

Introduction to modeling

“Modeling, although seemingly objective, should be seen as a subjective activity in which the world view of the modeler is an integral part of the process.”

Haywood and Haywood, 2002; cited in Taylor, 2003

What is a model?

- A model is a *simplified* representation of a real system or process
- The *output* of a system is the end result of the operation of all of the pieces or components of the system
- Alteration of system *inputs* influences those components and may affect the output
- Models may be used to demonstrate or predict the effects of such alterations when it is not practical to alter the real system

Reasons to build models (I)

- Through the process of constructing a model, the understanding of the system being modeled is often improved:
 - “Models not only mimic real systems in a more comprehensible way, but may go beyond description and lead to conclusions contrary to intuition.”

Reasons to build models (II)

- Models can be used to determine how a system might respond to different events or interventions
 - It may not be practical, or even possible, to experimentally alter real systems
 - Models provide an alternative experimental approach

Reasons to build models (III)

- Model building often highlights gaps in existing knowledge about a system:
 - “During the modeling process, areas where our knowledge of the system is fundamentally lacking are often identified, so that field research can be directed more effectively.”

Reasons to build models (IV)

- Models can facilitate communication
 - Complex systems can be expressed in simplified form
 - Multiple components and their interactions can be separated and described
 - Model results can be conveyed succinctly
 - It is possible to communicate model output *too* succinctly: be careful!

What is an epidemiologic model?

- The systems of interest are epidemiological phenomena:
 - The spread of an infectious disease in a population
 - Interactions between host and parasite or host and vector populations
 - The efficacy of disease control measures like vaccination or culling

Reasons to build epidemiologic models

- Models may be used to assess disease behavior under a variety of conditions
- Models may be used to compare the efficacy of different disease control strategies
- Model construction is inexpensive, relative to experience with actual disease outbreaks

Epidemiologic modeling: Disease dynamics

- 'Threshold theorem' of epidemics
 - Pioneering modeling work by Kermack and McKendrick¹ (among others) demonstrated that:
 - For an epidemic to grow, the number of susceptible individuals within a population must be greater than some threshold value
 - Some susceptible individuals will survive an epidemic without being infected
- Spread of foot-and-mouth disease within a dairy herd²
 - Model results indicate that, by the time 1% of a dairy herd of 1000 animals shows clinical signs of FMD, 65% to 97% of the herd will already be infected

¹Kermack and McKendrick, 1927

²Carpenter *et al.*, 2004

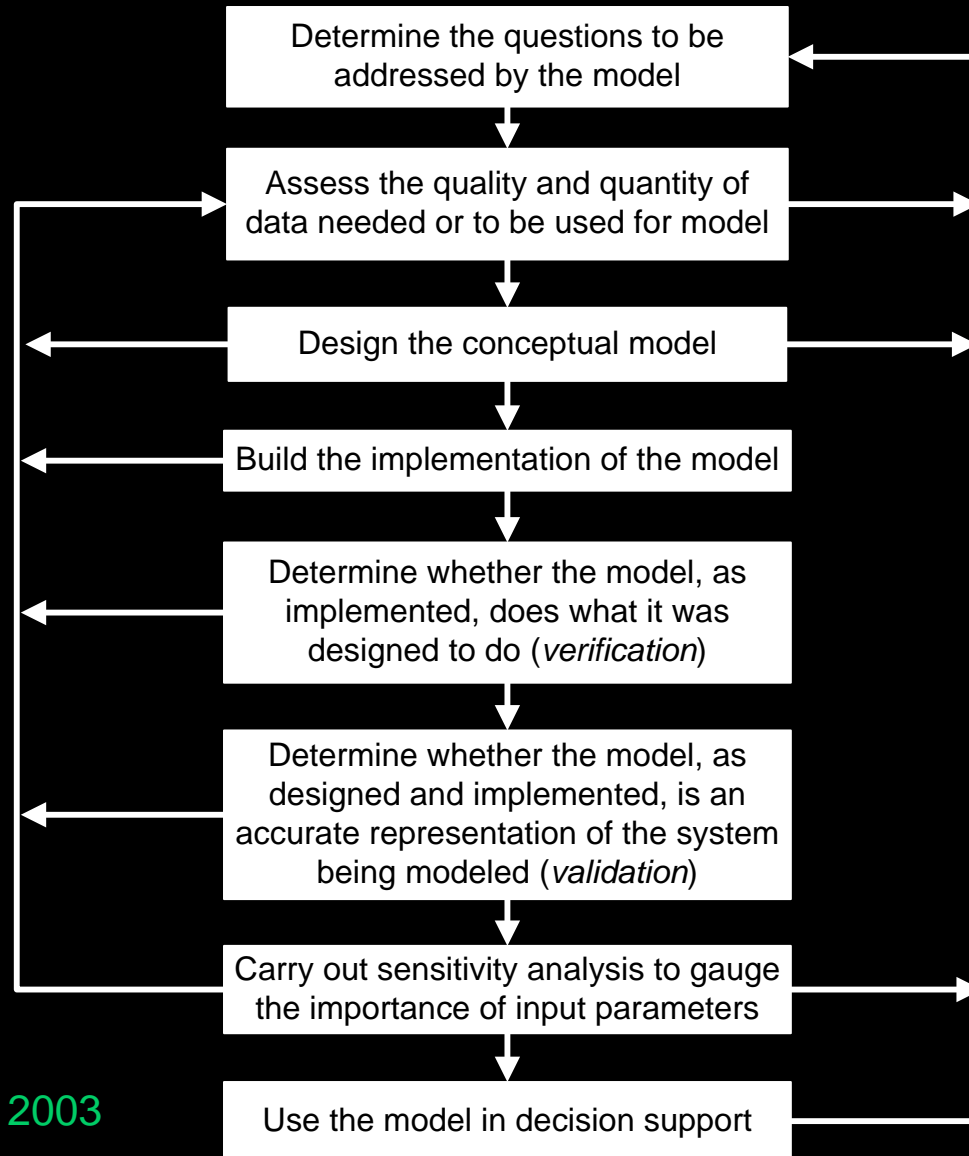
Epidemiologic modeling: Disease control

- Measles-Mumps-Rubella vaccine coverage^{1,2}
 - MMR vaccination programs attempt to cover 95% of the population
 - This number is derived from model-based estimates of the proportion of the population that must be immune in order to prevent an epidemic

¹Anderson and May, 1991

²Anderson, 1992

Stages in model building



The importance of assumptions in modeling

- All models are based on a set of assumptions
 - Assumptions that simplify aspects of the system
 - Assumptions about uncharacterized or unknown aspects of the system
- These assumptions should be explicitly stated and continuously re-assessed
- Models should be examined to identify “hidden assumptions” that might impact the model outcome
- If the assumptions behind a model are invalid or incorrect, then any output from the model is suspect

The importance of data in modeling

<i>Epidemiological knowledge</i>	<i>Data quality and quantity</i>	
	<i>Poor</i>	<i>Good</i>
<i>Poor</i>	<ul style="list-style-type: none">• Exploration of hypotheses	<ul style="list-style-type: none">• Hypothesis testing
<i>Good</i>	<ul style="list-style-type: none">• Simplified representation of past events• Guarded use for prediction of future events	<ul style="list-style-type: none">• Detailed representation of past events• Prediction of future events

The importance of simplicity in modeling

- What are the questions to be addressed by the model?
- What information is required to answer those questions?
 - Is this information (actual data or expert opinion) available?
 - What is the quality of available information?
- What aspects of the system are irrelevant for the problem of interest?
 - Can these be left out of the model?

Simplicity is a double-edged sword

- Simple models are more easily understood and communicated
- Simple models can be used to gain understanding and insight into how a real system works
- Overly simplistic models may be misleading or invalid
 - The assumptions behind the model may not be true
- The apparent precision of model outputs may convey a false sense of accuracy

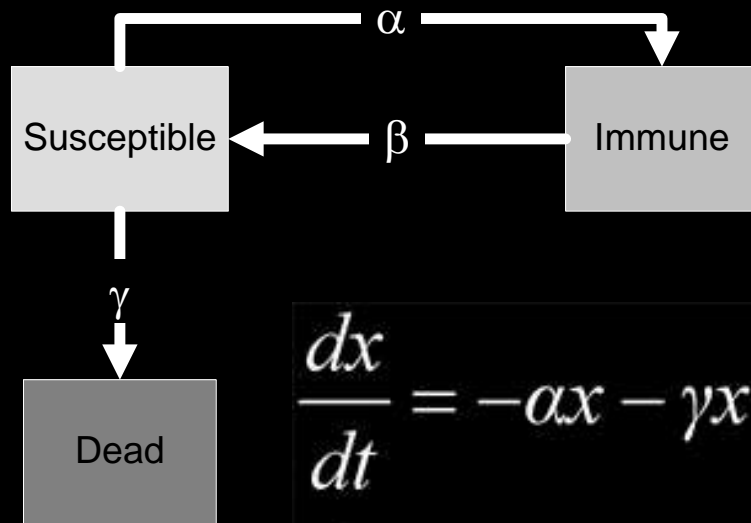
Model building is an iterative process

- Are the model results sufficient for the question being addressed?
- Are the assumptions valid? Should model output be re-generated with a different set of assumptions?
- Would it be useful to incorporate more complexity in the model?
- Does the model suggest areas for additional research and data collection?

Approaches to modeling: Mathematical modeling

- Models are based on mathematical expressions that describe the system
- Analytical solutions are available
- Subtypes include:
 - Differential calculus models
 - Chain binomial models (*e.g.*, Reed-Frost)
 - Markov chain and related models

Differential calculus modeling: A simple example



$$\frac{dx}{dt} = -\alpha x - \gamma x + \beta y$$
$$\frac{dy}{dt} = \alpha x - \beta y$$

Where

x = susceptible individuals

y = immune individuals

- The model is based on determining rates of change
 - e.g., between two or more “compartments” within a population
 - Susceptible to immune, upon vaccination (rate = α)
 - Susceptible to dead, upon infection (rate = γ)
 - Immune to susceptible, upon loss of immunity (rate = β)

Chain binomial and Markov chain modeling

- Several hours of examples over the next two days...

Approaches to modeling: Simulation modeling

- Models attempt to mimic processes that occur within a system: they emphasize “realism rather than mathematical rigour” (Miller, 1976)
- Mathematical and statistical representations of those processes are still used
- Closed-form solutions are generally not available
- Simulation models are often more transparent than (especially complex) mathematical models
 - The model is easier to explain to non-specialists

For the rest of the week, we will...

- (Re)view some key epidemiological principles
- Examine simple mathematical (Reed-Frost-based and Markov chain) models (today and Tuesday)
- Develop some simple simulation models (Tuesday)
- Work with more sophisticated simulation models (Wednesday and Thursday)
- Evaluate the results of simulation models (Friday)
- Explore some other problems and approaches for epidemiologic modeling (Friday)

Questions?

Recommended reading

- Taylor, N. 2003. Review of the use of models in informing disease control policy development and adjustment. A report for the Department for Environmental, Food, and Rural Affairs, UK. <http://www.defra.gov.uk/science/documents/publications/2003/UseofModelsInDiseaseControlPolicy.pdf> (*Chapters 1, 3, 4, and 8 are especially useful*)
- Miller, W.M. 1976. A state-transition model of epidemic foot-and-mouth disease. In Ellis, P.R., Shaw, A.P.M., and Stephens, A.J., eds. New Techniques in Veterinary Epidemiology and Economics, Proceedings of a Symposium, University of Reading, England: ISVEE I. <http://www.sciquest.org.nz> (*This paper includes a nice description of the simulation modeling process.*)
- Thrusfield, M. 2005. Veterinary Epidemiology, 3rd ed. Oxford: Blackwell Science Ltd. (*Chapter 19 provides a brief introduction to several types of models*)

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- Teclaw, R.F., 1979. Epidemic modelling. Technical report no. 6 in A study of the potential economic impact of foot and mouth disease in the United States. In McCauley E.H., Aulahi N.A., Sundquist W.B., New J.C., and Miller W.M., eds. St. Paul, MN: University of Minnesota.
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