# Overview of the Agent-Based Modeling Process

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## Key Take-Home Messages from this Morning

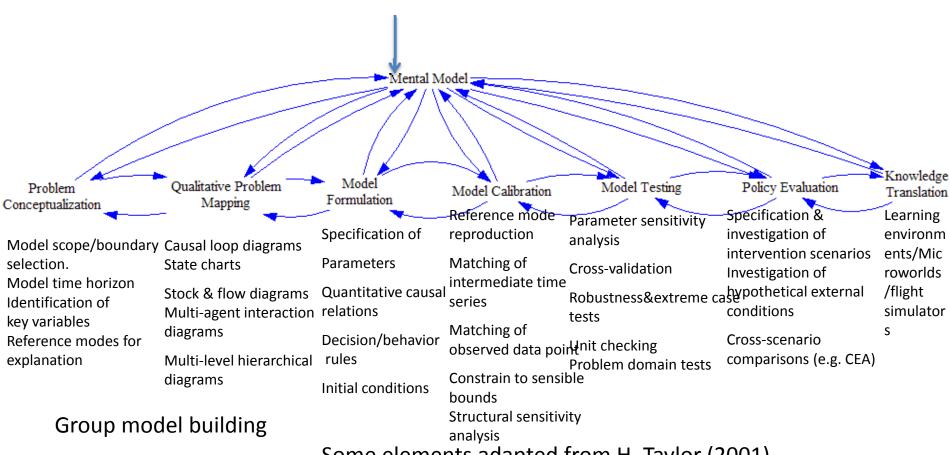
- Models express dynamic hypotheses about processes underlying observed behavior
- Models help understanding how diverse pieces of system work together
- SD focus on feedbacks as the fundamental shapers of dynamics
- Models are specific to purpose
- System dynamics includes both qualitative & quantitative components
- SD models admit to formal reasoning & analysis

## What models are not...

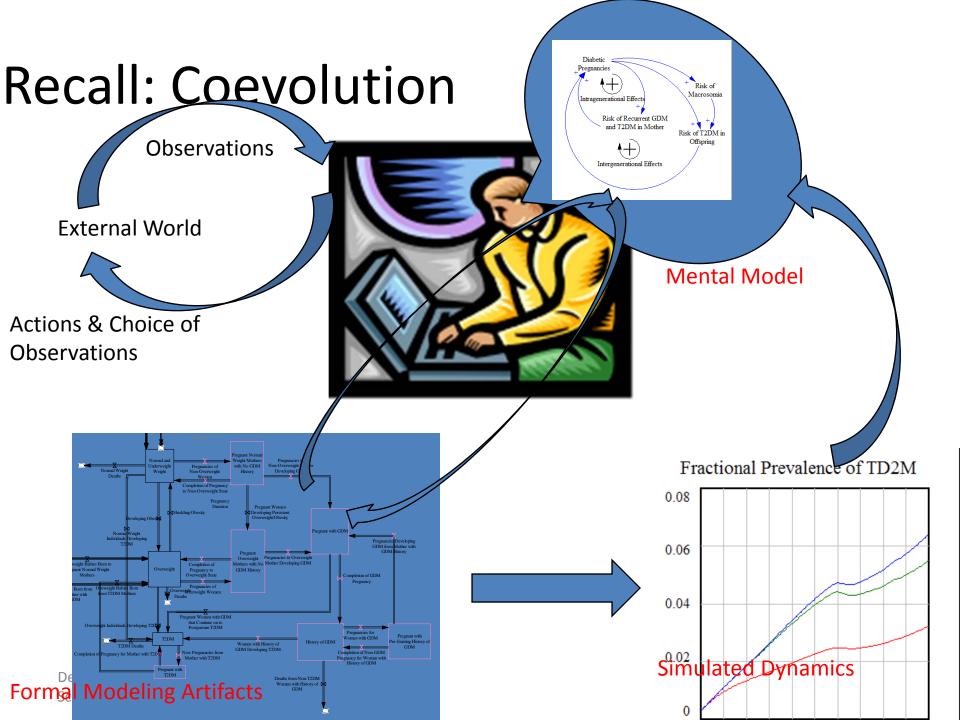
- Crystal balls
- Perfect representation of real system
- Dependent upon complete data
- Replacements for traditional (e.g. epidemiological) analyses
- Black boxes for decision making

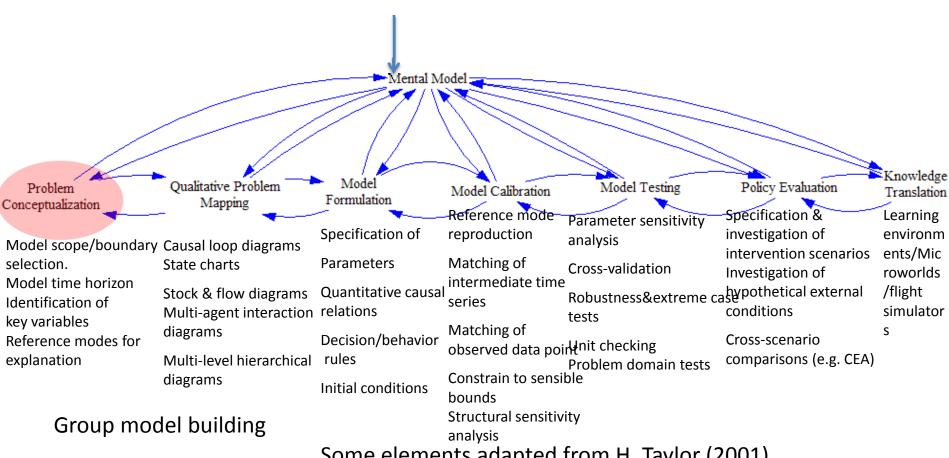
## Overview of Modeling Process

- Interdisciplinary team
- Best: Iteration with modeling, intervention implementation, data collection
- Often it is the modeling process itself rather than the models created – that offers the greatest value



Some elements adapted from H. Taylor (2001)





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# Identification of Questions/"The Problem"

- All models are simplifications and "wrong"
- Some models are useful
- Attempts at perfect representation of "real-world" system generally offer little value
- Establishing a clear model purpose is critical for defining what is included in a model
  - Understanding broad trends/insight?
  - Understanding policy impacts?
  - Ruling out certain hypotheses?
- Think explicitly about model boundaries
- Adding factors often does not yield greater insight
  - Often simplest models give greatest insight
  - Opportunity costs: More complex model takes more time to build=>less time for insight

## Importance of Purpose

Firmness of purpose is one of the most necessary sinews of character, and one of the best instruments of success. Without it genius wastes its efforts in a maze of inconsistencies.

Lord Chesterfield

The secret of success is constancy of purpose.

Benjamin Disraeli

The art of model building is knowing what to cut out, and the purpose of the model acts as the logical knife. It provides the criterion about what will be cut, so that only the essential features necessary to fulfill the purpose are left.

John Sterman

### **Common Division**

- Endogenous
  - Things whose dynamics are calculated as part of the model
- Exogenous
  - Things that are included in model consideration, but are specified externally
    - Time series
    - Constants
- Ignored/Excluded
  - Things outside the boundary of the model

# Example of Boundary Definition

Fiddaman

A Feedback-Rich Climate-Economy Model (1998)

#### Table 1: Model Boundary

Endo	genous
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Economic output

Consumption

Interest rates

Investment

Embodiment of energy requirements in capital

Energy prices

Energy production

Energy technology

Depletion

CO<sub>2</sub> Emissions

Carbon Cycle

Atmosphere and ocean temperature

Climate damages

#### Exogenous

Population

Factor productivity

Autonomous energy efficiency improvement

Oil/gas and coal prices (1960-1990)

Nonenergy CO<sub>2</sub> emissions

Greenhouse gases other than CO<sub>2</sub>

#### Excluded

Labor mobility and participation

Money stocks and monetary effects

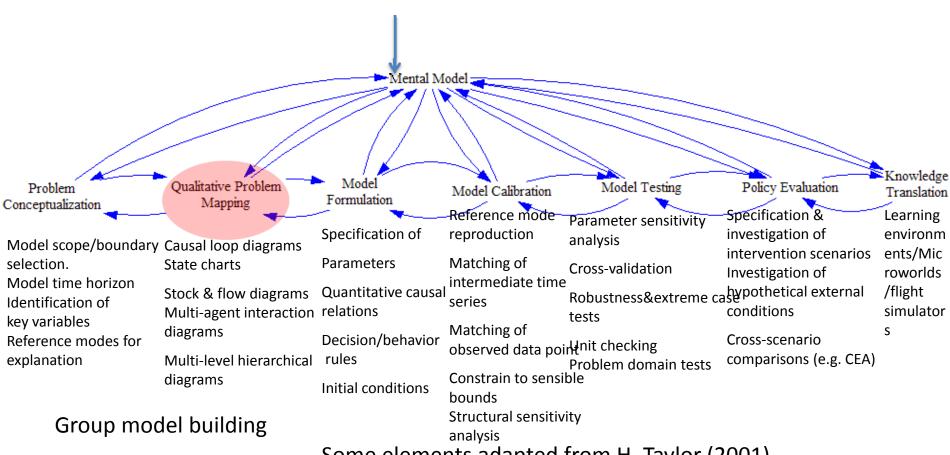
Non-energy resources

Regional disaggregation

Sectoral disaggregation (other than energy)

Fossil-fired electric power generation

Inventories and backlogs



Some elements adapted from H. Taylor (2001)

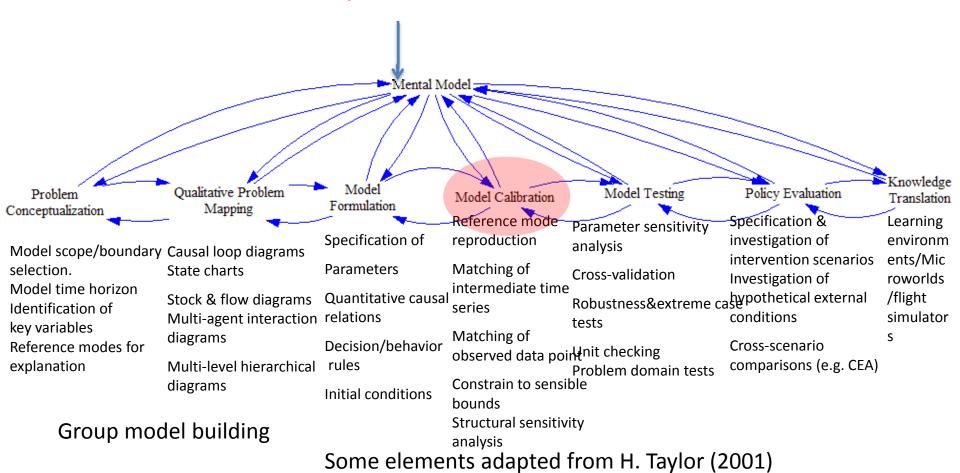
## **Model Formulation**

- Model formulation elaborates on problem mapping to yield a quantitative model
- Key missing ingredients
  - Specifying formulas for
    - State transitions
    - Flows (in terms of other variables)
    - Intermediate/output variables
    - Initial states
  - Parameter values

## Sources for Parameter Estimates

- Surveillance data
- Controlled trials
- Outbreak data
- Clinical reports data
- Intervention outcomes studies
- Calibration to historic data
- Expert judgement
- Systematic reviews

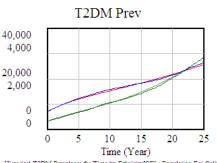
Parameter*	Description	Baseline value	Reference
		(units)	
μ	Entry/exit of sexual activity	0.0056 (years <sup>-1</sup> )	Garnett and
			Bowden, 2000
с	Partner change rate per	16.08 (years <sup>-1</sup> )	Approximated
	Susceptible		from Garnett
			and Bowden,
			2000
β	Probability of infection per	0.70	Garnett and
	sexual contact		Bowden, 2000
φ	Fraction of Infectives who	0.20	Garnett and
	are symptomatic		Bowden, 2000
1/y	Latent period	0.038 (years)	Brunham et.
			al., 2005
1/σ	Duration of infection	0.25 (years)	Brunham et.
			al., 2005
θ	Asymptomatic recovery	1.5	Garnett and
	coefficient		Bowden, 2000
$1/\pi$	Duration of naturally-	1 (year)	Approximated
	acquired immunity		from Brunham
			et. al., 2005



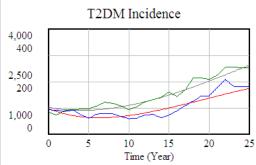
## Calibration

- Often we don't have reliable information on some parameters
  - Some parameters may not even be observable!
- Some parameters may implicitly capture a large set of factors not explicitly represented in model
- Often we will calibrate less well known parameters to match observed data
  - "Analytic triangulation": Often try to match against many time series or pieces of data at once
- Sometimes we learn from this that our model structure just can't produce the patterns!

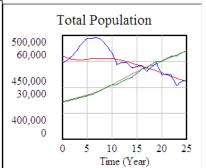
## Single Model Matches Many Data Sources



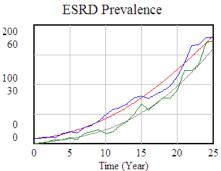
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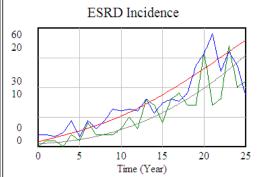
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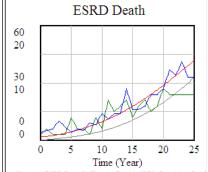
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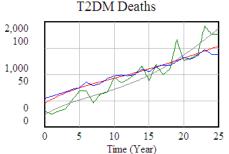
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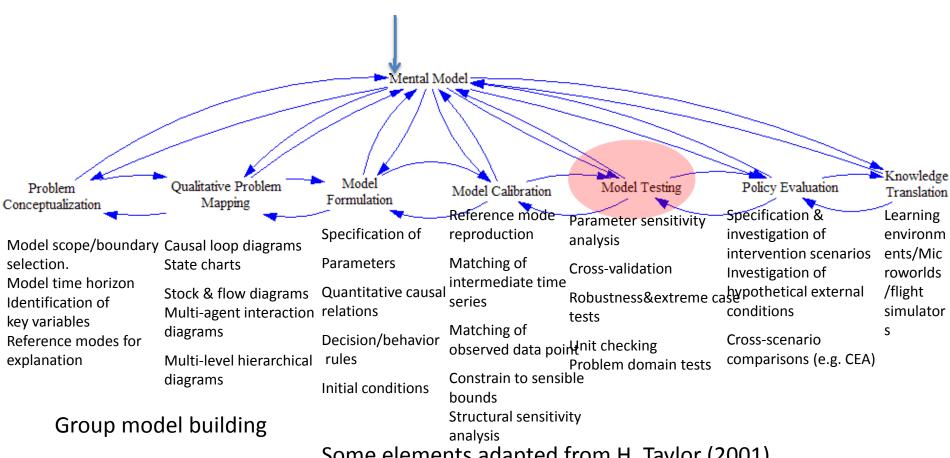
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# Sensitivity Analyses

- Same relative or absolute uncertainty in different parameters may have hugely different effect on outcomes or decisions
- Help identify parameters that strongly affect
  - Key model results
  - Choice between policies
- We place more emphasis in parameter estimation into parameters exhibiting high sensitivity

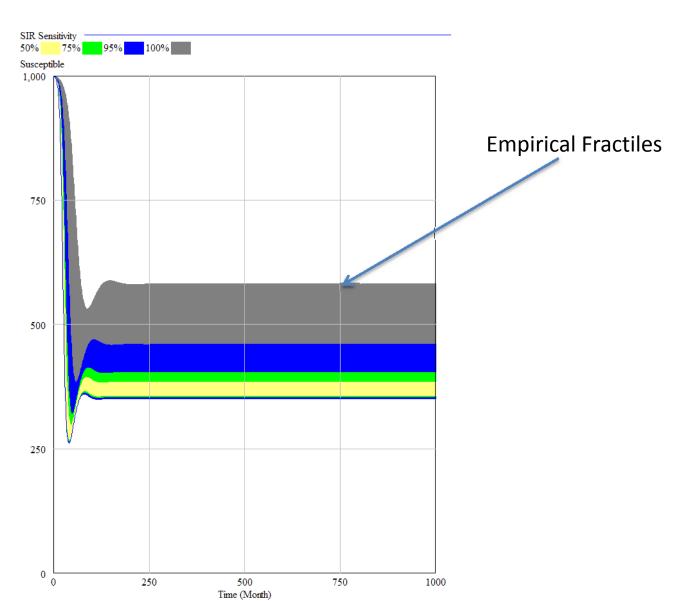
## Sensitivity in Initial Value

- Frequently we don't know the exact state of the system at a certain point in time
- A very useful type of sensitivity analysis is to vary the initial value of model stocks
- In Vensim, this can be accomplished by
  - Indicating a parameter name within the "initial value" area for a stock
  - Varying the parameter value

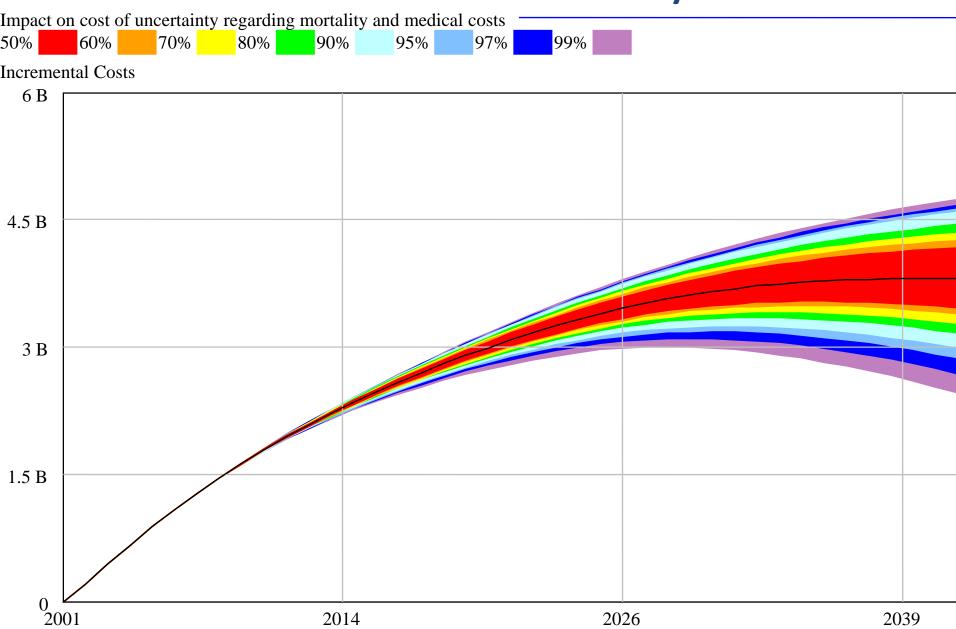
# Imposing a Probability Distribution Monte Carlo Analysis

- We feed in probability distributions to reflect our uncertainty about one or more parameters
- The model is run many, many times (realizations)
  - For each realization, the model uses a different draw from those probability distribution
- What emerges is resulting probability distribution for model outputs

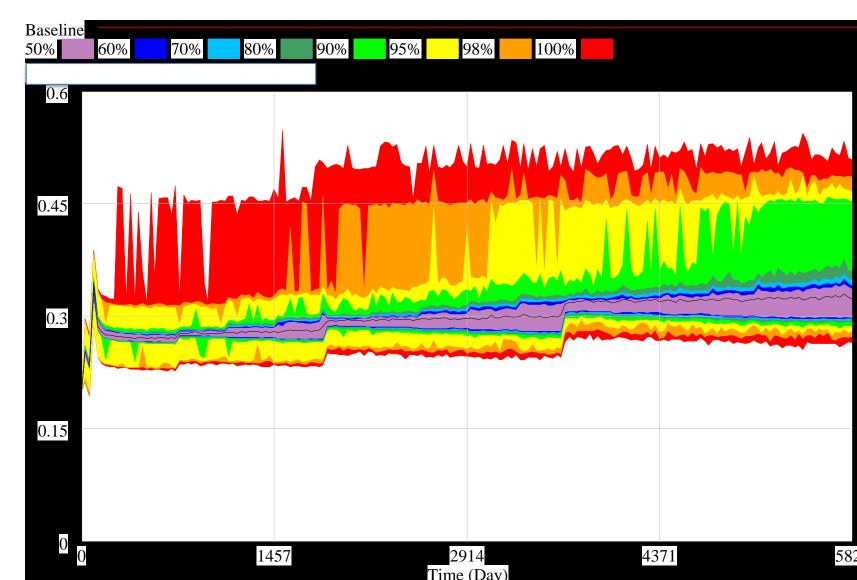
# **Example Resulting Distribution**



# **Static Uncertainty**



# Dynamic Uncertainty: Stochastic Processes



# Mathematical Analysis of Models

System Linearization (Jacobian)

$$\begin{bmatrix}
-\beta \text{ Infectives} - \delta & -\beta S - \delta \\
\beta \text{ Infectives} & \beta S - \frac{1}{\mu + \frac{\tau \text{ Infectives}}{h}} + \frac{\text{Infectives }\tau}{\left(\mu + \frac{\tau \text{ Infectives}}{h}\right)^2 h}
\end{bmatrix}$$
-Point Criteria  $\dot{S} = -c\left(\frac{I}{N}\right)\hat{\beta}S + R\delta = 0$  State space diagram

Fixed-Point Criteria  $\dot{S} = -c \left(\frac{I}{N}\right) \hat{\beta} S + R\delta = 0$ 

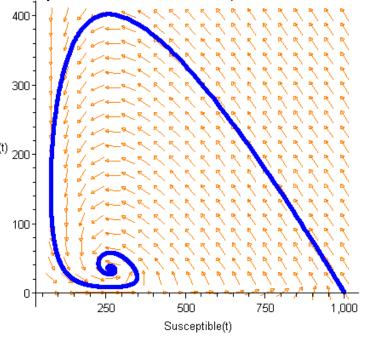
$$\dot{I} = c \left(\frac{I}{N}\right) \hat{\beta} S - \frac{I}{\mu + \tau \frac{I}{h}} = 0$$

$$\dot{R} = \frac{I}{\mu + \tau \frac{I}{h}} - R\delta = 0$$

Eigenvalues (e.g. for stability analysis around fixed-point)  $^{''}$   $^{200}$ 

$$\begin{split} &\frac{1}{2}\,\beta\,\mathcal{S} - \frac{1}{2}\,\frac{1}{\mu + \frac{\tau\,\, Infectives}{h}} + \frac{1}{2}\,\frac{\,\, Infectives\,\tau}{\left(\mu + \frac{\tau\,\, Infectives\,\tau}{h}\right)^2\,h} - \frac{1}{2}\,\beta\,\, Infectives\,- \frac{1}{2}\,\delta \\ &+ \frac{1}{2}\left(\left(\beta\,\mathcal{S} - \frac{1}{\mu + \frac{\tau\,\, Infectives}{h}} + \frac{\,\, Infectives\,\tau}{\left(\mu + \frac{\tau\,\, Infectives}{h}\right)^2\,h}\right)^2 - 2\left(\beta\,\mathcal{S} - \frac{1}{\mu + \frac{\tau\,\, Infectives}{h}}\right)^2 + \frac{1}{\mu + \frac{\tau\,\, Infectives\,\tau}{h}} \\ &+ \frac{\,\, Infectives\,\tau}{\left(\mu + \frac{\tau\,\, Infectives}{h}\right)^2\,h}\right) \left(-\beta\,\, Infectives\,-\,\delta\right) + \left(-\beta\,\, Infectives\,-\,\delta\right)^2 + 4\,\beta\,\, Infectives\,\left(-\beta\,\mathcal{S} - \delta\right)\right)^{\frac{1}{2}} \end{split}$$

State space diagram (reasoning about many scenarios at once)



# Applied Math & Dynamic Modeling

- Although you may not use it, the dynamic modeling presented rests on the tremendous deep & rich foundation of applied mathematics
  - Linear algebra
  - Calculus (Differentia/Integral, Uni& Multivariate)
  - Differential equations
  - Numerical analysis (including numerical integration, parameter estimation)
  - Control theory
- For the mathematically inclined, the tools of these areas of applied math are available

# Comments on Mathematics & Dynamic Modeling

- Many accomplished & well-published dynamic modelers have limited mathematical background
  - Can investigate pressing & important issues
  - Software tools are making this easier over time
- Can gain extra insight/flexibility if willing to push to learn some of the associated mathematics
- Achieving highest skill levels in dynamic modeling do require mathematical facility and sophistication
  - To do sophisticated work, often those lacking this background or inclination collaborate with someone with background

# Examples of Mathematical Insights from System Dynamics Models

- Identification of long-term behavior
  - Eventual outcome(s)
  - The impact of parameters on outcomes
  - The robustness of these outcomes to disturbance
- Insight into key causal linkages driving the system at each point in time
- Identification of high leverage parameters (interventions)
- Explanation for elements of observed behavior

