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Applying System Dynamics to the Food Loss and Waste Problem: a Literature Review[1]

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Abstract

Although it has been around for over 50 years, system dynamics can still be considered as an emerging methodology to analyse food value chain problems. From over 400 peer-reviewed articles identified as potentially applying system dynamics models to agricultural systems, less than 40 focus specifically on food value chains. None of these articles applied a systems dynamics model to empirically analyse the impact of biophysical and socioeconomic factors on food loss and waste. In this paper, the aim is to provide a synthesis of the usefulness of system dynamics to agricultural systems issues, focusing particularly on the problem of food loss and waste. Key principles and concepts of system dynamics modelling are reviewed, some validity tests for the system dynamics model are highlighted, system dynamics is compared with other modelling approaches and the advantages of using this type of model are emphasised. Then, some examples of its applications to food value chains problems are reviewed, including a focus on policy issues, and a proposed empirical system dynamics model for analysing the problem of food loss and waste in a developing country context is illustrated.

***Keywords**:* System dynamics, SD model, agriculture, food loss and waste

Introduction

The problem of food loss and waste is global. Available estimates point to volumes of food loss and waste at about one-third of worldwide food production (FAO, 2018) – roughly 1.3 billion tonnes of food costing almost $US 1 trillion each year. Broadly, food loss and waste can occur at every stage of food value chains; however, the relative importance of the stage in which it occurs may vary across commodities and countries. In developed nations for instance, food loss and waste (or simply food waste) seems to be a major problem at the downstream end of value chains. In contrast, in developing countries this problem is most commonly important at the upstream end of value chains, and it is

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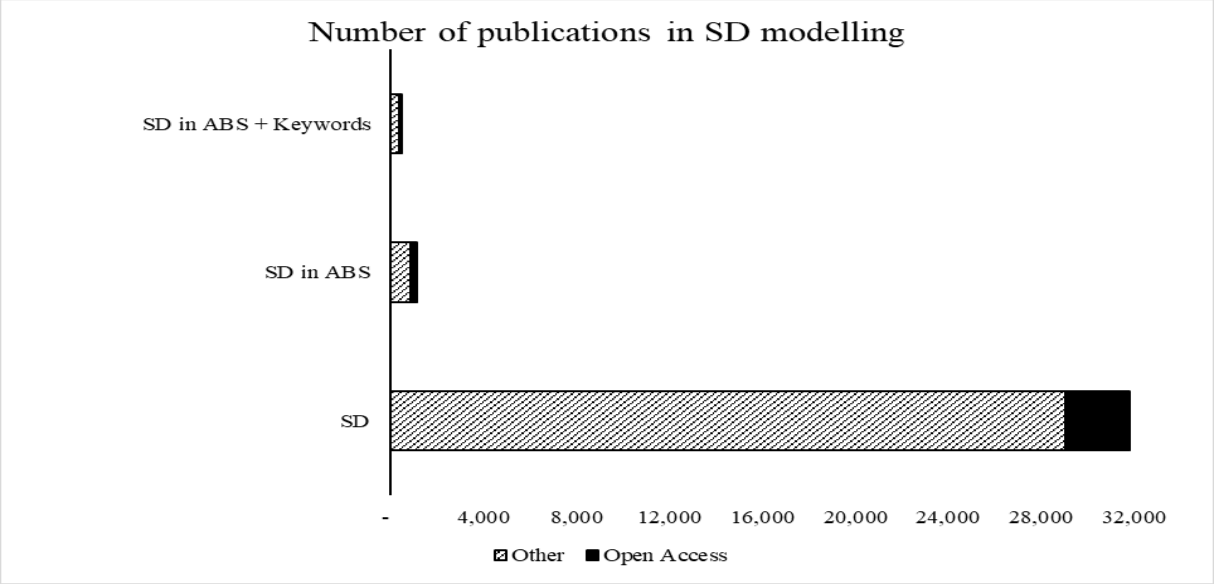
regarded as postharvest losses (FAO, 2011). Regardless of the stage of the value chain in which it occurs, implications of food loss and waste are spread throughout the economy; and system dynamics (SD) models can offer an appropriate and comprehensive approach to analyse the short and long run implications of this problem to the broader economy.

When the term "system dynamics" is searched in academic databases (such as SCOPUS[2]) nearly 32,000 peer-reviewed publications are returned, which include journal articles (17,908), conference papers (11,983), book chapters (686) and other forms of publications. However, over 50 per cent of these publications fall under the Engineering field and less than 4 per cent (about 1,130) are under the Agricultural and Biological Sciences (ABS) field. When any of the keywords "value chain", "supply chain" or "agricultur*" is combined with SD limiting the field to ABS, the total number of publications is reduced to 483 (Figure 1). About 406 of these are journal articles, of which 86 are classified as open access to readers. From the overall articles in ABS that contain any of the above specified keywords, fewer than 40 applied SD models to food supply (or value) chain problems and only one focused on the problem of food loss and waste in crops in a conceptual SD modelling approach.

Figure 1. Numbers of peer-reviewed publications in agriculture using SD



Source: SCOPUS (2019)

System dynamics, as described by Forrester, is "a professional field that deals with the complexity of systems" that "involves interpreting real life systems into computer simulation models that allow one to see how the structure and decision-making policies in a system create its behavio[u]r" (2010, p. 1). Five major processes comprise SD up to the point where policy changes can be implemented, and new dynamics returned to the model (Figure 2). These processes are well described by Forrester (1994).

Overall, SD is about describing and understanding the behaviour of the system under study; designing model equations that relate the state and control variables within the system; estimating parameters; and simulating the model. Once confidence in the model is achieved, it can be used to identify appropriate alternative policies through simulation. Step 5 in Figure 2 is more about reaching consensus on the appropriate changes to be implemented in step 6. However, as Forrester (1994) acknowledges, that is the greatest challenge in SD, as it involves many stakeholders for the particular system, who have different views and beliefs.

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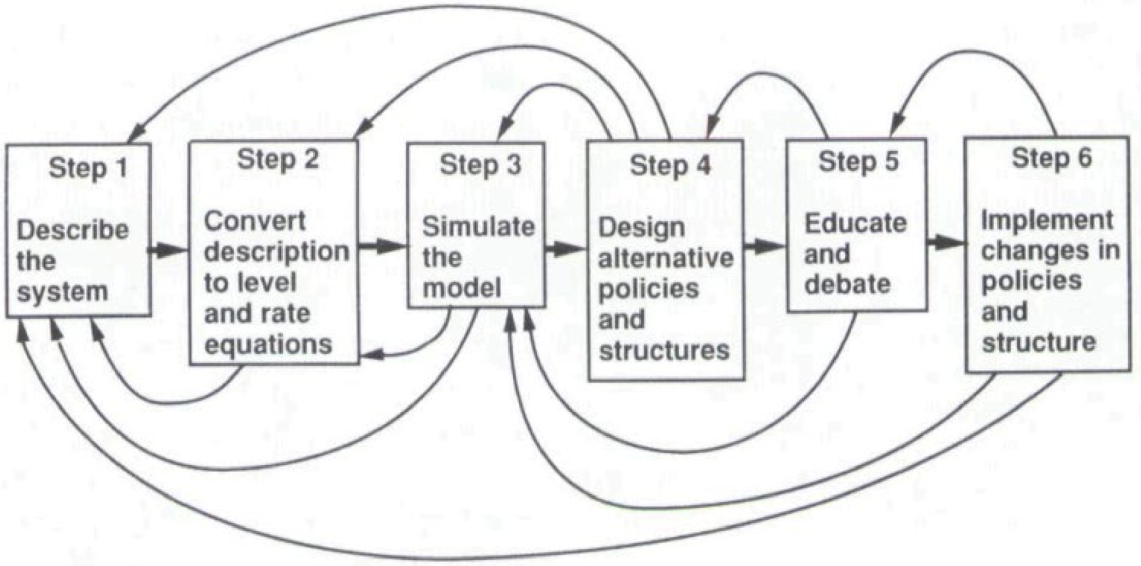
[2] Searched from 23 October to 5 November 2019.

Figure 2. System dynamics processes



Source: Forrester (1994)

In general, SD is regarded as a practical tool to assist policy makers in solving particular problems in a decision-making process (Sterman, 2000, p. ix). Globally, minimising food loss and waste is of great concern, which requires some policy intervention. System dynamics can be a useful tool to assist in this matter. To date, there have been no studies that have used SD to empirically analyse the biophysical and socioeconomic aspects in agricultural systems that lead to food loss and waste in crops. Galli, Cavicchi, and Brunori (2019), focusing on food as a broad category, used a SD model to analyse the impact of social drivers on the problem of food waste (i.e., downstream value chain food loss and waste). These authors focused on the implications of food assistance programs to food waste reduction and food supply, towards achieving a food poverty alleviation goal. On the other hand, Farrell, Tozer, Kenyon, Ramilan, and Cranston (2019) used a SD model to assess ewe wastage in sheep and beef farms, which is a different context to loss and waste in food crops.

The aim of this paper is to highlight the usefulness of SD models to agriculture, with a particular focus on biophysical and socioeconomic factors within food value chains that result in food loss and waste. The next section reviews the major drivers of food loss and waste across value chains. Then, the principles that guide SD modelling are described, validity tests recommended for this type of model are reviewed as are the major advantages of using SD models over other models. Examples of past studies applying SD to different agricultural systems problems are provided, including the usefulness of this type of model for drawing policy perspectives. Finally, a conceptual SD model is presented that could be used to analyse the problem of food loss and waste in a developing country context.

Food Loss and Waste and its Major Drivers

In the agricultural crop context, food loss and waste is an issue that arises from the crop's harvesting period to its final destination at the consumer level. Here, the FAO definition of food loss and food waste is followed. FAO (2011) defines food waste as the decrease in quality or quantity of edible food mass intended for human consumption that occurs specifically at the end of the food value chain, being mainly related to retailer and consumer behaviours, whereas food loss is defined as an issue that takes place at any of the early stages of the value chain – from production to processing – due mainly to issues such as logistics and infrastructure. So, along this continuum of paddock to plate, a number of key drivers of food loss and waste can be identified.

For Canali et al. (2014), the nature of the product (e.g., perishability), technologies in use, organisational and political inefficiencies along the value chain, as well as social factors including consumers' expectations and individual behaviour, are some of these key drivers. They classify the drivers of food loss and waste into four main categories: technology, business management and economy, legislation and policies, and consumer behaviour and lifestyles. Within each category, the authors identify several sub-drivers for each stage of the value chain, some of which are summarised in Table 1. The relative importance of each of the food loss and waste drivers varies according to the specific region or country context. For instance, FAO (2011) refers to structural differences in the way food is lost and wasted between regions with substantially different economic contexts. Whilst for medium- and high-income countries the majority of food is wasted at later stages of the value chain (retailer and consumer levels), for low-income countries it is wasted at earlier stages, particularly at the producer level.

Cerciello, Agovino, and Garofalo (2018) also identify other potential social drivers of food loss and waste related to demography, such as population density, elderly dependancy and immigration ratios, as well as gender dominance. These authors found a positive relationship between population density and food loss and waste, and a negative relationship between the other variables and food loss and waste. These outcomes seem to be particular to a household context, since the study by Cerciello et al. (2018) focused on urban food waste. Parfitt, Barthel, and Macnaughton (2010) also point to urbanisation as one of the key drivers for food loss and waste, though from a different perspective. They argue that increased urbanisation and consequent reduced availability of labour for agriculture – aligned to the limited marketing efficiencies to ensure affordable prices of food particularly for low-income consumers – is also an important driver for food waste.

Parfitt et al. (2010) point to other socioeconomic dimensions such as dietary transitions (mainly for higher-income consumers) and increased food prices and quality competition from international trade as other driving factors of food loss and waste. Segré, Falasconi, Politano, and Vittuari (2014) add food price inflation as another driving factor of food loss and waste, which impacts on consumers' choice and purchasing power.

In general, the relative importance of all the major drivers that contribute to food loss and waste in value chains can be efficiently accounted for in SD models. Clearly, food loss and waste is also a dynamic problem, where loss early in the chain restricts availability later in the chain, and waste later in the chain depends on the cumulative decisions of earlier chain participants. SD models are therefore particularly well-suited to analysing this problem.

Principles of System Dynamics

As defined by Forrester, "[a] dynamic system is one which changes with the progress of time. The parts interact to create a progression of system conditions. There is a basic structure common to all such systems, whether they be the systems encountered in engineering, in management, in economics, in nature, in psychology, or in any purposeful relationship of components" (Forrester, 1968, p. 1).

Forrester (2007, 2009, 2010) argues that SD is beyond systems thinking. While for some, both "system dynamics" and "systems thinking" appear to be interchangeable terms, Forrester (2007) views the latter as merely a description and acknowledgement of the existence of complexity in real life problems. On the other hand, SD is more about a "quantitative and dynamic simulation analysis" to understand behaviour that reveals the inconsistencies within one's mental model for a particular problem (Forrester, 2007).

Table 1. Drivers of food loss and waste

Food Value chain Segment	Drivers of food waste related to			
	Technology	**Business Management and Economy**	**Consumers' Behaviour and Lifestyles**	**Legislations and Policies**
Production	• Obsolete or inefficient equipment and machinery • Food contamination • Inappropriate (or limited) storage facilities • Lack of adequate technology to deal with climate conditions (ex. Weather forecasting)	• Inappropriate production and trade planning • Limited access to capital	• Market expectations • Consumers needs and demands	• Regulatory standards (ex. Grading) • Inappropriate Governments policies to incentivize (over)production
Distribution and logistics	• Inappropriate (or limited) storage facilities • Inappropriate transportation	• Product grading, sorting and labelling • Inappropriate transport facilities		
Processing and Wholesale	• Obsolete or inefficient equipment and machinery • Inappropriate packaging	• Inappropriate production and trade planning • Low cost of food discarding • Market expectations	• Consumers' needs and demands	• Regulatory standards (ex. Grading) • Regulatory measures (ex. Best before dates) • Lack of policies to disincentive waste
Retail and Food Services	• Poor handling skills • Inappropriate (or limited) storage facilities • Food contamination	• Low cost of food discarding • Inappropriate packaging • Market expectations	• Consumers' needs and demands	• Regulatory measures (ex. Best before dates) • Lack of policies to disincentive waste
Household	• Inappropriate (or limited) storage facilities	• Food price • Brand trust	• Consumers' needs and demands	• Lack of policies to disincentive waste

Food Value chain Segment	**Drivers of food waste related to**			
	Technology	**Business Management and Economy**	**Consumers' Behaviour and Lifestyles**	**Legislations and Policies**
			• Knowledge, awareness and attitude • Inappropriate buy planning • Demographic aspects	

Source: Adapted from Canali et al. (2014)

Mathematically, SD models can be described as a set of integral and differential equations represented as stocks and flows. In a generic econometric model analogy, stocks and flows can be described as the dependent and independent variables, respectively. Whilst a stock (Equation 1) represents the accumulation over time for a particular variable, flows (Equation 2) determine the rate of changes in stocks (Sterman, 2000). In a generic example of the food loss and waste problem, the current amount of food loss and waste can be regarded as the trigger for the control actions required to reduce the levels of loss and waste. Over time, the volume of food loss and waste (stock) may change according to the success rate of the control actions (flow) (Figure 3). Stocks and flows are also known as state and control variables, respectively (Hannon & Ruth, 2001).

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0) \qquad \textbf{(1)}$$

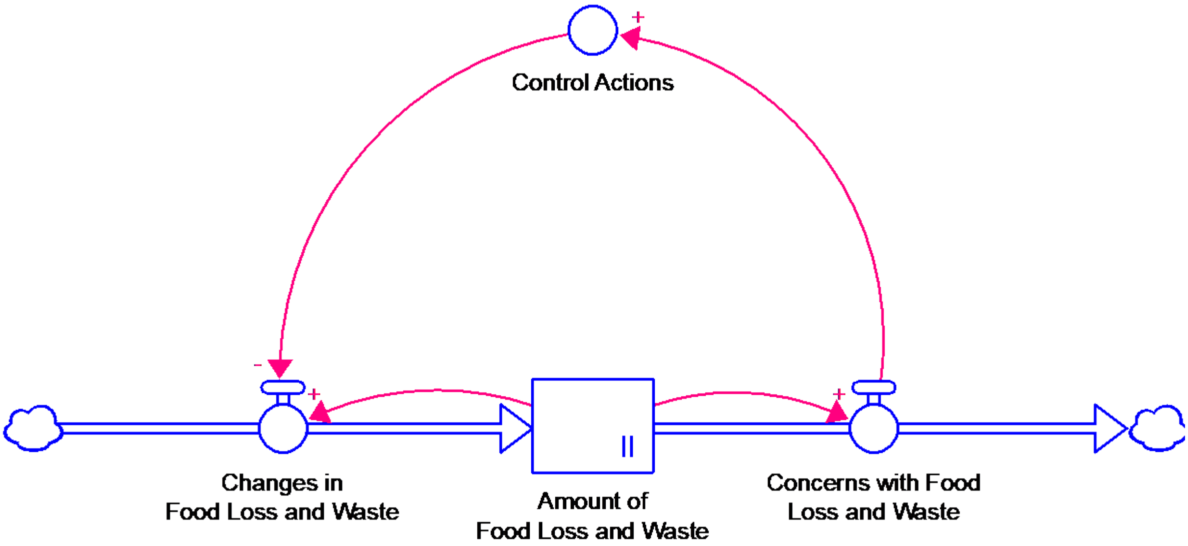
$$d(Stock)/dt = Inflow(t) - Outflow(t) \qquad \textbf{(2)}$$

where *Inflow(s)* and *Outflow(s)* are the inflow and outflow values at any time *S*, between the initial time (t_0) and current time (t).

In addition to stocks and flows, feedback loops form an important concept in SD modelling. They represent the system's endogeneity in the natural reactions to actions introduced in any real-life system. This is a contrast to a common one-way thinking approach, where once a problem is identified, one takes some actions expecting to solve a particular issue without any reaction or feedback from within the system (Forrester, 2009).

In most (if not all) real life problems, however, any action to solve a particular problem is likely to cause future reactions that will demand other actions. The feedback loops are illustrated in simple terms for the generic case of food loss and waste in Figure 3. Increasing concerns about food loss and waste trigger demand for actions to bring the problem under control. Actions that are successful in reducing food loss and waste result in reduced concerns, so future control actions may be relaxed accordingly. As in Figure 3, a positive impact of one variable on another is called a positive or self-reinforcing loop, and a negative one is called a negative or self-correcting loop (Sterman, 2000).

Figure 3. Stocks, flows and feedback loops representation of SD



Source: Adapted from Roberts (1978) and Forrester (2009)

In general, any SD model should comprise different stocks and flows interconnected by self-reinforcing and self-correcting loops. Whilst the self-reinforcing loops act to amplify the effects in the system, self-correcting loops act to re-establish equilibrium; and the interaction between the two, along with nonlinearities and time delays, is what determines the dynamics of any system (Sterman, 2000).

Auxiliary expressions and arbitrary parameters (e.g., "Concerns with Food Loss and Waste" in Figure 3) are also common in SD models. They are used to regulate the flows or, in the case of auxiliary expressions, to describe some arithmetic relationships between stocks, flows and arbitrary parameters (Rozman et al., 2013). Figure 3 is a simple example of the interrelationships between stocks, flows and arbitrary parameters (or expressions) in a generic model for the problem of food loss and waste.

Validity Tests for System Dynamics Models

System dynamics, like any modelling approach, is an artificial representation of real-world problems and, therefore, needs to be tested and validated for its accuracy in describing and representing the empirical reality (Forrester & Senge, 1979). Forrester and Senge (1979) identify 17 tests that can be implemented. The authors group them into three main categories aimed at assessing the structure of the model in describing the real-world system, its ability and robustness to replicate behaviour, and its effectiveness in providing appropriate policy recommendations. Sterman (2000) classifies the validity tests into seven categories. In Table 2, the testing approaches described by Sterman (2000) are merged with the classification initially adopted by Forrester and Senge (1979).

Although recommended, implementation of all the tests may be impractical. Forrester and Senge (1979) identify model structure tests as compulsory for SD models. Testing approaches for that purpose are described in Table 2. Examples of model structure tests used in past studies include dimensional-consistency, boundary-adequacy, extreme-conditions and parameter-verification (or integration error) tests (Marín-González, Parsons, Arnes-Prieto, & Díaz-Ambrona, 2018). Marín-González et al. (2018) also applied some model behaviour tests – according to Forrester and Senge (1979) classification – to assess the behaviour representation and sensitivity of their model. The usefulness of validation tests is unquestionable, and they are important to identify any limitations on a conceptual model as exemplified in the study by Dordkeshan, Shamsudin, Mohamed, and Radam (2017).

Advantages of a System Dynamics Approach

In general, any system modelling approach is about using mathematical representations to describe relevant features of a system under analysis in order to make inferences (Woodward, Romera, Beskow, and Lovatt, 2008). Apart from SD, a range of different systems modelling approaches using different methods and mathematical representations can be identified. Some examples include statistical methods (e.g., regression analysis), spatial analysis (including GIS) methods and simulation approaches (Zvoleff & An, 2014).

SD is one example of simulation approaches. Others include network models, discrete event simulation and agent-based models (Van Niekerk et al., 2017). The main difference between simulation approaches such as SD and statistical methods, for example, is the use of numerical integration methods, as an alternative to analytical methods, to solve a system of ordinary differential equations (Nicholson, Simões, Lapierre, & Van Amburgh, 2019).

While statistical methods, in particular regression analysis, are likely the most used for studies involving dynamics, they display limited abilities to effectively capture dynamics in complex systems derived from reciprocal causation, compared with simulation methods (Zvoleff & An, 2014). Nonetheless, Zvoleff and An (2014) classify regression analysis as more attractive to analysts because

Table 2. Model structure tests recommended for SD models

Tests	Purpose	Ways to implement or test
Structure-Verification Test	To compare the structure of the model with the real-world system that it represents.	• Use of policy structure or causal diagrams; • Use of stock and flow maps; • Direct inspection of model equations; • Partial tests to the model for the intended rationality of decision rules; • Experiments to elicit mental models and decision rules of system key stakeholders and actors; • Behaviour comparison between disaggregated sub-components of the model and the aggregated model; • Sensitivity and policy analysis to the model, with and without suspect structures.
Parameter-Verification Test	To compare parameters in the model to conceptual and numerical knowledge of the real-world system.	• Parameter estimation using statistical methods; • Calibration to sub-components of the model using partial model tests; • Information comparison against experts' opinions and literature review; • Use of experience for a judgemental assessment.
Extreme-Conditions Test	To identify flaws in the model structure and reveal omitted variables.	• Direct inspection of the model equations; • Model's response test to extreme values in an individual (or a set of) variable(s); • Model's assessment for conformance to basic physical laws (e.g., how the model performs if no crop production is assumed).
Boundary-Adequacy Test	To assess the model's appropriateness and inclusion of all relevant structure. It is about developing convincing hypotheses, which the proposed model structure can answer.	• Use of policy structure or causal diagrams; • Use of stock and flow maps; • Direct inspection of the model equations.
Dimensional-Consistency Test	To assess the adequacy of equations in the model.	• Direct inspection of the model equations; • Use of dimensional analysis software.

Source: Adapted from Forrester and Senge (1979) and Sterman (2000) it is relatively easy to implement, and to interpret results. SD is an efficient approach to combine large and complex sets of information about a real-world system and to artificially test behaviour using different scenarios (Winz, Brierley & Trowsdale, 2009). However, other methods, such as regression analyses for instance, are also an integral part of many SD models. Van Niekerk et al. (2017) discuss the pros and cons of an SD approach over other simulation approaches. The authors highlight the existence of many similarities between SD and agent-based models, which they consider the most appropriate simulation methods for agricultural systems. Due to agent-based models being "constructed at an individual (micro) level" and not easy to validate and verify (p.135), Van Niekerk et al. (2017) suggest that it is not an appropriate model to apply to some agricultural systems problems compared with an SD approach. Winz et al. (2009) also describe SD as flexible and an easily adaptable testing and learning approach for dynamic simulations.

Examples of System Dynamics Model to Agricultural Systems Problems

Almost five decades since Forrester's first modelling work (as mentioned in Forrester, 2007), SD can still be considered an emerging methodology for food value chain problems. From the overall 406 journal articles identified as potentially applying SD models to an agricultural context, fewer than 40 are related to food value chain problems as suggested from their respective titles; and only 23 of these articles could be accessed. Nevertheless, 17 out of these 23 articles effectively apply the SD model. Table 3 highlights the articles considered most relevant, which focus on food security, food wastage and economy-wide implications.

The first example in Table 3 is Galli et al. (2019), who applied a conceptual SD model to assess the implications of food assistance programs in reducing food waste. The authors focused on social and managerial aspects as the key drivers of food waste, looking to food as a broad category. They emphasized particular aspects such as the role of food banks (and the social aspects related to it) in food aid as well as managerial issues that impact on the degree of food recoverability for donation. Farrell et al. (2019) also concentrated on wastage, though focusing on animal value chains (sheep and beef). These authors investigated the interactions between biological (e.g., animal production cycle), operational (e.g., wool production) and marketing (e.g., inputs supply and demand) subsystems and their implications for farmers' current and prospective profitability. In the model of Farrell et al. (2019), however, wastage is treated as an exogenous variable.

Dordkeshan et al. (2017) applied an SD model to a specific food crop value chain problem. They analysed the economic implications of the removal of the import quota for rice in Malaysia. The dynamics modelled in their study focused mostly on marketing aspects that impact on rice price formation and trade. On the same theme of analysing the economic impact of policy changes, Dizyee, Baker, and Rich (2017) assessed the implications of beef export liberalisation in Botswana. Apart from a marketing subsystem that ultimately impacts on profitability, Dizyee et al. (2017) expanded their model to account for biological (e.g., production cycle) and climate (e.g., rainfall) subcomponents that impact on animal production in Botswana.

Another example highlighted in Table 3 is Marín-González et al. (2018), who assessed the impact of smallholder endowments on food security focusing on the example of intercropping (maize and bean) system producers in highland areas in Central America. In this study, the authors accounted for the interaction of climate, biological and operational (e.g., labour) subsystems on the availability of food for farmers as well as on their profitability. Agricultural inputs and food prices were exogenously assumed in that study.

Examples of other studies applying a SD model to different agricultural value chain problems include De Wit and Crookes (2013), Ibanez, Martinez-Valderrama, Taguas, and Gomez (2014), Abdulla and

Arshad (2017) and Van Niekerk, Brent, Musango, and De Kock (2017). The common theme in all of these studies is their focus on economic implications within their SD models.

The study by De Wit and Crookes (2013) examined the financial and ecological implications to farming activities from decision-making on irrigation farming in arid zones in the Western Cape province of South Africa. Van Niekerk et al. (2017) also focused on the Western Cape; however, their goal was to analyse the financial and environmental implications of a transition to a "green economy" for food crop production systems. Ibanez et al. (2014) assessed the implications for farmers' economic gross margins of water erosion in olive-growing areas in Spain. Abdulla and Arshad (2017) examined "the structural factors that led to a decline in rubber area and natural rubber production" in Malaysia, aimed at proposing "strategies to enhance productivity and returns for smallholders".

To some degree, all of these studies capture more than one of the complex dynamics that influence agricultural systems such as biological, climate, environmental, management and marketing dynamics. They demonstrate how SD can be used to analyse different and complex problems in agricultural systems.

Table 3. Examples of past studies using SD to food value chain problems

Author(s)	Value Chain(s) Analysed	Aim of the Study	Examples of Subsystems Modelled
Galli et al. (2019)	Food (as a broad category)	Assess the implications of food assistance programs to food waste reduction and food supply in Italy	• Social • Managerial
Farrell et al. (2019)	Sheep and Beef	Assess the implications of ewe wastage for productivity and profitability of farmers in New Zealand	• Biological • Operational • Marketing
Marín-González et al. (2018)	Maize and Bean	Assess the impact of smallholder endowments on food security in highland areas in Central America	• Biophysical
Dordkeshan et al. (2017)	Rice	Assess the economic implications of the import quota policy removal for rice in Malaysia	• Marketing
Dizyee et al. (2017)	Beef	Assess the economic implications of beef exports liberalization in Botswana	• Biophysical • Marketing

SD Model for Policy Analysis Concerning the Problem Food Loss and Waste

Although currently limited, applications of SD to analyse the implications of different drivers of food loss and waste along value chains are possible to assist in informing policymaking decisions. For example, in some developing countries market access is one of the major causes of food loss and waste, particularly at the farm level. This is due in part to poor road infrastructure and, hence, only a small fraction of farmers in these countries engage in trade for their surplus production. In such cases, improvements in legislation and policies could be vital to minimise the impact of market dynamics on food loss and waste. The potential impacts of new legislation or policies should be assessed prior to implementation; for which SD models can play a relevant role.

Hence, SD can be an important tool to assist in assessing the implications of specific policy changes to a whole value chain. The endogenous approach of the SD methodology is appropriate to capture the overall value chain reaction to specific changes within a system such as the potential impact of government programs aimed at minimising the problem of food loss and waste, at least within a domestic value chain perspective. This model is also appropriate to analyse complex problems for which data availability may be a limitation (Forrester, 1996). In developing countries, access to and availability of data has been one of the major limitations for analysts.

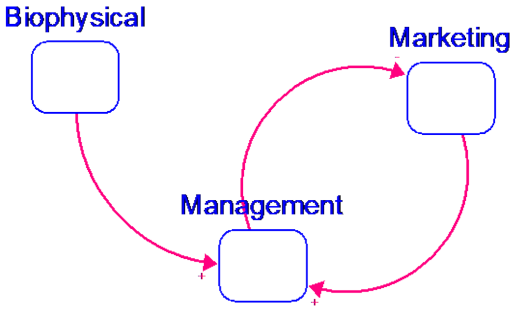
Theoretical Application of System Dynamics to Food Loss and Waste Problems

Broadly defined, food loss and waste can be perceived as a complex issue in agricultural systems. At the upper end (upstream) of the value chain – from production to processing, and where some define it as simply food loss (Segré et al., 2014) – sub-components related to climate, biological and management subsystems can be perceived as some of the key drivers of food loss and waste. Other sub-components of these subsystems are also important for food loss and waste – or simply food waste – at the lower end (downstream) of the value chain. As highlighted in Table 1, Canali et al. (2014) point to some management aspects (e.g., production plans, technology in place for food production and storage) and climate-related aspects among the drivers of food loss and waste. Marketing dynamics are also important in explaining food loss and waste. Misalignment between producers' expectations and consumers' demand, for instance, can result in excessive food loss and waste along the value chain (Canali et al., 2014).

The hypothetical empirical model illustrated in this section focuses on food loss and waste at the upstream end of value chains, which is a typical case in many developing countries. Different factors contribute to the overall level of post-harvest losses (PHL). Apart from the marketing forces that determine the amount of a product traded and the resulting surplus that is prone to be wasted, climate-related issues and management practices also determine the overall level of PHL. Climate plays an important role in the upsurge of agricultural pests, whilst management practices play an important role in terms of either handling practices or storage choices that would affect the overall PHL.

Figure 4 is a conceptual SD model that takes into account the interaction of the biophysical, management and marketing subsystems to explain the overall PHL. Figure 5 shows in detail the major components of each of these subsystems. The model in Figure 4 (and 5) has been developed to analyse the short- and long-run economic implications of PHL in a specific cereal in a developing country context. In a model like the one in Figure 4, climate-related variables (e.g., temperature and rainfall) are taken as exogenous variables that impact on food production as well as on the amount of food loss observed immediately at the farm level. Climate may impact directly (e.g., through the occurrence of extreme weather conditions that reduce yield) or indirectly (e.g., through the creation of favourable conditions for an upsurge of on-farm and off-farm pests and diseases) on food loss and waste at the farm level. Despite the exogeneity assumption for the climate-related variables, long-run analyses are possible given the flexibility of SD models in being able to combine other modelling approaches (e.g., the use of stochastic models for the exogenous variables) within the modelling process.

Figure 4. Subsystems of a conceptual model to assess food loss and waste at the farm level



The biophysical subsystem is detailed in Figure 5a (variables are defined in the Appendix). In Figure 5b, the management subsystem is seen as well as the bridge linking the biophysical (Figure 5a) and marketing (Figure 5c) subsystems. Whilst the biophysical subsystem determines the effective production levels in each period, the marketing subsystem describes the interaction between supply and demand forces. Management aspects, on the other hand, impact on the storage of the resulting surplus. The simplified representation of the management subsystem in Figure 5b is due to the typically limited availability of information to model that subsystem, and it illustrates the practicability of system dynamics models to deal with such situations.

Apart from the impact of climate-related variables, socioeconomic factors at the postharvest stage such as farmers' management practices, storage conditions and barriers to access domestic markets result in high levels of PHL in some developing countries. Major consequences of those high levels are increased risks of food insecurity, higher prices of food domestically and, eventually, increased dependency on imports. In cases where barriers to regional trade are not prohibitive or effective, domestic producers in the border regions are likely to export their produce in order to generate some household income, further increasing the risks of food insecurity.

In the model described in Figure 4, and unlike the ones from other studies, food loss and waste is treated as an endogenous problem occurring at the farm level in two stages. In the first stage, socioeconomic factors interact with climate variables to result in PHL before storage (PHL1). In the second stage (PHL2), PHL is caused by oversupply and limited storage capacity. Under a conceptual SD model like this, different potential government interventions to minimise the impact of socioeconomic factors such as postharvest management practices and barriers to trade can be tested to assess their overall impact on the value chain performance including to PHL levels.

Given the specificity of each situation and the purpose for which a model is constructed, different variants of a model such as those in Figures 4 and 5 can be used to assess the endogeneity that determines the amount (and cost) of food loss and waste, not only at the farm level but anywhere along a specific value chain.

An article using this model to study the maize sector of Mozambique has now been published (Popat et al., 2022). The results suggest that climate-related factors cause a significant amount of food loss each year, but marketing forces also play an important role, particularly in periods when domestic production increases sharply. The impact of potential interventions in the value chain were also tested. As expected, the results suggest that with effective policies to increase production, the cost of loss is likely to increase sharply if no other forms of intervention are included in a policy package to improve storage, transportation and marketing. A combination of increased production and other forms of intervention may result in more efficient economic results.

Figure 5a. The biophysical subsystem

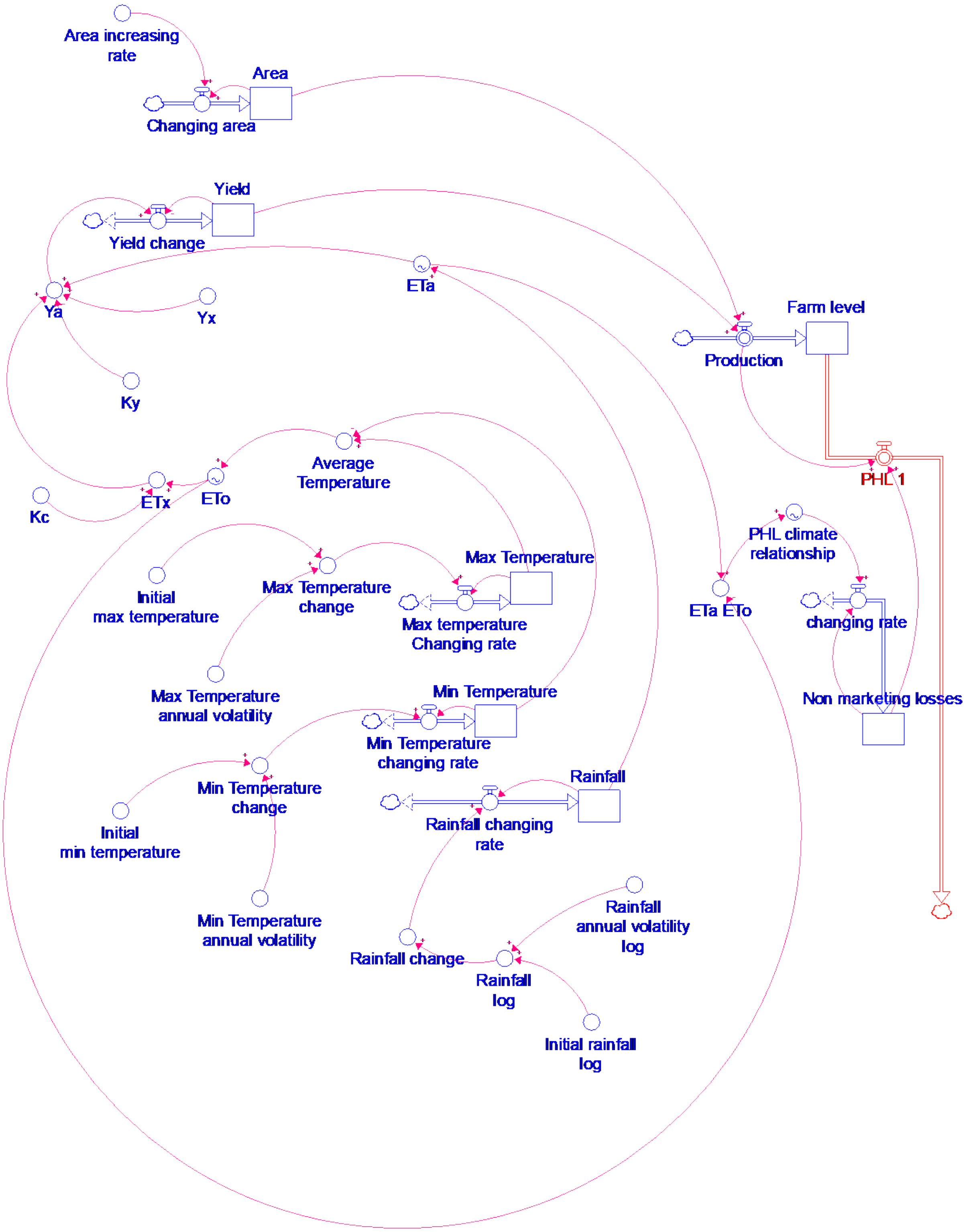


Figure 5b. The management subsystem

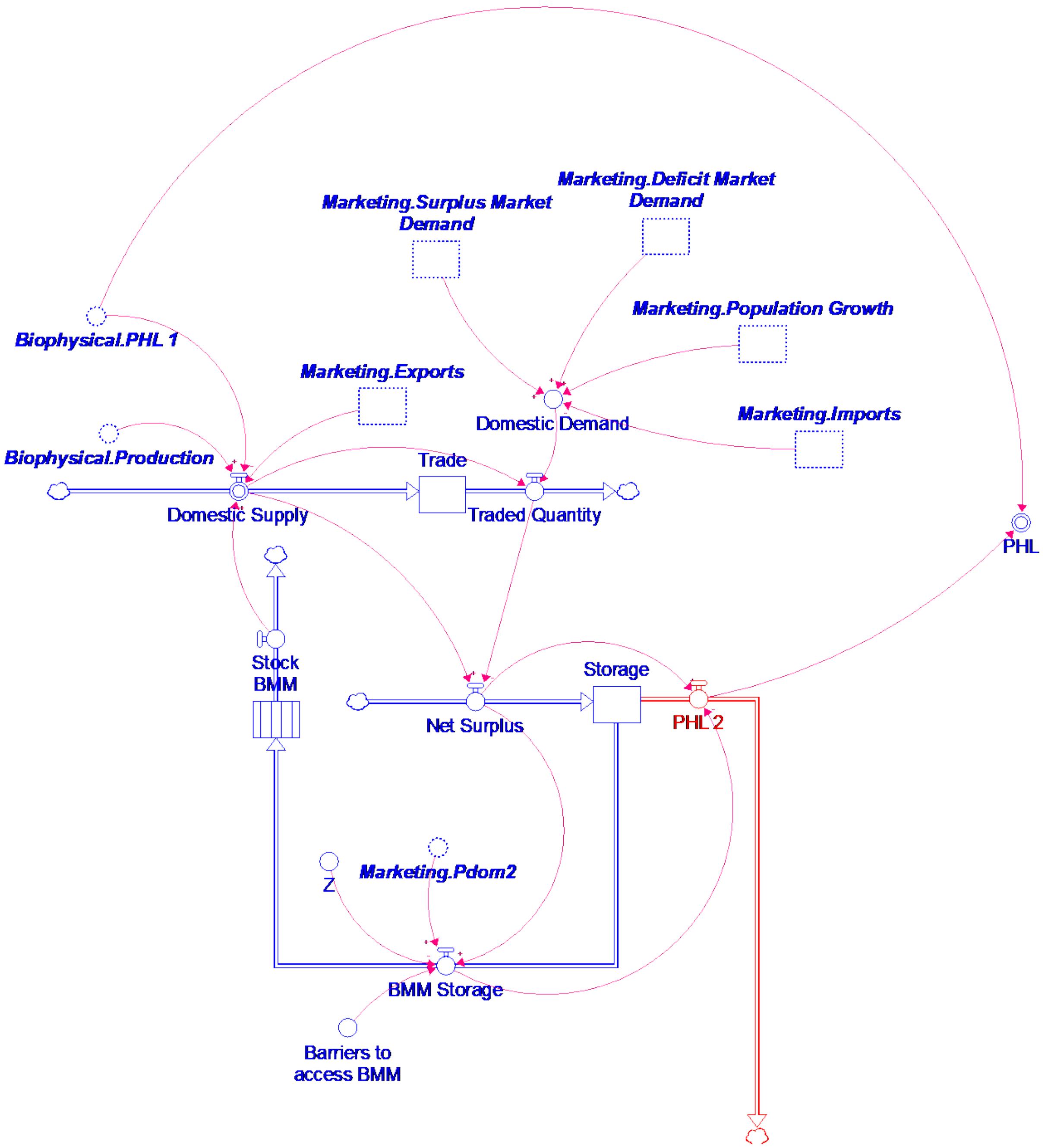
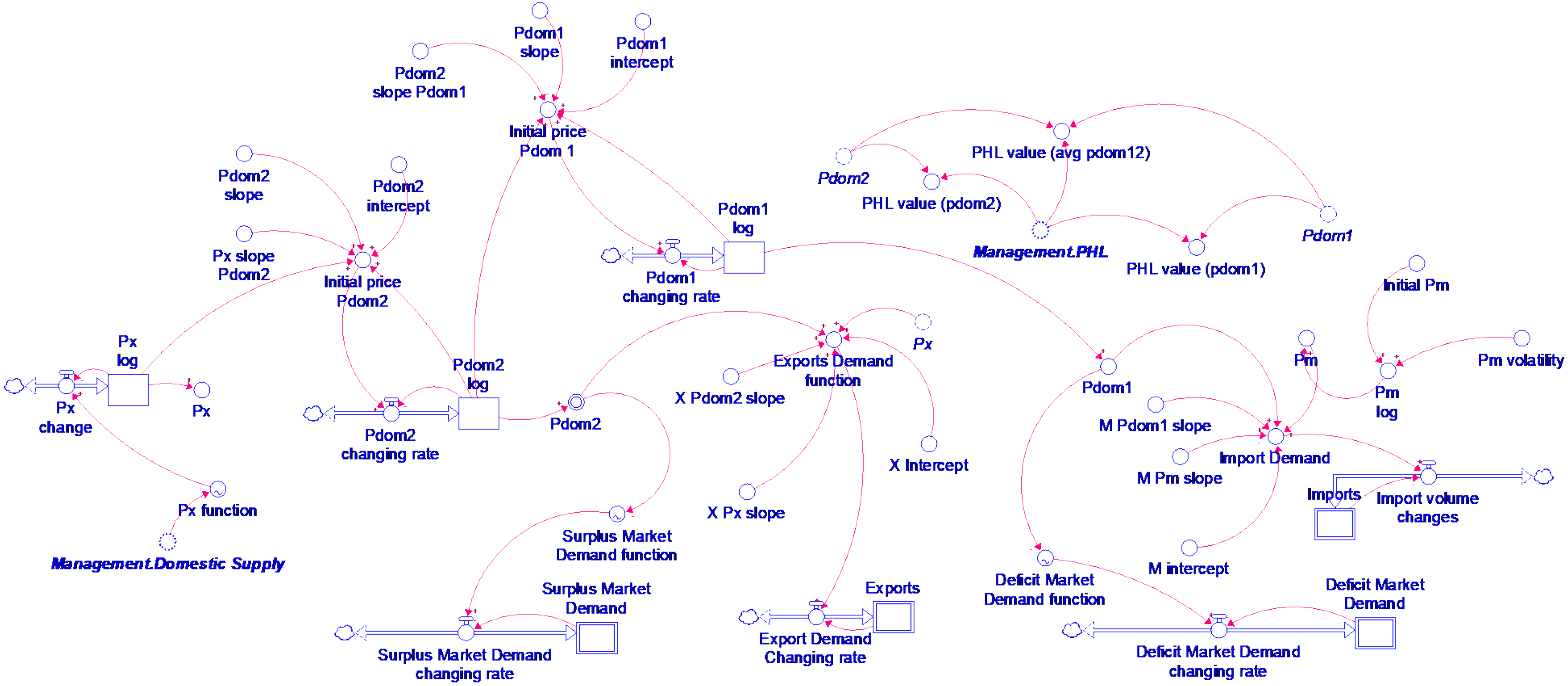


Figure 5c. The marketing subsystem



Conclusion

This paper reviews some of the core literature on system dynamics models and shows the appropriateness of applying this modelling approach to agricultural systems problems with a particular focus on food loss and waste. Over nearly 50 years, system dynamics models as proposed by Forrester have been an important tool for policy analysis with applications in a range of fields. Nonetheless, to date, applications of system dynamics models to food value chain problems have been limited and no peer-reviewed article has used this type of model to empirically analyse the impact of biophysical and socioeconomic factors on food loss and waste. This paper reviews the key concepts that need to be understood in order to implement system dynamics models and describes some examples of applications of this modelling approach to agricultural systems problems. As highlighted, system dynamics has a number of advantages over other modelling approaches. But as with any model, it also needs to be assessed in terms of its ability to describe a particular problem and its usefulness for policy recommendations. Validity tests for system dynamics models, as proposed by pioneer authors in the field, are consolidated into five categories to provide a concise summary that can be used by practitioners. The strengths of the system dynamics model for policy analysis of complex systems are identified in reference to other modelling approaches. Finally, a generic conceptual example of potential applications of system dynamics to food loss and waste problems is also presented.

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Appendix. Variables definitions and units

Variable	Description	Unit
Area	Harvested area	(x 1,000) ha
Ya	Maize yield	ton/ha
Prod	Maize production	(x 1,000) ton
Cons	Consumption	(x 1,000) ton
M	Imports	(x 1,000) ton
X	Exports	(x 1,000) ton
PHL	Postharvest losses	(x 1,000) ton
Pdom1	Maize price in Maputo	USD/ton
Pdom2	Maize price in Chimoio	USD/ton
Pm[a]	Maize price in South Africa	USD/ton
Px	Maize price in Malawi	USD/ton
Pop	Population	people
Temp	Temperature	^{o}F (converted to ^{o}C)
Rain	Rainfall	Inches (converted to mm)
ETx		mm
ETa		mm

[a] Except for prices from the import market, which is at the wholesale level, all other prices are at the retail level.