text, would benefit most from the current book, whereas those looking for a broader exposition with greater context for theory, practice, and applications in biology will not be particularly well-served.

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An Introduction to Mathematical Epidemiology. *By Maia Martcheva.* Springer, New York, 2015. \$79.99. xiv+453 pp., hardcover. ISBN 978-1-4899-7611-6.

In 2008, I published an introductory textbook explaining the basics of mathematical epidemiology for a nonexpert audience [1]. It covered simple epidemic models, the basic reproductive ratio (and, in particular, its failure, which was one of the first publications to do so), vector-borne diseases, fitting models to data, and discrete epidemic models. I did so with a lightness of touch with respect to the mathematical details. *An Introduction to Mathematical Epidemiology* covers simple epidemic models, the basic reproductive ratio (and, in particular, its failure), vector-borne diseases, fitting models to data, and discrete epidemic models. To be fair, it also covers global stability, multistrain disease dynamics, optimal control, age- and class-structure, and immuno-epidemic modeling.

This isn't necessarily a problem, as there's utility in presenting these topics with the mathematical details filled in, as in the first half of the book. The new material is also worthy of consideration. It's unacceptable that the source material isn't referenced at all, however. There are even statements like "some researchers believe that it should not be called a reproduction number" (p. 110) without any attributions.

In general, the book presents a variety of ordinary differential equation (ODE) models. These are fine, although it does become a bit samey after a while. However, the models chosen are somewhat simplistic. In particular, a variety of deadly diseases are modeled—e.g., malaria (p. 70) or TB (p. 165)—with the assumption that there is no death rate due to disease. This appears to be done so that the models are more tractable, but they ignore the biological reality of the situation. Indeed, the concept of a disease-specific death rate is not introduced in any of the models until over halfway through. This is highly unrealistic.

The definition of chaos is missing topological transitivity (p. 81), which is entirely misleading: wholly unstable systems are also aperiodic and have sensitive dependence on initial conditions, but they aren't chaotic. There are also numerous issues with the proofreading, such as comma splices (e.g., pp. 116, 224, 389, 422) and glaring typos like "is always grater than" (p. 153). Sloppiness like this and the lack of referencing makes this book far less useful than it otherwise might be.

Where the book excels, however, is when it gives us the MATLAB code (p. 127) and resources for finding data (p. 125) and model fitting (p. 129). This is superb. Students can input their own code and can start digging for real-world data to use to fit their models. The twelve pages that deal with this are the undoubted highlight of the book. More like this would have been excellent.

In summary, this is a book that means well but has significant flaws. The sameness of each chapter containing what are essentially small variations on the basic ODE models makes it a slog to read at over 400 pages. There are some variations and some more MATLAB code in the last few chapters, but it's too little, too late. It's unclear who the audience for this book would be; mathematicians surely want more challenges than just simple ODEs, whereas biologists would be unlikely to wade their way through all the mathematical details. However, the material on data fitting is excellent.

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Certified Reduced Basis Methods for Parametrized Partial Differential Equations. *By Jan S. Hesthaven, Gianluigi Rozza, and Benjamin Stamm.* Springer, Cham, Switzerland, 2016. $69.99. xiv+131 pp., softcover. ISBN 978-3-319-22469-5.

One of the most exciting and fascinating challenges of numerical mathematics for the next several years will be to bring the power of modeling and simulations to real-world engineering problems (broadly understood) within short timelines. Ideally, one would like to have almost real-time quantitative responses for problems that require complex methods of solution. Having more powerful hardware is clearly not sufficient to address the demands coming not only from the engineering world but also from medicine and clinics, to mention just one application, since high-performance computing facilities are not necessarily easily accessible. The answer to this demand is likely to come from a combination of computer science and mathematics ingredients—infrastructure and methods, hardware, and software.

In this scenario, an extremely promising and effective tool arising from the mathematical side for solving partial differential equations depending on one or more parameters—as invariably happens in real applications—is provided by the *reduced basis method*, originally developed in the groups of T. Patera and Y. Maday. Traditional Galerkin methods (like finite elements) for representing the solution of a partial differential equation pursue a sort of "general purpose" approach, where the approximate solution is represented by means of a generic (piecewise polynomial, but also trigonometric or exponential) set of functions not designed for a specific problem, but rather useful for virtually countless differential problems. This versatility implies that all the problem-specific information is carried by the coefficients of the finite-dimensional expansion with respect to the selected set of basis functions. This generally requires many degrees of freedom. Consequently, the numerical problems feature large dimensions and eventually high computational costs. The reduced basis method still relies on the Galerkin framework, following the idea that the selected basis function set is customized or "educated" about the problem to be solved. The problem-specific information is captured by both the basis functions and the coefficients. Giving up versatility may reduce the number of degrees of freedom required for the reliable approximation of the problem at hand, with a computational advantage. This may be useful in the extremely common situation of parametrized partial differential equations. As a matter of fact, in modern engineering the challenge is quite often the identification of those parameters or the detection of their optimal values for the minimization (maxi-