



Exploring agricultural production systems and their fundamental components with system dynamics modelling



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ARTICLE INFO

Article history:

Received 14 January 2016

Received in revised form 18 April 2016

Accepted 19 April 2016

Available online 4 May 2016

Keywords:

Sustainability

Agriculture production systems

System dynamics modelling

Drivers

Farming policy

ABSTRACT

Agricultural production in the United States is undergoing marked changes due to rapid shifts in consumer demands, input costs, and concerns for food safety and environmental impact. Agricultural production systems are comprised of multidimensional components and drivers that interact in complex ways to influence production sustainability. In a mixed-methods approach, we combine qualitative and quantitative data to develop and simulate a system dynamics model that explores the systemic interaction of these drivers on the economic, environmental and social sustainability of agricultural production. We then use this model to evaluate the role of each driver in determining the differences in sustainability between three distinct production systems: crops only, livestock only, and an integrated crops and livestock system. The result from these modelling efforts found that the greatest potential for sustainability existed with the crops only production system. While this study presents a stand-alone contribution to sector knowledge and practice, it encourages future research in this sector that employs similar systems-based methods to enable more sustainable practices and policies within agricultural production.

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1. Introduction

Agricultural production systems undergo rapid changes in response to shifts in production expenses, consumer demands, and increasing concerns for food safety, security, and environmental impact (Hanson et al., 2008; Hendrickson et al., 2008). An overriding concern is the need to develop sustainable production systems that address societal concerns for environmental impacts and nutritional value, while maintaining an economically feasible

production system for farmers. Sustainable agricultural production per Sassenrath et al. (2009) is: “an approach to producing food and fibre which is profitable, uses on-farm resources efficiently to minimize adverse effects on environment and people, preserves the natural productivity and quality of the land and water, and sustains vibrant rural communities” (p.266). In aligning with this definition, the five general goals that must be addressed by sustainable production systems are therefore: supplying human needs, enhancing the environment and natural resource base, increasing efficiency of resource use, improving economic viability of farming, and enhancing quality of life for producers and society.

One way to accomplish these sustainability goals has been to employ integrated agricultural production techniques. Integrated agricultural production is a mixed enterprise approach to farming that uses natural resources through the combination of crop and livestock inputs and outputs to promote environmentally beneficial farming practices (Hendrickson et al., 2008; Boller et al., 2004). A major benefit of integrated agricultural production is its inherent ability to distribute, and thereby minimize, farmer risks through the diversification of enterprises, allowing farmers to exploit a higher

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spectrum of marketing channels (Hendrickson et al., 2008). Despite the fact that integrated production can greatly minimize overall risk, it presents a substantial challenge in administering the complex trade-offs of each individual farming component. Examples of these challenges include timing of operations, the type of equipment used and allocated, and the timing of agricultural markets, in concert with a range of other social, environmental, economic and technological considerations (Hendrickson et al., 2008; Archer et al., 2007, 2008; Halloran and Archer, 2008).

At the core, the challenges in both single and mixed-enterprise agricultural production exist in the task of operationalizing the interactions between disparate measures of productivity and sustainability, and necessarily require adequate understanding of the complex interactions between environmental, social, and economic drivers. For example, ecological systems contain a multitude of diverse components, interacting non-linearly and dynamically in both space and time (Wu and Marceau, 2002). As Wu and David (2002) mention, “An obvious challenge in modelling complex ecological systems is, then, to integrate the rigor of reductionism with the comprehensiveness of holism.” Similarly, social drivers are often tenuous, highly changeable, and difficult to quantify (Ramalingham et al., 2008). In addition, environmental drivers that impact farming management choices are not always straightforward, a fact that is exemplified by the substantial loss of Conservation Reserve Program (CRP) lands to greater economic return from corn production for biofuels (Hartman et al., 2011; Fargione et al., 2009).

Past research has approached these complex aspects of agricultural production through the use of modelling. Many models are available that track crop and animal production for decision support, such as GPFARM (Great Plains Framework for Agricultural Resource Management), among others (Rauff and Bello, 2015). These models include mechanistic and statistical approaches to model biophysical processes, and in some cases link these processes to economic or multi-objective optimization to guide management decisions. While these models typically simulate bio-physical processes in great detail, their usefulness is often hampered by the need for large amounts of input data and by requirements for extensive calibration and validation before each use. Also, while these models are often complex, limiting their usefulness, the methods simplify the systemic and dynamic interdependencies necessary for intrinsically complex agricultural systems planning (Ramalingham, 2014). While Tanure et al. (2014) proposed a mathematical model for use in decision support systems for farm management to be applied within dynamic systems models, their models have not yet been applied to real agricultural production systems.

Here we assert that methods within the realm of such fields as complexity science, i.e. “systems thinking”, could be better-fit to holistically understand agricultural system complexity, especially given the added task of considering social drivers and impacts. Complex systems are typically characterized by interconnected and interdependent elements and dynamic feedback processes (also known as “loops”). Through these processes, certain behaviours often emerge that are contrary to what was planned for or expected (Ramalingham et al., 2008; Sterman, 2000). Our approach to agricultural system complexity focuses precisely on these three concepts – namely, (i) the interconnection and interdependence of factors, (ii) dynamic feedback processes between these factors and (iii) the emergent behaviours that result – to study the systemic interaction of factors that influence sustainability. Here we direct our attention to complexities of agricultural production including societal, environmental, and economical aspects. Specifically, we are interested in understanding the structural form of “drivers”, which are key factors that systemically and dynamically interact to influence system sustainability. Of the many methodologies

and tools that exist to tackle problems of this type, we elected to use system dynamics modelling because of its ability to explicitly address problems with systemic and dynamic drivers, allowing an improved understanding of emergent problems and behaviours (Churchman, 1968; Sterman, 2000).

Our objective with this study was to make a novel contribution to the sector by developing a preliminary system dynamics-based approach to understand sustainable agricultural production. In doing so, we hope to encourage a dynamic systems-based paradigm shift in agricultural systems analysis. The questions that guided these research efforts were:

1. What drivers influence agricultural production systems?
2. How do these drivers systemically and dynamically interact to influence sustainability?
3. Which type of production enterprise has the greatest chance for sustainability?

To answer these research questions and accomplish our study objective, we use the system dynamics modelling environment, STELLA (isee Systems, 2015) to capture and model the complexities between human (social), environmental, and economic interactions. Of the many software suites (e.g., VENSIM and POWERSIM) or programming languages (i.e., C++ and Java) available for building and simulating system dynamics models, we chose STELLA (isee Systems, Lebanon, NH) because of its low cost, intuitive and user-friendly (no programming is required) interface, and widely recognized modelling iconography. We demonstrate the utility of this approach through a sustainability assessment of three different agricultural production systems (single or mixed enterprise systems) using a qualitative and quantitative systems dynamics model that incorporates various aspects of crop and animal production to output indices of economic, social and environmental sustainability. We present a detailed overview on the data and modelling aspects of this study. We then proceed with an example analysis of model outputs and implications to present a methodology for future modellers to leverage this work and continue building informative models to better understand this complex and important topic of sustainable food production.

2. Data and modelling

This section presents the methodological steps to develop the system dynamics model of three distinct agricultural systems. We begin by providing a brief overview of the systems dynamic modelling approach, highlighting the key modelling aspects that guided our model building process. We then describe the types of data we used to construct a qualitative and quantitative system dynamics model, followed by a synopsis of the key aspects of model development and analysis.

2.1. The system dynamics modelling approach

System dynamics modelling presents a means to describe and simulate dynamically complex issues through the structural identification of feedback, and in many cases, delay processes that drive system behaviour (Sterman, 2000; Pruyt, 2013). Since the formation of the modelling concept by Jay Forrester in 1959, the method itself has been used for a broad spectrum of applications including the modelling of complex ecological and economic systems (Costanza and Gottlieb, 1998a; Costanza et al., 1998b; Costanza and Voinov, 2001), many of which address, to some extent, the social implications of system behaviour (Wu and Marceau, 2002; Bossel, 2007; Ford, 1999a). A system dynamics modelling approach was chosen for this research given its proven ability to go beyond

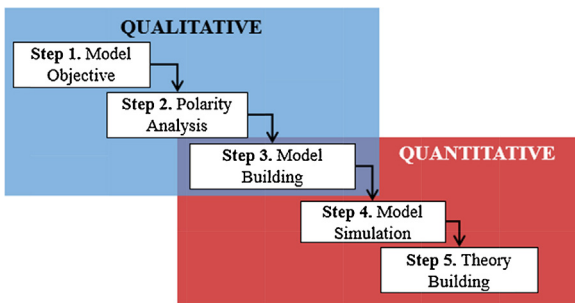


Fig. 1. An illustration of the system dynamics modelling process.

the inherent limitations of linear and static models to include the dynamic interactions between factors at play in an interconnected system (Richmond, 2001; Sterman, 2000; Wolstenholme, 1982; Meadows, 2008; Walters and Javernick-Will, 2015).

System dynamics modelling generally takes on two complimentary forms: *qualitative modelling*, where the end goal is to develop causal loop diagrams (CLD) that represent dynamic factor interaction (Wolstenholme, 1990; Luna-Reyes and Andersen, 2003); and *quantitative stock-flow (SF) modelling*, where the end goal is to model and simulate the dynamic effects of factors and their interaction. In many cases, qualitative modelling is used to inform subsequent quantitative modelling and simulation with quantitative modelling tools such as STELLA or VENSIM, serving as a conceptual framework for the interaction of factors within an SF model (Wolstenholme, 1990).

The process for developing system dynamics models typically follows an iterative progression that begins with the clear expression of the modelling objective, and proceeds with identification of factors and their dynamic interaction through polarity analysis and dynamic hypothesis casting and diagramming, followed by model simulation and interpretation. While the merging of qualitative and quantitative modelling can greatly enhance the utility and explanatory power of a system dynamics model, a formal framework that merges these approaches does not exist (Luna-Reyes and Andersen, 2003; Wolstenholme, 1999; Pruyt, 2013). Thus, we present a five-step modelling process using a combination of recommended modelling processes from Pruyt (2013), based on Richardson and Pugh (1981) and others (Forrester, 1993; Wolstenholme, 1990; Sterman, 2000), displayed in Fig. 1.

In this process, the first three steps are primarily qualitative, and the latter two steps are primarily quantitative, where a unifying step (Step 3) overlaps in the task of translating a CLD into an SF model format (Pruyt, 2013). Polarity analysis entails drawing factor interaction diagrams (CLDs) through which the dynamic interaction between factors is hypothesized. CLDs are composed of arrows (causal influences) between factors and pair-wise factor polarities represented as positive (+) (i.e., an increase or decrease of one factor causes an increase or decrease in the other factor) or (−), which is the opposite of a positive influence (i.e., an increase or decrease of one factor causes a decrease or increase in the other). Completed CLDs allow the identification of circular causality between factors

known as feedback loops, processes or mechanisms, which are the unit of analysis for dynamic behaviour (Richardson, 2011). Analysis of feedback loop polarity provides insight into the root causes of system behaviour, taking the form of either *reinforcing loops* (exponential increase or decrease, typically indicated with an “R” in CLDs) or *balancing loops* (restorative or goal-seeking, typically indicated with a “B” in CLDs).

The structural interaction of factors within CLDs can enable the building of SFs using the similar structure in combination with parameterized variables to provide simulation using real world data. A structural comparison between a CLD and an SF is shown in Fig. 2, where the translation of the primarily qualitative CLD to a quantitative SF form involves connecting factors into functional parameters: stocks (squares), flows (valves) and converters (circles), where the “stock and flow” model finds its name. Stocks accumulate or discharge entities by inflows and outflows, similar to water in a bathtub. It is through modelling the accumulation or discharge within a stock that simulation of dynamic behaviour becomes possible. Converters are used in various capacities to invoke weighted influences, mathematical influences, or simply maintain unit consistency, and are often placed by the modeller to make certain influences and conversions explicit. An SF model simulation in many different forms offers a “virtual world”, through which to analyze the relative influence and impact of factors on model behaviour through sensitivity analyses, or determine how feedback structure influences behaviour using loop dominance analysis (Richardson, 1984; Ford, 1999b).

A notable weakness with system dynamics modelling is the difficulty, if not futility, of model validation based on how model outputs and behaviour accurately represent the real world (Mohapatra et al., 1994; Bossel, 2007; Vennix, 1996; Mirchi et al., 2012; Sterman, 2000). With system dynamics modelling there are two primary validity concerns: “construct validity” (a gap between the problem that is modelled and the model itself), and “internal validity” (the influence between these variables is not true-to-life) (Olivia, 1996; Barlas, 1996). In light of these validity concerns, the system dynamics modeller must ask the question: How likely is it that the factors chosen to represent the system actually describe the real problem or system behaviour (e.g., construct validity)? Furthermore, how likely is it that the assumed factor interactions represent how factors truly interact (e.g., internal validity)? In most cases, no feasible means exists to definitively answer questions of this nature for system dynamics models. To attest to this truth, many systems modelling experts argue that assessing the true validity of model structures is not feasible (Forrester, 1962; Forrester and Senge, 1980; Barlas, 1996; Sterman, 2000; Coyle and Exelby, 2000), largely a result of not having access to proper data (Mirchi et al., 2012). In spite of these challenges, the prevailing view of systems modelling experts is that model validity should be assessed based on its “usefulness with respect to some purpose” (Barlas, 1996, p.186). In other words, the real benefits from systems modelling is manifest in the form of useful information that may be gained by engaging in the modelling process itself, where knowledge gained by the modeller(s) for how system structure influences behaviour is far more important than obtaining a “correct answer”

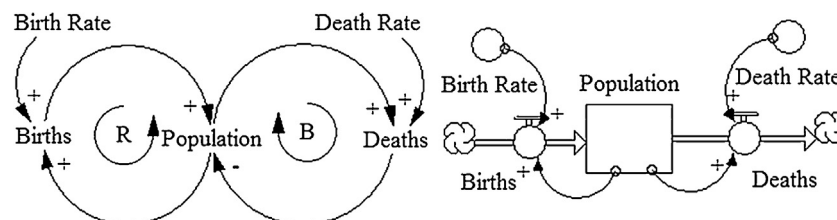


Fig. 2. An example of a Causal Loop Diagram (CLD) modelling population dynamics (left) and the associated Stock Flow (SF) diagram (right).

(Bossel, 2007; Vennix, 1996; Box and Draper, 1987). However, in order for system dynamics models to operate as tools for decision makers, the modeller must still be able to explain and rationalize the interrelationships between factors and sub-systems (Mirchi et al., 2012). Accordingly, in this study we rigorously develop the structural relationship between factors by exploiting the benefits of both qualitative (hypothesized structure) and quantitative (simulated structure) system dynamics modelling approaches.

In this study, we follow the model building and analysis process presented in Fig. 1, using a modified framework shown in Fig. 3, specifically tailored to model the dynamic processes within the agricultural production systems. First, to hypothesize the preliminary structure of our model, we used interviews with agricultural producers to identify key drivers for particular decisions within varying types of agricultural production systems in northeastern and southeastern United States (Sassenrath et al., 2010; Halloran et al., 2011). Then, using these data, we develop a CLD that depicts how the interviewed producers implicitly or explicitly indicated how these drivers influenced each other. We then use this CLD to develop the structure of an SF systems dynamics model, which we parameterize and simulate using field data for three predominant production systems (one-enterprise systems: row crops, extensive livestock, and mixed systems: integrated crop and livestock). The qualitative and quantitative outputs of both the CLD and SF models are then used to evaluate sustainability based on indices of economy, environment, and social welfare.

2.2. Data sources and collection

In this section, we detail the types of data we used, and the collection methods employed to gather these data. We begin by describing the qualitative data gathered in the form of farmer opinions that we used to build a CLD, and then proceed by discussing the type of data used to parameterize an SF model.

2.2.1. Producer interviews

The first step of this research was to gather data in the form of producer opinion to identify important drivers of farming practices on sustainable production. To accomplish this task, we used data collected by Sassenrath et al. (2010) in the form of interviews with agricultural producers in Orono, Maine, and Auburn, Alabama, to identify information on the drivers that influence the management choices farmers make with their farming practices. Farmers who participated in these interviews had a diverse range of farming enterprises (i.e., crops, livestock, integrated farming), farm sizes, crop types, production and marketing strategies, and growing practices (e.g., organic versus nonorganic). The rationale for this large range was to compare and contrast common principles, criteria, and indicators that exist across these two physiographic regions of Orono, Maine and Auburn, Alabama (Sassenrath et al., 2010).

In the interviews, producers were asked two overarching questions: How do factors most influence your long-range production decisions?; and What aspects of your operation will you change in the next 5 years? We then used a coding analysis of meeting notes and recordings to identify a set of similar drivers mentioned by producers to delineate these drivers into four specific areas: social/political quality, economic, environmental and technological, defined in Table 1 (Hanson et al., 2008). Many of these drivers were then used to construct the CLD.

2.2.2. Stock-flow model parameterization

The interaction between important drivers identified through the producer interviews allowed us to build and parameterize an SF model. The model was parameterized with information from the upper Midwest for the three predominant crops in the region (corn, soybeans and wheat) and one animal system (cow/calf).

For the three crop types, we parameterized yields, tillage impacts on crop yield, crop production costs, and labour, based on data from field research conducted at the Swan Lake Research Farm near Morris, MN (Archer et al., 2007; Archer and Reicosky, 2009). Livestock production costs and weaning rates were parameterized based on Minnesota Farm Business Management records for West Central Minnesota from 2006 to 2008 (Center for Farm Financial Management, 2010). We based crop price distributions on detrended 1989–2008 Minnesota cropping season annual averages (NASS, 2009), using fertilizer prices from 2005 to 2008 average prices for the North Central U.S. (NASS, 2009). To serve as a proxy for soil quality, we used soil conditioning index factors from the Soil Conditioning Index Worksheet (NRCS, 2003). Grain and forage nutrient content, and cattle nutrient requirements were then parameterized based on NRC (2000) values for total digestible nutrients (TDN), where forage production was based on 1998–2007 Stevens county alfalfa yields (NASS, 2010), and grazing utilization was assumed to be 50 percent.

2.3. Model development

In the following section we describe the model building steps in detail to show how both the qualitative and quantitative model were built through the process of conceptually mapping important drivers (CLD diagramming), and then model building using the aforementioned parameters (SF modelling). We also outline and define the important characteristics of model inputs and drivers. For an overview of all SF model parameter values and meanings inputs, the reader is referred to Table A1 in the Appendix.

2.3.1. Qualitative systems (causal loop) diagramming

A causal loop diagram (CLD) represents the systems-based conceptual framework characterizing the dynamic drivers of a particular behaviour. Using the drivers and their influences summarized in Table 1, we created the CLD shown in Fig. 3 using Vensim PLE (Ventana Systems, Harvard, MA). Here we focused on the most fundamentally important overarching drivers for sustainability found through the producer interviews, namely: *Environmental Quality*, *Economics*, and the tie between *Livestock Production*, *Crop Production* and *Social Quality* (shown in bold in Fig. 4). In order to create logical ties between certain producer-referenced drivers, we opted to add a few additional intermediary drivers. For example, we indicate values related to livestock production constraints and considerations such as *herd size*, *available feed*, and *animal nutrient demand*. While many of the drivers in Fig. 4 are relatively self-explanatory, it is worth mentioning a few that are not so obvious. For example, we intend the significance of *tillage practices* as an indicator of the level of tillage intensity as encompassed by the methods used to till the land, as well as the frequency with which tilling practices are employed. Additionally, soil quality, a driver that is linked to the main driver *Environmental Quality* (Table 1) is influenced by *tillage practices*, *manure input*, *forage biomass*, and *plant nutrient demand*. Soil quality is the output of these drivers, and is described using the soil conditioning index (SCI), described in the parameterization process.

As described in the CLD (Fig. 2) influence polarities are either positive (+) or negative (-). An example for how these influence polarities were ascertained can be seen with the connection Herd Size (-) → Available Feed. As the number of head of cattle increase, the feed available to meet the caloric demands of the cattle would be expected to decrease. Similarly, social quality is impacted by the amount of time workers have to work, thus *Livestock labour* (-) → *Social Quality*, indicating that as labour increases, social quality decreases. An example of a positive polarity influence exists between *Economics* (+) → *Acreage*, where an increase in economics would enable an increase in funds to purchase more

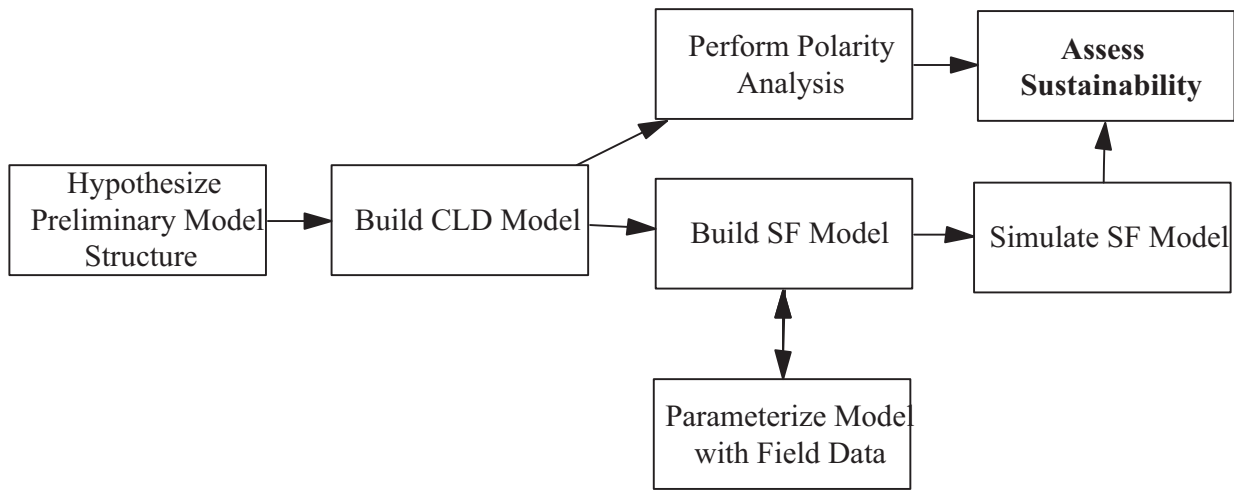


Fig. 3. The framework for agricultural production systems modelling with system dynamics implemented in this study.

Table 1 Emergent drivers and their definitions from the Sassenrath et al. (2010) study.

Driver	Sub-driver	Definition	Unifying model parameter	Influenced by parameter
Social Quality	Lifestyle	Farming as a way of life with deep roots in family and heritage	Social Quality (Time; Protein)	Crop Labour Livestock labour Crop produced Meat produced
	Old vs. New	Contrast between old and new generational strengths, weaknesses, change, risk, influence on diversify, acceptance on new ideas		
	Commitment to community	Local support and relationships, the influence this has on regional identity, breadth of crop selling and marketing channels		
	Environmental stewardship	Precedence of environmental preservation both locally and globally through production practices		
	Acquisition and use of information	The use (and acceptance) of available information to make decisions on strategic crop selection and diversification		
Economic	Feelings on policy	Aversion and concerns, activity, in government policy, involvement in policy decisions	Livestock Production Crop Production	Herd size Soil quality Manure applied to crops Acreage Supplemental Feed demand Nutrient demand costs Crop Yield Tilling Costs Manure application to crop cost Livestock sold Economics
	Risk Management	Acknowledgement and appreciation of risk, and mitigation of risk through crop and livestock diversification, or support through government policies		
	Marketing output and net return	Marketing channels, and influence this has on crop types inventories based on demand) Influence over market prices	Economics	
Environmental Quality	Farm size	The influence of farm size on production strategies	Acreage	Nutrient demand Forage biomass Tillage practices Manure produced
	Soil type and topography	Rocky vs. steep vs. flat, erodible vs. non-erodible, nutrient-rich vs. nutrient poor	Environmental Quality	
	Cover crops	The use of ground cover to improve soil organic matter		
	Geographic distribution Pests	Distribution of population centres and the influence on marketing options Crop damage due to the presence of pests		
Technology	Education	The use of university, extension and federal scientists to expand knowledge on farming techniques	Tillage practices	Acreage
	Mechanization	Implementation of new mechanized technologies to improve production		
	Internet	Exploitation of internet benefits to follow price trends, markets and to establish marketing channels		

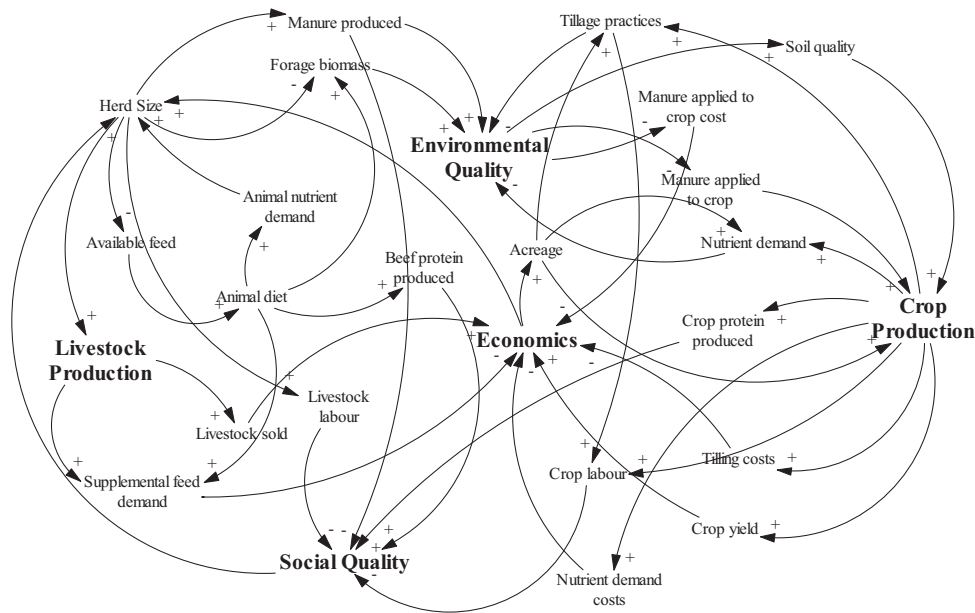


Fig. 4. CLD of production drivers (principle drivers are in larger bolded font). The positive (+) or negative (–) impact of a practice on a factor is indicated at the head of the arrow linking the two parameters, e.g., Animal Diet (+) → Beef Protein Produced.

acreage. Each of the influences in the CLD were created using this rationale. To complete the CLD required making important and difficult assumptions regarding the polarity of influence between the drivers: *acreage on nutrient demand*, *acreage on tillage practices*, and *tillage practices on crop labour*, and the associated effect on Environmental Quality. Here we assume, that as *acreage* increases, *nutrient demand* (taken here as the amount of nutrients (i.e., N and P) required by a crop at the farm level) would go up, implying a positive (+) polarity. In addition, as *acreage* increases, the amount of land to be tilled also increases, implying a positive (+) polarity of influence on tillage. Increases in *tillage practices* including increasing tillage intensity and frequency would increase the amount of *crop labour* required, implying a positive (+) polarity of influence on *crop labour*. Assigning the polarity of influence between each model variable in this way allowed for the creation of a final CLD.

2.3.2. Quantitative systems (stock-flow) modelling

We used the CLD in Fig. 4 as a structural guide for the construction of an SF model developed in STELLA (see Systems, Lebanon, NH). The complete STELLA SF model that resulted is shown in Fig. 5. Similar to the CLD, it was necessary to add additional converters (noted as small circles in the SF model) to explicitly portray important formulas and parameters used to designate driver influences. Due to the size and complexity of this SF, we have demarcated the model into subsystems called “sectors”, to compartmentalize key model modules used to subsequently evaluate production system sustainability. The model was logically broken into five sectors to provide a clearer and cleaner representation of the major drivers outlined in the CLD: *Environmental Quality*, *Social Quality*, *Economics*, *Livestock Production*, and *Crop Production*. In order to sectorize the STELLA model into these sub-systems, it was necessary to create numerous “ghosts” for both stocks (signified by dashed boxes) and converters (signified by dashed circles), which represent shared model components between sectors.

As SF models are inherently quantitative, it was necessary to numerically define each of the model parameters, through formulas, direct numerical values, or normalized graphical functions. Graphical functions are useful tools within STELLA to invoke non-linear relationships or trends between two variables in place of hard numerical data. In the appendix, we present each type of model

parameterization, both for formulas, numerical data (Table A1), and graphical functions (Fig. A1). We present a definition for each of the five sectors below, where a full summary of model parameters is presented in Table A1.

2.3.2.1. Crop production. In this model, the *Crop Production* component models production of three crops: corn, soybeans, and spring wheat. In the model, crop production is driven by *Target Yields* for each crop, where actual yields are influenced by *tillage practices*, and by changes in soil quality parameters (*SoilPAm*, *SoilDistRate*, etc.). Target yields are used to calculate nutrient (N and P) demands, which are then used to calculate fertilizer and manure applications in the *Economics* and *Environmental Quality* sectors. Additionally, crop residue production (*ResAmt*, *Residue*, and *TotResGraz*) is calculated from grain yields using a separate harvest index for each crop, where residue production is linked to the *Livestock Production* and *Environmental Quality* sectors.

2.3.2.2. Livestock production. The *Livestock Production* sector is modelled as a “cow-calf enterprise”, where herd size is determined over time by the influence of reproduction rates (*WeanRate*) and limited by available feed (*AvailFeed*). Increases in herd size are calculated as the number of females in the herd (*NumFemales*) multiplied by the weaning rate per female. Animal sales are calculated based on available feed with excess animals sold when feed demand exceeds a user-determined maximum percentage of available feed, and additional animals are retained when feed demand falls below the minimum percentage of available feed (*minFeedUse*). Available feed is calculated based on animal diet, which is modelled on a Total Digestible Nutrients (TDN) basis. Supply of TDN is calculated as the sum of available TDN from dedicated grazing land (pasture or range), crop residues, and supplemental feed (the stock *Supplement*). Demand for TDN is calculated based on herd size (*HerdSize*), which is also used to calculate manure production (*ManureStock*). *ManureStock* is directly linked to the environmental quality and economics sectors and indirectly (through nutrient balance and soil quality impacts) to the crop production sector. A social feedback factor (*SocPres*) is included to force herd size reductions when manure production and utilization get out of balance (explained in more detail under Section 2.3.2.5).

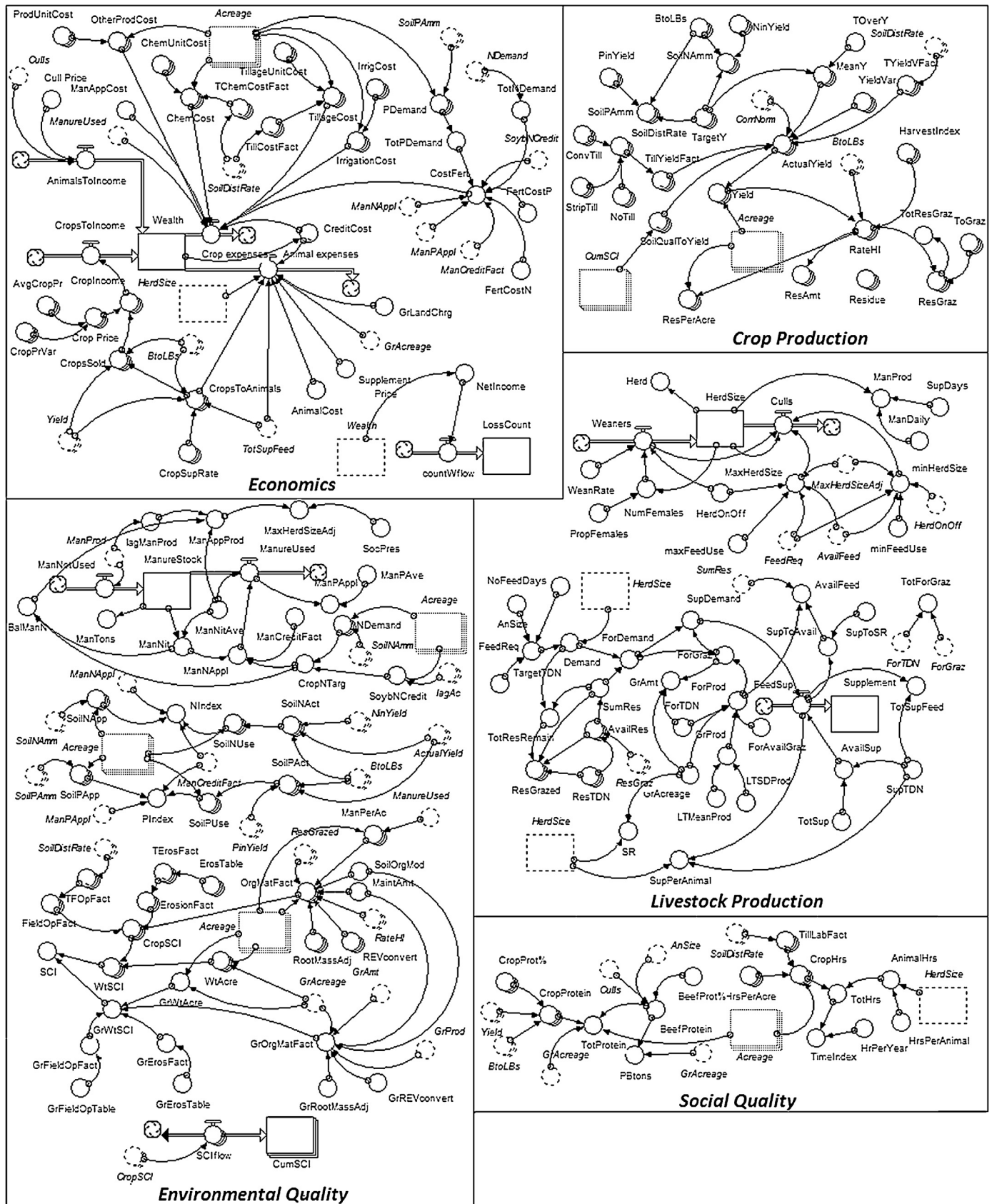


Fig. 5. SF model with each sector labelled. Full details of parameters are given in Appendix Table A1.

2.3.2.3. Environmental quality. The *Environmental Quality* sector models three environmental indicators: excess manure production, excess nutrient use, and soil conditioning index. The Soil Conditioning Index (SCI) considers the dynamics of soil conditions based on tilling practices and soil organic matter (NRCS, 2003). In particular, the SCI considers the availability (or dearth) of organic matter (*OrgMatFact*), field operations based on the frequency and ferocity of soil disturbance (*FieldOpFact*), and soil erosion (*ErosionFact*). In the model, Nitrogen (*NIndex*) and Phosphorus (*PIndex*) indices are used to represent fertilization and manure, which is animal waste produced in excess of that which can be used on-farm.

2.3.2.4. Economics. The *Economics* sector models wealth variability (stock *Wealth*) over time as influenced by crop and livestock production, *AnimalsToIncome* and *CropIncome*, respectively, where annual flows into wealth include crop and livestock sales. Annual flows out of wealth include *Crop* and livestock (*Animal*) production *Expenses*. Crop production expenses are itemized, including costs for: irrigation (*IrrigationCost*), chemical (*ChemCost*, pesticides), tillage (*TillageCost*), manure application (*ManAppCost*), fertilizer (*CostFert*), and other associated management operations. Irrigation, tillage, and chemical costs were entered as a constant cost per acre for each crop. Manure application cost is constant per unit of manure applied, while fertilizer costs are tied directly to nutrient demand, with fertilizer applied based on target yields. We consider a “manure credit” to exist for any manure that is applied to the crop in place of purchased fertilizer. Manure credit is subtracted from total nutrient demand in calculating fertilizer costs. All other crop production costs are included as a constant cost per acre for each crop.

Livestock production expenses include grazing land charges (*GrLandChrg*) and costs of purchased supplemental feed (*SupplementPrice*). We consider all livestock production costs as a constant cost per animal, and supplemental feed purchases are reduced by feeding a portion of the crops produced on-farm. However, this also reduces crop sales and crop income. All animals in excess of what can be supported by available feed are sold each year. The current parameterization assumes a cow-calf system; however, calves and cull cows are not tracked separately, so revenues from animal sales are on a generic value per head basis.

2.3.2.5. Social quality. The *Social Quality* sector models aspects of production internal and external to farming. The internal social value of time is based on hours required to perform crop (*CropHrs*) and animal management practices (*AnimalHrs*), where the external social value models the caloric value of the production output (*TotProtein*). We assume increasing labour reduces the flexibility of the farmer to spend time on leisure pursuits, and thereby decreases social quality. As an external social quality, we use the net protein produced per acre, representing societal concern for adequate food quantity and quality. Although not modelled directly as a social quality indicator, the previously mentioned social feedback factor (*SocPres*) is included in the model that links excess manure production to livestock herd size limits. This factor serves as a proxy for the influences excess manure may have on social perceptions (e.g. due to odour or impacts on visual amenities) and the potential feedback of these perceptions on livestock production (e.g. through peer pressure, zoning, or other regulations). This factor ranges from 0 to 1 and can be adjusted to represent different levels of social pressure resulting in restrictions on manure balance or indirectly on animal production. When the factor is set to 0, manure balance has no effect on herd size. Increasing the factor puts tighter bounds on manure balance. When the factor is set to 1, manure production and utilization must strictly balance each year or herd size must be reduced to bring utilization and production back into balance.

2.4. Model simulation and analysis: assessment of sustainability

We performed separate analyses on both the qualitative (CLD) and quantitative (SF) models. Our objective in analysing the CLD was to characterize feedback loop polarity to improve the applicability of the SF simulation outputs and findings. Regarding the former, loop characterization was the goal of these efforts, assuming the relative number of reinforcing to balancing loops allows for the understanding of driver sensitivity and importance and considering that each loop has the same strength. This awarded important insight into relative driver importance on production sustainability within the SF model. Analysis of the SF model involved running model simulations and evaluating the outputs of the environmental, social, and economic indices used to determine sustainability.

Conducting the loop balance analysis using the CLD model entailed systematically identifying and characterizing feedback loops involving the key model drivers: *Environmental Quality*, *Social Quality*, *Economics*, *Livestock Production* and *Crop Production*. We used the “Loops” tool in VENSIM to identify feedback loops involving these key parameters. We then summed the combined polarity for each feedback loop, noting that an odd sum of negative polarity influences indicates a balancing loop, whereas an even sum indicates a reinforcing loop (Richardson, 1984). Through this comparison between reinforcing and balancing loop, it was possible to compare each of these five drivers in terms of their relative stability, assuming that a higher difference between reinforcing and balancing loops would indicate a higher instability or stability, respectively.

To perform the SF model simulations, we first assumed a farm size of 1200 acres. For Crop Only, the acreage was evenly divided between corn, soybeans and spring wheat. Livestock Only simulations assumed 1200 acres grazing land for the cattle herd, while for the integrated crop/livestock simulation, 600 acres was dedicated to grazing lands and the remaining 600 was equally divided between the three crops. The time horizon for each model simulated production over 100 years. Given the stochastic nature of model outputs, each simulation was performed 100 times, and the output averaged. The social pressure parameter (*SocPres*) to limit manure production was arbitrarily set as 0.5. Additionally, for stocks that accumulated (wealth and manure), the yearly production was averaged. The average values for each index were then normalized for comparison of sustainability between the different production system scenarios.

3. Results and discussion

This section discusses the findings from our qualitative and quantitative systems modelling analyses. As previously mentioned, insight from these modelling efforts are deduced by two distinct means: first by analysing loop polarity characteristics of model drivers using the CLD alone, and second, through analysis of SF model outputs using sustainability indices. Finally, we discuss implications from the combined insight of these two analyses, along with future research that leverages these findings and research methods.

3.1. CLD loop polarity analysis

Direct comparison between loop polarities for key model parameters allowed for the assessment of driver sensitivity and stability based on the relative difference between the number of reinforcing and balancing loops. In Table 2, we present a semi-quantitative overview of loop polarity for *Environmental Quality*, *Social Quality*, *Economics*, *Livestock Production*, and *Crop Production*, with the values of interest being the difference between the number

Table 2

Loop polarity analysis results for each driver.

Driver	Num. reinforcing(+)	Num. balancing(-)	Total loops	Difference	Dominance
Environmental Quality	58	61	119	-3	Balancing
Social Quality	43	50	93	-7	Balancing
Economics	55	60	115	-5	Balancing
Livestock Production	15	15	30	0	Neutral
Crop Production	60	63	123	-3	Balancing

of reinforcing loops and balancing loops that directly involve each driver. Evaluating the difference between the number of reinforcing and balancing loops for each driver revealed two important conclusions about driver influence on agriculture system sustainability. First, the absolute difference provides insight into driver stability, where a high difference would indicate either a high stability (balancing) or high instability (reinforcing). Second, the relative number of loops, characterized by a negative or positive difference, helps us assume the overall behaviour of each driver within the CLD; where a positive difference indicates the drive is dominated by reinforcing loops (an overly unstable and potentially destructive influence); and a negative difference indicates the driver is dominated by balancing loops (an overly stable and potentially limiting influence). We must again note that these analyses both assume each loop is of equal strength, and as such, potentially represents this complex system inaccurately. Despite the difficult task of qualitatively analysing loop driver sensitivity, we considered this inaccuracy worth the potential insight into agricultural system sustainability it provides when coupled with the quantitative SF model.

The polarity analyses in Table 2 indicates the difference in loop polarities from largest to smallest are: *Social Quality* (-7), *Economics* (-5), *Crop Production* (-3), *Environmental Quality* (-3), and *Livestock production* (0). Using the rationale for driver stability (or sensitivity) mentioned previously, the largest positive and negative loop differences imply a high potential for instability (reinforcing) or stability (balancing). Based on our results, it appears that each driver would tend towards the latter, stabilizing or balancing out any reinforcing system behaviour. Put another way, each driver (apart from *Livestock Production*, which is neutral) would act to limit exponential growth or decay in agricultural system behaviour, be it economic gain, environmental deterioration, or social influence. This means the system, as we have interpreted it here in the CLD (Fig. 4), for either a single or mixed-enterprise system, would over time trend towards a stable production “state”, whether that state be favourable (sustainable) or unfavourable (unsustainable). The most influential drivers of this behaviour would be *Social Quality* and *Economics*, given their proportionately higher loop polarity differences.

Richer information is available if we look at the nature of factor interaction in the balancing loops surrounding these drivers. Indeed, it was found that the drivers that predominantly limited exponential increase or decay (reinforcing behaviour) in the system as a whole were *Social Quality* and *Economics*, as one would expect, given the higher number of balancing loops for each of these drivers. Generally, balancing loops from *Social Quality* and *Economics* appeared in the form of their reinforcing loop predecessor, with a main difference being the inclusion of cost and social influence into each loop. For example, the limiting influence of *Economics* on *Environmental Quality* becomes evident in the balancing loop:

Environmental Quality (-) → *Manure applied to crop cost* (-)
 → *Economics* (+) → *Acreage* (+) → *Crop Production* (+)
 → *Nutrient demand* (-).

which means: If *Environmental Quality* increases, the cost for manure necessary to improve soil quality decreases, which improves producer wealth, thereby enabling the producer to purchase more land to produce more crops; however, as crop production increases, nutrient demand also increases, in turn negatively influencing *Environmental Quality*. Similarly, an example of the balancing influence of social aspects on *Economics* loops is seen here:

Economics (+) → *Acreage* (+) → *Crop Production* (+)
 → *Crop Labour* (-) → *Social Quality* (+) → *Herds size* (+)
 → *Livestock Production* (+) → *Livestock Sold* (+)

which means: While increased wealth would improve crop production, increasing crop labour (i.e., time working) would adversely affect *Social Quality*, and as a result, would limit herd size, and adversely influence livestock production and any associated economic gain. This tenuous influence of labour on social quality and the corresponding effect on economic gain similarly exists with livestock labour, in this alternative case decreasing crop production and yield. Thus, we posit that the highest sensitivity (and greatest influence) of model drivers on agricultural system sustainability in general would be *Social Quality*. Although it is difficult to deny the influence of *Economics* on key aspects of agricultural production system sustainability, *Social Quality* has the highest loop polarity difference. This finding indicates that social aspects of agricultural productions systems, while buffering against destructive outcomes to environmental or economic sustainability, could conversely slow down, or limit, long-term sustainability or success overall. Additionally, social influences were found to limit production within the animal-crop nexus of mixed-enterprise systems, as shown above where *crop labour* influences *Social Quality*, which thereby influences *herd size*. This implies that the most influential driver on mixed-enterprise system sustainability in particular could be social sustainability.

3.2. SF model analysis

Simulating the three farming system scenarios enabled us to compare and contrast the findings from the previously described polarity analysis. This comparison is made using quantitative outputs from the SF model in the form of sustainability indices for crop only, animal only, and integrated animal-crop agricultural production systems. As a means to combine these key findings and evaluate the sustainability of each of these three agricultural systems, we present a radar chart (Fig. 6), which shows index values for the key model parameters and drivers influencing the sustainability indices, i.e.,: *time* and *protein* [social]; *wealth* [economic]; and *SCI*, *Manure*, *P-Index*, and *N-Index* [environmental].

Through a simple assessment of these indices (where higher values are more favourable) we find the greatest economic sustainability would result from Crops and Animals, second being Crops and last being Animals Only. We can logically deduce that given the economic benefits of cost and productivity, and the potential for resource sharing for integrated production systems (i.e., Crops and Animals), that the likelihood of higher wealth would

Table 3
Sustainability Index ranking.

Production system	Social (protein and time)	Environmental (SCI)	Economics (wealth)	Ranked Sum
Crops only	1	3	2	6
Animals only	2	1	3	6
Crops and Animals	3	2	1	6

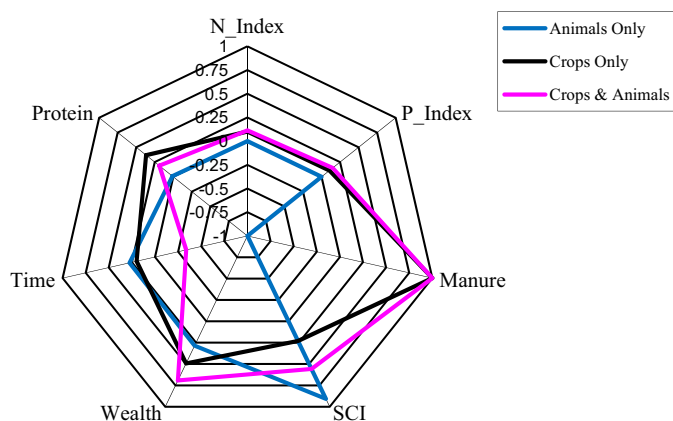


Fig. 6. Summary of sustainability indices and key model parameters.

be far greater. In contrast, given that we designate time as a surrogate for internal *Social Quality*, Crop and Animal systems have a drastically lower internal social quality index, due to the inherently time-intensive activities of managing two distinct production enterprises. However, *Social Quality* also includes the amount of total protein produced as an external social benefit from the production system. For social sustainability, the highest combined protein and time exists for the Crops Only production system. While this may be initially surprising, based on our model assumptions of land suitable for crop production, it is possible to produce more vegetable protein (especially with soybean) per acre than livestock protein. However, this would ultimately depend on the mix of land available. On the contrary, if some of the land is unsuitable for crop production, then a mixed system might produce more total protein. It is important to note that this does not take into account social views of protein quality, where generally as living standards improve, diets move towards greater amounts of meat protein instead of plant proteins. Nor does it account for the total nutritional value of food needed to support optimal human health.

For environmental sustainability, both Crops Only and Crops and Animals have relatively similar environmental indices for N and P. However, the resultant SCI is substantially greater for Crops and Animal agricultural production since manure is incorporated in this integrated system, using the excess production of manure to increase soil organic matter and reducing the need for supplemental fertilizer applications. Additionally, less land would be tilled as more land would be used for grazing. Animal production systems have N and P values at null because accumulated manure is not specifically applied to crops and is instead disposed of. Despite having no N and P, Animals Only overall had the highest SCI, since erosion and tilling would be minimal, and available organic matter in the soil would likely remain unchanged.

To determine the combined sustainability of the three agriculture systems analyzed here, we conclude with an overview of sustainability based on a simple ranking of each sustainability index in Table 3. First, environmental sustainability (based on the SCI) was found to be the greatest for Animals Only, second for Crops and Animals, and last for Crops Only. Thus, Animals Only has the greatest environmental sustainability, yet was found to have the lowest economic sustainability (based on wealth gained). Mixed systems

(Animals and Crops) were found to have the highest economic sustainability and relatively high environmental sustainability, but in agreement with the previous polarity analysis, have the lowest social sustainability due to proportionately higher time it would take to run the farm. Crop Only systems had the highest social sustainability overall and compared well with the other sustainability indices. Table 3 shows the sum of ranks for each sustainability index for each agricultural production system have an equal potential for sustainability. However, we showed through polarity analysis that social sustainability is likely the most influential on overall production system sustainability, especially for mixed-enterprise systems. Thus, given that each production system received an equal score, it would appear Crops Only systems are the most sustainable overall.

These findings are intriguing, as integrated crop enterprises have been regarded by many as a promising means to address economic and environmental challenges in sustainable food production (Hanson et al., 2008; Hendrickson et al., 2008). On the contrary, our results imply this may not be the case if one considers the interwoven social drivers – particularly producer leisure time – that could influence overall agricultural production system sustainability. Apart from the inclusion of social drivers, however, there are assumptions made within our model that may have favoured Crop Only systems based on an optimistic consideration of soil quality and land use. For example, our model considers each acre of land is used to its full capacity for crop production. However, in the common case where a section of farmland has poor soil quality, forcing crop production would likely imply a lower crop production, and thus, a lower economic benefit due to the higher cost of nutrient inputs. Had this case been modelled, the associated rating for economic sustainability would have been lower, thereby favouring the Crop and Animals or Animals Only enterprise scenarios. Additionally, it is possible that forcing crop growth in nutrient-poor soil could actually have detrimental impacts on environmental sustainability per a lower SCI, in turn resulting in a lower environmental sustainability rating. In the case of variable soil quality, a more economically and environmentally sustainable option would be a mixed enterprise system (Crops and Animals) to utilize land with low quality soil for livestock, or, in situations where soil quality is uniformly poor, a livestock only production system (Animals Only). While our model does not explicitly consider the effects of poor soil quality, and thus variability in viable cropland, future systems models that do include parameters of this type could greatly improve the quality and utility (i.e., validity) of our model through future model calibration activities.

4. Conclusions

This paper demonstrates progress in farming systems modelling through the use of system dynamics modelling. The model afforded exploration of driver interactions within three distinct production systems (Crops Only, Animals Only, and integrated Crop and Animal systems), and determined the relative impact of management inputs and drivers on sustainability indices. An exciting observation of this systems study was its potential to capture elusive, qualitative social factors in a measurable analysis system. Of particular note is the impact social quality parameters play on the potential sustainability of production systems. We believe information in this form, gathered from the systems paradigm, can be used to develop and

evaluate more economically, environmentally and socially acceptable production systems. As measured by the sustainability indices used here, single-enterprise crop production systems are more sustainable than single enterprise systems consisting of livestock alone, or mixed-systems with crops and livestock.

Analysis of the qualitative and quantitative system dynamics models provided two distinct forms of information to arrive at these conclusions. Analysis of the CLD (Fig. 4) provided quasi-quantitative insight into factor sensitivity, highlighting the dynamic influences demonstrating that the *Social Quality* driver would likely be the most influential on production system sustainability and success. This dynamic information provides rich insight into the aspects that cause potentially destructive reinforcing feedback behaviour, or conversely, stabilizing balancing behaviour. However, while this analysis can give us an idea of the drivers that are most stable or sensitive, this metric does not show the relative dominance or strength of the feedback loops and therefore can only provide a means to superficially assess stability, without knowing the relative strengths between internal drivers and sub-drivers of loop dominance. Additionally, it is not possible through direct analysis of CLDs to explicitly assess sustainability of single or mixed-enterprise agriculture production systems based on our metrics of economics, environment and social factors. Therefore, a quantitative analysis provided through an SF perspective was indeed a necessary and valuable compliment to this study.

The SF model (Fig. 5) allowed for quantitative assessment of economic, social, and environmental sustainability for all three farming systems. In doing so, we were able to successfully meet the objectives of this study by elucidating the systemic and dynamic interaction of drivers that influence sustainable agricultural production. In addition, through SF modelling, it was possible to evaluate which agricultural system was most likely to have the greatest social, economic and environmental sustainability. The findings from these modelling efforts, while allowing us to arrive at conclusions that are relatively intuitive (i.e., Animals Only will have the least negative environmental impacts on soil), also made it possible to arrive at less intuitive conclusions (i.e., Crops and Animals are less socially sustainable but most economically sustainable). Through this systems analysis, we were able to discuss these complex systems in a way that support these intuitions.

Other equally, if not more important, questions arise given the findings from this study. As we now have a systems model that

represents agricultural system complexity, and now know explicitly, through qualitative analysis, of the existence of many feedback loops driving dynamic behaviour, the next question becomes: which of these feedback loops is the most impactful or “dominant”? Digging deeper into model variables, what are the most important drivers of economic, social, and environmental sustainability? While analyses that specifically answer these questions are not presented here, future research will benefit the body of knowledge dedicated to agricultural production sustainability by further investigation of these most impactful drivers and feedback loops. This may be accomplished through further analysis of this study’s findings using methods such as feedback loop dominance analysis (Richardson, 1984; Ford, 1999b). In addition, future research would complement this study by working through group model building exercises with producers to ensure the subjectivity of these models, on the part of the researcher, is minimal (Vennix, 1996).

Future research efforts could improve model utility and applicability by calibrating model parameters and links through, for example, the inclusion of variability in model parameters for soil quality and land use, and a more detailed measure of production for human nutrition. Moreover, future modelling efforts could be particularly impactful through examination of production systems for other regions of the US and the world, to compare and contrast the relative economic, environmental, and social impacts of management decisions and degree of integration on production system sustainability. We believe a willingness by policy makers and producers to utilize similar modelling efforts in the future will improve understanding on the important drivers influencing agricultural system productivity and environmental, social and economic sustainability, and enable the creation of more adaptable and responsive management practices and production strategies for truly sustainable agricultural production systems.

Acknowledgements

The authors would like to express our appreciation for the many farmers and ranchers who contributed to this study. This manuscript is contribution number 16-194-J from the Kansas Agricultural Experiment Station. This research was supported in part by a grant from CONICYT (REDES 140045).

Appendix.

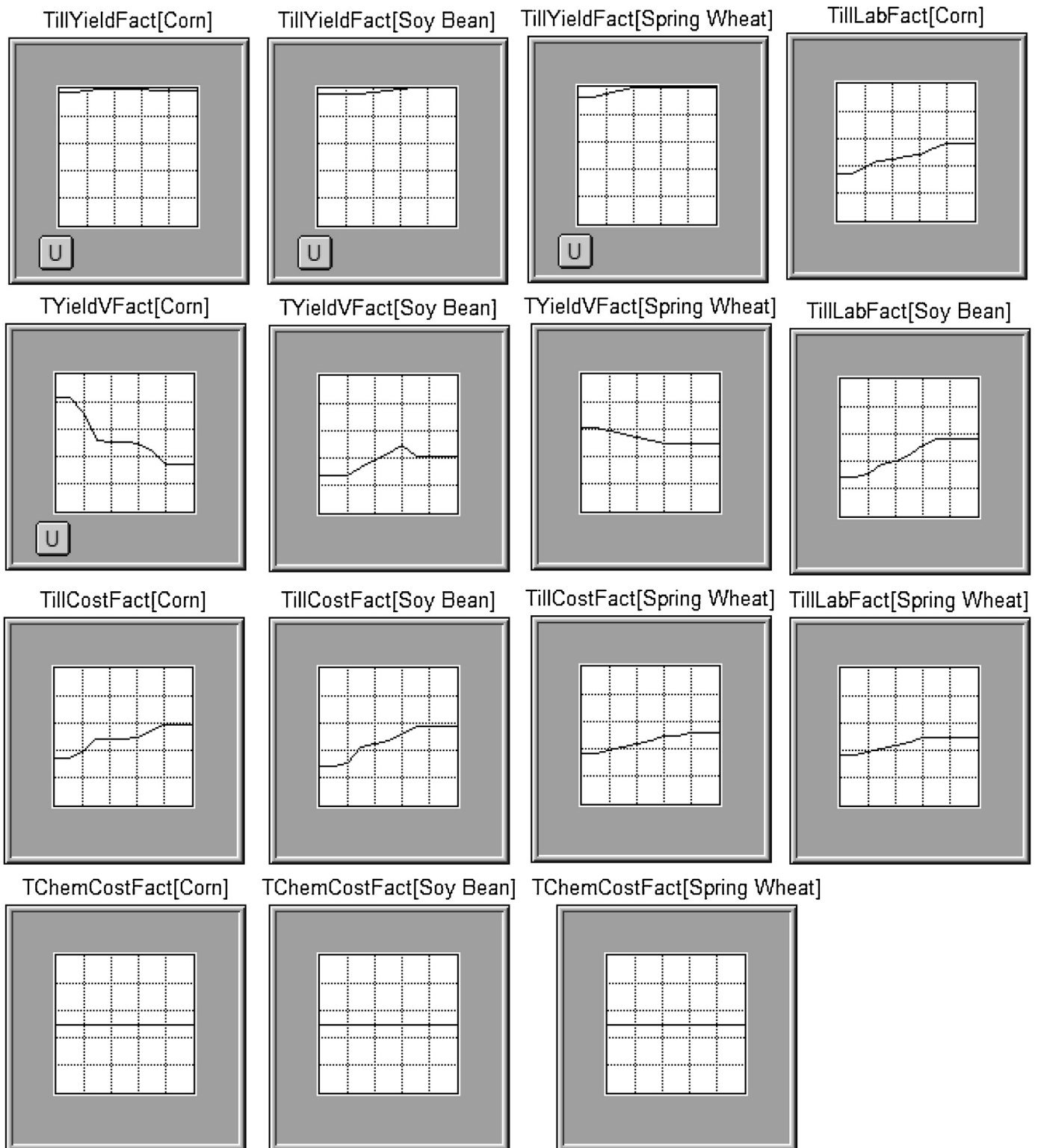


Fig. A1. Graphical functions used in the Stock Flow model.

Table A1
Stock Flow Model Parameter Summary.

Parameter	Value	Unit	Meaning
Initial stock conditions			
HerdSize	350	Heads	Size of the herd at start of model
Wealth	150,000	\$USD	Amount of money at start of model
Manurestock	0	lbs	Accumulation of Manure produced by animals
Crop			
InitAc[corn]	200	acre	Initial area of corn production
InitAc[Soy Bean]	200	acre	Initial area of soybean production
InitAc[Spring Wheat]	200	acre	Initial area of spring wheat production
TargetY[Corn]	160	bu/ac	Target yield for corn
TargetY[Soy Bean]	45	bu/ac	Target yield for soybean
Target[Spring Wheat]	55	bu/ac	Target yield for spring wheat
YieldVar[Corn]	14	bu/ac	Standard deviation of corn yield
YieldVar[Soy Bean]	5	bu/ac	Standard deviation of corn yield
YieldVar[Spring Wheat]	5	bu/ac	Standard deviation of corn yield
CornSoyCorr	0.8		Correlation coefficient for soybean and corn yield
CornWheatCorr	0		Correlation coefficient for wheat and corn yield
SoyWheatCorr	0		Correlation coefficient for soybean and wheat yield
HarvestIndex [Corn]	0.5		Harvest index for corn (portion of above ground biomass that is grain)
HarvestIndex [Soy Bean]	0.4		Harvest index for soybean (portion of above ground biomass that is grain)
HarvestIndex[Spring Wheat]	0.42		Harvest index for spring wheat (portion of above ground biomass that is grain)
TOverY			
Livestock			
ToGraz[Corn]	0.4	lbs	Portion of corn crop residue that is grazed
ToGraz[Soy Bean]	0	lbs	Portion of soybean crop residue that is grazed
ToGraz[Spring Wheat]	0.4	lbs	Portion of spring wheat crop residue that is grazed
SupDays	90	day	Days per year that supplement is required
maxFeedUse	1.10		
PropFemales	0.95		Proportion of livestock herd that are females
Ansize	0.2		Qualitative factor for size of each animal, used to adjust feed use per animal
GrAcreage	600	acre	Grazing land area
LTMeanProd	7640	lbs/ac	Long-term mean forage production
SupTDN	0.61		Total digestible nutrient content of supplement feed to cattle
ForAvailGraz	0.7		Portion of forage production that is available for grazing
LTSProd	860.0	lbs/ac	Long-term standard deviation of forage production
TotSup	800,000	lbs	Total supplement available
Use Supplemental Feed?			Enables or disables use of supplemental feed
Economic and social			
TillageUnitCost[Corn]	79	\$/ac	Machinery operation cost for corn production
TillageUnitCost[Soy Bean]	79	\$/ac	Machinery operation cost for soybean production
TillageUnitCost[Spring Wheat]	69	\$/ac	Machinery operation cost for spring wheat production
IrrigCost[Corn]	0	\$/ac	Irrigation cost for corn production
IrrigCost[Soy Bean]	0	\$/ac	Irrigation cost for soybean production
IrrigCost[Spring Wheat]	0	\$/ac	Irrigation cost for spring wheat production
AvgCropPr[Corn]	2.92	\$/bu	Corn crop sale price
AvgCropPr[Soy Bean]	7.5	\$/bu	Soybean crop sale price
AvgCropPr[Spring Wheat]	5.12	\$/bu	Spring wheat crop sale price
CropPrVar[Corn]	0.629		Standard deviation of corn price
CropPrVar[Soy Bean]	1.42		Standard deviation of soybean price
CropPrVar[Spring Wheat]	1.03		Standard deviation of spring wheat price
CropSupRate[Corn]	0.06		Maximum portion of corn grain used as livestock supplement
CropSupRate[Soy Bean]	0.01		Maximum portion of soybean grain used as livestock supplement
CropSupRate[Spring Wheat]	0		Maximum portion of spring wheat grain used as livestock supplement
ChemUnitCost[Corn]	22	\$/ac	Pesticide cost for corn production
ChemUnitCost[SoyBean]	10.5	\$/ac	Pesticide cost for soybean production
ChemUnitCost[Spring Wheat]	10.5	\$/ac	Pesticide cost for spring wheat production
ProdUnitCost[Corn]	200	\$/ac	All other production costs for corn
ProdUnitCost[Soy Bean]	150	\$/ac	All other production costs for corn
ProdUnitCost[Spring Wheat]	110	\$/ac	All other production costs for corn
AnimalCost	270	\$/head	Animal production cost excluding feed
FerCostN	0.47	\$/lb N	Unit cost of nitrogen fertilizer
Supplement Price	0.05		Price of supplement purchased for cattle feed
FertCostP	1.15	\$/lb P	Unit cost of phosphorus fertilizer
GrLandChrg	26	\$/acre	Grazing land annual cost
ManCreditFact	0.90		Portion of manure nutrient content credited in calculating fertilizer demand
Cull Price	600	\$/head	Sale price for livestock sold
ManAppCost	12.7	\$/acre	Cost to apply manure to crop land
CropAcResp	0		Crop acreage response factor, controls how rapidly crop area can be adjusted between crops
SocPres	0.5		Social pressure factor, controls how sensitive the level of manure stockpiled is to social pressures
Tillage and environment			
TillYieldFact[Corn]	Function		Effect of tillage on corn crop yield
TillYieldFact[Soy Bean]	Function		Effect of tillage on soybean crop yield
TillYieldFact[Spring Wheat]	Function		Effect of tillage on spring wheat crop yield
TYieldVFact[Corn]	Function		Effect of tillage on variation in corn yield
TYieldVFact[Soy Bean]	Function		Effect of tillage on variation in soybean yield

Table A1 (Continued)

Parameter	Value	Unit	Meaning
TYieldVFact[Spring Wheat]	Function		Effect of tillage on variation in spring wheat yield
TillCostFact[Corn]	Function		Effect of tillage on corn machinery costs
TillCostFact[Soy Bean]	Function		Effect of tillage on soybean machinery costs
TillCostFact[Spring Wheat]	Function		Effect of tillage on spring wheat machinery costs
TChemCostFact[Corn]	Function		Effect of tillage on corn pesticide costs
TChemCostFact[Soy Bean]	Function		Effect of tillage on soybean pesticide costs
TChemCostFact[Spring Wheat]	Function		Effect of tillage on spring wheat pesticide costs
TillLabFact[Corn]	Function		Effect of tillage on labour required for corn production
TillLabFact[Soy Bean]	Function		Effect of tillage on labour required for soybean production
TillLabFact[Spring Wheat]	Function		Effect of tillage on labour required for spring wheat production
SoilOrgMod	1.0		Adjustment factor for the minimum amount of organic matter required to maintain soil organic matter levels
GrFieldOpTa	0.96		Level of tillage intensity on grazing land. Used in calculating Soil Conditioning Index
ErosTable[Corn]	0.5	ton/acre	Soil erosion rate on corn land.
ErosTable[Soy Bean]	0	ton/acre	Soil erosion rate on corn land
ErosTable[Spring Wheat]	0.5	ton/acre	Soil erosion rate on corn land
GrErosTable	0	ton/acre	Soil erosion rate on grazing land

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