

A Hybrid Model of Decision-Making Under Uncertainty

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Modeling Decision Processes is Important to Engineering Systems Research

Some examples:

- Engineering decisions
 - Problem framing – how large will you draw the box?
 - Optimization: Pareto set decisions; defining parameters, constraints, variables
- Management and Policy decisions
 - Predictions of how a population respond to a change
 - Interpretation and use of model results
- Individual choices and preference
 - Modeling product demand and market share can help determine costs, production scale, advertising campaigns, environmental impacts
 - Modeling consumer product preference allows the design of more preferable products

Decision Fundamentals

All decisions share common concepts

- Collecting relevant knowledge
- Framing prospects and associated outcomes
- Assessing the likelihood of outcomes
- Valuing the prospects and outcomes
- Making a choice
- Observing the outcome
- Iteration!

Research on Decision Fundamentals

Collecting relevant knowledge

Framing prospects and associated outcomes

Assessing the likelihood of outcomes

Valuing the prospects and outcomes

Making a choice

Observing the outcome

Iteration!

Heuristics and Biases

Construction of
Preferences

Choice Modeling

Reinforcement Learning
Motivational Research

Approaches to Modeling Decisions

- **Observe decisions**
 - Fit real-world decision data to a model
 - Is the model applicable to new decision situations?
- **Self-explicated decisions**
 - Ask “Why?”
 - Quantitative or qualitative analysis to form model
 - Varying levels of usefulness and accuracy, depending on decision
- **Experiment with decisions**
 - Measure choices in an experimental setting
 - Estimate empirical model to predict choices
 - Heuristics, biases, and construction of preference can be studied as experimental manipulations
 - Subject to experimentally-induced biases, limits of knowledge provided in experiment
 - Expensive and cognitively taxing

A new approach to Decision Modeling:

“First Principles” Hybrid

- Analogy: Engineering

Physical constants can either be deduced from experiments or derived from mathematical representations (or both).

- We hypothesize that certain components of a decision can also be modeled empirically or derived from psychological representation (or a combination of the two).

Advantages of Hybrid Decision Modeling Approach in Engineering Systems

- Ability to match levels of information in user decision-making and engineering systems, as well as uncertainty in parameters
- Particular to System Dynamics: Incremental changes in systems can be balanced with decisions based on incremental information updates
- Can use both empirically-estimated and first principles representations of decisions in the same model

Case Study: Prospect Theory

Modeling decision making under risk

Consider a simple decision involving risk:

- The decision maker chooses one option from a pair of options, where each option offers its outcomes probabilistically
- We observe repeated decisions
- Observations summarized as a vector of binary codes 011010001... indicating the choices made by the decision maker
- Report the proportion of times 1 is selected

Typical Empirical Decision Models

- Observations are binary and reported as proportions
- Typical models impose a latent, unobserved construct that is continuous and a transformation maps the construct to choice probability, for example, a logit choice model
 - $Z = XB + e$ for design matrix X , unknown parameter vector B and error vector e
 - $1/(1+\exp(z))$ maps Z to the interval $[0,1]$

Behavioral Highlights from Decision Making Research

- Risk aversion in gains
- Risk seeking in losses
- Loss aversion

Classic decision making models under risk do not treat gains and losses separately, but behaviorally there is much evidence that people respond differently.

Gains and Losses

- $(1, \$3000) > (.80, \$4000)$ (80%)

Consistent with “risk aversion”

- $(1, -\$3000) < (.80, -\$4000)$ (92%)

Reversal: risk seeking in losses

The Value Function

- Risk aversion in gains implies concavity of the value function
- Risk seeking in losses implies convexity of the value function
- Loss aversion implies the value function is steeper in losses than in gains

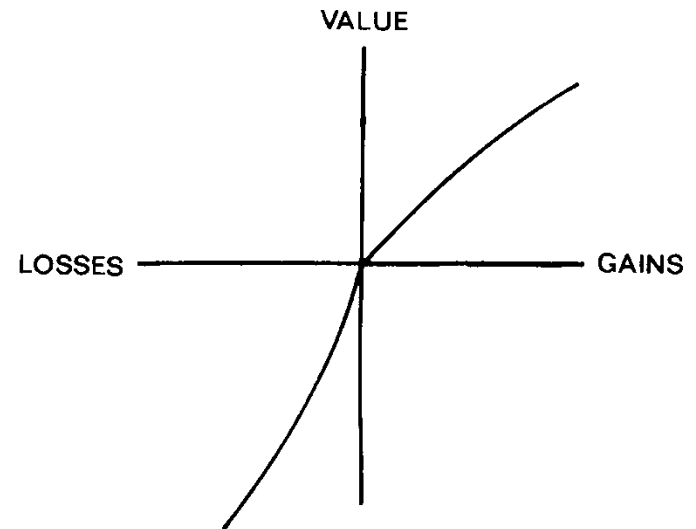


FIGURE 3.—A hypothetical value function.

Typical Functional Form: Two piece power

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x)^\beta & \text{if } x < 0 \end{cases}$$

α = risk aversion parameter (gains)	0.88
β = risk seeking parameter (losses)	0.88
λ = loss aversion	2.25

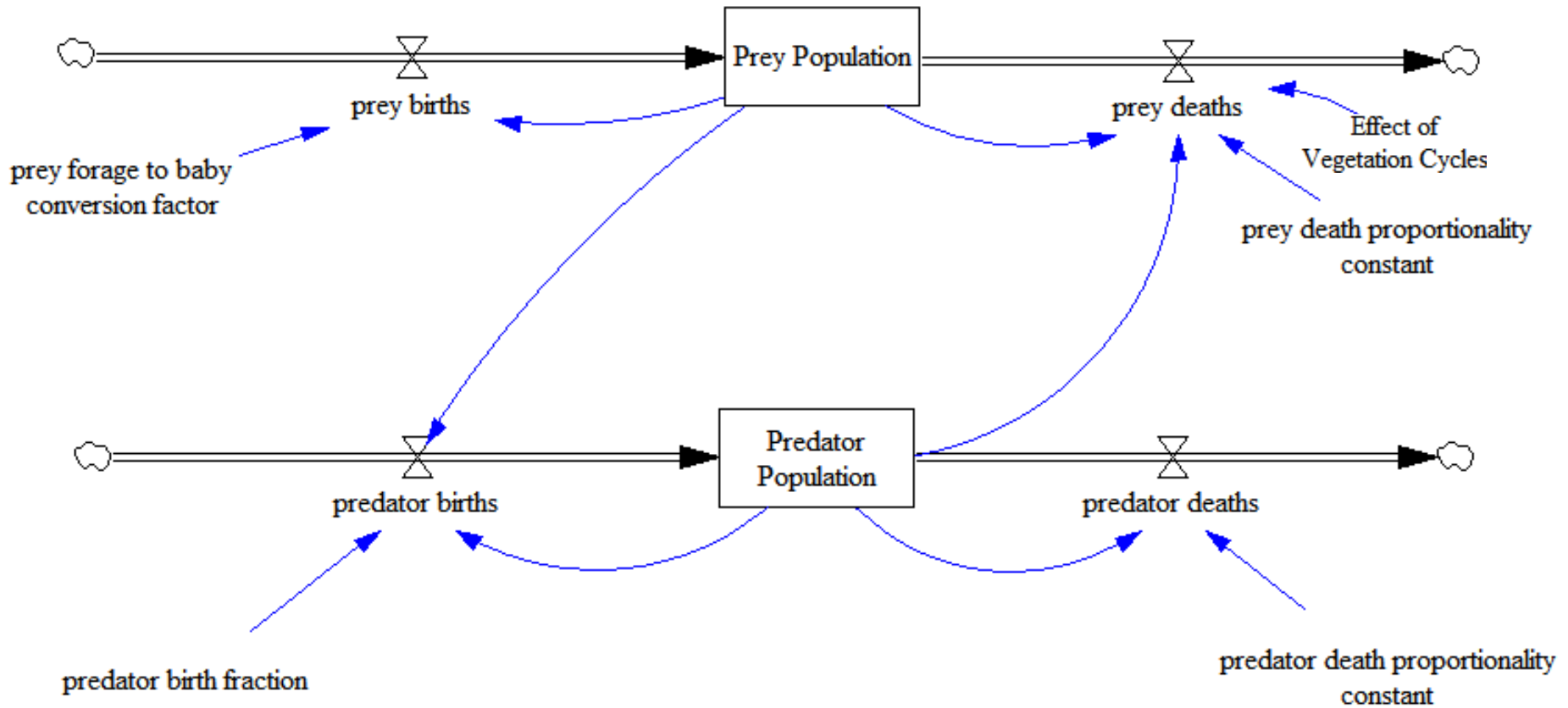
Limitations in the literature

- Structure is empirically inferred from choice
- No theoretical mechanism, merely descriptive
- Learning is not typically modeled
- Feedback rarely occurs, so preference changes in response to changing environment are rarely examined

Cumulative Prospect Theory (CPT)

- Combines the value function with a risk weighting function to arrive at a reasonable predictive model of how people make decisions
- Weighting function left for future discussion
- Integration with System Dynamics is fluid because CPT hypothesizes that outcomes are evaluated as incremental gains and losses

Simple Example

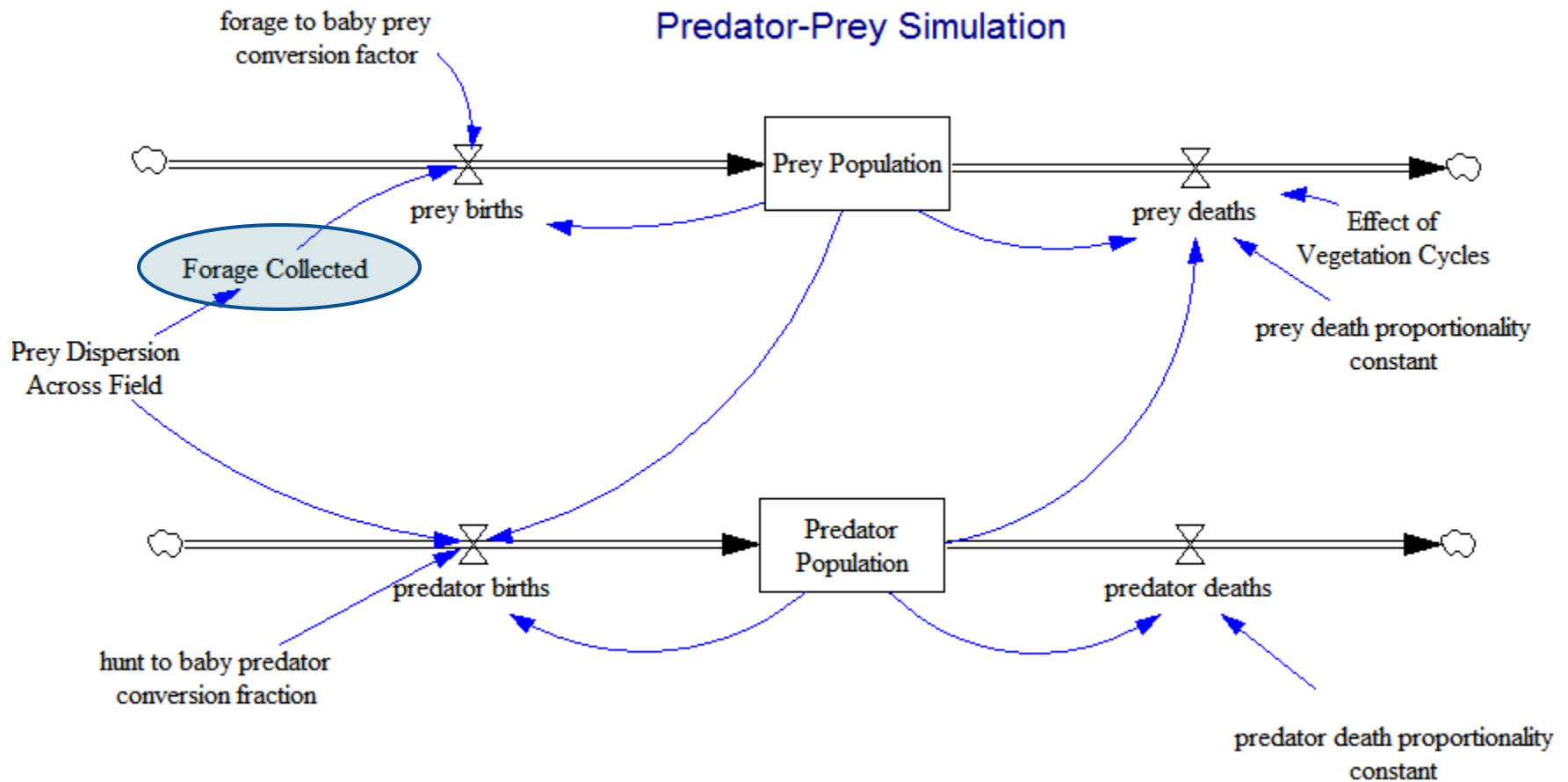


Source: <http://www.shodor.org/refdesk/BioPortal/model/VSpredatorPrey?level=college>

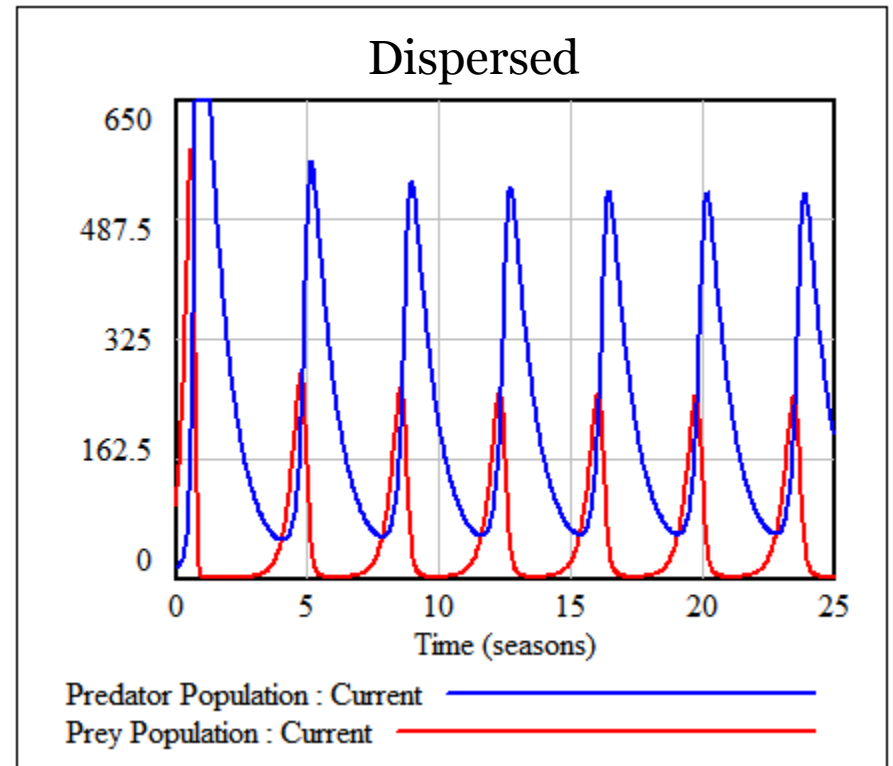
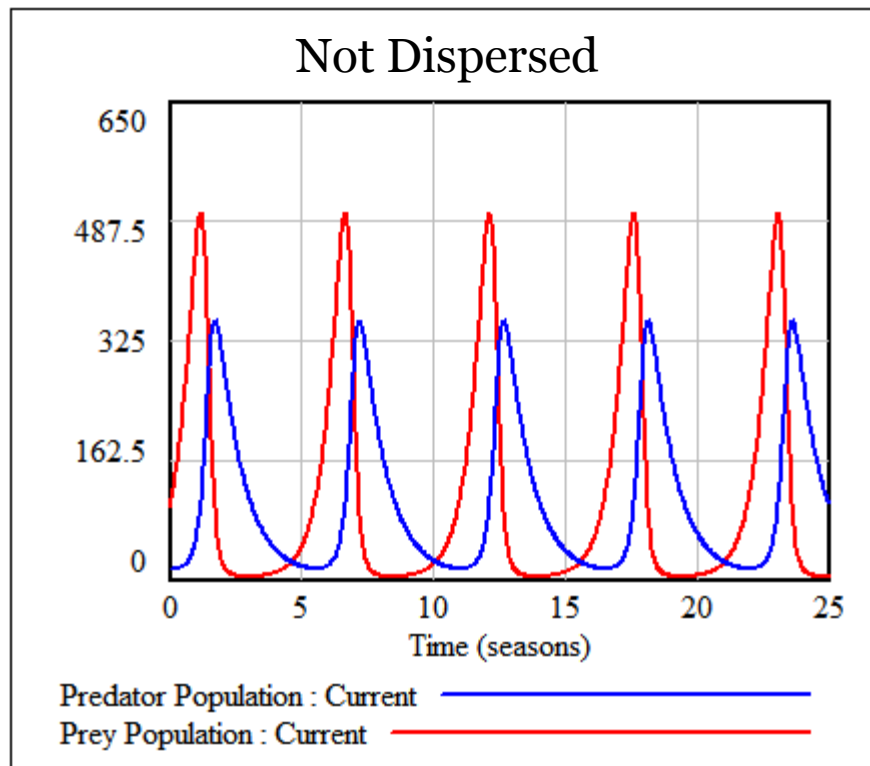


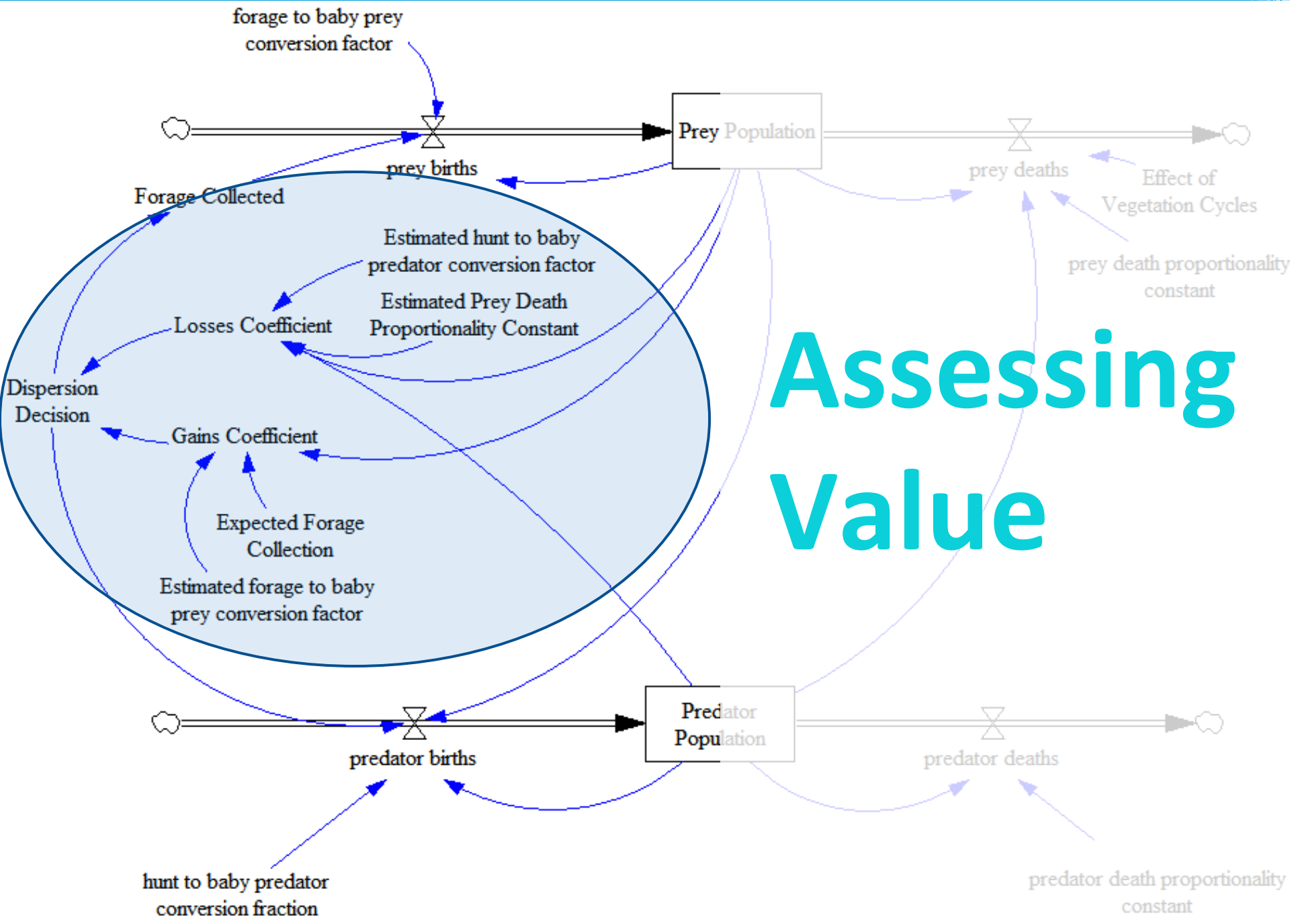


The sheep experiment.

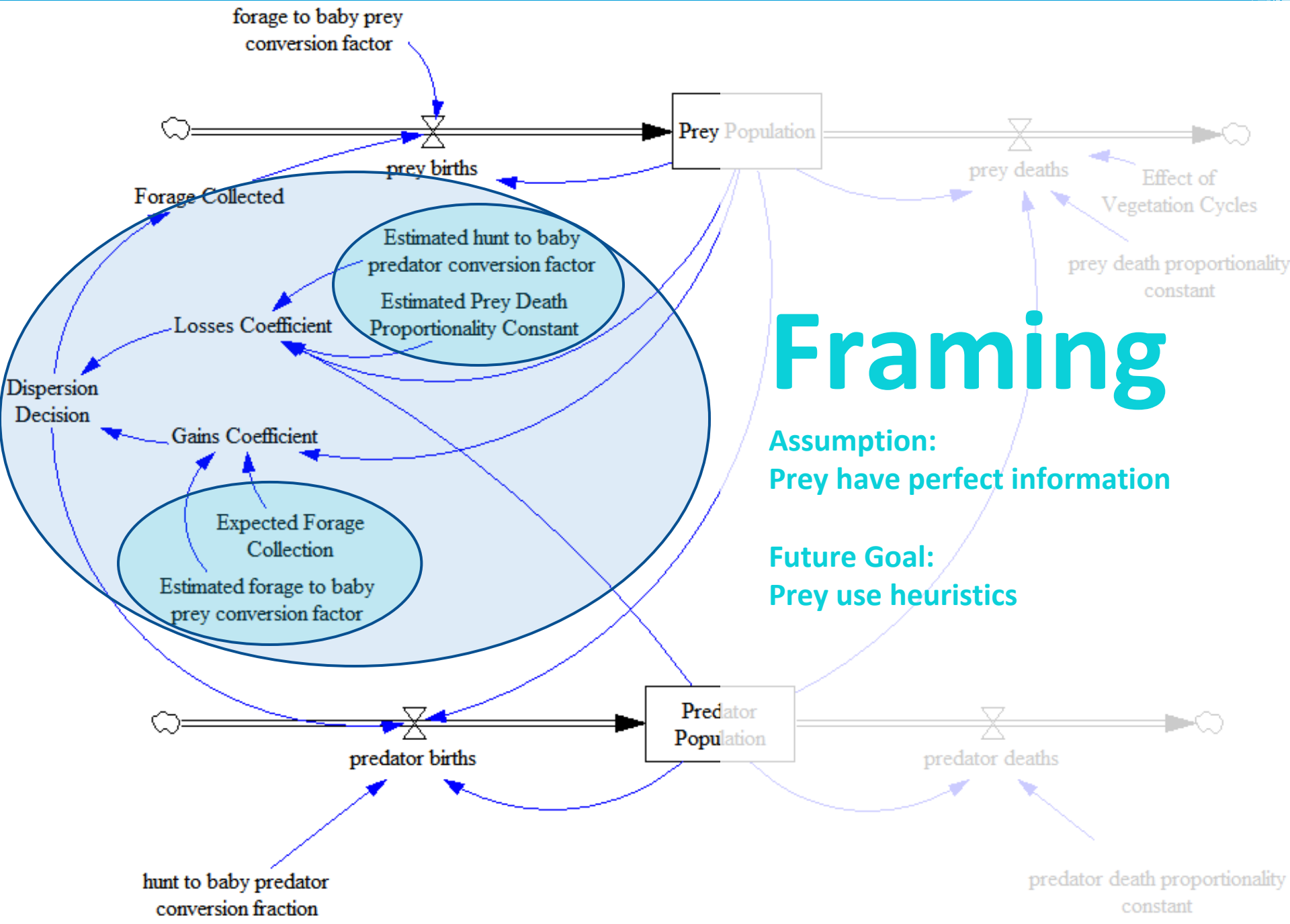


Results “Herd Mentality”

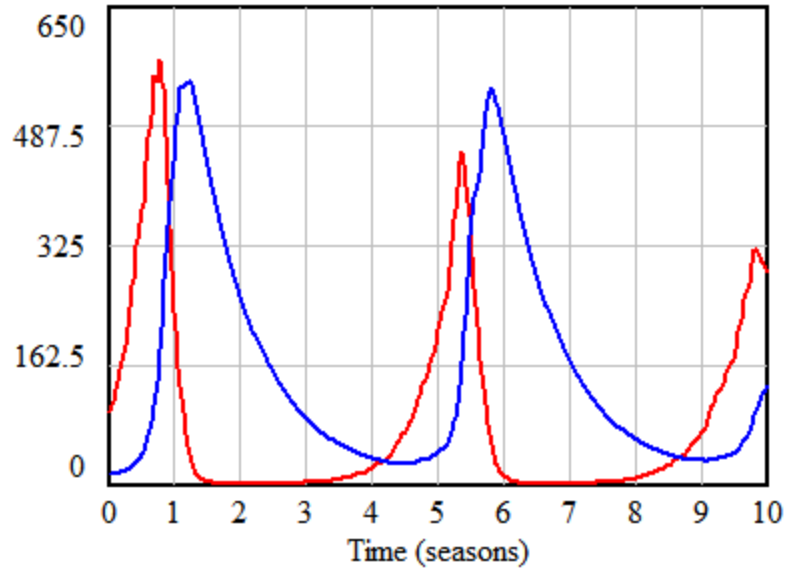




Assessing Value

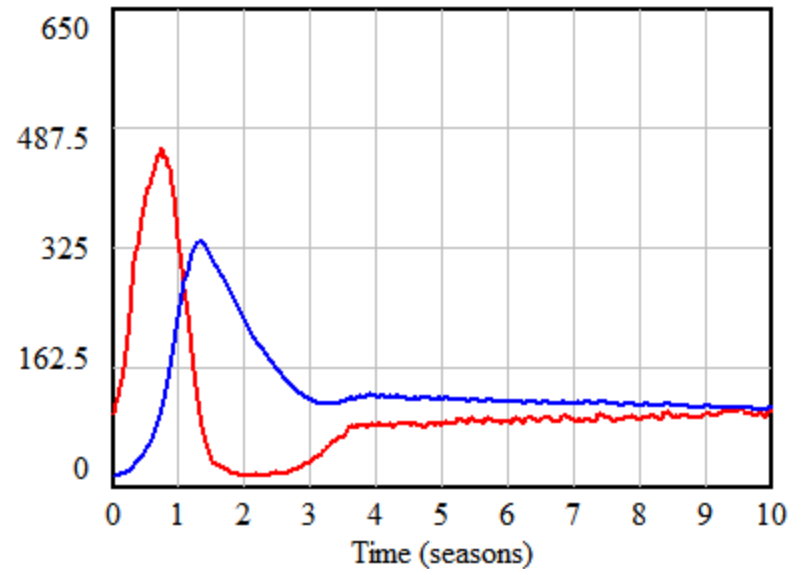


Random Dispersion Decision



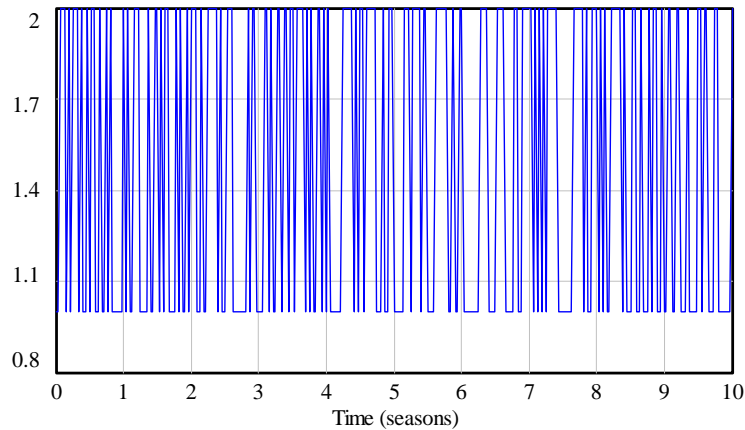
Predator Population : Current —————
Prey Population : Current —————

Engaged Dispersion Decision

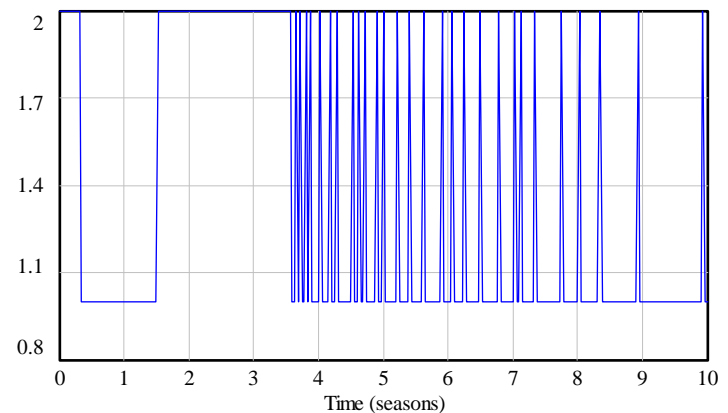


Predator Population : Current —————
Prey Population : Current —————

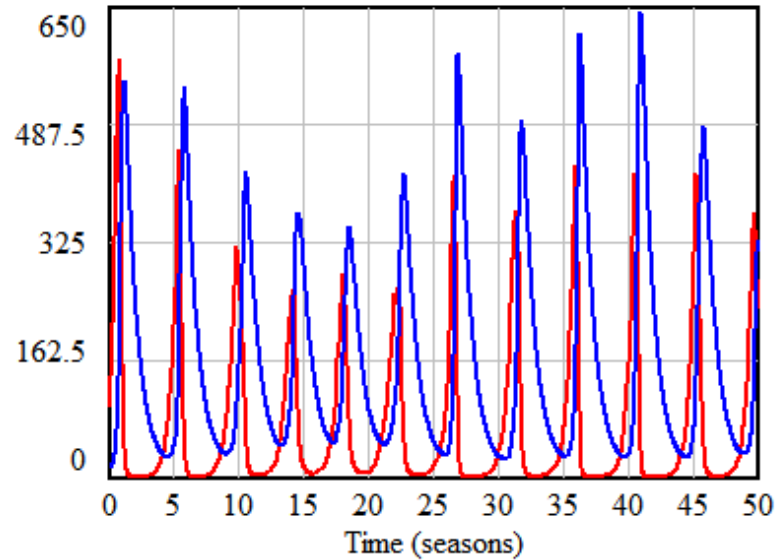
Dispersion Decision



Dispersion Decision

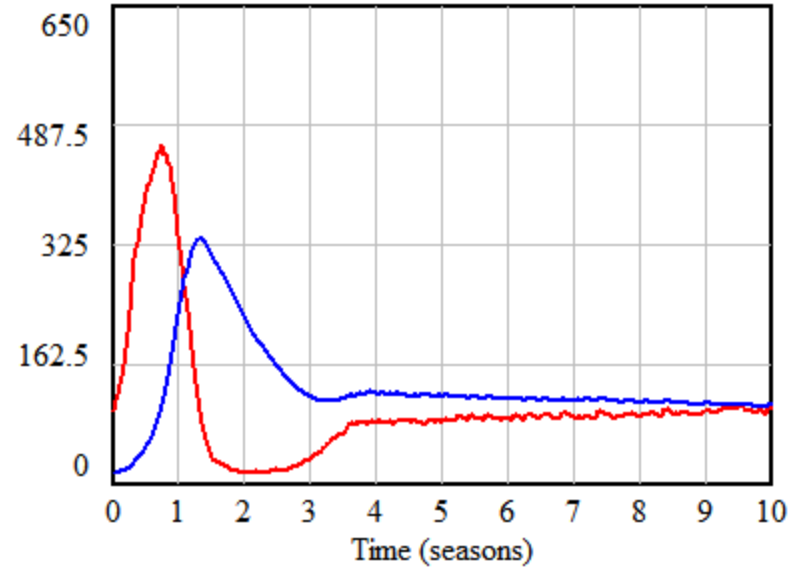


Random Dispersion Decision



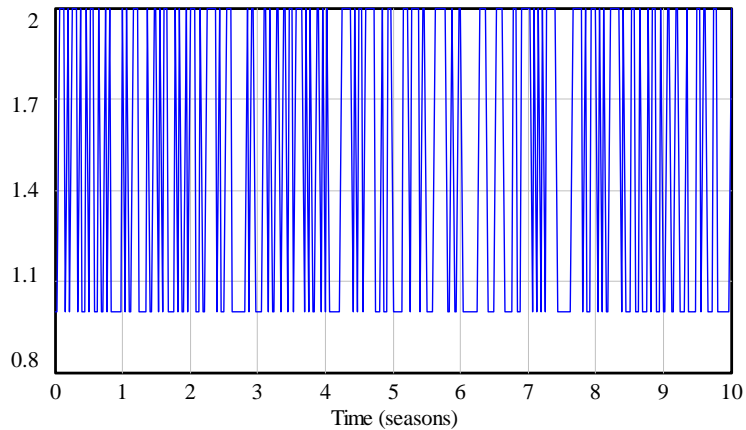
Predator Population : Current ————
Prey Population : Current ————

Engaged Dispersion Decision

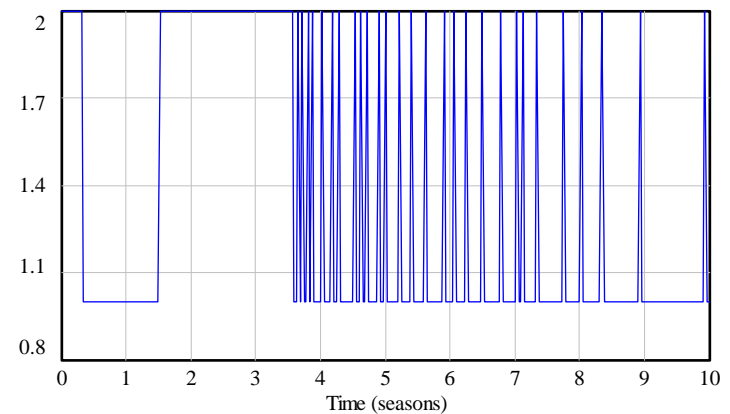


Predator Population : Current ————
Prey Population : Current ————

Dispersion Decision



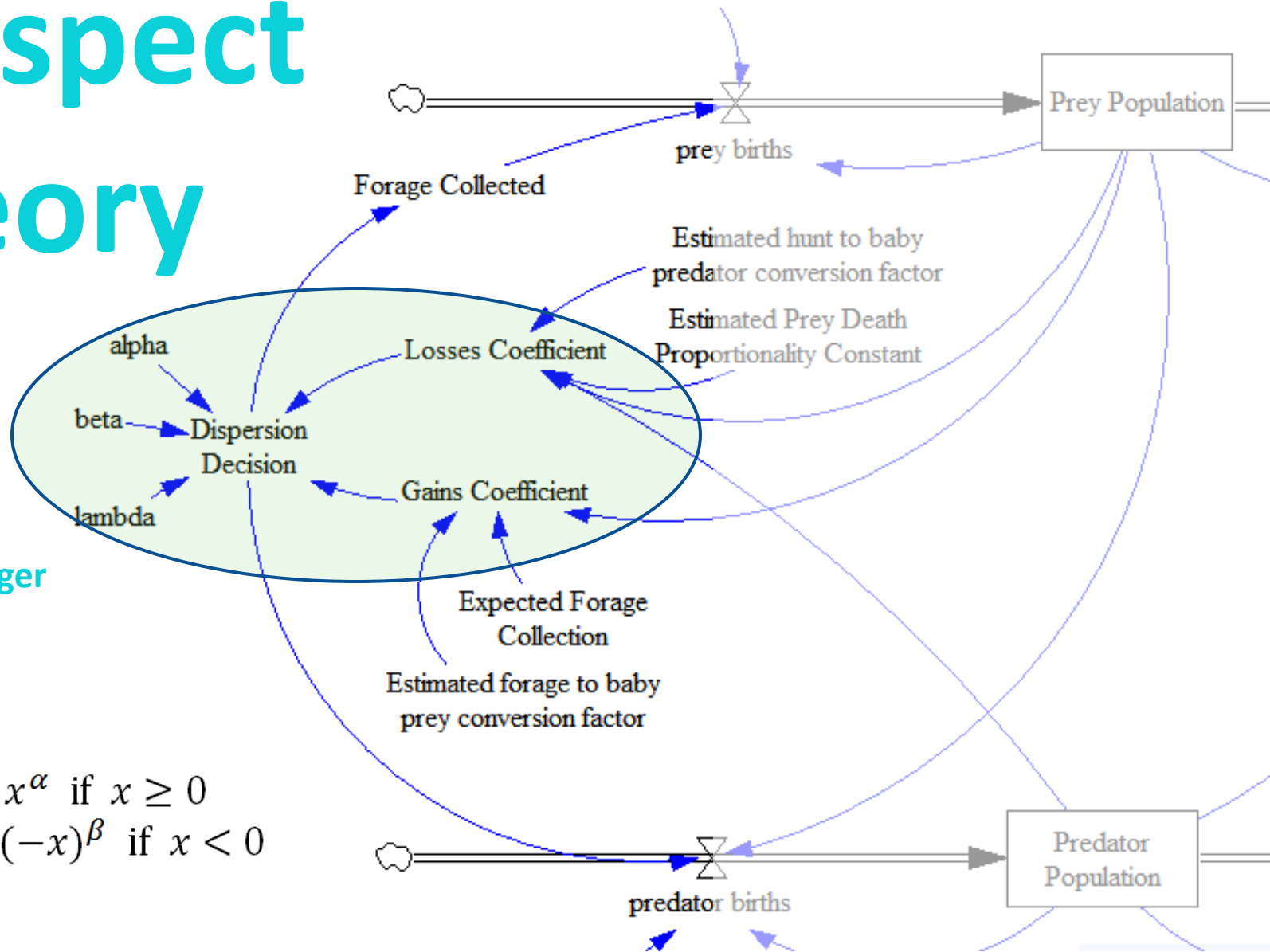
Dispersion Decision



Prospect Theory

Loss loom larger than gains.

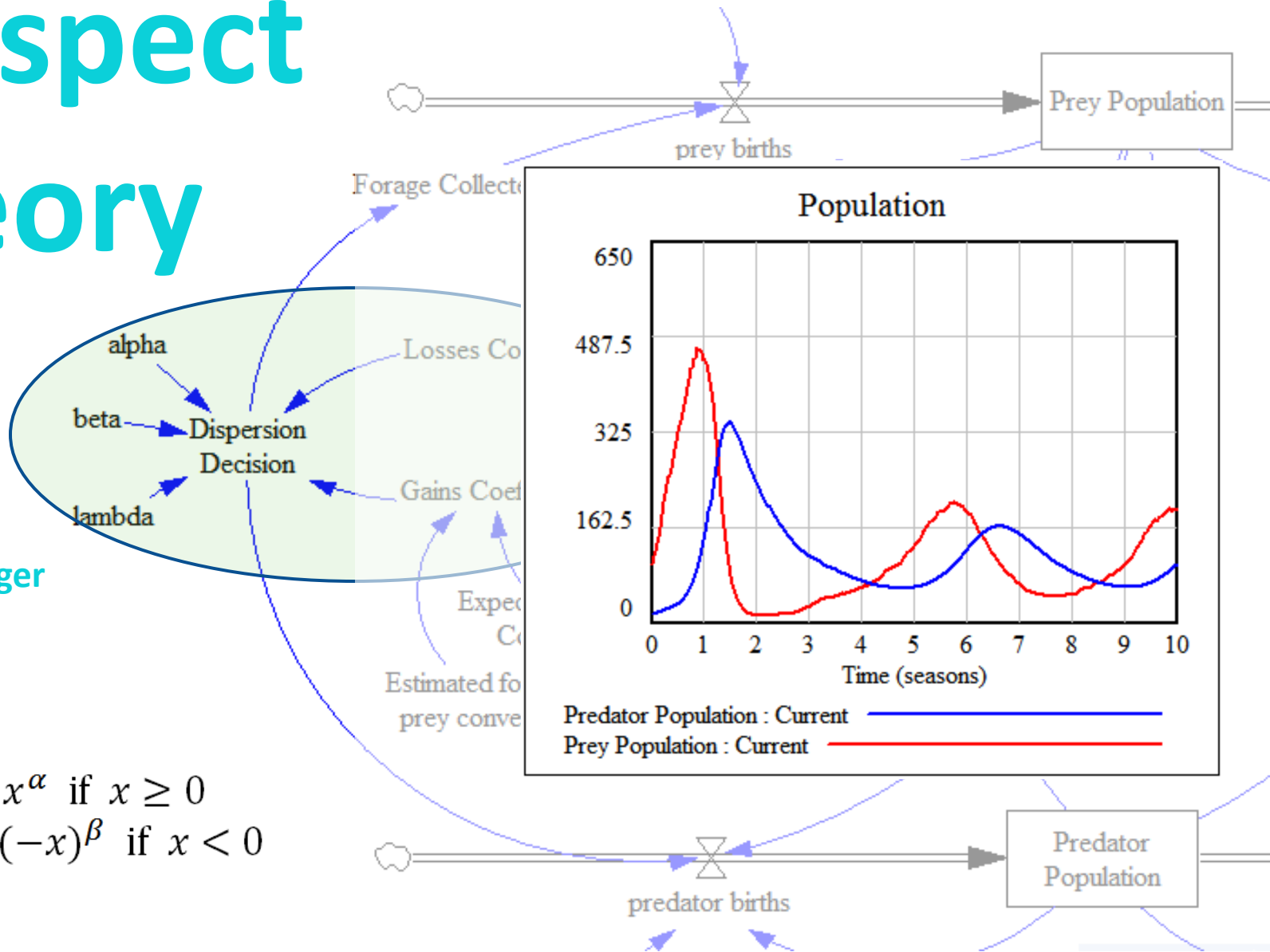
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Prospect Theory

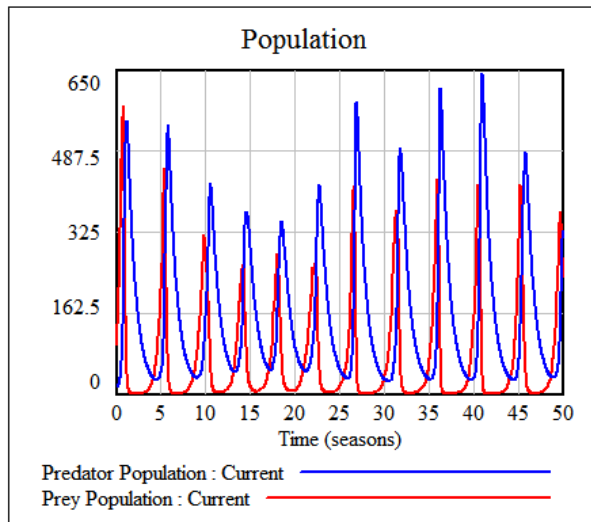
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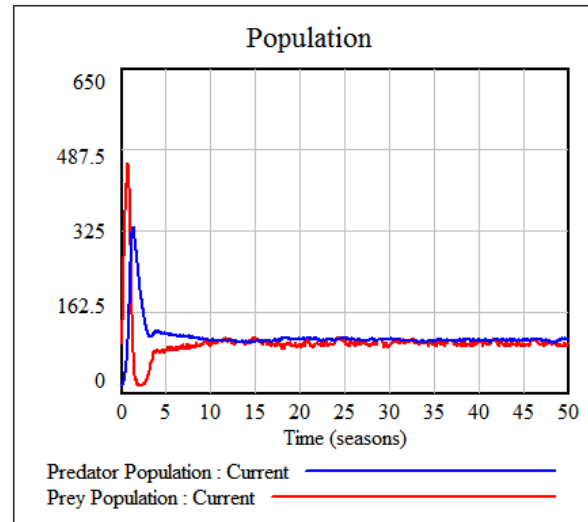


Prospect theory acts as a dampener, perhaps working well with imperfect information and heuristics in decisions.

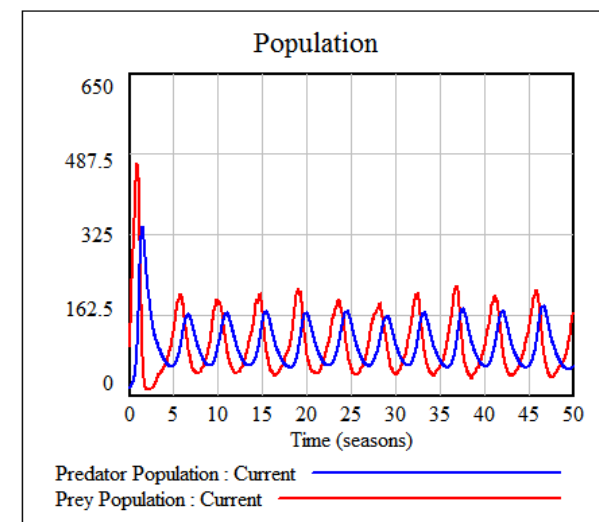
Random Decision



Max Value:
Gains/Losses Equal Value



Max Value:
Losses Loom Larger than Gains



Next Steps

- Remove hard-coded prospect theory coefficients
- Remove perfect information from prey's decision
- Add heuristics
- Add reinforcement learning
- What prospect theory coefficients will develop?

Looking forward

- Engineering and product choice models
 - Can we predict demand for new products using only principles from psychology and current “known” product information?
 - Is the level of detail enough to produce useful results?
 - What will customer inputs to this process look like?
- Encouraging people to buy sustainable products
 - What happens to green product sales when we increase/decrease social desirability bias?
 - Can we activate certain judgment heuristics using product design to increase demand? For example, increased trust of environmental impact information provided by company, or decreased cognitive dissonance.
 - Experiment with motivation for behavior change and reinforcement learning with respect to sustainable product purchase and use decisions