In Proceedings of 17th International Conference on Intelligent Tutoring Systems

Recognizing Novice Learner's Modeling Behaviors

Sungeun An[1], William Broniec[1], Spencer Rugaber[1], Emily Weigel[1], Jennifer Hammock[2], and Ashok Goel[1]

[1] Georgia Institute of Technology, Atlanta GA 30308, USA
[2] Smithsonian Institute, Washington DC 20002, USA
sungeun.an@gatech.edu

Abstract. Modeling is an important aspect of scientific problem-solving. However, modeling is a difficult cognitive process for novice learners in part due to the high dimensionality of the parameter search space. This work investigates 50 college students' parameter search behaviors in the context of ecological modeling. The study revealed important differences in behaviors of successful and unsuccessful students in navigating the parameter space. These differences suggest opportunities for future development of adaptive cognitive scaffolds to support different classes of learners.

Keywords: Ecological Modeling, Modeling Behaviors, Parameterization, Cognitive Scaffolds, Learning Analytics.

1 Introduction

Scientific modeling is a complex cognitive process that requires integrating a variety of thinking skills and background knowledge in an investigative process [13]. Thus, studies examining middle school, high school, and college students' engagement with scientific modeling have highlighted a broad range of issues, including parameterization [15][24][27][29]. Parameterization is the task of selecting values for a model's parameters and equations to define and/or test traits of a system's key behaviors [15][24]. The parameterization task is often difficult due to a lack of domain knowledge and the high dimensionality of the parameter search space [26]. First, domain knowledge is required to constrain a range of possible values for a parameter (e.g., a sheep will usually give birth to between 1 and 2 litters). Second, parameter search strategies are required to systematically test the hypothetical changes in a model with the large number of parameters and the large range of values. As the parameterization in modeling is an important and difficult skill for novice learners, it is necessary to understand why it is difficult for them and how they struggle with it in order to provide them with cognitive support.

This paper is a preliminary step towards the creation of a learner model and technology-based cognitive scaffolding for scientific modeling. Thus, the goal of this paper is to understand how novices explore the parameter space and identify successful/unsuccessful parameter search behaviors. The research questions associated with this effort were: 1) How do novices explore the parameter space? 2) How do parameter search behaviors relate to the success/unsuccess of the modeling task? Answering these questions requires discovering learning behavior patterns and developing a learner's mental model, which can be learned from data mining, especially learning analytics [8][9].

In this study, we collected log data of 50 college students to observe their parameter search behaviors and identify modeling behavior patterns by comparing the differences between the groups who completed the task successfully and those who were unsuccessful. The publicly and freely available modeling environment called VERA was used in the experiment (https://vera.cc.gatech.edu/, [1][2]). Although many studies have identified novices' difficulties in parameterization [15][24][27][33] and developed cognitive scaffolds to support the parameterization task [4][5][12], they were limited due to the dependence on the predefined expert models, reference models, or data. Instead, we posit that interactive cognitive support should recognize the modelers' differing intentions and strategies as well as give personalized feedback according to the recognized behaviors to help them test various hypotheses and ideas.

Our contributions are threefold. First, the results complement the body of research on modeling behaviors for novice learner's success and struggles. Second, our log data study provides quantitative evidence for the model-fitting behaviors found in other protocol studies (for example, [15][24]) and suggests that general-purpose cognitive support may be insufficient for many students. Lastly, insights about the novices' unproductive modeling behaviors suggest useful directions for designing adaptive scaffolds.

2 Related Work

2.1 Understanding Novices' Difficulties in Parameterization

Prior research has shown a number of difficulties for students doing quantitative modeling by presenting a detailed analysis of their cognitive processes [15][24][27]. The students typically struggled with defining and manipulating the system parameters and deciding what parameter values to use in their equations. Most students had a strong focus on adjusting model parameters to fit the empirical data or the given simulation output graph without deeply thinking about the system [24][27]. Many students had a hard time understanding the indirect effects of manipulating the large number of simulation parameters and the large range of values that can appear in a model [15]. Consequently, the students tended to focus on the individual parameters separately instead of understanding the direct and/or indirect interactions among the components of a system as a whole [15][24]. The students' difficulties in exploring the parameter search space have negative correlations with the quality of the model that students created [24]. Therefore, previous research emphasized the importance of adequate scaffolding that takes a top-down approach during parameterization so that students can focus on explaining the underlying mechanism [15][24][27].

Although these studies examined novices' difficulties during model parameterization due to the high dimensionality of the parameter search space, they did not necessarily investigate why such difficulties emerge and how novices explore the parameter space. In this study, we investigate how learners manipulate the parameter values and how they use the output to guide adjustments to their models in detail to identify behavioral signals and build a learner model. In addition, previous studies typically used directed observations and verbal protocols to identify the difficulties of novices while working on a modeling task. In this study, we used students' interaction log data for detailed analysis that provides a more objective analysis.

2.2 Adaptive Scaffolding during the Parameterization Process

Cognitive scaffolding provides support to learners while they are learning a new task and enables them to do certain tasks that they may not be able to do without the support [10]. Adaptive scaffolding recognizes learners' behaviors, intervenes when they are in need of help, and reacts to different behaviors and issues during the task [19][20]. Various scaffolding strategies have been proposed to help learners develop models, such as giving feedback and hints on the student's model as well as the student's modeling process. For example, sample equations have been given to support students' quantification of models along with the model diagrams they match and the output they yield [11][15]. Real-world datasets have been given to help them set real-world quantities to use for parameters in their models [5][15]. Expert models and reference models have served as ground truths to assess students' models and give feedback by comparing against behaviors generated by a correct expert model [4][5][28].

Most scaffolds only provide support with regard to setting up and defining the parameter values as defined scenarios, datasets, or reference models [4][5][11]. Typically, the system monitors modelers' models and gives corresponding feedback when there is a mismatch between the learners' models and the correct expert model or dataset [4][5]. However, students may have different modeling goals, which sometimes do not match the example model (e.g., students may want to explore ecological collapse rather than stability). To support testing of new ideas or making novel hypotheses, adaptive scaffolding should also be provided during parameter exploration to support various modeling trajectories.

3 VERA for Ecological Modeling

VERA is an intelligent web-based ecological modeling application that allows learners to explore ecological systems and perform "what-if" experiments [1][2]. In Fig. 1, the top image shows a screenshot of the model canvas in VERA where a learner can build a conceptual model by adding biotic, abiotic, and habitat components and defining the relationships among them. Conceptual models of ecological phenomena in VERA are expressed in the Component Mechanism Phenomenon (CMP) language [17] that derive from the Structure-Behavior-Function theory of modeling complex systems [14].

On the model canvas, the simulation parameters of each component that can affect its simulation behavior can be changed in the right panel. To help learners quantify the model, VERA uses the Smithsonian's Encyclopedia of Life (EOL) digital library to retrieve the structured data about the species and suggest the parameter values of its lifespan, body mass, offspring count, reproductive maturity, etc. [2][21]. VERA also uses genetic algorithms for parameter optimization to fit the model to the data. [7].

After constructing the conceptual model in the model canvas, VERA generates an agent-based NetLogo simulation (https://ccl.northwestern.edu/netlogo/, [31][32]) based on the model and the simulation parameters (See the bottom image in Fig. 1) [18]. In this way, VERA integrates both qualitative reasoning in the conceptual model and quantitative reasoning in the agent-based simulation on one hand, and explanatory reasoning (conceptual model) and predictive reasoning (simulation) on the other. At the start of the COVID-19 pandemic, VERA Epidemiology (VERA-Epi) was created to support agent-based versions of compartmental epidemiology models [6]. Thus, the infrastructure of VERA has a degree of domain generality.

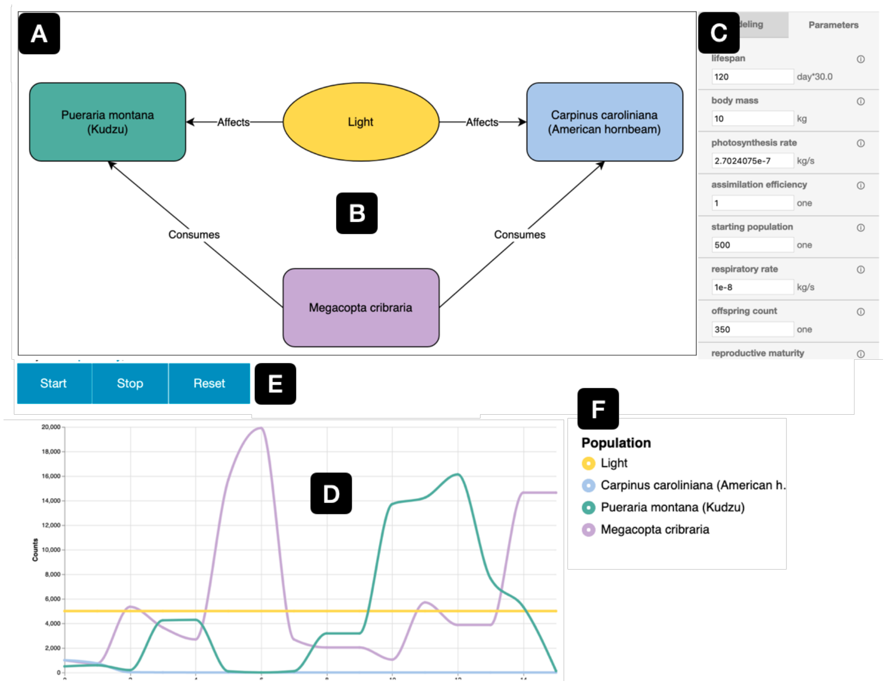

Fig. 1. The VERA system. (A) The model canvas, which provides a CMP model of the kudzu food web. (B) Model components. (C) Simulation parameters. (D) The simulation output graph – x axis: Time (months); y axis: Population. (E) Start, Stop, and Reset of the simulation output. (F) The model components on the simulation results screen.

4 Study

We conducted an experiment in a live classroom setting to understand how novices navigate the modeling parameter space while interacting with the modeling system. The study was conducted during one 50-minute class period in an undergraduate biology class at Georgia Institute of Technology, a large, public R1 institution in the southeastern US.

4.1 Participants

A complete log data of 50 students who are enrolled in an Introductory Biology course in Fall 2019 was recorded (N=50). Given the nature of the course and the students' self-assessments, the students were novice biologists and modelers who had limited biology knowledge or experience in modeling. On a 1-5 Likert scale, the average familiarity with biology was 2.80. The average self-perceived familiarity with modeling was only 2.22. The students did not receive any extra monetary compensation or course credit for their time. The students were asked to do this as an in-class exercise relevant to what they were learning for the course. Three researchers motivated students by moving around the classroom checking how they are doing and answering their questions. Additionally, two instructors of the course were sitting back in the classroom to observe the study. While the number of students enrolled in the class was 220, in our analysis we included only the students attended the class on the day of our intervention, performed the class activity, consented to study, and completed all of the assignments related to the intervention (e.g., pre-test, in-class test, and training session). Students who missed any of these steps were eliminated from our analysis.

4.2 Procedure

Before the day of the class intervention, the students took a biology pre-test as a class assignment to assess their baseline biology knowledge. During the intervention, we spent approximately 15 minutes training the students on the concept of scientific modeling and the use of the system. We introduced each of the modeling and simulation tabs and the meaning of each simulation parameter, and then walked through one scenario of building and revising a model. Next, the students were instructed to spend 25 uninterrupted minutes to complete a modeling task on a pre-built (kudzu) model (Fig. 1). The experiment instructions were given through a Qualtrics survey. After the exploration, students took an in-class biology test. All the students in the class used the modeling application on their own laptops during the study.

4.3 Modeling Task

Without knowing the effects of the values of the kudzu bug population (KBP) in advance, the students were asked to manipulate the population to select the best value for the ecosystem stability (e.g., making sure that kudzu, the kudzu bug, and American hornbeam all survive, creating a predator-prey cycle). The students were first asked to observe the simulation results of the initial model that manifests a fast-growing kudzu population. Then they answered three multiple-choice questions to test their understanding about the phenomenon. Then they were asked to alter the KBP between 1 and 1000 to provide what they thought to be the optimal value for the KBP for the stability of the ecosystem (in terms of kudzu, kudzu bug, and American hornbeam) and explain their reason in a short text. The initial model given to students manifested a fast-growing kudzu population when KBP is 1.

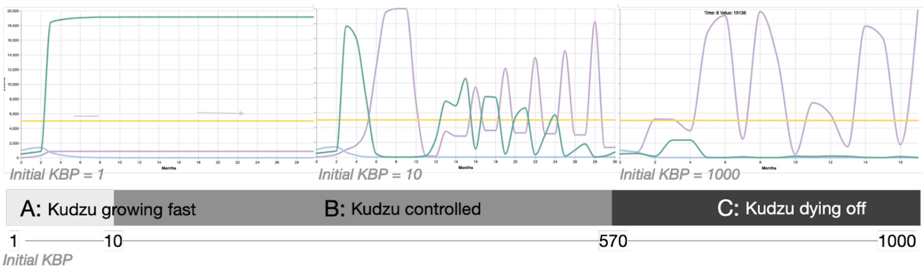

Fig. 2. The parameter spaces of the Kudzu Bug Population (KBP) and the simulation output graphs for each space.

4.4 Data

We analyzed the 50 students' log data and their submitted answers through Qualtrics. To use the students' biographic and school performance data, we obtained institute records to de-identify and pair the data obtained during the study and the class performance data. This was done in accordance with an Institute Review Board protocol (H18258). The class performance data included students' pre-class biology test and in-class biology test scores, and the score on the exercise questions that were given about the kudzu behaviors during the modeling task.

The students' log data during the modeling task was analyzed to create a set of features that were considered important and commonly used in prior work on analyzing and assessing behaviors [3][8][9][25]. Along with the features derived from prior work, we created three new features to get additional information about the modeling behaviors. In particular, we selected 10 features to analyze different modeling behaviors including *1) the total number of attempts, 2) time spent on simulation* (e.g., observing the simulation results)*, 3) time spent on revision* (e.g., changing the parameter values for each iteration)*, 4) the number of simulation pauses, 5) the median of the attempted values, 6) the number of the attempted values in false ranges* (e.g., out of the success range)*, 7) redundancy (*e.g., revisiting previously explored ranges)*,* and *8-10) three test scores.*

Deviation was used to identify how evenly the students explored the space by calculating the standard deviation of the frequency of each space. For example, if student A tried three numbers in range between 10 to 570 (Parameter Space B in Fig. 2) and student B tried three numbers in range between 1-570 (Space A and B), student A will have a higher *deviation* than student B. *The number of explored spaces (num explored)* was created to identify how broadly the students explored the space by counting whether they explored each of the three result spaces. For example, *num explored* is 1 if he/she explored only one space (either A, B, or C), 2 if two spaces were explored, and 3 if all three spaces (A, B and C) were explored. *Success/Unsuccess* was created to determine whether the modeling task was successful or unsuccessful based on the students' answers. If the selected KBP value was between 10-570, it was given a score of 1 (Success); otherwise, 0 (not a success). Consequently, a total of 13 features were used for analysis.

4.5 Results

Dimension Reduction. We used LDA as a dimension reduction technique to find a linear combination of the modeling features that were predictive of task success [13]. The first component of the LDA model and the biology knowledge feature were used as a new set of features for the analysis. We scaled the feature values as few values have different quantities which would impact the linear regression algorithm. Fig. 3 shows all students plotted with the biology knowledge and the first LDA component with their respective success labels.

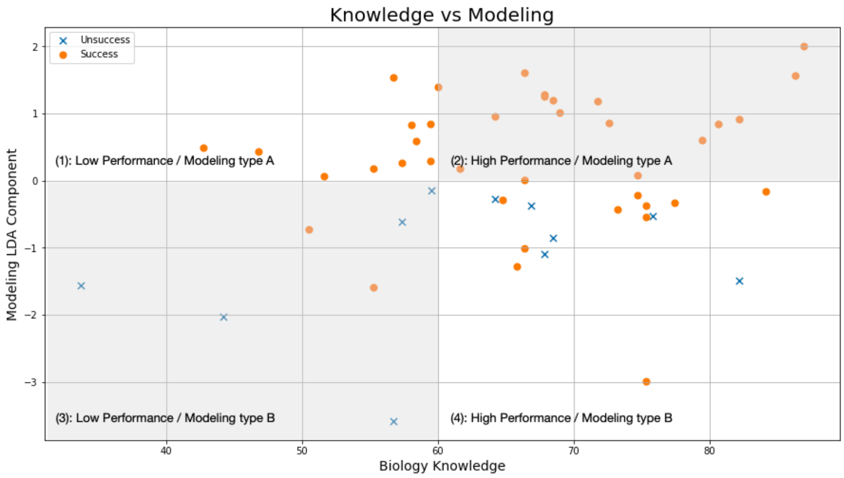

Fig. 3. The scatter plot based on the LDA component and biology knowledge.

As shown in Fig. 3, 78% of the students (N=39) found the parameter value that fits in the successful range (expressed by orange "o"); 22% of the students (N=11) did not find the right parameter range (expressed by blue "x"). The students are divided into four different categories and represented in each quadrant based on the performance and the modeling type: (1) low performance/ modeling type A, (2) high performance/ modeling type A, (3) low performance/ modeling type B, and (4) high performance/ modeling type B.

The task success strongly correlates with the modeling type ($r = 0.5265$, $p < 0.0001$) while it does not strongly correlate with the biology knowledge ($r = 0.1939$, $p = 0.1771$). Specifically, the modeling behavior A presented in quadrants 1 and 2 is considered a more successful behavior than that in quadrants 3 and 4. For example, among the modeling type A in quadrant 1 and 2, 100% of the students successfully completed the task whereas among the modeling type B, only 47.6% of the students successfully completed the task. Among the high-performance group, 81.5% of the students successfully completed the task. Among the low-performance group, only 72.22% were successful.

LDA Features and Modeling Features Correlations. We looked into how the original modeling features are correlated with the values of the first LDA component and how much they contributed to the different modeling types A and B. All the features showed statistically significant correlations except for *deviation* ($r = -0.24$, $p < .5$). The most significant features predictive of task success were *the total number of attempts* ($r = -0.65$, $p < .001$), *the number of attempted values in false ranges* ($r = -0.72$, $p < .001$), and *the number of explored spaces* ($r = -0.56$, $p < .001$). which are all negatively correlated with task success. The positively correlated modeling features are *the time spent on simulation* ($r = 0.29$, $p < .05$) and *the time spent on revision* ($r = 0.35$, $p < .05$), and *redundancy* ($r = 0.42$, $p < .005$).

Table 1. Summary of the parameter search patterns and descriptive statistics for successful and unsuccessful students. Values are means (std error in brackets).

Pattern	Relevant Feature	Successful	Unsuccessful
The students iterated more times	*The total number of attempts*	4.28 (1.50)	5.81 (2.56)
	The number of simulation pauses	2.92 (1.46)	3.30 (1.52)
The students spent less time in observing the simulation results and changing the parameter values	*The time spent on revision* (normalized)	134.72 (85.02)	105.61 (55.36)
	The time spent on simulation (normalized)	21.09 (17.09)	14.32 (4.87)
The students navigated in false ranges	*The number of explored spaces*	1.74 (0.63)	2.18 (0.40)
	Deviation	1.27 (0.63)	1.48 (0.88)
	The number of the attempted values in false ranges	0.89 (0.88)	1.81 (1.16)
The students revisited the already explored values and spaces	*Redundancy*	46.15% (18 out of 39)	72.72% (8 out of 11)

Modeling Behaviors. From the results, some patterns of parameter search can be derived. The unsuccessful modeling behavior type B was more wandering. This means that the students who fall into the modeling type B category iterated many times, and their attempted values were more likely to be concentrated in the false ranges as they navigated different parameter spaces. Table 1 is the summary of the parameter search patterns of unsuccessful students who show modeling type B (e.g., all unsuccessful students showed modeling type B, see Fig. 3). Note that the patterns of successful and unsuccessful students are in complete contrast to each other.

Doing many iterations is a commonly found behavior of novice search strategies in modeling [15][24][29]. Our study additionally reveals how and why the students' parameter search behavior is inefficient. The model-fitting behaviors observed by [15] and [24] were quantitatively observed (e.g., trying similar values on a certain space). In web search studies, [30] found two extreme learner groups: explorers and navigators, one being highly variable and one being highly consistent. Our results indicate somewhere in between showing both variability and consistency in their search interaction. For example, the students of model type A were consistent in that their attempted values were well balanced and less redundant, but also variable in that they tried broader space than the students of model type B. Nonetheless, we expect that results can be varied by task (e.g., well-defined task and complex sense-making tasks) and interface affordance (e.g., numeric input and slide bar).

4.6 Design Implications for Adaptive Cognitive Scaffolding

The above results provide insight into adaptive scaffolding for modeling based on the recognized parameter search behaviors and issues. The following design implications may also be applicable to other quantitative modeling tools or systems that require parameterization, including defining and adjusting the parameter values.

First, one common problem identified among unsuccessful students is that they repeatedly explore the similar values that produce similar simulation outputs. Agent-based models are stochastic, and the system behavior emerges out of interactions among a large number of components [23]. Consequently, the students have to test similar values many times to see their expected outcomes as it is difficult to predict which component and parameter value changes the system behavior significantly. In other words, the students heuristically have to learn the sensitivity of the parameters through trial and error as each parameter has a different degree of effect on the simulation results (e.g., some simulation parameters react more sensitively than the other parameters). For example, Fig. 2 shows discrete spaces for KBP that produce significantly different simulation behaviors. Such discrete spaces can be identified by automatically comparing the simulation outputs and using them to suggest different spaces.

Second, the students that were unsuccessful in the modeling task often explored a non-valid parameter search space. For example, we provided the students with a range of numbers with which to explore the parameter space, but without this constraint, it is more likely that students would take more time trying more numbers to find the valid space. While the learner can freely explore the parameter space by experimenting with various parameter values, the constraints can help the learner know whether his or her model makes sense in the real world and explore the parameter space more efficiently and effectively. In this process, the domain knowledge, such as the notion of exponential growth, logistic growth, and carrying capacity in ecology, can be leveraged to help narrow the parameterization space.

Third, the parameter values tried by the students were concentrated in one specific region of the space. In this paper, the parameter space was divided into three meaningful regions based on the kudzu behaviors (Fig. 2). Along with helping learners to search the parameter space, it is also important to have them understand the model as a whole by having them exploring the three different parameter spaces rather than focusing on one space. Although these spaces were divided manually by the researchers, the similarities of the simulation results in different regions can be calculated to identify the distinct spaces. Then, the interactive tool can encourage learners to observe the unexplored spaces or to revisit the space to compare results, gain a deeper insight into structure of the parameter spaces, and see the meaningful patterns.

Last, while previous studies such as [4][28] assumed that there were right or wrong models based on the expert or reference models, the learner can also try different values just to test new ideas or make new predictions, for example, to probe whether the model responds in predicted ways across a range of values. The system thus should be able to recognize what the learner is trying to achieve in the model to give appropriate guidance. For example, when searching the parameter space, increasing values can be a signal to suggest the range of values of the next parameter search space; decreasing values can be a signal to suggest the range of values of the previous search space.

5 Conclusion

We draw three preliminary conclusions from this research. First, our work confirms several findings from earlier work reported in the literature: parameterization in scientific modeling of complex phenomena is difficult because of the large number of parameters in a model and the large ranges of the values of the parameters, and that many learners struggle with parameterization. We observed this struggle even with college-level biology students. Second, general-purpose cognitive scaffolding in intelligent modeling environments like VERA is not sufficient for many students. The incompleteness and imprecision of the default values of the system parameters still leaves a large problem space of parameter values to be searched. Third, this suggests that intelligent learning environments need adaptive cognitive scaffolding to help learners navigate the large search spaces. The provision of heuristics for the search might be one such scaffolding yet to be evaluated.

In our study, we explored the parameter search strategies with one model component and parameter. Having the learners explore far more complex space (many components and many parameters) may give us different insights into parameter search strategies. This work is an early step in understanding learners' parameterization search patterns and leaves many exciting questions to be answered with further research. The ability to classify a learner's search strategy is an interesting problem on its own, but a learner-specific adaptive interface could test the feasibility of applying this type of results in real-time and build learner profiles that will enable personalized interaction.

Acknowledgements

This research was supported by an US NSF grant #1636848 (Big Data Spokes: Collaborative: Using Big Data for Environmental Sustainability: Big Data + AI Technology =Accessible, Usable, Useful Knowledge!) and the NSF South BigData Hub. This research was conducted in accordance with the Institute Review Board protocol #H18258. We thank Robert Bates for his help in constructing the VERA system. We thank anonymous reviewers of previous drafts for their helpful comments and suggestions.

References

1. An, S., Bates, R., Hammock, J., Rugaber, S., & Goel, A. (2018, June). VERA: popularizing science through AI. In *Proceedings of the International Conference on Artificial Intelligence in Education* (pp. 31-35). Springer, Cham.
2. An, S., Bates, R., Hammock, J., Rugaber, S., Weigel, E., & Goel, A. (2020, July). Scientific Modeling Using Large Scale Knowledge. In *International Conference on Artificial Intelligence in Education* (pp. 20-24). Springer, Cham.
3. Aula, A., Khan, R.M., & Guan, Z. (2010) How does search behavior change as search becomes more difficult? In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. pp. 35–44.
4. Basu, S., Biswas, G., & Kinnebrew, J.S. (2017) Learner modeling for adaptive scaffolding in a computational thinking-based science learning environment. *User Modeling and User-Adapted Interaction* 27(1), 5–53.
5. Bridewell, W., Sa nchez, J.N., Langley, P., & Billman, D.: An interactive environment for the modeling and discovery of scientific knowledge. *International Journal of Human-Computer Studies* 64(11), 1099–1114 (2006)
6. Broniec, W., An, S., Rugaber, S., & Goel, A. K. (2020). Using VERA to explain the impact of social distancing on the spread of COVID-19. arXiv preprint arXiv:2003.13762.
7. Broniec, W., An, S., Rugaber, S., & Goel, A. K. (2021) Guiding Parameter Estimation of Agent-Based Modeling Through Knowledge-Based Function Approximation. In *Proceedings of the AAAI 2021 Spring Symposium on Combining Machine Learning and Knowledge Engineering* (AAAI-MAKE 2021) -Stanford University, Palo Alto, California, USA, March 22-24, 2021.
8. Buckley, B.C., Gobert, J.D., & Horwitz, P. (2006) Using log files to track students' model-based inquiry. In *Proceedings of the 7th international conference on Learning sciences.* pp. 57–63.
9. Buckley, B.C., Gobert, J.D., Horwitz, P., & O'Dwyer, L.M. (2010) Looking inside the black box: Assessing model-based learning and inquiry in BioLogica. *International Jour-nal of Learning Technology* 5(2), 166–190.
10. Collins, A., Brown, J.S., & Newman, S.E.. (1988) Cognitive apprenticeship: Teaching the craft of reading, writing and mathematics. Thinking. *The Journal of Philosophy for Children* 8(1), 2–10.
11. De Jong, T., & Van Joolingen, W.R.: Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research* 68(2), 179–201 (1998)
12. Duque, R., Bollen, L., Anjewierden, A., & Bravo, C. (2012) Automating the analysis of problem-solving activities in learning environments: the co-lab case study. *Journal of Universal Computer Science* 18(10), 1279–1307.
13. Flick, L.B. (2000) Cognitive scaffolding that fosters scientific inquiry in middle level science. *Journal of Science Teacher Education* 11(2), 109–129.
14. Goel, A. K., Rugaber, S., & Vattam, S. (2009). Structure, behavior, and function of complex systems: The structure, behavior, and function modeling language. *AIEDAM* 23(1), 23-35.
15. Hogan, K., & Thomas, D. (2001) Cognitive comparisons of students' systems modeling in ecology. *Journal of Science Education and Technology* 10(4), 319–345.
16. Hunter, E., Mac Namee, B., Kelleher, J.D. (2018) A comparison of agent-based models and equation based models for infectious disease epidemiology. In *Proceedings of the Irish Conference on Artificial Intelligence and Cognitive Science (AICS)* pp. 33–44.

17. Joyner, D. A., Goel, A. K., Rugaber, S., Hmelo-Silver, C., & Jordan, R. (2011, July). Evolution of an integrated technology for supporting learning about complex systems. In *Proceedings of the IEEE 11th International Conference on Advanced Learning Technologies,* pp. 257-259. IEEE.
18. Joyner, D. A., Goel, A. K., & Papin, N. M. (2014, February). MILA--S: generation of agent-based simulations from conceptual models of complex systems. In *Proceedings of the 19th international conference on Intelligent User Interfaces*, pp. 289-298.
19. Joyner, D. A., & Goel, A. K. (2015, March). Improving inquiry-driven modeling in science education through interaction with intelligent tutoring agents. In Proceedings of the 20th international conference on intelligent user interfaces (pp. 5-16).
20. Liu, J., Wong, C.K., & Hui, K.K. (2003) An adaptive user interface based on personalized learning. *IEEE Intelligent Systems* 18(2), 52–57 (2003)
21. Martınez, A.M., & Kak, A.C. PCA versus LDA. (2011) *IEEE Transactions on Pattern Analysis and Machine Intelligence* 23(2), 228–233.
22. Parr, C. S., Wilson, M. N., Leary, M. P., Schulz, K. S., Lans, M. K., Walley, M. L., ... & Corrigan Jr, M. R. J. (2014). The encyclopedia of life v2: Providing global access to knowledge about life on earth. *Biodiversity Data Journal,* (2).
23. Railsback, S. F., & Grimm, V. (2019). *Agent-based and individual-based modeling: a practical introduction*. Princeton university press.
24. Sins, P.H., Savelsbergh, E.R., & vanJoolingen, W.R. (2005) The difficult process of scientific modelling: An analysis of novices' reasoning during computer-based modelling. *International Journal of Science Education* 27(14), 1695–1721.
25. Tabatabai, D., & Shore, B.M. (2005) How experts and novices search the web. *Library & information science research* 27(2), 222–248 (2005)
26. Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating parameter estimation and sensitivity analysis of agent-based models: A cookbook using NetLogo and R. Journal of Artificial Societies and Social Simulation, 17(3), 11.
27. VanLehn, K. (2013) Model construction as a learning activity: A design space and review. *Interactive Learning Environments* 21(4), 371–413.
28. Vattam, S. S., Goel, A. K., Rugaber, S., Hmelo-Silver, C. E., Jordan, R., Gray, S., & Sinha, S. (2011). Understanding complex natural systems by articulating structure-behavior-function models. *Journal of Educational Technology & Society,* 14(1), 66-81.
29. White, B.Y., & Frederiksen, J.R. (1998) Inquiry, modeling, and metacognition: Making science accessible to all students. *Cognition and instruction* 16(1), 3–118.
30. White, R.W., & Drucker, S.M. (2007) Investigating behavioral variability in web search. In *Proceedings of the 16th international conference on World Wide Web.* pp. 21–30.
31. Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems approach to making sense of the world. Journal of Science Education and technology, 8(1), 3-19.
32. Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. Cognition and instruction, 24(2), 171-209.
33. Wu, H.K. (2010) Modelling a complex system: Using novice-expert analysis for developing an effective technology-enhanced learning environment. *International Journal of Science Education* 32(2), 195–219.