Learning about a Moving Target in Resource Management: Optimal Bayesian Disease Control

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Overview

Resource managers are faced with difficult choices regarding imperfectly observed and dynamically changing systems. Existing techniques required modification to address disease management problems.

Testing for subclinical infectious diseases facilitates selective culling and provides information that improves the efficiency of subsequent applications of broad-based controls, e.g. additional testing and monitoring.

We apply our methodology to the control of bovine tuberculosis in New Zealand's cattle herds and compare to less comprehensive approaches. Bovine tuberculosis represents a subclinical disease with complex transmission dynamics (both among cattle and between cattle and disease vector populations (e.g. possums)).

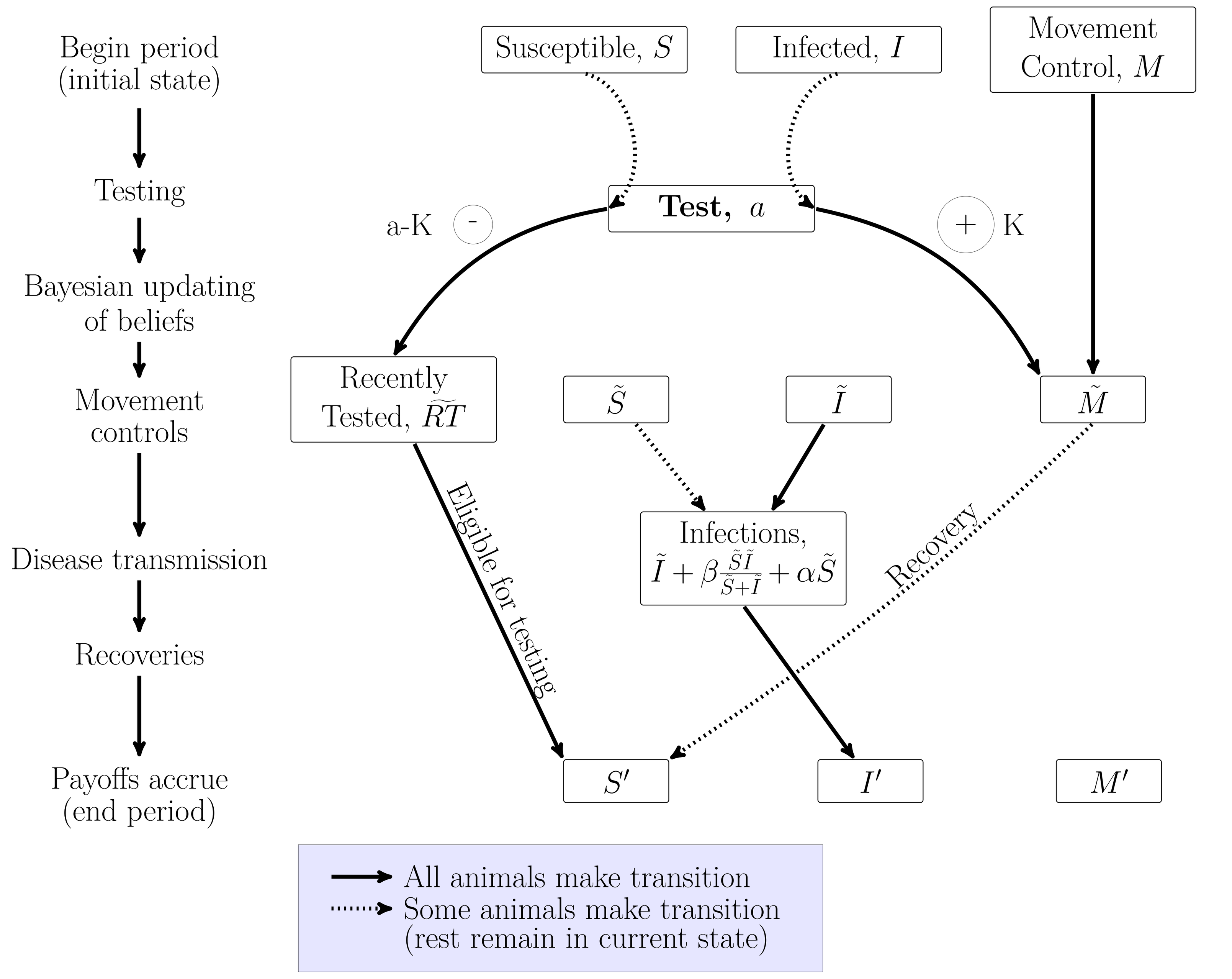
Objectives

i. Compare the value of accounting for physical dynamics and learning in disease management
ii. Develop and refine a methodology for assessing dynamic decision making under uncertainty when the uncertain state is changing and continuous

Methods

- We extend the existing literature of optimal control of disease by allowing for uncertainty regarding the state of interest: disease prevalence.
  - Use a Partially Observable Markov Decision Process (POMDP) framework.
  - Modeling challenge: prevalence changes over time with new infections and recoveries. These changes may be small or large.

System Diagram



Physical Dynamics

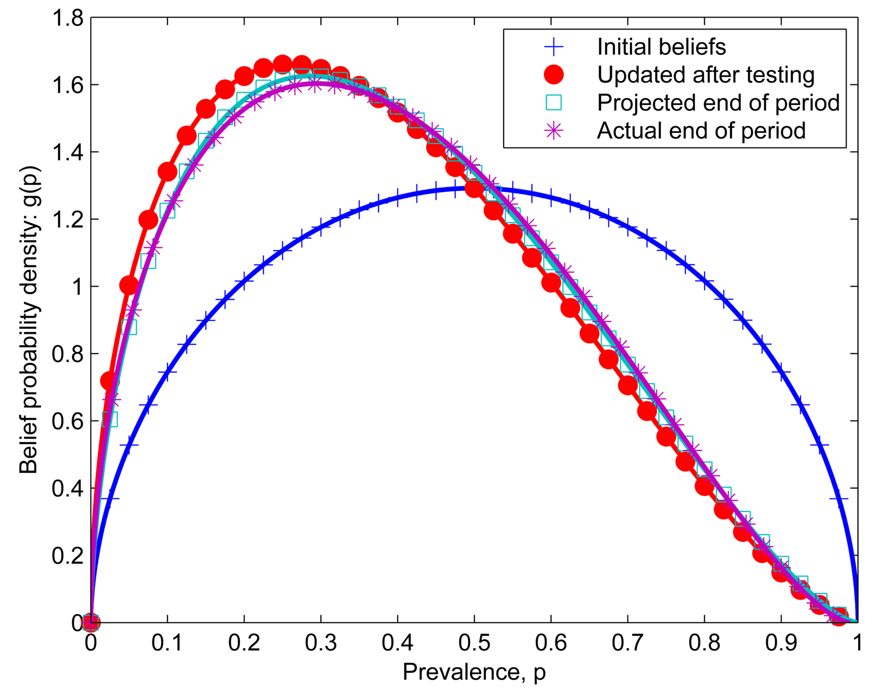
- Meta-population model
  - Herds are susceptible, (latently) infected, under movement controls or recently tested
- Populations transition twice
  1. Testing moves susceptible herds to recently tested group and infected herds to movement controls
  2. Susceptible herds are infected by animal movements and disease vectors; recently tested and movement control herds return to the susceptible population

Equations of motion:

$$S' = (1-\alpha)(S-(a-K)) - \beta\frac{SI}{S+I} + \gamma(M+K)$$
$$I' = I - K + \beta\frac{SI}{S+I} + \alpha(S-(a-K))$$
$$M' = (1-\gamma)(M+K)$$

Information Dynamics

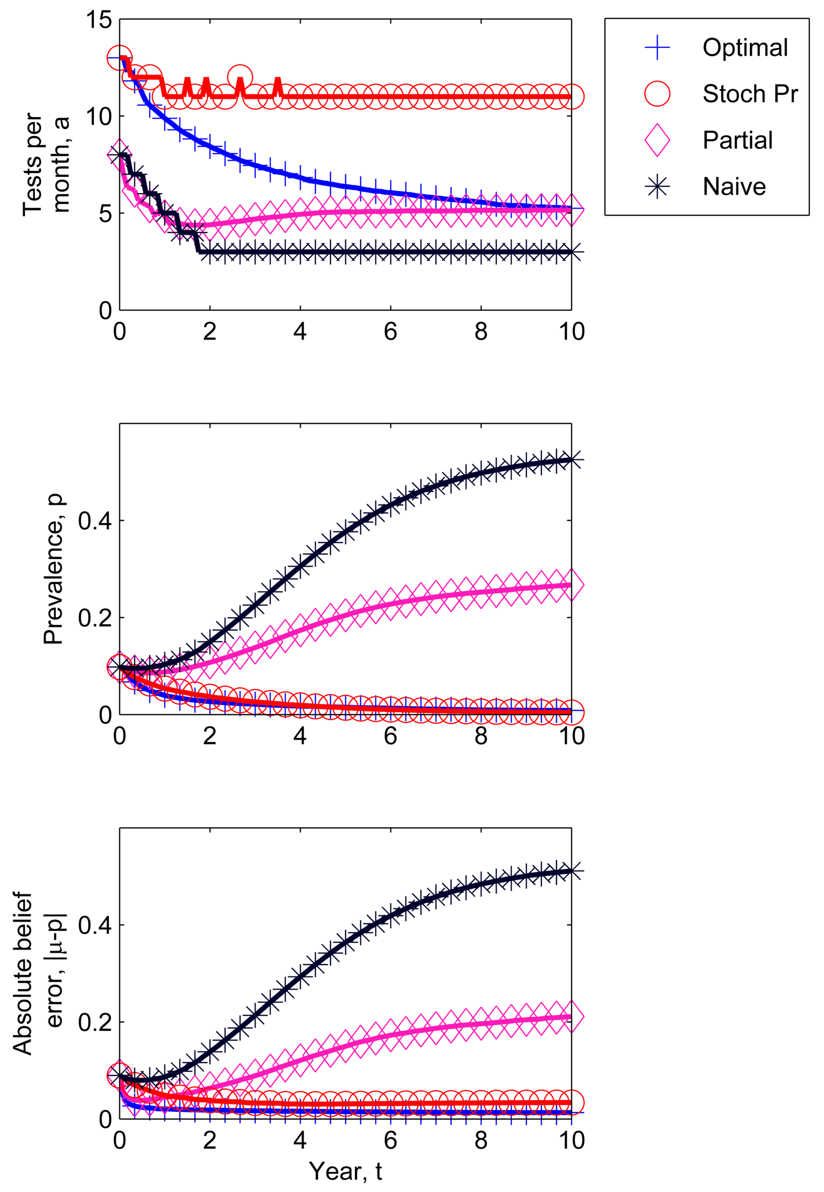
- Beliefs about prevalence are modeled as a beta dist.
- Updating in two steps:
  1. Bayesian updating to account for test results
  2. Density projection to capture shifts in beliefs resulting from known physical dynamics.



Manager Comparison: Testing Rate, Prevalence and Belief Error

We examine four managers that update their beliefs differently based on new infections and test results.

- All managers account for prevalence reductions resulting from selective culling of identified facilities.
- Initial beliefs are shared across managers.
- Results are averages from 5,000 Monte Carlo simulations with randomly drawn initial prevalences.
  - Averages are shown in figures.

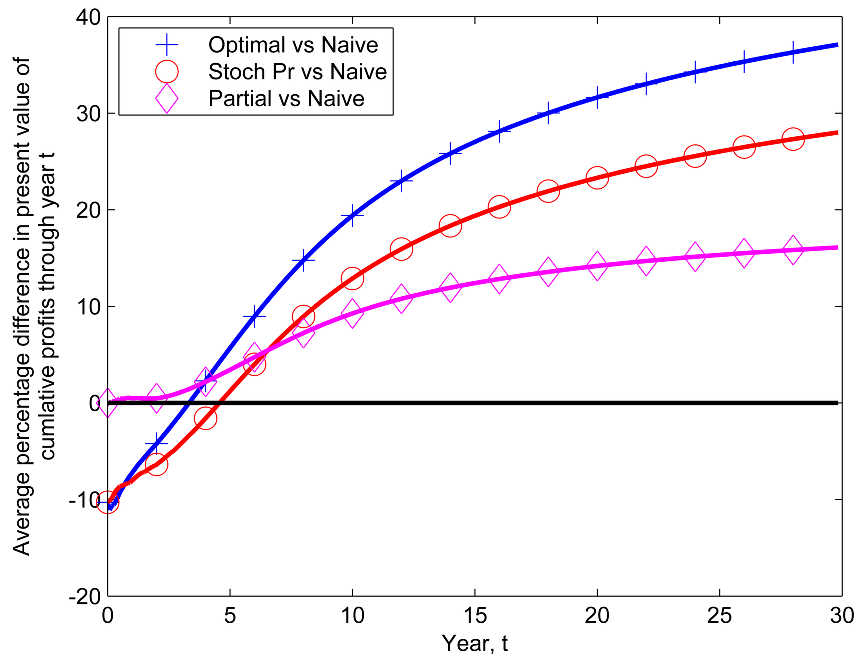


Managers:

1. Optimal manager: considers both test results and infections.
   - High initial test rate that declines over time
   - Prevalence quickly declines
   - Beliefs are the most accurate
2. Stochastic programmer: accounts for new infections but not test results.
   - High test rate throughout
   - Prevalence quickly declines (similar to optimal)
   - Beliefs are somewhat accurate
3. Partial (Bayesian learner): considers test results but not infections.
   - Moderate test rate throughout
   - Moderate prevalence
   - Beliefs are moderately inaccurate
4. Naive: accounts for neither new infections of test results.
   - Low test rate throughout
   - Prevalence quickly takes off
   - Beliefs are the most inaccurate

Welfare Comparison

The distinct testing rate paths result in qualitatively different cumulative welfare (measured in producer profits minus testing costs) trajectories. We compare each of these trajectories to the Naive manager in percentage terms.

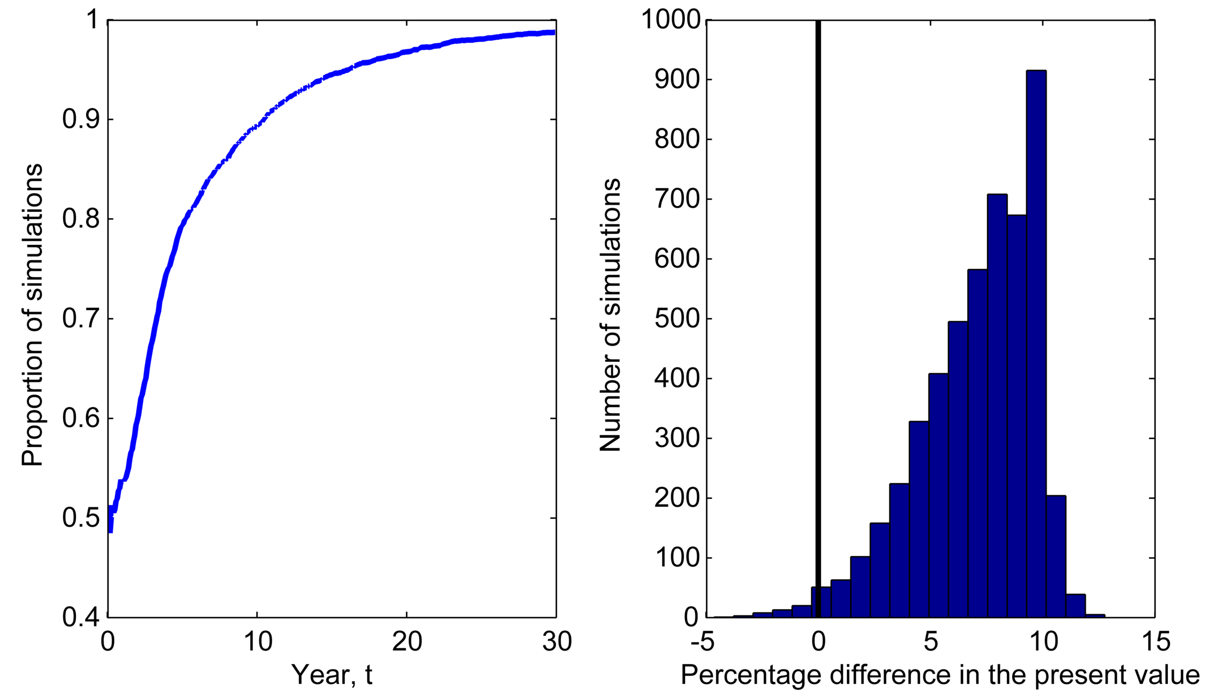


Important features:

- Ignoring transmission leads to lower initial testing rates.
  - High initial welfare that declines as prevalence takes off
  - Partially alleviated by learning
- Stochastic programmer successfully drives down prevalence, but at the cost of excessive testing.
  - In the absence of learning, high testing rate reduces prevalence for a wide range of initial prevalences.
- Gains from learning are immediate and grow over time.

Model Performance Comparison: Optimal vs. Stochastic Programmer

- Concern: average percentage differences in cumulative welfare are driven by outliers.
- We compare the present value of cumulative welfare across the most successful managers (Optimal and Stochastic Programmer)



Important features:

- The proportion of simulations where the Optimal manager's cumulative profits exceed stochastic programmer's is monotonically increasing.
- Optimal manager realizes greater welfare in the majority of simulations (98.7%).

Conclusion

- Substantial gains are realized from accounting for both physical dynamics and learning lead to substantial incremental gains.
  - Accounting for physical dynamics is more important than accounting for learning and uncertainty.
- Learning allows managers to compensate for inaccuracies in beliefs and fundamental errors in understanding of the physical system.

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