Using system dynamics methods for the impact assessment of animal diseases: Applications to Rift Valley Fever and food safety interventions in pigs

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INTRODUCTION

Animal diseases are responsible for a number of economic impacts, affecting those involved in the livestock sector as well as a range of ancillary sectors that directly or indirectly depend on livestock. In much of the developing world, livestock serve both livelihood functions and as a potential pathway out of poverty (Perry and Grace, 2009). Animal-source foods are also an important source of protein for the poor; they enhance physical activity among children and reduce morbidity from illnesses (Sadler et al., 2012). In such contexts, livestock contribute to household food needs, income, draught power for crops, an asset base, and various social functions, suggesting that the impacts of animal disease occurrences, and in particular their ramifications on poverty, may be difficult to tease out (Rich and Perry 2011; Randolph et al., 2007; Perry and Grace, 2009).

While disease impacts are most obvious and direct in the livestock sector itself, disease outbreaks have a variety of downstream impacts. In particular, supply chain linkages among various interconnected stakeholders modulate shocks from the impacted animal sector along agro-food supply chains and consumers. Some diseases, particularly those of a zoonotic and transboundary nature, can generate spillovers to other economic activities (tourism, health services, trade and transport, environment, etc.) in which the indirect effects of disease outbreaks can far outweigh direct ones. Moreover, an additional component of impact concerns public and private responses to the real or perceived risk of the disease and their potential effects rather than just the actual, direct on-farm impacts (Rich and Roland-Holst 2013). Thus, any policy interventions need to address stakeholder reactions, interests, and incentives that could either reinforce or undermine both risk management and outbreak response programs (Rich et al. 2013).

At the same time, not all livestock diseases impact the economy in the same way. In particular, diseases can vary in their impact depending on whether they are epidemic or endemic, zoonotic or confined to animal populations, transboundary or locally concentrated, and the extent to which local, regional, national, or international externalities exist (table 1). For example, transboundary diseases such Rift Valley Fever (RVF) or foot-and-mouth disease (FMD) have impacts on local and international trade, with numerous effects on other sectors such as crops that use livestock as an input to production. By contrast, some diseases may have less in the way of international impacts, but may have local impacts and/or externalities on the environment (e.g. the impacts of acaracides for tick-based disease on groundwater stocks) (Rich and Perry 2011).

We synthesize the universe of disease impacts by overlaying two separate conceptual frameworks. First, Rich and Perry (2011) identify five dimensions of disease impact based on the characteristics of the disease and their setting: (i) disease characteristics, (ii) production systems characteristics, (iii) market characteristics, (iv) livelihoods characteristics, and (v) control characteristics. Second, Rich, Roland-Holst, and Otte (2013) look at disease impacts at different levels of aggregation i.e., (1) household or farm level impacts, which can include non-farm related livelihoods impacts; (2) cattle sector impacts; (3) general livestock sector impacts, including substitution effects at production and consumption levels; (4) national-level value chain impacts based on the forward and backward linkages of livestock with other sectors of the economy, particularly agriculture; (5) downstream national level impacts in non-agricultural sectors such as tourism, as well as other externalities such as effects on the environment, wildlife, and (for zoonotic diseases) human health; and (6) impacts at the global or sub-regional levels due to international trade bans, for instance. Figure 1 distills this combined framework graphically, while table 2 applies it in the context of RVF to show the various impacts of disease at different levels of analysis.

This framework for assessing animal diseases suggests a need for more holistic, systems approaches to impact assessment. Numerous methods have been suggested and applied in an animal health economics context over the past 20-30 years (see Rich, Winter-Nelson, and Miller 2005 for a review), with an overwhelming majority of these relying on the simple computation of disease costs at a farm-level. These methods largely ignore the behavioral response that animal diseases engender upon different stakeholders (Rich et al. 2013; Rich, Roland-Holst, and Otte 2013). A particular gap remains at meso levels such as the value chain in quantifying impacts among different stakeholders. Most value chain studies of animal diseases tend to be qualitative and descriptive, suggesting potential critical control points, but lacking empirical rigor in comparing between different intervention options (Rich and Wanyoike 2010; Rich and Perry 2011). Indeed, as noted by Rich (2007) and Rich and Perry (2011), what is crucially missing is a way to close the feedback loop between the impact of disease and the behavioral response to it throughout the value chain.

In this paper, we propose the use of **system dynamics** (SD) as a way of better addressing the multifaceted impacts of animal diseases. As elaborated below, SD models have the advantage of modeling the interface of disease dynamics with production and behavioral dynamics, including downstream activities in the agrifood value chain, which are not possible to model in other meso-level platforms (e.g., multimarket models, social accounting matrices). Moreover, as dynamic simulation models, they can be used to conduct scenario analyses of different policy interventions (disease-related, production-related) and their predicted *ex-ante* impact on the system over time. In this manner, SD models give us a useful framework for assessing tradeoffs, particularly in climates of increasingly scarce resources (Rich et al. 2013).

AN OVERVIEW OF SYSTEM DYNAMICS MODELS

An SD model is a dynamic model that maps out the flows, processes, and relationships between actors that exist within a complex system (Sterman 2000). SD models have been used in a variety of applications, including economics, ecology, public policy, natural systems, and environmental sciences, among others. Fundamentally, SD models are simulation approaches in which the *evolution* of the process is of interest rather than a specific equilibrium or "optimal" solution. Indeed, SD models are essentially systems of differential equations with no "closed-form" solution, where comparison of the evolution of different simulation runs based on alternative shocks to the system over time is the primary mode of analysis.

SD models utilize another key difference relative to standard modeling frameworks – they use a graphical interface for modeling. That is, rather than coding the system in a programming language (e.g., such as GAMS, SAS, R, or Matlab), a graphical interface is used to construct the structure of system relationships, with many structural relationships automatically calculated by the software through the linking of graphical relationships. This not only eases model conceptualization and communication, but also allows for the multidisciplinary development of models from users of various backgrounds.

SD models have a number of key building blocks and concepts:

- Stocks are accumulations at a particular point in time. In a livestock context, stocks could be the number of animals held by farmers, animals (or meat) traded by different value chain actors, or animals in a particular disease state (infected, susceptible, etc.);
- Flows are the rate of change in a stock. The amount present in a particular stock at time *t* depends on how much enters the stock (inflows) and how much exits (outflows);
- Converters (or parameters) modulate the relationships between stocks and flows, and could include technical parameters that define how fast particular inflows or outflows influence the volume of a stock at a point in time.

Perhaps the simplest metaphor for these initial building blocks of SD models is that of a bathtub. In figure 2, a simple model is illustrated in the iThink modeling software (http://www.iseesystems.com) that graphically models this example. The rectangular shape labeled as "Water in Bathtub" represents a stock. We denote two types of flows entering and exiting the bathtub. These are illustrated by the thick arrow shapes entering ("Water entering tub") and exiting ("Water existing tub) the stock. We have one converter, named "Water valve," that regulates the speed of inflow of water into the tub. In figure 2, the value for the parameter "Water valve" could be based on technical or other information at hand. However, the software automatically calculates the stock/flow relationship, which is formally defined as a differential equation. In iThink, as with other SD modeling platforms (e.g. Vensim, Powersim, STELLA), model equations are stored in the background, but are not directly programmed as such.

We provide another example of an SD model in figure 3. Here, we represent the standard SIR (susceptible-infected-removed) model from epidemiology in iThink. Before explaining figure 3 in depth, it is useful to write out the standard SIR equations defined below in equation (1). Recall that *S*, *I*, and *R* are different states of nature of the population (i.e., susceptible to disease; infected with disease; or removed from the system, either by death, exits through sales, or natural recovery), while the parameters β and α represent the infection rate and time to recover, respectively:

$$\frac{dS}{dt} = -\beta SI$$
$$\frac{dI}{dt} = -\alpha I + \beta SI$$
$$\frac{dR}{dt} = \alpha I \qquad (1)$$

In figure 3, our stocks are the three different states of nature – susceptible, infected, and removed. Our system has two flows – a transition from susceptible to infected ("infection rate") and from infected to recovered ("recovery rate"). The latter flow depends solely on the inverse of duration of illness (i.e., α in equation (1) above, which is equal to 1/D, where D is disease duration) multiplied by the number of infected individuals in the system. The former flow depends on β, the infection rate, which is the product of the contact rate between individuals, how infectious the disease is ("infectivity"), and the total population, as well as the mixing of susceptible and infectious individuals in the system.

Figure 3 highlights an additional important component of SD models – the concept of *feedback*. Feedback is the process by which changes in one part of the systems affects other parts and, consequently, impacts the original component over time (McGarvey and Hannon 2004). In SD models, we can predict different types of system behaviors based on the combination of feedback patterns that exist.

We consider two types of feedback patterns in SD models. *Positive feedback (also called a reinforcing feedback loop)* is a state in which behavior is reinforced over time, whether positively or negatively (see figure 4a). Such behavior takes an exponential shape. For instance, in the feedback between, say, eggs and chickens, more eggs leads to more chickens, which leads to more eggs and so on. By contrast, *a balancing loop (also called a negative feedback loop)* is one in which there is behavior that counteracts change (see figure 4b). As a simple example, consider the feedback loop between chickens and road crossings. More chickens leads to more road crossings, but more road crossings leads to fewer chickens (ostensibly squished on the road from crossing!). More generally, as noted in figure 4b, balancing (or negative) loops incorporate some sort of corrective action, often due to a gap between a desired state and the actual state. In such feedback loops, we observe behavior that converges on a steady state (see figure 4b) (Sterman 2000).

When we observe multiple feedback structures in the same system, we can predict behavior based on the relative strength of feedback loops at different points in time. For instance, S-shaped growth (figure 4c) results from the combination of a reinforcing loop and a balancing loop. In such systems, the reinforcing loop dominates system behavior at early periods of time until limits on resource availability start to bind, switching system dominance to the balancing loop and converging on the level of carrying capacity. Oscillation behavior (figure 4d) arises when balancing loops have delays between different actions, preventing a convergence to a steady state. S-shaped growth with overshoot (figure 4e) is a variant of S-growth in which the balancing loop has delays, while overshoot and collapse (figure 4f) is characterized by switching from reinforcing to balancing loops with eroding (non-renewable) carrying capacity.

In our SIR example from figure 3, we have three feedback loops – one positive or reinforcing loop and two balancing or negative loops. Our positive loop is that between our infected population and infection rate – the more infected people in our population, the greater the infection rate, and the greater the infection rate, the more infected people will be in our population. Counteracting this are two balancing loops. First, consider the feedback between the susceptible population and infected rate – the greater the susceptible population, the greater the infection rate. However, as the infection rate rises, there will be a smaller susceptible population to infect. Similarly, as the number of infected individuals rises, the recovery rate rises. But, as the recovery rate rises, fewer people will be infected in the future. The behavior in the SIR model is illustrated in figure 5 for each of the states. The positive feedback loop dominates the two negative feedback loops at early stages of the epidemic, but as the pool of susceptibles falls (due to prior infection), the number of newly infected people falls, with the recovery rate rising faster than new infections at later periods in the epidemic.

Delays are also an important component of SD models. As noted earlier, delays can modulate and influence different feedback structures (see figure 4). We consider three different types of delays – material delays, pipeline delays, and information delays. A material delay is a delay in the flow of goods within the manufacturing or supply chain process, but in which there is the mixing of goods within the delay process. For instance, suppose there is a one-week delay between the delivery and use of an input and the final output. In a material delay, the length of delay is an *average* delay period – some goods may finish earlier or later than the average. This type of delay captures the mixing of goods within a process. By contrast, a pipeline delay is a fixed period delay in a process. For instance, in the manufacturing of a good on an assembly line, all products take the same amount of time to be transformed from input to output. An information delay captures delays in perception. For example, there could be delays in expectations on orders or prices that influence ordering or production behavior with a lag.

OPERATIONALIZING SYSTEM DYNAMICS IN LIVESTOCK SYSTEMS AND VALUE CHAINS

SD models have been used in a number of recent livestock applications. Rich et al. (2011) proposed the use of system dynamics (SD) tools in livestock settings to model livestock value chains, given the complexity of both production and market transactions. Rich (2007) developed a framework in which a simple livestock supply chain was integrated with an epidemiological model of poultry disease, with changes in disease and control strategies affecting value chain dynamics, and vice-versa. Hamza (2012) developed a similar structure in the context of sea lice control in Norwegian salmon, integrating the epidemiology of the host-parasite relationship with intervention options and an assessment of cost-effectiveness. Similarly, Naziri, Rich, and Bennett (forthcoming, 2014) implemented an SD model of the Namibian cattle value chain in which herd dynamics, FMD risk status, and downstream cattle marketing were integrated to assess the cost-effectiveness of alternative protocols to implement commodity-based trade protocols. Rich, Perry, and Kaitibie (2008) used an SD approach to look at the competitiveness of Ethiopian beef exports to the Middle East under an SPS certification program. Ross and Westgren (2006) developed an SD model of entrepreneurial behavior in hog value chains in the United States. Recently, Hamza et al. (2013a, b) has expanded these models to look at the marketing of smallholder livestock in their different value chains in Botswana and Mozambique, respectively. The common thread in all of these applications was the need to capture the feedbacks within complex livestock systems, in terms of the interactions between biology, markets, and external shocks.

To motivate how we can use SD in livestock systems, we first start with a simple model of supply and demand developed by Whelan and Msefer (1996). This model is the foundation for modeling market dynamics within a complex system, to which more complex relationships such as the biology of animal production, interfaces with animal disease, and modeling of downstream value chain actors can be added.

The initial building blocks of the supply and demand model are a stock-flow diagram, illustrated in figure 6. Both supply and demand are calibrated by price relationships (more details on price formation can be found in figure 7) as in a neoclassical economic model. The simple example of Whelan and Msefer (1996) used graphical functions of supply and demand, though supply and demand functions can be more explicitly defined based on econometric data (see Rich and Roland-Holst 2013 for an example).

Figure 6 also highlights the pivotal role of inventories in the model. The stock of inventories is the key component that not only regulates inflows of supply and outflows of sales, but also is responsible for price adjustments. Unlike a neoclassical model of supply and demand in which prices quickly adjust to shifts in the supply or demand curve, an SD model relies on the relationship between actual inventories and desired inventories (defined as the parameter "Inventory ratio") to change prices. When actual inventories exceed desired inventories, there is pressure on the system to reduce those inventories, which arises by reducing prices. Similarly, when desired inventories are too low relative to actual inventories, prices are bid up to encourage the building up of inventories. Desired inventories in figure 6 are a function of demand and the number of weeks of stock desired by a decision-maker.

Price formation in the model is also modeled as a stock-flow relationship (figure 7), based on the inventory relationships discussed above and in turn influencing how much is supplied and demanded in the system. Price is modeled as a stock, with the level of price changing each period based on the inflow "Change in Price". This inflow is modeled as a biflow, which means that the flow can either be positive or negative (i.e., prices can go up or down). "Desired price" is the product of the parameter "Effect on price" and the stock "Price". "Effect on price" graphically defines the inverse relationship between price and the inventory ratio – recall that when the inventory ratio is large, prices should fall and vice-versa. "Effect on price" could also be defined analytically as a function as with supply and demand. The gap between "Desired Price" and "Price" is what changes prices in subsequent periods and affects supply and demand. The model further assumes a delay in the adjustment of prices based on decision-makers' perceptions on price adjustment times. In the steady state, "Inventory ratio" will be valued at 1, which means that "Effect on price" will be 1 and "Desired Price" will be equal to "Price".

The Whelan and Msefer (1996) model is at the core of modeling value chains using SD. In livestock settings, we elaborate upon this setting by expanding our supply and demand relationships, but the basic market interactions with more complex models are the same.

We first illustrate how to expand the supply side of the model to incorporate livestock production. Our starting point is modeling the population structure of livestock. Here, we start with a stock-flow relationship of the life cycle of a typical animal from birth to final sale or death. Figure 8 illustrates a simple population model for female cattle (male cattle can be likewise modeled) based on the DynMod model developed by Lesnoff (2008). Each stock represents a state of nature for an animal (juvenile animals, sub-adult animals, adult animals). Animals move between different states of nature through flows between stocks that are calibrated based on various probabilities of sale or death (purchases of animals, while not modeled here, could be added). The entry of new animals depends on the stock of female adult animals and technical parameters related to parturition and prolificacy rates.

Within the female part of livestock demographics are decisions whether to hold animals for breeding or to sell them. In commercialized systems, these decisions are based on price movements but in a developing country setting, they could also be dictated by various livelihood considerations (e.g., school fees or other family necessities). In figure 8, we consider a simple elasticity-type response to the decision to sell animals. However, other SD models incorporate a separate stock for breeding stock and consider the difference between actual breeding stock and desired breeding stock. The latter could be determined by carrying capacity, income levels, etc. In figure 9, we present a similar population model of poultry that illustrates how a breeding stock could be modeled in the system. Note that the transitions in figure 9 are less complex than in figure 8, as the latter model was developed explicitly to replicate the dynamics embedded in the DynMod model. Note further in figure 9 the interaction between the population model and downstream inventory. In the rest of the model (not shown), the demand, price, and inventory modules are analogous to the supply/demand model illustrated in figures 6 and 7.

We can extend the demand side of the model as well to examine dynamics downstream in the value chain. Figure 10 models the cattle value chain in Botswana based on Hamza et al. (2013a). The model includes three main sectors: (1) production, (2) domestic marketing, and (3) export marketing. The model also includes a policy module that governs changes in trading and management practices resulting from different policy scenarios. In the lower portion of the figure, we present a simplified model of livestock population dynamics. Exits from the stocks of calves (weaners) and adult cattle go to different markets, including export markets and different domestic markets of various quality profiles. Some sales are made via intermediaries such as feedlots. Price movements in different end channels are endogenized and influence producer behavior to sell or hold animals, but only partially as livestock herds are also maintained as a source of assets. The model further considers the feedbacks between environmental carrying capacity and producer profitability, as limits to the resource base (calibrated by available rainfall) influence cattle mortality and fertility (Hamza et al. 2013a).

The model was used to explore the viability of market liberalization and investment policies. In Botswana, the Botswana Meat Commission (BMC), a government parastatal, strictly regulates exports. BMC is the monopsony buyer of animals for export and the monopoly seller of meat for export. This market structure depresses the prices paid to producers at levels less than export parity, reducing incentives for producers to supply BMC and reducing throughput at BMC abattoirs, resulting in increasingly high losses for BMC.

One proposed reform is to partially liberalize the export market by allowing the sale of live weaners to South Africa, though this could have significant impacts on different value chain actors and the dynamics of the cattle sector in Botswana. Model results indicated a very marginal improvement in producer income from such proposed partial market liberalization and very modest reductions in the profitability of feedlots and BMC. However, the mitigating factor in fully opening up markets is the continued presence of FMD in Botswana. Scenarios that alternatively consider investments in FMD control in conjunction with market liberalization are significantly much more lucrative for producers as well as BMC, with the latter benefitting more from market access to European markets from FMD control than from the loss in its monopoly power (Hamza et al. 2013a).

In a meso-level context, model structures as discussed above are extremely useful in the development and analysis of policy scenarios at a value chain level. As discussed earlier, SD models are extremely adaptable to the modeling of value chain dynamics in a way that other meso-level approaches, such as multimarket models or social accounting matrices (SAMs), are not. Multimarket models at the level of the value chain, for example, would necessitate the modeling of numerous and overly specific supply and demand relationships that would be difficult, if not impossible, to econometrically parameterize. They could also omit the structure of various institutional, non-economic, and/or livelihoods aspects of the value chain that SD models can more easily incorporate. Similarly, SAMs are much more aggregated than SD models in their treatment of livestock markets – indeed, many SAMs do not have livestock accounts at all – while SD models can capture a multiplicity of different marketing channels and producer and consumer segments. Modeling market and biological dynamics as well as integrating economics with epidemiological phenomena is also problematic with either multimarket models or SAMs. For instance, the multimarket model of FMD control in South America of Rich and Winter-Nelson (2007) was only loosely integrated with a epidemiological model (incidentally an SD model programmed in STELLA, see Rich (2008)), with the market and biological dynamics in the multimarket model were nowhere near as realistic as those found a more structured herd demographic approach in an SD model.

Given our extended livestock supply/demand model, we can consider the incorporation of a number of other modules that influence this system and, in turn, are influenced by market and biological dynamics. Consider first the influence of animal disease in our system. As noted by Rich (2007), one of the underappreciated and under-analyzed dimensions of the impact of animal diseases is the failure to incorporate the feedbacks between disease evolution and behavior. Most animal health studies look only at the one-way impact of disease i.e., the impact of disease on producers or other actors. However, actions taken by producers also influence the course of disease. For instance, distress sales made by afflicted producers during an outbreak can modulate the duration, intensity, and spatial spread of disease. A unique advantage of SD models is their ability to capture these feedback effects. In turn, given these feedbacks, decision rules can then be added and endogenized as well - Duintjer Tebbens and Thompson (2009) did this when looking at the prioritization of interventions for human diseases based on their cost-effectiveness, which can shift over time (see figure 11 for an SIR model incorporating their approach).

Rich and Roland-Holst (2013) recently looked at the impact of FMD in Cambodia. In their SD model, they considered the interaction of FMD and disease control interventions on market dynamics, the means by which market dynamics and response to disease (e.g., market closures, distress sales) influence disease evolution, and how related downstream markets are affected. In the latter case, they considered the impact of FMD on rice markets, given that cattle are a source of draught labor for plowing.

While declining in importance – only about 5 percent of farmers in Cambodia rely on cattle for plowing – these impacts are particularly relevant for smallholders.

Figures 12 through 14 provide snapshots of the disease and rice modules of the model. The supply and demand side of the livestock model is analogous to what was earlier presented in figure 8, and figures 6 and 7, respectively. In figures 12 and 13, we model an SIR model (recall figure 3), with an added flow to incorporate a vaccination policy. The key to integrating an SIR model with our herd population model is to ensure balance between the population within the SIR model and the livestock demographic model. This requires ensuring that entry into the disease model comes from births and purchases, while non-disease related exits come from natural mortality and sales (figure 12). Similarly, deaths from FMD need to be added to the livestock demographic model (not shown). Finally, we need to ensure that there is population balance between the epidemiological and biological modules (figure 13).

In figure 14, we model rice as a supply-demand model. Supply and demand are calibrated through the use of a simple double-log functional form based on elasticities from the literature. The duration of the FMD outbreak, modeled by the stock "FMD duration counter" and the proportion of land impacted calibrates how much aggregate rice yields are reduced as a result of an FMD outbreak.

We illustrate some suggestive results from this model in figure 15(a)-(h) below. In these simulations, we considered the following:

- <u>Scenario 1:</u> A baseline scenario (status quo) against which to compare results from other scenarios, with production data and population calibrated to fit population growth in Cambodia (about 1.5% per year);
- <u>Scenario 2:</u> An initial FMD outbreak in week 280 affecting an initial group of 1,000 animals. We assume that 20% of domestic markets are closed during the outbreak until less than 1% of the population is infected – at this point, 90% of markets are open. Once the proportion of infected animals is less than 0.02%, we assume that all markets re-open;
- <u>Scenario 3:</u> A similar sized outbreak as in (2) but in which distress sales last for 10 weeks instead of 4;
- <u>Scenario 4</u>: A similar sized outbreak as in (2) but in which only 60% of markets are open during the major part of the outbreak (instead of 80% as in (2));
- <u>Scenario 5:</u> A similar sized outbreak as in (2) but where paddy crops affected by FMD are 27% of total production instead of 5%, based on alternative data cited in Rich and Roland-Holst (2013).

Rich and Roland-Holst (2013) found that herd dynamics are influenced by the relative changes in prices induced by the outbreak. Initially, there is a small surge in distress sales, but with resulting market closures, there are incentives to hold animals (panels (a) and (b)), causing herd populations to rise. Depressed supplies and sales cause prices to spike in the meat market, which are exacerbated when distress sales occur over a short period of time (panels (c) through (e)). At the same time, differences in the time in which distress sales take place have no appreciable impact on the evolution of disease (panels (f) and (g)). However, scenario 4, in which 40 percent of markets are closed, considerably amplifies these affects, particularly on prices, trade, and the number of infected animals, which rise relative to the other scenarios. The rice scenario (scenario

5) has a very modest impact on traded rice and rice prices, causing a slight decline in domestic trade and a slight increase in prices during the initial harvest year in which the outbreak takes place. However, these impacts reverberate over time, as price effects in the year of the outbreak, combined with the fact that the outbreak continues at low levels over subsequent years, amplify these impacts over the remainder of the simulation.

The applicability of this model to the case of RVF control is clear. As noted in Rich and Wanyoike (2010), market movement bans were an important feature of RVF control during the 2007 outbreak. However, delays in market closure combined with distress sales had important impacts on the spread of disease, as well as on livelihoods later given the severe reduction in prices associated with the impact. While not modeled in the Cambodia paper, extending this framework to incorporate downstream interactions and impacts (as in the Botswana model of Hamza et al. (2013a)) would not only better quantify the totality of disease impact but also help gauge the behavioral reaction and practices of downstream actors such as traders on disease transmission. Rich and Wanyoike (2010) inventoried the various downstream impacts of RVF, particularly on livelihoods in local communities, but more precise quantification of these impacts was not possible at a meso level. An SD framework would provide greater guidance on potential economic impacts as well as a framework to model *ex-ante* the effects of alternative intervention strategies. This is an area where ongoing RVF impact assessment work could benefit from such an SD model.

A complication of RVF is that it is a vector-borne disease. So far, we have only considered animal diseases that are primarily spread through animal contacts. However, latent mosquito populations that emerge during *El Niño* events initially seed RVF outbreaks. This requires not only looking at animal movements, but host-parasite interactions as well. The sea lice model of Hamza (2012) is instructive here. Sea lice are a parasite which attack wild and farmed salmon populations, reducing weight gain and productivity of younger fish, and causing mortality during severe infestations. Sea lice control measures involve controlling the vector population through either in-feed or chemical treatments, or the use of cleaner fish that feed on the lice population. The sea lice model of Hamza (2012) used SD techniques to model both host-parasite interactions and the cost-effectiveness of different treatment options. Figure 16 models the causal-loop diagram of the evolution of the sea lice population, while figure 17 illustrates treatment options for sea lice control based on government mandated thresholds of sea lice populations in production areas at different times in the year. An interesting feature of this model is the ability to run treatment scenarios in real-time, adjusting treatment policies as the simulated outbreak unfolds. This approach could provide a more realistic modeling of RVF disease dynamics that is integrated within their spatial context and the livestock market dynamics present there.

Data needs for calibrating SD models of animal disease and livestock value chains are relatively modest. Table 4 summarizes some of the key parameters that are required. One of the important data collection needs is a shift in approach towards gathering information about dynamic behavior and phenomena while building upon traditional value chain data collection means. As SD models address dynamic systems, it is crucial to obtain information on production and trade *per unit time*, for example. Issues such as the seasonality of prices and production play an important role, as do non-economic considerations such as livelihoods rationales for marketing livestock that may not follow market-based rationales. A crucial aspect of using an SD model is modeling the system structure and processes appropriately, including feedback and behavioral mechanisms.

So far, we have looked at the integration of animal diseases within livestock value chains. However, other types of market shocks can affect livestock value chains and mitigate market access for smallholders. Food safety regulations are an emerging obstacle for smallholders to access increasingly quality-conscious markets in developed and developing countries alike. The lack of smallholder compliance with food safety regulations often arises due to a host of production practices that are often rooted in traditional behavioral practices or social norms that are difficult to change. Market-based incentives are one means to raise food safety levels, but need to be sensitive to the socio-economic and socio-cultural context in which production and decisions take place. A key attribute of any such intervention is linking behavioral change with improvements in livelihoods and market access.

Two SD models of behavioral change are potentially instructive here. Feola and Binder (2010) developed what they term an "integrated agent-centered" (IAC) approach that looks at the behavioral drivers and reactions behind individual decisions. Figure 18 illustrates their framework, highlighting how expectations, habits, social norms, and network considerations can influence behavior within a system. Figure 19 applies this general framework in a causal-loop diagram of the disuse of personal protective equipment against pesticide contamination among farmers in Colombia (Feola, Gallati, and Binder 2012). In this model, different simulations related to improving education, influencing peer networks, improving treatment, and reducing the cost of equipment were run to examine their influence on farmer perceptions and behavior on the use of safety equipment. The authors found that no single policy would bring forth sustainable behavioral change, with a need for either constant outside pressure or an internal participatory approach to change mindsets (Feola, Gallati, and Binder 2012).

A second model by Ulli-Beer, Anderson, and Richardson (2007) looks at modeling behavioral change towards recycling practices in Switzerland. Their model (see figures 20 and 21) is potentially more applicable in a value chain setting in the sense that it could be overlaid in the production or marketing decisions at a node (or nodes) within the chain. In their model, they consider the behavioral feedbacks that could arise from different types of policies that mandate the separation of material for recycling. For instance, the imposition of a garbage bag fee is intended to make it costlier for those that do not separate rubbish. However, the unintended effect of such a policy was that the volume of non-recycled solid waste fell, reducing revenues of the trash authority and creating a budget deficit. Raising the garbage fee further, however, did not impact separating behavior and made the quality of separated rubbish worse (Ulli-Beer, Anderson, and Richardson 2007). Their model simulations (see figure 21) looked at alternative scenarios of taxes and fees to induce recycling behavior in the wake of these behavioral feedbacks. This approach at a value chain level could allow one to assess which combination of practices could be most effective in terms of behavioral uptake as well as on the performance of the value chain itself.

CONCLUSIONS

SD models are particularly amenable to the analysis of livestock systems and value chains. By modeling the entire value chain and highlighting the dynamic feedbacks among and between the actions of different nodes, SD models overcome many of the limitations inherent in sectoral approaches to economic analysis. Moreover, by using a common modeling platform (e.g., iThink, STELLA) to look at the interactions between different phenomena (e.g., animal disease and livestock markets), SD models provide a unique unified framework for analysis and simulation that is easily assessable across a multitude of disciplines.

Of course, SD models are not the only platform in which to conduct livestock value chain analysis in a systems setting. For instance, network models and agent-based models (ABMs) provide alternative vantage points on system-wide behavior. Agent-based models look at a much more micro-level of analysis – the level of the individual decision-maker – to simulate aggregate system behavior (see Rich, Winter-Nelson, and Brozovic 2005 for an example in a FMD setting). Similarly, network models specifically look at individual-level market and social interaction patterns, and could be used to understand how social interactions influence trading patterns or other types of marketing behavior. SD models, by contrast, are more aggregate, or meso-level, models, looking instead at the level of a representative agent or set of agents. Nonetheless, SD models are very much complementary to network models and ABMs, given their systems vantage point and incorporation of behavioral feedbacks in their analysis. Future research should elucidate upon these complementarities, particularly in animal health settings.

SD models represent an important evolution in value chain analysis (VCA) more generally. While traditional value chain analysis has provided a number of important insights over the past 15 years, it has generally remained qualitative and descriptive, and incapable of empirically comparing and prioritizing between different intervention options. SD models allow us a means to build upon the strengths of traditional VCA by overlaying an empirical framework and structure on top of the qualitative description of the value chain, generated value chain maps, and insights into issues of governance and upgrading. As demands for analysis at the value chain level grow in importance among donors and policy makers, SD models provide us with a powerful tool to contribute to policy debates.

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Table 1
A simple typology of animal diseases

		Type of animal disease	
		Chronic/endemic	Epidemic
Human populations affected	No	(a) Helminthiasis, mycoplasmoses	(b) FMD, classical swine fever, African swine fever, PRRS
	Yes	(c) Zoonoses and food-borne diseases (e.g. brucellosis, rabies salmonellosis)	(d) Avian Influenza (e.g. HPAI H5N1, H7N9)

Source: Rich and Roland-Holst (2013).

Table 2
The impacts of animal diseases based on different dimensions and characteristics of epidemiological and economic impact: an application to RVF

Dimension of impact	**Disease characteristics by level of analysis**					
	Level 1: Farm	***Level 2: Cattle sector***	***Level 3: Livestock sector***	***Level 4: Agricultural/ Value-chain***	***Level 5: National***	***Level 6: Global***
Disease characteristics						
Severity of disease	High mortality in cattle – strong livelihood impacts in pastoral settings	High mortality impacts: production systems oriented at risk management rather than productivity		Trade bans at local level further accentuated by disease effects	Intensity fuelled by animal movements	Strong externality impacts across borders
Frequency	Sporadic, timing often coincides with periodic *El Niño events*					
Mode of transmission	Primarily through combination of vector (mosquitoes) and animal contacts (local, regional, global)					
Spatial spread	Transboundary fuelled by pastoral and animal movements (local, regional, and global)					
Public health	Yes, particularly at farm/processor levels					
Production characteristics						
Production system	Generally extensive, pastoral (particularly in Africa)	Predominance of traditional, informal markets, loose value chain linkages			Transboundary movements important	
Production cycle	Long production cycles for cattle, sheep, and goats					
Population size	Variable population sizes					Impact depends on net import/export status
Importance of by-products	High, particularly in terms of meat, milk, hides, manure, and animal traction					
Market characteristics						
Level of commercialization and market integration	Smallholder and commercial sectors both affected; large impacts in pastoral settings and domestic markets			Market access impacted for smallholder and commercial sectors		Informal marketing problematic for transboundary spread
Scope of value chains	Relatively simple, arms-length transactions, with limited value-adding or innovation downstream					
Non-sector impacts				Impacts in agricultural and service sectors based on forward and backward linkages		Impacts in agricultural and service sectors based on importance of trade
Level of socio-economic development	Generally low in affected regions					
Livelihoods characteristics						
Role of livestock in livelihoods	High importance in pastoral settings					
Cultural importance of livestock	High importance in pastoral settings					
Control characteristics						
Effectiveness of current control technologies	Vaccines exist, though mobilization and administration difficult given sporadic nature of disease. Vaccination usually achieves about 20% coverage. Vector control also exists, but application sporadic.					
Resource requirements for control	Costs associated with vaccines, delivery, and laboratories; donor support has been crucial in the past					

Dimension of impact	Disease characteristics by level of analysis					
	Level 1: Farm	***Level 2: Cattle sector***	***Level 3: Livestock sector***	***Level 4: Agricultural/ Value-chain***	***Level 5: National***	***Level 6: Global***
Maintenance costs for control	Importance of sero-surveillance in difficult environments; CAHW and participatory epidemiology play key roles					Coordination necessary across borders
Externalities related to disease control			Possible positive externalities of vector control		Environmental consequences on carrying capacity.	
Institutional capacity	Strong international coordination with local partners in successful campaigns					

Source: Adapted from Rich, Roland-Holst, and Otte (2013), supplemented by information from Rich and Wanyoike (2010).

Table 3
Alternative market scenarios of FMD impact in Cambodia

Scenario	Initial number of animals infected with FMD	Distress sale period	Markets closed	Paddy affected
S1	*Baseline: No FMD outbreak*			
S2	1,000	4 weeks	20%	5%
S3	1,000	10 weeks	20%	5%
S4	1,000	4 weeks	40%	5%
S5	1,000	4 weeks	20%	27%

Source: Rich and Roland-Holst (2013)

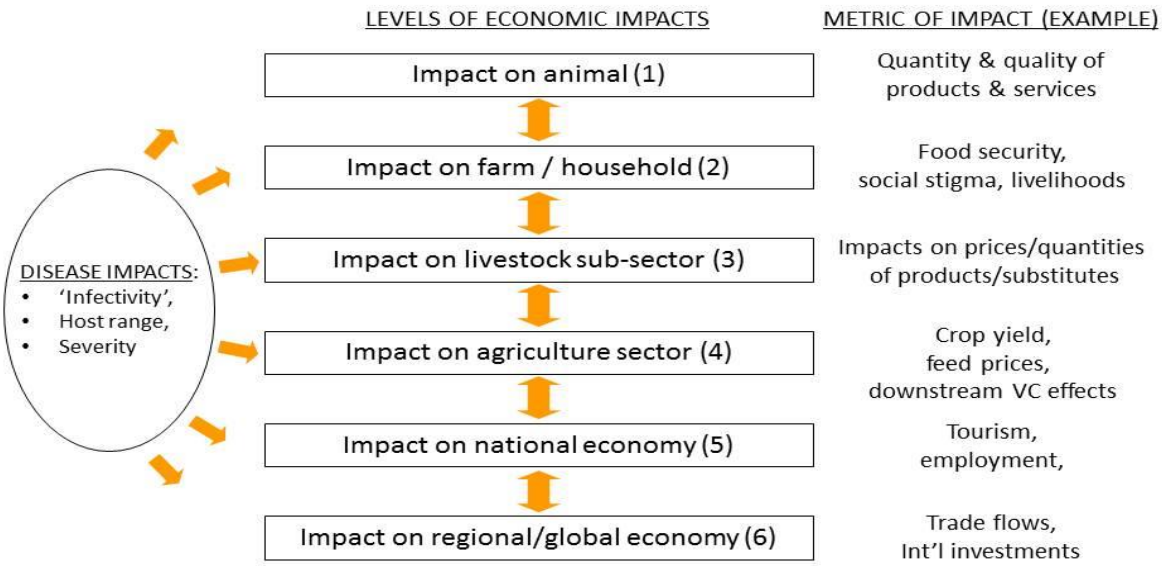
Table 4
Data requirements for developing integrated quantitative value chain models

Type of data	Description	Possible sources
Livestock demographics & population dynamics	• Initial stocks of animals • Shares of age/sex classes in livestock populations • Mortality rates by age/sex class • Average life span by sex • Parturition rate (by month) Net prolificacy rate (average proportion of animals born alive per parturition)	National statistics, farm surveys, interviews with key informants
Animal movements data	• Offtake rate by sex/age class • Movements of animals to/from region	Farm surveys, interviews with key informants
Elasticities	• Supply • Demand • Income	Derived from household surveys, published estimates
Value chain process variables	• Period of time taken between farm sales and market arrivals • Period of time taken between sales from farms and slaughter (weeks) • Inventories of meat (weeks)	Farm/trader/processor surveys
Epidemiological data	• Contact rates between animals • Between-farm contact rates • Infectivity rates • Mortality by age/sex • Vaccination coverage • Incidence rates (this is a result of some of the above)	Farm surveys, interviews with Veterinary Services, epidemiology literature
Market prices	• Prices of animals by sex/age class	Farm/trader surveys, national statistics,

Type of data	Description	Possible sources
	• Prices of meat by cut • Prices of major crops • Rental prices of animals for draught labor • GDP and GDP per capita	interviews with processors/retailers
Control costs	• Medicine costs • Additional feed costs • Treatment costs • Vaccination cost	Farm surveys, interviews with Veterinary Services
Draught labor parameters	• Number of animals used per hectare • Duration animals used for plowing • Time of the year animals used • Yields of rice/other crops using draught labor • Yield loss associated with lack of draught labor • Time animals unavailable for draught labor due to disease	Farm/trader surveys, national statistics, interviews with Veterinary Services and Extension Services

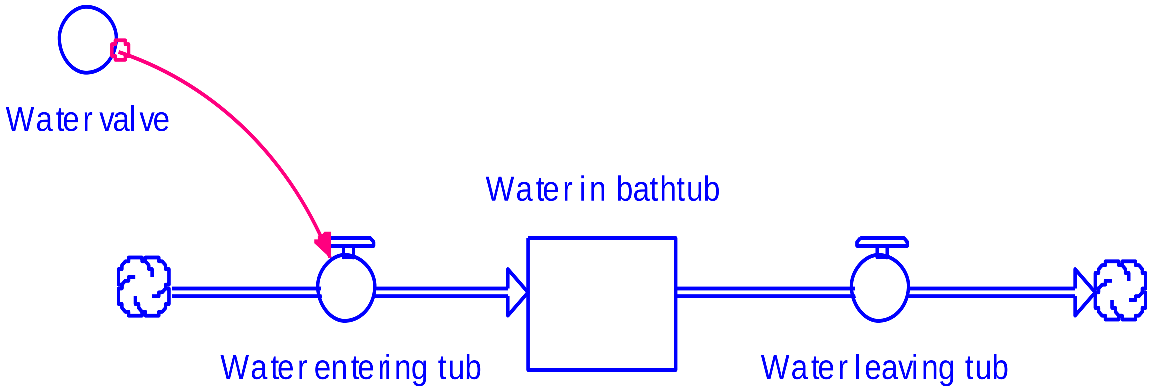
Source: Rich and Roland-Holst (2013)

Figure 1
Interactions of disease characteristics and levels of economic impact



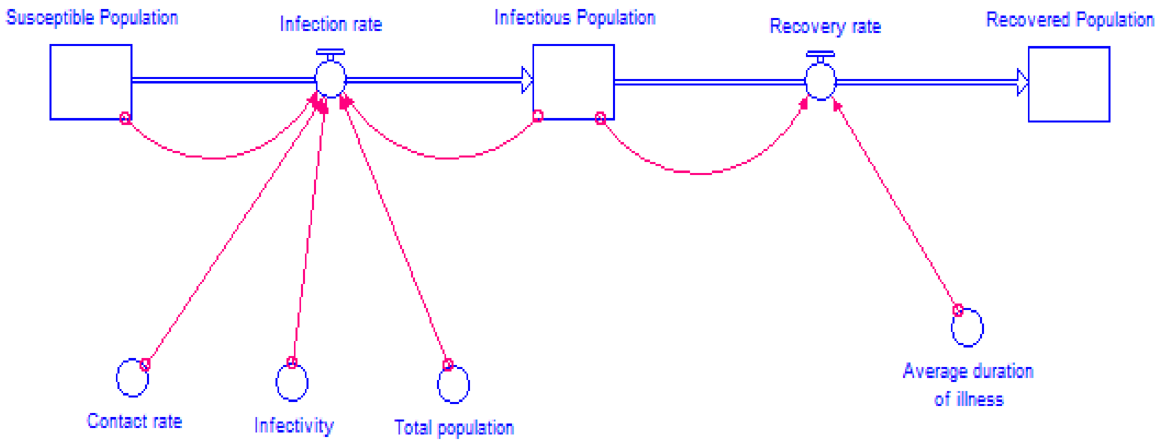
Source: Rich and Roland-Holst (2013), based on Rich, Roland-Holst, and Otte (2013).

Figure 2
A simple example of stocks, flows, and converters in iThink



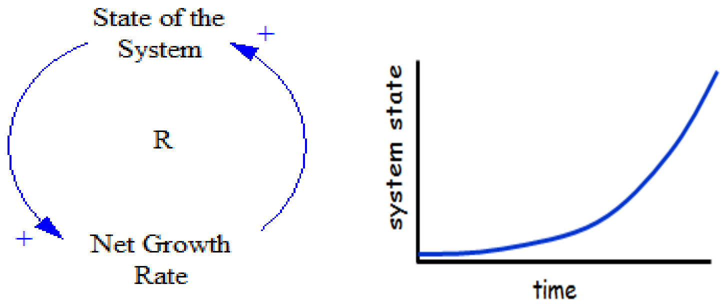
Source: Based on Sterman (2000).

Figure 3
A simple SIR model of disease spread in iThink

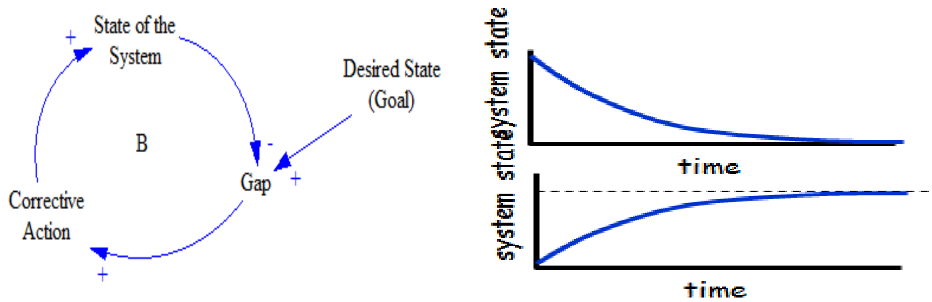


Source: Adapted from Sterman (2000)

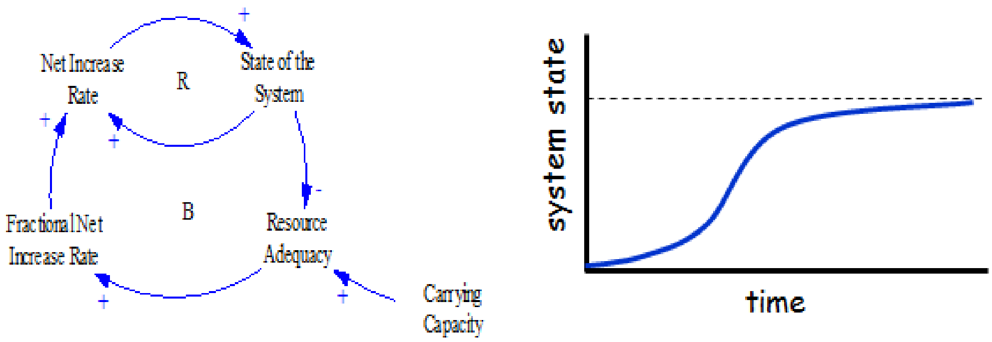
Figure 4
Common feedback structures in SD models



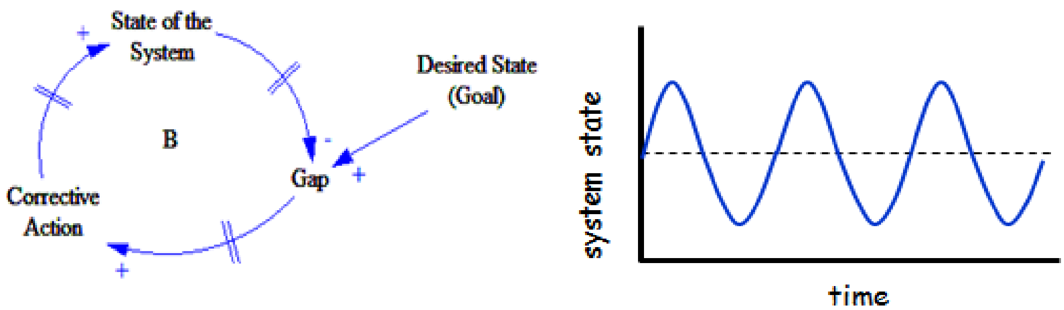
(a) Positive feedback (reinforcing loop)



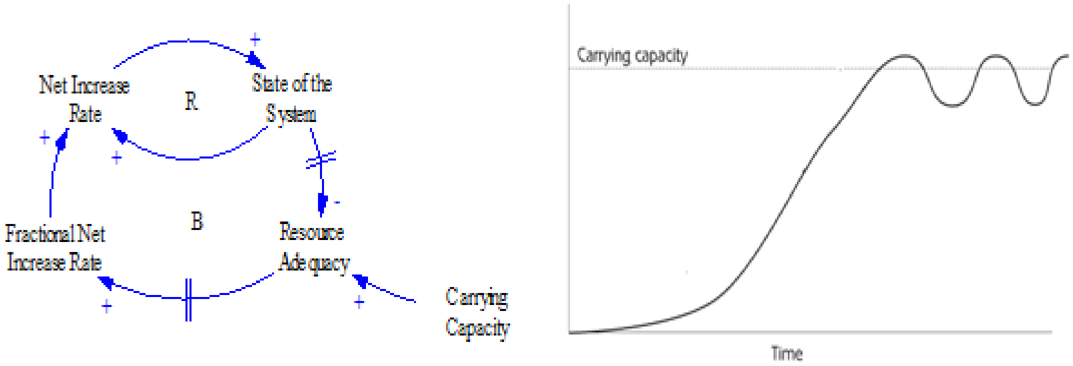
(b) Negative feedback (balancing loop) – goal-seeking behavior



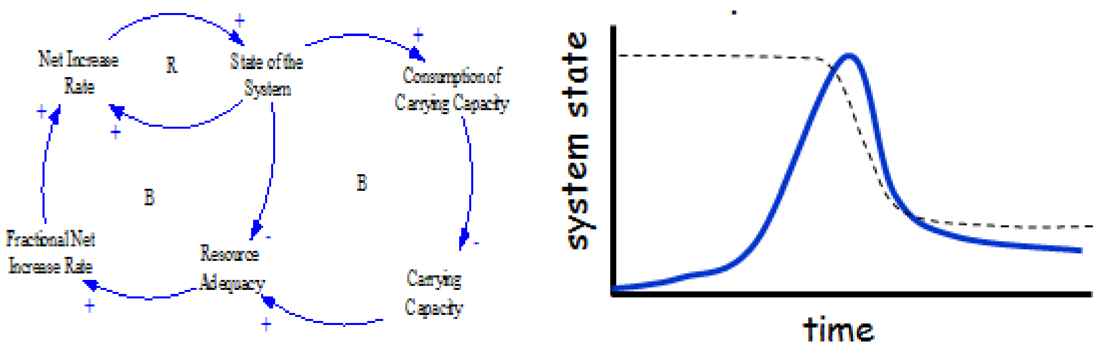
(c) S-shaped growth



(d) Oscillation



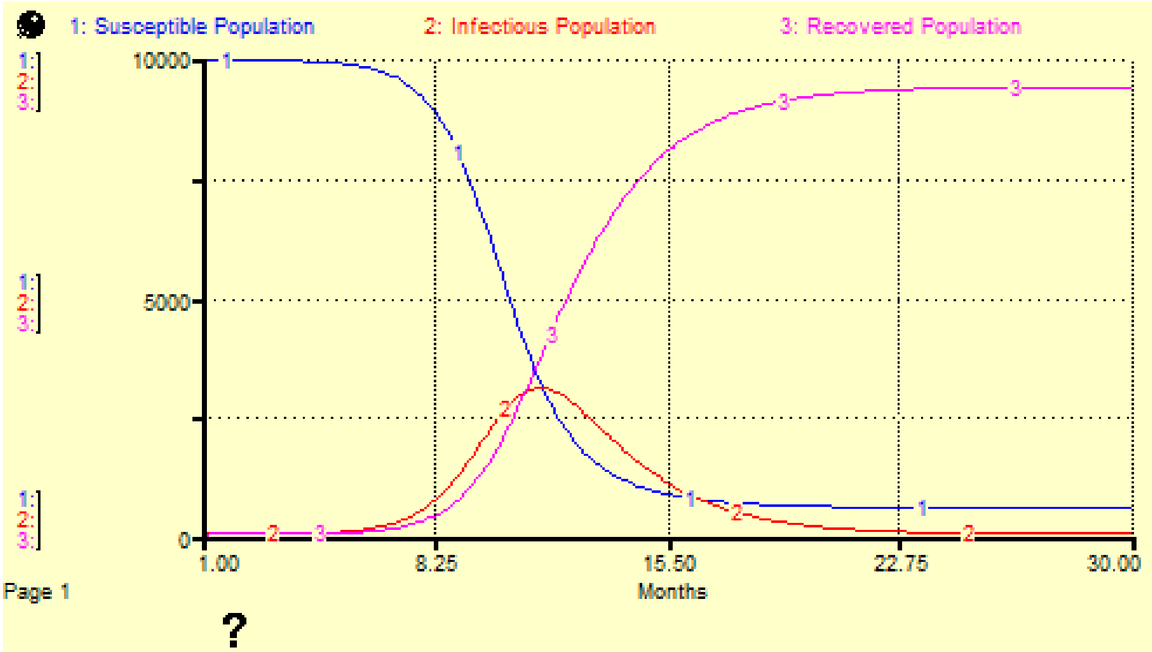
(e) S-shaped growth with overshoot



(f) Overshoot and collapse

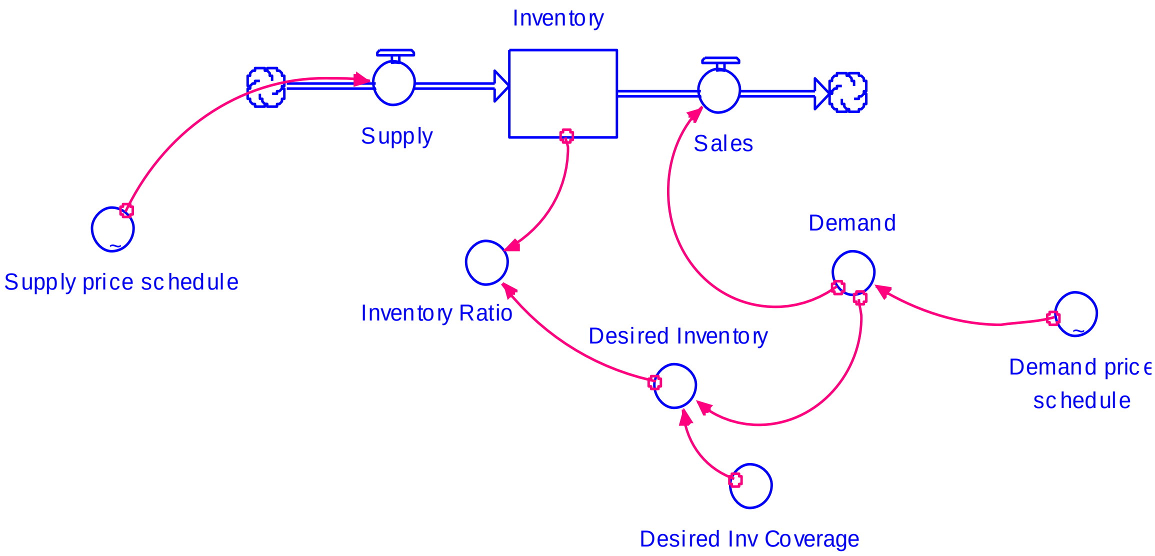
Source: Sterman (2000)

Figure 5
Model dynamics from the SIR model



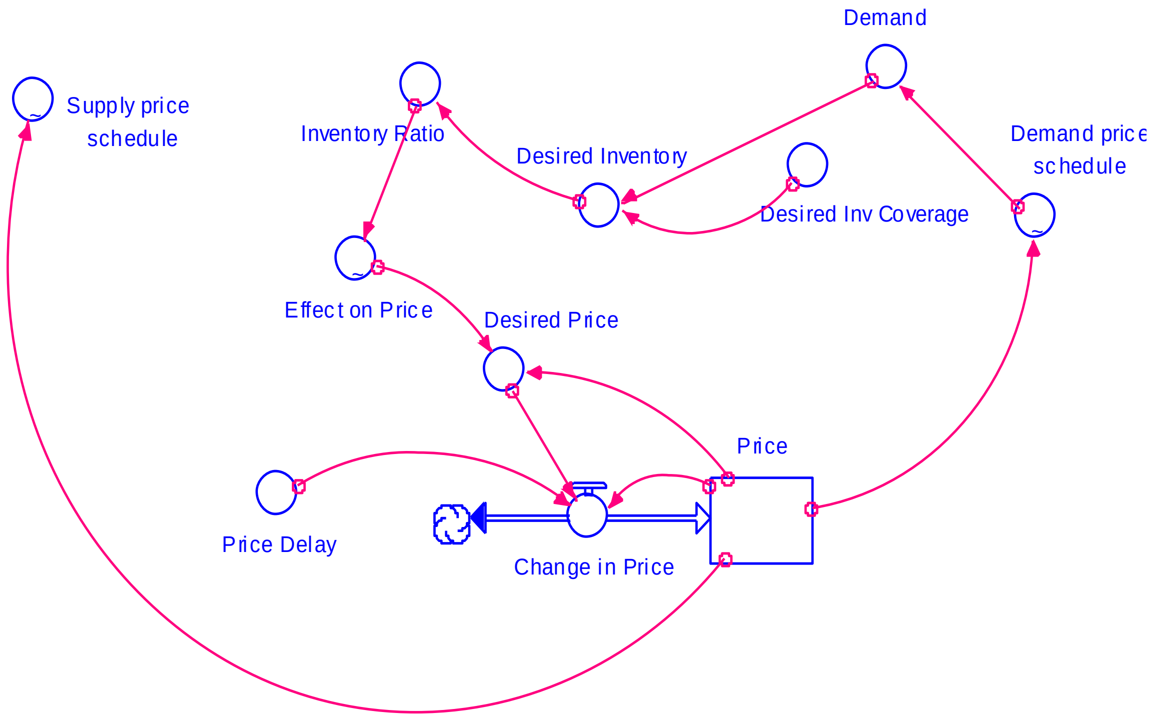
Source: Model simulations using the model in figure 3.

Figure 6
A simple SD model of supply and demand



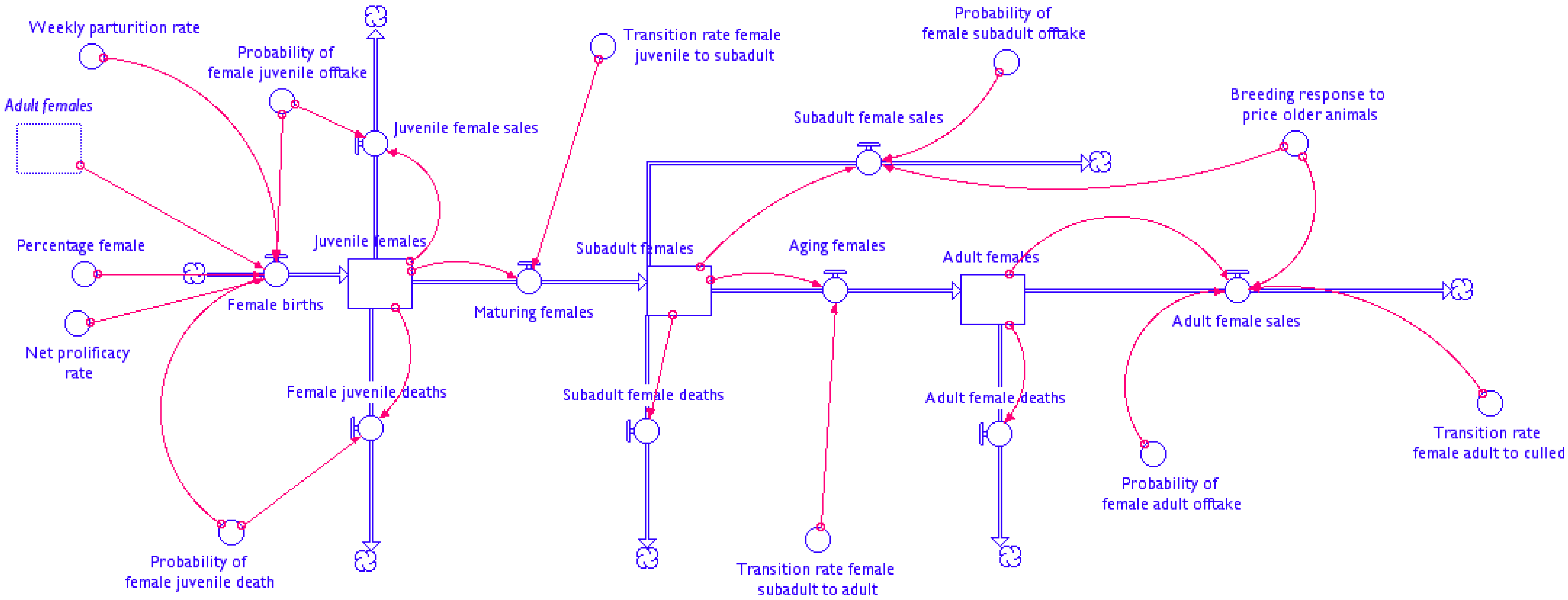
Source: Whelan and Msefer (1996)

Figure 7
Price formation in an SD model of supply and demand



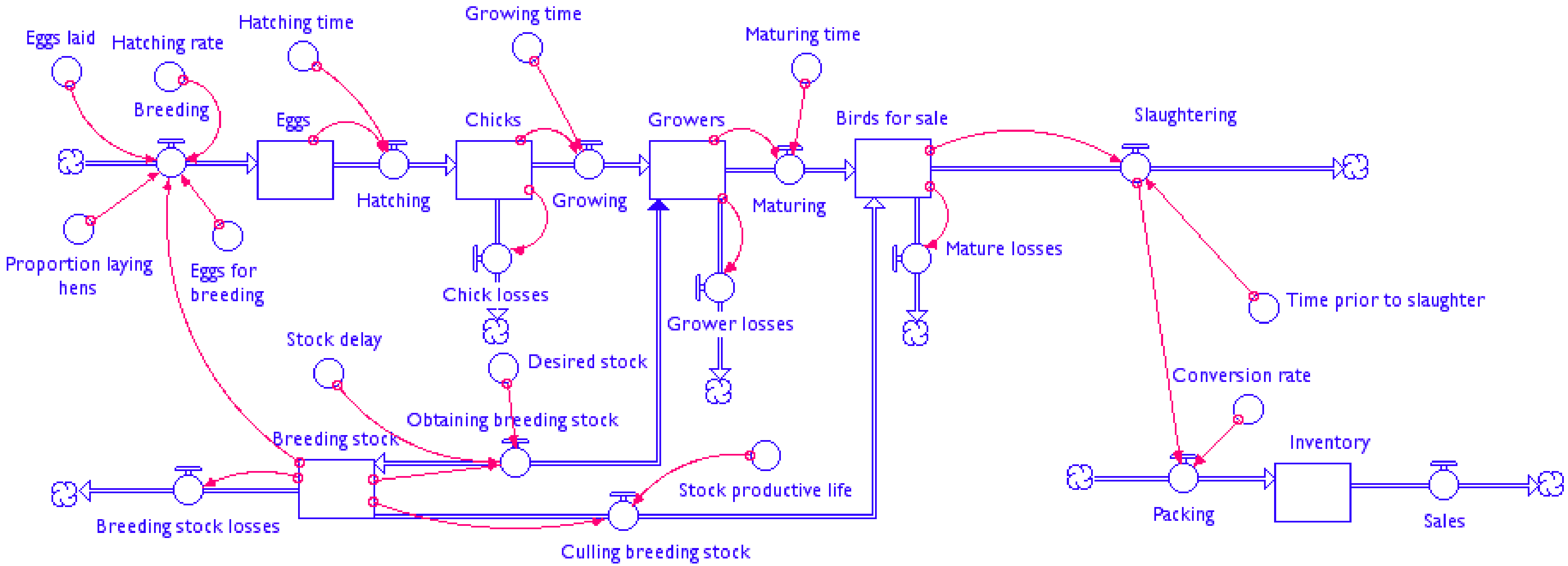
Source: Whelan and Msefer (1996)

Figure 8
An SD model of livestock population dynamics



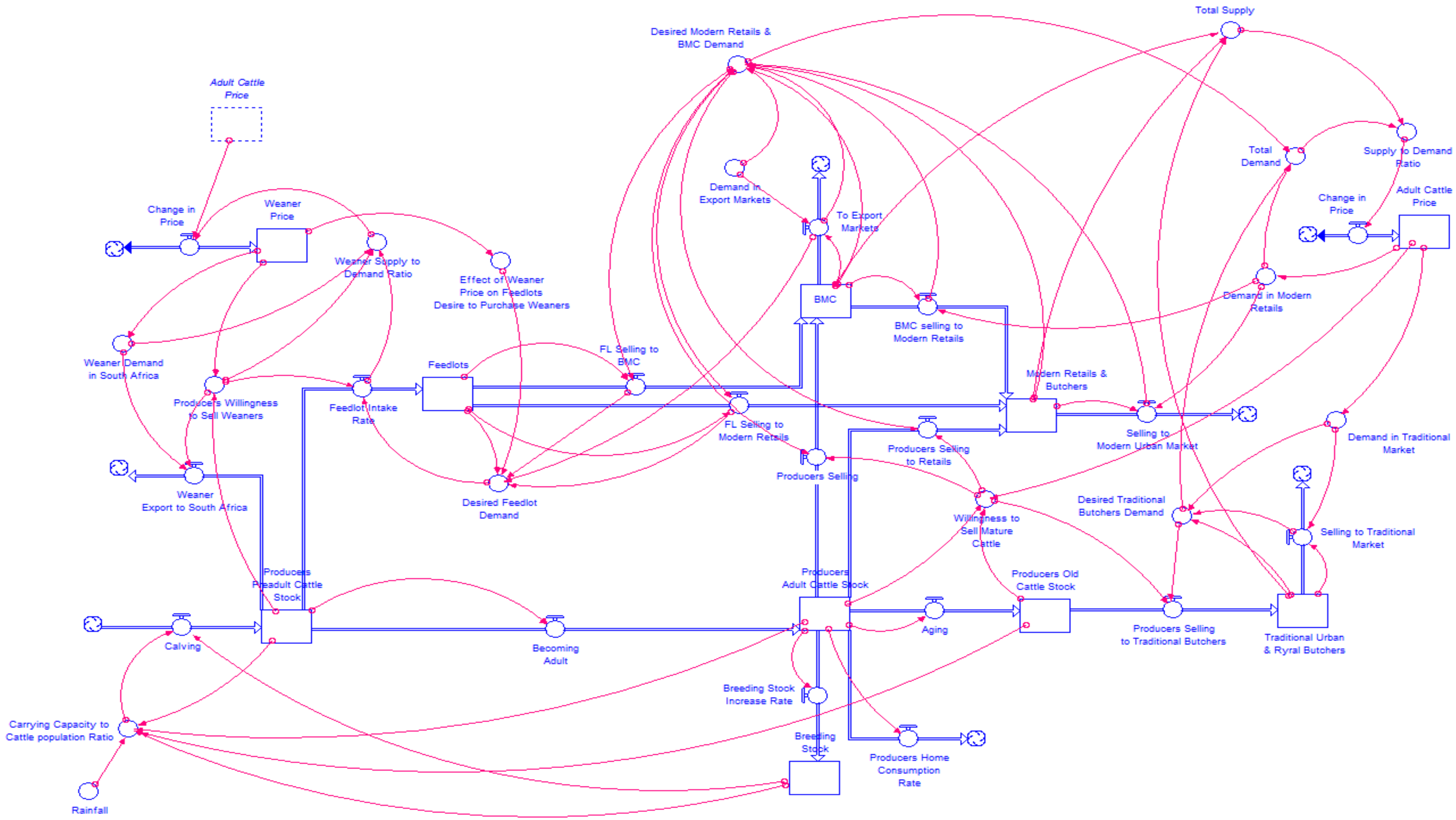
Source: Rich and Roland-Holst (2013), based on the DynMod model of Lesnoff (2008)

Figure 9
An SD model of poultry population dynamics



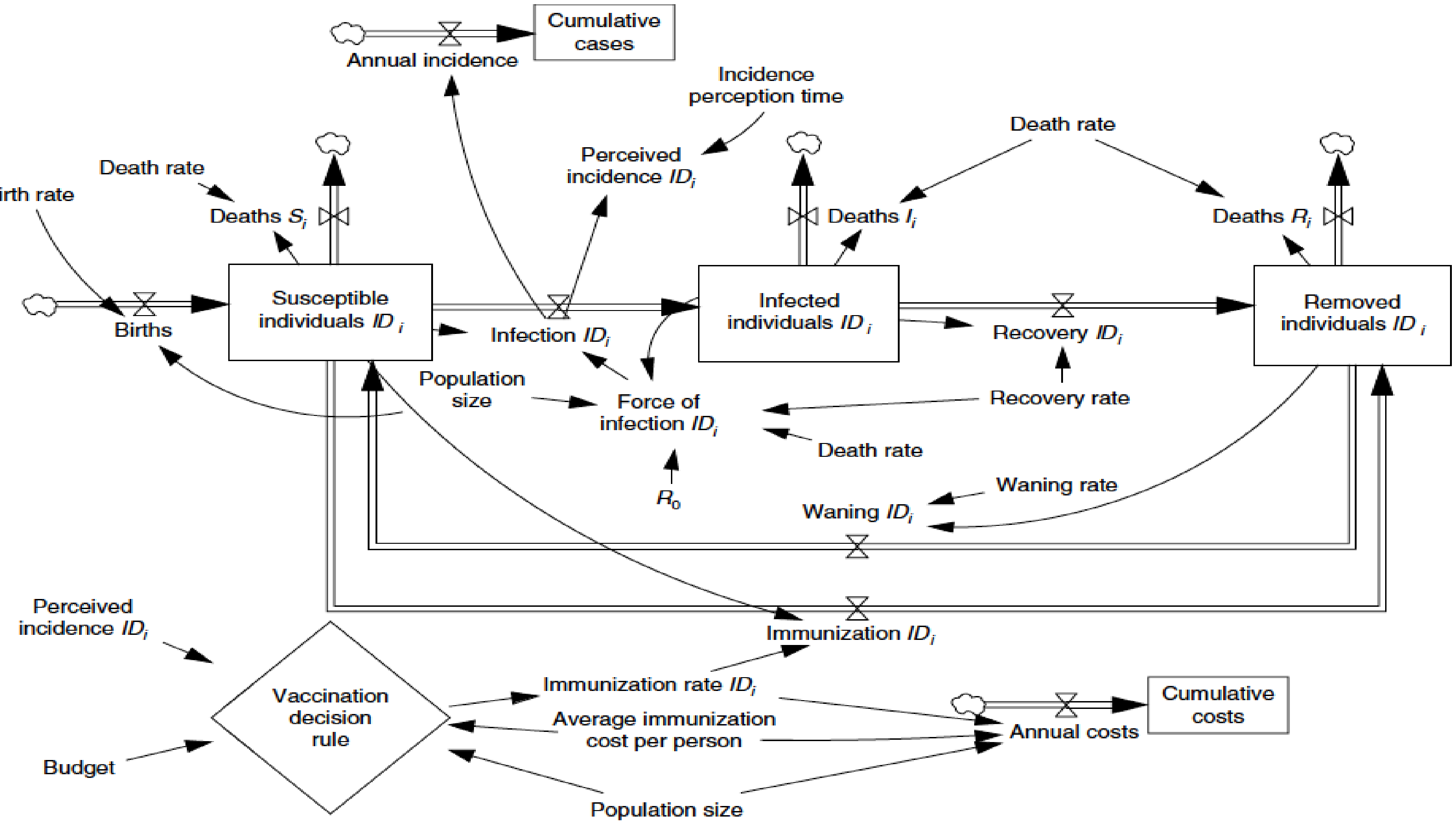
Source: Rich (2007)

Figure 10
An SD model of downstream actors in a livestock value chain



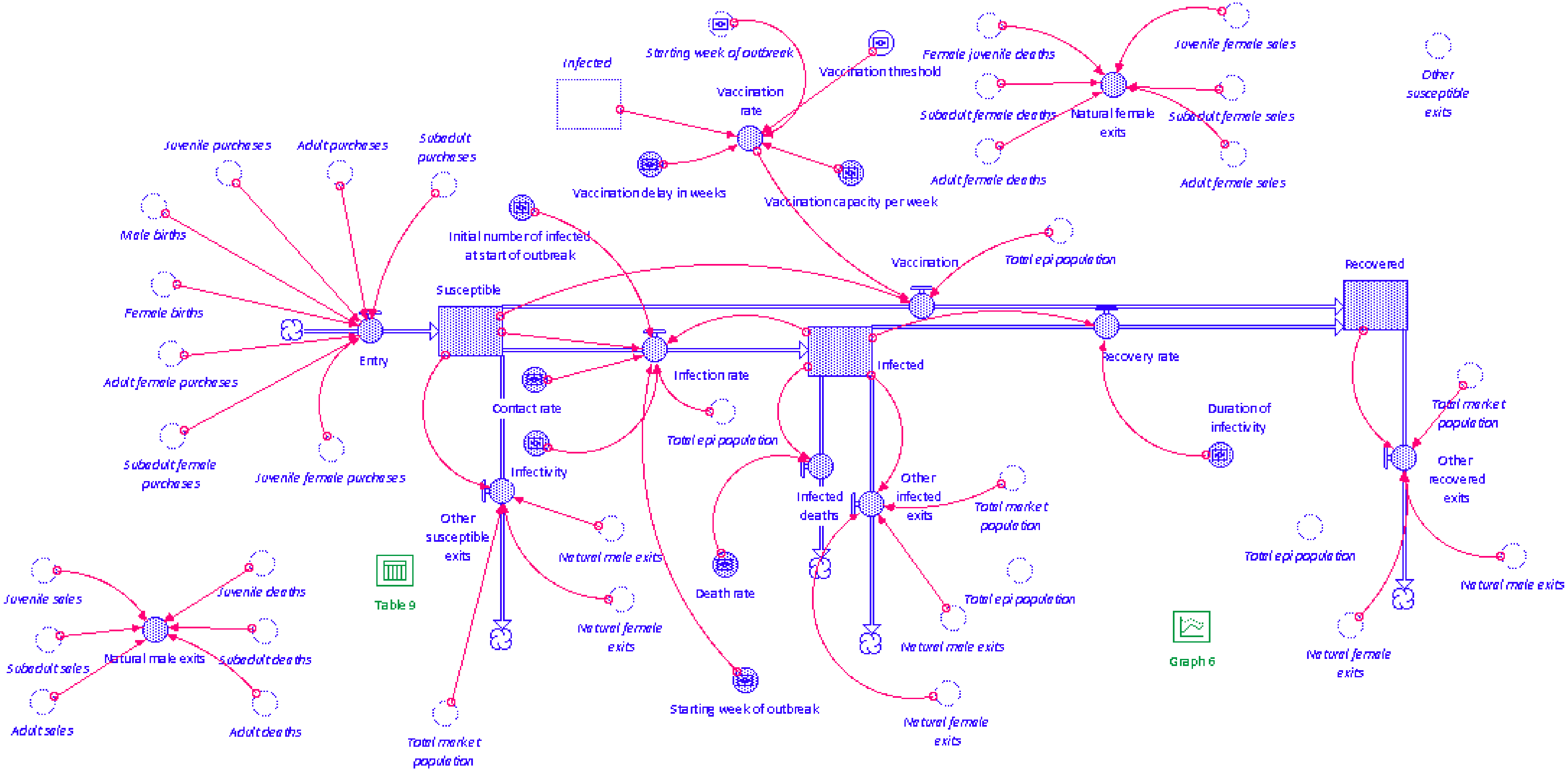
Source: Hamza et al. (2013a).

Figure 11
Incorporating decision rules in an SD model of disease



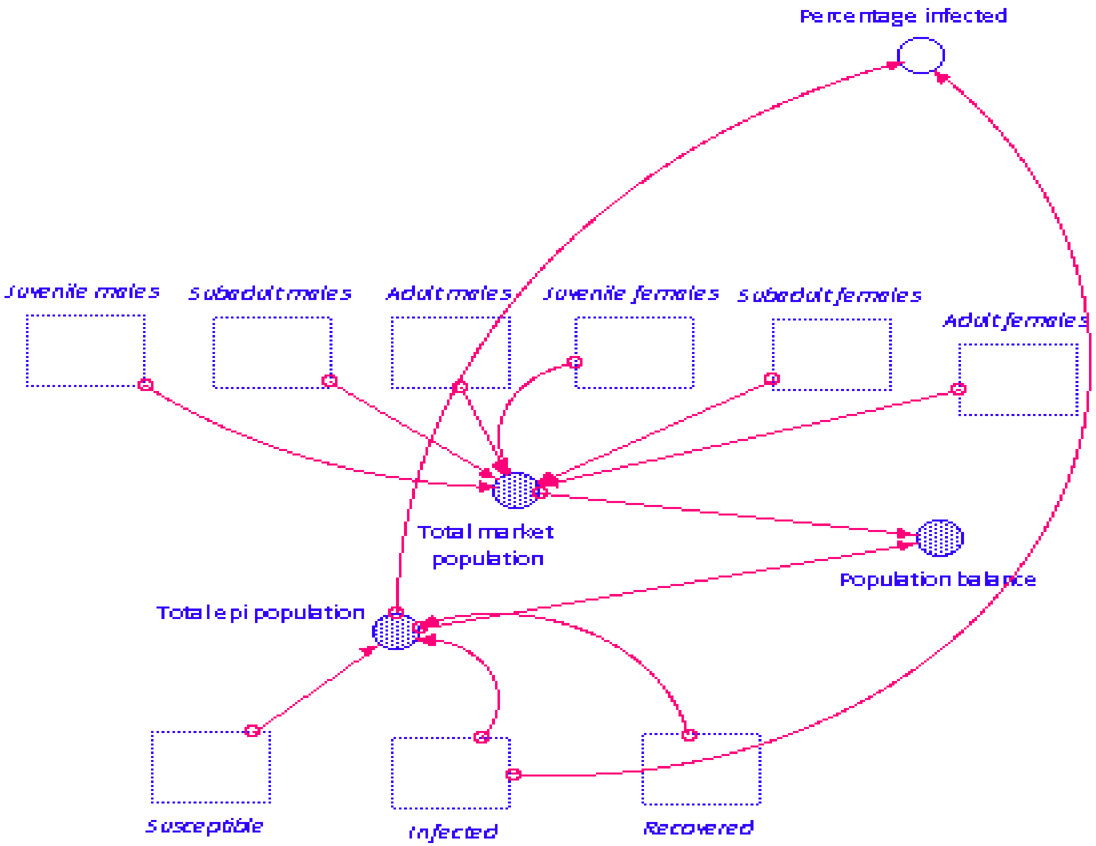
Source: Duintjer Tebbens and Thompson (2009)

Figure 12
An extended SIR model of animal disease



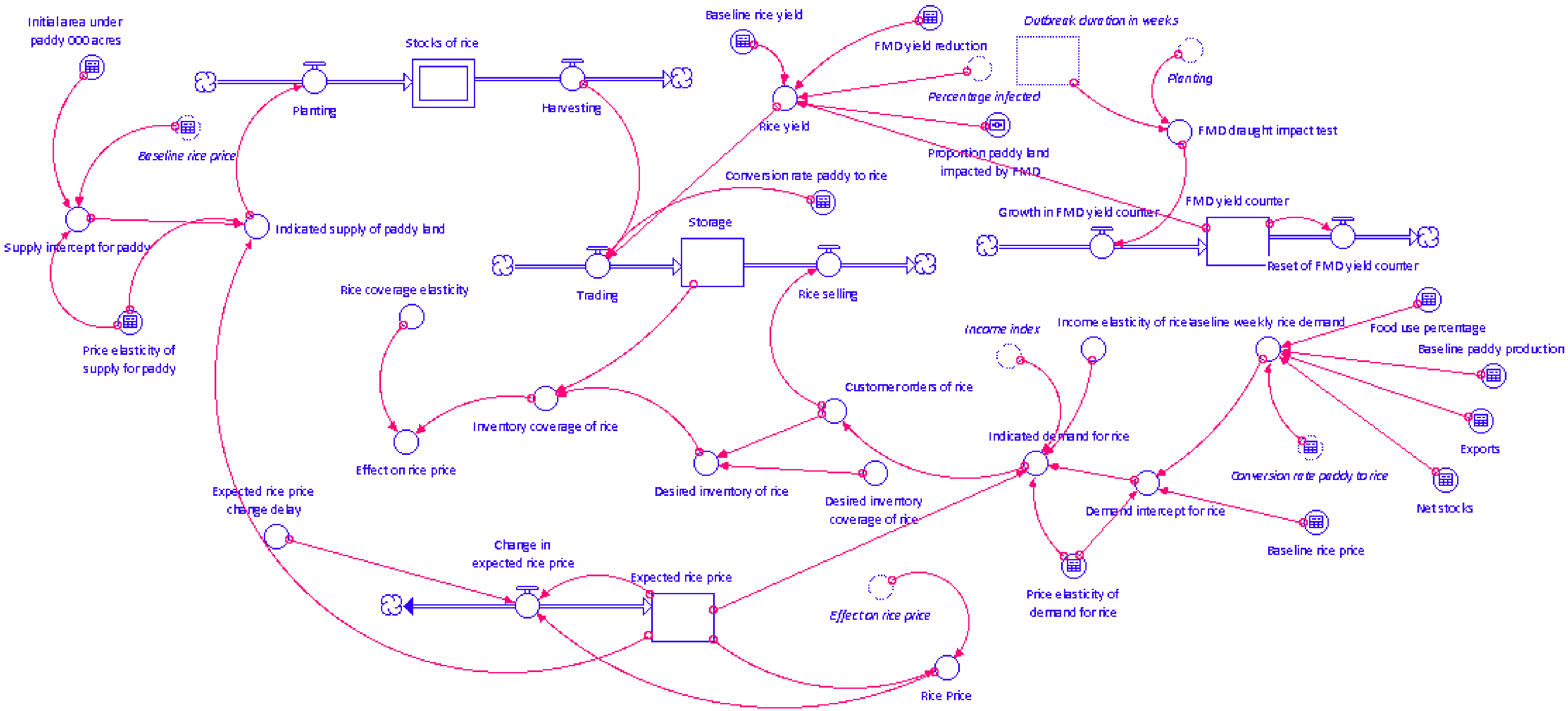
Source: Rich and Roland-Holst (2013).

Figure 13
Balancing epidemiological and economic population in an integrated disease control model



Source: Rich and Roland-Holst (2013)

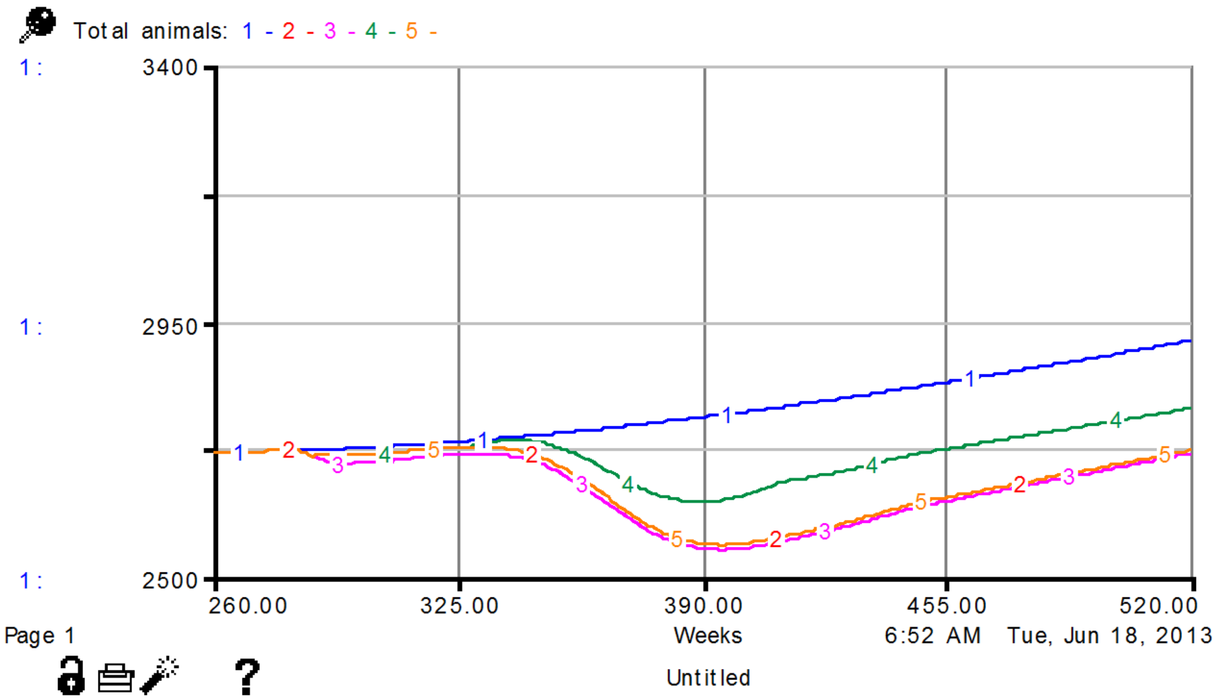
Figure 14
Integrating related markets in an SD model (crop-livestock systems)



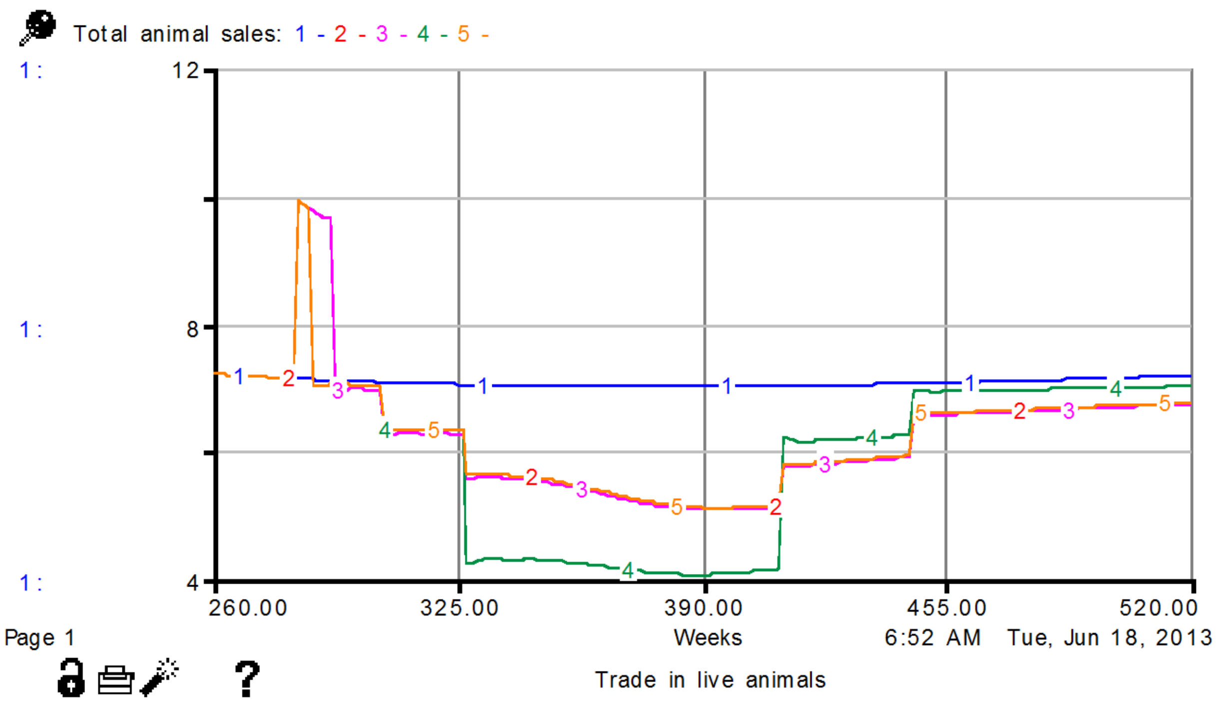
Source: Rich and Roland-Holst (2013)

Figure 15
Results from an integrated SD model of FMD in Cambodia

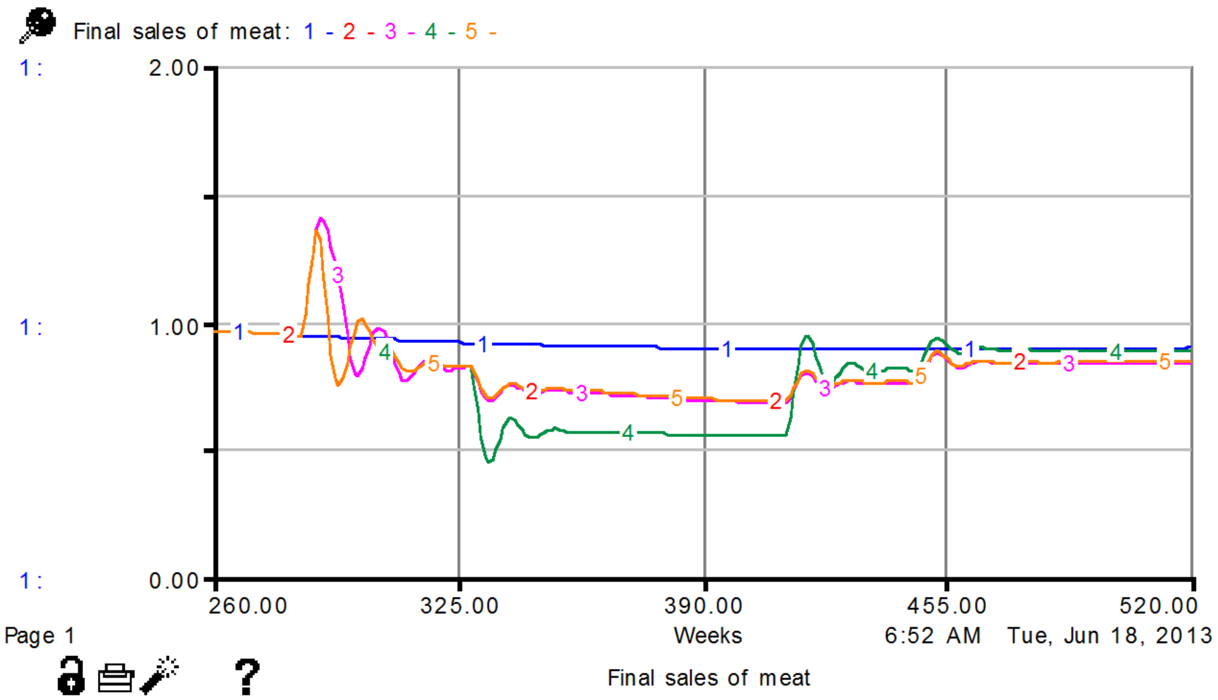
(a) Herd dynamics



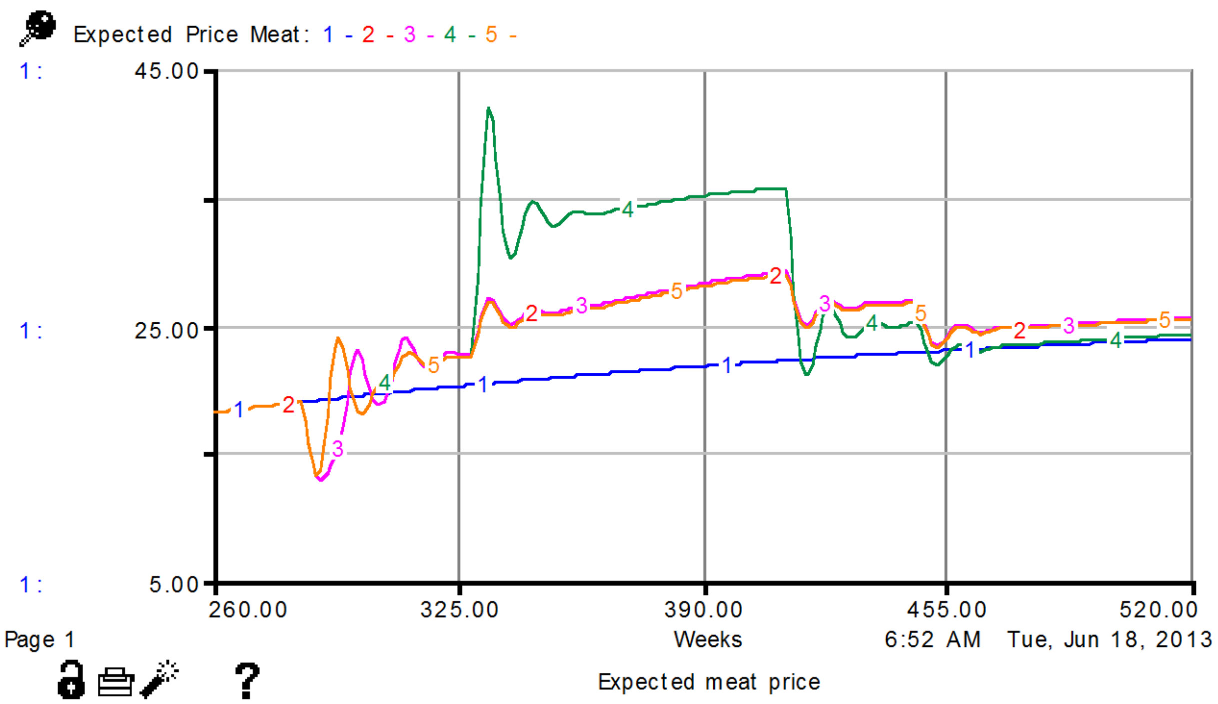
(b) Total animal sales



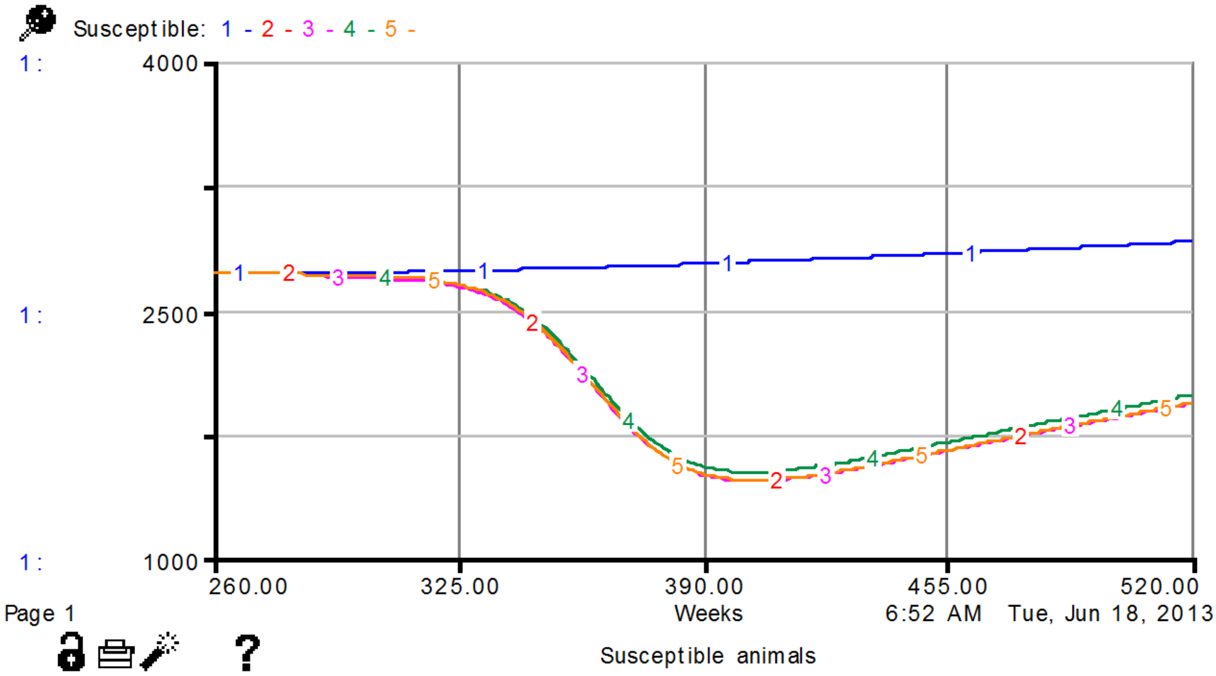
(c) Total meat sales



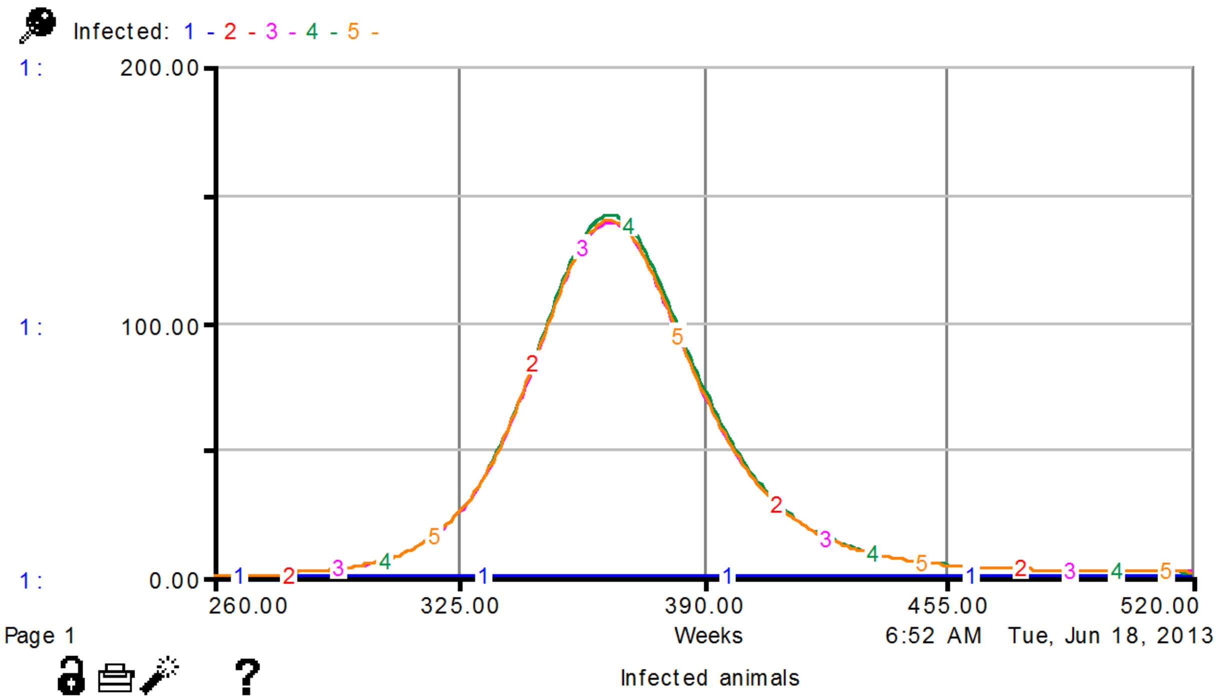
(d) Expected prices of meat



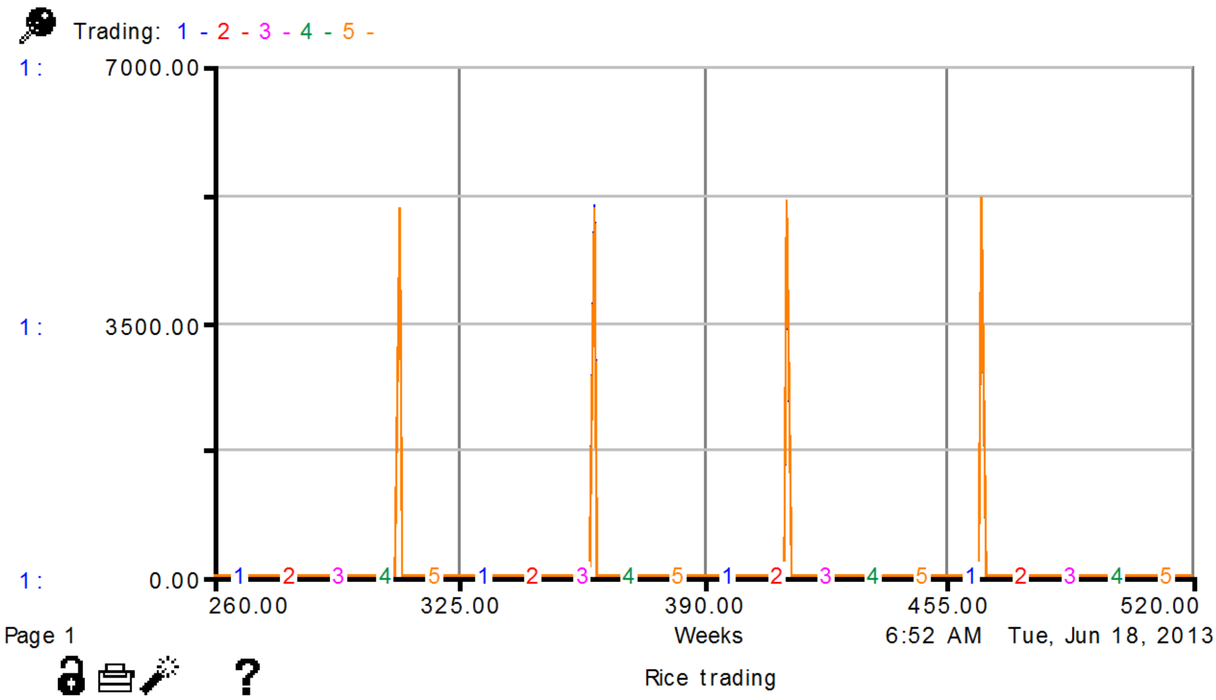
(e) Evolution of susceptible population during the FMD outbreak



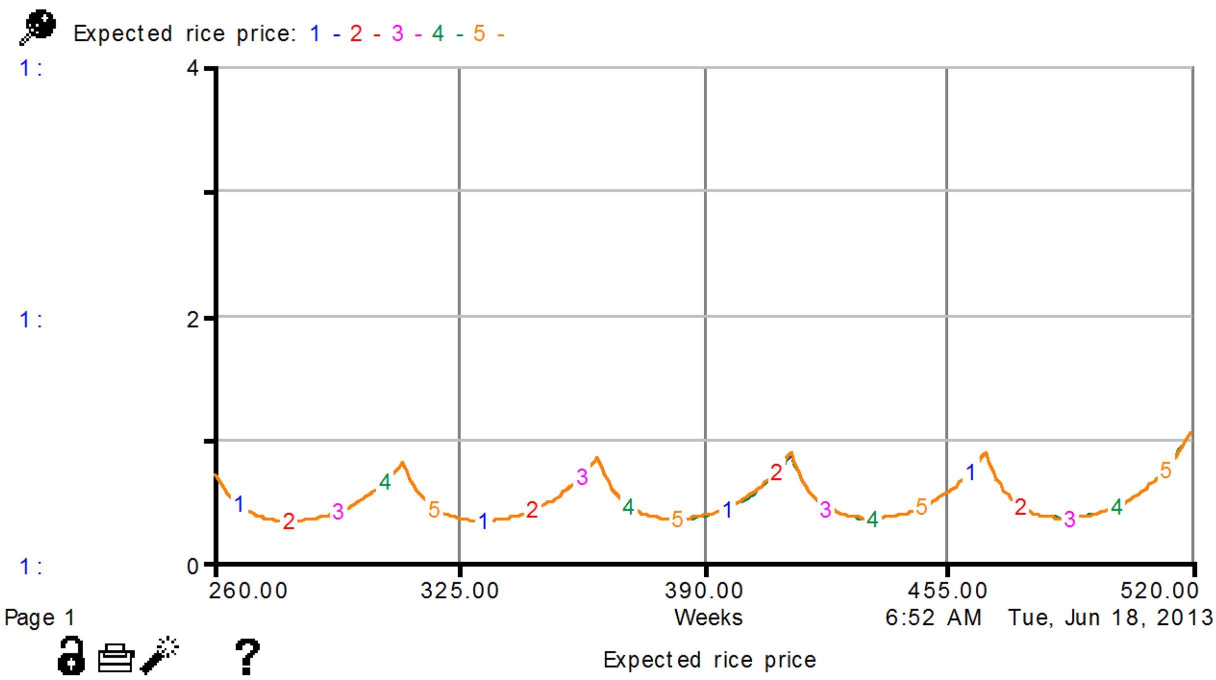
(f) Evolution of infected animals during the outbreak



(g) Trading of rice stocks

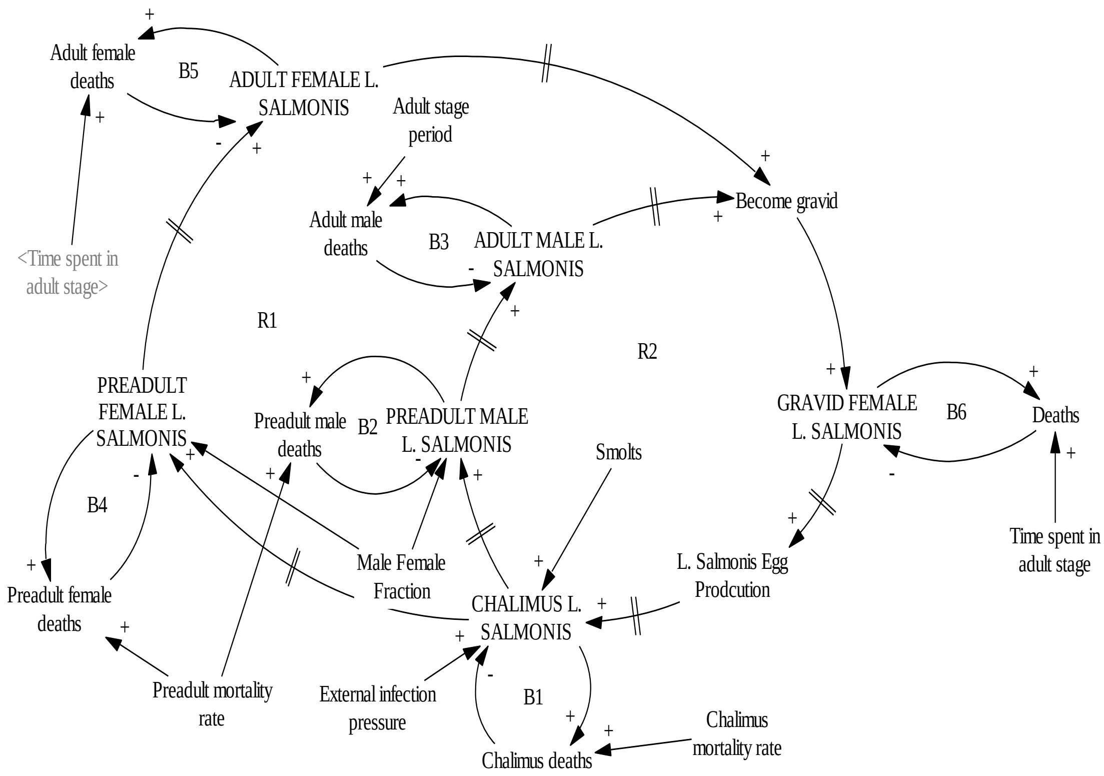


(h) Evolution of rice price movements



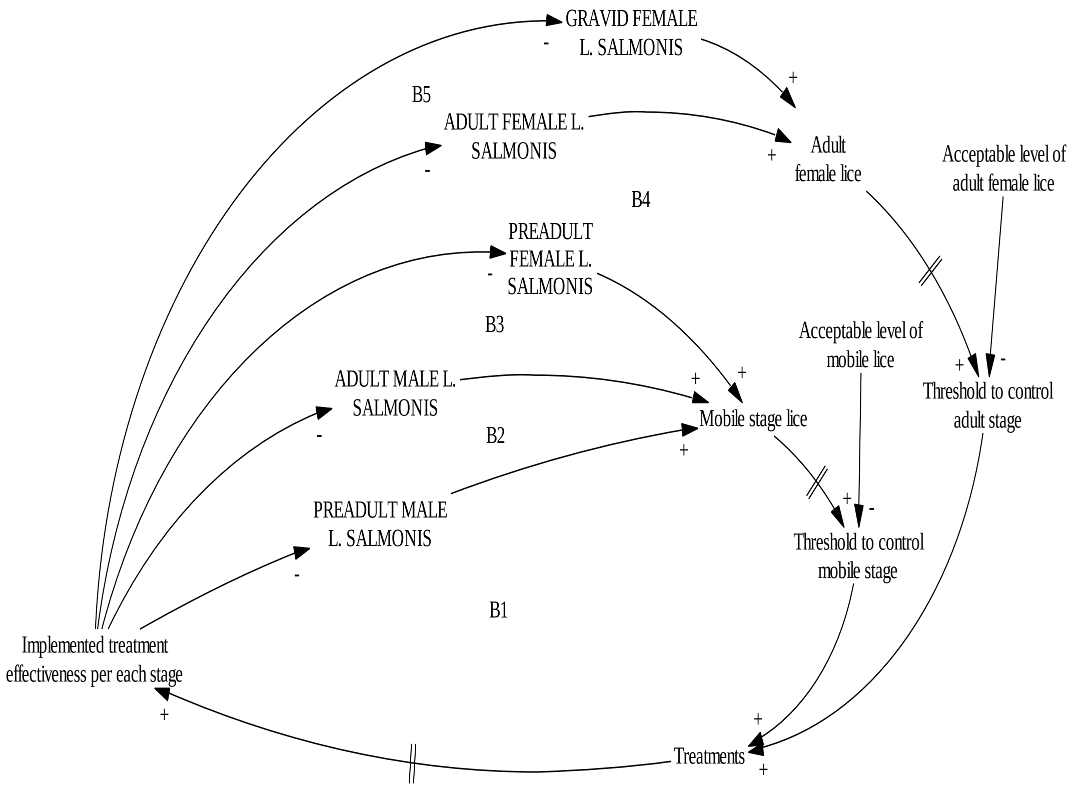
Source: Rich and Roland-Holst (2013)

Figure 16
Dynamics of sea lice population growth



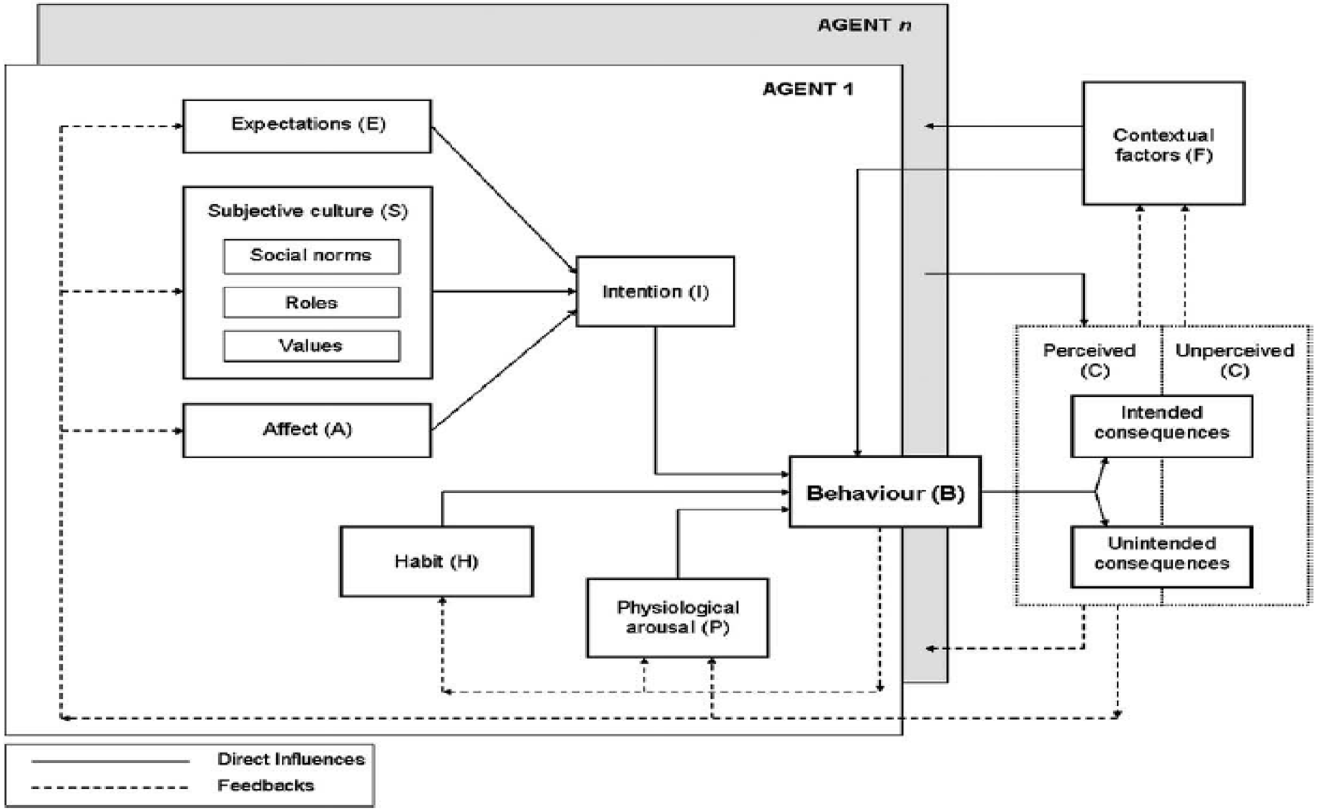
Source: Hamza (2012)

Figure 17
Policy options to control sea lice in farmed salmon



Source: Hamza (2012)

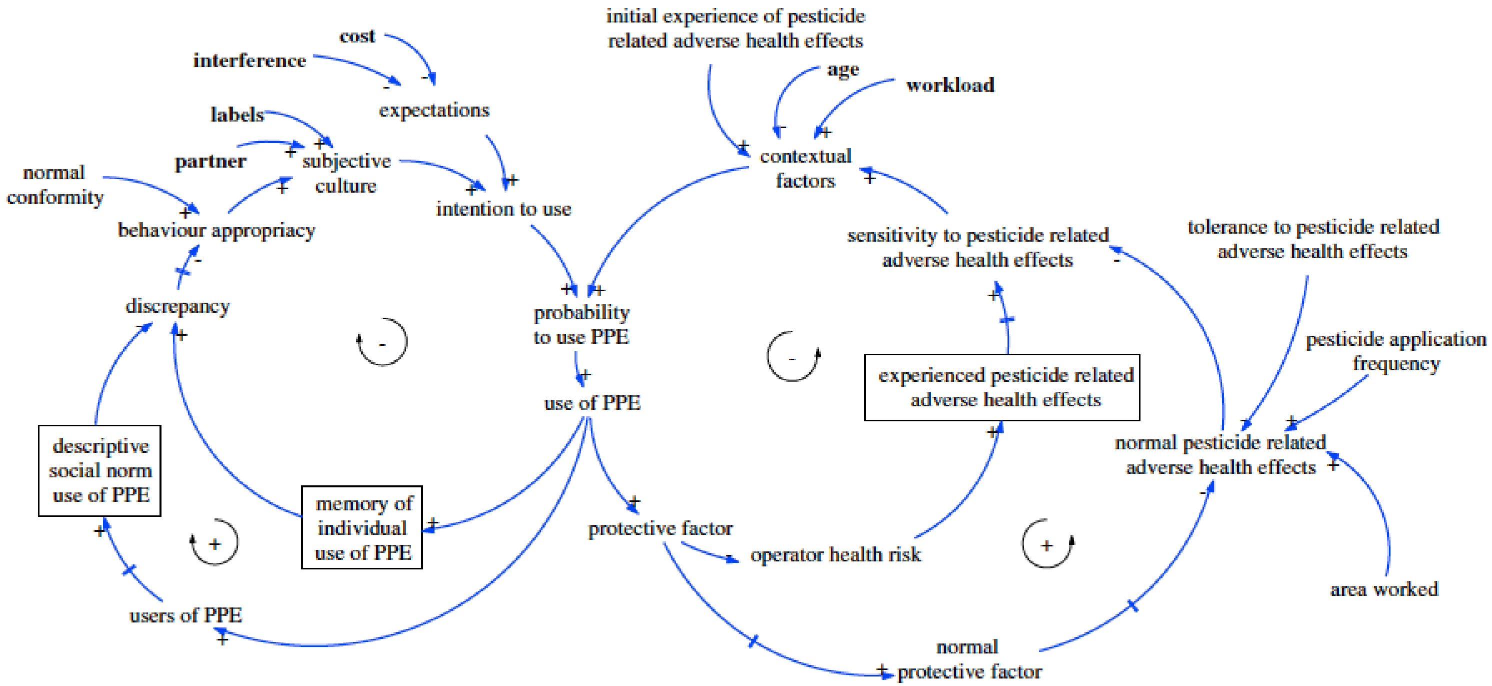
Figure 18
Schematic of the integrative agent-centered framework



Source: Feola and Binder (2010)

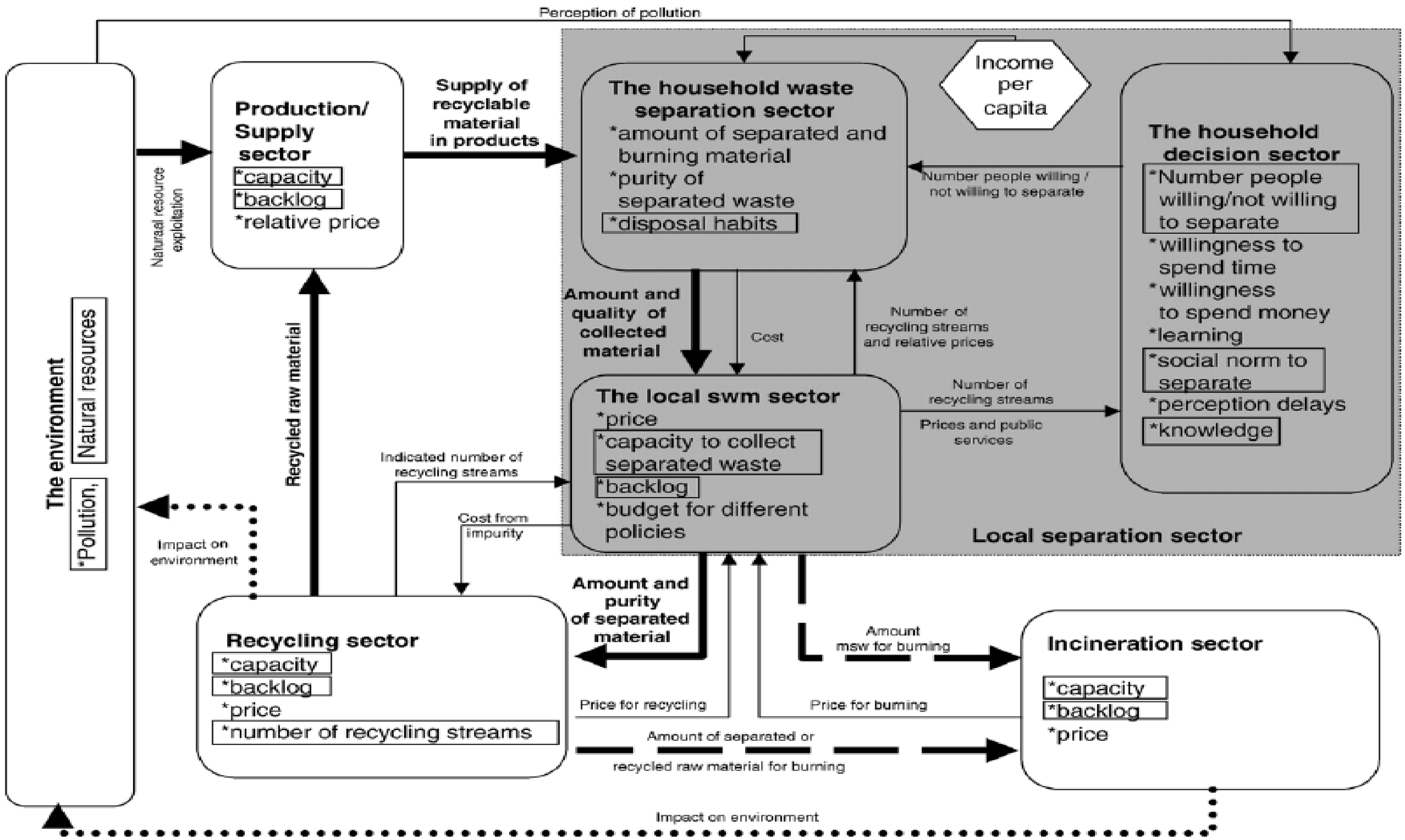
Figure 19

Causal-loop diagram of pesticide use behavior among farmers in Colombia



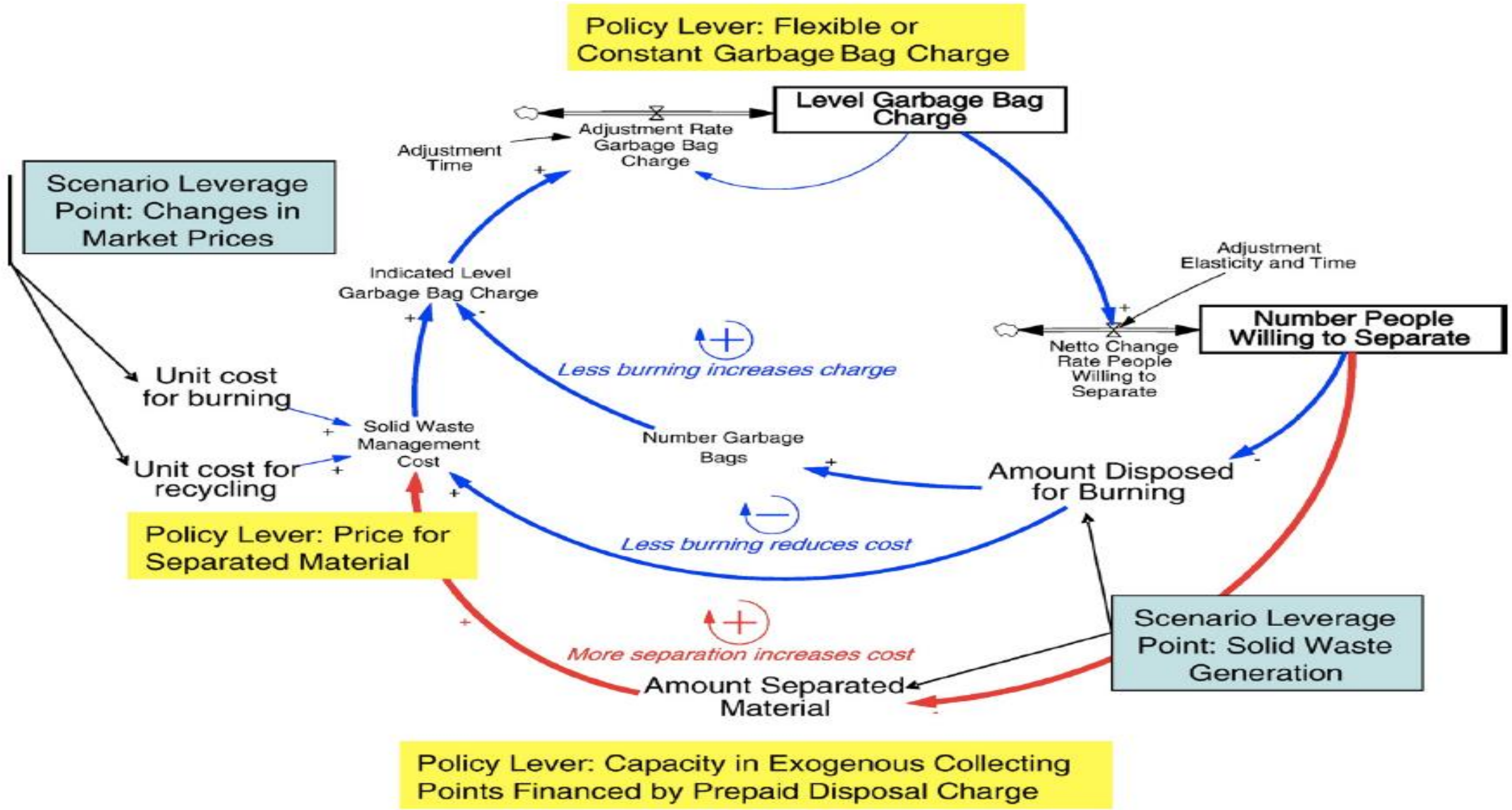
Source: Feola, Gallati, and Binder (2012)

Figure 20
Model structure to examine behavior towards recycling in Switzerland



Source: Ulli-Beer, Anderson, and Richardson (2007)

Figure 21
Policy interventions to influence behavior towards recycling in Switzerland



Source: Ulli-Beer, Anderson, and Richardson (2007)