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Embedding online, design-focused data visualization instruction in an upper-division undergraduate atmospheric science course

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ABSTRACT

An interdisciplinary undergraduate atmospheric science modeling course was cotaught at a midsize public university by three professors from atmospheric science, statistics, and design using a blended learning approach. The in-class portion of the course taught upper-level students numerical weather prediction modeling and statistical evaluation methods. Online modules were used to teach data visualization techniques and three foundational design principles upon which their efficacy depends : legibility, visual hierarchy, and appropriate use of color. Geoscience students need data visualization skills to prepare for careers in government, industry, and research that increasingly require work with big data and communication with diverse collaborators and audiences. This article focuses on the instructional approach for the visualization component of the course—specifically, the three teaching innovations used: online modules, an interdisciplinary teaching team, and design-focused data visualization instruction. Although course enrollment was low at four students, several valuable lessons were learned that can improve the teaching of visualization in geoscience courses, including the utility of structuring visualization instruction around two separate but complementary visualization skills: visualization for analysis and visualization for sharing knowledge. Evaluation of students' visualization work at the conclusion of the course demonstrated improvement in the foundational design principles as well as improved ability to select appropriate visualization strategies for different situations. The methods used to assess these improvements are presented alongside illustrative examples of student work. Pre- and postcourse surveys indicate the students felt more confident in creating data visualizations upon completion of the course, and qualitative assessments of student work confirm increased application of foundational design principles in visualizations created by the students. The authors argue that teaching visualization as an online supplement to other geoscience instruction is a potentially replicable model for improving students' learning about visualization. This is especially true when such instruction relies on open-source programs and materials and leverages interdisciplinary expertise in course design.

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Purpose and learning goals

Visualization is a critical skill for geoscience students to master in order to create accurate mental models of foundational concepts, to analyze the results of a broad range of experiments, and to communicate findings effectively with their teachers, classmates, and broader audiences (Gilbert, 2008; Iwasa, 2016; McDermott, Rosenquist, & van Zee, 1987; Titus & Horseman, 2009). Work in several fields—design, journalism, information visualization, and visual rhetoric—has led to an interdisciplinary understanding of what makes a visualization effective and to established visualization conventions and practices (Cairo, 2014; Harold, Lorenzoni, Shipley, & Coventry, 2016; Higgins, Baslie, Van Hecke, Zissman, & Gilkeson, 2017; Kostelnick, 2013; Krause, 2017; Moere & Purchase, 2011; Monmonier, 1991). However, science educators are seldom exposed to these design principles and are therefore unlikely to be able to pass them on to their students (Gilbert, 2008; Mathewson, 1999; Rodríguez Estrada & Davis, 2015; Trumbo, 1999).

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Supplemental data for this article can be accessed at here.

In cases in which geoscience educators are well versed in visual forms of communication, they may be hindered in creating successful introductory lessons or course modules on visual communication and visualization by their longstanding and discipline-specific expertise (Paxton, Frith, Kelly-Laubscher, Muna, & van der Merwe, 2016; Stofer, 2016). Consequently, geoscience students commonly have poor visualization skills, which adversely affects their ability to grasp foundational concepts, analyze data, and communicate scientific knowledge (Black, 2005; Libarkin & Brick, 2002). With the current widespread public skepticism regarding scientific inquiry, preparing students with visualization skills that can improve their communication of science is also gaining societal significance (Black, 2005; Crider, 2015; Fox & Hendler, 2011; Makri, 2017). To address this critical gap in geoscience education knowledge, we conducted a pilot study that incorporated design-focused instruction on visualization into an upper-level atmospheric science course. Visualization instruction was grounded in a typology that helps science students identify which data visualizations are best suited to different situations: visualization for data analysis, to aid in drawing scientific conclusions, and visualization for sharing knowledge, to communicate scientific findings to broader audiences (Hepworth & Canon, 2018; Shoresh & Wong, 2012). The visualization component of the course had four learning goals:

1. Students select data visualization strategies appropriately matched to the visualization purpose (data analysis or sharing knowledge).
2. Students apply the design principle of legibility when creating data visualizations.
3. Students effectively combine colors when creating data visualizations.
4. Students employ the design principle of strong visual hierarchy when creating data visualizations.

Because the focus of the semester-long course was not visualization alone, these learning goals were implemented through an interdisciplinary, coteaching approach using online modules. This article focuses on the visualization modules and three distinct teaching innovations that were incorporated: online modules; an interdisciplinary, coteaching team; and design-focused data visualization instruction.

The course as a whole—including the sections on data visualization and also the elements focusing on numerical weather prediction (NWP) modeling and statistical evaluation methods, which are not discussed in detail in this article—sought to address multiple interrelated knowledge gaps in undergraduate geoscience education related to the increasing prevalence of big data in science careers and the need for skills to manage and analyze large datasets (Donovan, 2008; Fox & Hendler, 2011; Lesh, Middleton, Caylor, & Gupta, 2008; Mellody, 2015; Moere & Purchase, 2011; Peterlin, 2010; Royster, 2013). The course innovation discussed in here provides a replicable model that geoscience educators can implement to incorporate visualization instruction into coursework that addresses all or a portion of these knowledge gaps, regardless of the specific geoscience content of the course.

Literature context

Visualization learning goals

Visual–spatial thinking has always been a key skill for success in the geosciences, and as growing quantities of data and dependence on computer analysis permeate many geoscience disciplines, students are increasingly called on to manage and analyze complex data and communicate the results visually (Johnson et al., 2006; Lesh et al., 2008; Libarkin & Brick, 2002; Maeda, 2013; McDermott et al., 1987; Mellody, 2015; Yoon & Min, 2016). Skills training in this area has consequently become increasingly urgent (Campbell, Overeem, & Berline, 2013; Ellwein, Hartley, Donovan, & Billick, 2014; Royster, 2013). As such, geoscience students need to be taught visualization for two different purposes: for analysis and for sharing knowledge (Shoresh & Wong, 2012). In practice, these two types of visualizations can be thought of as visualizations to aid in analyzing data and visualizations to communicate findings to broader audiences (i.e., presenting the data analysis results to someone unfamiliar with the research; Hepworth & Canon, 2018).

Visualization for analysis encompasses the construction of mental visual concepts and the production of visualization objects—charts, graphs, diagrams, maps, plots, and sketches—for the purpose of gaining conceptual knowledge of the scientific principles contributing to the problem of interest and making the data easier to digest visually. Visualizations in this context are tools to facilitate scientific discovery by leveraging human information processing, pattern recognition, and visual perception, and they are used either individually or collaboratively within a research group (Valle, 2013; Wong, 2012). These types of visualizations are common in the geosciences, in which datasets are large and it would be impossible to analyze the data and draw conclusions without visual examination.

Visualization for sharing knowledge is the production of visualizations for the purpose of communicating scientific information to any audience that has not participated in the particular experiment, research project, or event. Visualization for sharing knowledge includes a wide range of visualization objects, including data-driven museum exhibits, figures typically found in academic papers, infographics, interactive and motion graphic illustrations, and visual abstracts. Visualizations for sharing knowledge may target different audiences, but they have the common trait of communicating scientific findings beyond the research group, after analysis has been concluded (Hepworth & Canon, 2018).

Both visualizations for analysis and visualizations for sharing knowledge are more successful when designed using best practices, although slightly different skills are emphasized in each visualization modality (Moere & Purchase, 2011). In particular, visualization for sharing knowledge requires extra consideration of audience, context, and purpose, ensuring that the visualization is carefully matched to its audience through selection of tone, jargon, and level of formality (Higgins et al., 2017; Krause, 2017; Tyler, 2006). This means that knowledge of the data is insufficient for the creation of a successful visualization for sharing knowledge; knowledge of the audience is also required (Rodríguez Estrada & Davis, 2015; Valle, 2013; Wong, 2011). Visualizations for sharing knowledge must be designed with reference to the context the image will be presented in, and with a clear understanding of the purpose of, the visualization. Combined with audience and context, purpose can guide decision making about what level of scientific detail must be conveyed and what the core message of the visualization should be (Higgins et al., 2017; Stephens, Edwards, & Demeritt, 2012).

Visualization Learning Goal 1 (stated above) emphasizes the importance of identifying the type and purpose of each visualization before creating it, whereas Learning Goals 2–4 are designed to give students the requisite skills to construct visualizations in accordance with best practices based on foundational design principles. This includes ensuring all text is clearly readable at the distance and in the conditions the visualization will most commonly be experienced (adhering to the principle of legibility—Learning Goal 2); use of color that promotes good legibility and visual hierarchy (adhering to the principles of color theory—Learning Goal 3); and ensuring all elements in the visualization are spatially arranged and sized so that the reader's attention is drawn to various components in an order that fosters comprehension (adhering to the principle of visual hierarchy—Learning Goal 4).

Adhering to these principles ensures that visualizations present data and concepts in ways that are optimal for human cognition and comprehension. For example, it is important to present five or fewer groups of information (as delineated by color, shape, shading, or position) in any one visualization, as this is the maximum number of "chunks" of information humans can comfortably process at one time (Benson et al., 2012). Also, when using colors to represent data in a visualization, it is important to use hues that are easily discernible from one another (Wong, 2010). These best practices can be applied in the production of visualizations in any discipline, including geoscience. Course modules were designed to address each of these skill areas: visualization for analysis, visualization for sharing knowledge, and best practices for designing both kinds of visualization.

Visualization education in the geosciences

In the geoscience education literature and beyond, there is a growing body of evidence on the value of visualization instruction in science classes (Gilbert, 2010; Kastens & Manduca, 2012; Paxton et al., 2017). Some authors have studied the benefits of creating visualizations, and others have focused on the effectiveness of students studying precreated visualizations; both have been deemed helpful (Cheng, Guy, Narduzzo, & Takashina, 2015; Dollahon, 2017; Kohnle et al., 2010). Student-created visualizations for analysis can quickly reveal the mental models held by students, allowing instructors to respond to inaccurate models more effectively (Ainsworth, Prain, & Tytler, 2011; Merhar, Planinsic, & Cepic, 2009; Wong & Kjaegaard, 2012). Much science education work has focused specifically on the benefits of visually oriented making during science class, such as drawing, when students make their thoughts "specific and explicit" (Ainsworth et al., 2011; Wong & Kjaegaard, 2012, p. 1037). This concept of visualization for comprehension of data or processes—or for the creation of accurate mental models—is of particular importance in geosciences, which are especially visual, but it is equally beneficial in disciplines like chemistry or astronomy, which may be considered more abstract (Crider, 2015; Kozma & Russell, 2005; Reynolds et al., 2005). Visualizations have been demonstrated to increase student comprehension and engagement both when produced by hand, such as by drawing or sketching, and on computer software, such as when visualizing the complexity of modern-day data (Peterlin, 2010; van der Veen, 2012). In general, this literature emphasizes the role of visualization as a tool for analysis, either of concepts or of data, which students can use to increase their personal understanding of scientific concepts and facilitate their collaboration in small groups.

Less common in the geosciences education literature (and in science education literature more generally) is instruction on visualization for sharing knowledge. Visualization for sharing knowledge is taught in a few university science classes—for example, in MIT's biomedical engineering courses, in which students make visual arguments with original research data (Craig, Lerner, & Poe, 2008). Such courses are not common, and although science communication skills are receiving more attention, visual communication skills like visualization are often left out of scientists' communication training (Rodríguez Estrada & Davis, 2015). However, Gordin and Pea (1995) pointed out that such instruction might serve to connect students with the real, day-to-day work of scientists and motivate them to guide their own inquiry. Overall, this work makes a case for incorporating visualization strategies in interdisciplinary geoscience education and suggests promising opportunities for bringing student-created data-driven visualizations into the classroom. Doing so also answers a wider call in the science education literature for more active learning experiences, interactivity, and an increased emphasis on teaching problem-solving techniques that students can apply in multiple disciplines (Cano, Chacón-Vera, & Esquembre, 2015; Edens & Potter, 2003; Ellwein et al., 2014; Ernst & Clark, 2007; Marshman & Singh, 2016; Zhang & Linn, 2011; Zuza, Garmendia, Barragués, & Guisasola, 2016).

This article reports on a proof-of-concept course designed to answer these calls in the literature by developing online course modules specifically targeted to address visualization purposes that are less frequently integrated into geoscience coursework: visualization for sharing knowledge and data-driven (as opposed to concept-driven) visualization for analysis. Visualization instruction was delivered through online modules because there is some evidence they are effective for student learning, and with the intention that they could eventually be used in a range of geosciences courses as a supplement to classroom instruction (Hill, Sharma, & Johnston, 2015). This approach is situated in blended learning theory, which suggests that careful integration of in-class and online learning experiences improves educational outcomes for students by engaging a broad range of learning styles, promoting active learning, and balancing instruction in theoretical and applied knowledge (Garrison & Kanuka, 2004; Jacobs, Gorman, Rees, & Craig, 2016; Sit & Brudzinski, 2017). Unique to this course, however, is the application of blended learning to embed and integrate expert instruction on an interdisciplinary topic (data visualization) into a discipline-specific course (atmospheric modeling). Geoscience courses are an ideal place to experiment with incorporation of visualization education, because geosciences, like visualizations, often blend qualitative and quantitative techniques and methods, and because teaching visualization skills can help geoscience students integrate their knowledge across multiple disciplines while developing the types of science skills in high demand for their future careers (Campbell et al., 2013; Stofer, 2016). The goal of the course as a whole was to enhance student understanding of atmospheric science concepts and models; improve student preparedness for upper-level, big-data courses; and, ultimately, to improve their readiness for government, industry, and research careers that involve working with big data.

Study population and setting

The course, titled "Computational Skills for Big Data: Analysis, Statistics, Visualization," was offered to upper-level undergraduate atmospheric science students at a mid-size public university. This course was taught as a special problems course and the prerequisites for the course were Intermediate Meteorology (junior-level atmospheric dynamics) or Calculus III and Statistics (for students who were not atmospheric science majors). These prerequisites were determined because the primary course focus was on numerical weather prediction modeling, and students were expected to conduct sensitivity testing for NWP model configurations, as well as to fit statistical distributions to their modeled data and observations.

Additionally, even though the course focused on atmospheric modeling, we wanted it to have broader appeal to math and science undergraduates interested in learning analysis methods for large datasets. The visualization modules developed for the course could be used in a lower-level undergraduate data analysis and computing course and would not require these same prerequisites. The students were not required to have previously taken a computational course; however, students in the atmospheric science curriculum typically take a first-year level computer science class within their first two years. The total enrollment was four students with the following majors: atmospheric sciences and physics major with mathematics minor, atmospheric sciences major with mathematics minor, atmospheric sciences major with creative writing and mathematics minor, and atmospheric sciences and secondary education majors. The group included three male students and one female student, three of whom were in the final semester of their degree program. Each student brought a different set of skills to the course based on previous academic preparation. The course met once per week for two and a half hours, and students were expected to complete the majority of their assignments during this class period, with an expectation that the remaining 40% of their workload would be completed outside of class time. Although the course had a small enrollment, it served as a proof of concept for future integration of an online visualization component into a first-year-level course, which will be modified based on the learning expectations for first-year college students. With this in mind, the online visualization course materials were created to be relevant to a broad range of student abilities (both lower- and upper-division students), and the visualization activities were designed to be engaging and scalable (i.e., logistically feasible with the larger class sizes that first-year courses typically have).

Materials and implementation

Course preparation

This interdisciplinary pilot course contained three subject areas: computational modeling, statistical analysis, and visualization. To cover these disparate subject areas, an interdisciplinary, coteaching approach was used, with three instructors teaching interrelated concepts in their respective areas of specialization. A design professor taught the visualization component, a math professor taught the statistics component, and an atmospheric science postdoctoral researcher taught the computational modeling and analysis component. An atmospheric science professor served as facilitator and manager of the course funding and logistics. Students in the course used open-source data from reputable sources in software programs such as MATLAB and R to conduct calculations, statistical analysis, and modeling, and to make information-based decisions. Three of the students did not have experience with R or MATLAB prior to the course. Students were able to learn the basic code for their projects, including the visualization R codes, while in class or during instructors' office hours.

The chosen subject of the computational modeling component was NWP, specifically using the Weather Research and Forecasting (WRF) model, due to the current high demand for this skill set in government, industry, and research. The WRF model is a widely used tool for weather forecasting and hindcasting (Skamarock et al., 2008). In the statistical component of the course, students were taught to conduct distribution fitting and hypothesis testing (e.g., Kolmogorov-Smirnov testing) on their WRF simulation results to compare time series of model results with observations. In the visualization component, students produced line, bar, and scatter plots comparing modeled data with observations in order to demonstrate the WRF model performance. Due to time constraints, it was decided that the visualization course content would be taught online, with students doing the bulk of the visualization work outside of class, whereas the computation and statistics components were taught during class time (see Figure 1). This had the added benefit of visualization modules potentially being available for use in other geoscience courses, with little modification. Visualization instruction—designed to improve students' capacity to work with data and communicate about the data, concepts, and models in the course—was provided alongside in-class material on statistical analysis.

Course structure

The course had three components: The computational modeling component ran over the first eight weeks of class, the statistical analysis component ran over the last eight weeks of class, and the online visualization component ran concurrently with the statistical analysis component (Figure 1). The first half of the course focused on teaching students to run WRF simulations using high-performance computing (HPC) environments, specifically by remote access to the Yellowstone supercomputer at the National Center for Atmospheric Research (NCAR) Wyoming Supercomputing Center (Computational & Information Systems Laboratory, 2012). Students were responsible for designing a sensitivity experiment using WRF simulations to compare numerical results for two simulations with the observations, making it a useful atmospheric science, statistics, and data visualization exercise. Students were also responsible for the completion of a course project, and the required deliverables included a seven-page report and a 20-minute oral presentation (a 15-minute presentation, with five minutes of questioning) of their findings. For the

Structure of interdisciplinary class components, with emphasis on visualization-related components

Week	Classroom instruction topic	Online Visualization topic	Office hours visualization support
Week 1	Introduction to Linux, High-Performance Computing, and Yellowstone		
Week 2	Numerical Weather Prediction Models, Microphysics, and WPS		
Week 3	WRF Initialization		
Week 4	Investigating and Analyzing WRF Data		
Week 5	Introduction to NetCDF and Matlab		
Week 6	External Data Analysis		
Week 7	External Data Analysis	Introduction to design for visualization	
Week 8	Midterm and Work on Projects	Visualization for Analysis 1: Type	
Week 9	Statistics Review: Hypotheses Testing, Estimation, Distributions	Visualization for Analysis 2: Color	
Week 10	Exploratory Data Analysis: Numerical and Graphical Summaries	Visualization for Analysis 3: Emphasis	
Week 11	Model Fitting, Goodness of Fit	Visualization for Analysis 4: Putting it into practise	
Week 12	Correlation/Regression Topics	Visualization for Sharing Knowledge: Visual abstracts	
Week 13	Multiple Linear Regression Topics		
Week 14	Wrap-up, End of Course Info		
Week 15	Final Project Presentations integrating visualizations for analysis and sharing knowledge		

Figure 1. Class structure, including how the visualization module aligned with class instruction and visualization-focused office hours hosted by the design faculty member. The design professor was physically present in the classroom in weeks 1-3, 7 and 11 to introduce the visualization module and reinforce online content. The design faculty was available for office hours consultations in weeks 7-15, to further support online module content.

report, students were required to provide technical background for the WRF physics scheme chosen for their sensitivity experiment and apply their newly acquired statistics and visualization skills to analyze their WRF sensitivity experiments and produce graphs of the model performance, respectively.

In the latter half of the course, the online visualization component was taught in three modules: introduction to producing visualizations using best practices, visualization for analysis, and visualization for sharing knowledge. The design professor was physically present in the classroom in weeks 1–3, 7, and 11 to introduce the visualization module and reinforce online content. The design faculty member was available for office hours in weeks 7–15 to further support online module content (Figure 1). In the first module, students spent one week familiarizing themselves with the online learning environment and required tools for making visualizations (R and Plotly, https://plot.ly/). In the second module, "visualization for analysis," students spent four weeks practicing making visualizations that used the three principles mentioned previously: appropriate color use, legibility, and visual hierarchy (Learning Goals 2–4). After learning about and practicing implementing each principle, students applied the principles to visualizations of their data, evaluating their model results compared with observations (demonstrating Learning Goal 1, visualization for analysis). In the third and final module, "visualization for sharing knowledge" (Learning Goal 1), students learned to visualize data in the form of a visual abstract, an extremely simplified, visual overview of a research paper's main argument. Visual abstracts were chosen as a visualization format due to their recent requirement for many journal articles, combined with the lack of readily available and clear instruction on how best to design them.

Visualization instruction was carefully scaffolded as recommended in the literature, with each week's work progressively building on and incorporating the previous week's learning (Crider, 2015; Ellwein et al., 2014; Langen et al., 2014; Libarkin & Brick, 2002). To help students produce high-quality visualizations, the first visualization activity required the students to design a line chart, bar chart, or scatter plot demonstrating good legibility, and the second week required them to produce a chart with good legibility and appropriate use of color. Students produced their visualizations for analysis (as part of the second module) in R, a widely used open-source statistical analysis software package. To help students produce high-quality visualizations, they were provided with well-designed fonts to use in their charts (Quadraat, Officina, and Scala). In addition, students were given sample R code that used several R libraries designed to produce visualizations that follow best practices with efficient code (e.g., ggplot2, showtext, ggrepel, assertthat, scales, and colorspace). Each provided R script generated a particular type of chart based on specific variables they needed to modify, including the variable for inputting their own data source. To produce their visual abstracts, students used online visualization software called Plotly (https://plot.ly/). This software provides a simple WYSIWYG (what you see is what you get) user interface for adjusting visualizations made with R code and was deemed to be more appropriate than R for creating the simplified design work typically contained in visual abstracts.

Course materials

The course materials for the online visualization modules were housed in the institution's learning management system, Canvas. These materials consisted of online visualization module content, rubrics, the syllabus, and discussion boards on which students posted their visualization work. Each module contained a video of the design professor introducing the activities and required reading covering relevant design principles. Each week, students were required to watch the video, read the assigned reading, and then complete the week's activities. The first module contained an activity in the form of a self-reflective video, in which students had to reflect on their previous experience with visualizations. The second module contained activities in the form of R codes. The heavily annotated R codes were written so that a novice R user could run them with minimal editing of the code required. Each activity required progressively more code editing by students, but requirements were still at the novice level. To use the R codes, students opened them in sequence, changed variables where indicated by annotations in the code, saved them, then ran them on the lab computers to produce their visualizations. The third module contained an activity in the form of instructions for using the online visualization tool, Plot.ly. These materials can be accessed in the supplemental files.

Evaluation

Overall design and strategy

There were two aims of the course evaluation: to assess students' perceptions of the importance of, and their skills in, visualization; and to assess student learning about visualization. To assess students' perceptions of their skills, pre- and postcourse surveys were used. To assess student learning, students' visualization work was qualitatively assessed (using a rubric-guided visual analysis of student work by the design professor) for success at achieving the four learning goals. IRB approval was granted prior to assessment activities being conducted. To determine whether the course innovation was successful overall, the instructors looked for evidence that foundational design principles were being applied in students' data visualizations in their final projects and that students reported improved familiarity with these design principles at the end of the course.

Data sources

The design professor evaluated gains in students' visualization skills by conducting a qualitative visual analysis of the visualizations they produced at the beginning and end of the course. Each student created a total of eight or nine visualizations in the class: three visualizations created through R code activities, one visual abstract, and between four to five visualizations for their final papers and final presentations. The design professor used a rubric and specialist expertise to identify appropriate use of design principles in these visualizations. The combination of rubric and expert knowledge of execution is a common evaluation method for assessing the execution of design principles by students in a wide range of fields (Giloi & Du Toit, 2013; Smith, 2013).

At course conception, instructors planned to measure the degree to which students followed this instruction by using rubric questions aligned with learning goals for the visualization component of the course (see Table 1). However, during the assessment process these rubric questions proved to be too vague for accurate assessment. Therefore, two separate, more detailed rubrics were created to facilitate the qualitative visual analysis of student visualization activities by the design professor: one for assessment of

Table 1. Alignment of visualization learning goals with initial qualitative visual assessment rubric questions.

Learning goal	Visualization qualitative assessment rubric questions
Students can create two kinds of visualizations—visualization for analysis, and visualization for sharing knowledge.	Are visualizations for sharing knowledge easy for their particular audiences to understand?
Students can effectively use the design principle of legibility in both kinds of visualizations.	Is all text in the data visualizations clearly legible?
Students can effectively combine colors in both kinds of visualizations.	Has the student used color in a way that supports legibility and visual hierarchy?
Students can effectively demonstrate the design principle of strong visual hierarchy in both kinds of visualizations.	Do the data visualizations embody a clear usage of the visual principles that yield an effective visual hierarchy?

Table 2. Final (more detailed) rubric for qualitative visual assessment of visualization for analysis.

	Insufficient	Sufficient	Good
Good chart practices			
Descriptive heading and subheading			
Axis indicator lines across plot			
Units of measurement in axis labels			
Easily intelligible legend			
Good visualization conventions			
Appropriate color selection			
Appropriate combining of colors			
Visual hierarchy—heading emphasis			
Legible font—legend			
Legible font—axis markers			
Legible font—axis labels			

Table 3. Final (more detailed) rubric for qualitative visual assessment of visualization for sharing knowledge.

	Insufficient	Sufficient	Good
Good visual abstract practices			
No heading			
One figure only			
Simple data selection			
Good visualization conventions			
Appropriate color selection			
Appropriate combining of colors			
Legible font—legend			
Legible font—axis markers			
Legible font—axis labels			

visualization for analysis and another, slightly modified version for assessment of visualization for sharing knowledge (see Tables 2 and 3). Combined, these two detailed rubrics allowed for forming thorough answers to the assessment questions that were initially posed and, consequently, better alignment with the visualization learning goals. Further detail about expectations for students in each of these assignments is provided in the Results section.

The visualization component of the course was evaluated with the well-respected and widely used Program Evaluation Tool developed by Michigan State University, which is highly reproducible in any class context (Henry, Mavis, Sleight, & Williamson, n.d.). This tool integrates curriculum goals and objectives with evaluation questions, sources of evaluation data, and methods of data collection. The primary sources of evaluation data for the visualization component of the course were pre- and postcourse surveys about the course content completed by students at the beginning and end of the course, respectively (available in the online supplementary information). These forms contained questions and multiple-choice answers using the phrasing recommended by Stanford University's Course Evaluation Committee (2013) and the customizable University of California–Berkeley Course Evaluation Question Bank (UC Berkeley Center for Teaching & Learning, 2017). Answers to the questions were in a qualitative form on a Likert scale, ranging from "not well at all" to "extremely well." The forms asked students to rank their own experience with big data skills, statistical methods, and visualization skills on the first day and the last day of class, respectively. The questions related to the visualization component of the course aligned with the learning goals visualization component of the course (see Table 1).

Data collection

Data were collected for the Program Evaluation Tool at the beginning and end of the course. Precourse surveys were administered online at the beginning of the second week of instruction, before visualization instruction commenced. Postcourse surveys were administered online during the last class of the semester, after students had completed their visualization activities and final projects. The pre- and postcourse surveys contained 11 identical questions relating to students' self-assessments of their own skills in all topics covered in the course. Seven of these questions related to the visualization portion of the course, with the remaining four relating to big data computation and statistical methods. The questions related to visualization were these:

- How well can you currently create data visualizations to interpret data?
- How important do you consider creating data visualizations to interpret data is?
- How well can you currently create data visualizations to communicate findings?
- How important do you consider creating data visualizations to communicate findings is?
- How well do you understand the role of legibility when creating data visualizations?
- How well do you understand the role of visual hierarchy when creating data visualizations?
- How well do you understand the importance of resolution and rendering when creating data visualizations?

The comparison of answers to these questions in the pre- and postcourse surveys was used to ascertain students' perception of their change in familiarity with class concepts. The precourse survey contained one additional question about how students heard about the course: "How did you hear about the course?" The postcourse survey contained one additional question: "How relevant do you feel this course is for your future career?" Data describing student change in visualization skills were collected by using rubrics to qualitatively assess all student visualization work after instruction had been completed.

Results

The assessment of students' visualization work showed that, overall, students demonstrated use of color, visual hierarchy, and legibility in visualizations for analysis. Figure 2 shows one student's progression in implementation of foundational design skills in their visualizations. In the first chart (Figure 2a), the student practiced implementing legibility, and in the second chart (Figure 2b), the student practiced implementing legibility in combination with appropriate color use and visual hierarchy. Although color use is not visible in the black-and-white figure, the color figure is available as a supplemental file.

In the visualizations created for their final papers (both visual abstracts and figures), most students effectively demonstrated use of foundational design

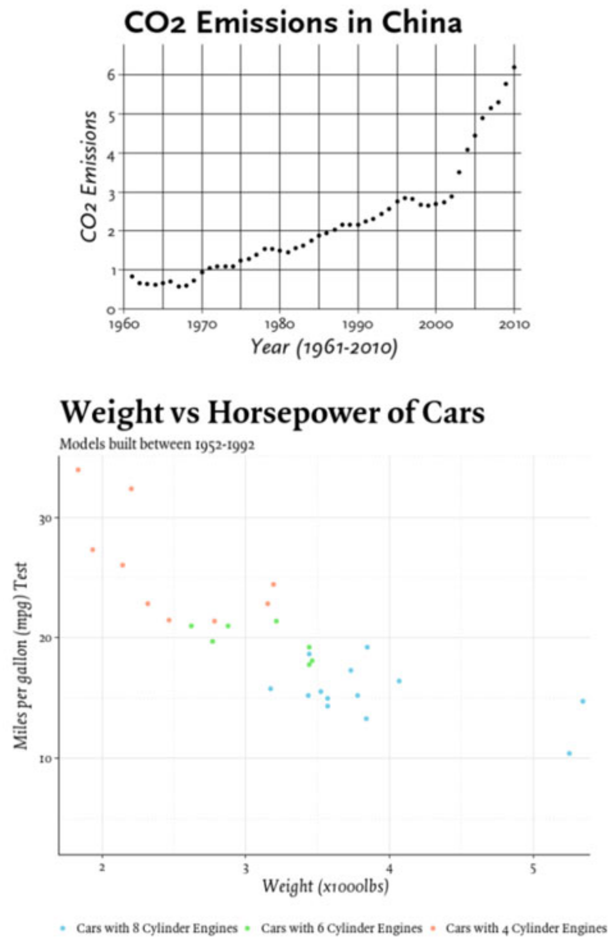


Figure 2. Student work demonstrating progression in skills. Figure 2a (top) is Student 1's execution of the activity that taught students legibility in a chart for data visualization for analysis. Best practice legibility has been demonstrated in this work by (a) using a font that is easily readable in black on a white background; (b) making the chart title the largest font size, bold, and left aligned; (c) axis labels made second largest font size, and italicized for emphasis that does not compete with the title; and (d) making axis indicator numbers small but still clearly readable when used in a printed academic paper. Figure 2b (bottom) is Student 1's execution of the activity that taught students to integrate legibility, visual hierarchy, and appropriate color use in concert in a chart for data visualization for analysis. It demonstrates use of legibility in the same ways as Figure 2a, with the addition of a subtitle in a smaller type size, to provide additional information while not competing visually with the title, and a legend. Addition of a subtitle and legend in their respective font sizes, styles, and positions is a demonstration both of legibility and of visual hierarchy. Visual hierarchy is also demonstrated in this work by lower saturation of *x* and *y* indicator lines in the chart field. Appropriate color use is demonstrated in this work by (a) consistent use of black for all type and x and y axis lines, combined with (b) three distinct, mid-level saturation hues for data points that stand out from one another, even when photocopied or reproduced in black and white. Unfortunately due to the limitations of publication, only the grayscale version is reproduced here.

principles, as represented by use of good chart and visual abstract practices and appropriate visualization conventions. Table 2 outlines the good chart practices and visualization conventions students were expected to follow when performing visualization for analysis (final figures). Table 3 does the same for expectations of students performing visualization for sharing knowledge (visual abstracts). Some visualization principles are employed in both visualization for analysis and visualization for sharing knowledge (for example, selecting appropriate colors in terms of hue and saturation, combining them effectively, and ensuring that all type is legible in terms of typeface, font weight, and font size). Others are required only in one visualization modality (for example, differing requirements for the presence and implementation of a chart header). Each student's individual effectiveness at meeting each of these criteria is outlined in Figures 3 and 4. Both figures contain one example of a student-created visualization, alongside a scored rubric used to assess its demonstration of foundational design principles. Figure 3 contains four examples (one from each student) of visualizations for analysis, as represented by one figure in each student's final paper, and Figure 4 contains four examples (one from each student) of visualizations for sharing knowledge, as represented by the visual abstract from their final papers. Although implementation of the principles by each student is varied, all students in the study demonstrated improvements in the quality of their visualizations between the first and last weeks of the proof-of-concept course, as assessed by a visual analysis of their work.

In the questions relating to visualization skills, students reflected that their skills had improved on several measures. Collectively, students' scores demonstrated an increase in their confidence with creating data visualizations for analysis and for sharing knowledge. Students felt greater confidence after the course than before it in their understanding of legibility and visual hierarchy. The pre- and postcourse surveys also included a question about industry readiness. In their response to this question, students indicated that the material covered was relevant to their future intended careers. This suggests that, from the students' perspective at least, the course was successful in its aim of improving the industry and research relevance of their skill sets.

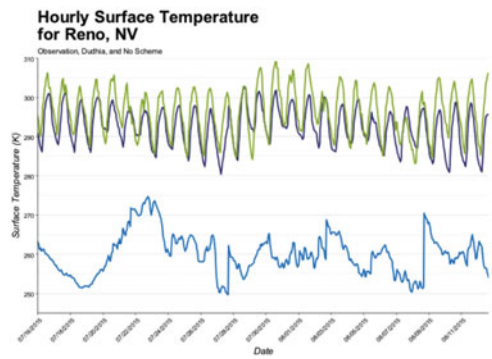
Students did not report any concepts being more or less difficult to grasp, but they did comment on frustrations with technology related to lab computers. In future course offerings, student improvement will be quantitatively assessed by assigning a visualization task at the beginning of the course before any design theory concepts are taught, and the task will be graded by the same rubric used to assess later visualization activities. At the end of the course, the scores for initial visualizations will be compared to those of the final visualization products.

Interpretations

Although the small number of participants in this proof-of-concept study makes definitive results difficult to ascertain, the study indicates that introducing geoscience undergraduate students to best practice visualization techniques by identifying two separate but complementary skills—visualization for analysis and visualization for sharing knowledge—through an online visualization component of their course is helpful for students' visual communication skills and the industry relevance of their skills. This interpretation is based on evidence that students successfully applied best practices for design in their class project visualizations. In all cases, students reported an increased familiarity with key best practices, especially the principle of visual hierarchy. This finding is promising because the course achieved several aims in a replicable format; online visualization content can potentially be attached to a wide variety of geoscience courses. The successes in the execution of the pilot course included integrating visualization exercises into the larger atmospheric modeling final project, preparing a suitably scaffolded visualization component, and delivering the visualization component online in a way that students found engaging.

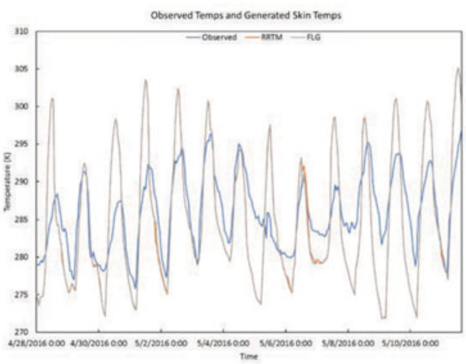
In terms of lessons learned before and during the course, setting up and running visualization exercises in R proved challenging due to a combination of hardware and software limitations in the lab where the classes were held. In discussions with instructors, students expressed frustration that the purchased fonts were only licensed for lab computers, so they could not be used outside of the classroom. Although the visualization module was delivered online, students completed all their visualization activities in the lab where the course met, because specific fonts and R libraries were required to create visualizations in R that demonstrated best practices. In future course offerings, open-source fonts will be used so license limitations will not prohibit use beyond the classroom. Another limitation was that some of the R libraries used proved temperamental when used together and required repeated cleaning of caches and restarts of lab computers to function properly in unison. In the future, R packages used in conjunction with one another will be more thoroughly tested on a wider

3a



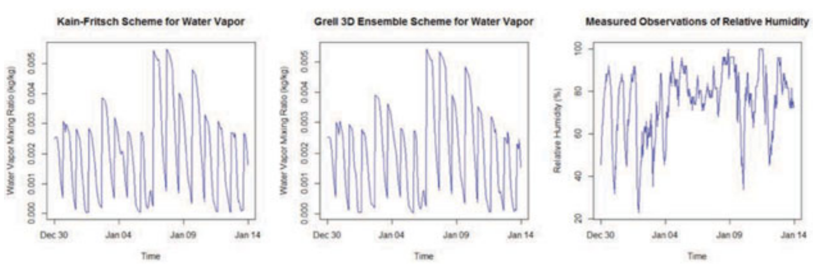
	INSUFFICIENT	SUFFICIENT	GOOD
GOOD CHART PRACTICES			
Descriptive heading & subheading			✓
Axis indicator lines across plot			✓
Units of measurement in axis labels			✓
Easily intelligible legend (2 data or more)	✓		
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection			✓
Appropriate combining of colors			✓
Visual hierarchy - heading emphasis			✓
Legible font - legend			✓
Legible font - axis markers			✓
Legible font - axis labels			✓

3b



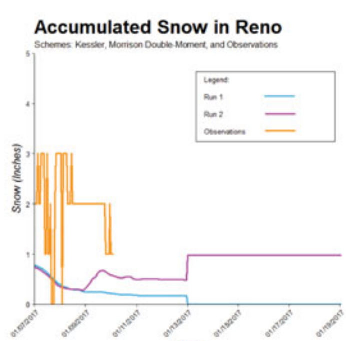
	INSUFFICIENT	SUFFICIENT	GOOD
GOOD CHART PRACTICES			
Descriptive heading & subheading	✓		
Axis indicator lines across plot	✓		
Units of measurement in axis labels			✓
Easily intelligible legend (2 data or more)		✓	
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection		✓	
Appropriate combining of colors		✓	
Visual hierarchy - heading emphasis	✓		
Legible font - legend			✓
Legible font - axis markers			✓
Legible font - axis labels			✓

3c



	INSUFFICIENT	SUFFICIENT	GOOD
GOOD CHART PRACTICES			
Descriptive heading & subheading		✓	
Axis indicator lines across plot	✓		
Units of measurement in axis labels			✓
Easily intelligible legend (2 data or more)			
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection		✓	
Appropriate combining of colors		✓	
Visual hierarchy - heading emphasis			✓
Legible font - legend			✓
Legible font - axis markers			✓
Legible font - axis labels			✓

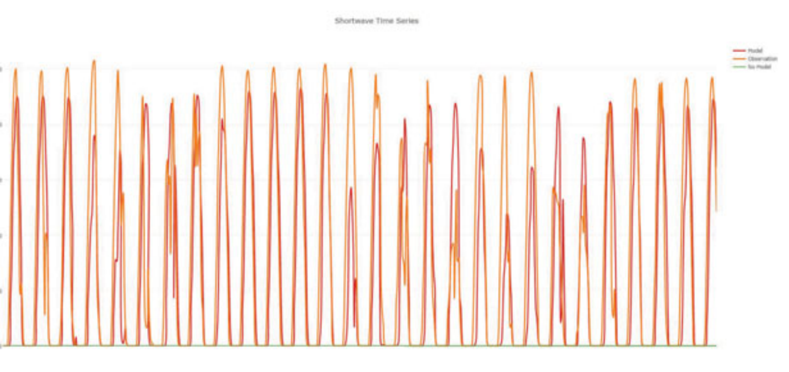
3d



	INSUFFICIENT	SUFFICIENT	GOOD
GOOD CHART PRACTICES			
Descriptive heading & subheading			✓
Axis indicator lines across plot	✓		
Units of measurement in axis labels			✓
Easily intelligible legend (2 data or more)		✓	
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection	✓		
Appropriate combining of colors	✓		
Visual hierarchy - heading emphasis			✓
Legible font - legend			✓
Legible font - axis markers			✓
Legible font - axis labels			✓

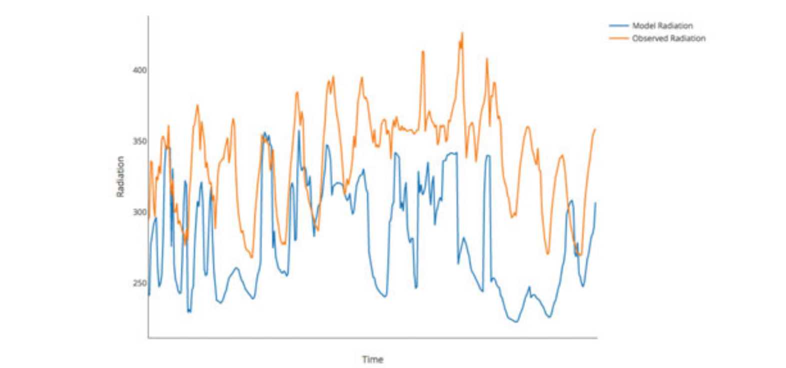
Figure 3. Figures created by students to show findings, using visualization for analysis, in their final papers with associated rubrics. Students were instructed to follow good chart practices by choosing an appropriate chart type for their data, using a descriptive heading and subheading, using faint axis indicators across the plot area (including units of measurement in axis labels), and including an easily intelligible legend. Students were instructed to follow good visualization practices and conventions by selecting appropriate colors (contrast and saturation) and legible fonts (weight, size, and style) and by demonstrating good visual hierarchy by using a clearly emphasized heading. Figure 3a (top box): Work of Student 1 demonstrates a descriptive heading and subheading, axis indicators lines used across plot area, units of measurement in axis labels, appropriate color use, good visual hierarchy, and legible fonts. Figure 3b (second box): Work of Student 2 demonstrates units of measurement in axis labels and legible fonts. Figure 3c (third box): Work of Student 3 demonstrates units of measurement in axis labels and legible fonts in all text. Figure 3d (fourth box): Work of Student 4 demonstrates appropriate headings, subheadings, and unit measurements, as well as legible fonts.

4a



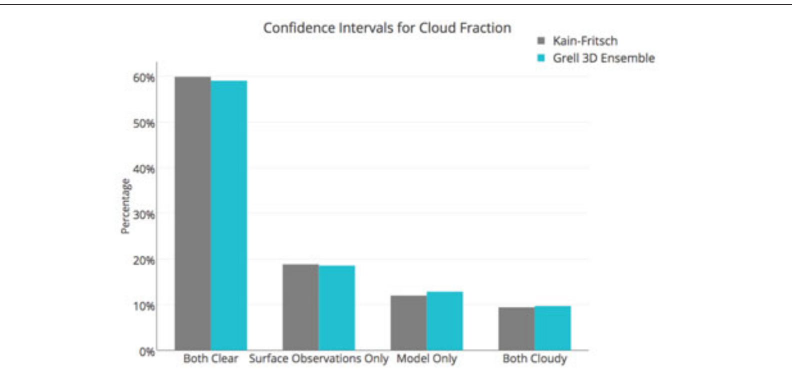
	INSUFFICIENT	SUFFICIENT	GOOD
GOOD VISUAL ABSTRACT PRACTICES			
No heading because visual abstracts sit directly under paper headings	✓		
One figure only		✓	
Simple data selection		✓	
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection		✓	
Appropriate combining of colors		✓	
Legible font - legend	✓		
Legible font - axis markers	✓		
Legible font - axis labels	✓		

4b



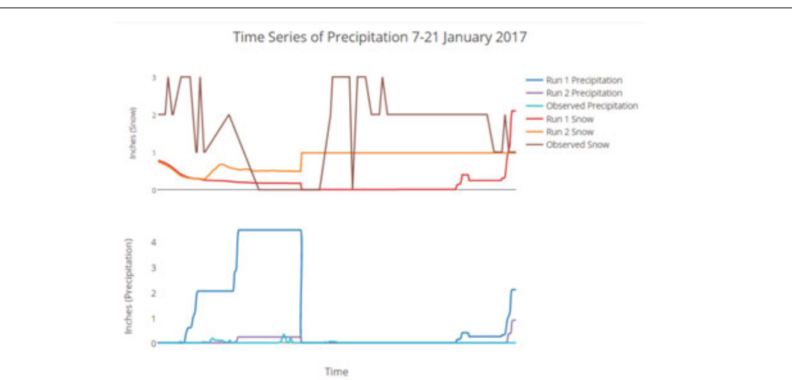
	INSUFFICIENT	SUFFICIENT	GOOD
GOOD VISUAL ABSTRACT PRACTICES			
No heading because visual abstracts sit directly under paper headings		✓	
One figure only		✓	
Simple data selection		✓	
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection		✓	
Appropriate combining of colors		✓	
Legible font - legend		✓	
Legible font - axis markers		✓	
Legible font - axis labels		✓	

4c



	INSUFFICIENT	SUFFICIENT	GOOD
GOOD VISUAL ABSTRACT PRACTICES			
No heading because visual abstracts sit directly under paper headings	✓		
One figure only		✓	
Simple data selection		✓	
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection			✓
Appropriate combining of colors			✓
Legible font - legend			✓
Legible font - axis markers			✓
Legible font - axis labels			✓

4d



	INSUFFICIENT	SUFFICIENT	GOOD
GOOD VISUAL ABSTRACT PRACTICES			
No heading because visual abstracts sit directly under paper headings	✓		
One figure only	✓		
Simple data selection	✓		
GOOD VISUALIZATION CONVENTIONS			
Appropriate color selection		✓	
Appropriate combining of colors			✓
Legible font - legend		✓	
Legible font - axis markers	✓		
Legible font - axis labels		✓	

Figure 4. Visual abstracts created by students to summarize the main findings in their final papers, using visualization for sharing knowledge, with associated rubrics. Students were instructed to follow good visual abstract practices by using one figure only without a heading and using simple data selection. Students were also instructed to follow good data visualization conventions, choosing appropriate colors (saturation and contrast) and legible fonts (typeface, weight, and size). Figure 4a, top box (work of Student 1), demonstrates simple data selection and appropriate color combination. Figure 4b, second box (work of Student 2), demonstrates simple data selection, appropriate color combination, and omission of heading. Figure 4c, third box (work of Student 3), demonstrates simple data selection and legible fonts for all text. Figure 4d, fourth box (work of Student 4), demonstrates appropriate color use and some legible fonts.
For full course materials, see supplemental files.

range of computers prior to instruction commencing. A final challenge was integration of the statistical analysis and visualization components of the course. Although visualization activities were well integrated into students' final projects, there could have been greater compatibility between visualization activities and statistical analysis instruction. As an example, guidelines for selecting visualization type could have been introduced concurrently with the statistical component on exploratory data analysis, as patterns in the data being explored will be revealed most clearly if the appropriate type of visualization is selected.

Limitations

Although the course was successful overall, there were some limitations. The small number of students ($n = 4$) limited our ability to test the suitability of the visualization component for a larger class. The evaluation design was limited by not including a test of foundational skills prior to design instruction that would have provided a baseline of understanding of students' data visualization skills to compare against their gains in the course. Because this was the initial course offering and the computational portion was very demanding, only three types of visualizations were taught, limiting student exposure to other useful visual concepts. In future course offerings, the visualization modules will introduce students to additional visualization types, including divided bar charts, layer charts, and radar charts. Additionally, if there had been more time available for visualization instruction, the students would have greatly benefited from a discussion of how to visualize four-dimensional (space and time) data from a complex model like WRF. Due to practical constraints, students only visualized two-dimensional summary data from their observations.

One challenge for replicability in other classrooms is that the qualitative visual analysis of student work is not easily reproducible without a design professor being involved in instruction. One way this could be improved is by creating a more detailed visualization evaluation rubric to be used by geoscience educators, including visual exemplars of insufficient and sufficient use of visualization conventions.

Implications for future use by other educators

The addition of an online visualization module to geoscience courses has great promise for providing a much-needed skill set to students. Ideally, in order to create an online visualization module in their own classes and achieve similarly positive results, geoscience educators would work with design educators at their institutions to devise exercises tailored to suit the fundamental scientific concepts they are teaching and the assignments they are using. A key component of such collaboration would be to secure funding to either buy out regular teaching time or offer overload salary to the coteaching faculty. Although the benefits of such interdisciplinary collaboration are great, university administrators are unlikely to agree to interdisciplinary coteaching arrangements without additional funding. Securing external funding has the additional benefit of gaining positive attention of administrators for a coteaching project that may otherwise be perceived negatively.

In situations in which it is not possible for geoscience educators to collaborate with design educators, it would still be possible to add an online visualization component to classes following the basic principle of teaching students the difference between visualization for analysis and visualization for sharing knowledge. The course structure outlined in this article would be suitable for this purpose, although new activities would have to be devised to make the specific codes relevant to other geoscience contexts. These new activities could be created by retrieving and modifying the R code activities provided as an online supplement to this article. When devising new activities, we recommend that educators use open-source fonts such as Google Fonts (https://fonts.google.com/) to avoid licensing issues. Although exercises in R were well received in general, we recommend that if educators use R-based exercises they should thoroughly test all R libraries used in the exercises before assigning them in order to reduce the likelihood of library incompatibilities. The visualization exercises could be highly simplified by requiring students to use pen and paper to draw visualizations instead of using R code. Hand drawing is sufficient to demonstrate the foundational design principles, although it may be insufficient for analysis of big data. Scaffolding each week's activities, as shown in this study, is also critical to success by allowing students to build on prior knowledge. If design educators are involved in replicating this visualization module component, we recommend using the rubrics for visualization for analysis and visualization for sharing knowledge from this course and relying on the design educator's knowledge to conduct a qualitative visual assessment using this rubric. If it is not possible to coteach with a design professor, we recommend development of rubrics with extensive visual examples for qualitatively assessing students' competence; ideally, geoscience educators would collaborate with design educators to create such a heavily illustrated rubric.

Conclusion

This proof-of-concept study demonstrated that embedding visualization-specific activities, principles, and readings within an atmospheric science course in the form of an online component has the potential to improve students' visualization skills both for analysis and for sharing findings. The students in the study all demonstrated sufficient use of best practices in design of the visualizations (as assessed in their final projects) and improved confidence in their visualization skills (as measured by pre- and postcourse surveys). We did not test for improved understanding of foundational visualization concepts, and this is an opportunity for further pedagogical research. Interdisciplinary coteaching was critical to the success of the course; the involvement of a faculty member with a design background allowed development of online visualization modules containing foundational design principles and best practices of visualization that the science and math faculty members did not possess. Consequently, by the end of the course students were able to produce visualizations of their atmospheric modeling that were easy to read, presented data clearly, and were appropriate for their given purpose.

As growing amounts of data become available for policy assessments, the need for skills in creating visualizations for sharing knowledge is growing across many fields, and educating geoscience students in such clear communication is one important way to address this need. Although the class size of this proof-of-concept course was too small to give definitive results, and further research on the use of online modules for teaching visualization is needed, the results are promising enough that we recommend further use of online visualization modules in geoscience classes and coteaching with design faculty in science classrooms. Teaching visualization as an online supplement to other geoscience instruction is a potentially replicable approach, especially when such instruction is carefully scaffolded, relies on open-source programs and materials, and leverages interdisciplinary expertise in course design. We also recommend further investigation into the effectiveness of this interdisciplinary coteaching approach with larger class sizes.

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