Simulation Modeling: Why & What

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Using Modeling to Prepare for Changing Healthcare Needs

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Example Areas Where Challenging to Make Effective Decisions

- **Computer systems operation**
- **Corporate strategy (e.g. project launching)**
- **Corporate operations (e.g. ordering policy, based on inventory & past orders)**
- **Municipal planning**
- **Managing an industrial or power plant**
- **Road network planning**
- **Project management**
- **Health care policy**
- **Health care operations**

A Common Theme: **The Behavior of the Whole is Greater than the Sum of its Parts**
Making decision based on narrow understanding can lead to “blowback”

Emergence

- **Interaction of very simple components can lead to surprising “emergent” dynamic patterns in the behaviour of a given component over time**
- **The patterns that are seen are quite different than what would be expected through any single component of the system**
- **These often relate to variables in the underlying system in complex ways $\Rightarrow$ It is frequently non-obvious how change in one area “ripples through” to changes in other areas**

Strengths & Weaknesses of Reductionist Approaches

- **Traditional scientific approaches have pursued a primarily reductionist strategy**
- **This strategy has offered profound insights into how mechanisms work in isolation, but limited understanding how the connections between mechanisms combine to yield overall behaviour**
- **Much observed behaviour is emergent – results from the collective interaction of a set of components, rather than any component in isolation**

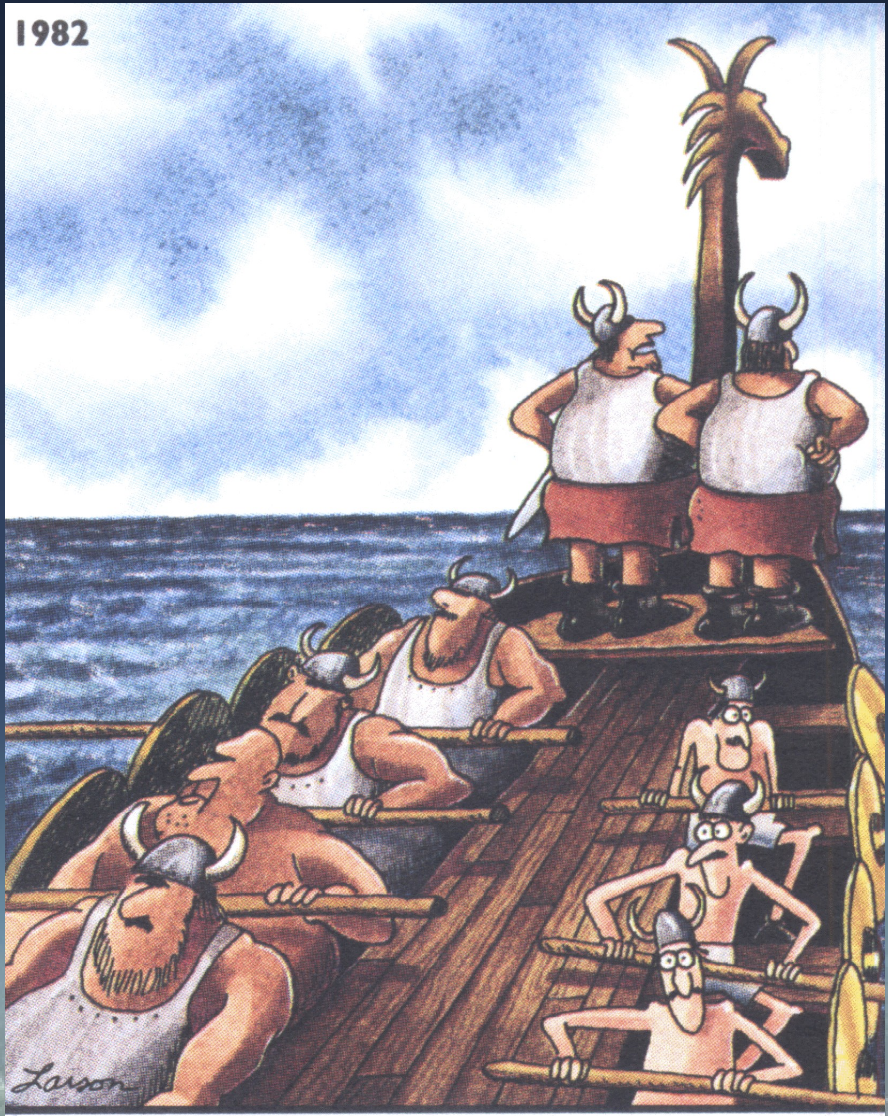
For Example…

- We understand in detail how a server, router, or network connection works, but adding one may drastically alter the performance of the system in unanticipated ways
- Profound understanding of physiology & immune function confers little understanding of how disease spreads
- We understand well the travel of cars on a single road, but we don’t understand how it will change traffic in the overall road network
- We know placing an order works, but are unclear how it will affect inventories & reordering elsewhere
- Identifying the genes offers limited understanding without knowledge of how they “work together”

Complex Systems Challenges

- **Counter-intuitive behavior**
- **Misperceptions**
- **Policy resistance**
- **Disproportionate impact**
- **These phenomena pose problems for**
  - *Learning from experience: Painful & slow*
  - *Coordinating: Actors in 1 area of the system often have poor sense as to how actions of actors in other areas of the system affect them $\Rightarrow$ risk of working at cross purposes*
  - *Deciding: Unclear tradeoffs between choices*
  - *Designing: Not clear how to best structure the roles/responsibilities of the actors, reporting,etc*

A Systems Problem



"I've got it, too, Omar … a strange feeling like we've just been going in circles."

Larson, The Far Side 1982

Examples of Systems Effects

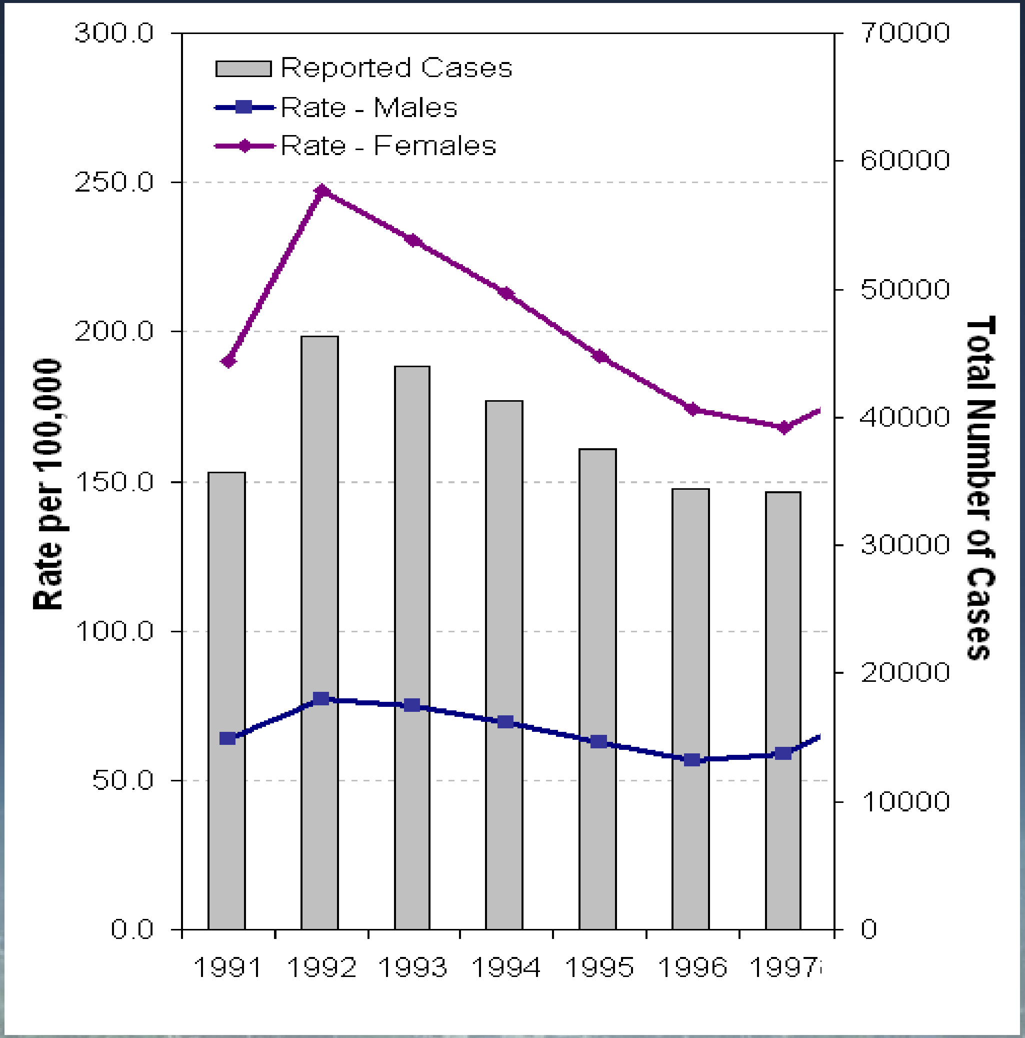
- **Brooks Law: Adding people to a late software project makes it later**
- **Metcalf's Law: The value conferred by a network goes up with the square of the number of nodes**
- **Building a new road worsens congestion**
- **Vaccinating just one more person drives a circulating infection out of population**
- **A "vicious cycle" involving trust leads to a project – or relationship – breakdown**
- **Arms races**
- **Commercial competition (e.g. laying fiber)**

Policy Resistance: Health

- *Development of pathogen drug resistance*
- *Cutting cigarette tar levels reduces cessation*
- *Cutting cigarette nicotine levels leads to compensatory smoking*
- *Targeted anti-tobacco interventions lead to equally targeted coupon programs by tobacco industry*
- *Charging for supplies for diabetics leads to higher overall costs by increases costs due to reduced self-management, faster disease progression*
- *ARVs prolong lives of HIV carriers, but lead to resurgent HIV epidemic due to lower risk perception*
- *Attempts to economize by understaffing STI clinics leads to long treatment wait, greater risk of transmission by infectives & bigger epidemics*
- *Antibiotic overuse worsens pathogen resistance*
- *Antilock breaks lead to more risky driving*
- *Natural feedback: Intergenerational "Vicious Cycles"*
- *Hygeine Hypothesis: Germ-free environments leads to greater vulnerability to allergies (also: later infections)*

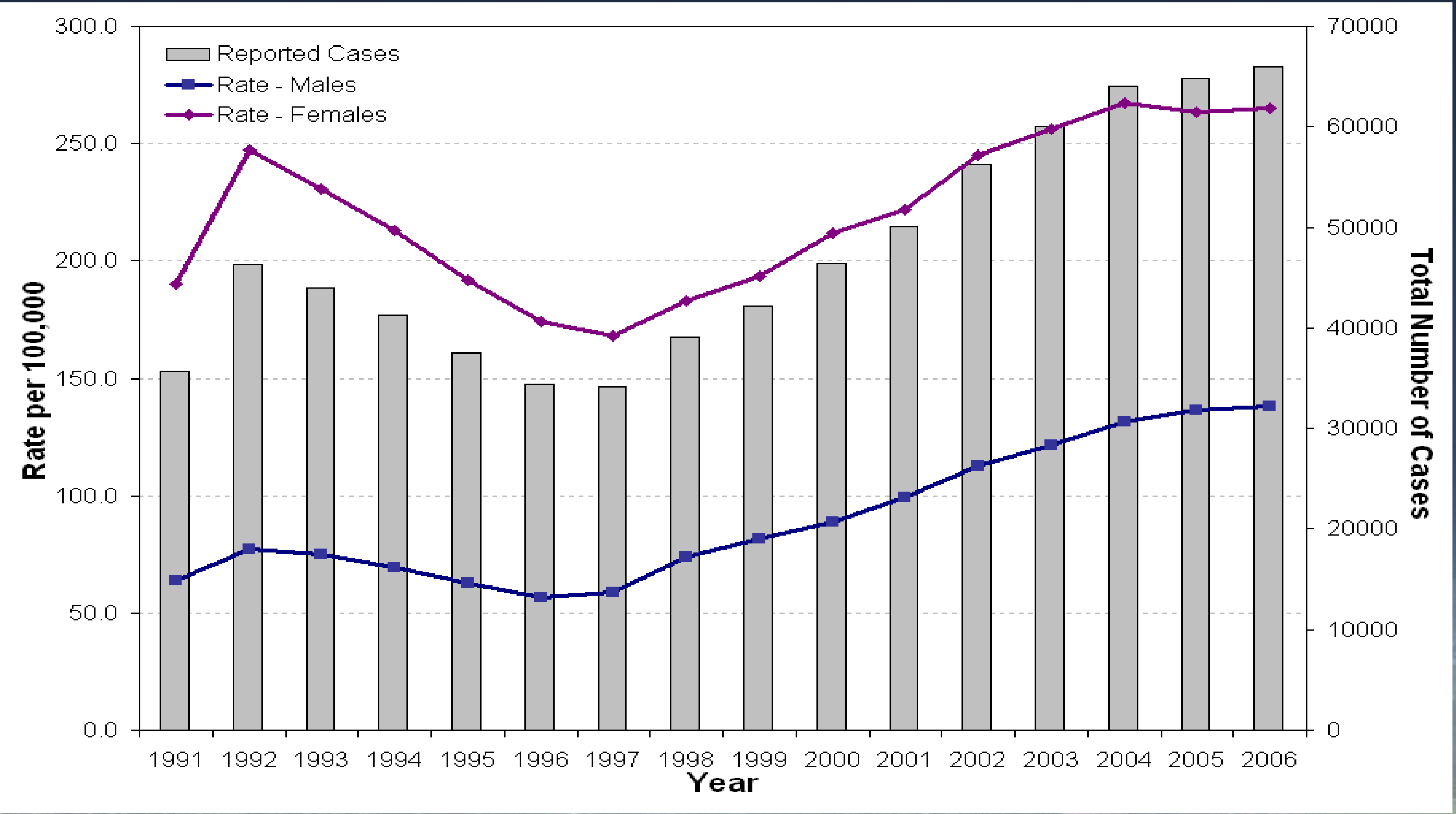
Extended Example:
Health Challenges

Choices as Seeking to "Redirect the Course of Change"



- **Adapted from Tom Wong, 2007**
- Data for 2005 and 2006 are preliminary and are anticipated to change
- Source: Surveillance and Epidemiology Unit, Community Acquired Infections Division, PHAC

Public Health as “Redirecting the Course of Change”



- **Tom Wong, 2007**
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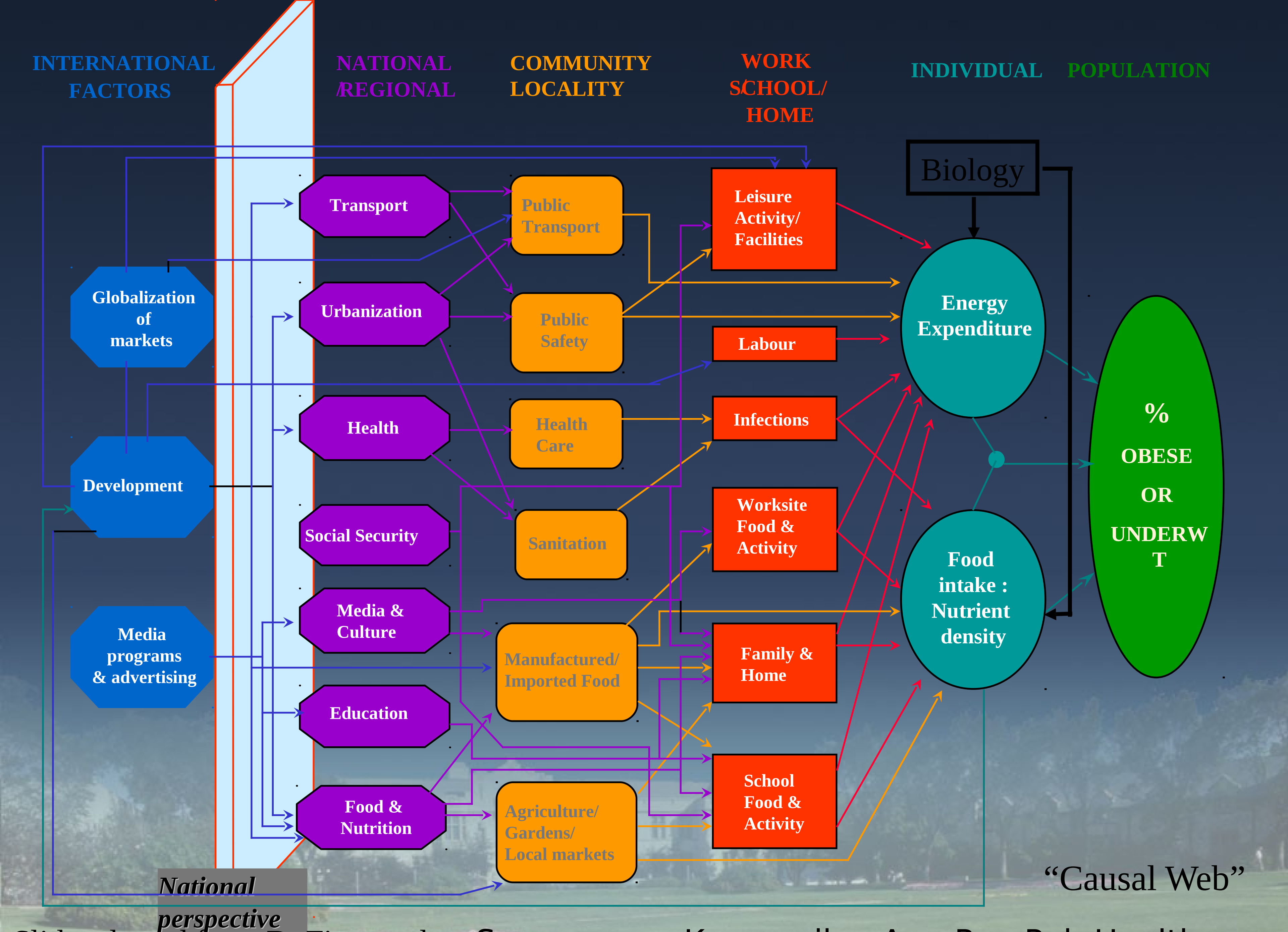
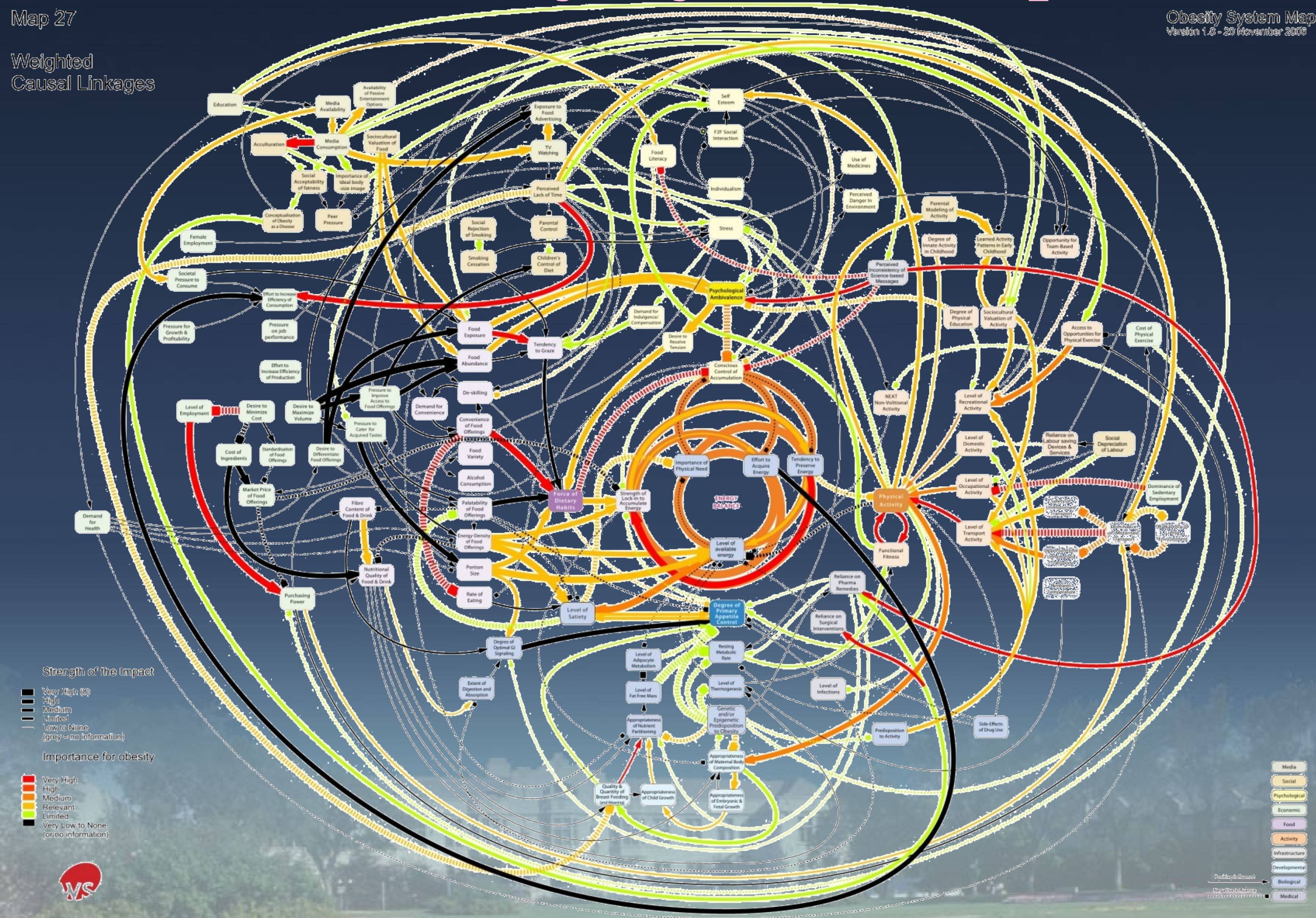
Making Effective Choices Often Requires Grappling with Great Complexity

- **Structural Complexity**
- **Dynamic Complexity**



Slide adapted from D. Finegood Source: see Kumanyika Ann Rev Pub Health

Obesity System Map



http://kim.foresight.gov.uk/Obesity/Obesity.html

Slide adapted from D. Finegood

Dynamic Complexity:
Exponential Growth & Decay

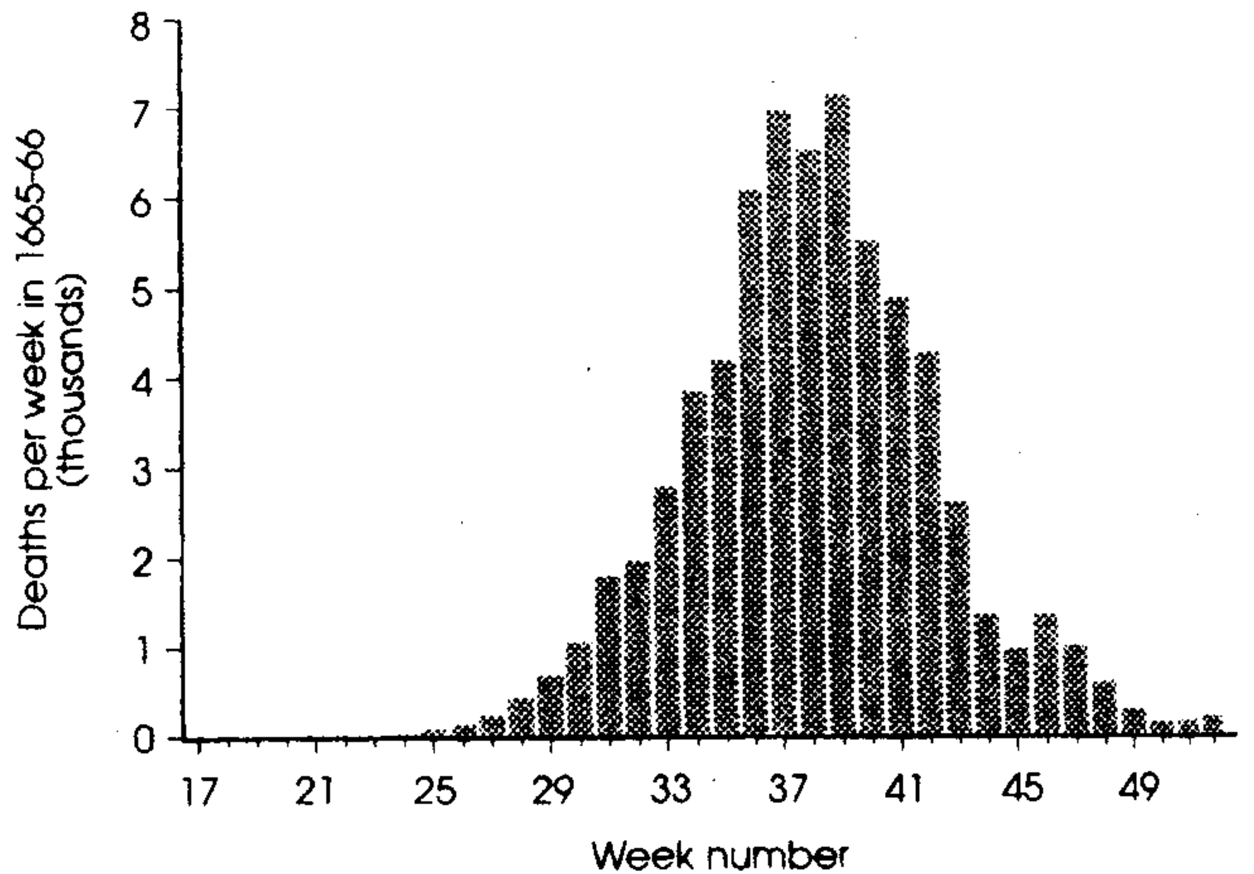
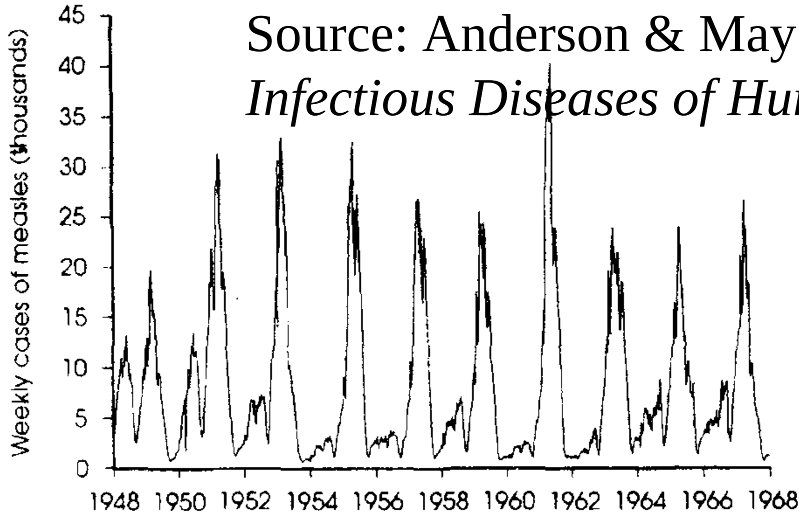


Fig. 3.11. Recorded deaths from the bubonic plague in London during the year (data from Brayley 1722).

Anderson & May
Infectious Diseases of Humans

Dynamic Complexity: Oscillations (Damped & Otherwise)

Source: Anderson & May
Infectious Diseases of Humans



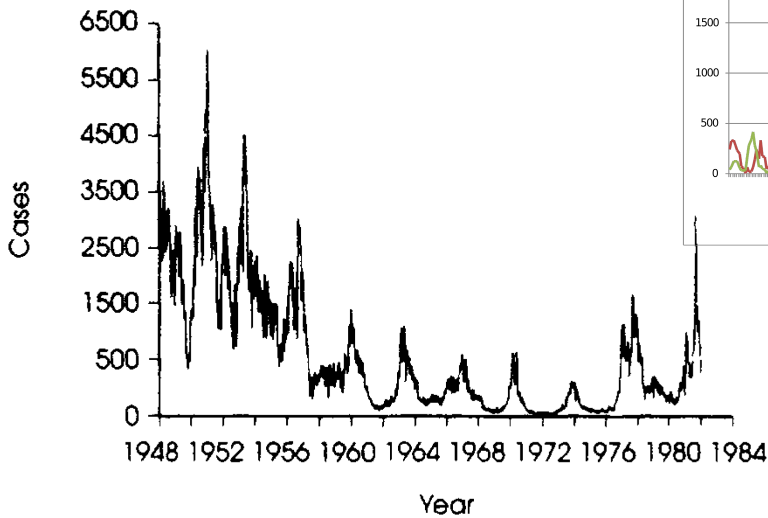
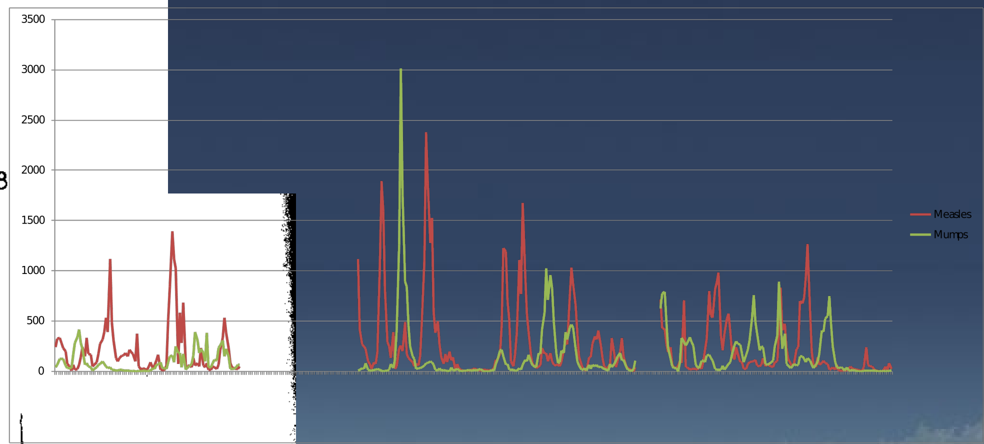


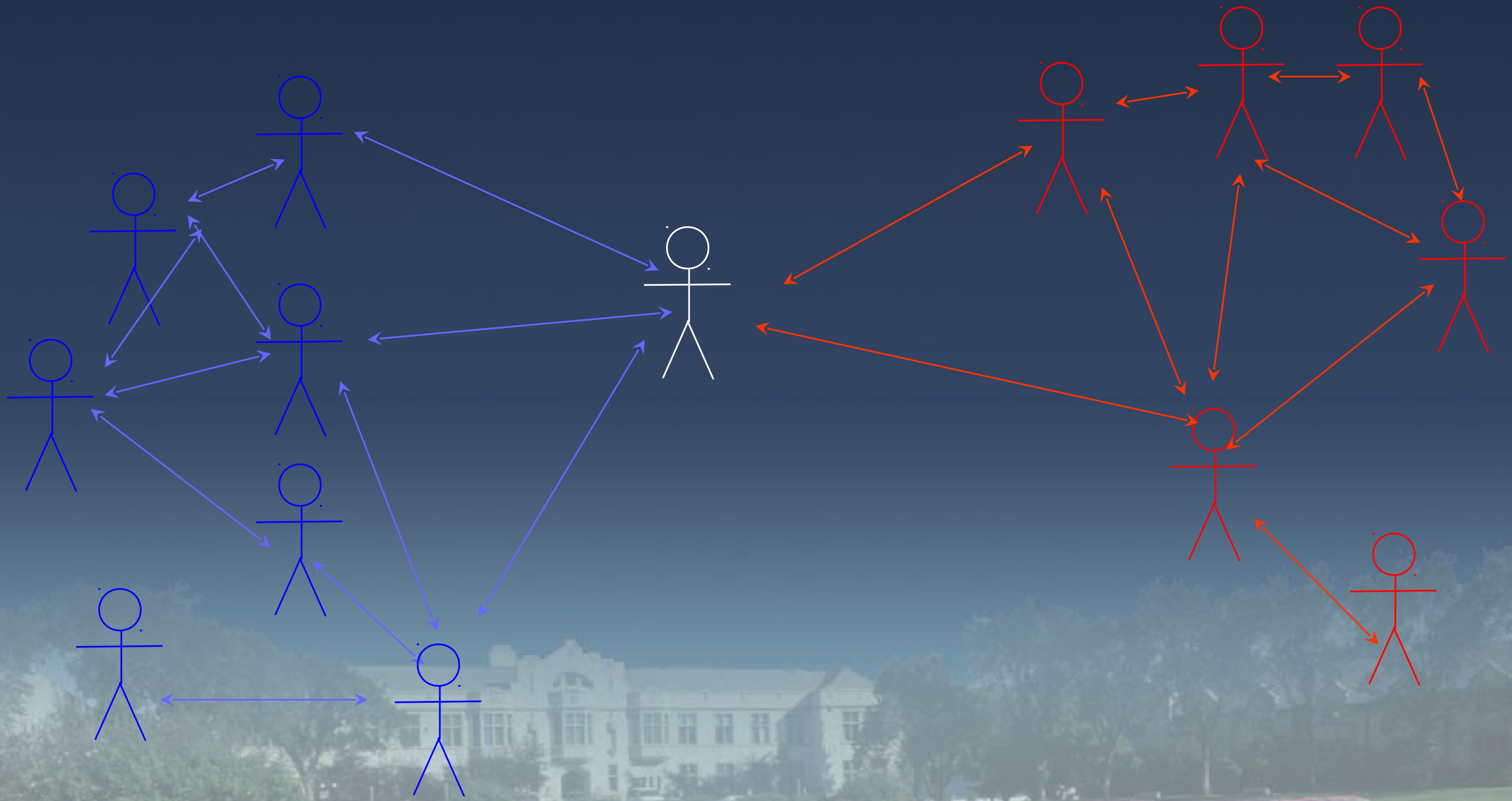
Fig. 6.8. Weekly case notifications of pertussis (whooping cough) in England and Wales for the time period 1948–82. Mass vaccination was introduced in 1956.



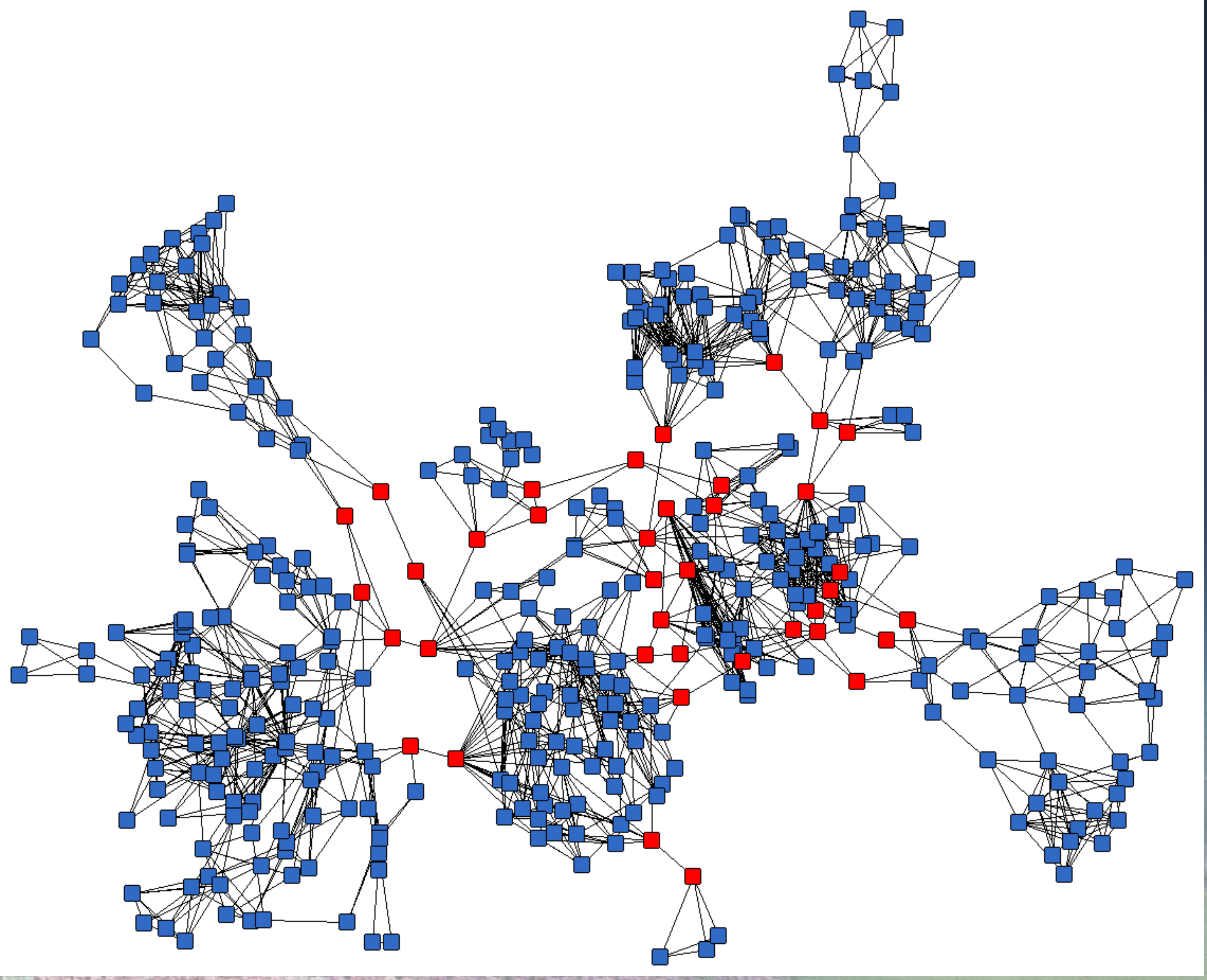
Dynamic Complexity: Tipping Points

- **Sufficiently fast delivery of treatment or high enough vaccination rates can prevent an infection from being able to establish itself**
- **While the components of the system are the same (most individuals remain susceptible), the population as a whole is protected**
  - *This "herd immunity" is a feature of the system as a whole, not of its individual pieces*

Heterogeneity in Position and Importance of Bridging Individuals

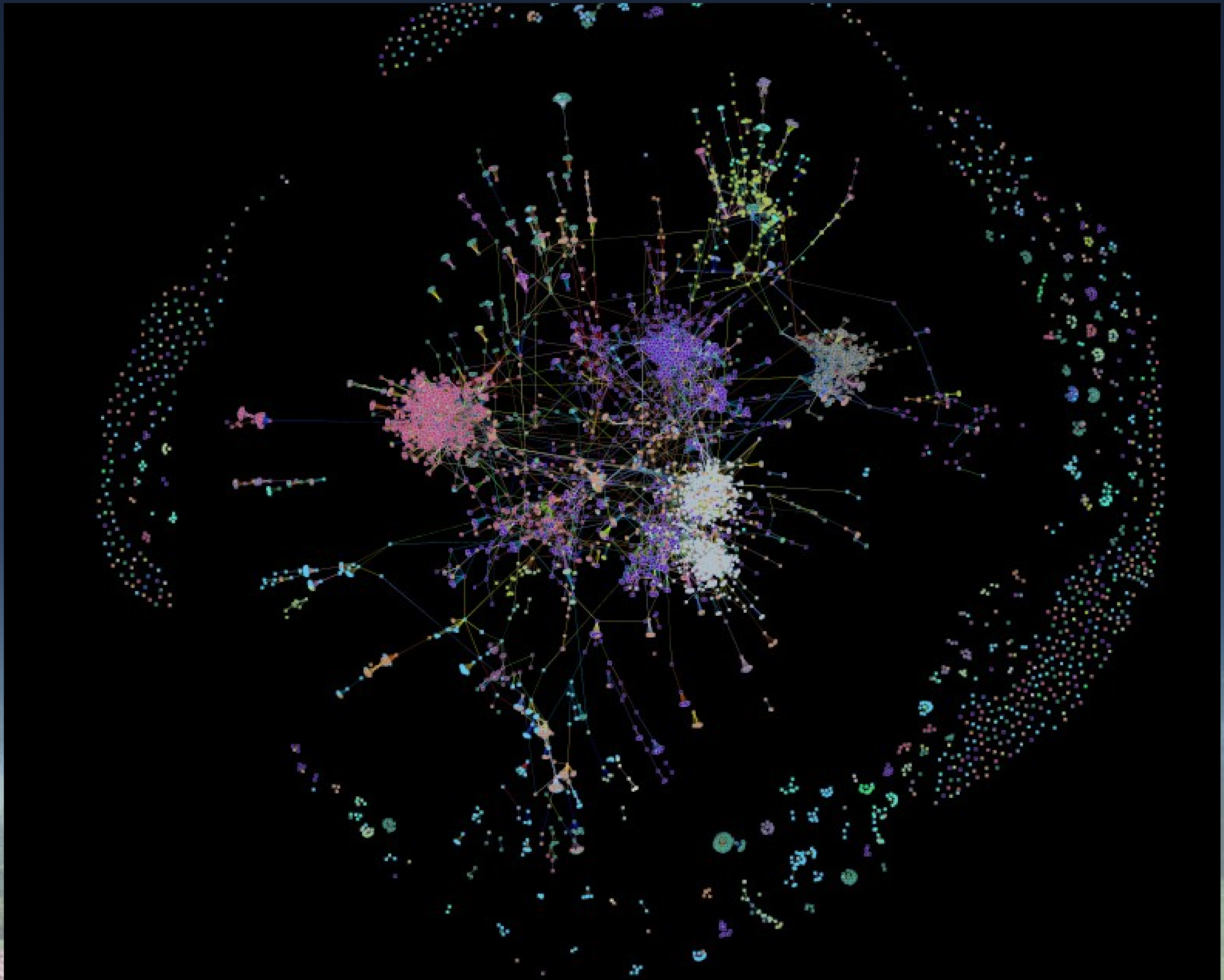


Identifying Bridging Individuals

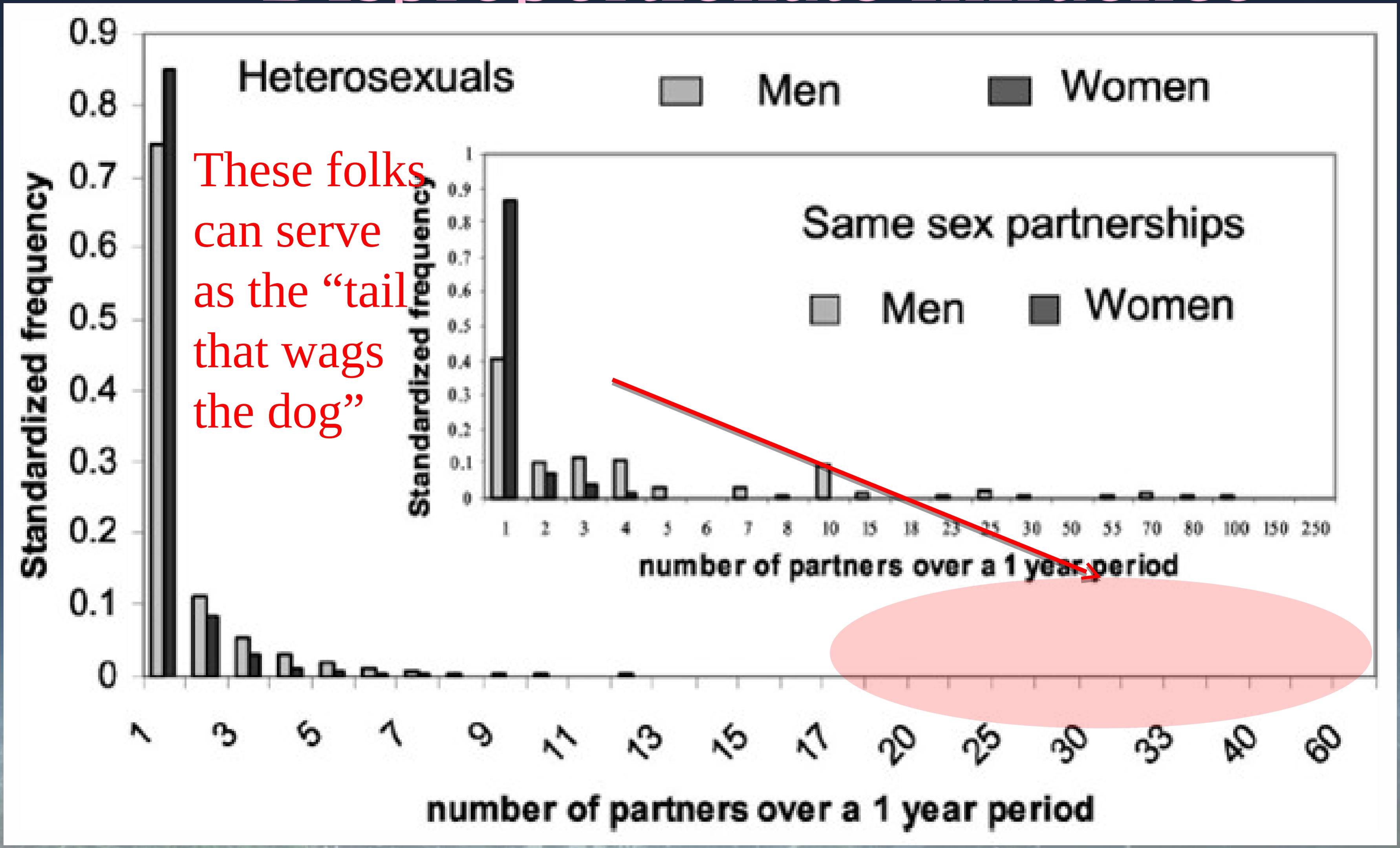


- Preliminary case contact network
- Restricted to nodes of degree 2+
- Data analysis & image: A. Al-Azem

TB Network Substructure

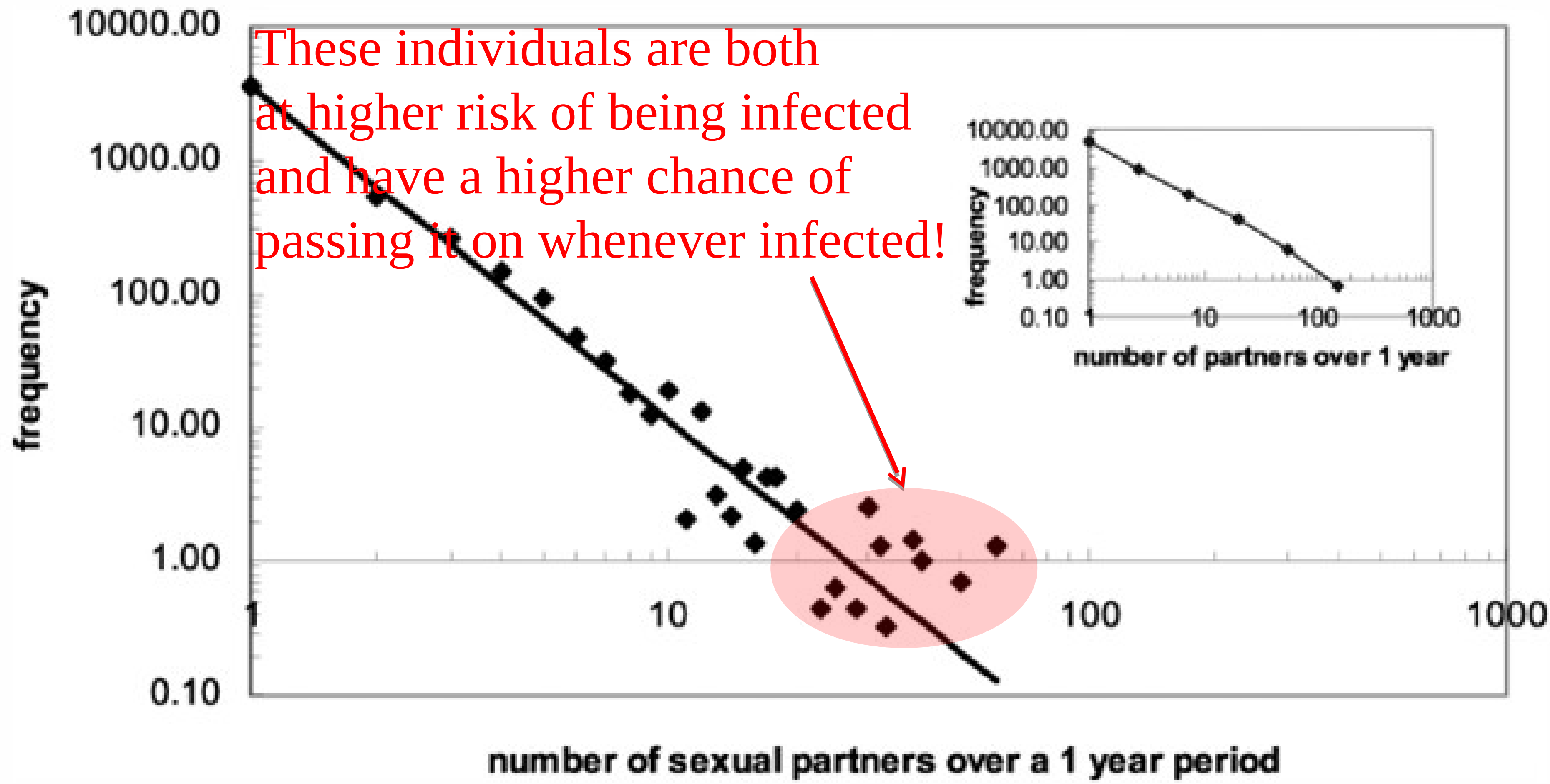


Heterogeneity can Yield Disproportionate Influence



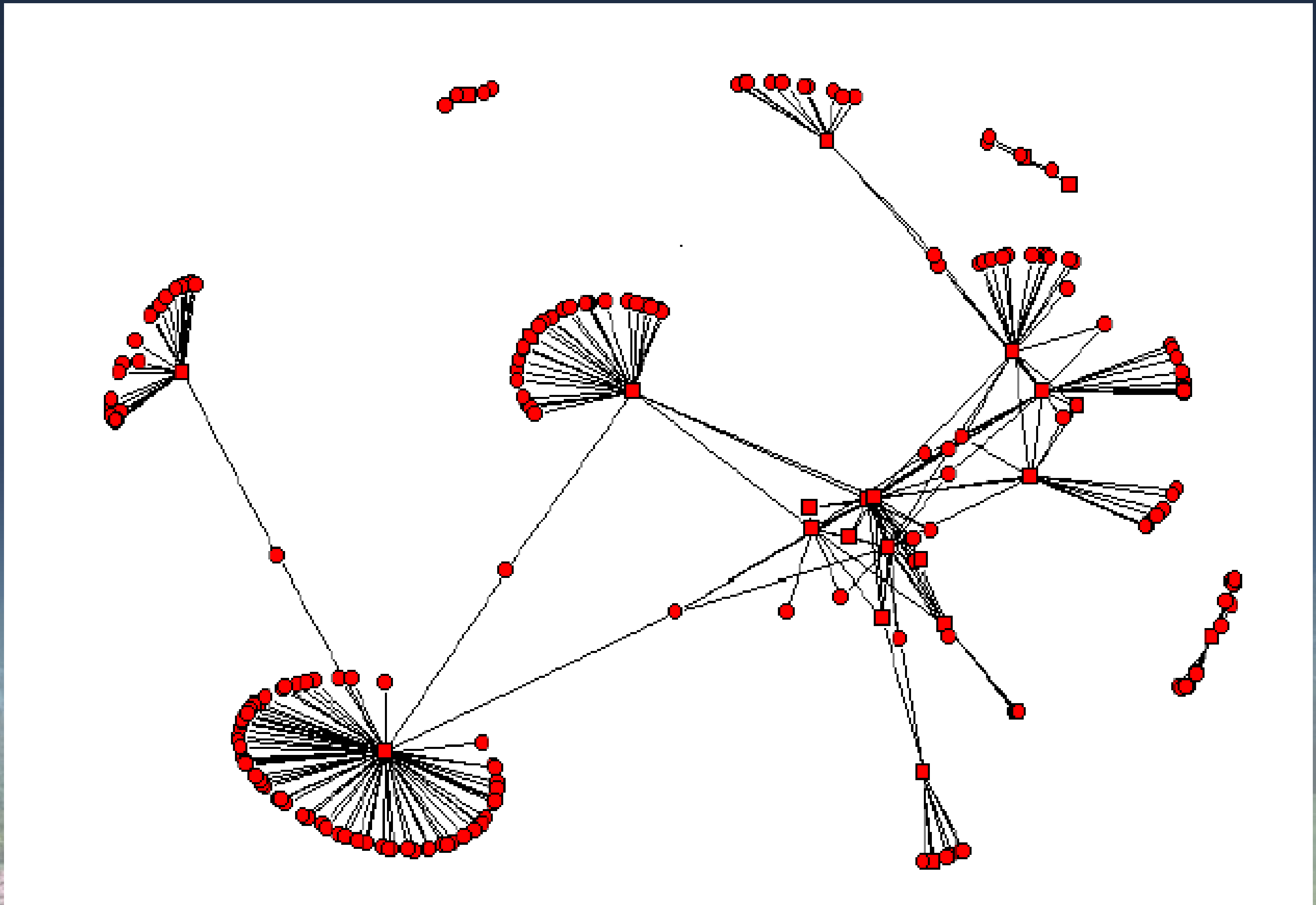
Schneeberger et al., Scale-Free Networks and Sexually Transmitted Diseases: A Description of Observed Patterns of Sexual Contacts in Britain and Zimbabwe , Sexually Transmitted Diseases, June 2004, Volume 31, Issue 6, pp 380-387

Associated Log-Log Graph

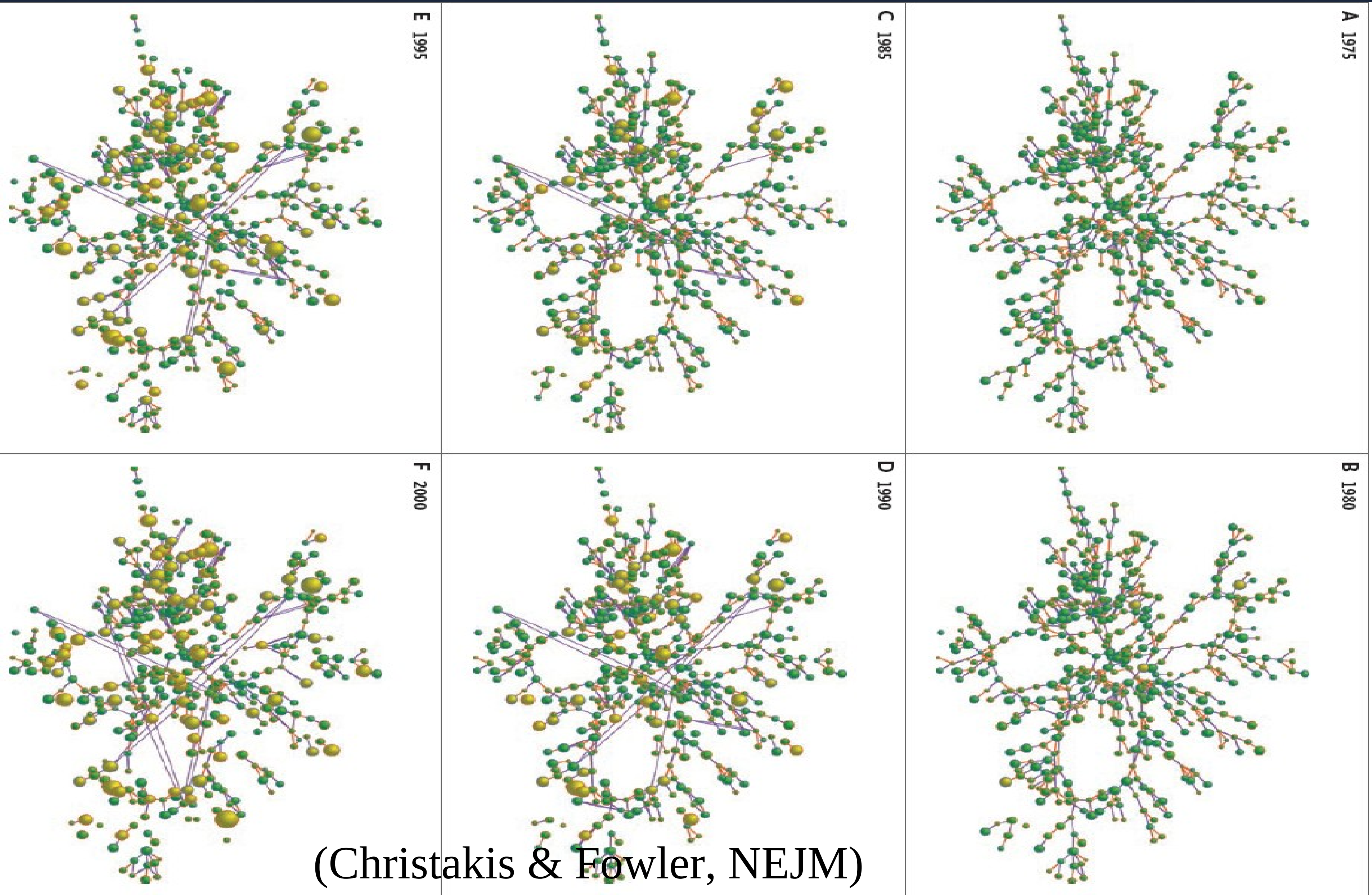


Schneeberger et al., Scale-Free Networks and Sexually Transmitted Diseases:
A Description of Observed Patterns of Sexual Contacts in Britain and Zimbabwe
, Sexually Transmitted Diseases, June 2004, Volume 31, Issue 6, pp 380-387

Persistence of Endemic Infection in Network "Cores"

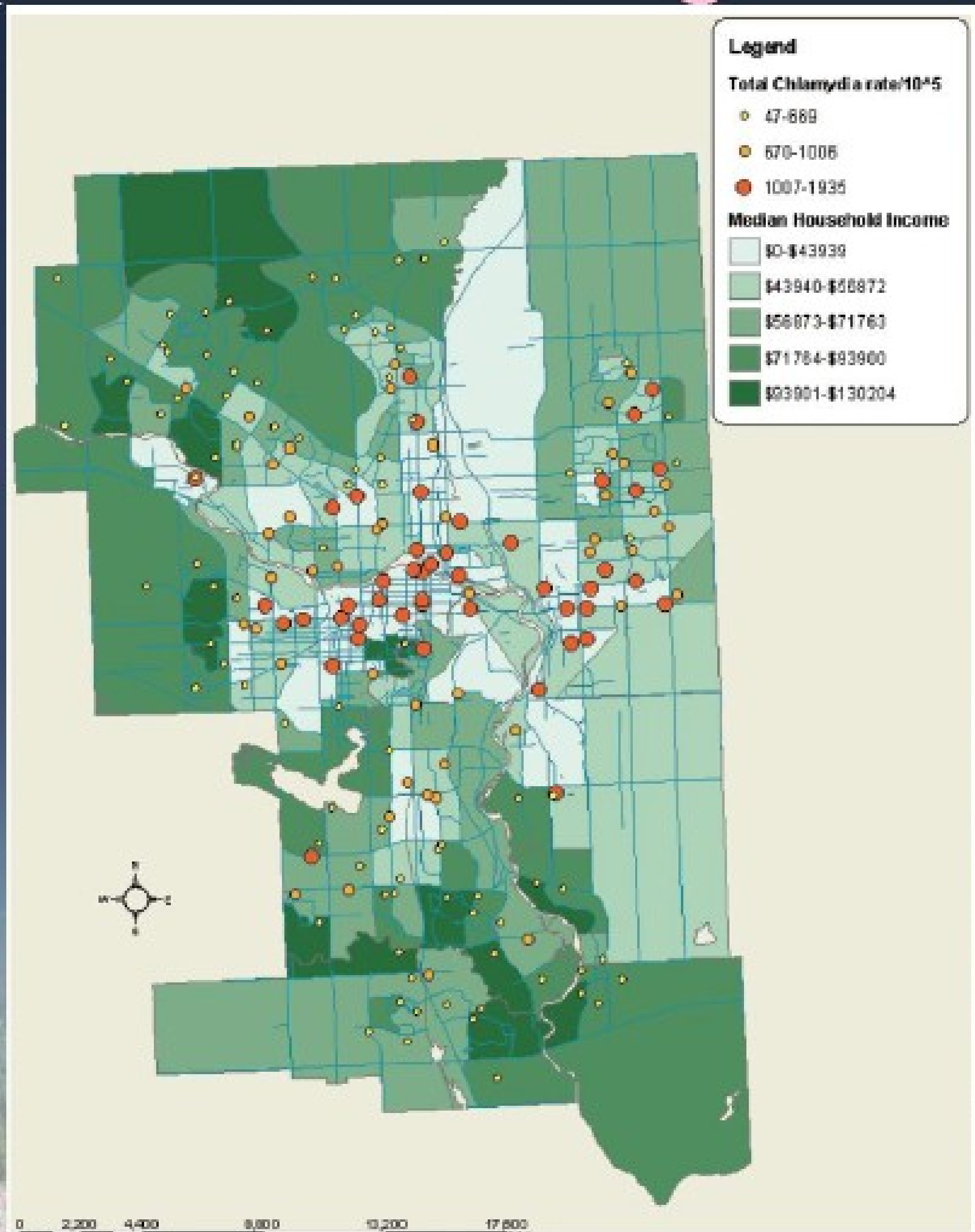


Network Spread of Obesity



(Christakis & Fowler, NEJM)

Spatial Patterning: Chlamydia

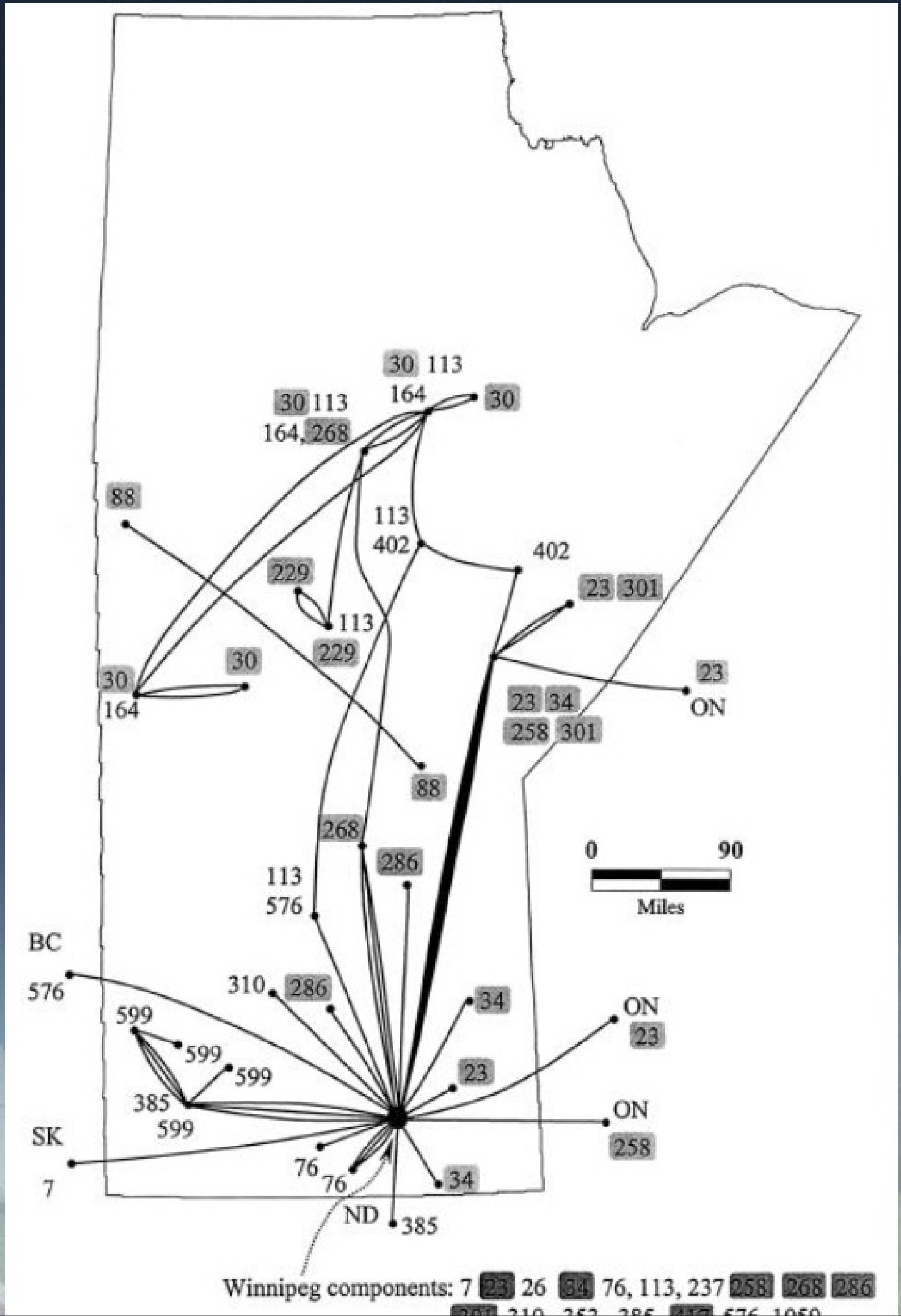


Sexually Transmitted Diseases, March 2008, Vol. 35, No. 3, p.291–297

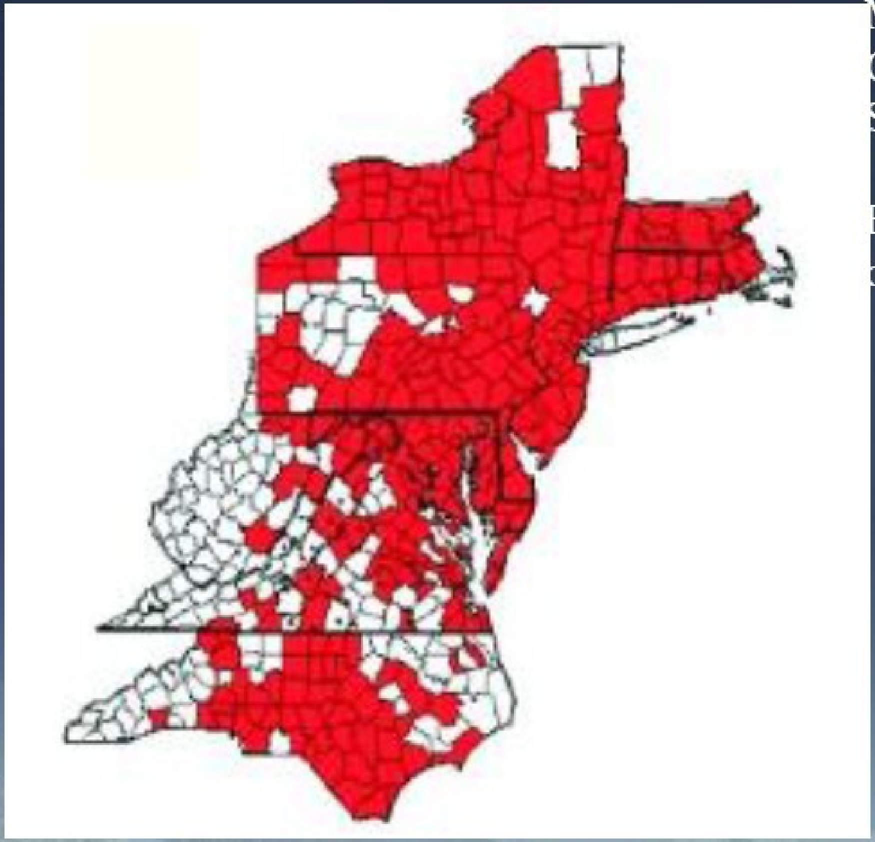
DOI: 10.1097/OLQ.0b013e31815c1edb

Chlamydia & Gonorrhea in Manitoba

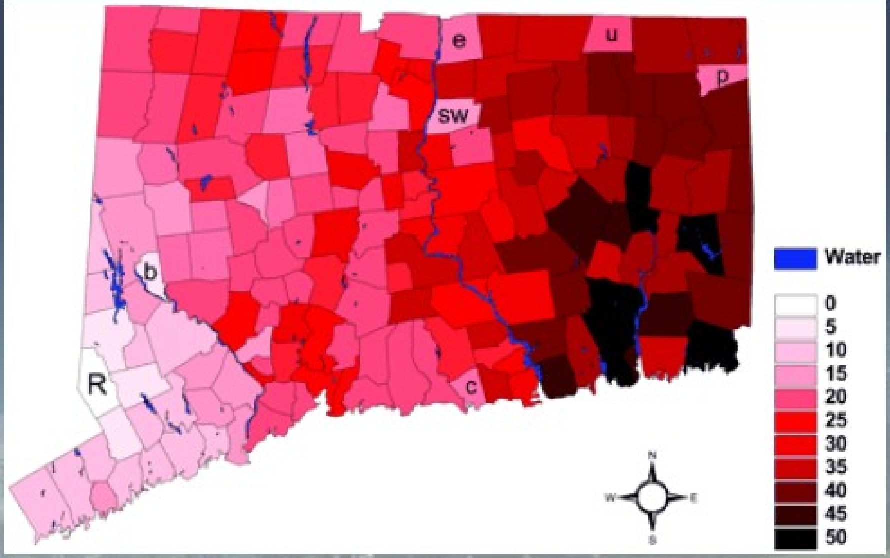
Wylie, J.L, Jolly, A. Patterns of Chlamydia and Gonorrhea Infection in Sexual
Networks in Manitoba, Canada Sex Transm Dis. 2001 Jan;28(1):14-24.



Spatial Spread (Rabies)



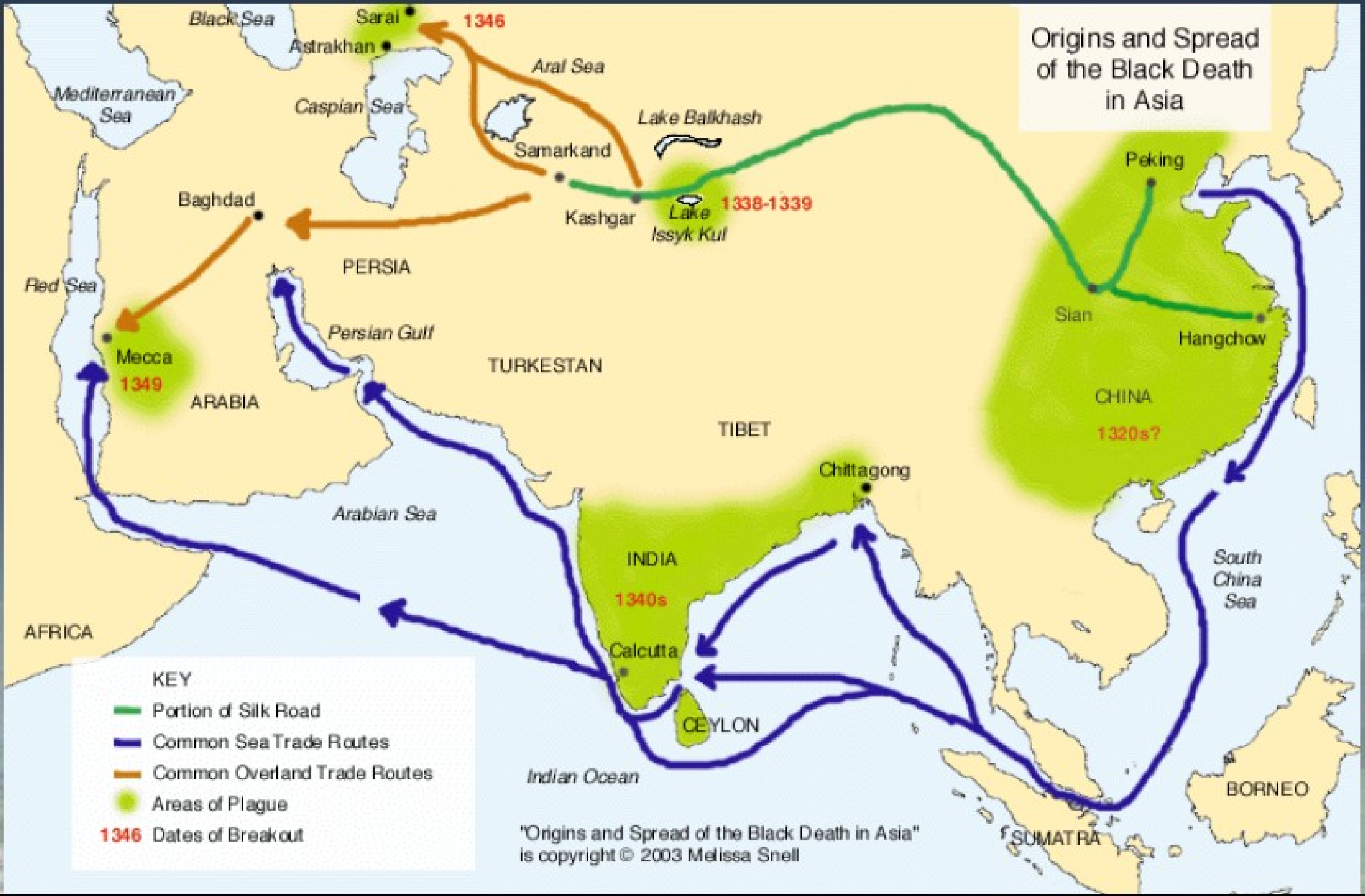
Marta A. Guerra,* Aaron T. Curns,* Charles E. Rupprecht,* Cathleen A. Hanlon,* John W. Krebs,* and James E. Childs*
Skunk and Raccoon Rabies in the Eastern United States: Temporal and Spatial Analysis.
Emerg Infect Dis. 2003 September; 9(9): 1143–1150.
doi: 10.3201/eid0909.020608



David L. Smith*†, Brendan Lucey‡, Lance A. Waller §, James E. Childs¶, and Leslie A. Real‡
Predicting the spatial dynamics of rabies epidemics on heterogeneous landscapes. PNAS March 19, 2002 vol. 99 no. 6 3668-3672

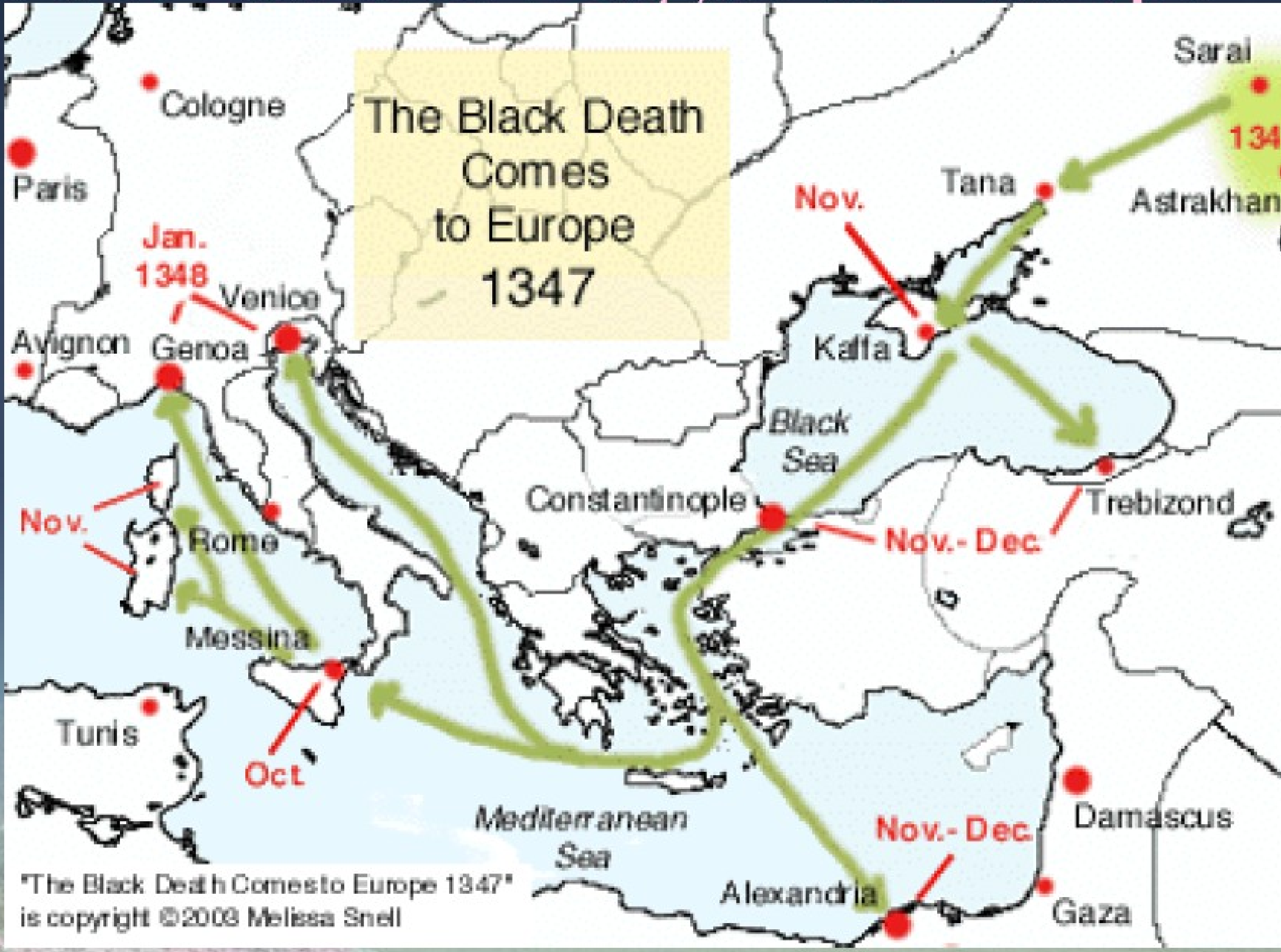
Transmission of Bubonic Plague in Asia

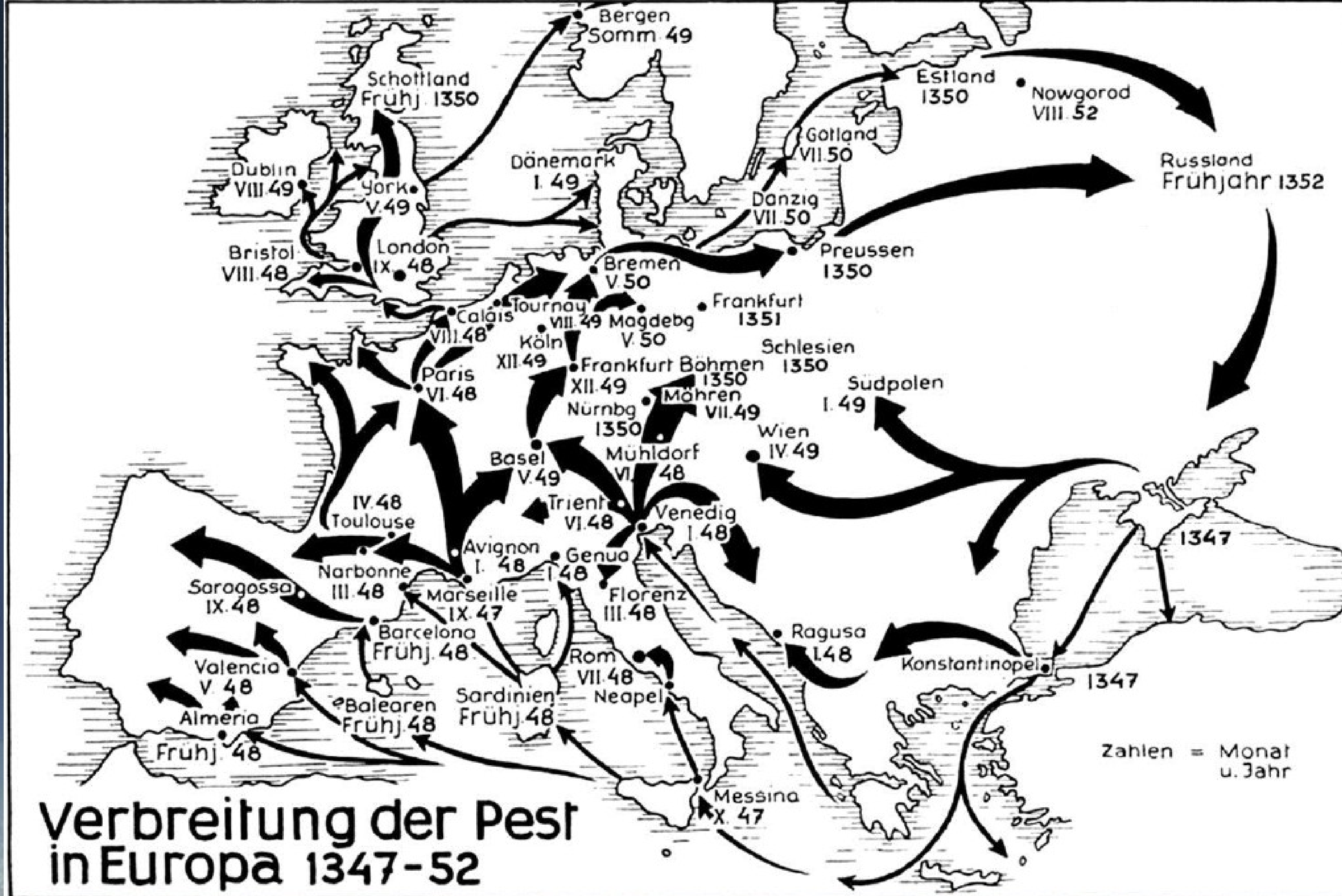
Snell, M. Origins of Plague. Possible sites of plague origin in 14th-century Asia. About.com, Medieval History. Accessed Feb 6, 2012.



Arrival of Bubonic Plague in Europe

Snell, M. The Black Death Comes to Europe, 1347: The arrival of the disease in eastern Europe and Italy. About.com, Medieval History. Accessed Feb 6, 2012.





Buchholz's 1956 map. From Ernst Kirsten, Ernst Wolfgang Buchholz and Wolfgang Köllmann, Raum und Bevölkerung in der Weltgeschichte: Bevölkerungs-Ploetz, 3rd edn, 4 vols. (Würzburg, 1965), iii, 94. © Verlag Herder. Reproduced by permission. From "A Plague on Bohemia? Mapping the Black Death", in "Past and Present May 1, 2011 vol. 211 no. 1 3-34",

Emergence Reflects Complexity of Underlying System

- **Interactions**
- **Delays**
- **Feedbacks**
- **Nonlinear: Risk, cost, intervention synergies**
- **Heterogeneity**

Agenda

- ✓ **Motivations for complex systems approaches**
- **Introduction to dynamic models**
- **Characteristics of Agent-Based dynamic models**
- **Tradeoffs associated with Agent-Based models (Time permitting)**

Systems Science:
"Putting the Pieces Together"

- **Systems science can help us visualize understand implications of connections between model components**
- **A key way in which system science aids this is through the use of simulation models**
  - *These models are simplified representations of a hypothesized situation that obtains in reality*
  - *The models help us reason about the implications of our understanding*

Simulation Models

- **Simulation models represent hypothesized *causal relationships* between diverse factors**
- **Models provide a provide a way to examine diverse consequences of changes in one area of the system to the whole system**
- **Models help us and system actors to understand**
  - *System vulnerabilities, leverage points*
  - *Ways of fruitfully changing system structure*
  - *Improved ways of working together*

Simulation Models as Dynamic Hypotheses

- **Simulation models can be viewed as *dynamic hypotheses* concerning the causal structure underlying observed patterns**
- **We need to understand causal structure to understand *counterfactuals* – how patterns would change if we were to change X**
- **All simulation models are computational realizations of a mathematical process**
  - *There are many dynamic mathematical frameworks for defining simulation models*
    - **All of these frameworks characterize processes**

Simulation Models as Dynamic Hypotheses

- **Explaining drivers for trends or anticipating intervention impact requires understanding processes underlying observables**
- **A model represents a hypothesis regarding the possible causal interaction of diverse factors often studied in isolation**
  - *Operationally captures a hypothesis for "how the system works" at certain level of description*
- **Model parameters: Detailed assumptions for particular epidemiological contexts**

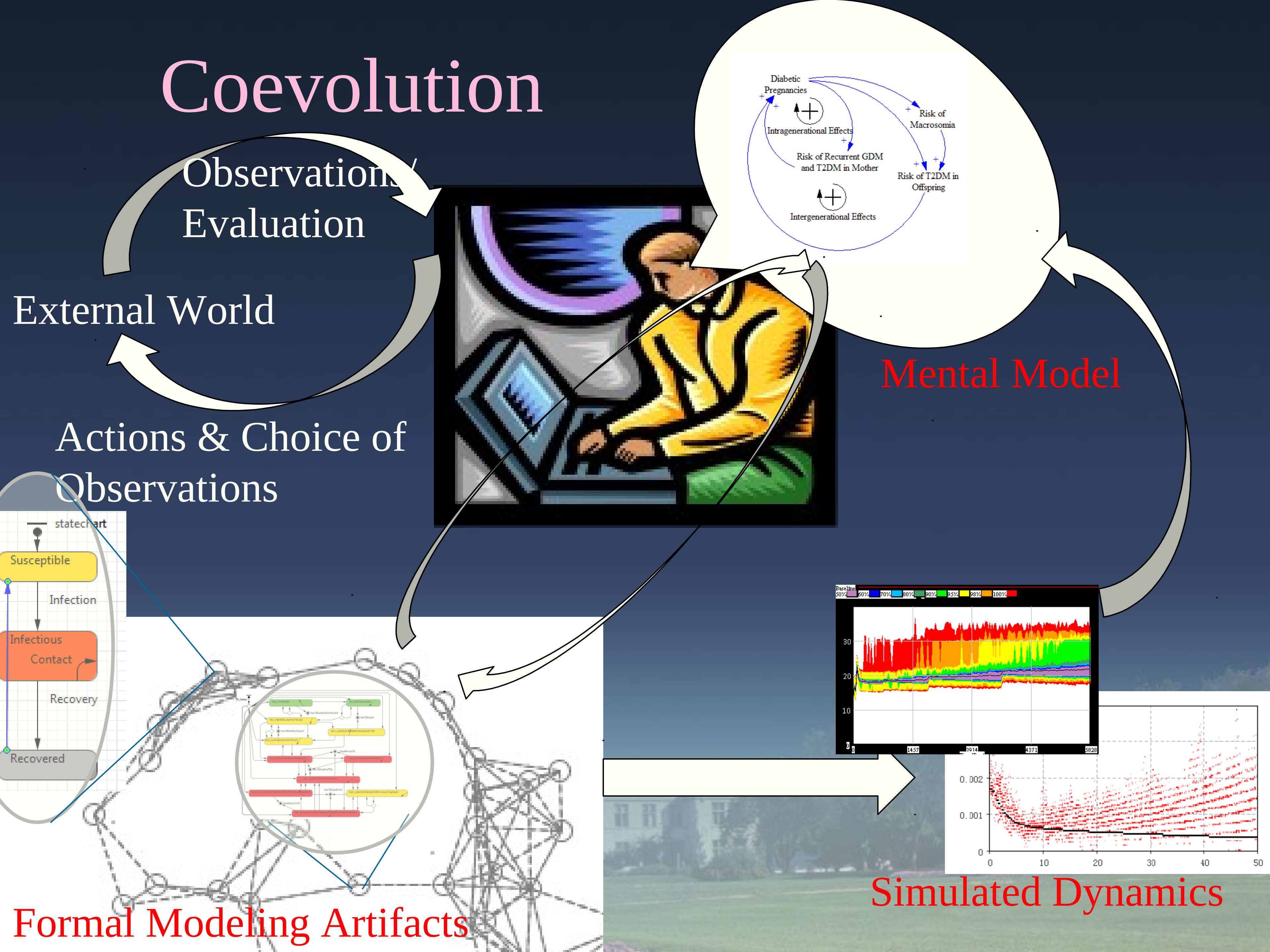
Analogy: Other Simulators to Improve Performance & Lower Risk

- **Pilot decision making: Flight simulators**
- **Climate policy: Climate simulators**
- **Process & power plants: Plant simulators**
- **Driver training: Vehicular simulators**
- **Street design & traffic flow regulation: Traffic simulators**
- **Construction coordination: Construction process simulators**

A Metaphor for Scientific Exploration

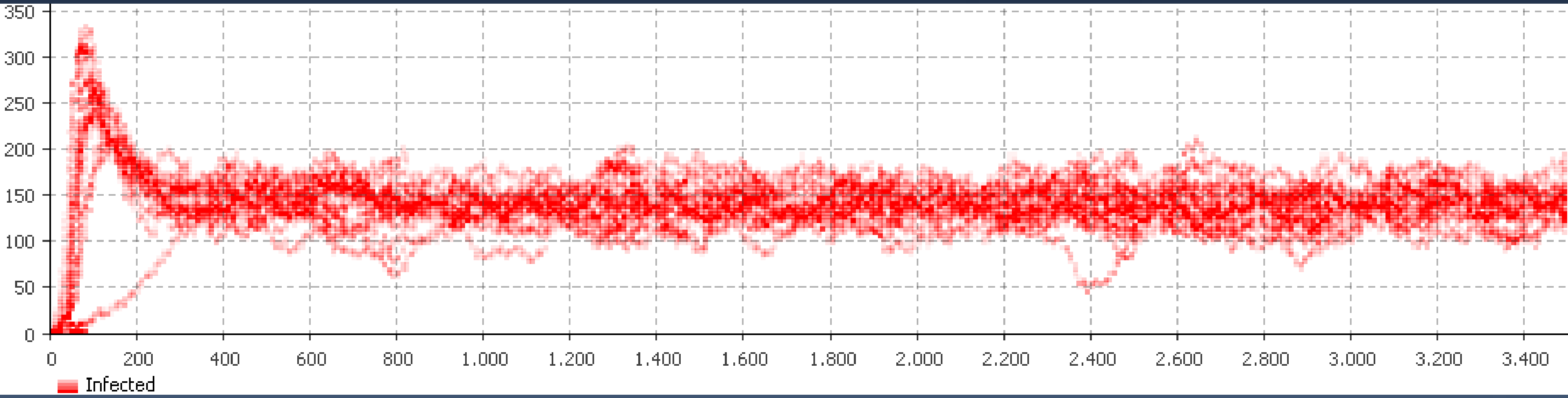
Simulation Models: Some Uses

- **Make explicit mental models of causality, for discussion and collective refinement**
- **Assist in management of complex situations**
  - *Serve as "What if" tool for identifying desirable policies*
    - Cost-effective/High-leverage/Robust
  - *Understand trends & help make sense of interaction of diverse information, processes*
  - *Prioritizing research/data collection & identifying inconsistencies*
  - *Understanding commonalities between contexts, infection spread*
  - *Evaluate statistical tools & study designs*
- **Communication (e.g. "learning labs")**

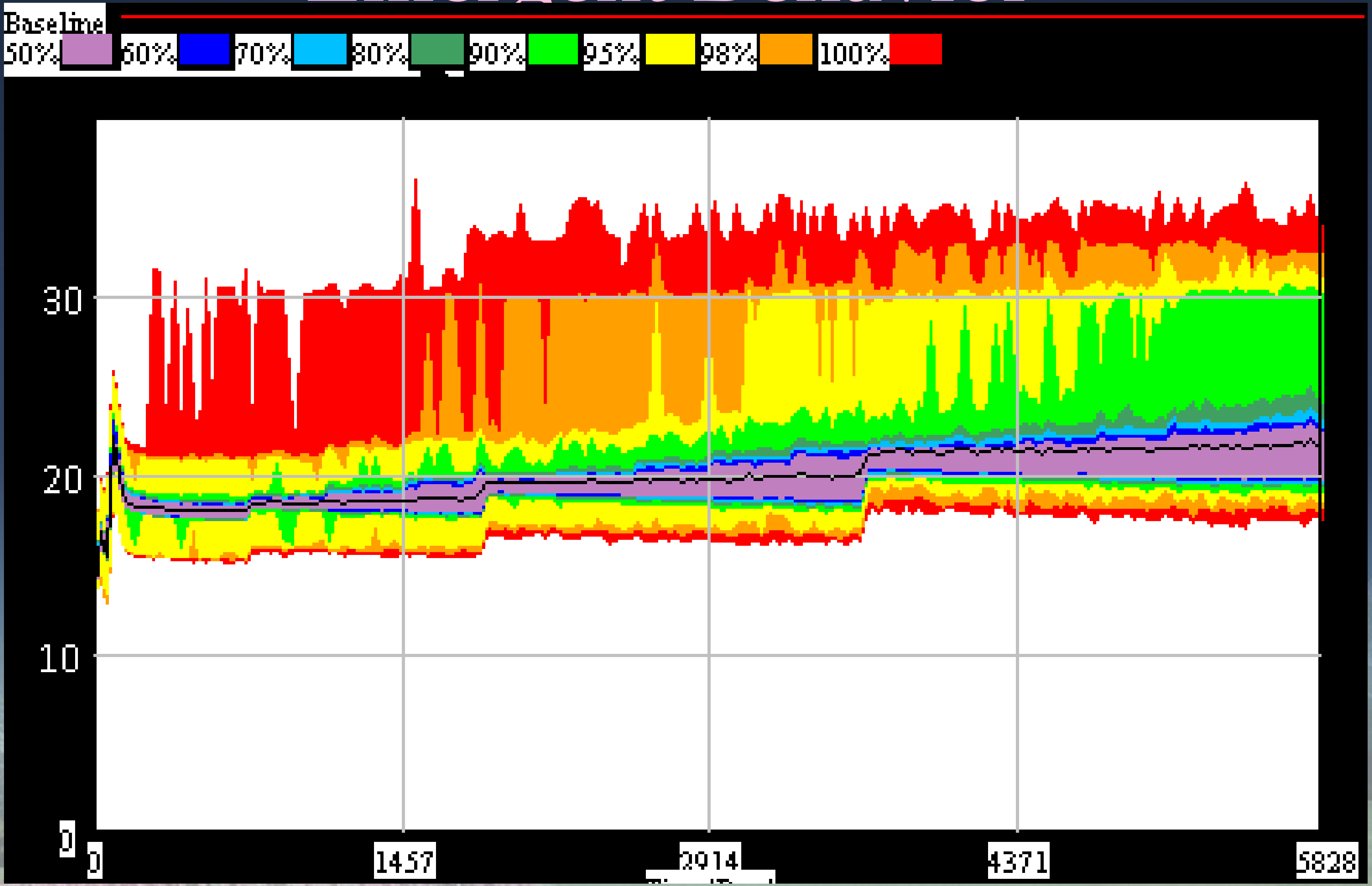


Coevolution
Observation / Evaluation
External World
Actions & Choice of Observations
Diabetic Pregnancies
Intragenerational Effects
Risk of Macrosomia
Risk of Recurrent GDM and T2DM in Mother
Risk of T2DM in Offspring
Intergenerational Effects
Mental Model
statechart
Susceptible
Infection
Infectious
Contact
Recovery
Recovered
Simulated Dynamics
Formal Modeling Artifacts

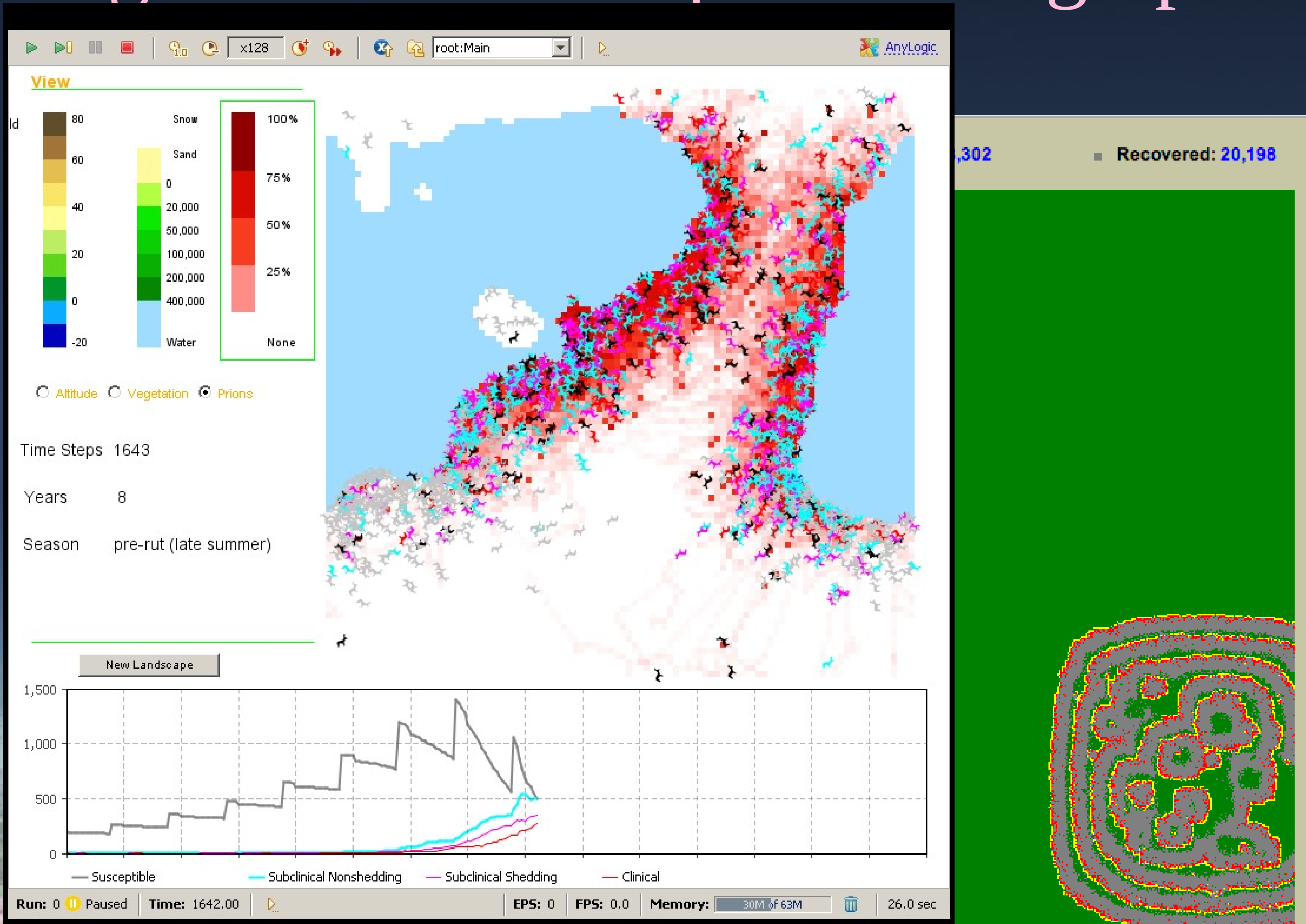
Emergent Behavior



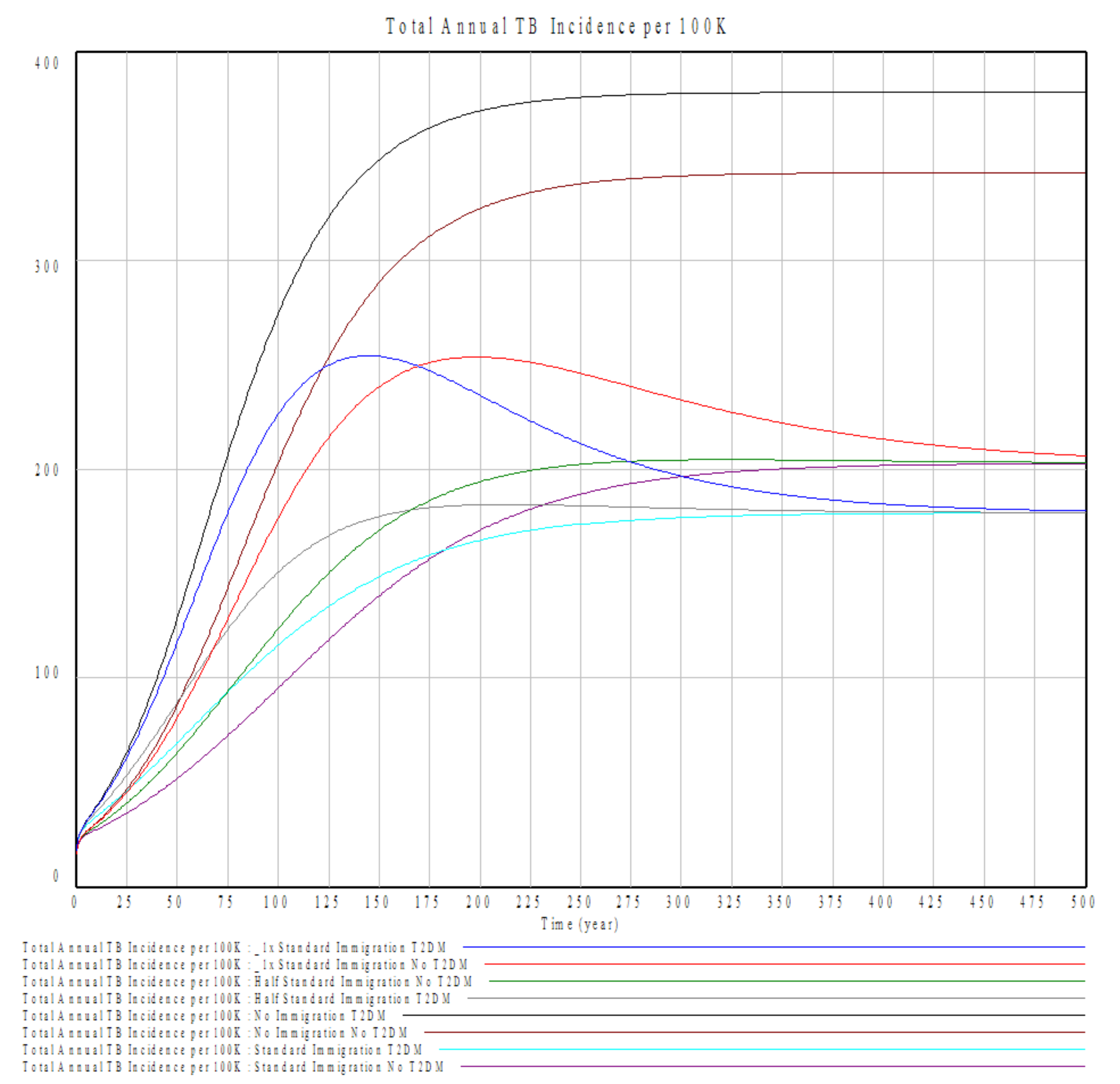
Emergent Behavior



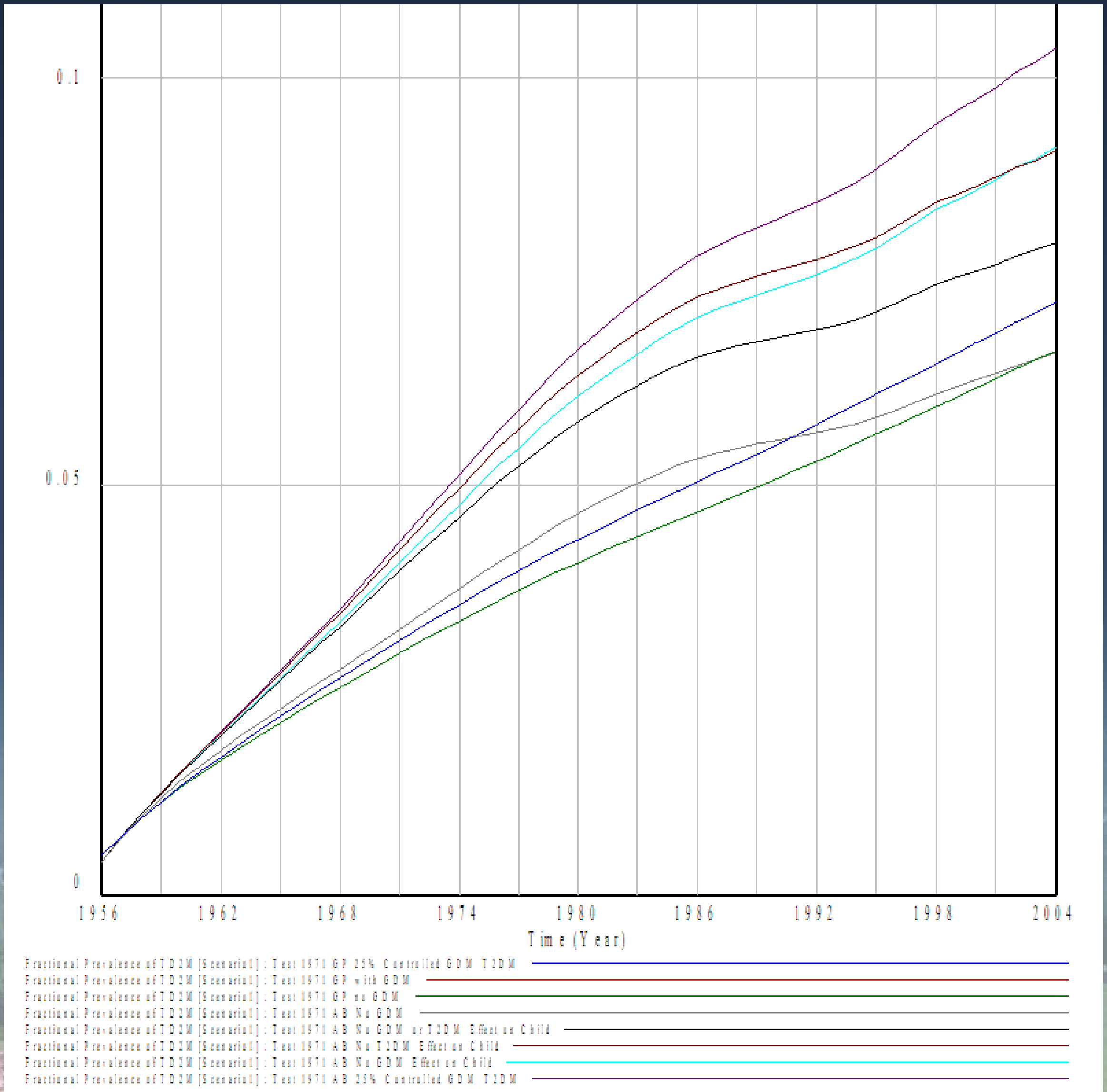
Emergent Behavior: Spatial/Geographic



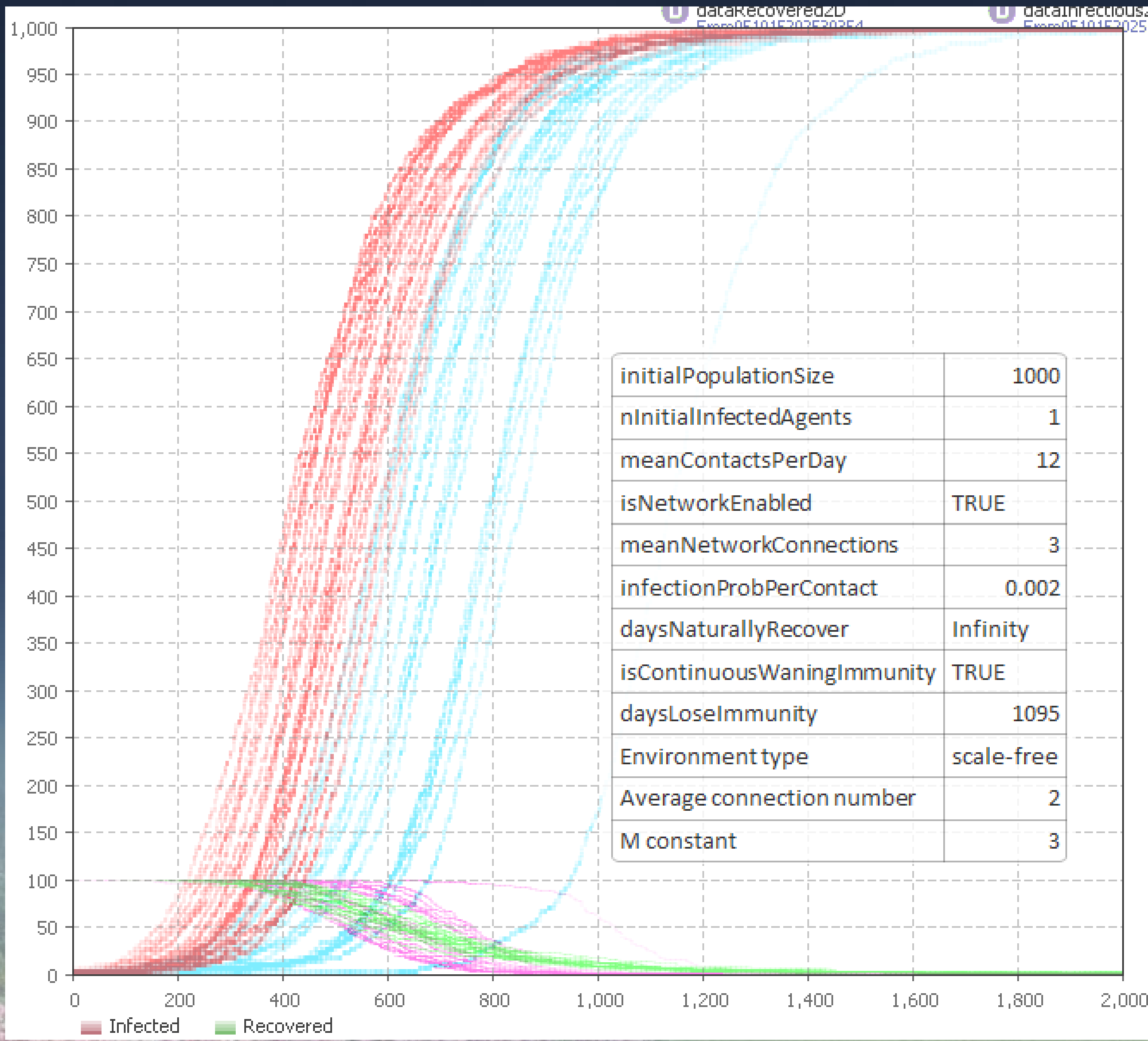
Scenarios for Understanding How Does X affect System



Policy Formulation & Evaluation



Policy Comparison: Stochastic Processes



Agenda

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- **Characteristics of Agent-Based dynamic models**
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Examples of Dynamic Modeling Approaches

System Dynamics Models

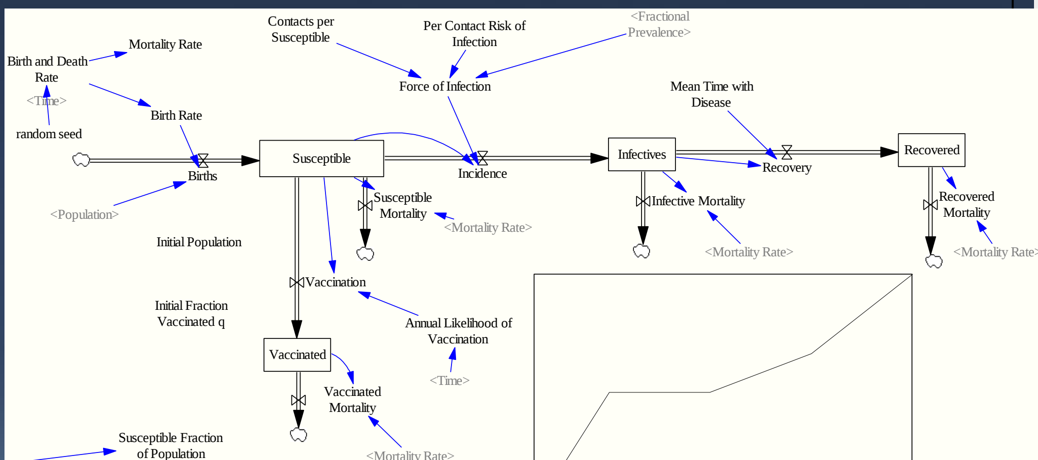
- *Feedback-centric modeling approach*
- *Focuses on feedbacks & accumulations*
- *Spans qualitative & quantitative methods*
- *Supports rich mathematical analysis*
- *Interactive model runs*

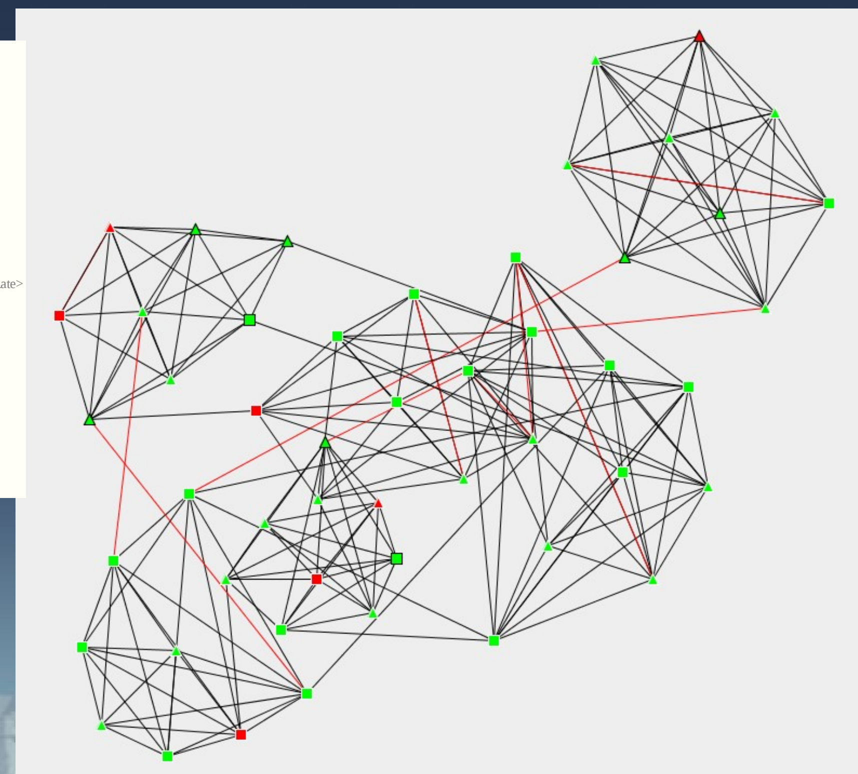
Agent-Based Models

- *Captures interactions between individuals within populations*
- *Captures individual histories & trajectories*
- *Gracefully represents network connections / nesting contexts*
- *Scalable capturing of heterogeneity*
- *Detailed policy planning*

Discrete Event Simulation **Simulates flow of individuals through processes Captures resource use**

Contrasting Model Granularity





Agent-Based Modeling

- **We can capture individuals in many ways**
- **I view Agent based models (ABM) as a type of individual-based modeling that encapsulates a given individual as a *software object* with**
  - *Methods*
  - *Properties*
- **Objects provide a convenient abstraction for individuals**
- **Agent-based models currently require writing at least some code in programming languages**
- **We can formulate SD models w/i agent-based tools**
  - *I view such models as simultaneously SD & ABM*
- **We can follow an SD process to build & use agent-based models**

Agent-Based Systems

- **Agent-based model characteristics**
  - *One or more populations composed of individual agents*
    - Each agent is associated with some of the following
      - State (continuous or discrete e.g. age, health, smoking status, networks, beliefs)
      - Parameters (e.g. Gender, genetic composition, preference fn.)
      - Rules for interaction (traditionally specified in general purpose programming language)
    - Embedded in an environment (typically with localized perception)
    - Communicate via messaging and/or flows
  - *Environment*
- **Emergent aggregate behavior**

Organization in ABM

- **ABM adopts the organizational style of object-oriented software engineering by clustering together the elements of state & behavior for entities**
- **This facilitates convenient representation of**
    - *Nested relationships (individuals in neighborhoods in municipalities, etc.)*
    - *Networked relationships (e.g. network of individuals, towns, farms, firms, etc.)*

Contrasting Organization in Aggregate Stock-Flow & ABM

Aggregate Stock & flow models

- **Within unit (e.g. city)**
  - *Subdivided according to state (eg # susceptible, # infective)*
  - *Each stock counts number associated with*
- **State f**
  are fou
  same
  - *Sum*
    stoc
- **Relati**
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Agent-based modeling

- **Within unit (e.g. city)**
  - *Subdivided according to constitutive smaller units (e.g.*

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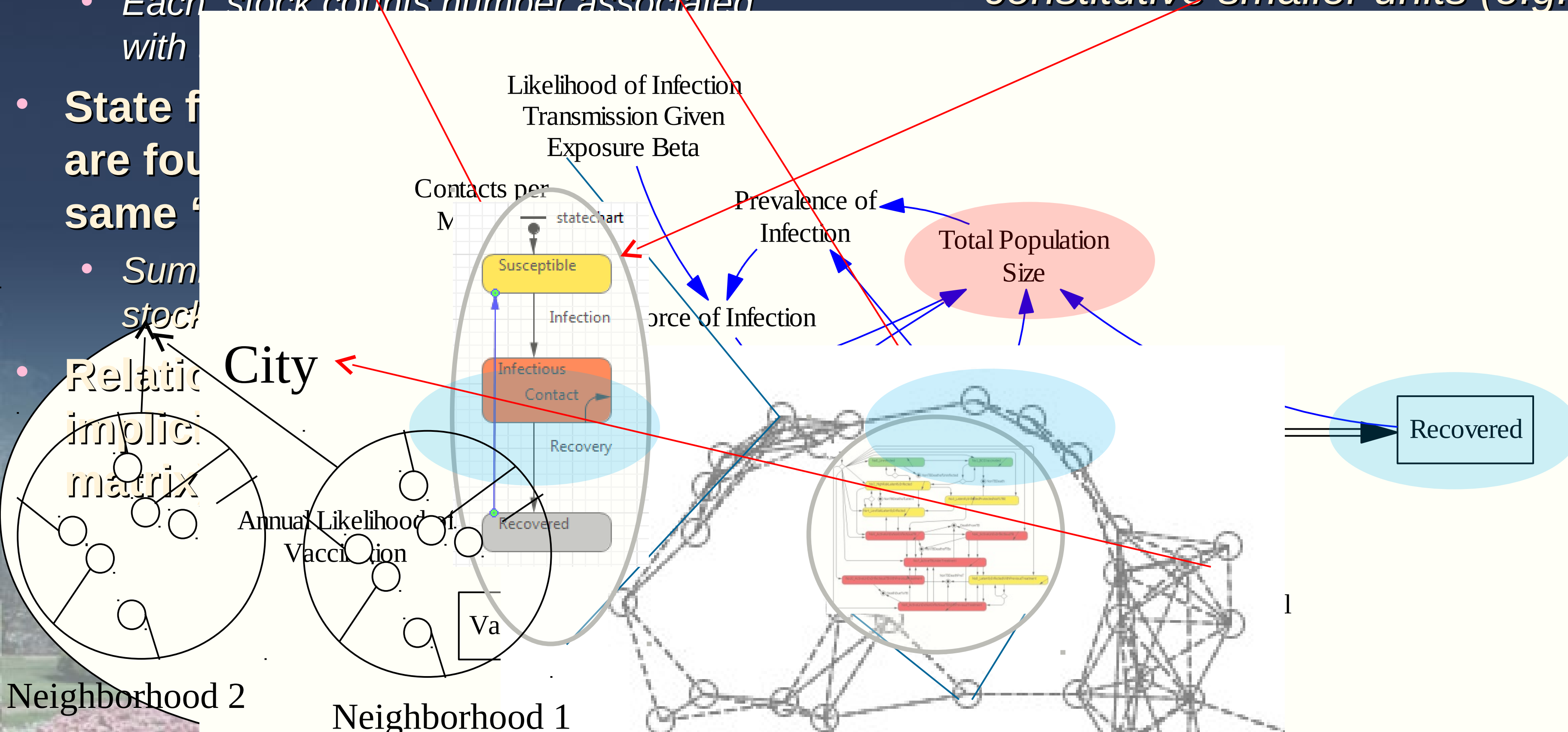
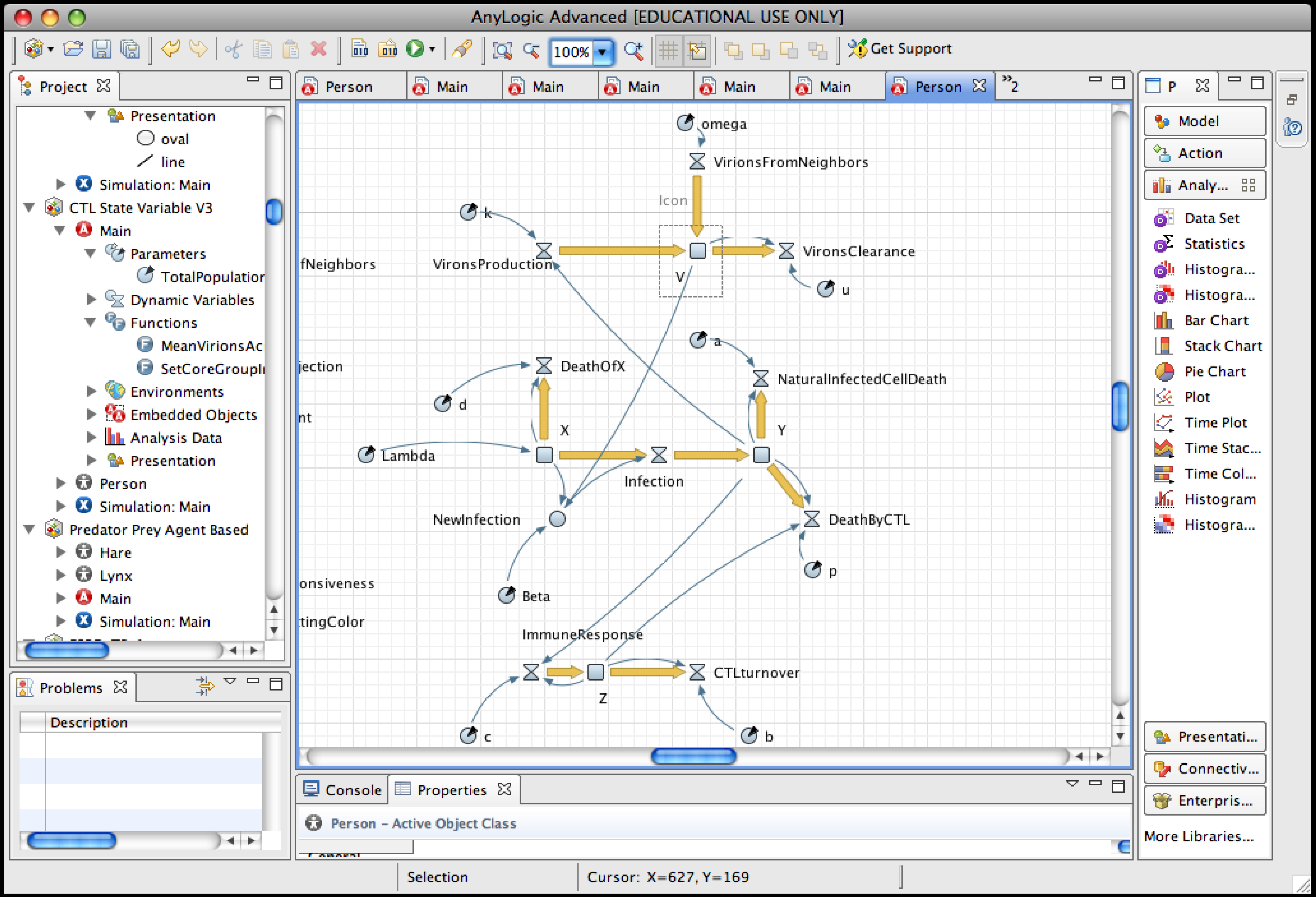


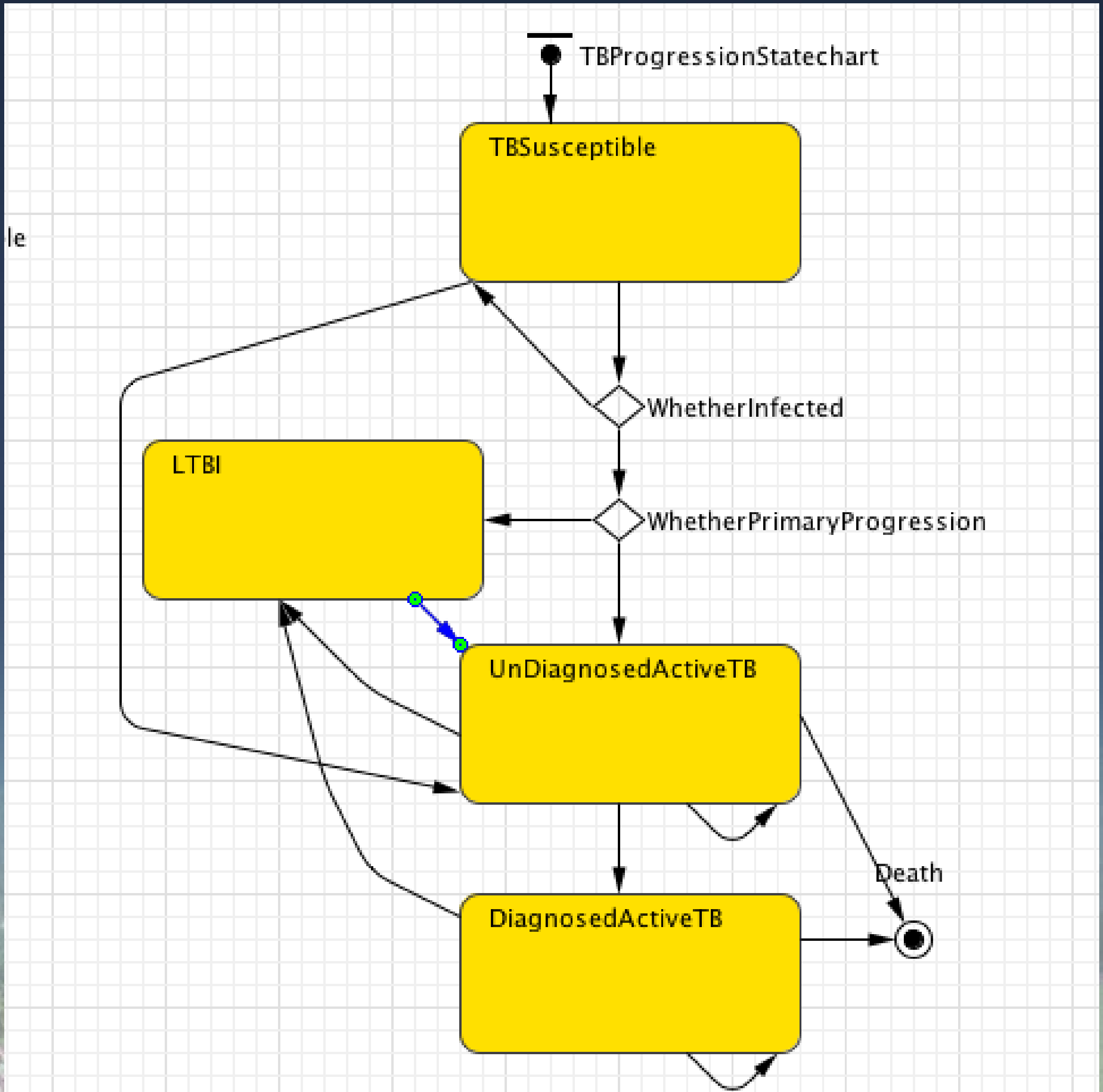
Elements of Individual State

- **Example Discrete**
  - *Ethnicity*
  - *Gender*
  - *Categorical infection status*
- **Continuous**
  - *Age*
  - *Elements of body composition*
  - *Metabolic rate*
  - *Past exposure to environmental factors*
  - *Glycemic Level*

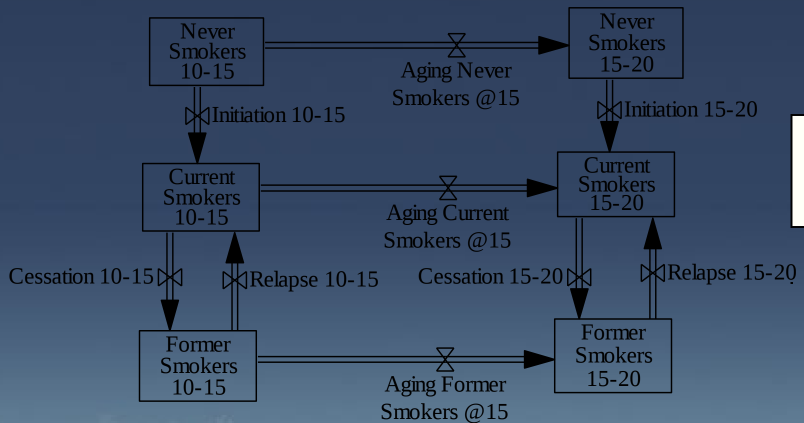
Example of Continuous Individual State

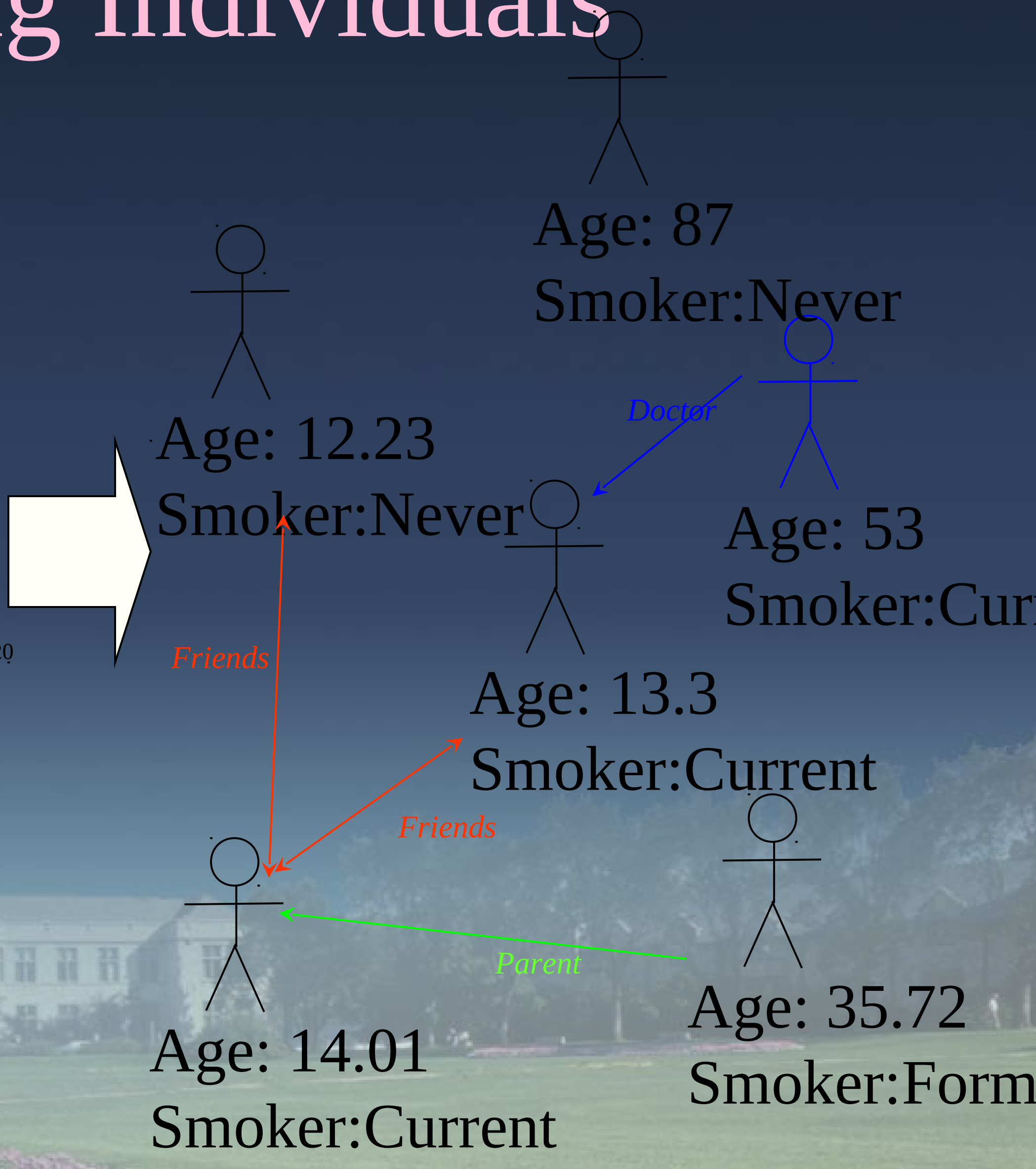


Example of Discrete States
Binary Presence in Discrete State

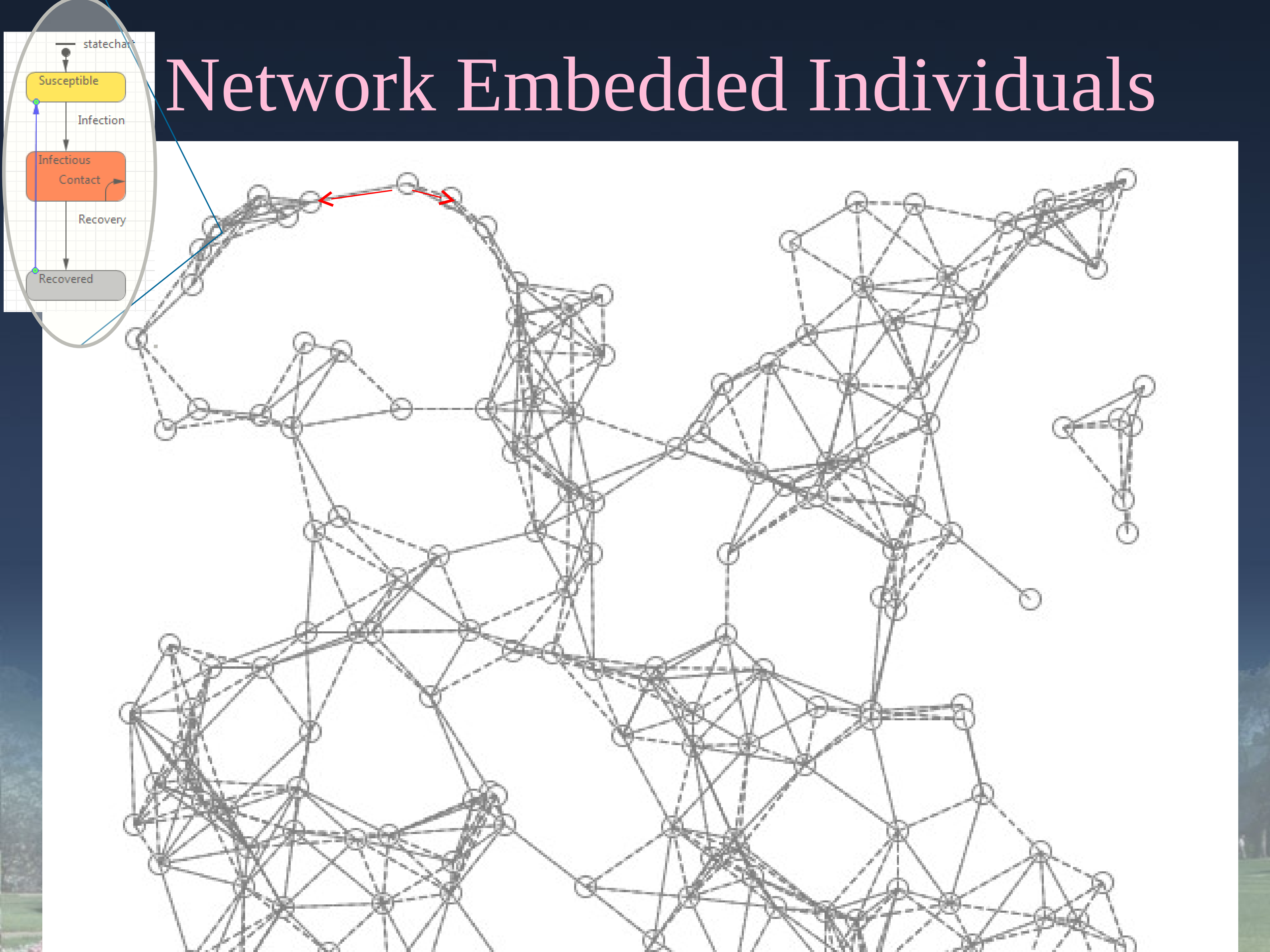


Interacting Individuals



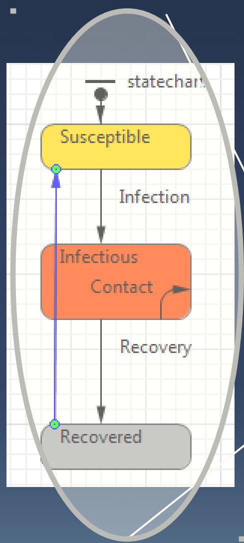


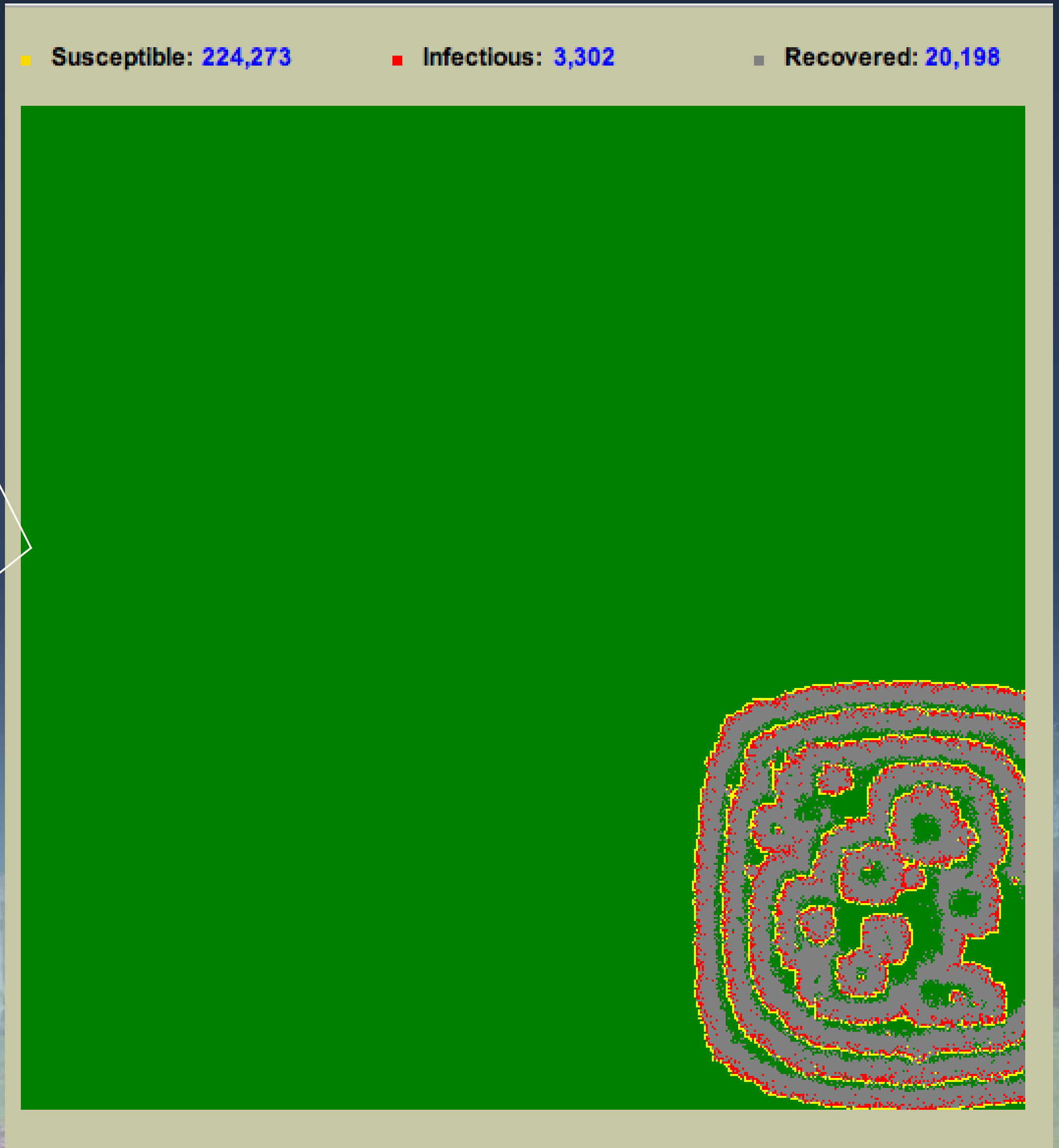
Network Embedded Individuals



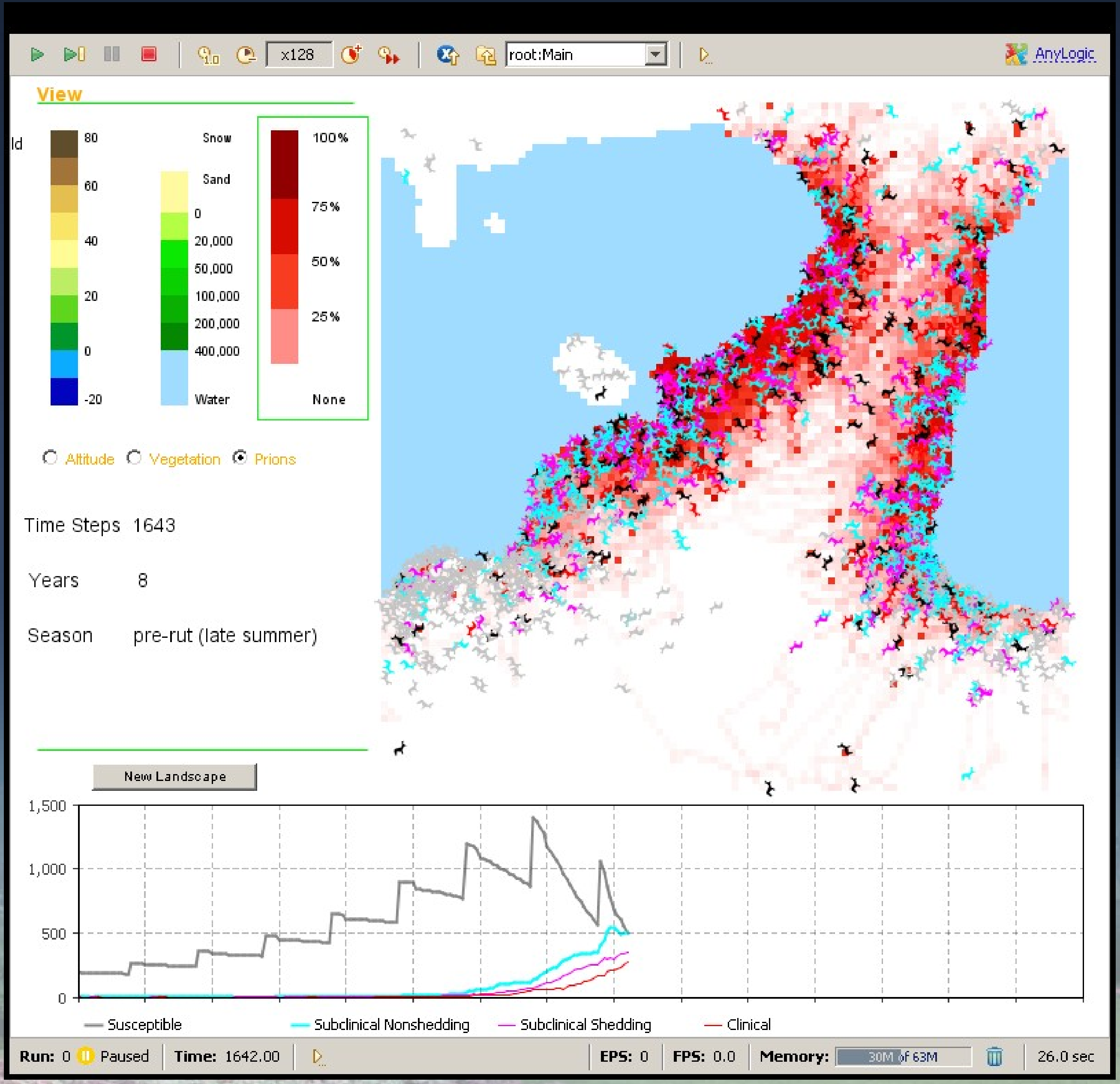
Irregular Spatial Embedding

Emergent Behavior in Regular Spatial Embedding





Aggregate & Spatial Emergence



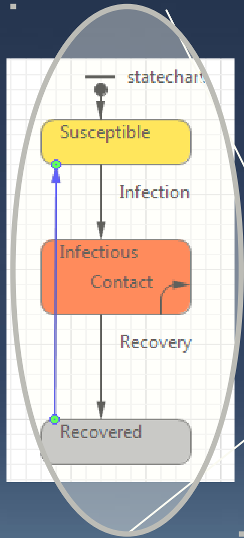
Emergent Behavior

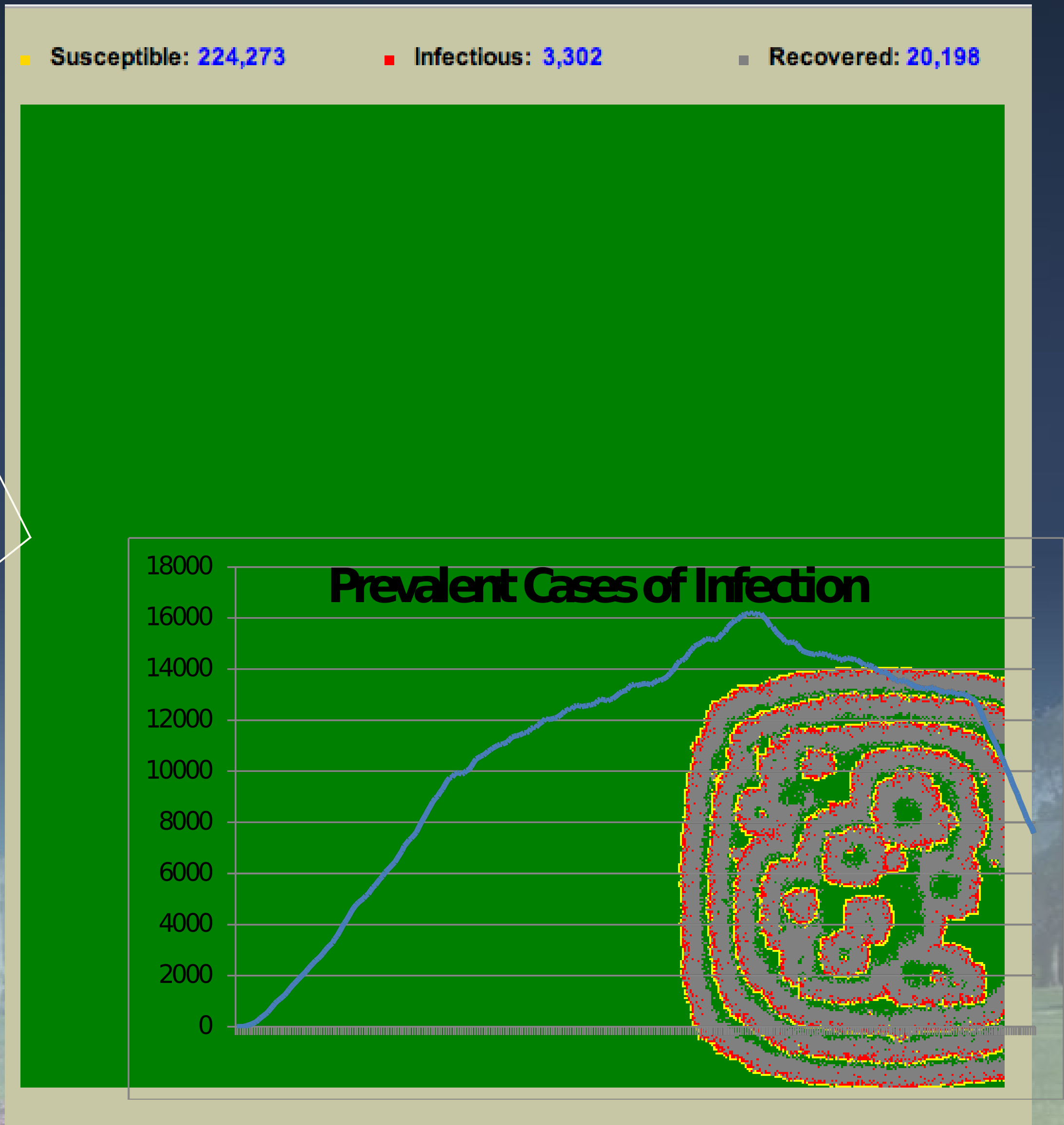
- **“Whole is greater than the sum of the parts”, “Surprise behavior”**
- **Frequently observed in stock and flow models as interaction between stocks & flows**
- **In ABMs, we see this phenomena not only at level of aggregate stocks & flows, but – most notably – *between agents***

Matters of Scale

- **It is straightforward to set up ABMs so that we have multiple (and possibly nested) levels of context present**
  - *Individual person / neighborhood / school / municipality / country*
  - *Individual deer / herd / ecoregion / population*
- **Emergent behavior frequently differs strikingly by scale**
  - *By their nature, some concepts (e.g. “Prevalence”) require at least a certain scale of analysis*

Emergent Aggregate Dynamics



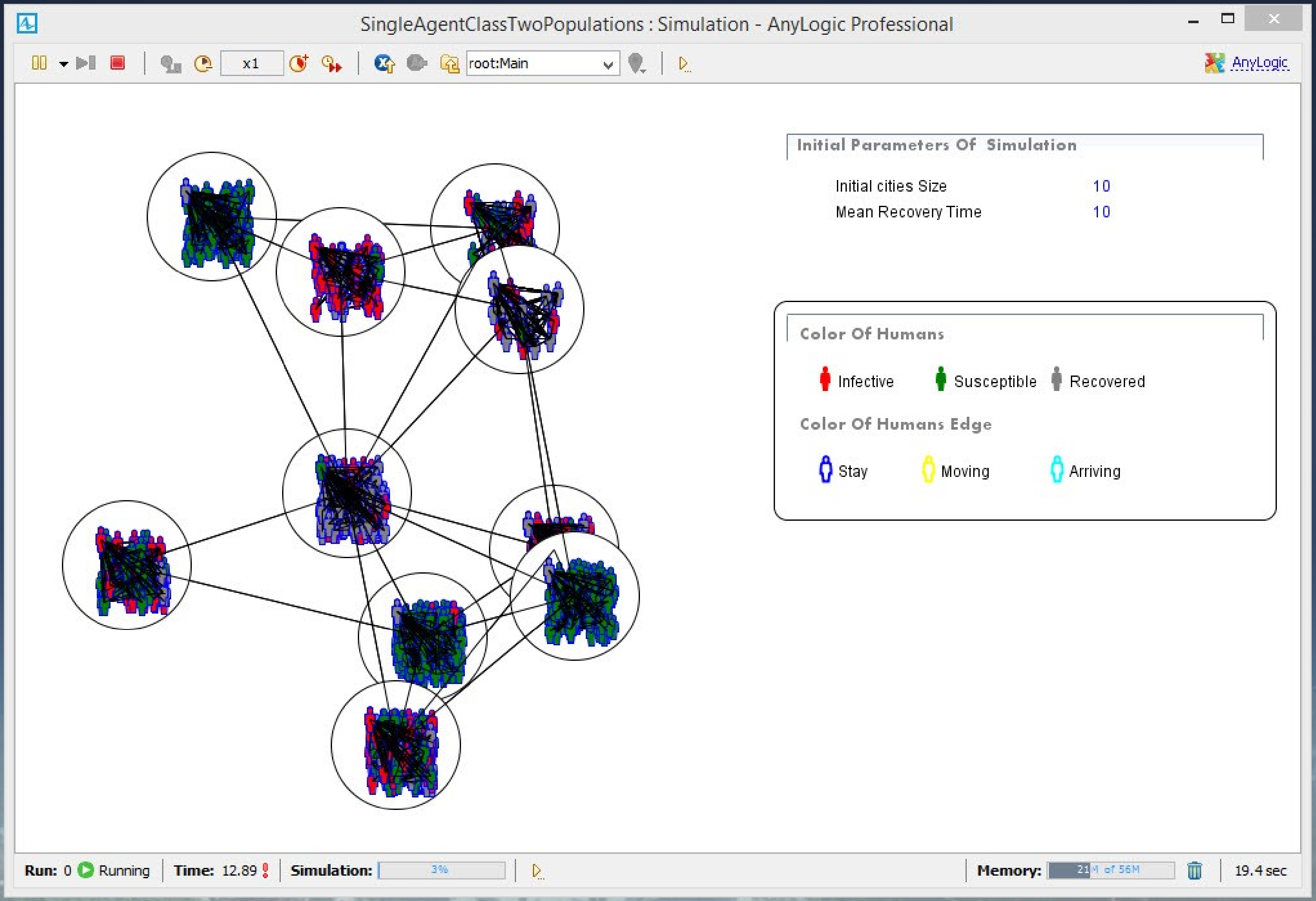


Susceptible: 224,273 Infectious: 3,302 Recovered: 20,198

Emergent Spatial Dynamics

These “waves” of infection by their very nature do not appear at the individual level, but instead are a distinctive spatial pattern.

A Multi-Level (Dynamic) Model



Conclusions

- **Interventions affecting public health are interventions in a complex system**
- **This complexity impacts intervention choice**
  - *Identifying "best" intervention is difficult!*
- **Systems modeling can help assist in the judicious choice of interventions**
- **Multiple modeling approaches can each offer unique perspectives on a system**
- **Broadly interdisciplinary teams help make good modeling possible**