

Hybrid System Science Methods: Some Observations

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Using Modeling to Prepare for Changing
Healthcare Needs

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System Science Methodologies: Highly Complementary

- Different modeling methodologies seek to answer different types of questions
- No one system science methodology offers a replacement for the others
- Significant synergies can be secured by using combinations of methodologies to address the same problem
 - As cross-checks on understanding where two or more can be applied
 - Exploiting competitive advantages

Multi-Framework Modeling

- We have found the use of multiple frameworks highly effective

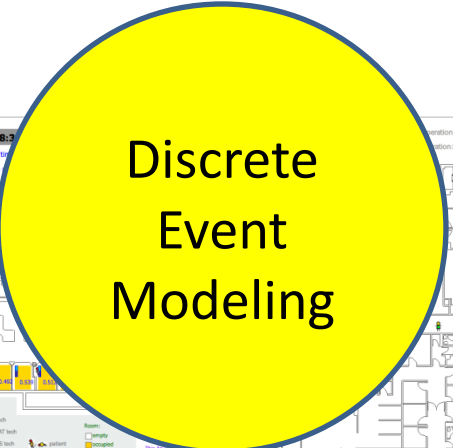
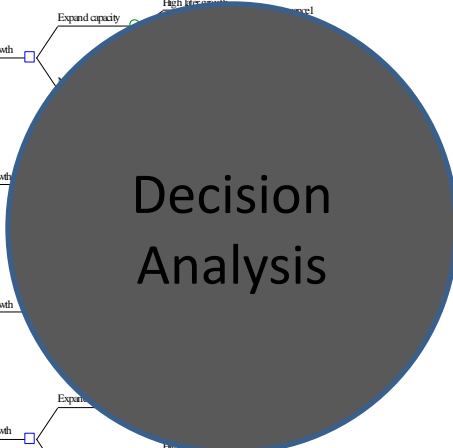
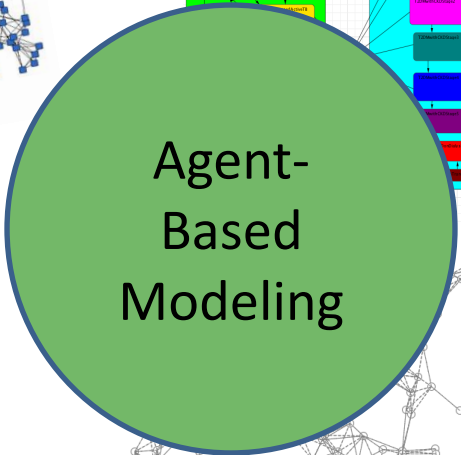
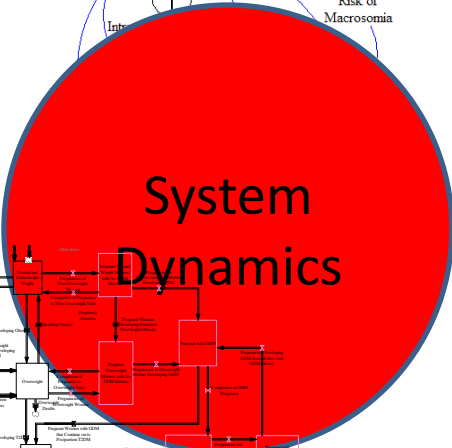
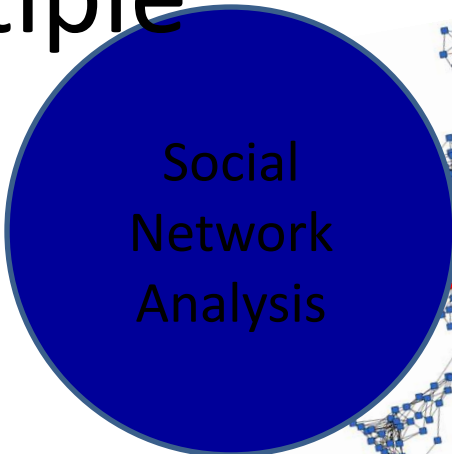
- Co-evolving multiple models for

- Cross-validation
- Asking different sorts of questions
- Revealing new questions to answer

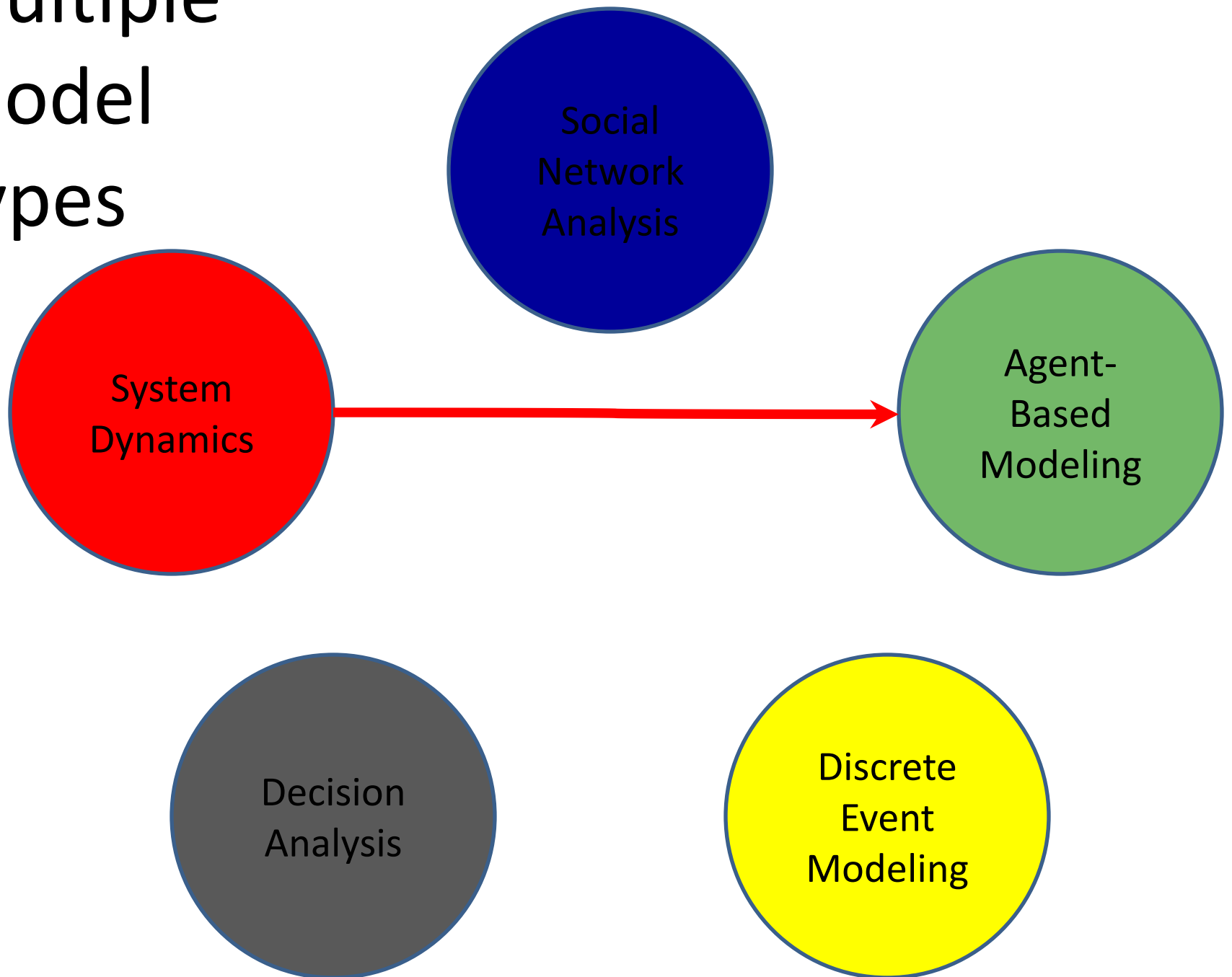
- Within a single model

- Dealing with questions at different scales
- Improving robustness of models
- Allowing for representation & changing of factors that are otherwise ignored

Reminder: Multiple Model Types



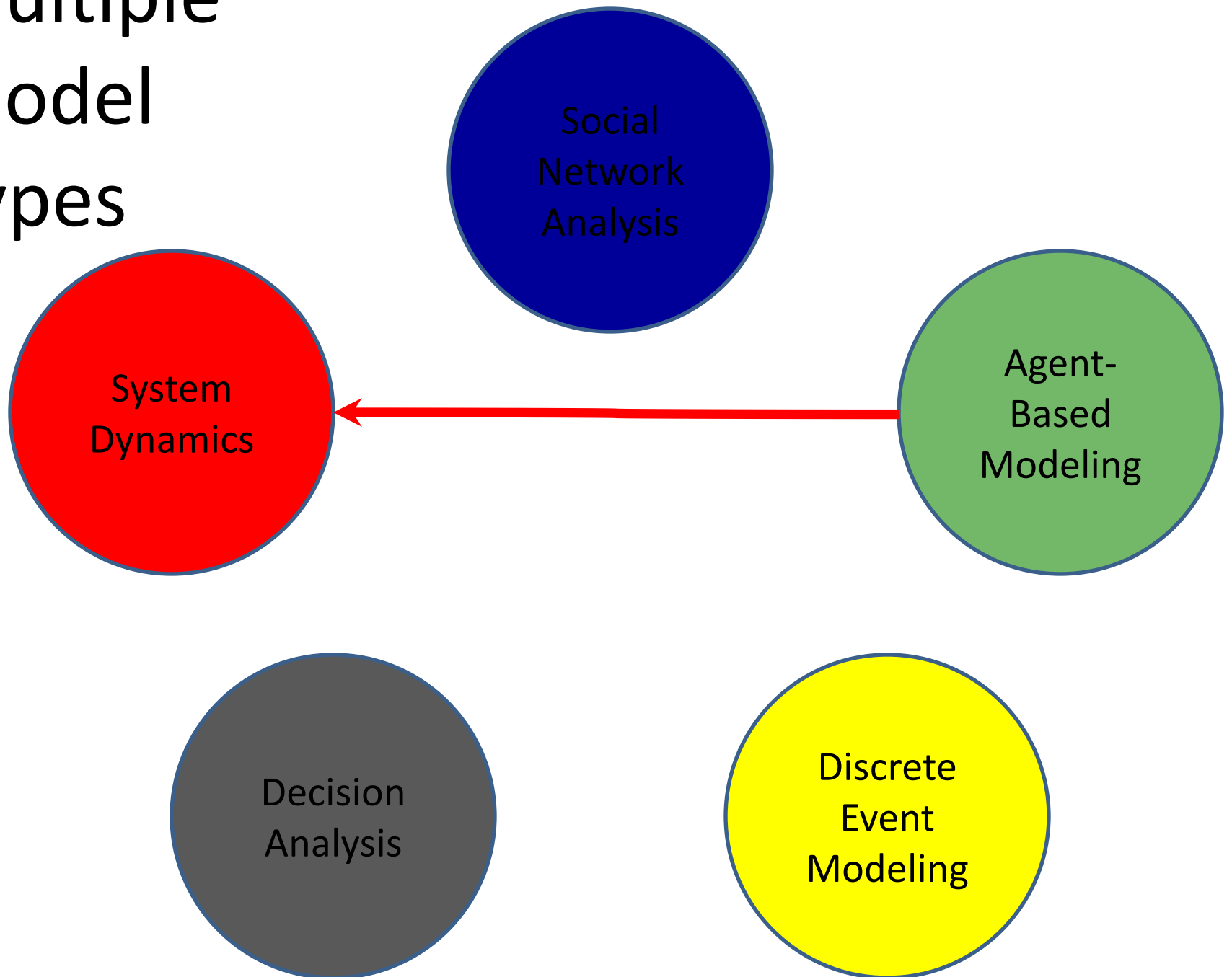
Multiple Model Types



System Dynamics Supporting ABM

- High level SD model drives global dynamics, which affects ABM dynamics
- Deriving calibrated parameter estimates for low-level model
- Focusing AB exploration
- SD within Agents: Stocks & flows drive continuous elements of agent evolution
- SD model is used to capture dynamics of lower interest population/infrastructure; ABM for the area of greatest interest
- Qualitative diagramming of
 - Interactions at a particular scale
 - Hypothesized drivers underlying emergent behaviour

Multiple Model Types



Agent-Based Modeling in Support of

- Cross-validating SD aggregation: Evaluating importance of ^{SD}
 - Stratification by heterogeneities
 - Stochastics
 - Network dynamics
- Aggregated agent behavior drives some flows in higher-level SD model(s)
- Giving insight into feedbacks to depict
- Investigating specialized interventions
 - e.g. Interventions that depend on individual history, network position, etc.
- Use to determine parameters for SD model



Hands on Model Use Ahead



Load Provided Model:
CTL State Variable V4



Hands on Model Use Ahead



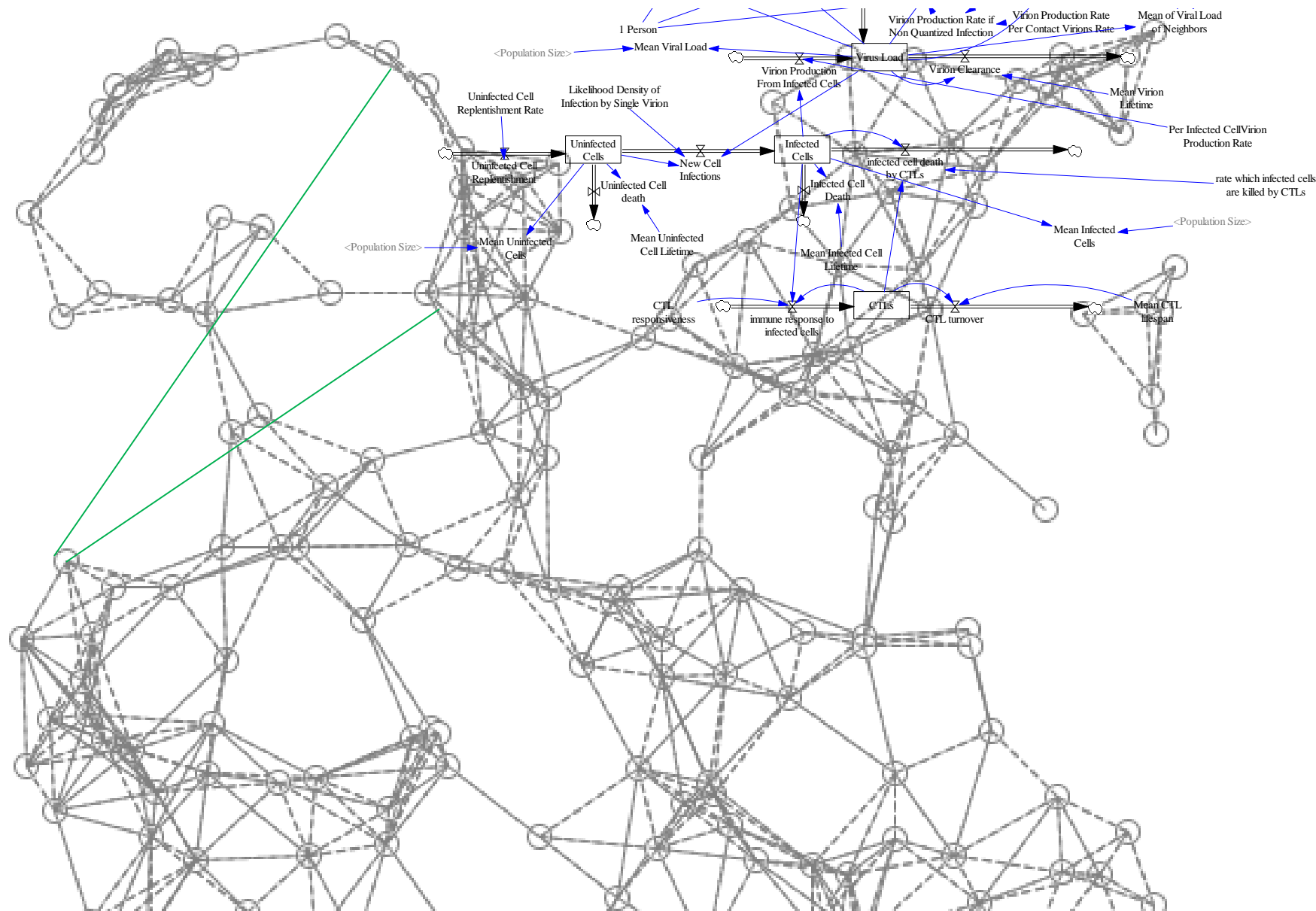
Load Provided Model:
GriddedSystemDynamics

System Dynamics &

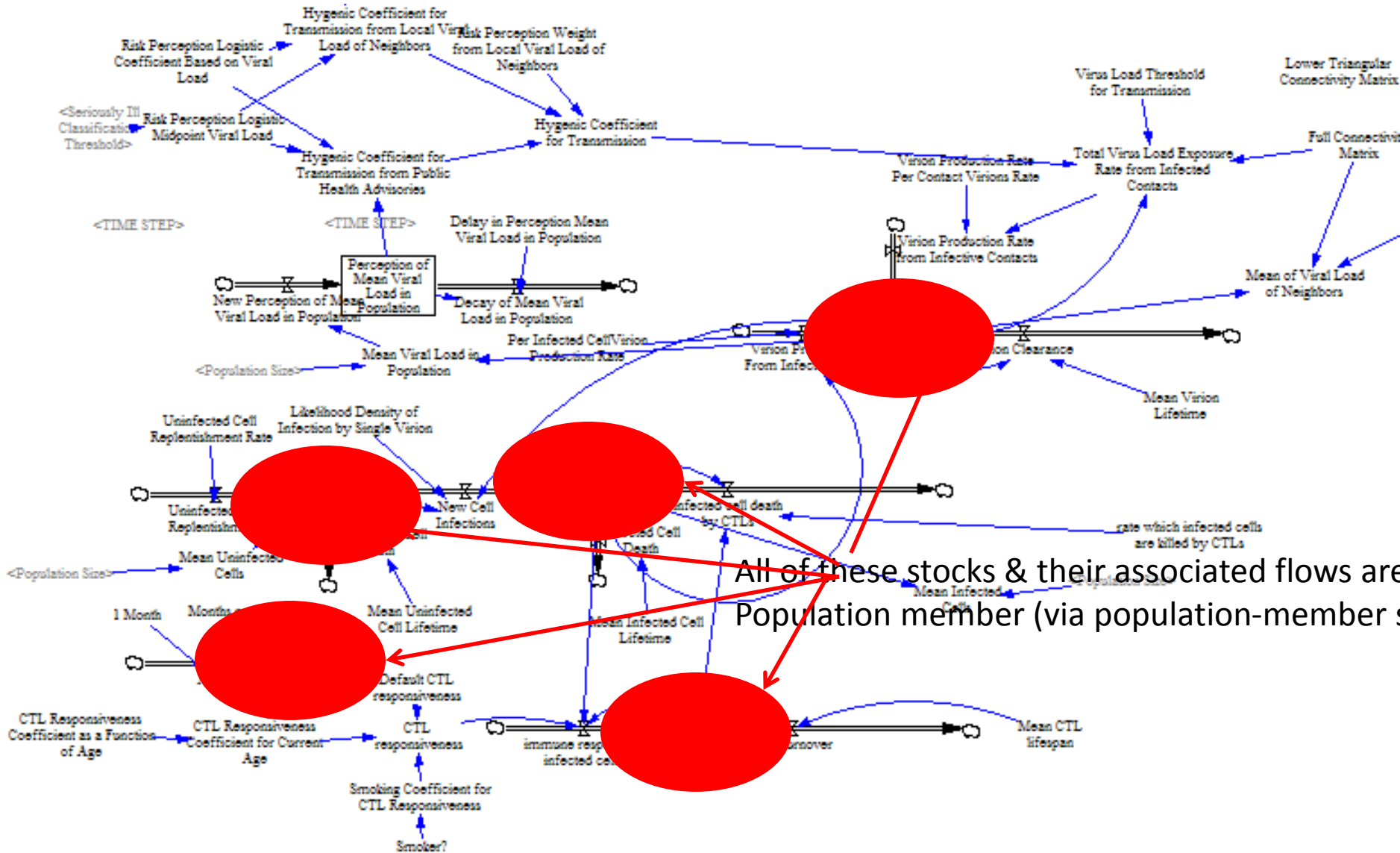
Individual-Based Modeling

- Individual-based models can be created using
 - Traditional System Dynamics software
 - Small populations:
 - Separate stocks for each individual
 - Hand-drawn connections
 - Larger Populations
 - Subscripting stocks by population member
 - Binary network matrices
 - Stock & flows in other dynamic modeling software
 - e.g. in AnyLogic (e.g., embedded in agents)
 - System Dynamics methodology
 - Feedback-centric reasoning
 - Process-based work

Network Embedded Individuals



Individual-Based Model in Vensim



Population-Member Subscripting

Editing equation for - CTLs

CTLs[Population] Add Eq

= +immune response to infected cells[Population]-CTL turnover[Population]

INTEG (

Initial Value 1|

Type

Level Normal Supplementary Help

Units: Tcell

Comment:

Group: .individual b Range: Go To: Prev Next << Hilite Sel... New

Errors: Equation OK

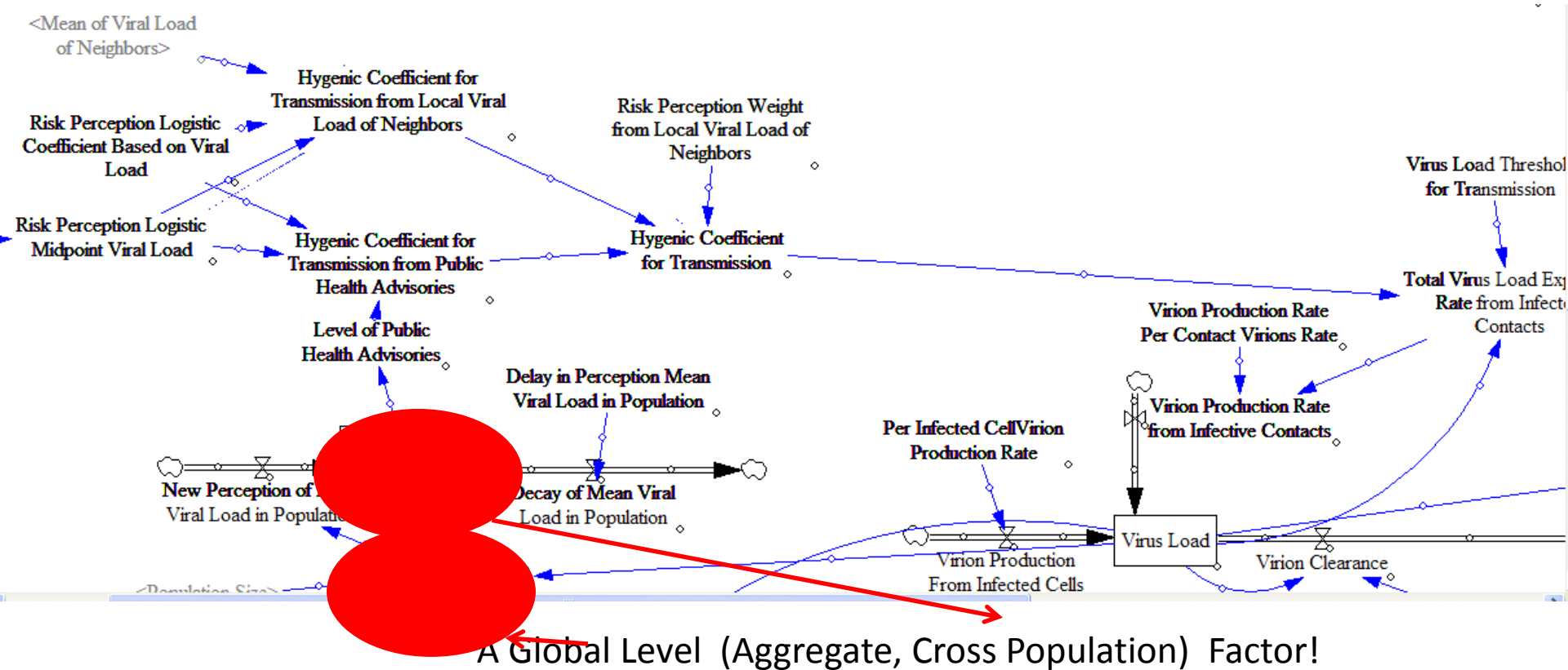
Variables Subscripts Functions More

Choose Variable... Inputs

CTLs
CTL turnover
immune response to infected cells

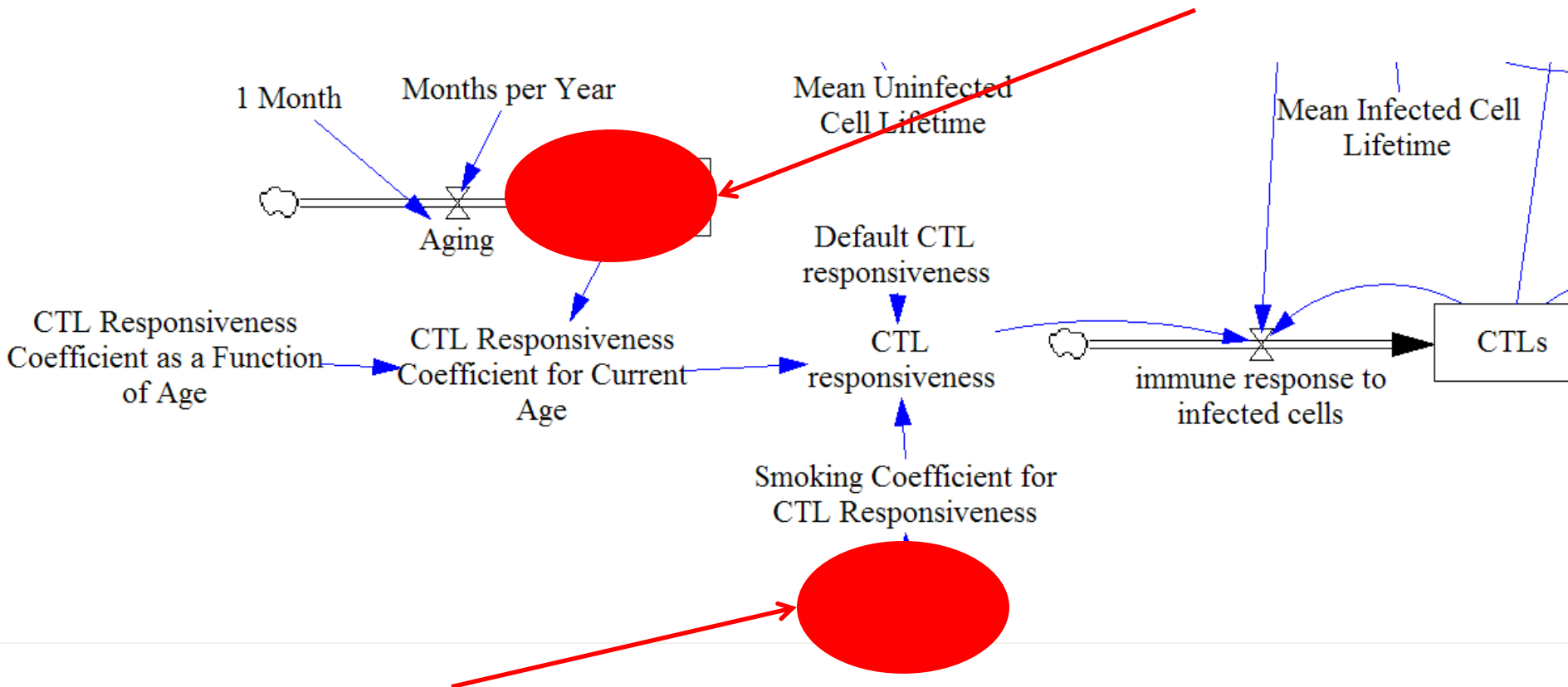
OK Check Syntax Check Model Delete Variable Cancel

Example Interactions between Global & Local Levels



Example Individual-Level Risk Factors

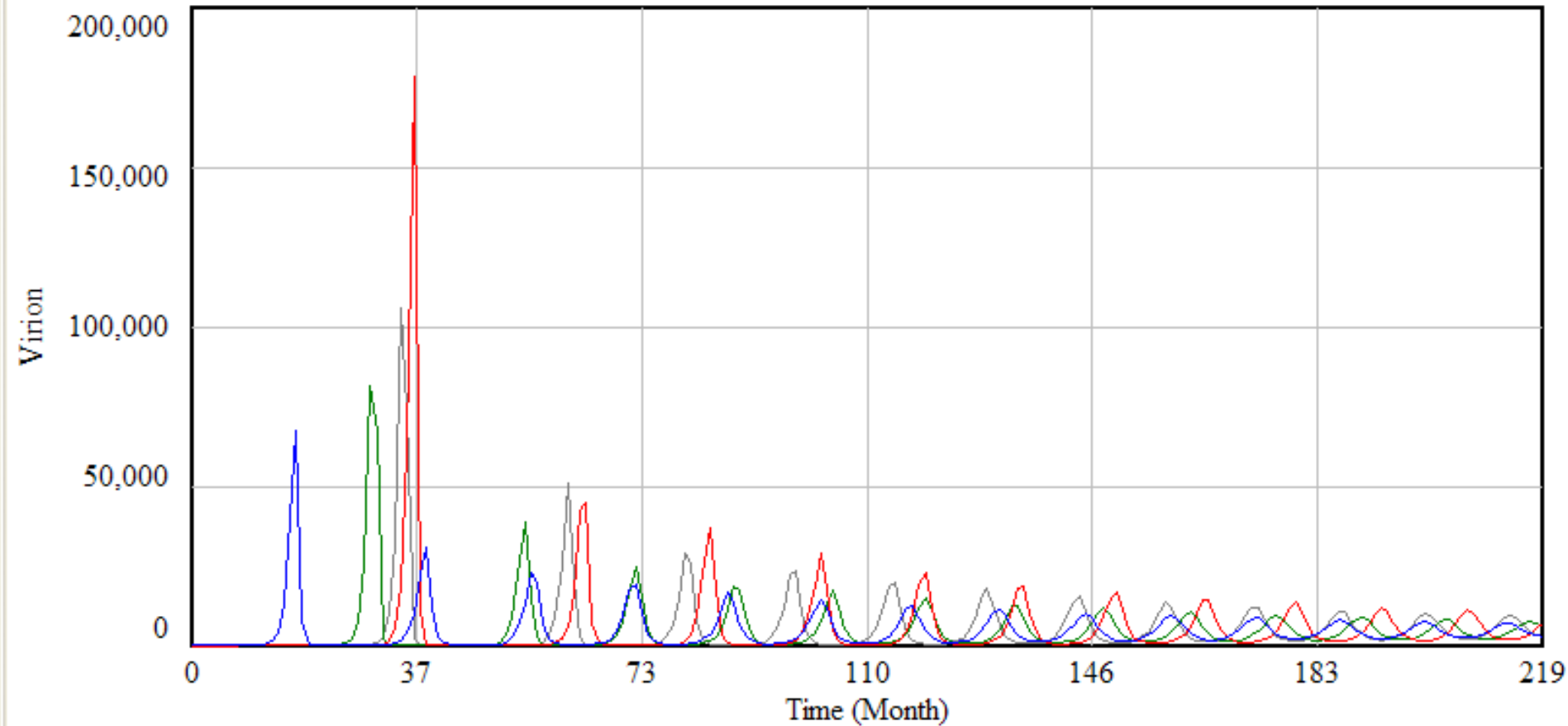
An Individual-Level Risk Factor



er Individual-Level Risk Factor (here, represented categorically, but we could
sent it as a continuous variable – e.g. cumulative smoke exposure, some estimate of
relative physiologic damage from smoke, a moving average of smoke exposure, etc.)

Impact of Risk Factors on Individual Dynamics

Virus Load



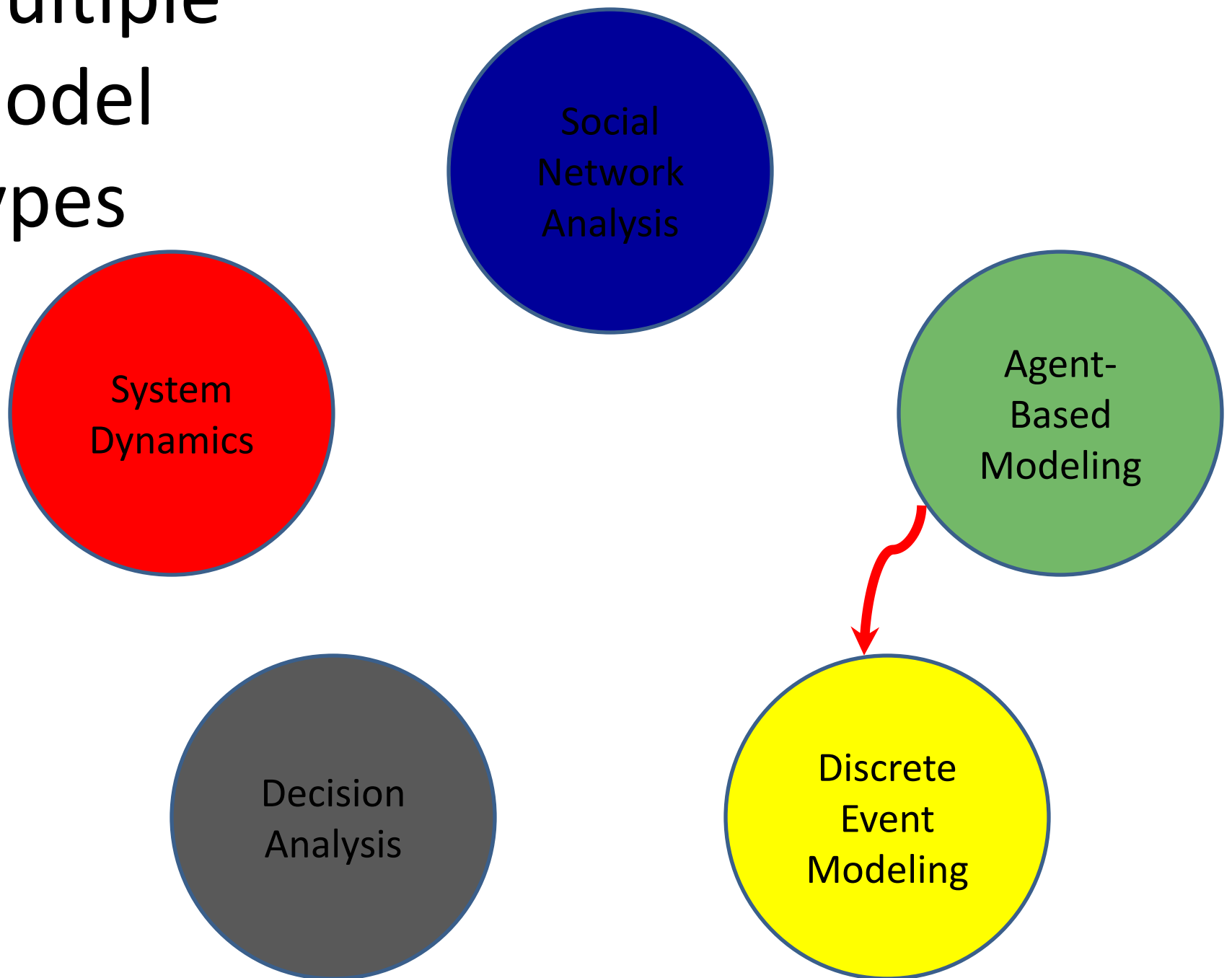
Virus Load[Person0001] : Test c=20

Virus Load[Person0002] : Test c=20

Virus Load[Person0003] : Test c=20

Virus Load[Person0004] : Test c=20

Multiple Model Types



Agent-Based Modeling in Support of DES

- Representing network of individuals in population outside of flow process
 - Prior to entry (development of conditions)
 - Following exit (e.g. trajectory dependent on quality of care)
 - Routing inflowing agents process based on agent's history of care
 - e.g. representing “catchment basin” of care facility

ABM & DES



Emergency Department

Jan 2, 2006 8:34:00 PM

Current interarrival time: 27.972

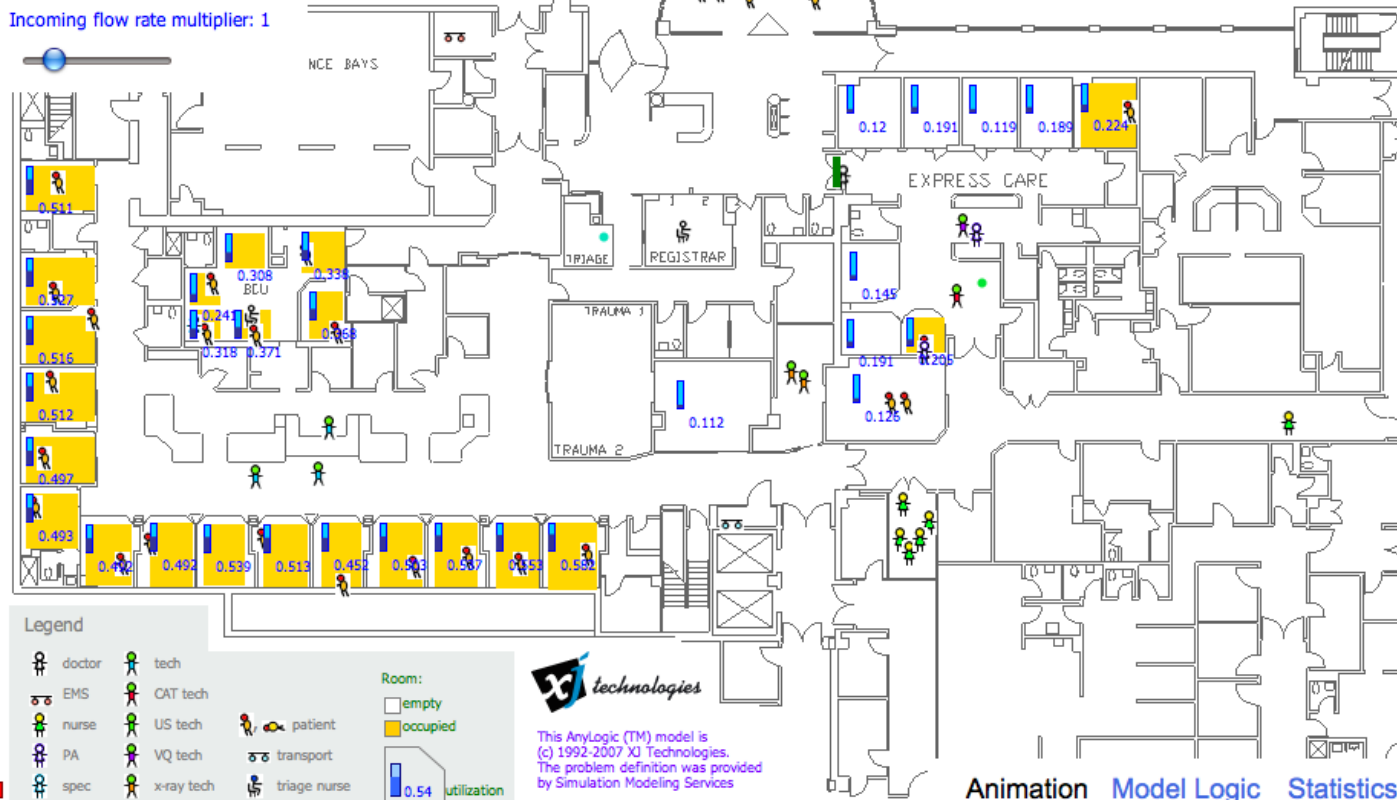
Incoming flow rate multiplier: 1

Percent of patients walked in: 86%

Avg queue size before registration: 0.069

EC start of operation: 11.0

EC end of operation: 23.0





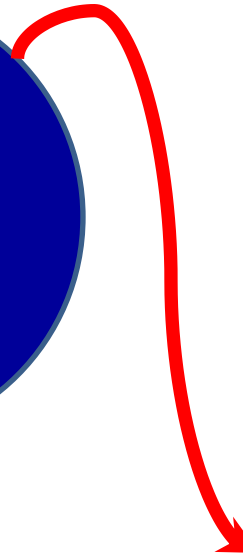
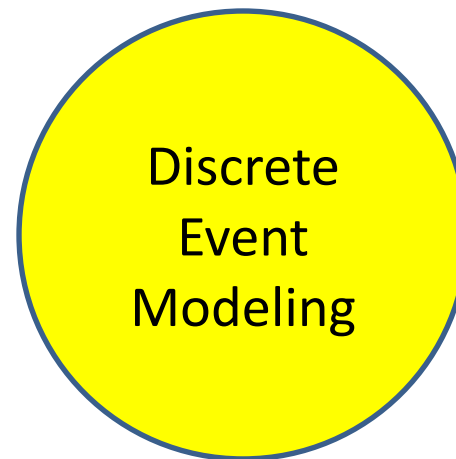
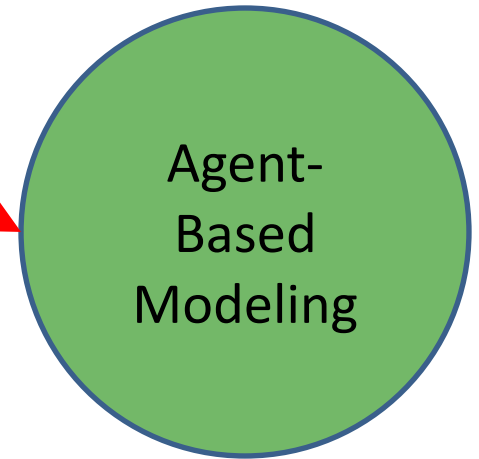
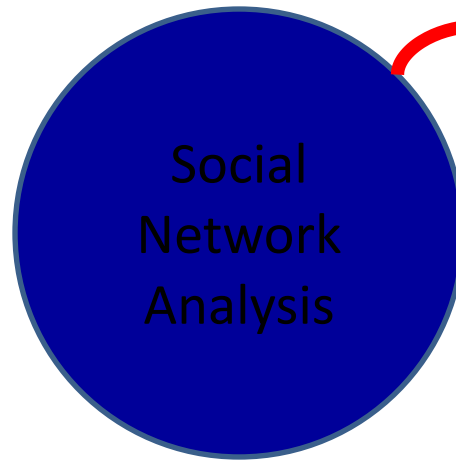
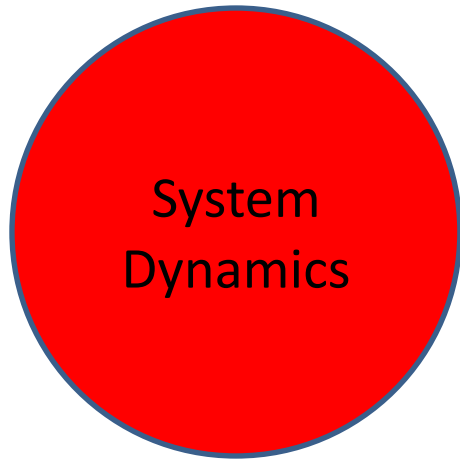
Hands on Model Use Ahead



Load Provided Model:

HybridABMNetworkModeling1

Multiple Model Types



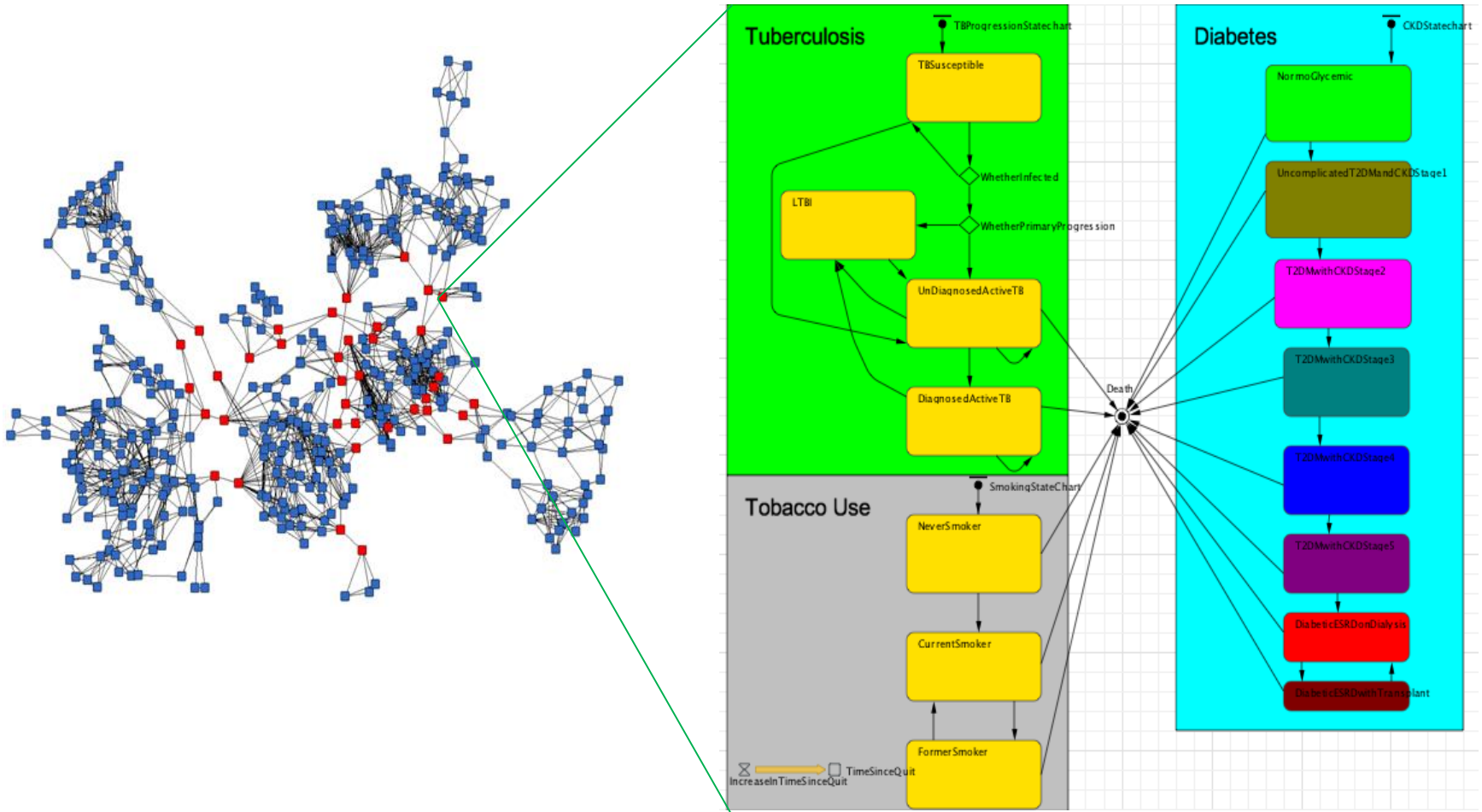
SNA Can Facilitate ABM

- Social network statistics that be used to formulate synthetic networks
- Identify patterns for calibration & investigation
- Cross-checks on ABM simulation findings
- Network visualization
- Highlighting diverse settings for contact

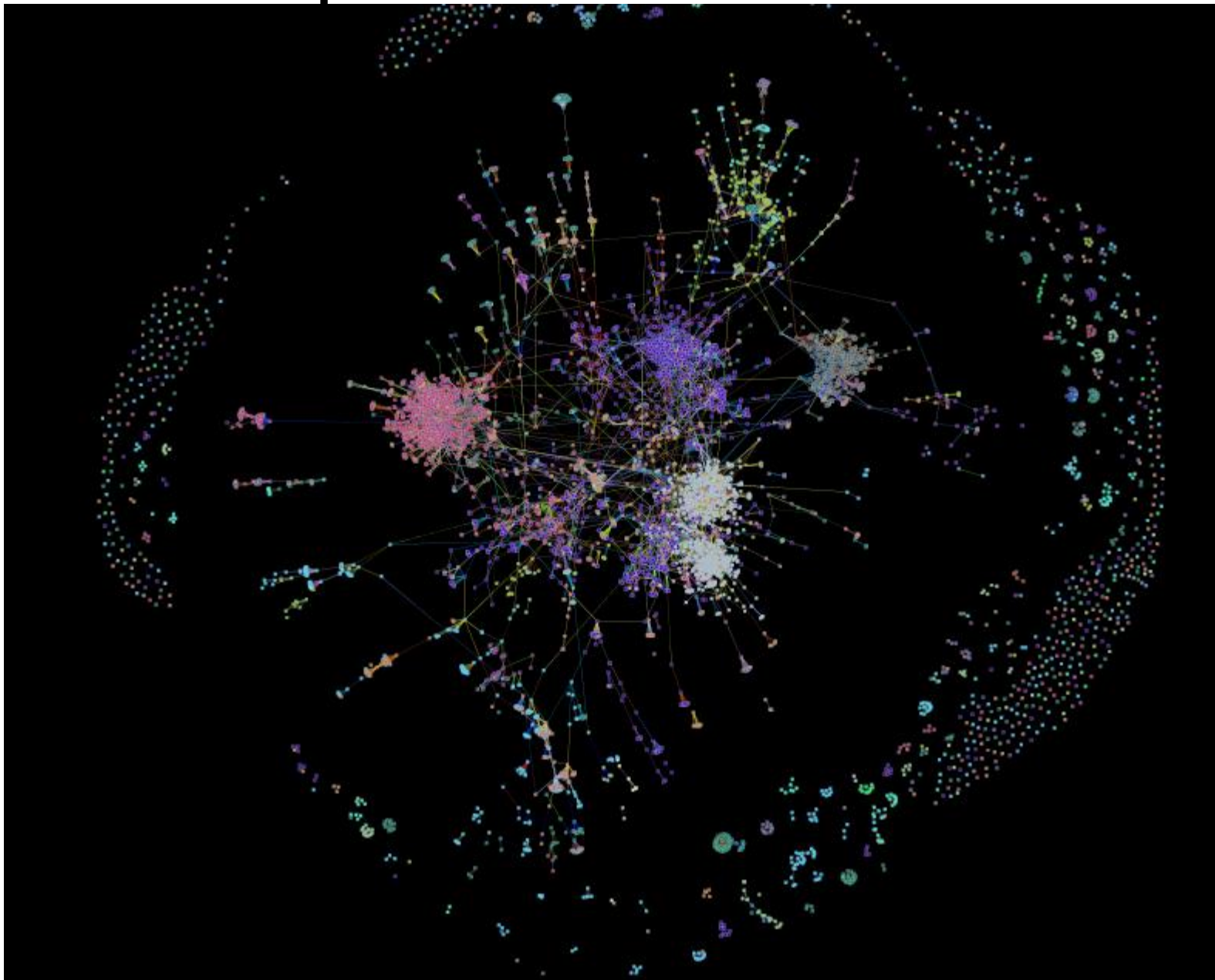
Challenges in Using Data from SNA in ABM

- SNA can provide an extremely valuable source of data to use for grounding ABM network structure
- It is relatively easy to get networks from software like Pajek into software like AnyLogic or Repast
- The bigger issue here is that we need to represent the hypothesized “true” spread of infection over the network
 - To do this, we need to represent the hypothesized underlying network that lies behind
 - Even the best of SNA data is highly incomplete (e.g. due to asymmetries in case-contact data, sampling in snowball sampling)

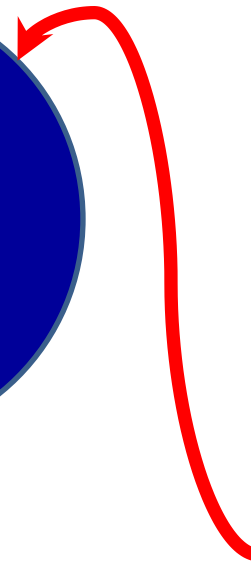
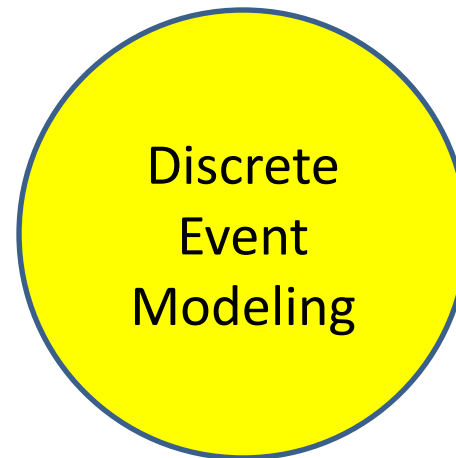
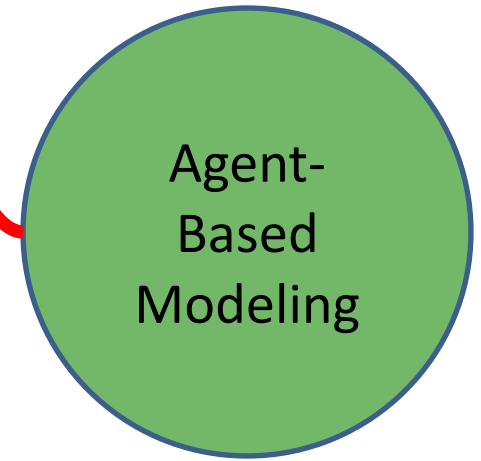
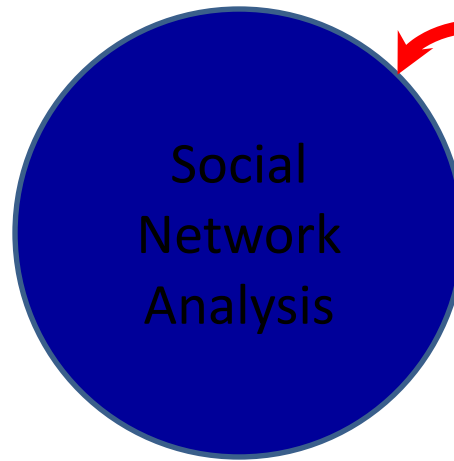
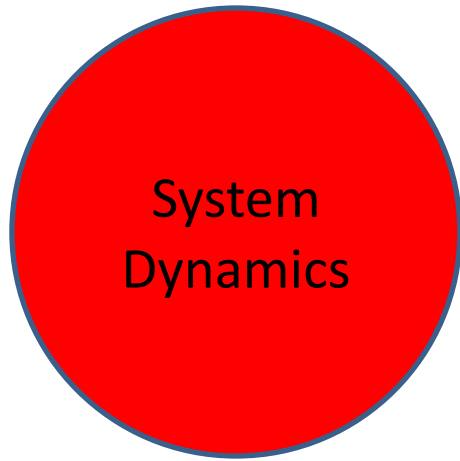
SNA Providing Context For ABM



Example Network Structure



Multiple Model Types



Agent-Based Modeling Facilitates SNA

- Exploring dynamic hypotheses to explain SNA patterns
- Formulating ideas for SNA metrics that could be
- highly effective (discriminatory) for identifying at-risk individuals
- Understanding dynamic implications of given network structure
- Understanding implications of changing network structure
- Evaluating SNA-informed interventions (e.g. SNA-metric prioritized contact tracing)
- Examining impact of additional collection of SNA

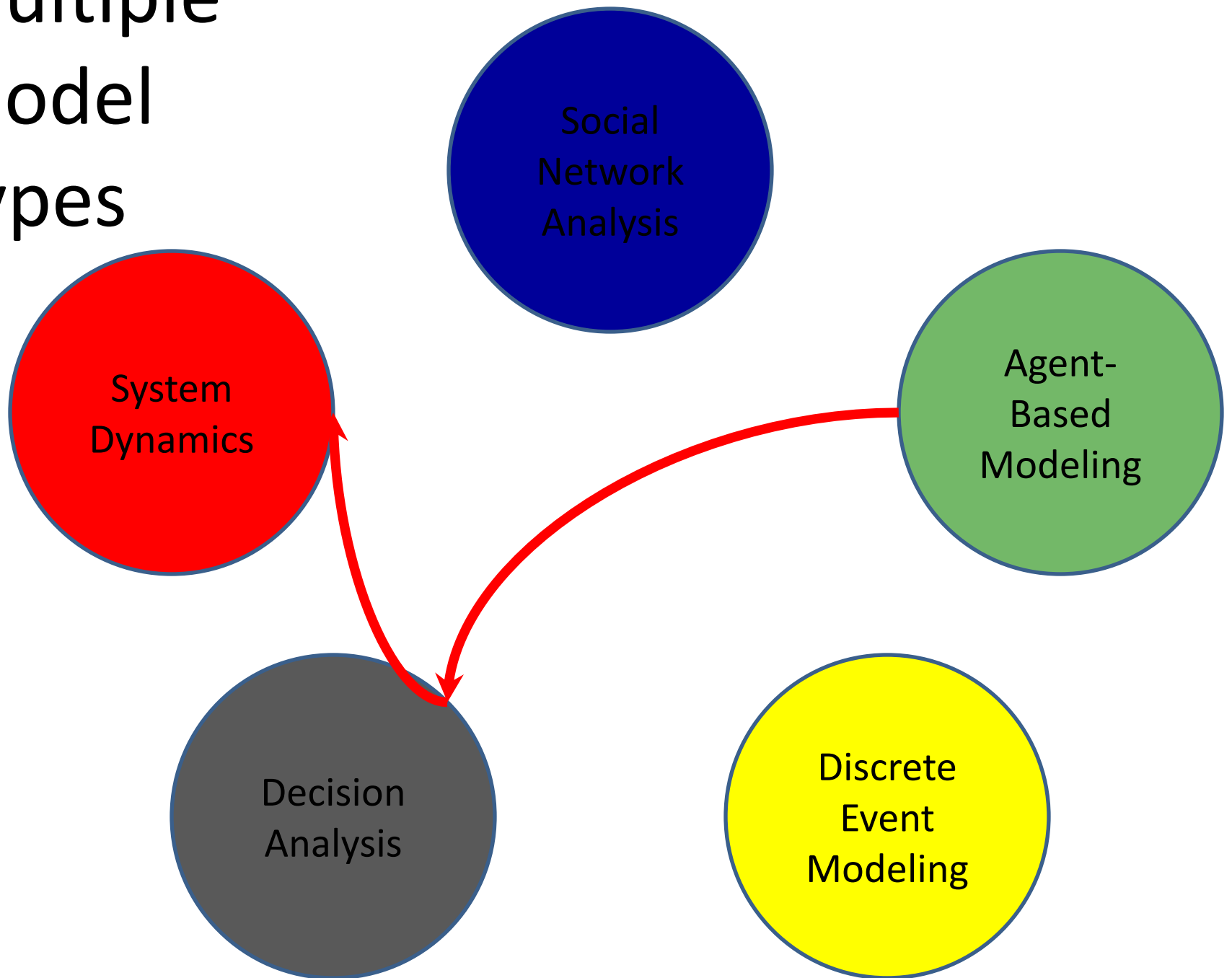
ABM To Explain Emergent Patterns Uncovered via SNA

| Network Degree | TB | | Mantoux Positive | | Mantoux Negative | | Total |
|----------------|-----|------|------------------|------|------------------|------|-------|
| | (N) | (%) | (N) | (%) | (N) | (%) | |
| All | 68 | 13.5 | 109 | 21.6 | 327 | 64.9 | 504 |
| 2 | 45 | 36.8 | 35 | 28.7 | 42 | 34.4 | 122 |
| 3 | 28 | 62.2 | 10 | 22.2 | 7 | 15.6 | 45 |
| 4 | 15 | 68.2 | 7 | 31.8 | 0 | 0 | 22 |
| 5 | 14 | 77.8 | 4 | 22.2 | 0 | 0 | 18 |
| 6 | 9 | 90 | 1 | 10 | 0 | 0 | 10 |
| 7 | 7 | 100 | 0 | 0 | 0 | 0 | 7 |
| 8 | 7 | 100 | 0 | 0 | 0 | 0 | 7 |

A.Al-Azem, Social Network Analysis in Tuberculosis

B.Control Among the Aboriginal Population of Manitoba2006

Multiple Model Types



Two Relevant Methodologies

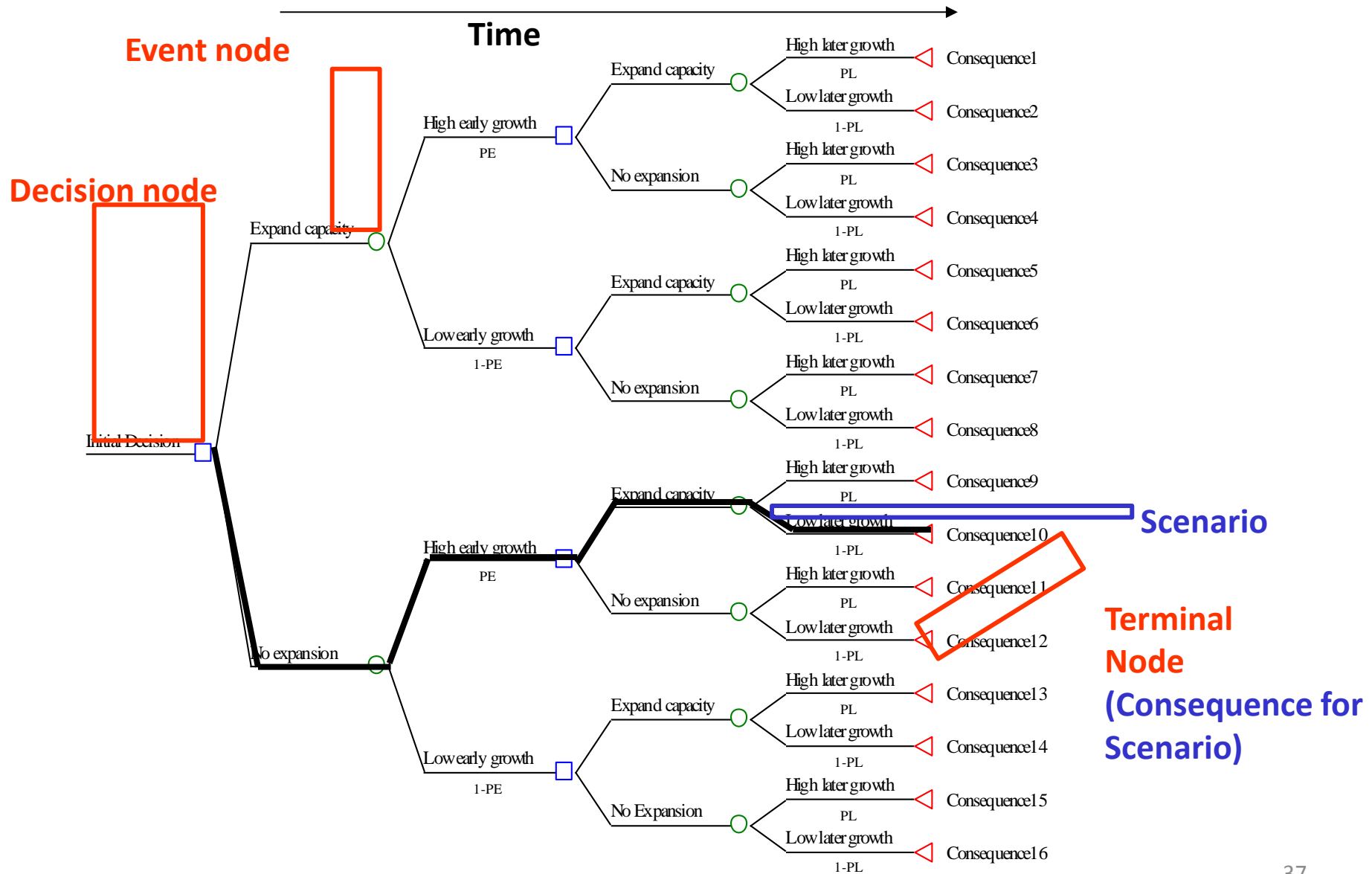
•Decision Analysis

- Good for decision problems under uncertainty w/known scenario consequences
 - No endogenous means of determining consequences
- Characterizes structured policy space
- Sophisticated statistical tools & Sensitivity analyses typical
- Identification of robust strategies via backwards induction
- Discrete
 - Events/decisions
 - Time

•Dynamic Modeling

- Good for representing complex system response to scenario (events and actions)
- Policy representation
 - Highly flexible
 - Less structured policy space
- Basic statistical tools
- Potentially continuous
 - Time
 - Events/decisions

Decision Tree To Structure Policy Space



Activity Analysis

- Offline sensitivity of likelihood impact on strategy selection
- Offline analysis (including Monte Carlo) of impact of likelihood change on risk profiles

Individual-Based Modeling in Vensim

Population Subscribing Tradeoffs

Advantages

- Conceptually simple
- Can SD tools
 - State trajectory file recording
 - Easy construction, structure visualization
 - No programming
 - Sensitivity analysis
 - Easy to aggregate

Disadvantages

- Difficult to visualize network structure & spread or spatial embedding
- Awkward to realize changing population size