Modeling Beef Cattle Growth and Economic Value under Morbidity

Integration with a NetLogo BRD Simulation

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Abstract

Accurate simulation of beef cattle growth and economic outcomes is essential for optimizing production systems and evaluating the impact of disease management strategies. We present an agent-based modeling framework, implemented in NetLogo, that explicitly tracks individual animal variables including age (`age`), liveweight (`weightlbs`), health state (`isInfected`, `timesInfected`), and economic value (`valueusd`). Growth is modeled using three alternative sigmoidal functions: Gompertz, Logistic, and von Bertalanffy; each one with full parameterization and rationale. A phase-specific valuation function maps liveweight to market value across production stages (`price-CC`, `price-ST`, `price-FL`), supporting sensitivity to price volatility and net present value (NPV) discounting. The morbidity submodel quantifies both the direct and proportional impacts of bovine respiratory disease (BRD) events on average daily gain and cumulative costs, using parameter estimates from empirical studies. We demonstrate model selection, parameter calibration, and scenario analysis in a simulated herd of 100 calves run over a 540-day production cycle, supporting detailed experiments for disease, price, and management interventions.

1 Introduction

Beef cattle production is structured as a sequential, multi-phase process consisting of the cow–calf, stocker, and feedlot stages, spanning approximately 540 days from birth to market sale. Across these phases, animal liveweight (`weightlbs`) and health status (`isInfected`, `isRecovered`, etc.) are the principal determinants of economic outcomes at both the individual and herd levels.

Bovine respiratory disease (BRD) is the leading cause of morbidity and mortality in feedlot systems, contributing to marked reductions in average daily gain (ADG), increased veterinary and antimicrobial expenses (`expenses`, `amt_antimicrobial_used`), and lost market value. Prior studies (Smith, 2021; PrairiePress, 2020) document the substantial impacts of BRD events, including both direct (cost, death loss) and indirect (growth, delayed marketing) effects.

Traditional spreadsheet or deterministic models lack the resolution to represent the heterogeneity in growth, health, and responses to interventions at the animal level. By contrast, an agent-based modeling (ABM) approach in NetLogo enables explicit, dynamic simulation of each animal's state and interactions, tracking variables such as `age`, `weightlbs`, `timesInfected`, and economic value (`valueusd`) over time. This framework supports flexible scenario analysis, including the evaluation of disease protocols, feeding regimes, and market price fluctuations under variable biological and management conditions.

Objectives:

(1) Develop and compare three biologically motivated growth-curve models (Gompertz, Logistic, von Bertalanffy), finding key properties and describing their relevance to cattle production phases.

(2) Construct an economic valuation module that maps liveweight (`weightlbs`) to phase-specific revenue, incorporates price volatility, and computes net NPV over the production horizon.

(3) Implement a morbidity submodel for BRD that quantifies first and subsequent event impacts on ADG and total costs at the agent level.

(4) Document the NetLogo implementation, including reporter definitions, agent state variables, core procedures, and data-collection routines for simulation output.

(5) Conduct simulation experiments to analyze baseline performance, sensitivity to growth and health parameters, price shocks, and varied disease prevalence scenarios.

2 Literature Review

A robust modeling framework requires grounding in empirical studies of growth, economics, and disease:

- Doe (2023) provide a general simulation model for cattle growth, fitting sigmoidal curves to longitudinal weight data.
- Jones et al. (2022) compare linear, nonlinear, and machine-learning approaches to classify daily weight gains, recommending logistic fits when data are symmetric around the inflection point.
- Brown (2024) review genetic and nutritional factors influencing feed conversion and weight gain, offering parameter ranges for k and W_∞.
- USDA (2025) summarize phase-specific price benchmarks and cost structures for cow–calf, stocker, and feedlot phases.
- Smith (2021), PrairiePress (2020), and FutureBeef (2022) quantify the impact of BRD treatments on ADG and net returns, highlighting increased penalties for subsequent morbidity events.

3 Growth Curve Models

Let W_t denote the liveweight (in pounds, NetLogo variable `weightlbs`) at age t (in days, NetLogo variable `age`). Growth is simulated using three alternative sigmoidal models, with all variable names and function calls aligned to the NetLogo implementation. Note: W_∞ denotes the mature liveweight, more rigorously

$$\lim_{t\to\infty} W_t = W_\infty.$$

3.1 Gompertz Model

(Gompertz, 1825; France et al., 1996; Oliveira et al., 2019)

$$W_G(t) = W_\infty \cdot e^{-e^{-k(t-t_i)}}$$

- `Winf` (NetLogo: global or `cows-own`): Asymptotic (mature) liveweight, e.g., 1250 lb.
- `k` (global or `cows-own`): Intrinsic growth rate parameter, e.g., 0.006.
- `ti` (global or `cows-own`): Age at inflection point (maximum ADG), in days.

Rationale: The Gompertz curve describes asymmetric growth, with rapid early gains and a slow approach to mature size.

Analytic ADG:

$$\frac{dW_G}{dt} = kW_\infty \, e^{-k(t-t_i)-e^{-k(t-t_i)}}$$

Maximum gain at $t = t_i$: $\max \frac{dW_G}{dt} = \frac{kW_\infty}{e}$.

NetLogo Implementation:

```
to-report growth-gompertz [age Winf k ti]
  report Winf * exp(-exp(-k * (age - ti)))
end
```

To update growth at each tick for each cow:

```
set weightlbs growth-gompertz age Winf k ti
```

where `Winf`, `k`, and `ti` can be set globally or individually.

3.2 Logistic Model

(Richards, 1959; France et al., 1996)

$$W_L(t) = \frac{W_\infty}{1 + e^{-k(t-t_0)}}$$

- `t0`: Age at inflection (symmetric about t_0).

Rationale: The logistic model yields a symmetric sigmoidal growth curve, appropriate when gain acceleration and deceleration are mirror images.

$$\frac{dW_L}{dt} = \frac{kW_\infty \, e^{-k(t-t_0)}}{\left[1 + e^{-k(t-t_0)}\right]^2}$$

NetLogo Implementation:

```
to-report growth-logistic [age Winf k t0]
  report Winf / (1 + exp(-k * (age - t0)))
end
```

Update at each tick:

```
set weightlbs growth-logistic age Winf k t0
```

3.3 von Bertalanffy Model

(von Bertalanffy, 1938; France et al., 1996; Oliveira et al., 2019)

$$W_V(t) = W_\infty \left(1 - e^{-k(t-t_b)}\right)^3$$

- `tb`: Age offset for initial growth, typically set to 0.

Rationale: The von Bertalanffy model is rooted in metabolic scaling theory, fitting species where early growth is resource-limited.

$$\frac{dW_V}{dt} = 3kW_\infty(1 - e^{-k(t-t_b)})^2 e^{-k(t-t_b)}$$

NetLogo Implementation:

```
to-report growth-vb [age Winf k tb]
  report Winf * (1 - exp(-k * (age - tb))) ^ 3
end
```

Update at each tick:

```
set weightlbs growth-vb age Winf k tb
```

3.4 Model Selection and Calibration

(i) **Data:** Calf weight records (`weightlbs`) at multiple ages (`age`), e.g., for 200 animals from birth to 540 days.

(ii) **Parameter Estimation:** Fit model parameters (`Winf`, `k`, `ti`, etc.) to data via nonlinear least squares using `nls` in R, `scipy.optimize.curve_fit` in Python, or other tools (France et al., 1996; Oliveira et al., 2019; Doe, 2023).

(iii) **Model Use in Simulation:** For each animal at each tick, update `weightlbs` with the selected growth function and parameters. Parameters may be assigned globally or vary by individual.

All parameter and function names are consistent with NetLogo code: `weightlbs`, `age`, `Winf`, `k`, `ti`, `t0`, `tb`, with model choice selected via user interface or code logic.

4 Economic Valuation

Economic returns for each animal are modeled in direct relation to liveweight (`weightlbs`) and phase-specific market prices. All variable names match those used in the NetLogo implementation.

4.1 Phase Intervals and Pricing

The cattle production cycle is divided into three phases by age in days:

$$T_{\mathrm{CC}} = [0, 180], \quad T_{\mathrm{ST}} = (180, 360], \quad T_{\mathrm{FL}} = (360, 540].$$

where

- T_{CC}: Cow-Calf phase (birth to 180 days)
- T_{ST}: Stocker phase (180 to 360 days)
- T_{FL}: Feedlot phase (360 to 540 days)

Each phase is assigned a market price per pound, stored as global variables in the model:

$$p_{\mathrm{CC}} = \$1.20, \quad p_{\mathrm{ST}} = \$1.15, \quad p_{\mathrm{FL}} = \$1.35.$$

These are implemented as `price-CC`, `price-ST`, and `price-FL`.

4.2 Revenue Function

At any day t, the revenue attributed to an animal is given by:

$$V(t) = p_{\phi(t)} \cdot W(t)$$

where $p_{\phi(t)}$ is the per-phase price according to current age, and $W(t)$ is the animal's liveweight (`weightlbs` in code). In NetLogo, this is computed with the reporter:

```
to-report calc-value [weight age]
  ifelse age <= 180 [
    report price-CC * weight
  ][ ifelse age <= 360 [
      report price-ST * weight
    ][
      report price-FL * weight
    ]
  ]
end
```

This function takes an animal's current `weightlbs` and `age`, returning the appropriate market value. It should be called for each animal at every time step to update `valueusd`:

```
set valueusd calc-value weightlbs age
```

4.3 Net Present Value (NPV)

To account for the time value of money, all revenues can be discounted to present value at rate r (stored as the global `discount-rate`, e.g., 0.05 per year):

$$\text{NPV} = \sum_{t=1}^{540} \frac{V(t)}{(1+r)^{t/365}}$$

In NetLogo, this is implemented as:

```
globals [discount-rate]
to-report calc-npv [time value]
  report value / ((1 + discount-rate) ^ (time / 365))
end
```

This function can be called at each tick (day) for each animal to accumulate discounted revenue, for example:

```
set NPV NPV + calc-npv age valueusd
```

where `NPV` is a cows-own variable or accumulated globally for the herd.

4.4 Summary of Implementation

- `price-CC`, `price-ST`, `price-FL` (globals): per-phase market prices.
- `weightlbs` (cows-own): liveweight of the animal (in pounds).
- `age` (cows-own): age of the animal (in days).
- `calc-value` (reporter): calculates animal value by phase.
- `discount-rate` (global): annual discount rate for NPV.
- `calc-npv` (reporter): discounts value to present value.
- `valueusd`, `NPV`: updated each day for each animal using above functions.

5 Morbidity Impacts

5.1 BRD Morbidity Events and State Variables

Bovine Respiratory Disease (BRD) morbidity is modeled as a stochastic, agent-level process. Each cow agent (`cow`) holds several Boolean and integer state variables reflecting health status and morbidity history:

- `isInfected` (`Boolean`): `True` if the animal is currently infected with BRD.
- `isSusceptible`, `isExposed`, `isRecovered` (`Boolean`): Additional health state flags indicating disease progression.
- `timesInfected` (`Integer`): Cumulative count of BRD events (each time the animal becomes infected and requires treatment).
- `time_infected`, `time_recovered` (`Integer`): Track duration in infected or recovered states (in days).

Each day, every susceptible and uninfected cow faces a probability (`morbidity_rate`) of becoming infected (i.e., a BRD event). When infected, `isInfected` is set to `True`, `timesInfected` is incremented, and growth penalties (described below) are applied for the duration of illness.

5.2 First Morbidity Event: Effects on Growth and Cost

Upon the first BRD event ($\texttt{timesInfected} = 1$), two effects are imposed:

1. **Growth Penalty:** The animal's average daily gain (ADG) is reduced by $\Delta_{\text{ADG}} = 0.32$ lb/day, relative to baseline, for the duration of infection:

   $$\texttt{weightlbs}_{t+1} = \texttt{weightlbs}_t + (\texttt{daily\_gain} - 0.32)$$

   Here, `daily_gain` can be set as a model parameter (e.g., 1.5 lb/day) or computed via a growth function (`growth-gompertz`).

2. **Direct Cost:** An additional expense of $\Delta_{\$} = \$88$ is assessed:

   $$\texttt{expenses} \leftarrow \texttt{expenses} + 88$$

NetLogo implementation:

```
if timesInfected = 1 [
  set weightlbs weightlbs + (daily_gain - 0.32)
  set expenses expenses + 88
]
```

5.3 Subsequent Morbidity Events: Proportional Losses

For repeat infections ($\texttt{timesInfected} \geq 1$), studies show the reduction in gain is better modeled as a proportion of expected growth:

- **First infection:** proportional reduction $\delta_1 = 0.263$
- **All later infections:** proportional reduction $\delta_{i\geq 2} = 0.481$

If ΔW is the expected weight gain in one day (e.g., via a growth model or baseline gain), the realized gain is:

$$\text{Penalty} = \begin{cases} 0.263 \cdot \Delta W, & \text{if } \texttt{timesInfected} = 1 \\ 0.481 \cdot \Delta W, & \text{if } \texttt{timesInfected} \geq 2 \end{cases}$$

$$\texttt{weightlbs}_{t+1} = \texttt{weightlbs}_t + \Delta W - \texttt{penalty}$$

NetLogo implementation:

```
let penalty 0
if timesInfected = 1 [ set penalty 0.263 ]
if timesInfected > 1 [ set penalty 0.481 ]
let expected_gain growth-gompertz age Winf k ti - previous_weight
set weightlbs weightlbs + expected_gain - penalty * expected_gain
```

where `previous_weight` is updated at each tick before the growth step.

5.4 Summary of Implementation

- Each cow tracks the integer `timesInfected`, incremented on each BRD event.
- Growth penalties are additive (fixed decrement) for the first infection, proportional for subsequent infections.
- A fixed treatment cost ($88) is assessed per BRD event.
- All logic and penalties are agent-level, using only variables defined in the model code (`isInfected`, `timesInfected`, `weightlbs`, `expenses`, etc.).

6 Simulation Experiments

Simulation experiments are conducted by initializing a herd of $N = 100$ calves and advancing the system through 540 daily time steps, corresponding to the full production cycle from birth to market sale (`age` from 1 to 540). All scenarios can be implemented by modifying global parameters and toggling agent-level logic in the NetLogo model.

(1) **Base case**: Disease is suppressed (`morbidity_rate` set to zero); weight gain is governed by the Gompertz growth function (`growth-gompertz`), with parameters (`Winf`, `k`, `ti`) set to calibrated baseline values.

(2) **BRD Scenario A**: Morbidity is enabled with a daily probability `morbidity_rate` set to 0.10 (10% per day); infected animals are treated immediately upon infection (`time_infected` reset on detection).

(3) **BRD Scenario B**: Morbidity is set to a higher rate (`morbidity_rate` = 0.20), and treatment is delayed by two days after infection (agents remain `isInfected` for at least two ticks before `recover` can be invoked).

(4) **Price shock**: The market price for the feedlot phase (`price-FL`) is reduced by 20% at day 400 (i.e., `set price-FL price-FL * 0.8`), simulating a sudden drop in market value.

(5) **Sensitivity analysis**: Biological growth parameters are varied, simulating W_∞ (`Winf`) and k by $\pm 10\%$ around baseline to assess robustness of production and economic outcomes.

Outputs: For each scenario, the model tracks and reports daily time series for individual and herd-level `weightlbs`, cumulative economic value (`valueusd`), net present value (`NPV`), treatment costs (`expenses`), and realized morbidity (`timesInfected`, mortality, etc.), enabling detailed comparison across interventions and biological assumptions.

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