
<td>The student completes the presentation in somewhat over 5 minutes.</td>
<td>The student completes the presentation within 5 minutes and it is clear that they have practiced.</td>
</tr>
<tr>
<td></td>
<td>SLO #5 (&quot;Formulate and investigate scientific research questions&quot;)</td>
<td>The ideas and information explained in the presentation were not clear and were not relevant.</td>
<td>The ideas and information explained in the presentation were clear and relevant.</td>
</tr>
<tr>
<td></td>
<td>3 points</td>
<td>3 points</td>
<td>3 points</td>
</tr>
<tr>
<td>Code</td>
<td>Correctness</td>
<td>Functionality</td>
<td>Tidiness</td>
</tr>
<tr>
<td>------</td>
<td>-------------</td>
<td>---------------</td>
<td>----------</td>
</tr>
<tr>
<td>SLO #2 (“Write, execute, and debug Python code”), SLO #6 (“Adopt best practices in programming”)</td>
<td>The student misuses code and does not produce reasonable results.</td>
<td>The student uses some coding techniques/tools learned throughout the quarter. The analysis produces reasonable answers that can be replicated with some effort.</td>
<td>The student properly and efficiently uses the coding techniques/tools learned throughout the quarter. The analysis produces reasonable answers that can be replicated easily.</td>
</tr>
<tr>
<td></td>
<td>The code does not run and has egregious errors.</td>
<td>The code is mostly able to run, but has some (small) errors.</td>
<td>The code runs efficiently with no errors.</td>
</tr>
<tr>
<td></td>
<td>The code breaks proper etiquette and should not be shared with others.</td>
<td>The code mostly follows proper coding etiquette. The organization is somewhat lacking and would need review before sharing.</td>
<td>The code follows proper coding etiquette. It is organized and commented effectively so that it can easily be shared with another person.</td>
</tr>
<tr>
<td></td>
<td>The student has made no effort to work through problems and hurdles.</td>
<td>The student has made some effort to work through problems.</td>
<td>The student has made a gallant effort to work through problems and documented in their code their best understanding of the problems they are facing.</td>
</tr>
<tr>
<td></td>
<td>The plots are unclear and do not make sense in the context of the project.</td>
<td>The plots are mostly clear and show some thought from the students about ways to present their data.</td>
<td>The plots are extremely clear and are effective tools to help the audience understand the results/analysis.</td>
</tr>
<tr>
<td>SLO #3 (“… visualize… oceanographic data with confidence using Python”), SLO #6 (“Adopt best practices in… data visualization”)</td>
<td>The colormaps are not appropriate for the data being shown.</td>
<td>The colormaps are appropriate for the data being shown.</td>
<td>The colormaps are appropriate for the data being shown and take into account colorblindness, and perceptual accuracy.</td>
</tr>
<tr>
<td></td>
<td>The plots are missing most/all labels or have improper labels.</td>
<td>The plots are labeled with general accuracy and completion.</td>
<td>The plots are labeled extremely accurately in a way that guides the audience through the figure.</td>
</tr>
<tr>
<td></td>
<td>The student made no effort to create original plots.</td>
<td>The student has made some effort to create original plots.</td>
<td>The student has created original plots that show the data/analysis in an extremely effective manner.</td>
</tr>
</tbody>
</table>
Table S3. Rubric used to assess students’ prior coding experience based on their written responses to the Assignment #0 survey during Week 1 of the course. Students were asked: “Do you have prior coding experience, and if so, with what language?” and “How comfortable do you feel using technology?” Responses to the first question were graded subjectively based on word choice on a scale from 1-5, using the keywords in quotes (e.g., “a little”) when present. As noted below, additional points were awarded to weight responses in favor of prior exposure to Python or similar high-level and/or interpreted languages (MATLAB, Java, R). Points were subtracted to account for less relevant prior experience. If no level of coding proficiency was provided, the base number used was from the students’ “comfort with technology” statement (“Very comfortable”: 4; “Fairly comfortable”: 2). Results are used in Fig. S3 in the Supplemental Materials and presented as the metric “Prior coding experience” in Fig. 6.

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>No experience</td>
<td>Minimal experience (e.g., “a little”, “small”, “tiny amount”)</td>
<td>“Some” or “moderate” experience</td>
<td>Experience</td>
<td>Experience (with full additions)</td>
</tr>
</tbody>
</table>

Additions (maximum total: +1.0) Subtractions (maximum total: -0.5)

+0.5 for one of MATLAB, Java, R
-0.5 if response mentions many years since their previous experience
+1.0 for Python or multiple languages
-0.5 if response mentions that their previous experience was not useful

Table S4. Mapping of university-administered IAS final course evaluation questions from 2015-2019 to 2020. The mapping allows the slightly different evaluation questions from the two periods to be compared in Fig. 2 and Fig. S1 in the Supplemental Materials. Metrics listed are the median of responses collected for each class.

<table>
<thead>
<tr>
<th>Paraphrased question</th>
<th>Original survey question(s) (2015-2019)</th>
<th>Original survey question(s) (2020)</th>
<th>Metric and units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time spent on course</td>
<td>On average, how many hours per week have you spent on this course, including attending classes, doing readings, reviewing notes, writing papers and any other course related work?</td>
<td></td>
<td>Hours per week</td>
</tr>
<tr>
<td>Time spent that was valuable</td>
<td>From the total average hours above, how many do you consider were valuable in advancing your education?</td>
<td></td>
<td>Hours per week, expressed as percent relative to response to question above</td>
</tr>
<tr>
<td>Expected grade</td>
<td>What grade do you expect in this course?</td>
<td></td>
<td>GPA scale (0.0-4.0)</td>
</tr>
<tr>
<td>Expected grade relative to other courses</td>
<td>Do you expect your grade in this course to be:</td>
<td></td>
<td>1-7 scale (“Much lower” to “Much higher”)</td>
</tr>
<tr>
<td>Effort invested relative to other courses</td>
<td>The amount of effort you put into this course was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effort to succeed relative to other courses</td>
<td>The amount of effort to succeed in this course was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>--------------------------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Participation relative to other courses</td>
<td>Your involvement in course (doing assignments, attending classes, etc.) was:</td>
<td>Relative to similar courses taught in person, your participation in this course was:</td>
<td></td>
</tr>
<tr>
<td>Intellectual challenge relative to other courses</td>
<td>The intellectual challenge presented was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Course as a whole</td>
<td>The course as a whole was:</td>
<td>The remote learning course as a whole was:</td>
<td>0-5 scale (“Very poor” to “Excellent”)</td>
</tr>
<tr>
<td>Course content</td>
<td>The course content was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Usefulness of course content</td>
<td>Relevance and usefulness of course content were:</td>
<td>Average of: “Usefulness of reading assignments in understanding course content was:”, “Usefulness of written assignments in understanding course content was:”, “Usefulness of online resources in understanding course content was:”</td>
<td></td>
</tr>
<tr>
<td>Facilitation of learning</td>
<td>Amount you learned in the course was:</td>
<td>The effectiveness of this remote course in facilitating my learning was:</td>
<td></td>
</tr>
<tr>
<td>Evaluation and grading techniques</td>
<td>Evaluative and grading techniques (tests, papers, projects, etc.) were:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reasonableness of assigned work</td>
<td>Reasonableness of assigned work was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organization</td>
<td>Course organization was:</td>
<td>Organization of materials online was:</td>
<td></td>
</tr>
<tr>
<td>Clarity of student responsibilities</td>
<td>Clarity of student responsibilities and requirements was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructor’s contribution to the course</td>
<td>The instructor's contribution to the course was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effectiveness of instructor’s teaching</td>
<td>The instructor's effectiveness in teaching the subject matter was:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quality of instructor answers and feedback</td>
<td>Average of: “Explanations by instructor were:”, “Instructor's ability to present alternative explanations when needed was:”, “Instructor's interest in whether students learned was:”, “Answers to student questions were:”</td>
<td>Quality/helpfulness of instructor feedback was:</td>
<td></td>
</tr>
</tbody>
</table>
Table S5. Open-ended questions asked in university-administered IAS mid-quarter and final course evaluations in 2020. Students’ anonymous responses are tabulated in Fig. 3 and are excerpted throughout this study.

<table>
<thead>
<tr>
<th>Evaluation period</th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid-quarter</td>
<td>What is helping you to learn in this course?</td>
</tr>
<tr>
<td></td>
<td>What is hindering your learning in this course?</td>
</tr>
<tr>
<td></td>
<td>What can your instructor do to improve your learning in this course?</td>
</tr>
<tr>
<td>Final</td>
<td>Was this class intellectually stimulating? Did it stretch your thinking? Why or why not?</td>
</tr>
<tr>
<td></td>
<td>What aspects of this class contributed most to your learning?</td>
</tr>
<tr>
<td></td>
<td>What aspects of this class detracted from your learning?</td>
</tr>
<tr>
<td></td>
<td>What suggestions do you have for improving this class generally?</td>
</tr>
<tr>
<td></td>
<td>If this course were offered remotely again, what suggestions do you have to improve the student experience?</td>
</tr>
</tbody>
</table>
Table S6. List of guiding questions offered to undergraduate student focus group for structuring their testimonial submissions, which are presented in Text S2 in the Supplemental Materials (also see Evaluation section “Student focus group”). Students were encouraged to address one or more of the questions in their submissions.

<table>
<thead>
<tr>
<th>Question</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. How did your prior experience with coding (or lack of prior experience) impact your experience with the course? If you have prior coding experience and it was self-taught, what do you see as the benefits of learning scientific programming in a structured environment rather than teaching it to yourself? If your prior coding knowledge was learned from course(s), how did we teach programming that was different and more or less effective than those past course(s)?</td>
<td></td>
</tr>
<tr>
<td>2. How did the accessibility elements that we implemented (e.g., captioning, syllabus late policy, extensions, not grading on attendance, breaks during class, virtual office hours, making slide decks available, video optional on Zoom, ability to use chat during class, no course prerequisites, extra credit opportunities, etc.) affect your success in the course?</td>
<td></td>
</tr>
<tr>
<td>3. How did the expectations and norms established in the course impact your experience?</td>
<td></td>
</tr>
<tr>
<td>4. How did you navigate the course policies we created on collaboration and original work? If you worked with a partner on assignments and/or the final project, what was your experience like?Was it productive/challenging/surprising, and how did the technological tools we used (Colab, Zoom) facilitate it? What advice would you give to professors who are teaching a programming course and want to create opportunities for collaboration?</td>
<td></td>
</tr>
<tr>
<td>5. How did the key course elements (recorded videos, in-class activities, assignments, final project, etc.) and technological platforms (Google Colab, Piazza, Zoom, Google Drive/Docs, Canvas) help or hinder your learning?</td>
<td></td>
</tr>
<tr>
<td>6. Instead of a textbook, we allowed use of external resources (e.g., documentation websites, Stack Overflow, etc.). How did this compare to having a textbook for the course?</td>
<td></td>
</tr>
<tr>
<td>7. How did guidance from the instructors and classmates (via Piazza or in class) help you complete assignments and shape and execute your final project?</td>
<td></td>
</tr>
<tr>
<td>8. In what ways did the class help you learn about oceanography sub-disciplines (marine geology, chemistry, physics, biology) or other earth science subjects adjacent to oceanography (e.g., cryosphere, meteorology, climate)? What value do you see in teaching programming in an oceanography curriculum rather than a computer science department?</td>
<td></td>
</tr>
<tr>
<td>9. How do you feel this course fit into your overall undergraduate education? How did this course prepare you for future research, like your senior thesis? In what ways do you feel more capable now that you have Python in your arsenal?</td>
<td></td>
</tr>
<tr>
<td>10. How do you feel this course shaped your career/life goals or motivation to pursue oceanography or data science during and after college?</td>
<td></td>
</tr>
<tr>
<td>11. What was it like taking this class during the pandemic? How does this course compare to other classes you’ve taken remotely during the pandemic?</td>
<td></td>
</tr>
</tbody>
</table>
OCEAN 215 | Autumn 2020 | **Final project**

**Project Description**

During this course, you will conduct a small scientific research project from start to finish. You will choose a topic, produce a scientific question related to your topic, suggest a hypothesis, locate data that will help support or reject your hypothesis, analyze/visualize this data using Python, and present your findings to the class. Along the way, you will be responsible for giving your input on other students’ projects and you will receive input from other students as well. To further reflect the collaborative nature of scientific research, we also encourage you to post any questions or challenges you encounter during this project to the class on Piazza. **If you wish, you may work with a partner on this project. See below for important information if you choose this option.**

The majority of this project will involve writing Python code to analyze and visualize your chosen data. We will dedicate a substantial amount of class time for this work, during which instructors and peers will be present to help you work through coding challenges. Throughout the quarter, there are a number of due dates for different parts (see the table above) designed to guide you through completing your research. The expectations for the deliverables of this project are detailed below:

1. **Topic check-in:** Consider a topic of research that you would like to examine. If you are having trouble identifying a topic, contact the instructors privately on Piazza so they can help you find something that interests you. Once you have identified your topic, create a private note to the instructors on Piazza in the ‘final_project’ folder that answers the questions below.
   - What research topics or questions are you interested in?
   - What type(s) of data would help you look into those topics/questions?

2. **Data check-in:** Locate data that will help you look into your selected topic. We will set aside some class time for students to work on this. You can start your exploration by using an internet search engine to look up background information on your topic and find possible data sources. You can also use the oceanography data repositories (e.g. PO.DAAC, NASA Giovanni, BCO-DMO, etc.) listed in the Class #1 slides. As always, the instructors are also available to help you locate a fitting data source. In the ‘final_project’ folder of Piazza, respond to the data check-in post with answers to the questions below. Make sure that your response is visible to the whole class.
   - What data set(s) do you plan to use?
   - What is one scientific question that you might be able to answer using these data?
   - What is your hypothesis? What do you anticipate the answer to your scientific question is, and why? (try to bring in scientific knowledge from previous courses, published literature, and/or reliable internet sources)

3. **Piazza responses:** Respond to at least 3 other data check-in posts written by your classmates on Piazza with an additional question that they might be able to investigate using their data or about their topic. To reflect the collaborative nature of research, where colleagues often help to dictate research priorities, you will choose one question suggested by a classmate and one question of your own to investigate.
4. **Project presentations:** Present the results of your project to the class in a 5 minute presentation. Presentation schedules will be posted to Canvas later this quarter. Your presentation should include the following:

- Scientific background on your topic [~1 slide]
- Two scientific questions (yours and a classmate’s from Piazza) with your hypotheses [~1 slide]
- Information about your data (How/when/where was it collected? What instruments were used? Are there any limitations to your data?) [~1 slide]
- Your process for obtaining, loading, cleaning, visualizing and analyzing the data. Describe your data file format(s) and structure(s) as well as any challenges you encountered [~1-2 slides]
- Answers to your scientific questions with associated plots and an explanation of your analysis results [~2-3 slides, ~2-3 figures]

5. **Slides and code:** Submit the slides from your project presentation, your data files/folders, and the code you wrote to analyze your data and create your figures. Your code should follow proper coding etiquette and your figures should be formatted properly. To submit your code, data, and slides, save them and put them in your individual class Google Drive folder. There is no written essay required for this project.

**NOTE:** Piazza posts that are required for the final project do not count towards the required 5 Piazza posts detailed in the syllabus.

**Pair programming option**

If you wish, you may work with a partner on this project. This could be a valuable opportunity to experience a research collaboration, work through coding challenges together, and accomplish even more analysis! If you choose this option, the following expectations supersede (override) the requirements listed elsewhere in this document:

- Starting with the **data check-in**, you and your partner may choose a single data set together, and share this identical data set on Piazza. However, please each offer a **different scientific question and hypothesis** in your Piazza posts (i.e. the two of you will come up with two questions and two hypotheses in total).

- For the **Piazza responses**, you and your partner should **each respond to three classmates’ posts** (not including your partner’s post), for a total of six posts. You will jointly choose **one question from a classmate and two questions of your own** to investigate for your project, for a total of three questions to investigate.

- For the **final project presentations**, please prepare a single **8-10 minute slideshow**, instead of a 5 minute slideshow. Include at least the number of slides specified above for each category. Trade off roles when presenting (i.e. each person should be presenting for about 4-5 minutes).

- You may submit separate Colab code notebooks, or a single joint Colab notebook. However, in all notebooks submitted, please indicate which student wrote each section of code using Python comments. **We expect that both partners will contribute approximately equally to writing code for the project.**

- You will be graded jointly and **will receive the same grade for the project**, except under extenuating circumstances to be determined on a case-by-case basis.
# Grading breakdown

<table>
<thead>
<tr>
<th>Project Part</th>
<th>Grading</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Topic check-in:</strong></td>
<td>Complete/Incomplete</td>
<td>10 points</td>
</tr>
<tr>
<td><strong>Data check-in:</strong></td>
<td>Complete/Incomplete</td>
<td>15 points</td>
</tr>
<tr>
<td><strong>Piazza responses:</strong></td>
<td>Complete/Incomplete</td>
<td>15 points</td>
</tr>
<tr>
<td><strong>Project presentation:</strong></td>
<td>See rubric</td>
<td>20 points</td>
</tr>
<tr>
<td><strong>Code:</strong></td>
<td>See rubric</td>
<td>40 points</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>(100 points total)</strong></td>
</tr>
</tbody>
</table>

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**Text S2. Testimonials shared by undergraduate student coauthors** (see Evaluation section “Student focus group” for more details). The students were encouraged to address one or more of the guiding questions listed in Table S6 in the Supplemental Materials in their submissions.

Other coding classes that I have taken have generally failed to place skills in the context of applications. Without examples of methods being used, there is less of an incentive to understand them. In contrast, this course provided the opportunity to work with oceanographic data, allowing us to recognize the significance of the methods we were applying. For instance, ocean glider data was used to teach about interpolation. This was engaging because we first visualized the original, non-interpolated data and could see the gaps due to the physical motion of the device, then compared this with the data interpolated using the same axes and color scale.

Additionally, the lack of a textbook in this course made it easier to approach methods beyond what we learned in class. Instead, we learned to answer questions by accessing online resources like Stack Overflow. Doing so developed essential skills and gave me the confidence to apply new concepts in my final project. This meant my research could be dictated by my curiosity and questions, as it should be, and not by the limitations of what concepts we had covered in class.

In general, research can seem intimidating to many students because it relies on an individual’s creativity. In other classes with exclusively rigid assignments and predetermined tasks, there is little opportunity for students to form original ideas, let alone develop them. In this class, we used creativity and critical thinking skills to develop a final project that answered an independently formed question. This experience has helped to prepare me for research. -O.B.

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I previously took a Fortran class at the Ocean University of China, which had two traditional lectures and one lab each week. In that class, most students were not engaged during the lectures, which led them to be bewildered when doing real coding. I have also been teaching myself MATLAB for three years, basically learning by doing tasks with the help of the internet. This process has often been time-consuming, and it has been hard to organize my notes in a logical way. In comparison to those experiences, this course provided a logical pathway into Python, especially for oceanography applications. Without this class, it would have taken ten times longer to acquire the same knowledge, which would also have been less clear.
In class, Zoom breakout rooms forced everyone to discuss and practice the coding, which in turn forced us to come well-prepared for class. Though Google Colab has limited storage (RAM) and is unable to process large data sets, it is great for starters. Most of my other classes have been about theory and previously derived conclusions in the field, but this class has provided a bridge between theory and practice. After taking this course, I would say that we can now start to connect math and data to discover the areas of science we are interested in. -J.L.

———

I have always viewed research as something that is extraordinarily complicated. This class demonstrated that knowing a few basic Python functions and packages can provide a solid foundation to start conducting research. Additionally, offering this class as part of an oceanography curriculum instead of relying on a computer science department allowed us to learn about programming skills in a way that directly applied to our interests and studies.

I liked the way that the course was set up, in which we learned the material in an asynchronous video first and then practiced it in class. This helped me to discover where my gaps in understanding were and to learn from other people who may have understood a concept better than I did. Google Colab may not be the most powerful programming platform, but it is streamlined and easy to use, which made it great for first-time coders like me. Piazza was also an exceptionally useful resource.

Many classes present an idealized version of how research works. This class didn’t. It was an important learning experience when my final research project didn’t yield the correlation I expected. This was frustrating since I put so much time and effort into the project, but it showed that a lack of correlation can be an important result and that one’s research doesn’t always have to produce a major scientific breakthrough. -R.M.

———

I came in with a little prior coding experience thanks to robotic projects that I completed with my father as a child. In taking this class, the love of coding that I had as a child was reignited. I hadn’t realized how beneficial and necessary knowing a programming language would be for research. Having Python in my arsenal opened up research opportunities that I wouldn’t have been qualified for before and can aid me in branching out beyond oceanography in the future. The great experience I had in this class – and my realization that research and coding are extremely integrated – inspired me to pursue a minor in Data Science.

In this class, the coding assignments were based on real-world problem solving. I loved having the opportunity to work with a partner because we coded in completely different ways, and it was fascinating to see those differences. We were more effective together because we learned to compromise and collaborate to find the cleanest and fastest method between the two of us. Writing code on Zoom was a good alternative to in-person collaboration because we could share our screens and help pinpoint issues in each other’s code. In addition, Piazza was helpful for me because it allowed anonymous or private questions, which avoids the uncomfortable feeling of asking a question that you think might be silly. I liked that we were able to get quick and helpful feedback on our code. It was a better way of communicating than those I have used in other classes, like email, which might get drowned out in a teacher’s inbox, or Slack, which doesn’t provide the anonymity that Piazza does. -I.O.

Supplemental References