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Understanding technology adoption through system dynamics modeling: implications for agribusiness management

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Abstract

This work demonstrates the utility of sophisticated simulation tools in aiding agribusiness managers' decision making. The system dynamics model developed here provides insight into the use of such models to evaluate potential adoption rates and diffusion patterns of yield mapping and monitoring technologies. The model allows for comparative analyses of the possible effects of different profit assumptions on adoption and diffusion.

1. Introduction

Managers in agricultural businesses are faced with an increasingly dynamic, complex, and uncertain environment in which to make decisions. A different set of tools is required to navigate this increasingly complex environment (Boehlje, 1999). Learning through the use of sophisticated management tools is the focus of the paper.

Rapid technological advances, information explosion, and the widening gap between the developed and underdeveloped countries of the world all contribute to today's complex environment (Daellenbach 1994). The complexity of the agricultural industry is well documented. Other factors that contribute to complexity in agriculture include demographic

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issues (poverty, high population growth, and income growth rates), dietary and consumer preference changes, government action, agricultural research, land use, and climatic changes (Pinstrup–Andersen and Pandya–Lorch, 1998).

The results of agribusiness decisions are not known ex ante and are often not immediately realized, thus contributing to the complexity of the environment. The seasonal nature of agriculture means the results of decisions made today regarding planting and chemical applications often take months to materialize. Further, decisions related to investments, technology adoption, market development, and agri-chemical research in the agricultural input sector can take years, or even decades, to yield results.

The characteristics of this environment, coupled with managers' less-than-perfect rationality, lead managers to formulate mental models of their environment and to rely, to some degree, on these during decision-making (Huff, 1990). System dynamics modeling is one of a number of tools that can help managers learn and revise their mental maps of their business environment, and thereby improve decision making and performance.

> "Managers and organization theorists often point to high-performing teams in sports or the performing arts as role models of flexibility, learning, and consistent quality. Yet most firms, unlike a basketball team or symphony, have no practice fields where managers' skills can be developed and team competencies enhanced. Opportunities to reflect, to experiment, to challenge and revise mental models may be even more important for learning in firms than in sports or the arts," (Senge and Sterman, 1994: 213).

System dynamics models can act as "flight simulators" that managers may use as a practice environment. They provide the opportunity for reflection and experimentation thus enabling decision makers to more fully comprehend the complex environment in which they work.

The adoption and diffusion of precision agriculture technologies encompasses a high degree of complexity in which to model and explore decision making. The complexity exists, in part, because the benefits of using such technologies are uncertain before adoption. Potential and current adopters of the technology learn about the benefits through information feedback within the system. Learning about the technologies' benefits influences the adoption process. Through system dynamics modeling and simulation, members of the agribusiness management community may gain insight into the causal factors influencing farmers' adoption decision making processes and, thereby, into the potential diffusion patterns resulting from those adoption decisions. Knowledge of how causal factors influence precision agriculture technology diffusion patterns may assist agribusiness decision-makers in strategic planning.

In this study, we examine how a tool that facilitates learning increases our understanding of technology adoption and diffusion. Learning models, such as the one employed in this research, can be useful as they make explicit time lags and complex factors in the adoption process. We use scenarios to illustrate the potential applicability of the model. These scenarios are not predictions of the future, instead, they allow us to imagine different, plausible alternative paths that could materialize (Mason, 1994), and through the model, gain a better understanding of potential outcomes. The key motivation in using such tools is to improve decision making and understanding of future changes.

2. Literature review

We draw from multiple research streams in our discussion of the usefulness of system dynamics modeling as a tool for agribusiness management. First, to understand the context of the example, we examine precision agriculture and diffusion literature. Next, we look at learning in system dynamics modeling.

2.1. Precision agriculture

Precision agriculture (PA) is the application of information technologies to production agriculture. The National Research Council (NRC) defines PA as, "... a management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production," (NRC, 1997: 1). PA includes multiple technologies impacting key farm management practices by characterizing the spatial and temporal variability in agronomic practices (also see Mulla and Schepers, 1997; Nowak, 1997). Key practices include yield monitoring, fertilizer applications, pest management, and drainage management.

The practical application of PA technologies faces agronomic and economic uncertainty. Many researchers believe that PA technologies will affect an evolutionary change in agriculture, rather than a revolutionary one. Recent PA research is inconclusive about the current profitability of PA practices (Lowenberg–DeBoer and Swinton 1997; Schnitkey et al., 1996). A few studies, do however, provide rates of adoption (Akridge and Whipker, 1996; Swinton, 1996; Khanna et al., 1999; Norvell and Lattz, 1999). In general, results show that farmers are willing, but not immediate, adopters of new PA technologies.

Of the PA practices, yield monitoring and mapping appear to be incurring the fastest acceptance among farmers (Khanna et al., 1999; Norvell and Lattz, 1999). A yield monitor refers to an on-the-go sensor that estimates the volume and moisture of grain flowing through the combine as well as the area covered by the combine. It then reports an estimate of the per acre yield on a display screen located in the cab of the combine. Yield mapping refers to the combination of yield monitor results with spatial information (longitude and latitude) and the creation of yield "maps" across fields. Yield mapping will precede other PA technologies in adoption because it provides information for evaluating the productivity effects of other practices (Pierce et al., 1997). Therefore, by modeling yield mapping technology adoption, we can gain insight into the potential adoption patterns of other PA technologies.

Currently, the cost of adding yield monitoring technology onto a combine is about $6,000. Yield mapping technology typically costs around $9,000. In addition, the mapping technology requires a subscription to a global positioning signal that varies in cost, but a medium quality signal is around $500 per year.

In addition to financial costs, some nonpecuniary costs of implementing this technology exist as well. One is calibration. Yield monitors need to be calibrated to actual yields. This must be conducted for each crop at the beginning of the harvest season and as conditions change. For example, if corn moisture varies substantially the monitor must be recalibrated to remain accurate. As with any new equipment, operator learning is necessary. Some farm equipment dealers offer half-day training to teach basic use of the yield monitors and transfer of data to a computer mapping program. However, the learning or management costs have been lowered as the technology has improved. Today's monitors and mapping programs are much more "user friendly" than those of a few years ago.

2.2. Diffusion models

The diffusion of innovations is a well studied subject by numerous researchers across multiple disciplines with the primary objective of understanding the mechanisms that motivate the innovation and diffusion processes (Rogers, 1995). Diffusion is distinguished from adoption as being the process by which a new product is spread among users, while adoption is treated as an individual, internal decision process (Rogers and Shoemaker, 1971; Mahajan and Peterson, 1979).

Many researchers have used mathematical (logistic functional form) models to study dynamic diffusion processes (Blackman, 1974; Mahajan and Peterson, 1978; Mahajan and Shoeman, 1977; Sharif and Ramanathan, 1981). Most of these models are deterministic, have a binomial form (adopt or not), and result in a typical S-shaped diffusion curve. Diffusion models increase in complexity through the inclusion of spatial, temporal and causal factors. According to Sharif and Ramanathan (1984), once a diffusion model takes on these factors, system dynamics should be used to ease the mathematical and computational complexity. Several diffusion models have utilized a system dynamics methodology (see Blackman, 1972a; Homer 1987; Finkelstein et al., 1984; Sharif and Kabir, 1976).

Our study incorporates both temporal and causal aspects. We utilize a system dynamics model to explore the adoption and diffusion of yield monitoring and mapping technology by Illinois producers. The model makes explicit the causal relationships that influence technology adoption and diffusion behavior. This simulation approach allows members of the agribusiness community to gain insight into the causal factors influencing farmers' adoption decision making processes and thereby into the potential diffusion patterns resulting from those adoption processes.

2.3. System dynamics modeling: learning and technology adoption

One advantage of using system dynamics models over more traditional models is the inclusion of feedback effects. This makes the model's output more realistic and exposes complexity that may be hidden in other modeling techniques. Thus, decision makers can more easily identify the interrelationships in the environment of the model. Feedback occurs in another level as well. As managers practice with the simulation, their understanding of the environment changes. They learn from the feedback the model gives them.

"Learning is a feedback process. We make decisions that alter the real world; we receive information feedback about the real world, and using the new information, we revise our understanding of the world and the decisions we make to bring the state of the system closer to our goals," (Sterman 1994: 291). Sterman's emphasis of learning through feedback is illustrated in Figs. 1 and 2. Single-loop learning can change a particular decision one might

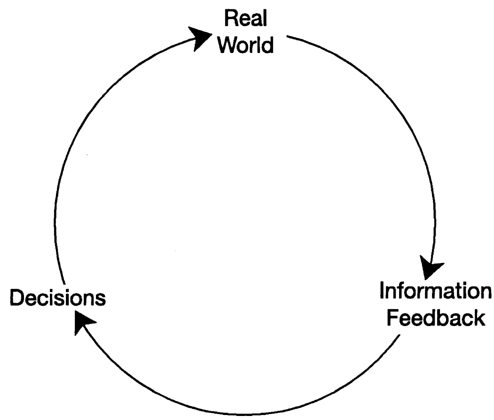

Fig. 1. Single-loop learning.

make (Fig. 1). However, feedback in double-loop learning actually changes how an individual thinks about a given problem (Fig. 2).

Homer (1987) utilizes feedback in a system dynamics model to explain the emergence of medical technology by modeling how the adoption process motivates the diffusion of new technology. He demonstrates how exogenous and endogenous factors impact the adoption process. Exogenous factors include such things as attributes of the technology, government intervention, initial perceptions, new purchase decisions, and the standard of performance. Endogenous factors are use, evaluation, and support.

Homer's model incorporates two feedback loops that are important to the adoption and

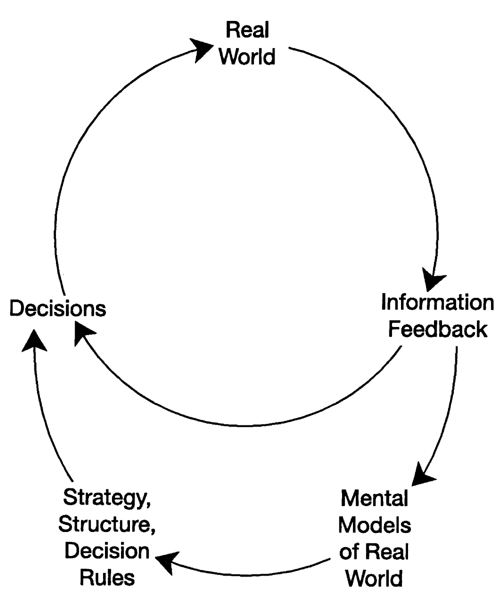

Fig. 2. Double-loop learning.

diffusion of technologies. The first loop is a word-of-mouth loop that links the fraction of adopters in the current period to future acceptance rates. The second important feedback loop is promotion. The promotion loop basically relates current annual purchase rates of the new technology to future levels of promotion.

The model employed in this paper builds on Homer's approach to model the adoption and diffusion processes of yield monitoring and mapping technologies. As in Homer's work, a system dynamics approach allows us to capture the time lags inherent in technology adoption and diffusion.

2.4. Simulation model

Our model, developed using the PowerSim® software package, focuses on the adoption and diffusion of yield monitoring and mapping (YMM) technologies. The model builds on work conducted by Nelson (1998). This section examines the assumptions and resulting behavioral characteristics of the simulation model. Next, it looks at the YMM technologies diffusion process. Then, the YMM technologies adoption process is discussed. Finally, the role of information flows in the system is explored.

Through PowerSim® we set up a time span and time increment for the simulation, 20 years in this case. It allows qualitative variables and relationships, and employs those in a mathematical equation framework to describe the causal relationships between variables in the system. Stock variables accumulate or deplete depending on flows (change rates) across time. For example, adoption level is a stock variable in this model that changes by the acceptance rate (flow variable) over time. The acceptance rate is a mathematical equation:

$$\text{Acceptance rate} = \text{Farmers} \times (\text{Map Adoption Rate} \times \text{Age Factor})$$

As the model progresses from year to year, the adoption level changes according to the acceptance rate algorithm. Research specifies (estimates) relationships regarding how acceptance rate is affected by other variables. Econometrics, theories, and expert judgment are incorporated in a given simulation run. The real power behind system dynamics modeling is in the comparison between variables across different runs.

The model assumes there is no limitation on diffusion throughout the production agriculture system, and that technology is readily available to all. In addition, producers are faced with a binary decision to adopt or not adopt. Once adoption occurs, a producer will not choose to return to nonadopter status. Monitoring technology adoption is a necessary condition before mapping technology adoption can occur. Finally, the cost of information technology is assumed constant over the span of the simulation.

These assumptions result in a number of behavioral characteristics in the model. Explicit temporal diffusion patterns are defined; however, spatial diffusion patterns are not explicitly identified. Moreover, the model behavior is defined through decision functions, which in turn regulate the physical and information flows. Thus, it is possible to examine potential future behavior and explore actions that would suggest alternative behavior through the model.

The model is affected by both exogenous and endogenous factors (Homer, 1987). The exogenous factors include the general profitability of production agriculture; the agronomic,

Table 1
Factors and decision processes for production agriculture's decision makers

Decision maker	Endogenous factors	Decision process
Farmer	Current use of YMM technologies Extent of information sharing and pooling Extent of word-of-mouth on their assessment of YMM technologies	Replace combine machinery Adopt or not adopt Share or pool PA information
YMM technologies providers	Continued development reducing technology cost Extent of promotional marketing on YMM technologies	Improve technologies Promote technologies
Yield mapping service providers	Continued development reducing technology cost Development of a market infrastructure supporting yield map interpretation Extent of promotional marketing on YMM technologies	Provide interpretation services
Agronomic and economic researchers	Amount of research influencing the understanding of PA knowledge to be applied to PA production enhancing practices Influence of environmentally friendly regulation on the diffusion processes of YMM technologies	Perform research

economic and technological capabilities of PA; potential government regulation; and farmer demographics in the region of interest. The endogenous factors are best understood in relation to the various decision makers in production agriculture as seen in Table 1.

Farmers, one of four types of decision makers in the system, decide when to replace machinery, whether to adopt the new technology, and whether to share information about their experiences using the new technology. All of these decisions influence technology adoption and diffusion. The model is centered around farmers' technology adoption decisions. However, technology providers (and other decision makers) can affect the system as they can both improve and promote the technology.

Following Homer's (1987) approach, we explicitly model agent decisions in relation to the exogenous and endogenous factors so as to explore interrelationships that affect the technology diffusion process. The relationships between the exogenous and endogenous factors are depicted in Fig. 3.[1] The exogenous factors (farm profitability, government regulation, and the initial conditions) combine with the endogenous variables (market support for new technology, research, technology learning, and performance) to drive the adoption decision. For example, the endogenous performance variable (Agronomic, Economic, and Technological Performance) is affected by a set of forces; directly through the endogenous factors of yield map interpretation support, research and technology learning; and indirectly through the exogenous factors of technological constraints, monitor performance in this case, and initial conditions. Every stock variable requires an initial level. These initial conditions are determined through study and observation.

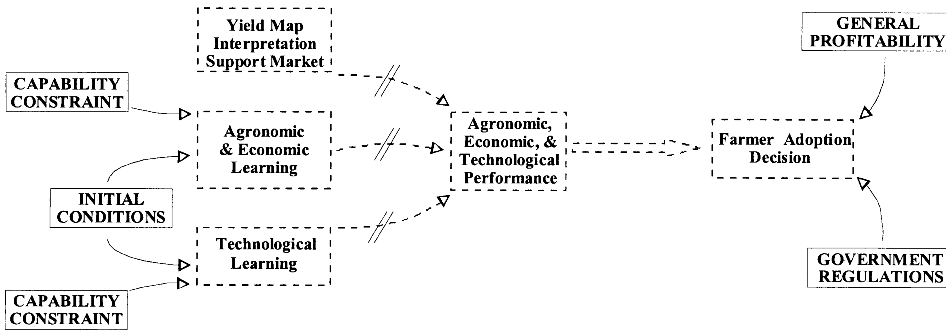

Fig. 3. Exogenous and endogenous factors' influence on yield monitoring and mapping adoption and diffusion.

Now we turn our attention to technology adoption. The adoption of yield monitoring and mapping technologies is modeled as a multistage process replicating the marketplace for these technologies. Further, in this model, the combine purchase decision is sequentially interrelated with the adoption of the technologies. Fig. 4 illustrates the model processes for monitor adoption. The farmers who have not adopted monitors, can do so in conjunction with a combine purchase or can purchase the monitor to install in an existing combine. In either case, the choice is driven by perceived costs and benefits. However, consistent with considerable decision theory research, perceived costs of a stand-alone purchase are higher than those of the monitor purchase within a new combine (Kahneman and Tversky, 1979).

Those producers who do not purchase a monitor in a given time period return to the pool of potential adopters. Those who do purchase, whether as a stand-alone or within a combine, add to the pool of potential mapping technology adopters. In addition, farm profitability

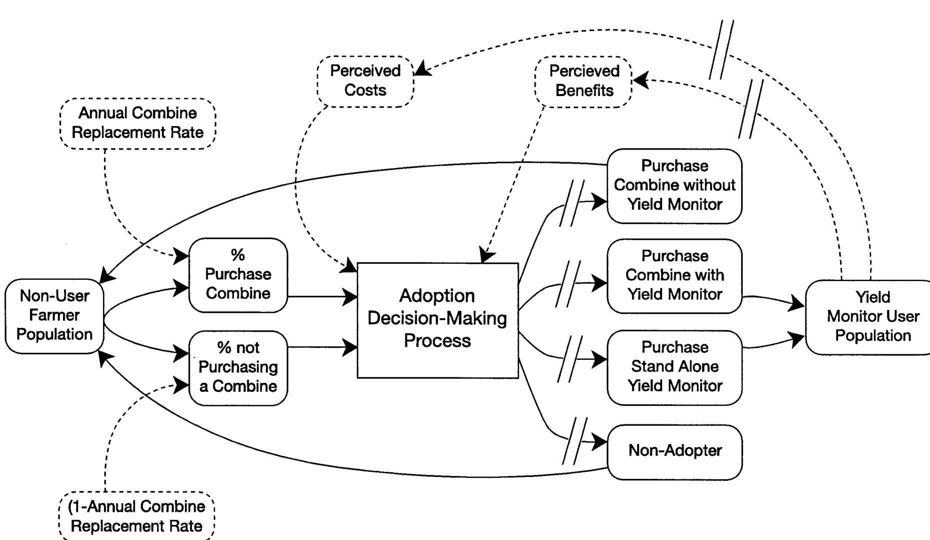

Fig. 4. Farmer acceptance of yield monitoring technology.

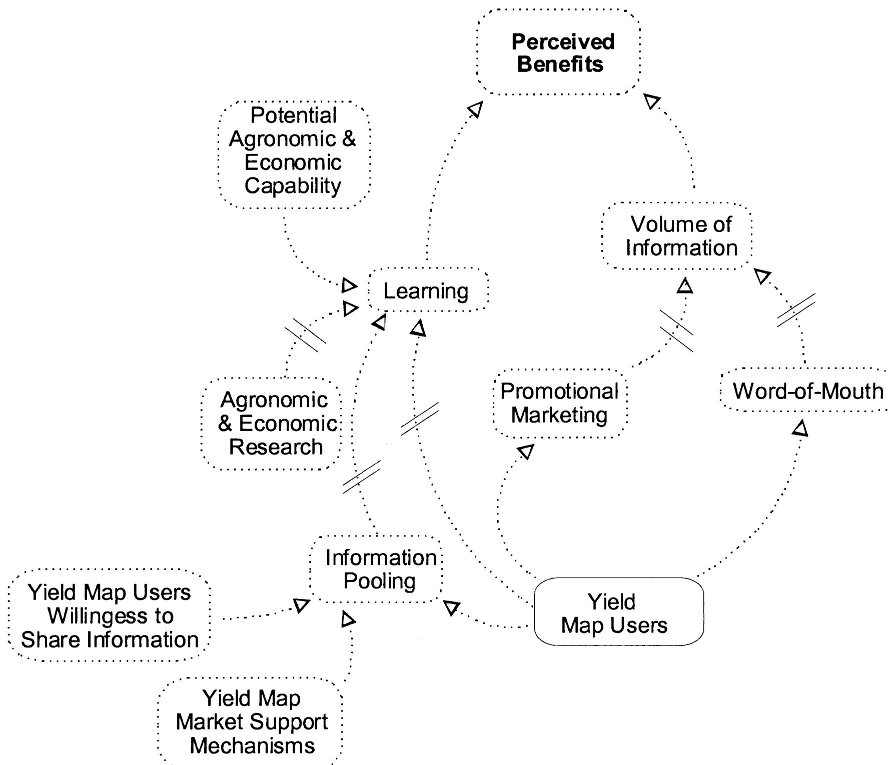

Fig. 5. Information dynamics.

influences the number of potential combine purchasers. Profit also has an indirect effect on YMM technologies adoption through the perceived benefits. Although not shown, similar processes are defined in the model to track the pool of actual and potential adopters of the mapping technology.[2]

Next we examine how the flow of information affects the system. For explanatory purposes, let's focus on how information affects the perceived benefits of yield mapping, which in turn influences technology adoption.[3] As shown in Fig. 5, the perceived benefits variable is driven by two variables, volume of information and learning. The volume of information variable is a function of promotional marketing and word-of-mouth influences, both of which are affected by the installed base of farmers who use yield mapping.[4] The learning variable is formed in a somewhat more complex fashion being affected by technology capabilities; agronomic and economic research results from, for example, universities and extension; and information pooling by the users of yield maps.

To illustrate the capabilities of the modeling tool, data and relationships for a specific setting of a six county area in Illinois are employed (Champaign, Douglas, Edgar, Ford, Iroquois, and Vermilion counties). Census data are used to segregate farm operators into three age categories; those up to 54 years of age, those 55 to 64, and those 65 years old and older. Age demographic categories are employed so that the model can explore the effect of

Table 2
Initial population and combine purchase rates

Age cohort	Combine purchase rate	Yield monitor users	Yield map users
Less than 55	25%	40%	20%
55–64	15%	20%	5%
Over 64	5%	5%	2%

differing time horizons (on the combine purchase decision) and on attitudes towards new technology adoption.

Both model conceptualization and populating the model with data required integration of disciplines and data sources. The conceptual framework was guided by economics, decision sciences, and system dynamics principles, as well as information regarding the technologies of precision agriculture. Wherever possible and appropriate, data from secondary sources, especially the Illinois Farm Business Farm Management system, were employed. In numerous instances, personal interviews with industry experts were employed to provide values for parameters for which secondary data does not exist or would not be appropriate.

3. Scenarios and results

Recall the purpose of this study is to provide insight into the usefulness of management tools in decision making for agribusiness management. Scenarios are formed by altering the levels of influential factors within the model. This allows us to observe the model's behavioral response. In this article, we evaluate potential adoption rates and diffusion patterns under different farm profit scenarios. The model's base scenario will be discussed as a reference point for gauging the behavioral responses of the subsequent simulations. Next, four profit scenarios are analyzed to provide insight into the use of the model to evaluate potential adoption rates and diffusion patterns of YMM technologies. As is demonstrated in this example, the model allows for comparative analyses of possible effects of different profit assumptions on adoption and diffusion rates.

The initial conditions of several influential factors within the model are made explicit before the base scenario results are discussed. First, the assumed initial conditions of critical coefficients and decision functions will be presented. Second, the base simulation results of YMM technologies adoption will be demonstrated. Then, the temporal aggregation of those adoption processes will be illustrated representing the diffusion patterns of YMM technologies for the base case.

The model is first run with profits fixed over a 20-year period.[5] This is the base case and it serves as a reference point for the different scenarios. The initial conditions of critical coefficients and decision functions are quantified by information gathered from published sources, industry representatives and industry experts. Table 2 shows the base case combine purchase rate and the initial user population percentages for the three age cohorts in the model. These numbers are consistent with estimates of the number of yield monitoring and mapping users given by field experts. Additionally, published surveys of farmers in this area or nearby areas reflect similar user rates (Khanna et al., 1999; Akridge, 1996).

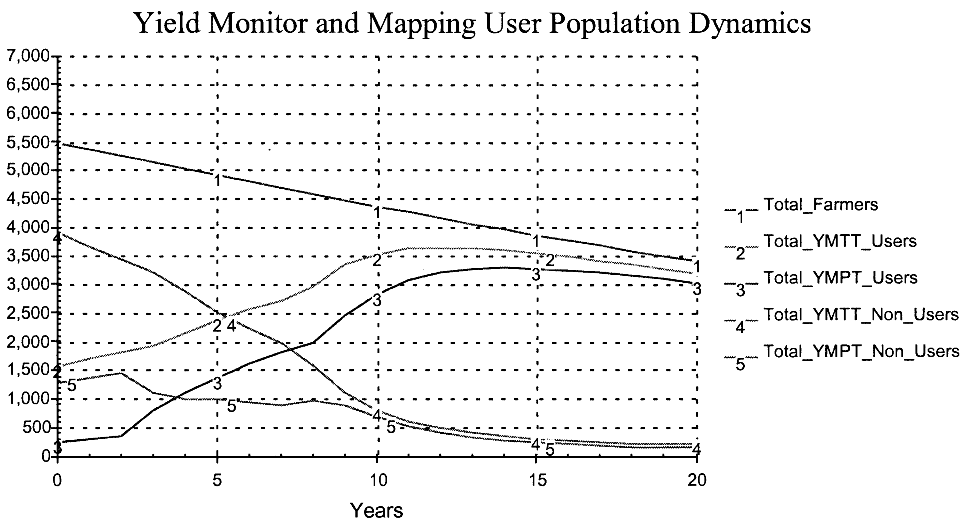

Fig. 6. Technology use for base case simulation.

From Fig. 6 we see that the number of farmers using yield monitor technology (Total_YMTT_Users) starts at approximately 1600 in the first year, then increases to roughly 3700 at year 12, before it decreases back to about 3200 in year 20. Even though the actual number of monitor technology users is decreasing, the percentage of users in the population remains relatively the same (~90%) over the last several years of the simulation. Likewise, the number of yield map users (Total_YMPT_Users) in the population starts at roughly 250, increases to a high of about 3300 in year 14, and then tapers off to about 3050 as the total population decreases. Again, the percentage of users in the population remains relatively constant (80%) towards the end of the simulation period.

As seen in Fig. 7, individual adoption decisions can be aggregated to represent technology diffusion through the population. In this study the diffusion rates for yield monitor technology (YMTT_User_Ratio) that we monitor through the various scenarios are 50%, 80%, and 90%. In the base case simulation, these are reached at 5.50, 9.75 and 13.50 years, respectively. Similarly, the yield mapping technology diffusion rates (YMPT_User_Ratio) of interest for this study are 30%, 50%, and 80%. In the base case simulation, these are reached at year 5.50, 8.50 and 13.00, respectively.

After the base case is established, multiple farm profitability scenarios are examined. In the following scenarios the only change to the model is in the assumption of farm profit levels.[6] The scenarios examined include the following:

A. Farm profits are low for six years then increase to a medium level for four years then increase to a high level;
B. Farm profits are low for six years then increase rapidly to high levels;
C. Farm profits are low for three years then increase to medium levels for four years then increase to high levels;
D. Farm profits are low for three years then increase rapidly to high levels.

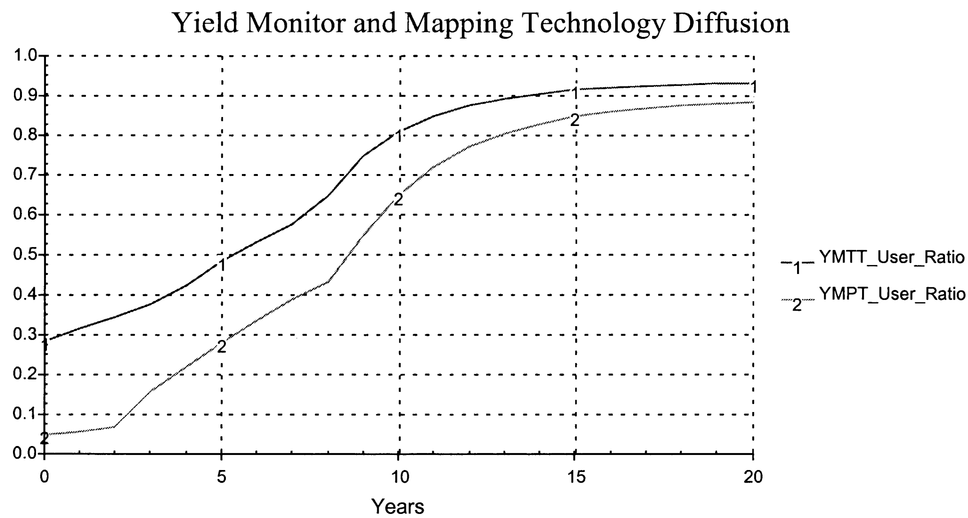

Fig. 7. Technology diffusion for base case simulation.

As illustrated in Fig. 8, all profit scenarios trend back to the medium level after four years of high profits occur. The diffusion graphs for each of the scenarios are roughly the same shape as in Fig. 8. However, the year at which the various levels of diffusion are attained differ between the scenarios, as is indicated in Table 3.

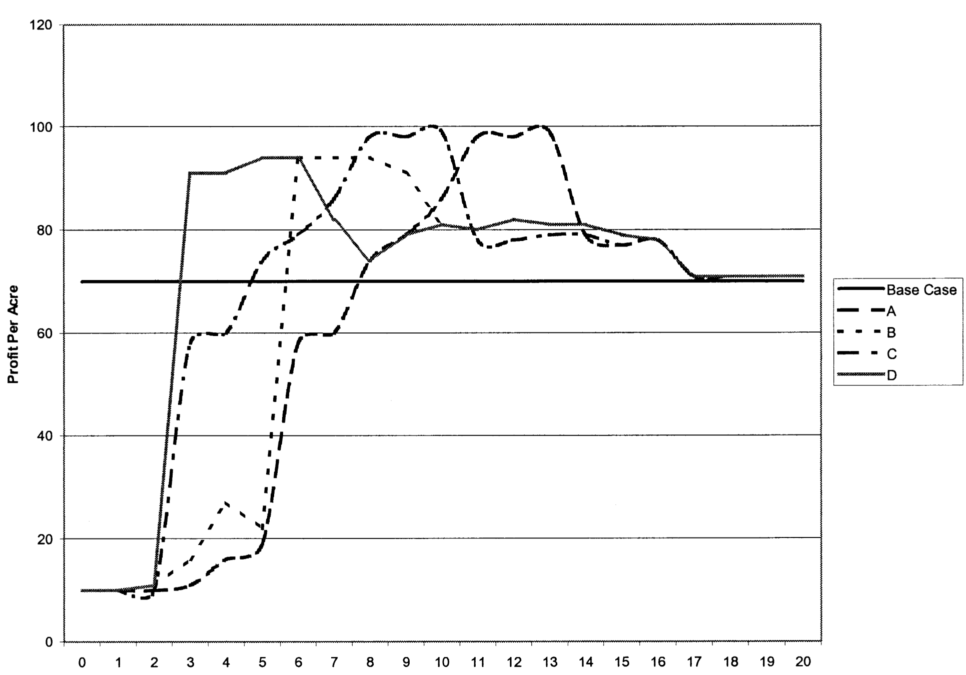

Fig. 8. Profit scenarios.

Table 3
Years diffusion levels attained

Scenario	Description low years	Speed of increase	Yield monitor			Yield mapping		
			Year diffusion level reached					
			50%	80%	90%	30%	50%	80%
Base	Profit fixed		5.50	9.75	13.5	5.50	8.50	13.00
A	6 yr	Gradual	7.00	12.00	15.5	8.25	10.50	15.00
B	6 yr	Rapid	6.25	9.50	13.5	7.50	8.25	12.75
C	3 yr	Gradual	6.00	9.75	13.5	6.00	8.50	12.75
D	3 yr	Rapid	4.50	7.75	11.5	4.50	6.50	11.00

Overall, diffusion rates are positively related to farm profitability. In addition, diffusion rates are negatively related to the length of time required to move from low to high profitability. For both the yield monitor and yield mapping technologies Scenario A, which has the longest time lag in attaining high profitability, results in the longest time period required to reach each diffusion level. As shown in Table 3, for Scenario A the yield monitor diffusion level reaches 50%, 80%, and 90% in years 7.0, 12.0 and 15.5 respectively. Yield mapping technology diffusion rates under Scenario A are 30%, 50%, and 80% in years 8.25, 10.5, and 15.0, respectively.

Scenario D, the shortest time lag required to reach high profitability, results in the shortest time period needed to attain each level of diffusion. Comparing Scenarios A with B, and C with D, demonstrates how the speed of recovery from low profits impacts the diffusion rates. Finally, each scenario results in diffusion rates that differ from the base case of constant profits.

These scenarios represent reasonable (but different) projections for future trends of overall farm profitability that may be held by different members of a management team. For example, currently Corn-belt farm incomes are depressed.[7] One manager may believe that farm profits will change slowly and the current depressed farm incomes will continue for a long period of time and that recovery will be gradual (similar to Scenario A). However, another member of the management team may believe that low farm profits will change rapidly because of droughts or other shocks to the system and therefore the current low profits will remain only for a short time and that the return to high profits will be rapid (Scenario D). This is a simple illustration of how managers may have different mental models of future farm profits. Each manager will, to some degree, base their decisions and plans on these models.

As demonstrated in this example, the system dynamics model may be used to simulate possible diffusion rates under each manager's beliefs. Managers are able to explore the possible results of different scenarios and learn about implications of their own beliefs and decisions as well as those of other managers. Managers have the opportunity to learn and modify their mental models in response to the simulation. In this way, models such as the one used in this study can be useful tools to develop, refine, communicate or build consensus on decisions or plans.

Other strategic decisions and planning situations that may be explored with this model include the timing of market entry, or the timing of a sales and promotional effort. Suppose a firm is planning to enter into a particular product line that is related to precision agriculture.

Further suppose, that the success of their entry into the market depends upon the number of potential users. Scenarios may be simulated to help managers understand the factors that influence the number of potential users under various conditions. This understanding can lead to more informed decisions regarding the timing of market entry. As another example, consider a firm anticipating a major sales and promotion activity. The best time to hire new sales staff and run advertisements may depend upon diffusion rates. The timing and amount of various sales, as well as the promotion levels can be explored within the system dynamics model used in this study. Again, the model simulations may illuminate complex interactions and resulting diffusion rates, which in turn can help managers better plan activities. These examples along with the scenarios presented in this study demonstrate how system dynamics models can be used to assist agribusiness managers in strategic decision making.

4. Conclusion

Managers in agricultural businesses are faced with a dynamic, complex, and uncertain environment in which to make decisions. The factors affecting decision outcomes change over time, results are not known at the time decisions are made, and often long lags exist between the time the decision is made and when results are known. One method managers can use to improve decision making in such an environment is the use of sophisticated management tools. These tools allow managers to explore the effects of different decisions, view outcomes, and learn about factors that influence results. That is, management tools can be like flight simulators in that they allow managers to learn about the potential implications of current decisions. Learning about the consequences of different decision options should improve managers' performance.

System dynamics modeling is one type of management tool. The advantage of system dynamics models is that they can incorporate many of the complexities of the actual environment that other models cannot. These models also incorporate time lags, feedback effects, and causal factors. They present information in an easy to understand, visual context. Thus, system dynamics models offer the potential to enable agribusiness managers to practice decision making.

The model developed and employed in this study is a system dynamics model of farmer adoption and the resulting diffusion of yield monitor and mapping technologies. The model incorporates complex, dynamic causal factors, time delayed realization of results, and feedback effects. As one example of how the model can be used to provide insight to agribusiness managers, simulations are run over varying levels of farm profits. The purpose of this work is to demonstrate the utility of sophisticated management tools, such as systems dynamics, in aiding agribusiness managers' decision making.

Notes

1. In Fig. 3, solid lines indicate exogenous factors, dashed lines indicate endogenous factors, and intersected lines represent time lags.
2. Some farmers install yield monitors without global positioning capability or they do not choose to subscribe to the positioning signal. In fact, a 1998 survey of Illinois

farmers showed that 19.5% owned yield monitors and roughly one-half of those had full global positioning capability and used the mapping technology (Norvell and Lattz, 1999).

3. Numerous other information linkages are defined in the model and are detailed in Nelson (1998) but are not shown here because their inclusion would make the paper too lengthy.
4. These are the feedback loops identified by Homer (1987) in the technology diffusion process.
5. A farm profit level of $70 per acre is extrapolated from FBFM (1999) using the actual average profits for the period 1992 through 1997.
6. Farm profits are designated as: Low profit is less than $50 per acre; Medium profit is between $50 and $85 per acre; and High profit is greater than $85 per acre.
7. Farm profits for 1998 were $14 per acre (FBFM, 1999).

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