Embedding System Dynamics in Agent Based Models for Complex Adaptive Systems

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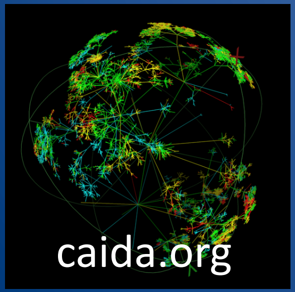
Last time on Topics in Computational Sustainability…

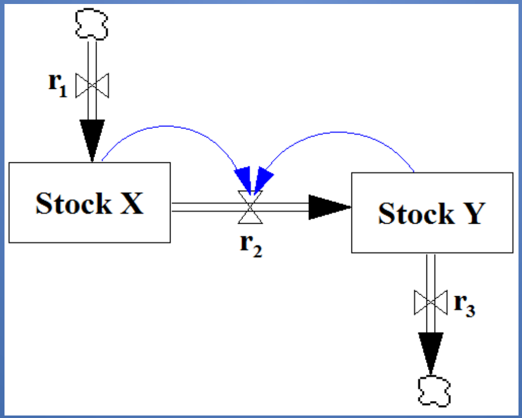
- We saw examples of different Complex Adaptive Systems
  - Disease control in Food/Animal Systems (Population Medicine)

  - Energy grids, social networks, ecosystems, ocean/ atmosphere systems, etc.



Last time on Topics in Computational Sustainability…

- We saw the System Dynamics approach to modeling CAS
- Systems of Ordinary Differential Equations (ODEs) model the flow of agents between different stocks.



- Many advantages: Easy model construction, parameterization, and validation. Efficient simulation algorithms.

System Dynamics: The Disadvantages

- The assumption that agents are essentially *homogenous*.

- Agent state space has one variable indicating stock membership.
- What about additional biological, social, economic state?
- Additional state could be dependent on stock membership.
- Can only target *interventions* based on stock-membership.
  - Can be uninformative to policy-makers.
- The assumption that agents have *well-mixed interactions*.
  - Unrealistic representation of the dynamics of many CAS.

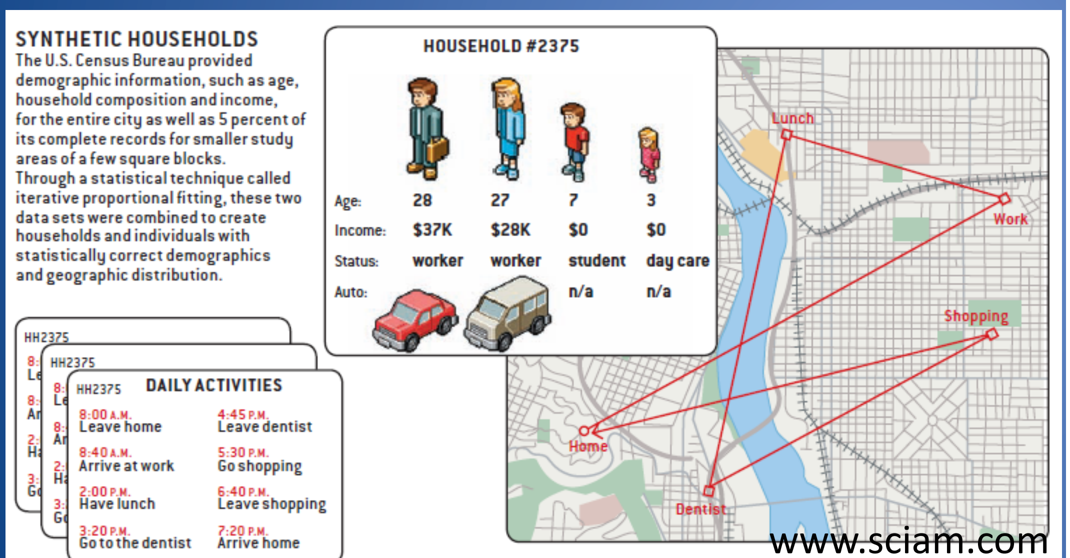
An Alternative: Agent-Based Modeling

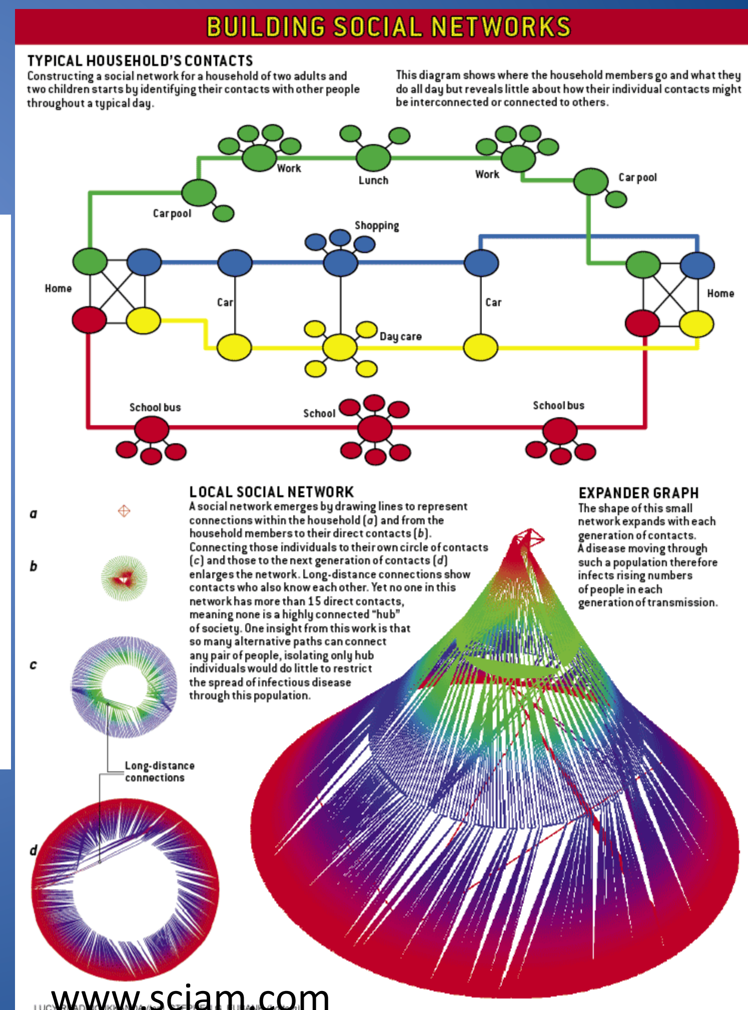
- The bottom-up approach
- Agents have heterogeneous state space updated through local interactions.
- Very general, high expressive power.
- The Cost:
  - Bottom-up construction, parameterization and validation is difficult.
    - Did we get all the feedback loops?
  - Simulation can have high time and memory requirements.
  - Models often become application specific.

Example: EpiSims

– Highly detailed

– Virtual laboratory





Striking a Balance

- *Goal*: Combine agent-based modeling and system dynamics to create models for CAS that retain the advantages of both paradigms.
- *Our Solution*:
  - Define a class of agent-based models with an embedded system dynamics model.
  - Give a simulation framework for these models.
    - Algorithm for model simulation.
    - Semantics of simulation framework specify how embedding occurs.

Our Class of Embedded Models

- We define an embedded model as a tuple *M* = (*S*, *A*, *O*, *U*, *D*, *V*)
- Let *Name* be a set of identifiers
- *S* is a set of *local state variable* names
  - Holds general agent state
- *A* is a set of *ODE state variable names*
  - A will contain one variable per embedded system dynamics model taking values that name stocks.
- Together, *S* and *A* divide the state space of agents.

Our Class of Embedded Models

- We define an embedded model as a tuple *M* = (*S*, *A*, *O*, *U*, *D*, *V*)
- *O* is a set of tuples of the form

  (*Name*, *Name*, **R**)

  Specifying the rates of transition between stocks.
- Reserve names *Gen* and *Des* for the source of generative flow and destination of destructive flow.
- *O* specifies the embedded system dynamics model.

Our Class of Embedded Models

- We define an embedded model as a tuple *M* = (*S*, *A*, *O*, *U*, *D*, *V*)
- *U* is a set of *local state update functions*
  - These functions model agent actions and interactions.
  - May read an agent's local state and ODE state variables.
  - Can only modify an agent's local state variables.
  - May suggest the generation or destruction of agents.

Our Class of Embedded Models

- We define an embedded model as a tuple *M* = (*S*, *A*, *O*, *U*, *D*, *V*)
- *D* is a set of *demographic functions*
  - These functions accept suggestions on agent generation and destruction.
  - May read an agent's local state and ODE state variables.
  - May modify the existing population of agents.

Our Class of Embedded Models

- We define an embedded model as a tuple $M = (S, A, O, U, D, V)$
- V is a set of *intervention functions*
  - May read and write to the entire state space of agents.
  - May modify the existing agent population.
  - Meant to model high-level actors with influence or control over the CAS.

Simulation framework

- Let Λ and Θ be updatable maps from agent and variable names to values.
- Let P be the current population of agents.
- Let P_{gen} and P_{des} be sets that hold suggestions on agent generation or destruction.

Simulation Framework

Algorithm 2 Execution of one time step for our simulation framework

Input: Embedded model $M = (S, A, O, U, D, V)$, set of agent names P, local state map Λ and ODE state map Θ.

$P_{gen} \leftarrow P_{des} \leftarrow \{\}$
for all local state update functions $u \in U$ **do**
  $(P_{gen}, P_{des}, \Lambda) \leftarrow u(P, P_{gen}, P_{des}, \Lambda, \Theta)$
end for
$(P_{gen}, P_{des}, \Theta) \leftarrow$ **ODESimulation**$(O, P_{gen}, P_{des}, \Theta)$
for all demography functions $d \in D$ **do**
  $P \leftarrow d(P, P_{gen}, P_{des}, \Lambda, \Theta)$
end for
for all intervention functions $i \in V$ **do**
  $(P, \Lambda, \Theta) \leftarrow i(P, \Lambda, \Theta)$
end for

Simulation Framework: Data Access

Algorithm 2 Execution of one time step for our simulation framework

Input: Embedded model $M = (S, A, O, U, D, V)$, set of agent names P, local state map Λ and ODE state map Θ.

$P_{gen} \leftarrow P_{des} \leftarrow \{\}$

for all local state update functions $u \in U$ **do**

  $(P_{gen}, P_{des}, \Lambda) \leftarrow u(P, P_{gen}, P_{des}, \Lambda, \Theta)$

end for

$(P_{gen}, P_{des}, \Theta) \leftarrow \mathbf{ODESimulation}(O, P_{gen}, P_{des}, \Theta)$

for all demography functions $d \in D$ **do**

  $P \leftarrow d(P, P_{gen}, P_{des}, \Lambda, \Theta)$

end for

for all intervention functions $i \in V$ **do**

  $(P, \Lambda, \Theta) \leftarrow i(P, \Lambda, \Theta)$

end for

Simulation Framework: Demographics

Algorithm 2 Execution of one time step for our simulation framework

Input: Embedded model $M = (S, A, O, U, D, V)$, set of agent names P, local state map Λ and ODE state map Θ.

$P_{gen} \leftarrow P_{des} \leftarrow \{\}$

for all local state update functions $u \in U$ **do**

$(P_{gen}, P_{des}, \Lambda) \leftarrow u(P, P_{gen}, P_{des}, \Lambda, \Theta)$

end for

$(P_{gen}, P_{des}, \Theta) \leftarrow$ **ODESimulation**$(O, P_{gen}, P_{des}, \Theta)$

for all demography functions $d \in D$ **do**

$P \leftarrow d(P, P_{gen}, P_{des}, \Lambda, \Theta)$

end for

for all intervention functions $i \in V$ **do**

$(P, \Lambda, \Theta) \leftarrow i(P, \Lambda, \Theta)$

end for

Simulation Framework: Interventions

Algorithm 2 Execution of one time step for our simulation framework

Input: Embedded model $M = (S, A, O, U, D, V)$, set of agent names P, local state map Λ and ODE state map Θ.

$P_{gen} \leftarrow P_{des} \leftarrow \{\}$
for all local state update functions $u \in U$ **do**
  $(P_{gen}, P_{des}, \Lambda) \leftarrow u(P, P_{gen}, P_{des}, \Lambda, \Theta)$
end for
$(P_{gen}, P_{des}, \Theta) \leftarrow \mathbf{ODESimulation}(O, P_{gen}, P_{des}, \Theta)$
for all demography functions $d \in D$ **do**
  $P \leftarrow d(P, P_{gen}, P_{des}, \Lambda, \Theta)$
end for
for all intervention functions $i \in V$ **do**
  $(P, \Lambda, \Theta) \leftarrow i(P, \Lambda, \Theta)$
end for

Embedded Model: Examples

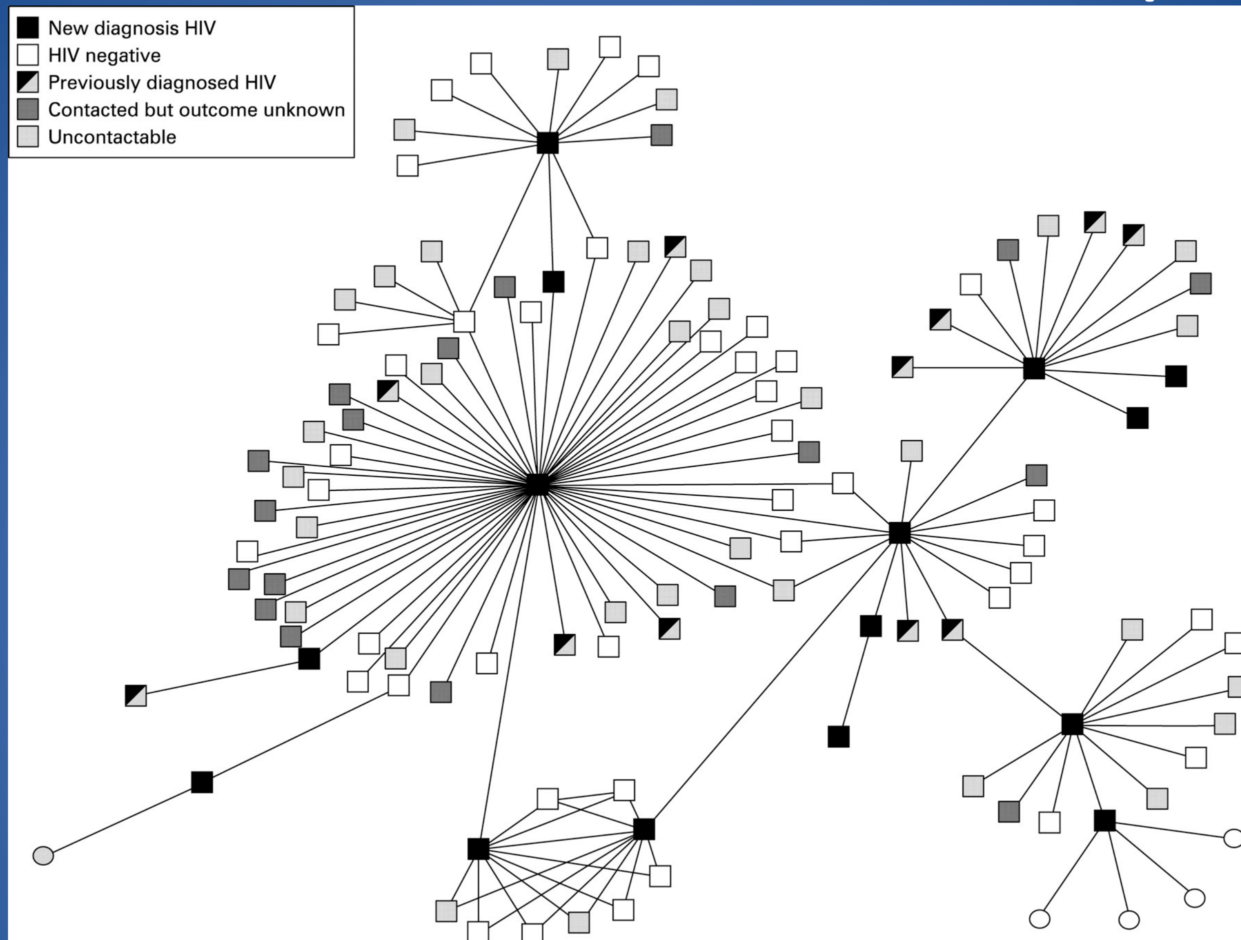
- Embedded models can be used for many CAS
  - Species distribution in ecosystems, information dispersion in a network, energy grids, etc.
- We give two examples of CAS from epidemiology that highlight the advantages of an embedded model.
  - Sexually Transmitted Infections (STI)
  - Johne's Disease (MAP)

STIs and the *well-mixed* assumption.

- WHO estimates 1 million people infected daily.
- Epidemics like HIV/AIDS impact world health and economy.

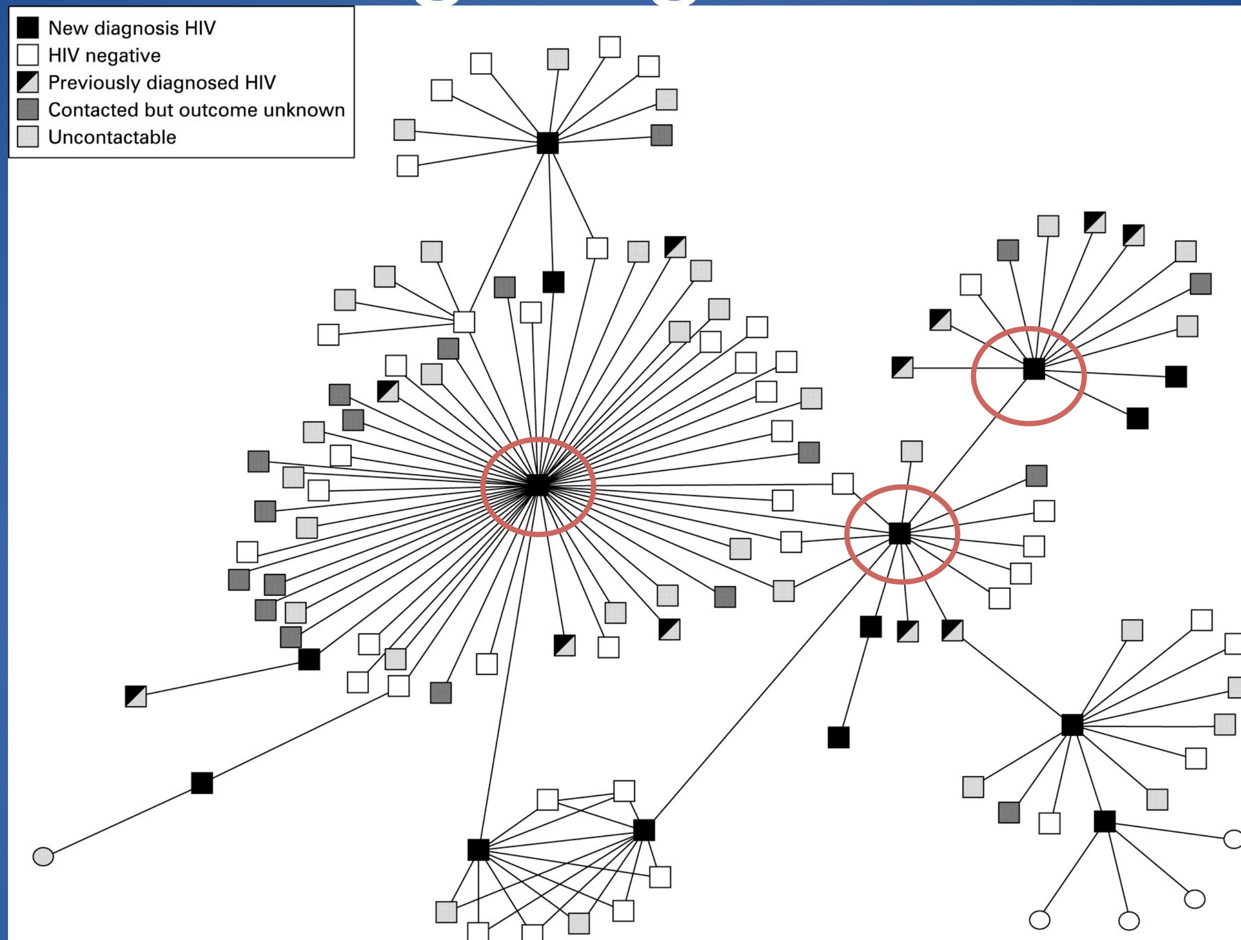
- Well-mixed assumption is fine for disease progression.
- Is it valid for transmission?

STIs and the well-mixed assumption.



- Sexual contact network in South Wales
- Network exhibits “small world” properties but is not well-mixed

STIs and targeting interventions



- Often, interventions to control STI outbreaks target agents based on their contact network (*contact tracing*)
- How can you model contact tracing with system dynamics?

STIs and targeting interventions

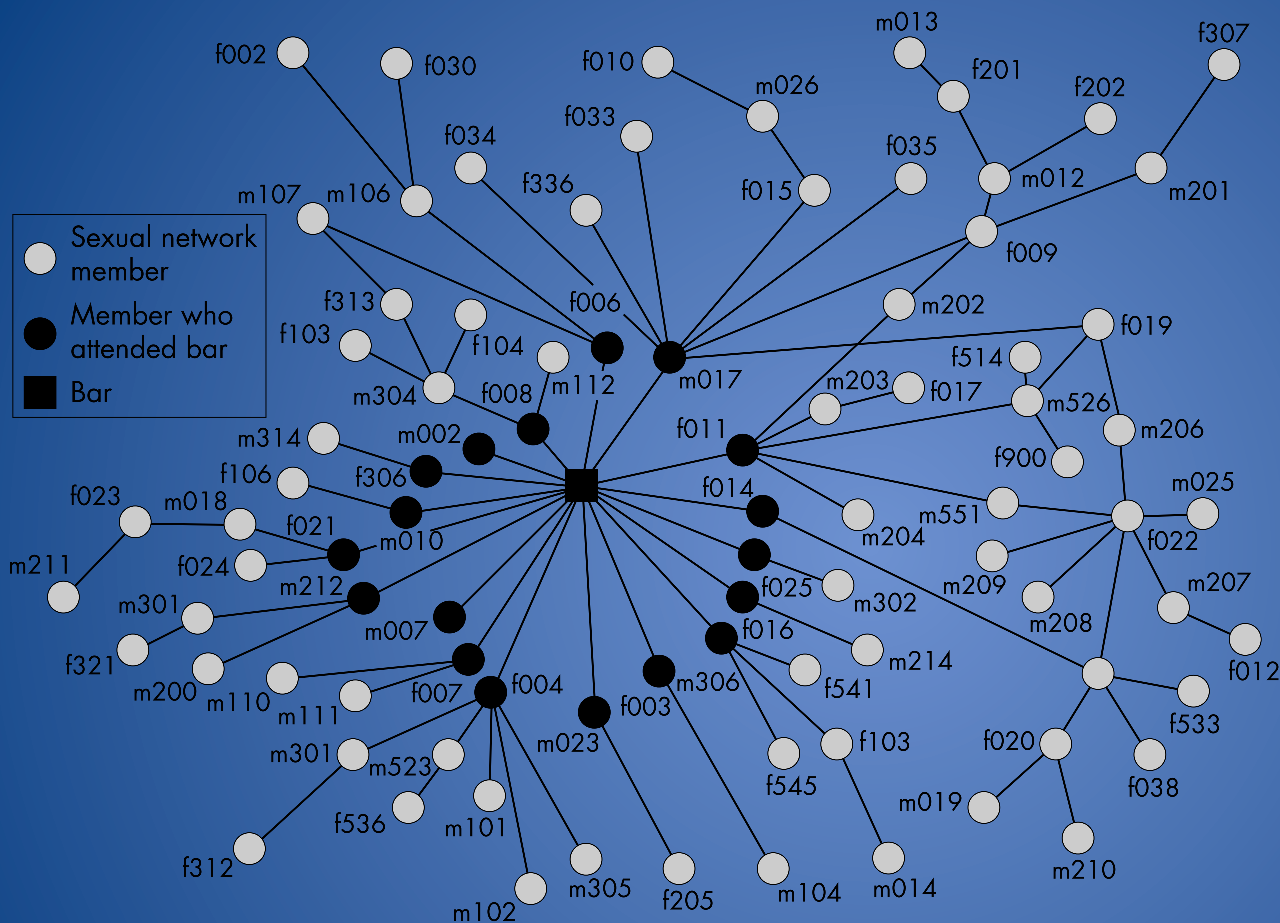
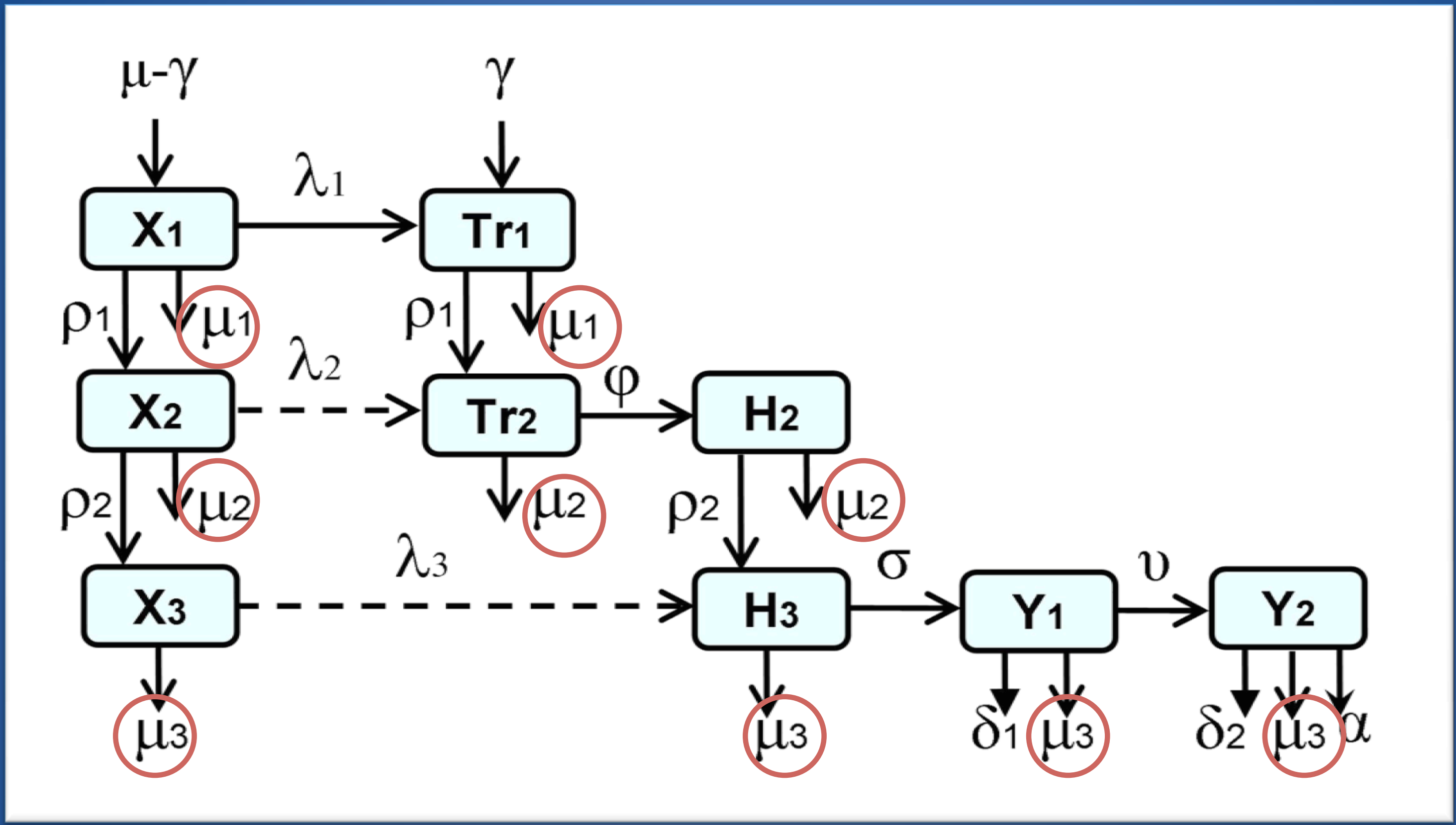


Figure 2 Network members (n = 89) viewed by their connection through a bar associated with gonorrhoea acquisition. A prefix to the unique identifier of "m" designates a male and "f" indicates a female sexual partner. Bar patrons possessed significantly higher information centrality measures compared to non-patrons (table 3).

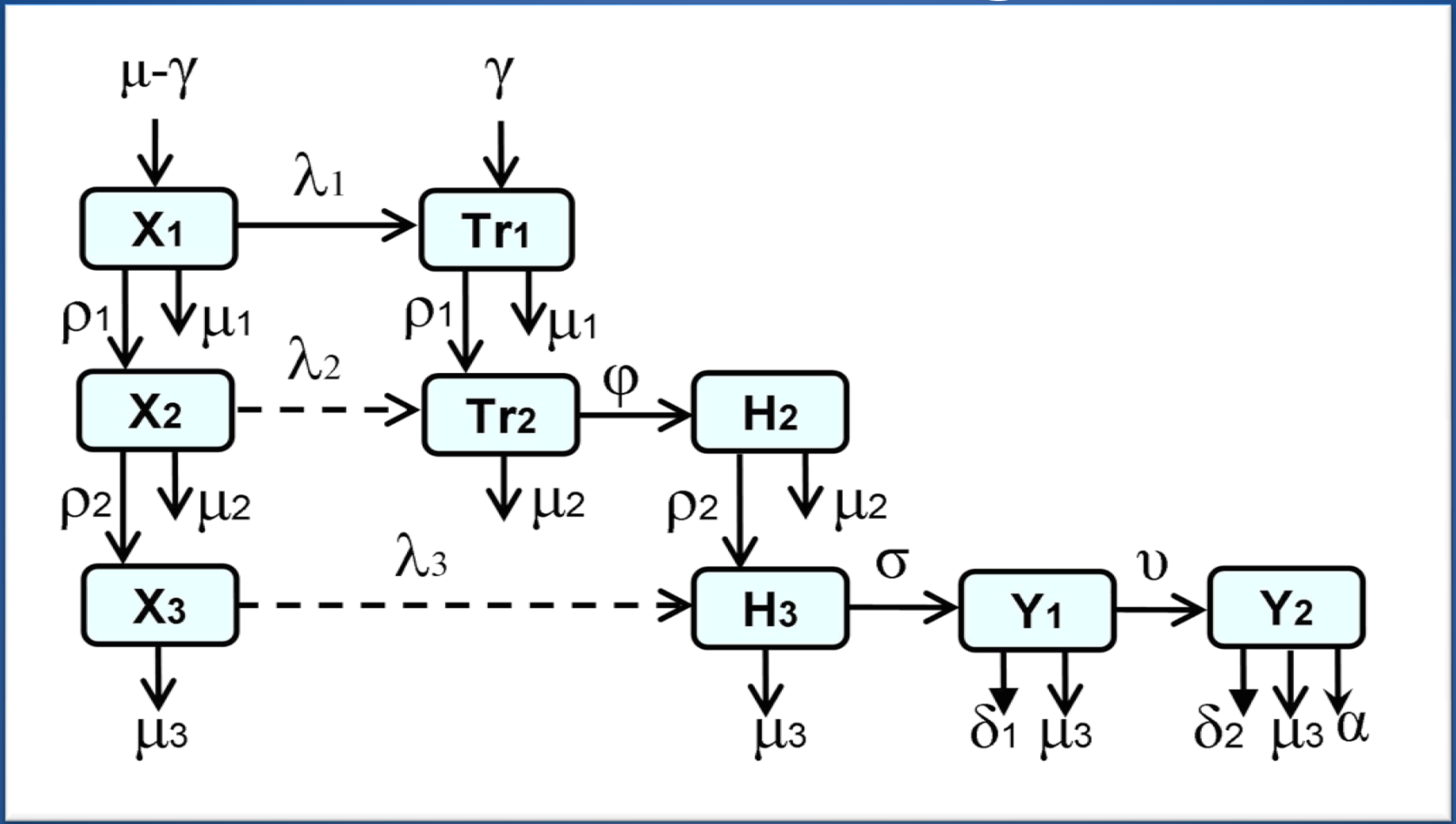
- Interventions also targeted at *locations*.
  - Additional state unattainable with ODE model.

MAP and modeling control



- Question: What are the μ s modeling?

MAP and modeling control



- Answer:
  - Animal death and *farmer management actions*
  - Farmer primarily controls farm by buying and selling animals.
  - Animal's economic value plays strong role in farmer's decisions.
  - Main objective is to make the most profit, not to control disease.
    - New management policies might be developed.

Embedded Model for MAP

- An embedded model solves many of these problems.
- Agent-based actions can model farmer's management policies.
- Extra economic state can be maintained for agents.
  - Total milk production, reproductive history, current pregnancy status, etc.
  - Milk production and reproductive functions dependent on MAP status.
  - Optimization!
- Management policies can be implemented mechanistically as in reality.

Embedded Model for MAP

- $M = (S, A, O, U, D, V)$
- *S* names local state variables that hold biological/economic data on cows.
- *A* names one variable that holds current MAP disease status.
- *O* specifies the MAP ODE model.

Embedded Model for MAP

- $M = (S, A, O, U, D, V)$
- The local update functions *U* maintain additional agent state.
  - Agent's reproductive status updated according to farm policies and biology.
  - Agent's milk production is tracked, and influenced by disease state.
  - Agent reproduction suggestions the generation of new agents.

Embedded Model for MAP

- $M = (S, A, O, U, D, V)$
- The demographic functions *D* model basic farmer management decisions.
  - Routine buying and selling of animals.
  - Value for each agent computed based on their current state (economic value).
  - Low value agents are removed from herd to make room for new agents.

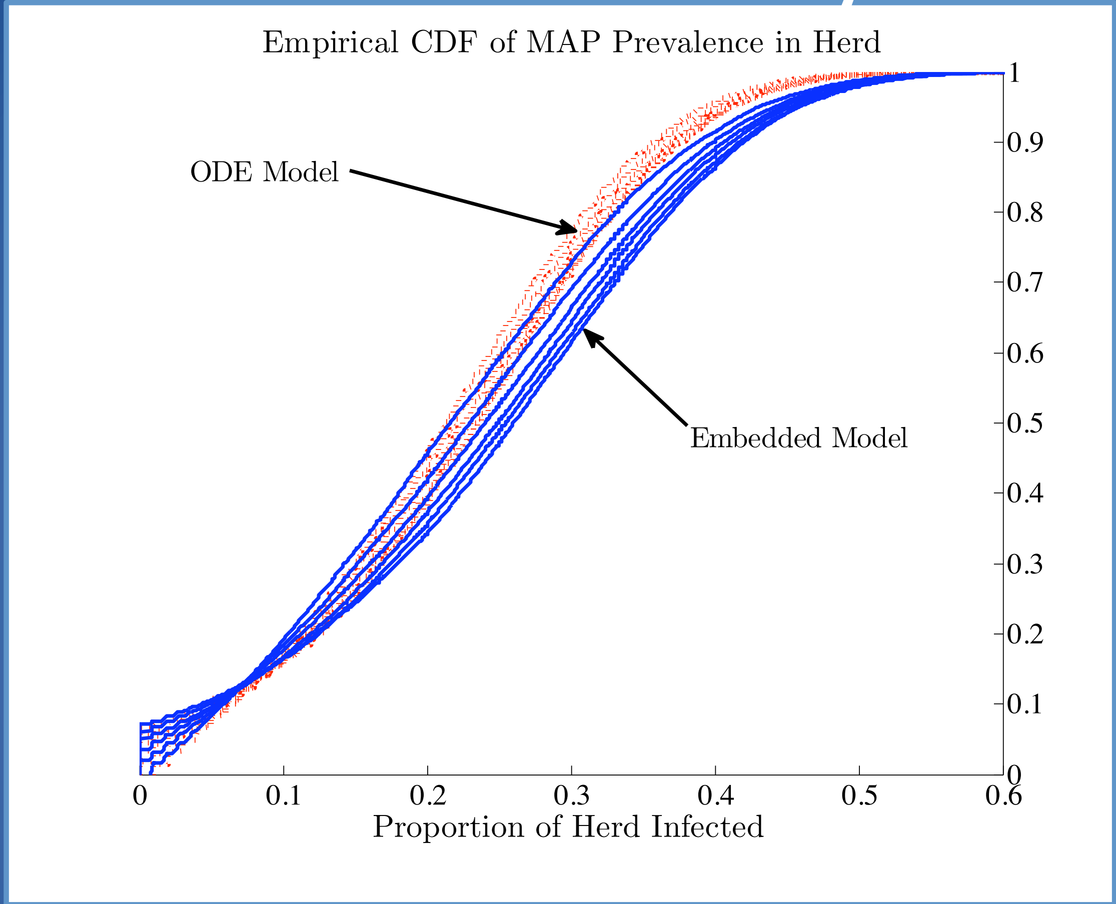
Embedded Model for MAP

- *M* = (*S*, *A*, *O*, *U*, *D*, *V*)
- The intervention functions V model controlling for MAP
  - Farmer tests for MAP every six months.
  - Two control policies:
    - ***Test-and-Cull***: Farmer removes test positive cows from herd when they're spotted.
    - ***Milk-Test-and-Cull***: Remove test positive cows from herd, but delay the removal of cows with high milk production.

Experimental Setup

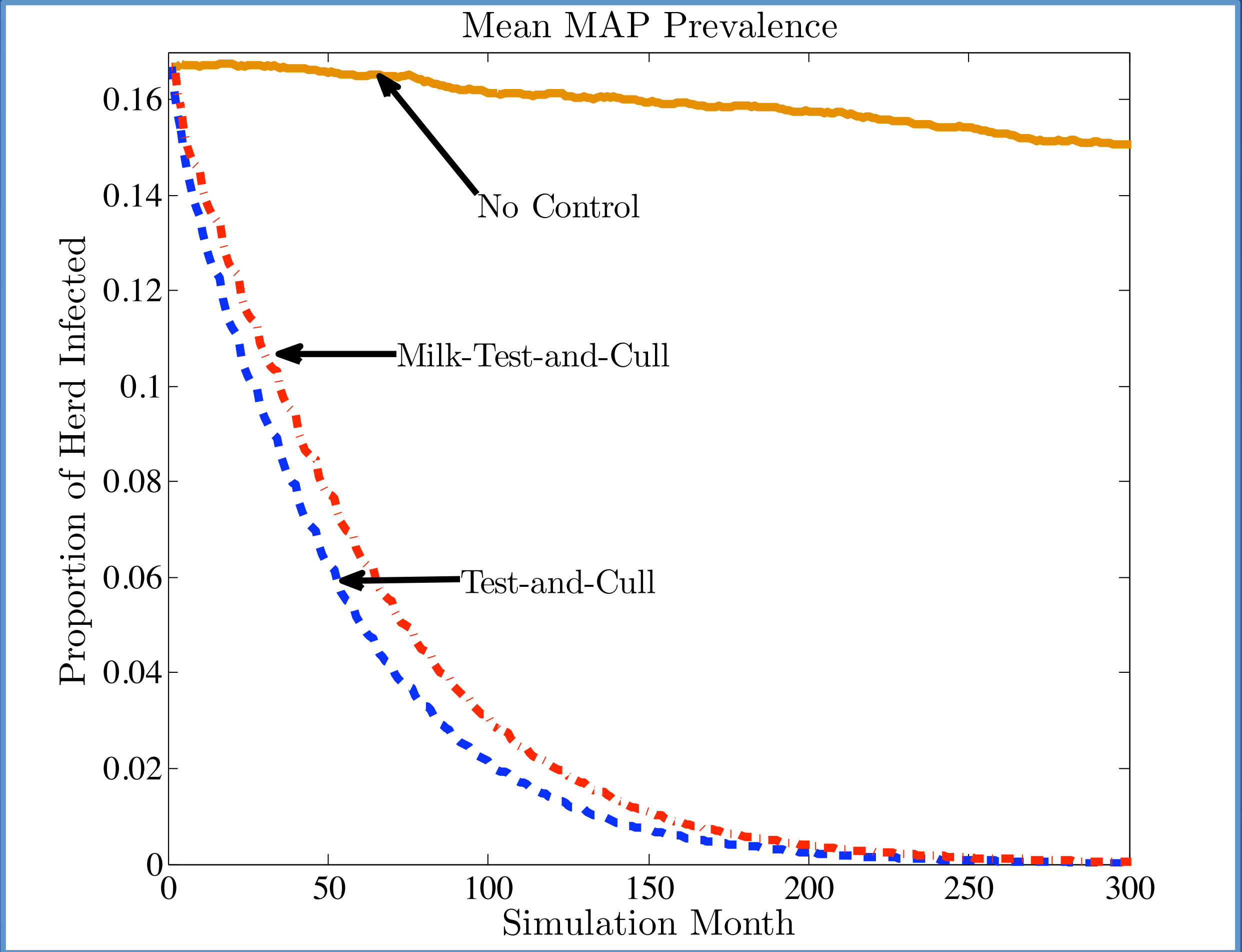
- Implemented simulation framework in Java.
- Constructed an embedded model for MAP on dairy farms.
- Ran 3 sets of 100,000 simulations:
  - 50 year run-up period to obtain *endemic equilibrium*
  - Control strategy used for next 25 years:
    - No control, Test-and-Cull, Milk-Test-and-Cull
- **Question**: Does the model produce accurate disease dynamics?
- **Question**: Which control strategy is "best”?

Results: Disease Dynamics



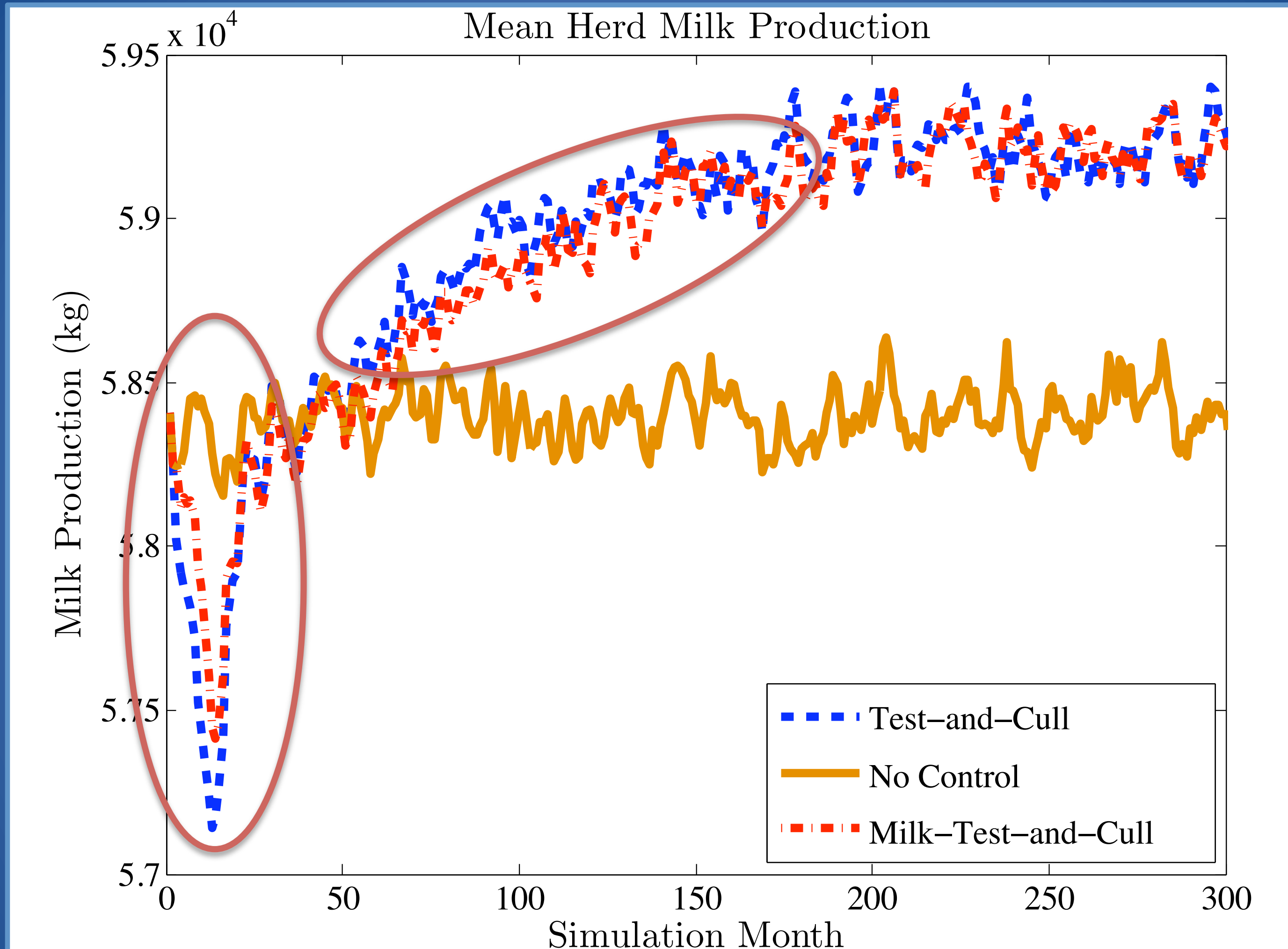
- Each line gives prevalence of MAP at five year intervals under no control.
- Distributions of results for both models are close.
- ODE results known to be valid.

Results: Disease eradication



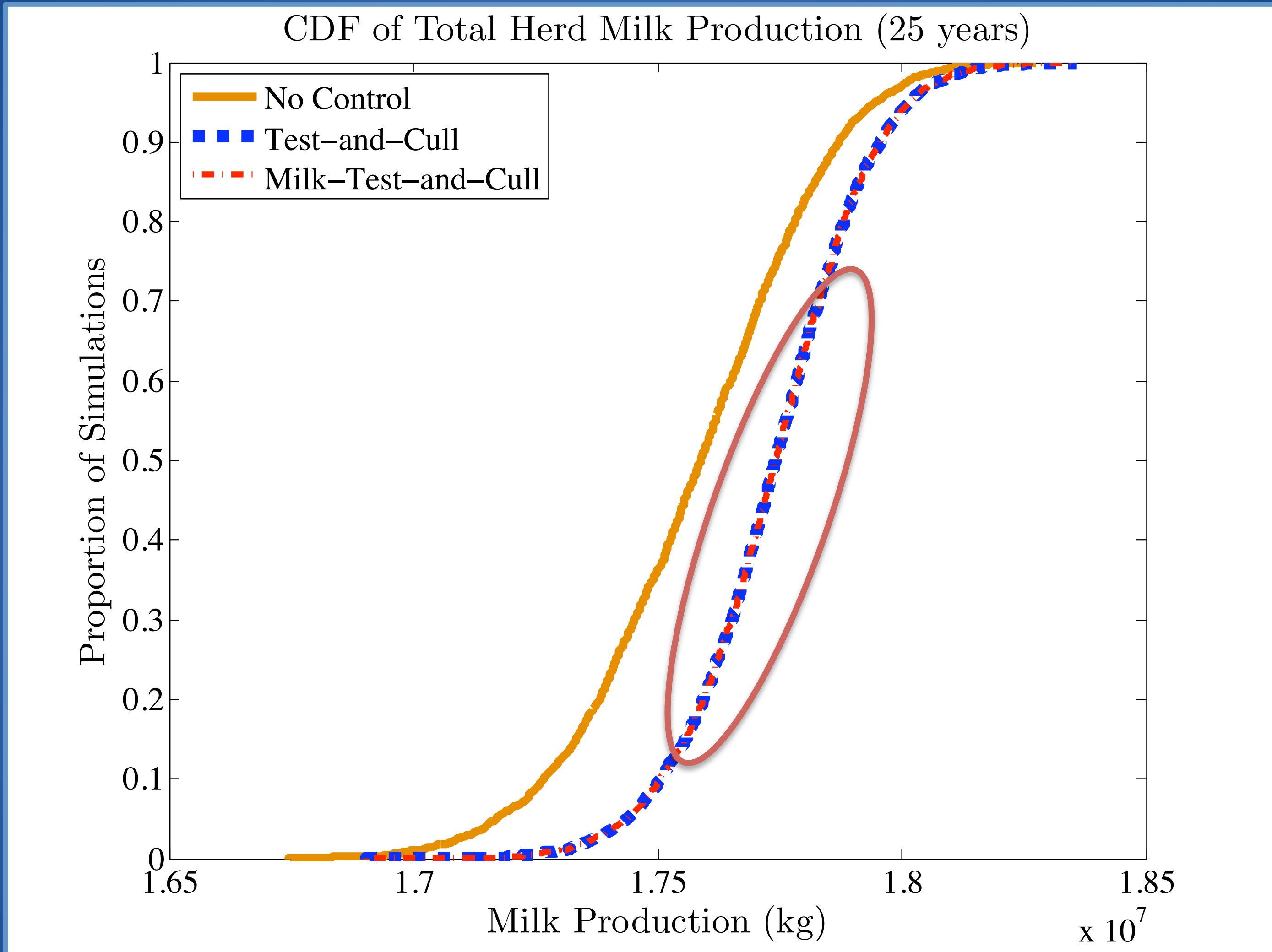
- Both Test-and-Cull and Milk-Test-and-Cull result in fadeout.
- Milk-Test-and-Cull, on average, has slower fadeout.

Results: Milk Production



- Milk-Test-and-Cull has short-term gains but may have long-term costs.

Results: Milk Production



- In the long term, both strategies have similar performance for total milk production.

Conclusions on Control Strategies:

- Both Test-and-Cull and Milk-Test-and-Cull result in MAP eradication.
- Both Test-and-Cull and Milk-Test-and-Cull have short-term costs.
  - Milk-Test-and-Cull mitigates these costs.
- Both strategies have similar long-term performance for milk production.
- ***Conclusion****: Milk-Test-and-Cull can be used to control MAP and mitigate the short-term costs of control without sacrificing long-term gains.*

Future work:

- New embedded models: Computational Sustainability seeks to influence many CAS.
  - Species distribution and social networks.
- Optimization:
  - Optimization problem is computationally difficult, and seeks to find an *optimal policy function*
  - Example for MAP:
    - $\Psi(\Lambda, \Theta)$ is a policy function that given the state space of all agents, returns a set of agents to cull.
    - $\Psi^*(\Lambda, \Theta)$ is an optimal policy function that given the state space of all agents, returns a set of agents to cull that is optimal in regards to economic output.
  - Techniques from Machine Learning and Game Playing could be very useful!