Transferability of Statistical Computational Thinking and Abilities to Field Related Applications: A Phenomenological Study of Ecology and Environmental Science Graduate Students

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April 28, 2017

Introduction

Background

Science, Technology, Engineering, and Mathematics (STEM) education has been placed on the front burner by nations throughout the world, "because these subjects are inextricably tied to economic development and success" [16]. The 2006 Spellings Report found that "fewer American students are earning degrees in STEM fields, medicine, and other disciplines critical to global competitiveness, national security, and economic prosperity." [26] The report calls for "universities and colleges to improve their curricula and instruction in science and math" [16] as a means of "keeping the nation at the forefront of the knowledge revolution" [26]. With the emphasis on STEM education throughout the nation, a larger number of undergraduate students are considering Master's and Doctoral degrees prior to entering the workforce. Ecology and Environmental Sciences are among the fields that require researchers and practitioners to possess a Master's degree in order to obtain permanent positions with either the state or federal government.
This research focuses on graduate students enrolled at a mid-size university in the Rocky Mountains, where Statistics 511 and 512 are courses required for the completion of a Master's degree in Ecology or Environmental Sciences. These terminal statistics courses intend to prepare graduate students for the statistical and computational problems they may face as researchers and practitioners. With the growth in computational power, the complexity of ecological models has followed, multiplying the computational, mathematical, and statistical expectations of researchers' abilities.

With these complexities in mind, this research aims to describe and understand Ecology and Environmental Science graduate students' abilities to transfer their classroom knowledge to more complex applications, relevant to their field.

Statement of Problem

In the current research environment, graduate Ecology and Environmental Science students are expected to learn both computational thinking, as well as computational tools and methods in order to become competent researchers and practitioners. Statistics 511 and 512 serve as terminal statistics courses for graduate Ecology and Environmental Science students, potentially providing them with the final statistical computational skills before they begin performing independent research.

Over past few years, it has been observed by the Statistical Consulting Center at this university that Ecology and Environmental Science graduate students seek out computational help for their research, thesis, and even dissertation, following the completion of these graduate statistics courses.

During the literature review, no studies were found on the development or assessment of computational thinking and abilities of graduate level science students, which conveys the substantial lack of understanding in how these students transfer their classroom knowledge to applications in their fields. Current research in the fields of biology, ecology, and science education are beginning to emphasize the need for both K-12 and undergraduate science students to become computationally literate ([20], [12], [11], [10], [9], [4]). These fields acknowledge the evolution of science, where modern researchers must engage in computing and understand how computer science is relevant to their work. Universities across the United States are beginning to feature multi-disciplinary courses and workshops in an effort to develop computational thinking for undergraduate science majors. These efforts are largely comprised of teaching students basic programming tools, computational tools, and understandings of the field of computer science. Researchers at Purdue University [12] and Tel-Aviv University have developed computational thinking courses, *Introduction to Computational Thinking* and *Computational Approaches for Life Scientists*, for undergraduate science majors that are guided by five main principles,

- laying the groundwork for computational thinking,
- presenting examples in a language familiar to the students,
- teaching in a problem-driven way,
- using a programming language that straight away allows students to focus on computational principles, and
- making effective use of visualization.

Current literature, focused on teaching computational thinking to undergraduate science majors through use of targeted computing courses, suggests potential deficiencies in computing courses for these such students. There is a natural application of the current literature to graduate students in scientific fields, where potentially many students have completed undergraduate science degrees in programs with little to no emphasis on computational thinking or computational tools.

By examining how Ecology and Environmental Science graduate students apply their computational skills, using qualitative methods, we are able to capture a more in-depth understanding of the successes and shortfalls they experience when implementing computational thinking and skills, given their background. With these understandings, graduate statistics teachers can modify their curriculum to account for these shortcomings, as well as find new methods to challenge students in the computational methods in which they demonstrate success. Additionally, if the research indicates substantial shortfalls in students' computational abilities with regard to applications in their fields, the Ecology and Environmental Science departments can assess their coursework involved in their graduate programs, with the possibility of adding a course specifically targeting computational abilities.

Statement of Purpose

The purpose of this phenomenological study is to understand and describe the transferability of statistical computation skills to field related applications for Ecology and Environmental Science graduate students at this university. Students' experiences in computational thinking will be investigated using both a qualitative survey of attitudes and experiences, and hands-on computational problems. At this stage in the research, we define the transferability of statistical computation abilities as the ability to apply acquired statistical computing skills from the 511 and 512 classroom to applications related to ecological fields. Unlike typical definitions of computational abilities which focus on a student's understanding and fluency of a computer program(s), we are choosing to include computational thinking in our definition of computational abilities. In relation to ecological applications, this can include, fluency in performing computing tasks (programming abilities), data structures, the ability to reason through problems with a given set of tools, as well as knowledge of resources that could provide assistance in solving a particular problem.

Research Questions

The primary research questions that guided this study were:

1. What factors (attitude, background, course content, etc.) impact Ecology and Environmental Science students' ability to reason through computational applications in their discipline?
2. In what ways (if any) do these factors inhibit or foster students' computational understandings and abilities, across different skill levels?

Review of Related Literature

Research in computational thinking for science majors is in its infancy, with only a handful of institutions performing research that specifically addresses how to teach and how students learn computational thinking. Primarily, the research being performed is implemented at the undergraduate level, with no research efforts made in the realm of graduate science students. Due to this gap in the literature, the reviewed literature were selected from research on computational thinking and abilities of undergraduate science students

Efforts in Understanding Computational Thinking

The most substantial efforts being made in understanding computational thinking are by researchers at the Harvard Graduate School of Education and researchers at EDC's Center for Children and Technology. Their efforts focus on "supporting and assessing the development of computational thinking through programming" [22] for both researchers and K-12 teachers. They have "relied primarily on three approaches: (1) artifact-based interviews, (2) design scenarios, and (3) learner documentation." [3] These scenarios were developed in collaboration with researchers at the Education Development Center and are used in the context of Scratch, a computer programming environment for use by elementary through high school students, created by the Lifelong Kindergarten Group at MIT Media Lab. The researchers at Harvard developed three different Scratch projects of increasing complexity, and in a series of interviews "students were presented with the design scenarios, which were framed as projects that were created by another young Scratcher. The students were then asked to select one of the projects from each set, and (1) explain what the selected project does, (2) describe how it could be extended, (3) fix a bug, and (4) remix the project by adding a feature." [22] Through these interviews, substantial contributions have been made in how to assess the ways students engage in computational thinking, with the ability to apply the structure of these interviews to other types of students and other types of computational thinking scenarios.

Computational Courses for Undergraduate Science Majors

Multi-disciplinary efforts have been made at Purdue, Carnegie-Mellon, Harvey Mudd, Princeton, and Winona State ([4], [6], [24], [25], [27], [28]) to create introductory computing courses with a focus on non-computer science majors, in particular science students, in fields ranging from physics to chemistry to biology. These courses are produced in collaboration with science faculty, and are intended to "lay the groundwork for computational thinking, present examples in a language familiar to the students, teach in a problem-driven way, use a programming language that right away allows students to focus on computational principles, and make effective use of visualization." [12] The structure of the computation course was informed by the physics, chemistry, and bioinformatics departments, where they provided computer science researchers with expectations on what they wished the students would learn. The structure of these undergraduate level statistics courses directly relates to the computational abilities of graduate level science researchers, as they may have graduated from an undergraduate program with no computational training. The concepts emphasized in the courses developed at Purdue, and elsewhere, can be used to inform the graduate level statistics methods courses what skills other scientific disciplines, such as physics, biology, and chemistry, believe to be the most important for students to grasp.

Given the current research focuses on assessing computational thinking and creating computational courses for undergraduate science majors, we see substantial gaps in understanding how these same issues relate to graduate science students. The statistical methods courses, taken by graduate Ecology and Environmental Science students, potentially serve as their final computational training prior to performing independent research. These such graduate level statistics courses, taken by graduate Ecology and Environmental Science students across the country, provide a natural extension to the current research on computational skills and thinking. It is the intention of this study to close this gap in research and understanding between the computational thinking and skills of undergraduate science students and that of graduate science students.

Methodology

Conceptual, Theoretical Framework

Inherent in the concept map informing this research, , are the assumptions of theoretical relationships between each of the factors. Initially for this study, we assumed students' motivation largely affects how well they are able to transfer their learned skills to applications in their disciplines. This motivation can be thought of as "a cycle in which thoughts influence behaviors, behaviors drive performance, performance affects thoughts, and the cycle begins again." [15] These thoughts could be self-efficacy based (mathematics, statistics, computer science, or environmental sciences), value based (the value the student places on the subject or acquiring knowledge about the subject), intrinsic in nature, extrinsic in nature, or from a variety of other factors.

The computational and statistical aspects of this framework initially were thought to exhibit Bloom's taxonomy. This theory describes the process of learning as a hierarchy of understanding, where students first understand low-level concepts (low-level programming and statistical methods) before thinking about them in more complex ways, and learning higher-level concepts. Each of these categories of understanding can interact with the others, as well as influence or be influenced by a student's attitudes and background. Each of these categories of understanding are then utilized by the students, in a feedback process, to solve application related problems.

Bloom's taxonomy separates student learning into 6 hierarchical categories: knowledge, comprehension, application, analysis, synthesis, and evaluation. This study will focus primarily in the first three stages of Bloom's taxonomy, describing how students progress from statistical computing knowledge to the ability to apply statistical computing skills to field related applications.

Limitations & Delimitations

The Statistics 511 and 512 courses serve a variety of graduate and undergraduate students. For this study, delimitations include selecting to focus on only Ecology and Environmental Science graduate students, in the spring of 2017. Potential limitations of this study include the computational, research, and statistical backgrounds of the students, as well as the amount of time that has passed since students took Statistics 511.

Assumptions

For this study, we believe the factors presented in the concept map could influence Ecology and Environmental Science graduate students' abilities to transfer their statistical computing skills to applications relevant to their field. These contributing factors, as well as the relationships between factors, may change following data collection and analysis.

The study made assumptions that the students interviewed would,

- truthfully report their coursework,
- truthfully report their research work,
- use all knowledge available to them in answering application questions, and \item will not exhibit the Hawthorne effect when being interviewed.

Method

For this study, a pragmatic phenomenological approach is appropriate as the intention is to understand and describe Ecology and Environmental Science graduate students ability to apply their statistical computing skills to applications in their field. The focus of this study, on the actions taken by students in the process of computationally reasoning through an application, lends itself naturally to a pragmatic framework. This framework allows for a focus on the process of finding a working solution, allowing for varied solutions rather than a single solution. [5]

The study focuses mainly on ontological aspects of students transferring skills to applications in their field, as we seek to explain how students came to a working solution, with many possible avenues they could have taken. The study also emphasizes factors in student axiological and epistemological beliefs that promote or inhibit student success, seeking to understand how students acquire the knowledge necessary to solve application problems, as well as assessing how students value this knowledge.

A phenomenological approach was used, as our intention is to understand and describe common computational thinking experiences between Ecology and Environmental Science graduate students. As all students involved in this study have experienced the same phenomenon, enrolling in the Statistics 511 and 512 courses, this study intends to describe the abilities of students, having experienced this common phenomenon, in applying their statistical computing skills to field related applications.

Positionality

As a doctoral student in Statistics, I am familiar with the course material of the Statistics 511 and 512 courses. Additionally, I have performed statistical consulting for graduate students in the Ecology and Land Resources, Environmental Science departments, and have seen a small number of computational components to these graduate students' research that they struggle with. In my coursework as a graduate student, I experienced computational shortfalls, where I was expected to have the ability to transfer concepts I had learned previously to a new, seemingly unrelated, problem. These experiences as a graduate student and a statistical consultant brought me to this topic of how graduate science students are able to successfully transfer their statistical computing abilities to applications.

The process by which I learn statistical computing skills has informed the study's hypothesized conceptual map. This map reflects the factors and hierarchy that influence my ability to learn new computational skills. Additionally, my philosophical beliefs reinforce the concepts in this map. For example, considering value as a large factor in student achievement, reinforces my pragmatic axiological belief that knowledge is based on the value the student places upon it. Additionally, the method of inquiry inherent in the study reflects my epistemological belief that acquiring the knowledge necessary for solving application problems can come from many possible venues.

Site selection, Context, Sample, & Sampling Procedures

Students were selected from the Statistics 512 course in spring of 2017. These students were sampled following their Spring Break, nearly halfway through the course. Only graduate students from the Ecology and Land Resources and Environmental Science departments were considered. These students are taking the course as a coursework requirement for their respective Masters programs.

In the context of this study, the graduate students involved have chosen to pursue a career in STEM, potentially due to distal factors, such as the nationwide push to inspire high school and undergraduate students to be interested in interest in science, technology, engineering, and math, over the last 10 to 15 years. Given the ever expanding array of STEM jobs, including those in the ecological and environmental science fields, researchers entering these fields are potentially expected to have more computational experience and expertise than in 2010. This distal factor, could have potentially impacted these students choice in pursuing a Master's degree in Ecology or Environmental Science. The structure of the Statistics 512 course in the spring of 2017 has a lab focus, enabling students to take the concepts learned during lecture and weekly apply them to statistical applications. The format of this course could be considered a proximal factor in student learning and achievement. Additionally, the structure of the Statistics 511 course, the semester each student enrolled, could also be considered a proximal factor.

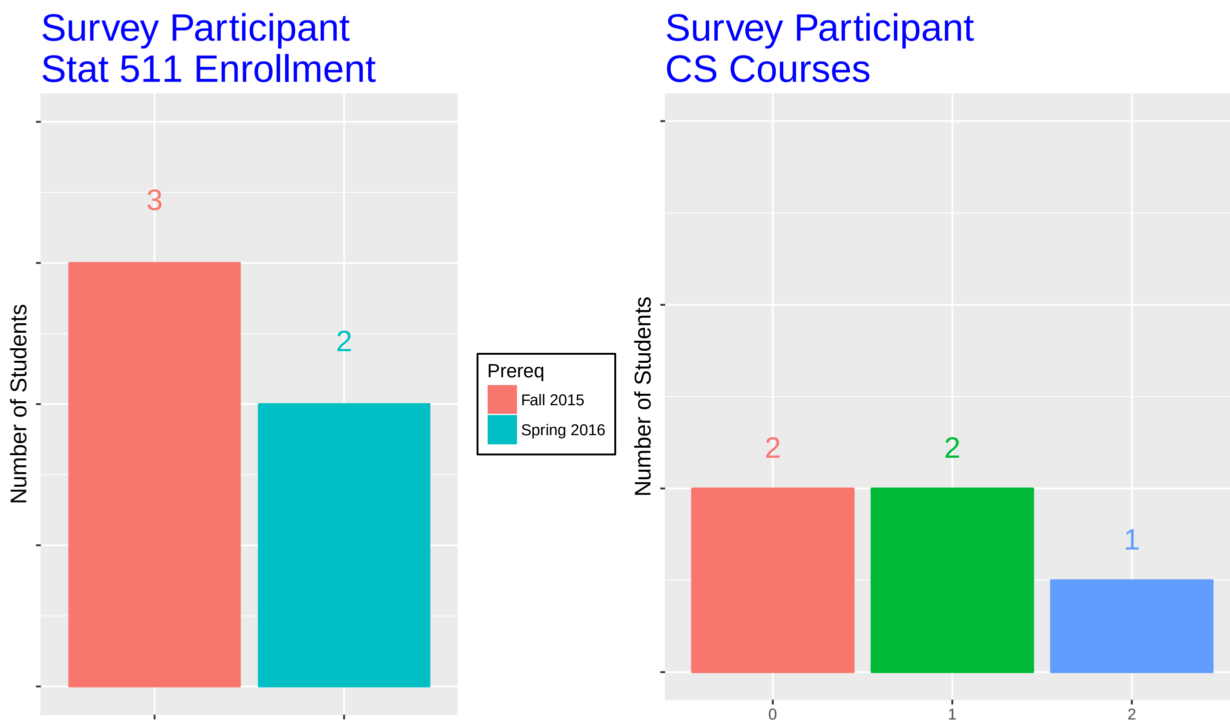
Students were requested to complete a survey detailing their previous courses, statistics, computer science, and field related, describe their computer programming abilities, and outline their research experience. There were a total of 17 graduate Ecology and Environmental Science students enrolled in this course, and a criterion sampling procedure was used. The students requested to participate in the study were selected so that,

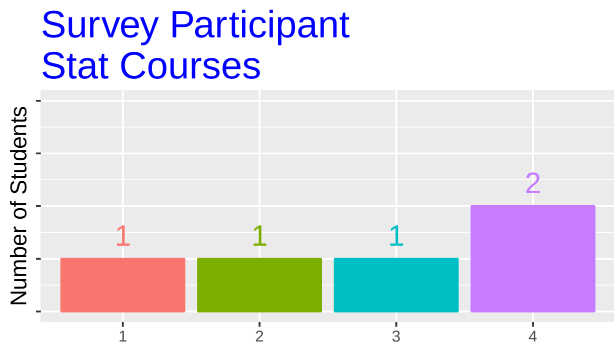
- they had taken Statistics 511 in the last 2 years,
- they had a variety of programming backgrounds, and
- they had a variety of levels of independent research experience.

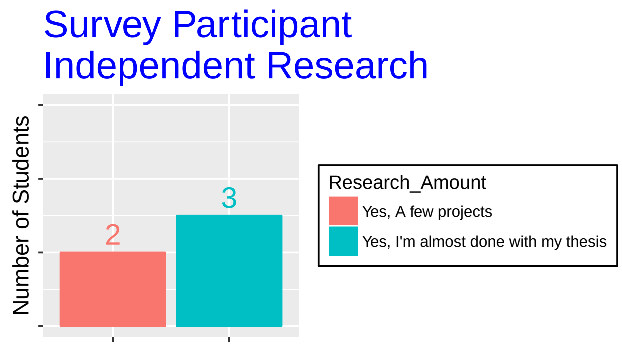
These 512 students were requested to participate in the preliminary survey, itemizing their course work, their program of study, and their independent research experience. A total of 16 students completed the survey, nine of which were graduate students in the areas of Environmental Science and Ecology. One of the viable students was not considered to participate, due to his proximity to the researcher. All of the eight remaining students were requested to participate in the study, of which five agreed. All of the students who agreed to participate identified as female. The table and plots below describe the demographics of the study participants.

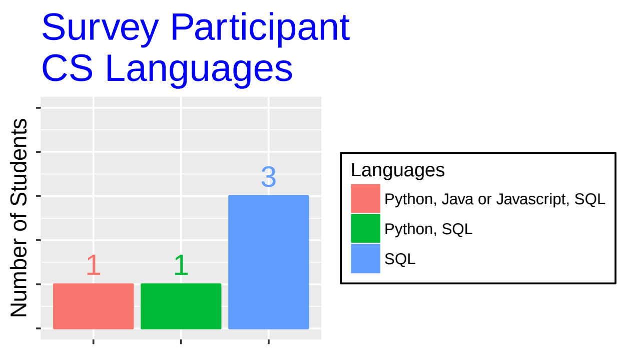
Name (pseudonym)	Degree	Program
Beth	Master's	Animal Range Science
Catherine	Master's	Environmental Science
Kelly	Master's	Ecology
Robin	Doctorate	Environmental Science
Stephanie	Master's	Environmental Science

Table 1: Sample Description




Survey Participant
Stat Courses
Number of Students
1
1
1
2
1
2
3
4


Survey Participant
Independent Research
Number of Students
2
3
Research_Amount
Yes, A few projects
Yes, I'm almost done with my thesis


Survey Participant
CS Languages
Number of Students
1
1
3
Languages
Python, Java or Javascript, SQL
Python, SQL
SQL

Overall, the students were predominantly seeking Master's degrees and had taken the prerequisite, Stat 511, course in the last three semesters. Very few had any experience taking computer science courses, where the students with computer science experience having taken courses early on in their undergraduate course work. SQL was the predominant language participants were familiar with, due to its background in database management and its use in Ecology and Environmental Science graduate courses. All students had experience with independent research, with three of the participants aiming to complete their Master's theses in the next year.

Data Collection

Following the preliminary survey, students who agreed to be interviewed were given a questionnaire detailing their coursework, assessing their experiences, and attitudes in computational thinking. These surveys were modified from validated computational thinking surveys administered at Harvard, which provided a rich rubric of assessing attitudes an evolving fluency in computational practices. [3]

Following the survey, students were asked to complete ecological applications of statistical computing. These problems assessed students' abilities to both statistically and computationally reason through applications, provide descriptions of how they computationally think through the problems, as well as outline the any gaps noticeable in students' ability to transfer their computational understandings to applications. Computational problems were developed in collaboration with Statistics faculty at the university, using data from the Blackfoot River, collected by Montana Fish, Wildlife, and Parks in years 1989 to 2006.

The survey and application interview are included as appendices.

Ethical Considerations

For this study, students were requested to work through statistical computation applications, and there was the possibility that students felt nervous, pressured, or fearful of not knowing a correct process to achieve the desired result. Additionally, as a doctoral student in statistics, it is possible that the students felt a large power difference, specifically regarding computational knowledge. To alleviate these feelings, the interviewer worked on the same problem beside the participants, acting as a collaborative peer. The interview protocol included the interviewer providing hints if/when a student got stuck or was unsure of how to proceed. This environment is believed to have helped aid suppressing fear and allowed students to more openly work through problems with the researcher.

Data Analysis

Interviews and survey responses for each participant were transcribed, with participants names removed and pseudonyms given. The interviews were analyzed, so as to describe the thought process of each student working through the application, describing the concepts they used to complete each task, why they believed these to be the correct concepts to use, and how they acquired their knowledge of these concepts. Themes specific to each individual's computational thinking processes were then be described, including, but not limited to, synthesis of experiences, coursework, and learned skills. With these individual themes, we were able to compare across individuals common themes that emerge. Additionally, data on attitudes towards computational thinking were analyzed similarly and paired with each individual. These pairs of experiences and attitudes were then analyzed for emerging qualitative trends, to aid in construction of a description of how different factors related to students' ability to transfer their understandings to applications.

Authenticity, Trustworthiness, Credibility, and Transferability

The "authenticity" of the study, it's ability to capture the true experiences of students' abilities to think through computational problems, is enhanced with the lack researcher engagement with students prior to their participation in the study. This ensured that no student felt more comfortable in the interview environment, working through the application, than any other student. Additionally, the "authenticity" of the study is enhanced through peer reviews of both the interview and computation questions. Statistics faculty teaching the Statistics 511 and 512 courses and faculty in the departments of Ecology and Environmental Sciences were asked to evaluate the clearness of the interview questions, and to assess whether the computational questions accurately tested levels of computational abilities necessary to perform applications in their fields.

To enhance the "confirmability" of the study, the ability of data to truthfully capture the experiences of the participants, participant checking was used. Participants were provided with an itemized detail of how they completed the problem and the transcription of their interview. This allowed participants to check for accuracy of their statements and the interviewers description of their thought processes in completing the problems.

Strengthening the "dependability" of the study, triangulation was used. Triangulation combats the potential instability of the results, allowing for the researcher to obtain data on students' attitudes toward computational thinking through two different avenues. The process of interviewing students regarding their attitudes and experiences with computational thinking, followed by hands-on computational problems allowed for triangulation of students' attitudes. The researcher had the ability to observe students' attitudes directly when working through computational problems, which allowed for validation of the experiences and attitudes the students had expressed during the interview.

Lastly, the threat to "reflexivity", as discussed in the Ethical Considerations section, was potentially alleviated with the interviewer working beside the students on the same problem, collaborating as their peer. This assuages the possibility of a large power difference between the participants and the interviewer, potentially impacting their ability to reason through difficult computational problems. The participants, having never encountered the interviewer prior to the interview, should have all felt the same comfort or discomfort in working through the problems and discussing their experiences with the interviewer.

Findings

The three main themes which emerged from the interviews are summarized below: (a) peer support, (b) a singular consultant, and (c) research experiences. The first theme describes how peer support has impacted participants' abilities to transfer computational skills to applications in their field. The second theme provides participants' descriptions of how an omniscient graduate student or faculty influenced their computational abilities. The third theme recounts how participants' independent research experiences have affected their computational abilities. In addition, their research experiences helped to emphasize the importance of computational literacy to their field. In the following section, themes are delineated with quotations from participants to ensure authenticity of descriptions of their experiences.

Peer Support

Students spoke of the support they have received from fellow graduate students when performing computational tasks. All of the participants described how, when they are unsure of how to complete a computational task for their research, they turn to fellow graduate students for help. Participants described instances when the computational tasks required of them were beyond their current knowledge or occasions when they had attempted to complete a problem with all of their knowledge and sought out help from a fellow graduate student. For example, Kelly, a Animal Range Science Master's student, shared that when she reaches a point in coding when she doesn't know how to do something she turns to one of her lab-mates.

I've been to a point where I didn't know how to do something with my knowledge or what I can find online, and then I'll go to one of my lab-mates.

Catherine, a Master's student in Environmental Science, spoke of the expectations of her advisers that the computational problems she was being asked to perform were "easy, since she had all the information."

However, she has had numerous experiences where she did not have the knowledge necessary to perform the task or she was missing “little caveats” that kept her from fully being able to perform the tasks. When faced with these problems, she “reached out to previous students that had taken the course.” Robin, a doctoral student in Environmental Science, reiterated Catherine’s experiences, describing how she reached out to other graduate students in other labs for help with computational problems. Stephanie, also a doctoral student in Environmental Science, described how when she is faced with computational problems beyond her knowledge she has never been forced to “go beyond talking to her lab-mates" for assistance.

However, Kelly has also had negative experiences when seeking computational assistance from graduate students not of close proximity to her.

When I’m struggling with something and I go to other grad students, they’ll say ‘I did this the other day. I’ll send you my code.’ I’ve found most of the time I don’t understand what they’ve done enough to plug in what I want and make it work. There have been a few times when making tables and plots and someone sends me their code and I can just plug in my data and it works just fine. I’ve had less success with that.

Singular Consultant

All of the participants, when describing whom they seek out for computational help, described an all-knowing past or current graduate student whom they seek out for computational assistance. These figures serve as a single consultant, with whom these students have had the “best,” most productive, experiences in finding solutions to computational problems that have arisen. For Beth, this single consultant comes in the form of a past graduate student from Animal Range Sciences who was hired to help faculty complete projects.

We have a guy who used to be a student in our department and then he was hired on again to help finish some projects, but he got his Master’s in Statistics. He is very helpful with [pointing out what’s wrong with your code]. He’s very good with code and if I have a quick question he can answer it.

For Kelly, another graduate student on the same project as her serves as this consultant. She described computational problems she has encountered in her thesis, when she turned to this particular graduate student for help, adding that other graduate students in their department also use this person as a consultant for their computational problems.

The other grad student on this project is so well versed in `R` *that he’s unofficially become the person that people go to with questions.*

Through her computational struggles, Catherine found assistance from previous graduate students from the department, but she found the most assistance from a previous graduate student “who had left the department and was off professionally somewhere else, but he still took the time to help walk me through [my code]."

One participant, Stephanie, a Environmental Science doctoral student, serves as the computational consultant for the many members of the Environmental Science department. With her experiences teaching herself `R`, she is able to “explain code in a way that makes sense,” says Robin a fellow Environmental Science doctoral student who often seeks out help from Stephanie. With an adviser from a computational background and a project which performs computer modeling, she “has to learn code.” Additionally, her laboratory often works in collaboration with faculty from the computer science department, where she and her lab-mates are taught computer science coding practices and jargon. “Stephanie has gotten good at teaching it, because everyone on our floor is like ‘I can’t do this, Stephanie help me,’ ” says Robin. Stephanie stated that graduate students seek her assistance “daily” or “at minimum two to three times a week.” In contrast, when Stephanie experiences difficulty in performing computational tasks, she finds solace in her lab-mates and ultimately, when necessary, with her adviser.

My entire lab works in the same room and my adviser’s door is always open. So if someone is having a major issue, whoever is in the room can hear that. If [my adviser] hears me ask [lab-mate] how to do something and he knows how, he just shouts how to do it. So it’s a very group oriented dynamic. I’ve never had to go beyond the people in my lab.

Independent Research Experience

The third theme was the computational knowledge students acquired while participating in independent research. Involvement in independent research helped students to take their course knowledge and transfer it to applications, seeing how messy non-classroom applications can be. These experiences came predominantly in the form of working as a research assistant prior to entering graduate school, collaborating on a project in the first year of graduate school, and performing research for a Master's thesis, or ultimately a doctoral dissertation. Catherine, who still faces everyday computational struggles, attributes the majority of her application specific computational knowledge to her experiences in independent research. She emphasized the importance of understanding how to work in a computing environment, such as `R`, which she learned from performing research, before she could begin to transfer the statistical knowledge she learned in the classroom.

What I struggled with is 511 covers theory really well, but since I was new I spent most of my time trying to figure out how to apply that theory in [`R`]. And even now I struggle transferring from `R` into actual statistical theory, when I'm writing my thesis. The way I had to approach it was I had to learn the `R` first, then I was able to look back on what I had actually done, in order to learn the statistics.

Kelly described her experiences with data management for her Master's thesis as producing the most substantial contributions to her computational abilities. Often she attributed her intuition for solving computational problems to experiences she had, "merging data sets" and learning to use conditional statements for her project. She emphasized the importance of her classroom 511 and 512 knowledge in understanding "what statistical method to use," but for becoming more computationally fluent she attributes that to her research experiences.

The data management stuff comes from independent research, trial and error, getting myself through.

Similar sentiments were voiced by Beth, with the majority of her computational knowledge stemming from her independent research. With the recommendation of her adviser she taught herself how to create an `Access` database to store her data. In storing her project in this manner, she was able to learn important concepts in data structures, subsetting data "using qualifiers and criteria," sorting data, all using SQL statements.

Conclusions

The intention of this study was to describe and understand what factors impact Ecology and Environmental Science graduate students' abilities to transfer their computational skills and understandings to applications in their disciplines. Students who participated in the study both described their experiences with computational thinking and abilities, related to applications in their field, and worked through computational problems, which challenged their computational understanding and abilities.

Three themes arose from the study, characterizing the factors with the greatest impact on the participants' computational abilities and understandings, as related to applications in their fields. First, participants voiced the importance of their experiences performing independent research as a substantial influence on their abilities to reason through and perform computational problems. Through independent research, the participants were able to play with real-world data and applications outside of what they saw in the classroom. These experiences also opened the door to the unease that comes when one is asked to perform computational tasks beyond one's knowledge. In these circumstances, the participants discussed their reliance on peers and singular consultants to aid them in accomplishing computational tasks.

The second and third themes, focus both on the participants acquisition of computational skills and understanding, as well as how they cope when faced with computational expectations beyond their knowledge and abilities. The theme of peer support was initially discussed by the participants, in their interviews, as a mechanism they use when their "code doesn't run" or when they are asked (or need) to do something outside of their current computational understandings. However, this theme continued to emerge as the participants worked through the computational problems, often attributing their knowledge of computational procedures to a friend or fellow graduate student helping them "do it with their data." These peers offer an avenue for students to seek help, often found to be more comfortable than asking an adviser, where the participants described both the fear of asking and “feeling dumb” as well as being “brushed off” because their adviser thought they should “be able to figure out how to do it.”

In a direct connection to the participants’ discomfort in asking for help from an adviser, the third theme of a singular consultant emerged. These singular consultants serve as an all-knowing individual, from whom the participants have either had the “best” experiences with, where the individual spends the necessary time to explain the concepts, or the consultant has always been capable of providing the participant with an answer to their problem. These figures serve a similar role to peers, where the participants are both able to seek computational help and acquire new computational skills and understandings through their interactions. However, as opposed to the help participants received from peers, the students never voiced any negative experiences when seeking help from these consultants.

The second purpose of this study was to describe how these factors impacted students’ computational abilities across different levels of understanding. The theme of research experiences, with its overall positive tone by participants, produced different experiences for students with fewer computational skills and understandings than students with more. The frustrations of simple tasks, such as subsetting data or removing NA’s, were felt by the participants who completed a Bachelors without any computational elements to their coursework, while those who were exposed to small amounts of computing in their undergraduate coursework, such as a GIS course or experience with `Access`databases, were able to begin computational tasks in their research walking and not crawling.

The largest difference in the impacts of a factor between computational skill groups, came in the theme of a singular consultant. One participant, Stephanie, who entered graduate school after completing a years work as a research assistant, working with `R`, instead serves as the computational consultant for the Environmental Science department. She still described the theme of seeking help from her peers, predominantly her labmates, but, for her, the singular consultant was her adviser. Potentially due to her larger computational understanding, Stephanie felt less of a power difference than other participants, when seeking help from her adviser.

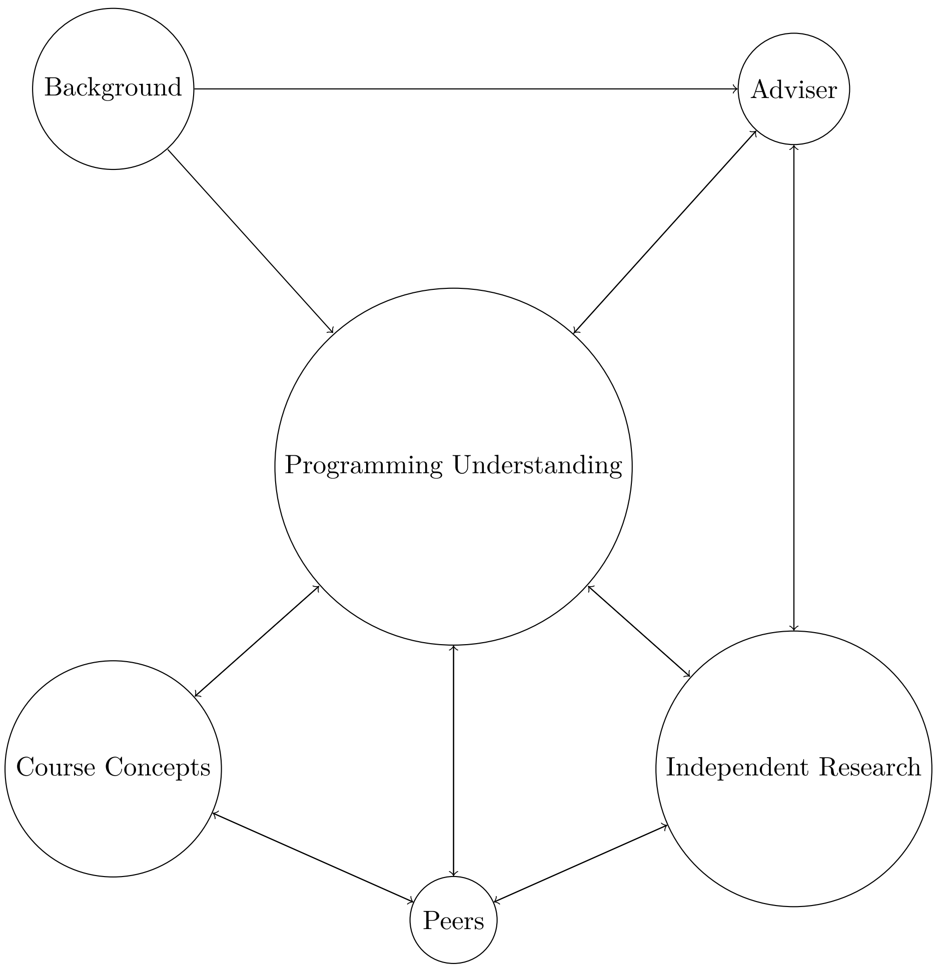
The findings of this study, reinforce the themes common in current literature on computational thinking and computational abilities of students in scientific fields. The interview protocol utilized in this study, provides a natural extension of the computational thinking interviews utilized at Harvard [3]. In the context of this study, artifact-based interviews were implemented, followed by computational thinking scenarios. The computational thinking scenarios given to the participants were of increasing complexity, similar to the protocol implemented at Harvard in the context of Scratch [3]. The participants were asked questions similar to those asked in the Harvard study, (1) how would you perform this task, (2) what is another method that could have been used to complete the task, and (3) how would you fix the following bug related to this task. These interviews provide support for the current research in computational thinking, and make substantial contributions to the understanding of how graduate students in ecological fields engage in computational thinking.

Additionally, this study provides an extension to the current research area of developing computational courses for undergraduate science majors. As all of the participants of this study completed Bachelors degrees in scientific disciplines, specifically ecological fields, without any introductions to computing, they support the theme that universities need to “lay the groundwork for computational thinking" in undergraduate coursework [12]. The computational gaps, found by this study, causing difficulties for graduate Ecology and Environmental Science students’ ability to work through applications in their fields can be used to inform graduate programs what skills their students may need to be directly taught, or are not learning in the current curriculum. These deficiencies in understanding and abilities can be used to inform the literature as to what multi-disciplinary efforts can be made to prepare graduate students in scientific fields to be computationally literate independent researchers and practitioners.

Due to the nature of how the sample was collected, the findings of this study are potentially limited to these participants. A benefit of criterion sampling is the breadth of experiences the researcher is able to capture from a small number of participants. As this study was able to capture the experiences of both Master’s and Doctoral students, as well as students from a variety of ecological fields, within the Ecology and Environmental Science departments, conclusions could possibly be transferred to students of similar backgrounds at this university. As all of the participants identified as female, we are forced to question if these experiences would be consistent for students who identified as male or did not identify as either gender. The power dynamics of females relating to their male advisers, and their discomfort in asking for computational assistance, could be found nonexistent for male students of similar backgrounds.

Discussion

The findings of this study, better informed the hypothesized concept map of how students acquire the skills necessary to perform applications in their fields. With the emergent themes describing where students are acquiring these necessary skills, the below concept map reflects these changes.



Unlike the hypothesized concept map that guided the research process, we found that the participants do not learn the concepts, related to accomplishing computational applications, in a hierarchy. The importance of background remains, however, for these participants the elements of background that proved to be of the most help were both undergraduate statistics courses and pre-graduate research. The role of the adviser replaces attitude in this map. The adviser plays an important role in students acquiring the computational knowledge necessary to perform applications, by both emphasizing the importance of these skills and introductions (or recommendations) for students to store their data in an `Access`database. The ability of many participants to understand both data structures, sorting, and filtering data was largely attributed to their experiences working with these `Access`databases. Additionally, this study found that, although they are not often used, advisers are viewed as an accessible way for students to better understand the computation necessary for their independent research projects, which overall contributes to better computational understanding and skills for these students.

At the center of the map, we find programming understanding, the bottleneck described by all students in their abilities to successfully accomplish computational applications in their fields. This understanding is informed, albeit weakly, by student's backgrounds and their advisers. However, the majority of the students' understanding comes from their course work, research, and collaboration with their peers. The programming understandings that these students attributed to their coursework, were primarily the low-level concepts described in the **Definition of Terms**. These concepts were found to not directly inform a students research, but instead the concepts were understood through the use of peer interaction prior to implementation in their own research.

The programming understandings informed by a student's independent research, in conjunction with peer collaboration, were described by participants to be largely high-level concepts. These understandings stem from the need to find computational solutions to the applications they are currently working with. These solutions often require higher level programming concepts, but they are accomplished without students learning the lower level concepts at work in the solutions.

Implications

This study better informs the faculty and staff and staff at this institution of the computational needs of graduate students in the fields of Ecology and Environmental Science. In the discussion of how students are acquiring the computational understandings necessary to successfully perform field related applications, we are able to see how both instruction and learning could be improved. It is possible that students are acquiring computational skills in the classroom, however there is also the possibility that the concepts being taught are not at a low enough level for students to understand them independently of their peers.

To better inform faculty in these departments, a thorough investigation of both the coursework (syllabus) and structure (lecture, laboratory, etc.) of courses completed by these participants could be performed. This will allow for a discussion of how to best teach these computational concepts, so that students leave the classroom with understandings they can immediately implement in their own research.

Apendix

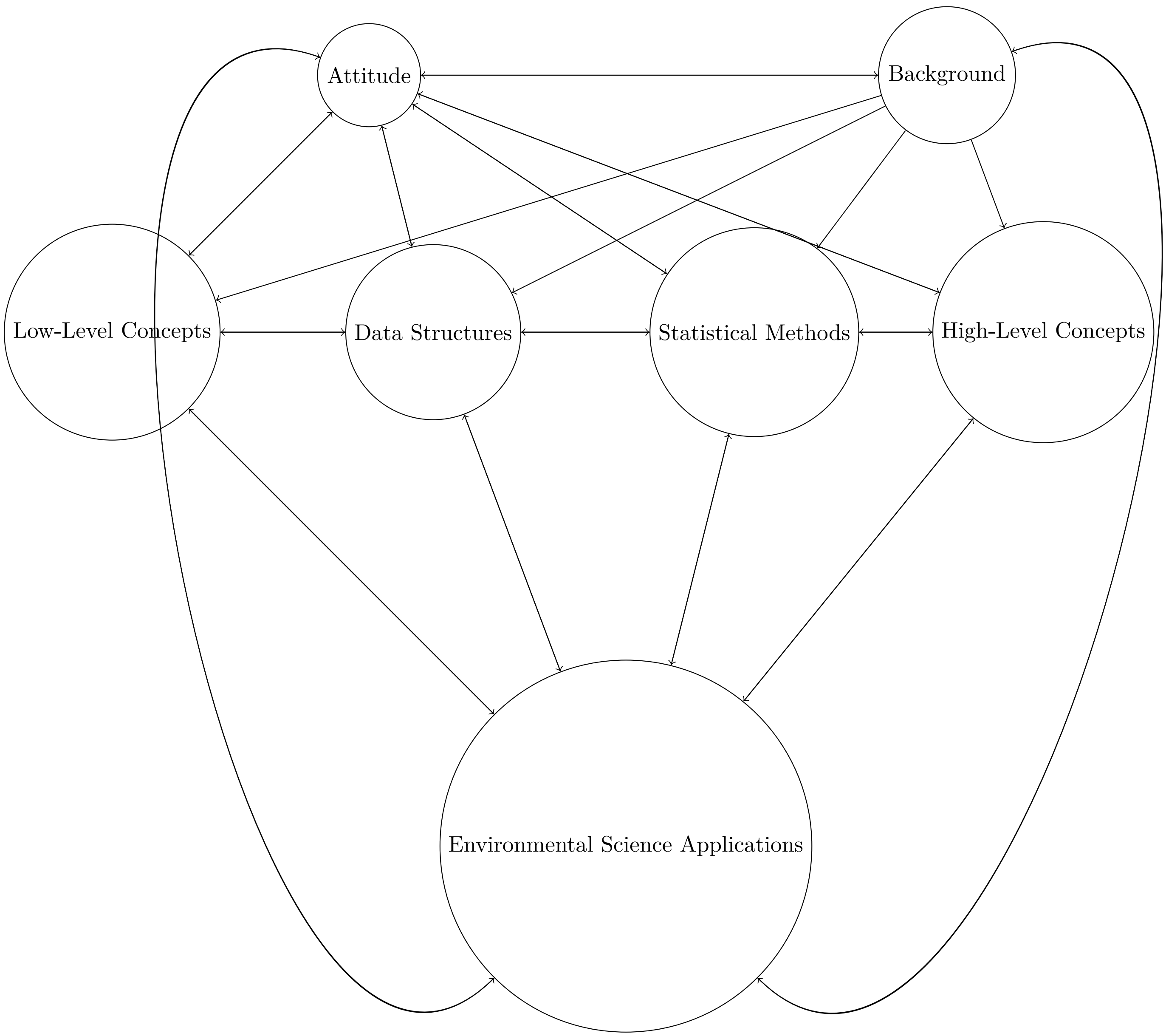


Figure 1: Concept Map of Computational Abilities and Understandings

Definitions of Terms

Background

The background could change a student's ability to reason through applications in a variety of ways. For example,

- it can be associated with what computer programming knowledge they have going in to the courses,
- it can be associated with what statistical and mathematical knowledge they have going in to the course,
- taking inquiry based statistics, mathematics, or courses related to their field can change their ability to reason through application problems, and
- beingg exposed to research based courses can shed light on how statistics and computer programming are being used in their field.

Attitude

As discussed in the literature of science education, student attitudes could affect learning and achievement in a variety of ways [23]. For example, a student could

- have a negative attitude toward taking statistics, computer science, or other computational courses,
- have low motivation in learning concepts taught in background and/or statistics courses,
- not value the material they are taught in STAT 511/512,
- remain calm or become irritated when working through new computational applications.

Low-level Programming Concepts

These are concepts potentially learned in a computer science (CS) course or a field related course. They are, however, concepts that are explicitly taught in STAT 511.

- Logical statements (e.g. if else, true/false)
- Using built in functions in R (or other software)
- Commenting their code, to know why they did what they did
- Trouble-shooting error messages

High-level Programming Concepts

These are concepts also potentially learned in a CS course or a field course. They are concepts explicitly taught in STAT 512.

- Building functions (from scratch)
- Objects and classes of objects (numeric/character/factor)
- Loops

- Conditional statements

Data Structures

These are concepts related to both basic and more advanced understandings of data formats. These concepts could have been introduced in an Introductory Statistics course, an -ometrics course, or a course related to their field. These concepts are explicitly taught in STAT 511.

- Data Format (what the data look like)
  - Retrieving the data (importing it, irregardless of format)
  - Naming variables
  - How to handle missing data
- Manipulating Data (data wrangling)
  - Creating variables (new or from existing variables, polynomials, and interactions)
  - Subsetting data (removing rows/columns)

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