A Decision Theoretic Approach to Crop Disease Prediction and Control*

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The pesticide application practices of California peach growers in controlling peach brown-rot are used to demonstrate how Bayesian decision theory procedures can be used to arrive at optimal crop disease control practices. Subjective probabilities of disease loss intensity are measured and used in the decision model. Information from an analyst (this researcher) is combined with farmers' subjective probabilities of disease loss by means of Bayes' theorem. Optimal pesticide use actions are computed for three different objective functions—maximum subjective expected returns, mean-standard deviation of returns, and maximum expected returns with a minimum income side condition.

CROP LOSSES due to many plant diseases are large and highly variable from season to season. For example, brown-rot of peaches damaged $13 million of fruit in 1965 but resulted in very little damage in many other years [22, p. 33]. There is public concern with the detrimental effects of increased pesticide use. Perhaps losses can be reduced and pesticide use restricted by applying pesticides only when conditions arise that are associated with disease development.

The farmer's disease control decision is complex. Incorrect pesticide use may result from an inappropriate view of the probability of disease development or misuse of disease forecasts. If he believes a high loss disease forecast and treats, and the disease doesn't develop, the cost of treatment is lost. If he ignores a true forecast and doesn't treat, the crop is lost. These errors are examples of Type II and Type I errors and they have different consequences [1, p. 103]. A program to assist farmers in the utilization of disease probability and disease prediction information may have substantial benefits.[1]

The presence of uncertainty in the level of crop loss indicates the need for a decision framework which treats uncertainty directly rather than minimizing its importance. This paper demonstrates how Bayesian decision theory procedures can be used to arrive at optimal disease control practices. This is only a suggested approach to how pesticide use decisions can be made. A comparison of the actual and optimal behavior appears in a separate article [2].

This analysis is based on the pesticide application practices of California peach growers in treating peach brown-rot. First, the relation of previous pesticide use models to the decision theory approach is shown. Then, procedures for assessing subjective probabilities of disease and combining this information with disease level forecasts are described. Optimal pesticide use practices for peach brown-rot control are presented for several objective functions. Finally, implications of this analysis for pesticide use are discussed.

Pesticide Use Models

There have been several attempts to unify thought on methods of selecting optimal pest protection actions. Stern [23, p. 45], emphasized the importance of pest densities as an indicator for the timing of pest control. He defined *economic injury level* as the lowest pest density that would cause damages whose dollar value was equal to the cost of control. Control is recommended when the pest population, which fluctuates about a general equilibrium level, approaches the economic injury level.

Several economists have investigated the quantity of pesticide to apply in the conventional marginal analysis framework. That is, the pesticide dosage is adjusted to the point where the ratio of the pesticide cost to the crop price is equal to the incremental gain in output from the pesticide input.[2]

The dosage levels of the economists and the

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[1] Various methods of measuring the aggregate welfare effects of a disease control program are considered in Carlson [1, ch. 6].

[2] See Headley and Lewis [10, p. 19] and Hillebrandt [12, p. 471] for an explanation of marginal analysis in pesticide use.

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pest density levels that the ecologists emphasize can be specified in terms of a decision theory payoff matrix. The complete set of pesticide input levels can be represented by the *actions* $a_1 \cdots a_m$. The pest density levels (or percent crop loss) can be treated as *states of nature* $\theta_1 \cdots \theta_n$. There is a crop yield and monetary *payoff*, $U(a, \theta)$, corresponding to each action-state of nature combination. For convenience in discussion, monetary payoff is considered to be equivalent to utility. In the empirical portion of the paper, other functional relationships between dollar returns and utility are considered.

The decision theory approach involves enumerating all possible payoffs and selecting the action that provides the best payoff.[3] Ramsey [18] and Savage [20] have forcefully argued that if a set of reasonable axioms of behavior is satisfied, then the best guide for decisions is the one based on subjective expected utility maximization.[4]

Decision Theory Procedures, Including Subjective Probabilities

The decision theory procedure described above can be presented more formally as

$$(1) \quad E(U) = \max_{a} \left[\sum_{\theta} U(a, \theta) \cdot P(\theta) \right]$$

where:

$E(U)$ = expected utility,
$U(a, \theta)$ = payoff (utility) derived from each action-state of nature pair, and
$P(\theta)$ = the decision maker's subjective probability distribution for the random variable θ.

The decision maker (farmer) may receive further information about the probable state of nature via a forecast z.[5] The farmer's subjective probability distribution is treated as a prior distribution. The decision maker or his analyst (extension or research person) is assumed to be able to observe and write the conditional distribution of z for a given θ, $P(z|\theta)$.

The prior probabilities and the conditional probabilities can be combined by means of Bayes' theorem:

$$(2) \quad \underset{\text{posterior probability}}{P(\theta \mid z)} = \underset{\text{prior probability}}{P(\theta)} \cdot \underset{\text{conditional probability}}{P(z \mid \theta)} \Big/ \underset{\text{marginal probability of forecasts}}{P(z)}$$

Jefferies [13, p. 29] asserts that this formula, which was first given by Thomas Bayes in 1763, is the fundamental rule involved in the process of learning from experience.

Let h be a decision function that selects the action with the highest payoff for each forecast received ($a = h(z)$). Then, substituting the posterior probability of equation (2) and $h(z)$ in equation (1), we have

$$(3) \quad E(U) = \max_{h} \left[\sum_{\theta} U(h(z), \theta) \cdot P(\theta \mid z) \right].$$

Posterior probabilities are used as weights in computing the expected payoffs for each decision rule. Then, the decision rule with the largest expected payoff is chosen.

A complication arises in Bayesian procedures when the observations (z) are collected and analyzed by a person other than the decision maker.[6] The decision maker has prior probabilities for the uncertain variable. The analyst has additional information. How are these two groups of information to be combined? The procedure followed in this analysis is to combine the decision maker's subjective prior probabilities and additional data he may have by means of Bayes' theorem. The analyst's observations are combined with his prior distribution by Bayes' procedure. The final step involves joining the two groups of data by a further application of Bayes' theorem. The assumptions implicit in this procedure are that the two persons' data are stochastically independent and that the posterior probabilities of one analysis can become the prior probabilities of subsequent decision problems. In the following section, disease forecasts from an analyst (this re-

[3] An excellent treatment of Bayesian decision theory can be found in several recent books. See, for example, [17] and [21].

[4] The major feature of this formulation of the decision problem which differs from that of Von Neumann and Morgenstern [25] is that it does not require a relative frequency definition of probability. The states of nature need not be repeated events.

[5] The variable z may not be directly observable; it may be related to observable variables (x) by $z = b(x)$, the coefficients of which can be estimated by regression analysis.

[6] Hildreth [10] discusses several methods the analysts can use to summarize data for their clients. The procedure followed here is essentially the same as that suggested by Halter and Dean [9].

searcher) are combined with the subjective prior information of peach farmers to determine optimal pesticide use.

It is obvious from this discussion of decision theory that subjective probabilities are as critical as utilities in computing expected utilities. Let us examine more closely the meaning and measurement of these probabilities.

De Finetti [5] and Savage [20] can be credited with giving probability a personalistic definition and using it in decision theory problems. They asserted that all uncertainty for a rational man could be defined as his degree of belief that a given event would occur or the extent to which he is prepared to act on this belief. We can contrast this behavioristic conception with that of *objective probability*, which is equivalent to relative frequency in a long series of repeated events, such as the chance of a six on many rolls of a fair die.

In many decision situations there may be no recorded series of repeated events upon which to compute objective probabilities. In this case, judgments (in probability form) of knowledgeable experts can be used. The major criticism of subjective probabilities is that they are often vague and imprecise. However, special procedures for evoking and measuring decision makers' subjective probabilities can help to overcome the vagueness problem.

Psychologists [7] have identified two basic methods of measuring subjective probabilities: (a) direct interrogation of subjects and (b) inference from the choices of subjects. The first method involves verbal articulation of perceived relative frequencies in density or commulative form. For example, one might ask, "How many years in twenty would you expect a loss of 0–5 percent, 5–10 percent, etc.? The inference procedure, on the other hand, places the subject in a simple decision situation and he makes choices based on the subjective probabilities he believes correct. The assumption is made that probabilities used to make simple choices are the same as those used in more complex decisions. Savage [20] outlines the choice measurement procedure in the form of a *standard lottery* (or standard gamble). Winkler [26] discusses variations of the direct and choice methods and presents an interview format for evoking probability judgments.

Brown-Rot Control in the Peach Industry

In this study subjective probabilities for the level of loss due to brown-rot were measured by three procedures. Density and cumulative distributions were obtained by direct questioning. Standard gamble questions were used as a checking device on some of the growers to insure that the probabilities given were the probabilities that the subjects were prepared to act upon.

Results from the three methods of assessment are shown in Figure 1. The subjective probability distributions plotted are the means of the sample of 76 growers.[7] The consistency of probabilities measured by the three techniques, the agreement of the subjective probabilities with an objective probability based on relative frequency of rainfall, and the general similarity of subjective probabilities among the peach growers indicate that the probability distribution of brown-rot losses is of the form shown in Figure 1. Various prior distributions can be used to test the sensitivity of decision rules to precision in the prior distribution.[8] However, due to the similarity of the various subjective probability distributions, only the density method priors will be used in the following analysis.

Five common pesticide actions that a grower might select to control peach brown-rot are: no spray (*NS*), one captan application (1C), two captan applications (2C), one sulfur application (1*S*), or two sulfur applications (2*S*). Seven states of nature are defined in terms of nonoverlapping percent crop loss intervals as follows: 0–5, 5–10, 10–20, 20–30, 30–50, 50–70, and 70–100.[9] The average production costs from a 1967 survey of growers serves as an approximation to current cost conditions [4]. Harvest costs and pesticide costs are influenced by the pesticide action taken. Pesticide material and application costs were 0, \$12.70, \$25.40, \$5.90 and \$11.90 per acre for no spray, one captan, two captan, one sulfur, and two sulfur applications, respectively. Reduction in losses associated with each pesticide action are averages from a series of peach brown-rot trials [1, p. 73]. Crop value is set at \$75 per ton and is usually

[7] There are several procedures for aggregating individual probability judgments [27]. The random sample mean is chosen in this study since it has some statistical justification.

[8] See Carlson [1, ch. 4, 5] for a sensitivity analysis of optimal fungicide actions to various subjective and objective prior probability distributions.

[9] These intervals represent a compromise between more groups for computational accuracy and a limited number of intervals for easing difficulties in evoking subjective probabilities [21, p. 254].

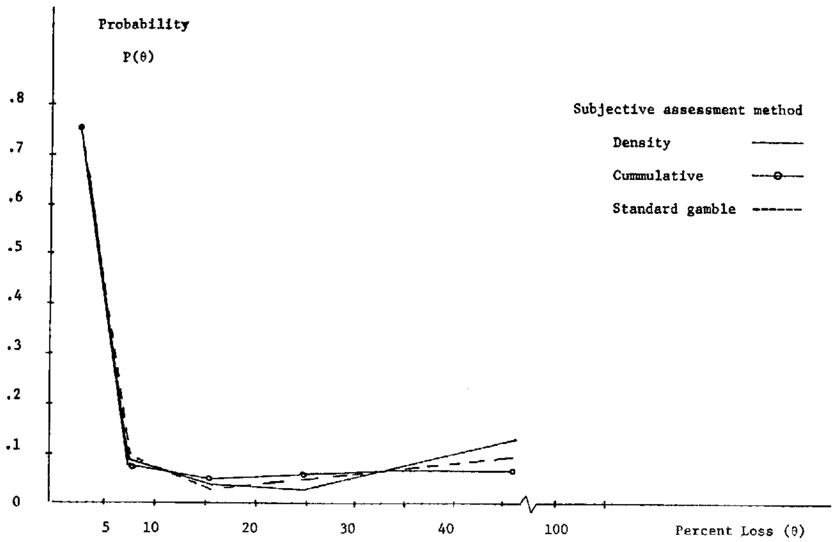

Figure 1. Prior probability distributions: frequency polygon indicating consistency for various assessment methods, late period, Modesto area.

Source: Table 4.1, in Carlson [1].

known prior to disease control time since the price is determined by negotiations between canners and a grower cooperative. Yields are based on California state averages for the past ten years for each varietal group.

With the above specification of pesticide effectiveness, costs, prices, and yields, net returns for each of the actions and states of nature can be computed by

$$U(a, \theta) = PT_k(R_iL_j) - FT_k(R_iL_j) - SC - S_i \tag{4}$$

where:

$i = 1, 2 \cdots 5$ pesticide actions,
$k = 1, 2, 3, 4$ varietal groups,
$j = 1, 2 \cdots 7$ crop loss levels,
$U(a, \theta)$ = management income per acre for each action a and state θ,
P = peach price per ton,
T = average state yield per acre,
R = average loss reduction of pesticide actions,
L = crop loss interval midpoints,
F = harvest cost per ton,
S = pesticide material and application cost, and
SC = all other production costs.

The intensity of brown-rot loss in any given year is influenced by the rainfall during the three-week period prior to harvest, the degree of fruit maturity, and the quantity of spores existing in the orchard. These three factors can be observed prior to spray decisions provided a 24–36 hour rainfall forecast is available.

A linear regression model was specified to predict disease loss. A cross-section survey of orchards and observations from greenhouse trials conducted by the author provided data for estimating the following regression equation:[10]

$$\begin{aligned} z &= 34.04 - 5.08x_1 + 3.89x_2' + .996x_3 \\ & \qquad\quad (2.52) \qquad (3.83) \qquad (14.9) \\ & \qquad\qquad\qquad\qquad\qquad R^2 = .799 \end{aligned} \tag{5}$$

where:

z = percentage peach crop loss due to brown-rot,
x_1 = fruit maturity index,
x_2' = predicted hours of rainfall,
= $.1928 + .535x_2$,[11]
x_2 = rainfall forecast index, and
x_3 = spore density index.

The numbers in parentheses are t ratios for the coefficients. The coefficients have the signs that

[10] Rainfall was simulated at various intensities, fruit were selected at all levels of maturity, spore levels varied from 0 to 90 percent. Alternative functional forms and estimation procedures to constrain the dependent variable to the 0–100 percent range produced similar results.

[11] Regression estimate based on rainfall forecasts and rainfall records of the Sacramento area, 1952–66 [1, p. 130].

Table 1. Optimal strategies and associated expected net returns for various loss forecasts[a]

Peach varietal group	Brown-rot loss forecasts						
	$\hat{z}_1$ 0–5	$\hat{z}_2$ 5–10	$\hat{z}_3$ 10–20	$\hat{z}_4$ 20–30	$\hat{z}_5$ 30–50	$\hat{z}_6$ 50–70	$\hat{z}_7$ 70–100
Extra earlies	75 *NS*	72 1*S*	71 1*C*	67 1*C*	53 1*C*	−16 2*C*	−99 2*C*
Earlies	14 *NS*	12 1*C*	9 1*C*	5 1*C*	−13 1*C*	−77 2*C*	−145 2*C*
Lates	120 *NS*	116 1*C*	113 1*C*	105 1*C*	77 1*C*	5 2*C*	−63 2*C*
Extra lates	127 *NS*	122 1*C*	116 1*C*	103 1*C*	69 2*C*	16 2*C*	−48 2*C*

[a] Numbers represent dollars per acre net returns; lower figures designate pesticide actions: one sulphur (1*S*), two sulphur (2*S*), one captan (1*C*), two captan (2*C*), and no spray (*NS*).

theoretical discussions of disease development suggest [6, p. 1]. Point estimates of disease loss ($\hat{z}$) from equation (5) have a standard error of 20.22 percentage points.[12]

Following the procedure outlined in the previous section, the analyst's posterior probabilities of disease loss (conditional forecasts from equation (5)), are combined with the decision maker's posterior probabilities.[13] The analyst's posterior probabilities have a truncated normal distribution. That is, the deviations about $\hat{z}$ are normally distributed between zero and 100 percent provided the observations (x) are generated by a normal process and the analyst has a uniform prior distribution for the regression model parameters [2]. The analyst's posterior probabilities and the decision maker's posterior probabilities are combined by means of Bayes' theorem.[14] The computation of the final posterior probabilities can be represented by

$$(6) \qquad P(\theta \mid \hat{z}) = P(\hat{z} \mid \theta) \cdot P(\theta \mid \cdot)/P(\hat{z})$$

where:

$P(\theta|\hat{z})$ = the probability of receiving θ level of disease loss when the analysts' forecast is for $\hat{z}$ percent loss,

$P(\hat{z}|\theta)$ = the conditional estimate of the probability of disease loss given the true disease loss θ from equation five [$P(\hat{z}|\theta) \propto P(\theta|\hat{z})$, the analysts' posterior probability],

$P(\theta|\cdot)$ = decision maker's subjective probability for θ level of disease loss, given no additional information, and

$P(\hat{z})$ = the marginal probability distribution of loss forecasts.

By utilizing the posterior probabilities of (6) and the $U(a, \theta)$ from (5) in equation (3), the optimal pesticide use strategies can be derived. Table 1 shows optimal pesticide applications and the associated expected net returns when various loss forecasts ($\hat{z}$) are received. Since each peach varietal group matures at a different time period, it receives different rainfall and has a different subjective prior probability distribution. The optimal strategy for the extra earlies is [*NS*, 1*S*, 1*C*, 1*C*, 1*C*, 2*C*, 2*C*] for the forecasts $\hat{z}_1$ to $\hat{z}_7$. In contrast, during the more susceptible late period the optimal strategy requires higher fungicide applications. Note that when $\hat{z}_7$ is the forecast, even very high pesticide treatments will not eliminate losses. The pesticide treatments reduce losses only 35–70 percent [1, p. 73]. The solutions did not change with twenty-percent changes in product prices or fixed costs or with yields changed to third quartile levels.

[12] The standard error of forecast is computed at data means and includes the standard error of forecast for the auxilliary equation for x_2' in additive fashion [1, p. 131].

[13] In this case the decision maker's posterior distribution is equivalent to his subjective prior distribution since he is assumed to have no additional information. It is written as $P(\theta|.)$ to indicate that it could be a conditional probability distribution.

[14] To obtain the distribution of the product of a truncated normal and the discrete distribution of the decision maker, the normal distribution was partitioned and used in a discrete fashion. In an attempt to treat distributions as continuous functions, a Weibull distribution was fitted to the subjective priors. The Weibull and normal variates were combined by a simple Monte Carlo procedure. The results were not appreciably different from the discrete approximation.

Table 2. Means and standard deviations of returns from various disease loss forecasts and various actions[a]

Action	Forecasts													
	$\hat{z}_1$		$\hat{z}_2$		$\hat{z}_3$		$\hat{z}_4$		$\hat{z}_5$		$\hat{z}_6$		$\hat{z}_7$	
	M	S	M	S	M	S	M	S	M	S	M	S	M	S
	dollars per acre													
NS	75	20	—	—	—	—	—	—	—	—	—	—	—	—
$1S$	74	14	72	20	—	—	—	—	—	—	—	—	—	—
$1C$	73	9	72	14	71	18	67	26	53	48	—	—	—	—
$2C$	62	8	61	11	60	15	57	21	46	39	−16	62	−99	35

[a] Based on subjective priors from the extra early varietal group.

Up to this point, the criterion of choice has been the strategy that maximizes expected net return to management. This criterion ignores risk aversion, survival, and other objectives of the firm. Let us consider several utility functions which incorporate risk, so that farmers' efforts to use pesticides as insurance against large losses is clarified.

The mean-variance (standard deviation) criterion has been advocated as a method of incorporating risk aversion in the firm's objective function [8, 15]. Means and standard deviations of net income were computed from the discrete approximation of the posterior distribution, $P(\theta|\hat{z})$. Table 2 gives means (M) and standard deviations (S) associated with actions and disease loss forecasts. The maximum expected return strategy is given by the uppermost figures for each forecast.

Many growers may not prefer the maximum expected return strategy. They may find that they are willing to sacrifice some amount of mean income to reduce the standard deviation of returns. For example, given a $\hat{z}_1$ forecast, the grower might give up \$1 in expected income to reduce (S) \$6 by selecting the $1S$ action rather than NS. When growers' aversion to risk is not known, tables of means and standard deviations for each action and forecast will permit the grower to select more or less cautious protective actions.

Another utility function which appears quite

Table 3. Critical levels of expected income for alternative disease control actions and disease level forecasts[a]

Action	α level	Forecasts						
		$\hat{z}_1$	$\hat{z}_2$	$\hat{z}_3$	$\hat{z}_4$	$\hat{z}_5$	$\hat{z}_6$	$\hat{z}_7$
		dollars per acre						
No Spray (NS)	.01	−74	−207	−260	−266	−400	−616	−633
	.05	26	−15	−62	−124	−271	−523	−621
1 Sulfur ($1S$)	.01	−18	−101	−134	−139	−223	−359	−369
	.05	45	20	−10	−49	−142	−301	−363
2 Sulfur ($2S$)	.01	7	−53	−77	−80	−140	−237	−244
	.05	52	34	12	−15	−82	−195	−239
1 Captan ($1C$)	.01	18	−33	−53	−55	−106	−188	−194
	.05	56	40	22	−1	−57	−153	−190
2 Captan ($2C$)	.01	17	−24	−41	−42	−84	−151	−156
	.05	48	35	21	2	−44	−122	−153
Optimal expected income strategy		NS	$1S$	$1C$	$1C$	$1C$	$2C$	$2C$

[a] Based on subjective priors for the extra early varietal group.
α = The probability of obtaining a smaller return.

useful for the disease loss protection decision is to choose the action that maximizes expected income subject to allowing income to fall below a critical (disaster) level with a specified low probability.[15] We might call this the restricted Bayes criterion. (Maximizing subjective expected utility is the Bayes criterion.)

Table 3 reports critical levels of income for various disease control actions and forecasts. The two specified levels of low probability tabulated are .01 and .05. The upper left figure indicates that if $\hat{z}_1$ is the forecast and no spray (*NS*) action is taken, the probability of receiving an income below $-\$74$ per acre is .01. The critical income for a .05 chance of disaster is \$26. The optimal expected income strategy is [*NS*, 1*S*, 1*C*, 1*C*, 2*C*, 2*C*]. However, if the restricted Bayes criterion is used, more cautious actions might be chosen. For example, if a farmer has a disaster level of $-\$50$ per acre for one varietal group with a tolerance probability of 1 percent, he would select 2*C* rather than 1*C* when the $\hat{z}_3$ or $\hat{z}_4$ forecasts are received. Although 1*C* has a higher expected return, it does not meet the side condition—it allows losses of $-\$53$ and $-\$55$ at 1 percent probability. Given the disaster levels and tolerance probabilities of growers, tables such as Table 3 permit growers to reflect their desire for survival by choosing a strategy that maximizes expected income and yet avoids major disasters.[16]

Implications for Pesticide Use

The above analysis yields recommendations that are different from present pesticide use practices. The survey of peach growers indicated that 38 percent routinely applied pesticides in the last three weeks prior to harvest, and 18 percent applied pesticides only on the later varieties; but 44 percent of the growers said that they would apply no pesticides for brown-rot control. The gain in expected revenues from the optimal pesticide use strategies can be computed by using the marginal probabilities of forecast $P(\hat{z})$ to weight the difference between returns with present and optimal pesticide use strategies. The expected gains for those who are presently not applying pesticides was \$25–\$40 per acre [2].

Using disease forecasts can also reduce pesticide use. When the 0–5 percent loss forecast is received, no pesticide should be applied. This is a very frequent forecast ($P(\hat{z}_1)=.75$) and could substantially reduce the social cost of pesticide use.[17]

Decision theory procedures appear to be applicable when disease control costs are high relative to product price, when the intensity of damage is highly variable from year to year, and when epidemics can be predicted with some reliability. In the author's opinion, these procedures are applicable to insect control of crops and livestock, weed control in crops, and even in the detection and treatment of some human ailments. (See, for example, reference [19] and other articles in the same volume.) Economic analysis of the costs and returns of pesticide use should include the feature that is pervasive in nature—uncertainty. This paper shows that human judgments, in probability form, can be helpful inputs in decision models. Sample evidence and farmer subjective probabilities were blended to derive improved pesticide use practices.

[15] This objective function is closely akin to that used in chance-constrained programming [3] and utility depending upon the probability of ruin or some focus of loss [16].

[16] In an attempt to determine the disaster levels of crop loss for peach growers, the sample growers were asked to give the level of income loss that would cause them to not operate the following year (See [1, p. 187]). The answers ranged from +\$50 to $-\$1{,}000$ per acre when no critical disaster probability was specified.

[17] Social costs or externalities have not been included in this study because of measurement problems. There appear to be no externalities associated with captan at present levels of use. However, as reviewer Headley kindly pointed out, recent experiments have shown that large captan dosages can deform embryos and alter genetic material [14, 24]. Sulfur may irritate the eyes of peach pickers. Once measured in terms of dollars, such costs can be added to the payoff matrix and lead to lower pesticide use recommendations.

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