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STORED-PRODUCT

Economics of Integrated Insect Management in Stored Corn

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ABSTRACT Insects can cause substantial damage to stored grain. In addition, consumers and therefore food processors are increasingly interested in chemical-free products. Integrated pest management (IPM) may increase farmers' profits while reducing their use of pesticides. This study uses a stochastic dynamic programming framework to model the economics of optimal insect control in corn, *Zea mays* L., stored on-farm with multiple controls conditional on the biophysical conditions of the grain in the bin. We find that for farmers who have a contract with a food processor, where there are quality premiums, the optimal management strategy depends on monitoring the biophysical conditions of the grain and the time period under consideration. For farmers who deliver to the commodity market, their current practices are optimal.

KEY WORDS insect management, stored corn, IPM, stochastic dynamic programming

Insect pests cause substantial damage to stored products throughout the world. In the United States, annual postharvest losses due to insects in corn, *Zea mays* L., and wheat, *Triticum aestivum* L., are estimated at ≈US$1.25–2.5 billion, accounting for 5–10% of the total value of corn and wheat produced (USDA 2005). In Indiana, the economic losses caused by insect damage in stored products were estimated at US$12 million in 1990 (Mason et al. 1994).

There is growing concern about insect-related food quality problems among farmers, elevators, food processors, and consumers. In particular, consumers' awareness of the potential hazards from chemical pesticides is increasing. The U.S. Government enacted the Food Quality Protection Act (FQPA) to reduce or eliminate risk from pesticide residues. Local grain elevators and food processors also have minimum requirements for the corn delivered to them in terms of the number of insect damaged kernels (IDK) and number of live insects (LI) per unit of weight. They apply penalties to any shipment of grain that fails to meet these quality standards and even reject the shipment if IDK and LI exceed a specified maximum allowable level. Generally, food processors have higher quality standards than elevators. Hence, grain rejected by food processors may still be sold to local elevators, but at a lower price provided that the level of insect damage is below the maximum level allowed by the elevators.

The presence of insects in stored grain affects farmers in two ways. First, the presence of live insects and the number of IDK beyond specified levels lead to price penalties or rejection of the grain by buyers. Second, the larvae of certain insect types burrow into the grain kernel where they mature to adulthood by which time they have consumed the major part of the grain kernel resulting in dry matter loss.

Several insect control methods have been developed that include cultural, biological, physical, and chemical techniques (Hagstrum and Subramanyam 2006). Due to growing consumer consciousness about food quality, chemical-free methods and integrated pest management (IPM) strategies for insect control are preferred (Anderson et al. 1996, Govindasamy and Italia 1999, Zehnder et al. 2003). One strategy is to ensure that the initial insect population is low and that the biophysical conditions in the storage bin are not conducive to insects by preventative sanitation (storing grain in clean, insect-free structures with clean surroundings) and drying grain before loading into storage to maintain a low moisture content (12–13%), which will reduce insect growth. In addition, several IPM-based methods are available to help manage insect pests in bulk grains (Hagstrum et al. 1999). Once grain is stored, the biophysical conditions in the bin can be monitored for insect control by 1) removing grain samples and counting the number of live and dead insects, 2) using insect traps to estimate the insect population, 3) using automatic insect traps to detect insect activity at different spots in the grain mass, and 4) using temperature sensors and data log-

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gers to collect hourly temperature measurements at different spots in the grain mass. Based on the monitoring results, one or a combination of different insect management strategies can be implemented as appropriate.

Using low-volume ambient air circulation (aeration) allows control of the biophysical conditions in the storage bin, thereby controlling insect population growth (Noyes et al. 1995; Maier et al. 1997, 2002; Reed and Arthur 1998). Particularly, farmers can use aeration to cool and maintain grain below 16°C, which is the lower temperature limit for survival, development, and reproduction for stored-product insects. Other techniques such as grain turning and properly-timed fumigation with phosphine can also prevent significant grain damage (CIMSPIP 2001). Although these techniques have been found to be very effective in controlling certain pests, they are expensive and so may not always be cost-effective (Flinn et al. 2003).

Literature on the economics of stored product pest management in large storage bins is scarce, and most of it is devoted to the study of the profitability of an individual intervention or the comparison of a few possible combinations of strategies with fixed input intensities and times of application. Rulon et al. (1999) used cost–benefit analysis to examine the profitability of grain chilling as a method for controlling insects. Adam et al. (2004) also used cost-benefit analysis to compare the profitability of strategies such as fumigation and aeration. Fox and Hennessy (1999) developed a method to determine the number of equally spaced interventions to minimize economic loss during storage and applied it to fumigation to control the lesser grain borer, *Rhyzopertha dominica* (F.), in wheat. Yigezu et al. (2008) used a stochastic dynamic programming approach to model the economics of optimal mold management in stored corn. This study is the first to model the economics of optimal insect control in stored grains with multiple controls in a stochastic dynamic programming framework. The advantage of this approach is flexibility in the combinations of interventions that can be considered and their spacing throughout the storage period.

The objective of this study was to determine the optimal combination, timing, and intensity of insect management and marketing strategies, conditional on the biophysical conditions of the grain in the on-farm bin. In particular, we evaluated the potential benefits of a labor-intensive, monitoring-based insect management strategy that involves decisions on aeration, fumigation and optimal timing of grain sales. For farmers who have a contractual commitment, the optimal time for selling their grain is determined by trade-offs between the premium offered by the processor for delivery of high-quality grain specified by the contract terms and the risk of failing to meet the quality standard and dry matter losses during storage. Farmers under contract may be forced to sell in the local cash market if their grain is rejected by the processor for failing to meet the quality standards specified in the contract. For farmers who do not have a contractual commitment, the optimal time for selling their grain is determined by the trade-offs between higher prices in the future and the higher risk of grain quality and dry matter losses due to insects during storage. This analysis determines whether monitoring-based insect management is more profitable than farmers' current practices; the economic cost of replacing fumigants with chemical-free IPM-based strategies in response to the FQPA; the optimal timing of grain sales conditional on its quality and the biophysical conditions inside the bin; and the minimum storage fee processors should pay to ensure an adequate supply of high-quality grain late in the storage season. Even though crops could be infested with insects before harvest, this study focuses on the postharvest grain damage due to insects in on-farm bins.

Materials and Methods

Farmers' Current Pest Management Practices. In total, six farmers from Indiana (three from Evansville, two from Rochester, and one from Loogootee) and two farmers from Illinois were interviewed regarding their stored corn pest management practices. These farmers all deliver to food processors that collaborated with Purdue on this research. The interviews with the farmers and food processors revealed that a shipment of food-grade corn can be completely rejected due to the presence of 2 LI per kg, an IDK in excess of 20%, or both. Moreover, grain is sold at a discounted price if the level of damaged kernels (including IDK) is between 6 and 20%. As a result, all of the farmers use a number of strategies to control pests in stored corn. Before harvest, which usually occurs between September and October, all of the farmers engage in sanitation activities, although the intensity of sanitation differs among farmers. They clean combines, trucks, augers, and dryers; sweep; vacuum; and blow (using leaf blowers or air compressors); and spray the interior of bins by using insecticides such as Malathion and Tempo before filling. They also clean the ground surrounding the bin and spray Roundup to kill weeds.

Recognizing the importance of maintaining low moisture content (MC) grain, the farmers attempt to dry their corn in the field. However, drying corn in the field is often not feasible due to weather. As a result, they may artificially dry it using either an in-bin drier (with a high air flow rate aeration fan) or a continuous-flow or batch drier. Once dried to a level of 16–16.5% MC, the grain is moved to storage bins where the hot grain is left to steep for 8–24 h and then is aerated using low flow aeration fans to cool it and also to dry it further to 14–14.5% MC.

The farmers then core the grain by hauling a truck load or two emptied from the bottom center of the bin to remove the fines and foreign material which usually are concentrated at the center of the in-bin grain mass. After coring, aeration usually continues in the fall until the in-bin temperature is below 4–5°C to inhibit pest development. The farmers usually do not aerate the grain in the winter and even during spring and the summer, if not sold until then. They routinely monitor the grain in the bin, which usually involves visual inspection and smell testing by opening the hatch on the bins. If the smell and visual tests indicate pest activity, the farmers walk on the surface of the grain to check if anything is wrong. If insects are detected, they have the bin fumigated by a professional. Typically, Indiana farmers who are not under contract with a food processor sell their grain when temperatures start to rise around the first half of March. Using this strategy, farmers are selling corn which is at low risk of insect damage, but they might be forgoing the possibility of higher prices during the summer that often more than offset the cost of storage.

Insects in Stored Corn. In Indiana, the maize weevil, *Sitophilus zeamais* Motschulsky, is one of the most damaging pests to stored corn (Maier et al. 2002). The maize weevil is a primary storage pest. It is an internal feeder whose adults attack whole kernels, with the larvae feeding and developing entirely within kernels (Storey 1987). The adults are long lived, with a life span of several months to 1 yr. Up to 150 eggs are laid by each female throughout her lifetime. Eggs are inserted individually into small cavities chewed in the kernel by the female. The cavity is then covered with a waxy secretion, sealing the egg into the kernel. Eggs hatch in ≈6 d at 25°C, and the larva develops within the kernel, excavating a cavity as it grows. More than one egg is often laid in a single kernel, but due to the cannibalistic behavior of the *Sitophilus* species in the larval state, only rarely does more than one adult emerge (Arbogast 1991, Danho et al. 2002). After four instars, pupation takes place within the kernel. Upon hatching, the adult chews its way out of the kernel, leaving a circular exit hole.

Complete development is possible at temperatures between 15 and 35°C. According to Howe (1965), the lower developmental threshold for most stored-product pests is ≈18°C, but the threshold for maize weevil development is between 10 and 15°C (Throne 1994). The optimal temperatures for growth and development are between 25 and 33°C, whereas 13 to 25°C and 33 to 35°C are considered suboptimal. At temperatures below 13°C and above 35°C, most insects die prematurely (Fields 1992).

Arthur et al. (1998) found that under laboratory conditions of 27°C and 60% RH, the life cycle of a maize weevil is completed in ≈6 wk. From among the immature stages, the four larval instars together take the longest duration, 18.1 d (Sharifi and Mills 1971). At 27°C and 70% RH, which are optimal for insect development, complete development takes 35 d. Mortality of juveniles increases in grain with MC below 13%, and eggs are usually not laid at all on grain below 10% MC. Development takes place most rapidly on grain with MC of 14–16% (Rees 1996).

Insect Growth Models. Throne (1994) conducted a laboratory study on the life history of immature maize weevils at temperature ranges of 10–40°C and relative humidity ranges of 43–76%, which would normally occur in storage. Throne (1994) estimated regression equations for the duration of development, fecundity, and survival rates for maize weevil. Using Throne's equations, researchers have built computer simulation models for maize weevil (Maier et al. 1996; Arthur et al. 1998, 2001; Meikle et al. 1999; Montross et al. 2002). Based on a time-varying distributed delay model (Mantesh 1976) for tracking insects through all developmental stages and for simulating variation in developmental time, Montross et al. (2002) developed a complex and highly data-intensive model that they called postharvest aeration and storage simulation tool–finite element model (PHAST-FEM). We use this model to generate data on insect population growth as a function of environmental conditions.

Bioeconomic Model. We use stochastic dynamic programming (SDP) to build a decision framework for the optimal management of insects in stored corn and use backward recursion to solve the model (Bellman 1957, Bellman and Dreyfus 1962). The objective is to maximize expected net profits where revenues depend on the timing of sales and grain quality (i.e., number of live insects and level of insect damage) and the costs of insect control actions, including monitoring, that accumulate over time. The control problem is modeled in discrete time with 19 periods of ≈2 wk each. For each period and each possible state of the system, the current actions that maximize the current period contribution to profit plus the expectation of future profits given that the optimal actions will be taken in the future is selected. By starting at the date corresponding to the end of the storage period, and recursively applying this calculation for successive earlier time periods, we arrive at the beginning of the storage interval, having calculated the optimal action in every period for every state of the system.

The state of the system is jointly defined by four variables: 1) the in-bin temperature (3–38°C in 5°C steps); 2) the cumulative number of LI with 60 levels between 0 and 21%, increasing in a geometric progression defined by $LI(i + 1) = 1.15 \times LI(i)$ to maximize the number of levels of LI and to have maximum resolution at low levels of insects where control is most effective, i.e., the most economically relevant range; 3) the cumulative number of IDK, which has the same levels and progressions as the number of LI; and 4) whether the grain has been sold. These states are denoted by the single index set *i*. Each state represents an outcome and is weighted by the probability of occurrence. The discrete states of nature and their probabilities can be viewed as an approximation to the continuous distributions that capture the nonstochastic and stochastic relationships among the random variables (Featherstone et al. 1990).

The set of controls (choice variables) in any given period *t* are denoted by the following:

A_{ti}: aeration strategy variable which takes values 1–3 (1, do not aerate; 2, aerate unconditionally; and 3, aerate conditionally, i.e., only when the in-bin temperature is at least 3°C greater than the ambient temperature) in period *t* and state *i*.

FUM_{ti}: fumigation variable (1, do not fumigate now; 2, fumigate now).

S_{ti}: selling variable (1, do not sell now; 2, sell to the elevator now; and 3, sell to the food processor now) in period t and state i.

Insect management decisions in the current period (t) affect not only the value of the stored grain in the current period but also its future values if it is kept in storage. Let π_{ti} (S_{ti}, A_{ti}, FUM_{ti}) denote the contribution of current period (t) actions to the expected net revenue given that decision (S_{ti}, A_{ti}, FUM_{ti}) is taken while the system is in state i. Thus,

$$\pi_{ti}\,(S_{ti}, A_{ti}, FUM_{ti}) = \begin{cases} -c(A_{ti}, FUM_{ti}) & if\ S_{ti} = 1, \forall\ A_{ti}\ and\ FUM_{ti} \\ B_{ti} \times Q_{ti} - c(A_{ti}, FUM_{ti}) & if\ S_{ti} = 2, \forall\ A_{ti}\ and\ FUM_{ti} \\ X_{ti} \times Q_{ti} - c(A_{ti}, FUM_{ti}) & if\ S_{ti} = 3, \forall\ A_{ti}\ and\ FUM_{ti} \\ 0 & Otherwise \end{cases} \quad [1]$$

where B_{ti} is price per unit of corn paid by the local elevator in period t and state i; Q_{ti} is quantity sold in period t and state i; $c()$ si cost function, which depends on the fixed costs, the aeration and fumigation decisions and monitoring cost; and X_{ti} is price paid by the food processor per bushel of corn in state i in a given time period t, which is given by

$$\mathrm{X_{ti} = Futures_t + Premium + Storage_t - Penalty_{ti}} \quad [2]$$

where $\mathrm{Futures_t}$ is Chicago Board of Trade futures price, which farmers can use to establish prices for delivery in December, March, May, and July at anytime during the marketing year; Premium is premium paid by the food processor for meeting minimum quality standards; $\mathrm{Storage_t}$ is storage payment per bushel paid by the food processor to the farmer in period t (this is a monthly payment starting in December); and $\mathrm{Penalty_{ti}}$ is penalty for failing to meet the minimum quality standards when the grain is in state i (moisture content, test weight, number of LI and IDK) in period t.

Note that the futures price is treated as independent of the state of the system. The price paid by the food processor does not include a basis. Although most grain price contracts include a basis this one does not for two reasons. First, the contracts we used to model the food processors price did not include a basis. Second, the basis in this region of Indiana is frequently "option" or zero.

Suppose that i and j are indices reflecting the possible states of the system in the current and next periods, respectively. Suppose also that $Ptij$ (S_{ti}, A_{ti}, FUM_{ti}) is the transition probability from state i in the current period t to state j in the next period conditional on the decision variables in period t and state i. If V_{ti} denotes the maximum expected profit function in period t given state i, given that the optimal policy is used for the rest of the time horizon, then the mathematical procedure for calculating the optimal policy for managing insect pests in the corn storage bin is based on the following recurrence relationship (Bellman's equation):

$$V_{ti} = \underset{S_{ti}, A_{ti}, FUM_{ti}}{Max} \left[\pi_{ti}\,(S_{ti}, A_{ti}, FUM_{ti}) + \alpha \sum_{j} (P_{tij}(S_{ti}, A_{ti}, FUM_{ti}) \times V_{t+1,j}) \right], \forall\ t,i \quad [3]$$

where Max is the maximization operator where maximization takes place over the control (choice) variables (S_{ti}, A_{ti}, FUM_{ti}); and α is the per period discount factor calculated as $\alpha = 1/(1 + (\mathrm{IR}/(24 \times 100)))$, where IR is the annual borrowing interest rate (8%). Even though the length of periods in this analysis ranges between 13 and 16 d, α is calculated with the assumption that each period contains 15 d.

The effects of the state variables i on the recurrence relationship are that higher initial in-bin temperature and higher number of LI and IDK lead to lower expected profit, whereas lower initial in-bin temperature and lower number of LI and IDK lead to higher expected profit. The recursion is initiated by setting the value function in the terminal period T to

$$V_{Ti} = \begin{cases} \underset{S_{it} = 2\ or\ 3,\ FUM_{ti} = 1\ or\ 2}{Max} (\pi_{Ti}(S_{ti}, FUM_{ti}) - FC/\alpha^T) & \text{if sale has not already occured} \\ -FC/\alpha^T & \text{otherwise} \end{cases} \quad [4]$$

where FC is fixed cost of drying and shrinkage and cost of temperature and insect monitoring equipment incurred at the beginning of storage, and $FC/\alpha T$ is the future value of these fixed costs in the terminal period T, which will be discounted to F in the first period via the recursion. The drying cost and shrinkage are treated as fixed costs because we assume all of the corn is dried to 14.5% MC before it is stored in the bin.

By recording the optimal activities in each state for each period, we derive the optimal management policy for this problem. This backward recursion is implemented using the General Algebraic Modeling Systems software (Brooke et al. 2005).

Data. The storage bin modeled in this chapter is round and made of corrugated sheet metal with a diameter of 10.97 m (36 feet), a height of 9.75 m (32 feet), and a capacity of 36,000 bushels of corn (Table 1). The drying cost is only the cost of electricity for drying the wet corn using a continuous or batch drier and does not include shrink cost. Shrinkage is calculated separately using the following formula % shrinkage due to drying = total number of % points dried (via drier and natural convection) $\times$ the water shrink factor plus shrinkage due to handling. The electricity cost in the variable cost category is the rate used to calculate aeration costs. Information about the premium and monthly storage payment to the farmers was obtained from a food-grade corn processor. The fumigation cost estimate per bushel was obtained from a private company that works in the study area.

Ten year average futures and cash prices for Evansville, IN, are used for determining the prices paid by

Table 1. Parameters used in the Stochastic Dynamic Program

Parameter	Units	Parameter value
Fixed costs		
3 HOBO temp data loggers per bin	$ per bin	195
10 temp sensors per bin	$ per bin	500
5 6-in. (15.2-cm) pipes	$ per bin	50
5 pitfall traps	$ per bin	50
Drying cost per % point per bushel	$	0.02
Variable costs		
2 flight pheromone traps (only after April 1)	$ per bin per period	15
Electricity cost (SUFG, 2005)	$/Wh	0.07
Fumigation cost	$/bushel	0.18
Time required for insect monitoring	h/bushel per round	0.000111
Other parameters		
Moisture content at harvest	%	22
Wage rate	$/h	10
Avg bin size	Bushels	36000
Food processor premium	$/bushel	0.55
Storage fee per bushel per month	$	0.03
Interest rate	%/yr	8
Penalty for damaged kernels in excess of the 3 and 6% thresholds for food processors and elevators, respectively	$/% point/ bushel	0.01

local elevators and food processors. The 1-yr period chosen was 1994/1995–2005/20066, with 1995/1996 and 2003/2004 dropped because they were drought years that have a very different price pattern than a typical year. The contracts with the food processor allow farmers to establish their selling futures prices using several different futures contracts such as the March, May, or July contracts. For simplicity, we assume that the only futures price available is the nearby contract, and we have smoothed these futures prices to eliminate price discontinuities that would otherwise occur when there is a change in the nearby futures contract, i.e., when the nearby price switches from the March contract to the May contract on the first day of the delivery period. The cash price offered by the local elevator was the simple average of cash prices over the 1-yr period.

Farmers typically monitor their bins every 2 wk and make insect management decisions based on the conditions in the bin. Hence, in this analysis, we divided the storage period (16 October–31 July) into 19 periods (13 periods of 15 d each, five periods of 16 d each, and one period of 14 d).

For the SDP model, state transition probabilities are needed for all 19 periods. Estimation of the joint transition relationships was required because naturally occurring or simulated data generally do not cover the full range of states of nature. As a result, we derived the state transition probabilities from estimated relationships and the distribution of the error terms.

The PHAST-FEM model developed by Montross et al. (2002) was used to generate the data that is needed to estimate the state relationships. The PHAST-FEM model used weather data which are taken from 1961 to 2005 observations of ambient temperature, ambient relative humidity, wind speed, and solar radiation for the Evansville area from the National Solar Radiation Data Base.

The insect growth component of the PHAST-FEM model is based on the work of Throne (1994) and the distributed delay model developed by Mantesh (1976). Insects complete their development in 6 wk under optimal growing conditions, and in several months under suboptimal growing conditions. As a result, we conducted 1,056 runs of the PHAST-FEM model for the whole storage period (16 October–31 July) by using 45 yr of weather data for Evansville, IN. These simulations were conducted using a Condor computing system (Litzkow et al. 1988).

Scatter plots of the insect growth rates (G_t) derived from the simulated data against initial in-bin temperatures (*Temp*) suggest a linear relationship (Fig. 1). The data set generated by the different simulations of the PHAST-FEM model is a balanced panel with 19 periods. The cross sections are all the combinations of the 45 yr and eight starting temperatures.

The random effects model fits this data very well because insect growth rates are subject to random changes in the ambient temperature. Moreover, the number of cross sections and hence the overall sample size is fairly large, which makes the random effects model more efficient than the fixed effects model. Hence, we implement the linear dynamic panel-data model developed by Arellano and Bond (1991) by using the *xtdpd* estimation method in Stata. This model handles unobserved panel-level effects, endogeneity problems due to lagged dependent variables used as explanatory variables, and omitted variables in both fixed and random effects models. We also use the robust estimation procedure with the heteroscedasticity and autocorrelation-consistent variance-covariance matrix to estimate the following linear relationship:

$$G_{it} = a + b^{*}Temp_{it} + v_i + \varepsilon_{it} \qquad [5]$$

where G_{ti} is insect growth rate given by the ratio of insect population at the end of and at the beginning of period *t; $Temp_{ti}$* is initial in-bin temperature in Celsius; *a* and *b* are intercept and slope, respectively, of the regression equation to be estimated; v_i is the deviation of insect growth rate of the *i*th panel from the average of all panels; and ε_{it} is the deviation of the insect growth of the *i*th panel from the average insect growth rate of all panels in period *t.*

If we start from a certain number of insects in the bin on 16 October while allowing for immigration to occur conditional on the outside temperature, and then the adult insects in the bin would start laying eggs when temperatures are favorable in October and perhaps early November. These eggs would then grow into larvae and prepare a protective cover in which they can survive dormant throughout the winter. The adult maize weevils would normally stay dormant as in-bin temperature starts to fall between November and January, but as in-bin temperature continues to

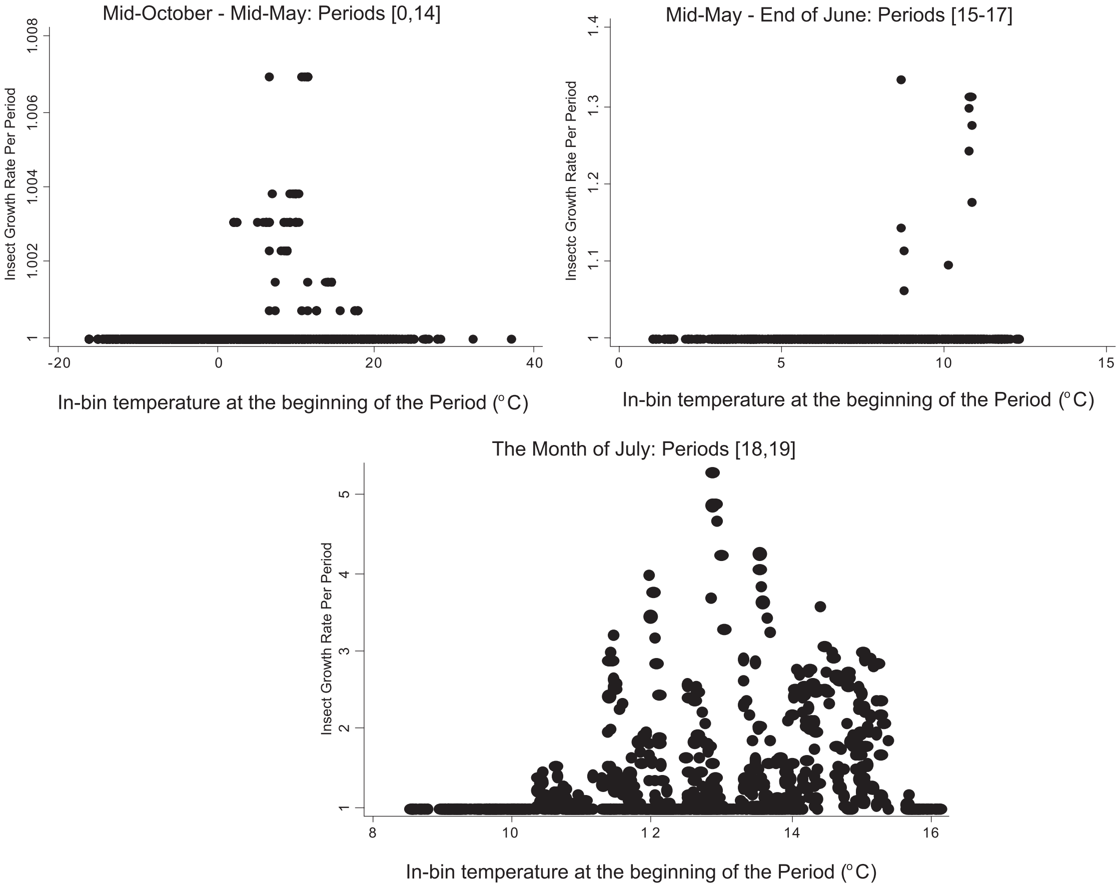

Fig. 1. Scatter plots of insect population growth rates against initial in-bin temperatures for the three storage regimes: no aeration.

fall after January, some of the adult insects start to die leading to a decline in insect population. The bin will have the smallest number of adult insects (often zero) during the cold winter season and then the larvae that were hibernating would simultaneously start to hatch when the in-bin temperature starts to rise sometime toward May, resulting in a spike in the number of adults (L. J. Mason, personal communication; http://www.ag.purdue.edu/entm/Pages/lmason.aspx). The simulated data from the PHAST-FEM is consistent with this process (see example in Fig. 2).

We assume there are no insect deaths due to changes in temperature and hence deal with only positive changes to eliminate the need for an additional state variable for the number of LI that would make this model computationally intractable due to the size of the state space. Even with this assumption, the trend in insect population growth is not uniform across all periods; hence, we use an autoregressive threshold model. Following the method for obtaining superconsistent estimators of the thresholds developed by Chan (1993), we identify two thresholds illustrated in Fig. 2 by the vertical lines at 15 May (period 14) and 30 June (period 18).

We therefore estimate equation 5 a total of 9 times—once for each of the three time periods defined by the two thresholds and for each of the three aeration strategies: no aeration, conditional aeration, and unconditional aeration (Table 2). The Gaussian quadrature method (see Preckel and DeVuyst 1992) is applied to generate a discrete approximation of the distribution of errors from the regression equations. These approximations are then used to generate the transition probabilities for the SDP model.

Results

Figure 3 shows the optimal insect management strategies conditional on the cumulative number of IDK and the in-bin temperature, during three time periods that are illustrative of how strategy changes over time. This optimal strategy is composed of decisions about whether the grain is to be kept or sold; the date of future sales if the grain is not sold in the current period; the buyer; and the optimal aeration strategy. Figure 3A illustrates the optimal strategy for the period between 16 October and 16 March. During this part of the storage interval, the optimal insect man-

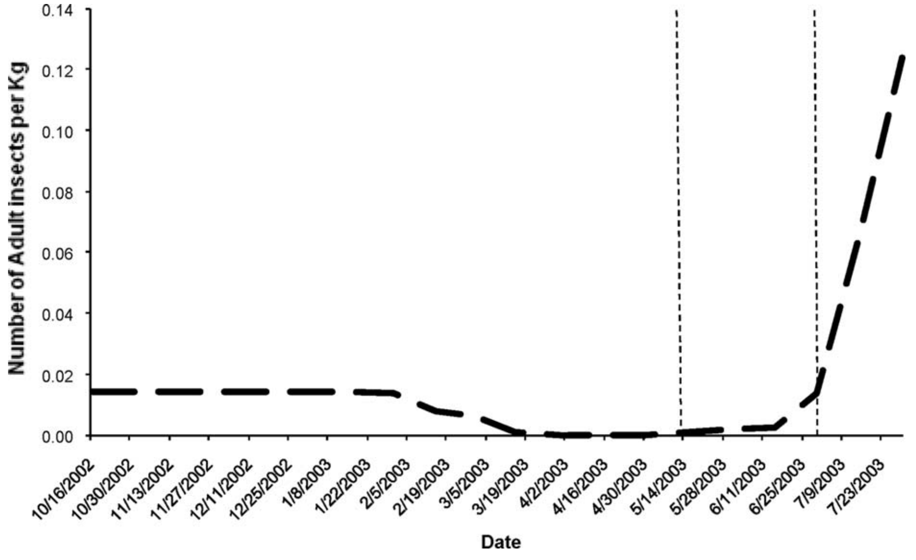

Fig. 2. Adult insect population predictions by the PHAST-FEM model starting from 13°C on 16 October 2002–2003.

agement strategy, regardless of in-bin temperature, when IDK is between 0 and 0.006% is to aerate conditionally and keep the grain until 31 July when it is sold to the food processor.

Figure 3B indicates the optimal strategy for the period 16 June–30 June. During this period when IDK is between 0 and 0.006% and in-bin temperature is below 5.5°C, the optimal insect management strategy is do not aerate the grain and sell it to the food processor either on 16 July or 31 July. Following this strategy, the farmer can expect to sell his grain to the food processor on 31 July with a small, positive probability of needing to sell on 16 July. (Although it is not indicated in the graph, the probability of selling on 16

Table 2. Regression estimates for the three storage regimes by aeration strategy

Aeration strategy	Period	Item	Regression estimate		P-Wald χ^2
			Constant	Temp (t)	
No aeration		Parameter	1.13512	1.68E-02	
	Period<=14	SE	1.01E-01	7.99E-03	
	(16 Oct.–15 May)	*P* value	0.0000	0.0360	0.000
		Parameter	−0.0076	8.07E-02	
	14<Period<18	SE	3.65E-01	1.93E-02	
	(16 May–30 June)	*P* value	0.9830	0.0000	0.000
		Parameter	3.7508	−0.0795	
	Period>=18	SE	0.6901	0.0293	
	(1–31 July)	*P* value	0.0000	0.0070	0.000
Unconditional aeration		Parameter	0.99997	8.57E-06	
	Period<=14	SE	4.29E-06	1.03E-06	
	(16. Oct.–15 May)	*P* value	0.0000	0.0000	0.000
		Parameter	0.7561	2.27E-02	
	14<Period<18	SE	3.85E-02	1.77E-03	
	(16 May–30 June)	*P* value	0.0000	0.0000	0.000
		Parameter	4.0741		
	Period>=18	SE	0.0733		
	(1–31 July)	*P* value	0.0000		0.000
Conditional aeration		Parameter	1.00005	0.00001	
	Period<=14	SE	5.11E-06	1.72E-06	
	(16 Oct.–15 May)	*P* value	0.0000	0.0000	0.000
		Parameter	0.9997	5.27E-05	
	14<Period<18	SE	2.55E-04	5.18E-05	
	(16 May1–30 June)	*P* value	0.0000	0.3100	0.008
		Parameter	0.0345	0.0968	
	Period>=18	SE	0.1200	0.0118	
	(1–31 July)	*P* value	0.7740	0.0000	0.000

[a] P-Wald represents the *P* value of the Wald chi-squared statistic for the overall fit.

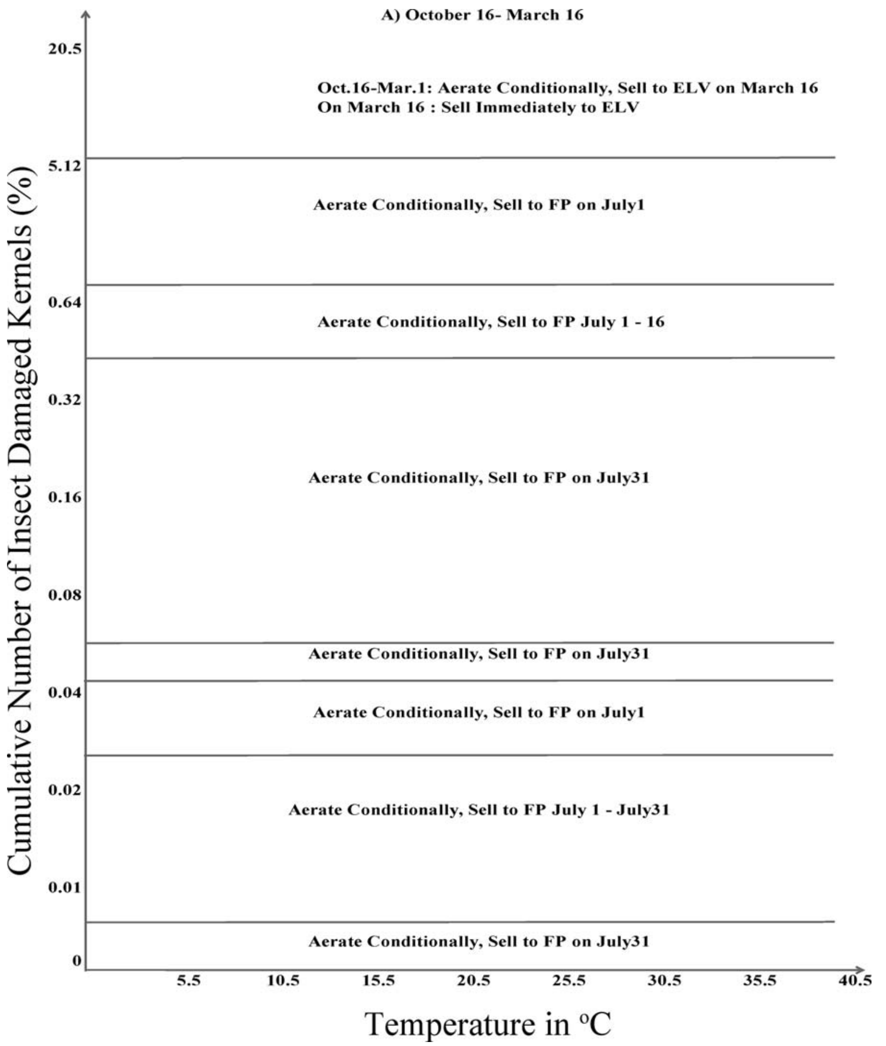

Fig. 3. (A) Optimal insect management strategies for 16 October–16 March: equal number of live insects and number of insect damaged kernels. (B) Optimal insect management strategies on 16 June: equal number of live insects and number of insect damaged kernels. (C) Optimal insect management strategies on 1 July: equal number of live insects and number of insect damaged kernels. (ELV, elevator; FP, food processor.)

July increases with IDK.) Similarly, Fig. 3C applies to the 1 July–14 July period. Two critical levels of cumulative IDK are common across all three figures. An IDK of 0.054% is the threshold that corresponds to 2 LI per kg. Below this level, corn is acceptable to both the elevators and food processors, but above this level, grain shipments would be rejected unless farmers fumigate the grain and kill the insects. An IDK of 6% corresponds to the level at which the food processor rejects the grain, and the only recourse for the farmer is to sell to the elevator. Thus, whenever IDK is below 6%, the farmer will sell to the food processor. As we move from left to right across the panels for a given temperature, the trend is to sell earlier. The exception to this rule occurs as we move across the 0.054% level of IDK where some earlier sales occur as farmers try to avoid the high cost of fumigation. In Fig. 3B (16 June–30 June), we observe a trend of generally later sales as temperature decreases. In Fig. 3C (1 July-15 July), this trend is repeated and is combined with a strategy shift at the level of 20°C below which conditional aeration is performed and above which aeration is not performed. This is because above ≈20°C in bin during the heat of the summer, there is a substantial probability of the in-bin temperature transitioning to over 35°C, which is high enough that insect growth is inhibited.

As a point of comparison, it is useful to consider the optimal strategy of a farmer who does not have a contract and hence must sell to the elevator. Because the storage-adjusted cash price peaks in mid-March, and because the probabilities of insect damage at levels that would trigger discounts (6% IDK) or rejection (20% IDK) are negligible, the optimal strategy is al-

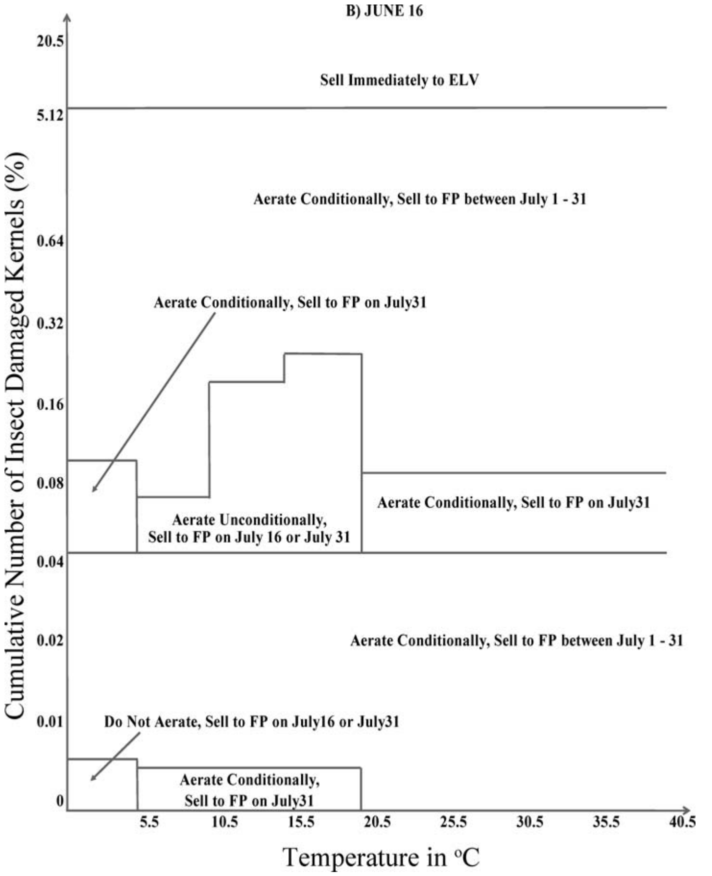

Fig. 3. (Continued).

ways to sell in mid-March. Starting from the average in-bin temperature (38°C), number of LI (0.2 per kg) and IDK (0.0054%) on 16 October, the model recommends conditional aeration until in-bin temperature is down to 3.5°C, after which grain should be kept without aeration until it is sold in mid-March. Thus, we see good agreement between the optimal strategy calculated by the model and farmers' observed practices. Given our economic assumptions, the resulting expected revenue less storage cost is $77,674 for the farmer without the contract. This is ≈23% below the $100,354 expected revenue less storage cost earned by the farmer with the contract who follows the IPM practices for insect control and grain marketing.

For the producer with a contract to deliver to the food processor, the optimal insect management strategy in each period depends on the in-bin temperature and the level of insect infestation. As in mold management (Yigezu et al. 2008), the results show that unconditional aeration to control insects in stored corn is dominated by conditional aeration the majority of the time. This is because, in addition to the higher cost of running fans, aerating unconditionally risks pushing hot air into cooler grain, especially at times when the ambient temperature is high, thereby increasing the in bin temperature to the 18–28°C range (which is favorable to insect growth) and increasing the risk of insect damage. The exception to this general rule occurs when grain temperature gets quite warm in the second half of June. In this case by aerating unconditionally, the in-bin temperature may be increased to levels above 35°C, which are high enough to slow insect growth.

Relative to aeration, fumigation is an expensive insect management strategy ($0.18/bushel). Consequently, the optimal strategy only uses fumigation when the number of LI at the time of sale is already above the rejection threshold. When there is a high probability of exceeding the 2 LI per kg threshold if grain is kept, then it is optimal to sell immediately and forgo the storage payment of $0.015/bushel/2-wk period rather than paying the high fumigation cost in the future. However, if the number of LI is already in excess of 2 per kg and the choice is between fumigating now and fumigating in the future, then keeping the grain with conditional aeration and fumigating at the time of sale is optimal provided that the level of IDK does not exceed the rejection threshold. This shows that in the presence of aeration, the strategy of equally spaced fumigation recommended by Fox and Hennessy (1999) is not optimal for this Indiana case. Model results also show that the typical farmer can avoid the

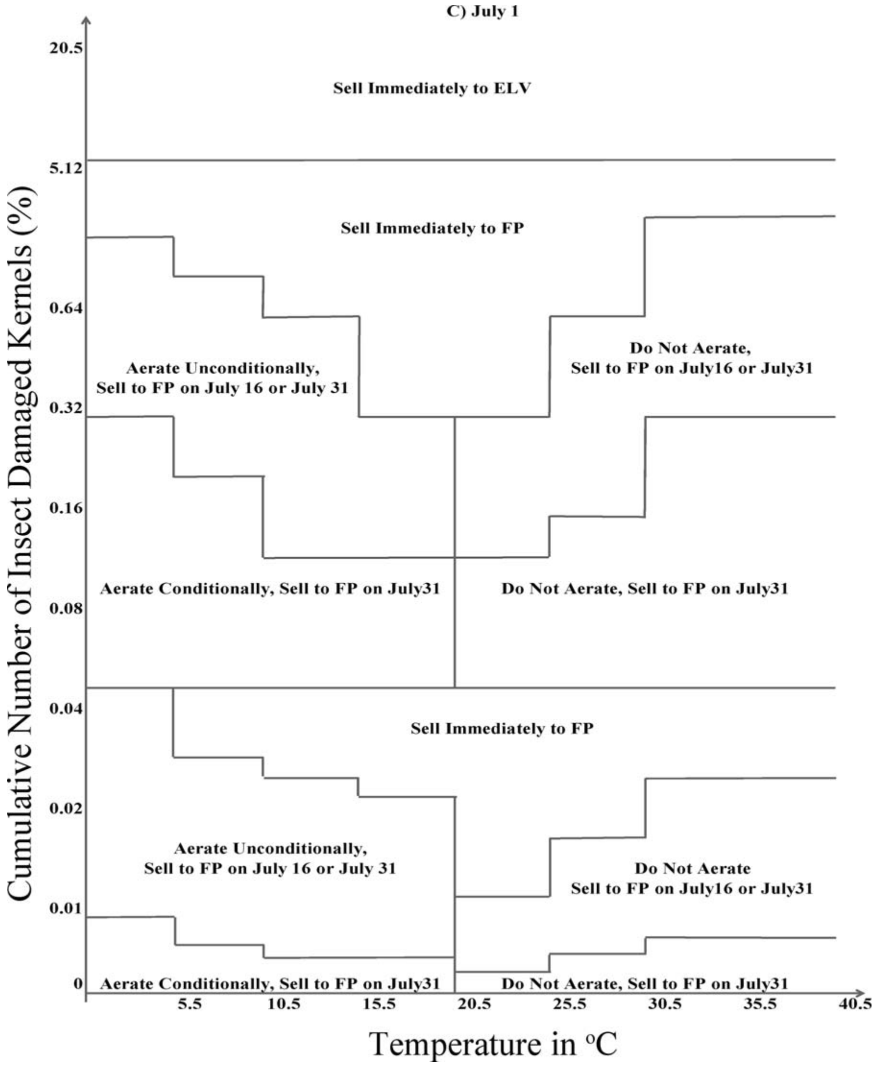

Fig. 3. (Continued).

use of fumigation simply by using aeration and sales strategies. These results are consistent with those of Adam et al. (2004) who found conditional aeration to be the most effective and least cost strategy to control the lesser grain borer in stored wheat. Based solely on the efficacy of controlling insect growth, Arthur et al. (2001), and Arthur and Flinn (2000) also concluded that conditional aeration is the most effective strategy.

If the farmer has the option of selling to the food processor, then the premium ($0.55/bushel) and storage payment ($0.03/bushel/mo) make selling to the elevator an option of last resort. The total price paid by the food processor is always higher than the local elevator provided that the grain is not rejected (i.e., IDK does not exceed 6% and/or the number of LI does not exceed 2 per kg).

From the perspective of the food processor, one important question is whether the premium and storage payment specified in the contract will provide sufficient incentive to farmers to deliver enough grain of acceptable quality later in the storage season. If we assume that farmers deliver their grain by 31 July to empty storage bins in preparation for the next harvest, then the food processor's goal would be to have enough grain delivered to meet their processing needs between 31 July and the after harvest, which would start late September/early October. Assuming that the food processor needs a 2-mo supply of quality grain delivered on 31 July, then to have enough grain at least one-sixth or 16.7% of the farmers' grain must meet the minimum quality standards and be stored until 31 July.

The amount of acceptable grain that farmers are willing deliver to the food processor at a given time during the storage period depends on the contract terms, the initial biophysical conditions in their grain bin (initial in-bin temperature and number of IDK) and the monthly storage payment paid by the food processor. To

Table 3. Percentage of quality grain deliverable to the food processor on 31 July

Initial in-bin biophysical conditions: mid-Oct.			% quality grain that can be delivered to the FP on July 31 for monthly storage charge of		
Temp	NLI	IDK (%)	1.5¢/bushel	1.74¢/bushel	2¢/bushel
	0.2	0.005	7.17	31.26	99.23
	0.23	0.006	7.69	24.78	98.07
38°C	0.264	0.007	4.63	24.66	25.54
	0.304	0.008	4.76	24.66	25.54
	0.349	0.009	4.83	24.66	27.16

estimate the minimum storage payments the food processor needs to pay contract farmers, we consider the following initial in-bin biophysical conditions: 38°C in bin, which is typical of hot grain coming out of a drier, LI in the range of 0.2–0.35 per kg, and IDK in the range of 0.005–0.009%. Table 3 summarizes the expected amount of grain that would meet the food processor's quality standards that farmers are willing to deliver on 31 July for the different levels of initial biophysical conditions and storage payments. These results show that the food processor can use the storage payment as an instrument to control the quality and quantity of grain that is supplied later during the summer.

The current storage payment in the study area is \$0.03/bushel per month, but a payment of \$0.0174 induces nearly 25% of the grain to be stored until 31 July. If insects are the only pest of concern to farmers, then even this reduced value is too high to achieve the goal of 16.7% delivery on 31 July.

Sensitivity analysis has been conducted on the prices of corn and electricity, the monthly storage payment, fumigation cost and the variable and fixed costs of monitoring. Results show that with few exceptions, the optimal policy is stable for up to 50% lower and 100% higher corn prices, 50% lower and 100% higher electricity prices, 20% lower and higher storage payment and 50% lower fumigation cost (there was no need to do simulations for higher fumigation costs because cost of fumigation is already so high that it is not among the optimal strategies unless the rejection threshold for 2 LI per kg is exceeded). The results were also stable for up to 400% and 2,000% higher variable and fixed costs of monitoring, respectively. With even higher values of most of the above simulation parameters, the optimal strategies start to change. For example, >50% lower corn prices, or >100% higher electricity prices or >20% lower storage payment make nonaeration along with early sales optimal. But overall, conditional aeration remains the dominant strategy and continues to yield higher expected profit relative to the traditional practice.

In conclusion, casual observations of farmer practices in the absence of a contract with a food processor—aerating conditionally until in-bin temperature gets to 3–5°C and then keeping grain without aeration and selling in mid-March—seem to be optimal. However for farmers with food processor contracts of the sort studied here, optimal insect management depends on monitoring the biophysical conditions of the grain and the time period under consideration. The optimal insect pest management strategy is to conditionally aerate and keep grain until the optimal time for sale, which will be 31 July unless the insect population or the damage caused by insects creates a substantial risk that the grain will be rejected by the food processor.

Thus, even with our assumption of a relatively labor-intensive monitoring program, the benefits of an IPM strategy outweigh its costs. This strategy avoids the use of chemical control methods in most cases, by relying heavily on conditional aeration and early sales, and only resorting to chemical fumigation in extreme cases where the number of live insects would lead to rejection by the targeted buyer.

One feature of our approach to analysis is that it allows us to estimate the fraction of grain that farmers will be able to store until the end of the storage interval. This will be grain available to processors from the end of the storage period (roughly 31 July) to the next harvest (roughly 1 October). This amount will be positively correlated with the storage payment that the processor uses to provide the farmer with incentive to store the grain and continue the IPM program.

It is noteworthy that some of the same controls used for insects are also used in an IPM program to control molds (Yigezu et al. 2008). Thus, application of aeration will have an affect not only on the growth of the insect population, but also on the incidence of molds. A promising extension of the work reported here will be to integrate the analysis of IPM for molds and insects. Because IPM pays for itself in the case of insects alone and molds alone (Yigezu et al. 2008), we expect IPM to be cost effective in a joint analysis. However, the nature of the control strategy and its level of net benefits are unclear. Such an integrated analysis will produce a more comprehensive analysis of the minimum storage payment that is needed for the processor to achieve a steady supply of grain throughout the year. Thus, we expect that the assessment of a multiple-pest IPM program that reflects the spillover benefits of controls will be a promising line for future work.

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