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The Value of Information in Herbicide Decision Making for Weed Control in Australian Wheat Crops

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Most weed control decisions are made with the benefit of some information about weather conditions and actual weed densities. This study is an investigation of the value of adjusting weed control decisions in response to these types of information. For a specific example, it is found that the expected value of information can reach 15% of expected gross margin. The value of information about yield prospects is higher than that for weed density. The value of information is markedly affected by the degree of risk aversion and the type of decision rule adopted. Use of information reduces the expected level of herbicide usage.

Key words: economic threshold, herbicide, pest, pesticide, risk aversion, risk-reducing input, value of information, weed.

Introduction

Herbicides are used in large quantities in agricultural systems of the developed world. Farmers increasingly have substituted herbicides for mechanical cultivation, improving soil structure and reducing on-site and off-site problems from soil erosion. However, associated with this increased use of herbicides have been problems of health and environmental risks and an emerging problem of herbicide resistance (LeBaron and Gressel).

Although largely ignored by agricultural economists prior to 1980, economic issues related to weed control have since received more attention. Recent analyses of weed economics issues include studies by Abadi-Ghadim and Pannell; Auld, Menz, and Tisdell; King et al.; Lybecker, Schweizer, and King; Marra, Gould, and Porter; Pandey and Medd; Pandey, Lindner, and Medd; Pannell (1990a, c); and Thornton et al.

Most weed control decisions are made with some knowledge about relevant weather conditions and some are made after weeds have germinated and can be observed. Appropriate responses to this information can improve efficiency of herbicide use. There have been several studies of information use in pest control decisions, including Antle (1988); Cammell and Way; Menz and Webster; Moffitt et al.; Stefanou, Mangel, and Wilen; and Thornton and Dent (1984a, b). However, there has been no analysis of information use in a weed control problem (Pannell 1991).

In common with other pesticides, herbicides increase yield indirectly by reducing damage from harmful agents. Lichtenberg and Zilberman showed that failure to represent this indirect effect in models of yield response can lead to serious biases. Yield response to herbicide application also has some distinctive characteristics which must be considered

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in economic analyses. Weeds reduce crop yield through competition for resources rather than by direct damage. They are less mobile than many insects and diseases, have longer life cycles, and chemicals used to control them are more likely to damage the crop than are other types of pesticide. Consequently, weeds require a different model structure with different functional forms.

Pannell (1991) also noted that, to date, all farm-level studies of information use in pest control have treated the pesticide as a binary variable to be applied at the recommended rate or not at all. There has been no analysis of information value in which treatment dosage has been modeled as a continuous variable.

This study addresses the following issues: (*a*) the extent to which use of information in weed control decisions increases producer welfare, (*b*) whether such information reduces risks faced by producers, (*c*) the impact of information on expected levels of herbicide usage, (*d*) the sensitivity of these issues to the degree of risk aversion, and (*e*) whether these issues are affected by the type of decision framework used, i.e., the treatment of herbicide dosage as a binary or continuous variable.

The next sections include further background to the study, as well as descriptions of the model used and of procedures and assumptions employed. Subsequently, results of the analysis are presented and discussed.

Background

Value of Information

Anderson, Dillon, and Hardaker outline a Bayesian framework for calculating the value of information under uncertainty. They described the process of finding the value of information as "cycling through preposterior analysis with varying experimental costs until a solution is found such that the utility of the Bayes strategy equals the utility of the prior optimal act. . . . [This is] a rather tedious trial-and-error job" (p. 117).

Anderson, Dillon, and Hardaker also pointed out, however, that the value can be closely approximated by an easier method. This is by calculating the difference between (*a*) the certainty equivalent value of the optimal (Bayesian) strategy with costless information, and (*b*) the certainty equivalent value of the prior optimal act. That is the approach taken here.

Because of variability between years, the benefits (*ex post*) of using information to adjust decisions will vary from year to year. Thus, the value of information calculated *ex ante* has a distribution. The mean of the distribution is the expected value of information. Information has two sources of value for risk-averse decision makers. One is the increase in expected profit, which reflects the increased probability of making a "correct" decision as a result of information use. The other is the reduction in income variability which information allows, reducing the risk premium. The total expected value of information is the increase in expected profit plus the reduction in risk premium.

The cost of information is not included in the analysis, so the results indicate the expected gross benefits of information use. Net benefits depend on the cost of obtaining and using information. Gross benefits, as estimated here, are useful to indicate the maximum amount a farmer should be willing to pay to obtain the information.

Note that in the following discussion, to "use information" means to base decisions on revised (posterior) subjective probability distributions. Of course, prior distributions are based on information of some sort, but it is up-to-date or "tactical" information which is the main focus of this study. Prior distributions are taken as given.

Information Used in This Study

This study consists of detailed simulations with a model previously estimated by Pannell (1990b). The model represents yield response to application of diclofop-methyl to control ryegrass (*Lolium rigidum*) in wheat. This problem was chosen because of its economic importance in Australia where farmers consider ryegrass to be one of their most significant weeds (Roberts et al.). It is also a weed which is commonly controlled with selective herbicides after crop emergence, giving maximum scope for information to affect the control decision.

Two types of information are considered: (*a*) information about rainfall prior to spraying leading to revised probability distributions of crop yield, and (*b*) information about the density of weeds present in the crop at the time of spraying. The first of these is considered because variability of rainfall is the major source of risk in Australian dryland crop production. The second is included because Pannell (1990a) found that in a deterministic decision framework, weed density is the variable which has the greatest impact on the optimal strategy for herbicide use.

There are some notable differences between these two types of information. In the case of initial weed density, precise information is available at relatively low cost simply by counting weeds in the crop. In principle, complete information about weed density could be obtained with sufficient effort (assuming all weeds have emerged), although in practice, densities are estimated by sampling. On the other hand, information about crop yield is quite imprecise. Climatic information is known up to the date of herbicide treatment, but for most of the growing season, weather patterns are unknown. Furthermore, even if complete weather information could be obtained, its implications for crop yield would still have to be inferred, so uncertainty about yield would not be eliminated. This is in contrast to weed density which can be observed directly.

In this study, information about initial weed density is assumed to be obtained by counting weeds in sample areas of the crop. Without counting, the farmer would have a subjective probability distribution for mean weed density. Conceptually, this subjective distribution could take any form, but for this study, a normal distribution with coefficient of variation of .4 is assumed. To determine the "actual" weed density, a number is drawn from a normal random number generator.[1] For simplicity, it is assumed that the density obtained in this way applies to the whole crop. In other words, without counting, there is uncertainty about the weed density, but counting provides perfect information and there is no spatial variability in weed density. This simplification means that estimates of the expected value of weed density information will be for perfect information and so will exceed the expected value of sample information actually obtained.

Information on wheat yield is obtained by observing rainfall from the start of the calendar year up to the date of the herbicide decision, 14 days after sowing the crop. The probability distribution of yield conditional on this rainfall information is estimated using a biophysical simulation model of soil-water balance and wheat growth based on the CERES model. The yield prediction obtained from this model is based on no weed competition and, thus, no herbicide application. The model is solved up to the date of the control decision using rainfall data for the specific season in question. Then rainfall data for a wide range of actual seasons are used to solve repeatedly the simulation model for the remainder of the year. Each solution gives a wheat yield and, in combination, the set of yields defines a conditional probability distribution. Daily rainfall data for Merredin, in Western Australia's eastern wheatbelt, from 1912 through 1987 are used in the analysis.

In obtaining the conditional probability distribution of yield, it is assumed that each of these historic seasons is equally likely to occur and that rainfall received after herbicide application is independent of rainfall received prior to application. Thus, the rainfall information for the first part of the season is not used to predict rainfall in the second part of the season. Even without predicting rainfall in the second part of the season, yield is conditional on early season rainfall because final yield depends on the timing of the first rains of the season (earlier rains result in higher yields) and on the level of water stored in the soil.

Like Thornton and Dent's (1984a) study, this approach might be described as "implicitly Bayesian." It does not employ the usual Bayesian approach of explicitly using "likelihoods" to derive a posterior probability distribution from the prior distribution and the observed information. Rather, the likelihoods are implicit in the posterior distributions which are derived directly using the biophysical simulation model.

If neither source of information is used, decisions are based on the prior subjective distribution of weed density and the long-run (unconditional) distribution of yield. If weed density information is used, it is assumed that weed density varies from year to year, but is known with certainty in each year. If yield information is used, decisions for each year are based on the conditional yield distribution given observed rainfall for the first part of the year.

The yield distribution derived above can be used to calculate for a single year the effects of information use on profit, risk, and herbicide use. Results are conditional on a particular pattern of rainfall for the start of the season. This would be useful for a farmer making a decision in that year. However, an aim of this study is to evaluate information use over the range of season types likely to be encountered in the long term. Clearly, the results will vary from year to year, so that for a given type of information used, there exists a long-run distribution of profit and herbicide usage. These distributions are estimated by repeating the procedure 76 times. For each year of rainfall data, the simulation model is solved for the period up to the treatment date and then for each of these season starts, it is solved for 76 season finishes.

The Model

Crop yield (Y) is represented using the following general form:

$$Y = Y_0[1 - D(W)], \tag{1}$$

where Y_0 is yield with no weeds present and D is the damage function representing the proportion of yield lost at weed density W.

Pannell (1990b) estimated the following damage function from experimental data on application of diclofop-methyl to control ryegrass in wheat:[2]

$$D(W) = 1 - \frac{.544}{1 + .544/(bW)}, \tag{2}$$

where b is marginal yield loss per weed at low weed densities. This was estimated as

$$b = .0172 \cdot \exp(-.801 Y_0) \cdot \exp(-5.70H), \tag{3}$$

where H is herbicide dose and Y_0 is weed-free yield. Equation (3) represents the lower competitiveness of weeds which have survived a herbicide application and the lower *relative* competitiveness of weeds in high-yielding crops.

W is a function of W_0 (pretreatment weed density) and $K(H)$ (proportion of weeds killed at herbicide rate H):

$$W = W_0[1 - K(H)]. \tag{4}$$

The kill function must be bounded by zero and one. Pannell (1990b) estimated the following logistic function:

$$K(H) = 1/[1 + \exp(F)], \tag{5}$$

where

$$F = -2.85 - .995 \ln(H) - .00559 W_0 - .00366 \ln(H) W_0, \tag{6}$$

and W_0 is initial weed density.

Finally, the weed-free yield, Y_0, can be reduced by phytotoxic damage from the herbicide. Pannell (1990a) used the following relationship for damage to wheat yield by diclofop-methyl:

(7) $$Y_0 = Y_p(1 - .149H),$$

where Y_p is potential yield in the absence of weeds and chemical damage.

Table 1 shows a summary of variables used in the above model presentation. In this study, uncertainty about yield due to climatic variability is represented as uncertainty about Y_p. Uncertainty about weed density is represented by specifying a distribution for W_0.

Further Assumptions

It is assumed that the weed control decision is made two weeks after sowing the crop, consistent with farmer behavior in the region. This is the period when diclofop-methyl is most effective against ryegrass. The sowing date varies from year to year depending on climatic conditions, so the date of the spraying decision also is variable.

The utility function used in the study is the power function which has decreasing absolute risk aversion but constant relative risk aversion. This form was chosen on the basis of empirical evidence that the degree of absolute risk aversion exhibited by many decision makers in agriculture is a negative function of their wealth (e.g., Hamal and Anderson). The functional form of the constant relative risk aversion utility function is

(8) $$U = a + b \cdot \pi^{(1-R_r)},$$

where U is utility, π is wealth (initial wealth plus income), R_r is the relative risk aversion coefficient, and a and b are parameters. Values of R_r were chosen on the basis of empirical evidence and theoretical arguments in the literature. Several studies using econometric approaches to estimate relative risk aversion have been published, producing estimates of 1 to 2 (Antle 1987), zero to 2 (Bardsley and Harris), and 1 to 3 (Myers). Other ranges for relative risk aversion suggested in the literature have included .5 to 1.2 (Newbery and Stiglitz), zero to 4 (Little and Mirrlees; Hamal and Anderson), and approximately 1 (Arrow). From this literature, it appears that values between zero and 1.8 should capture the risk attitudes of most farmers.

The numerical analyses are conducted using mean values for costs, prices, weed densities, and yields considered reasonable for the shire of Merredin in Western Australia's eastern wheatbelt: wheat price \$144 tonne^{-1}, diclofop-methyl cost \$48 per kg, weed-free and herbicide-free yield 1.14 tonnes ha^{-1}, initial weed density 100 to 400m^{-2}, crop area 1,000 ha, and recommended herbicide rate .375 kg active ingredient ha^{-1}. (Currency is Australian dollars throughout. In September 1993, A\$1 = US\$.65.) In all analyses, the value of information is calculated on the basis of 1,000 hectares of crop (a typical area in the study region) and then converted to a per hectare figure.

Decision Frameworks

Two approaches to decision making for herbicide use are compared in the study. One is the calculation of optimal herbicide rates consistent with the marginal analysis approach to input selection familiar to economists. Pannell (1990a) showed that the profit maximizing herbicide dose is positively related to both weed density and weed-free yield. Thus, information on either of these variables is valuable because it allows the farmer to adjust herbicide rates to more profitable levels. This approach is relevant only if farmers are willing to adjust their rate of herbicide application to suit the conditions at hand. While this is common practice in some regions, in others, farmers rarely deviate from recommended rates of chemicals. For these farmers, an economic threshold rule may be more relevant.

The economic threshold is defined here as the combination of weed density and weed-free yield above which a fixed recommended herbicide rate is preferred to zero herbicide application. Pannell (1990a) illustrates a two-dimensional threshold of this type. It can be thought of as a weed density threshold which varies depending on the expected weed-free yield. A farmer using this decision rule would first make an estimate of the weed

Table 1. Variables in the Model of Yield Response to Herbicide Application

Variable	Unit	Description
b	—	Proportional yield loss per weed as $W \rightarrow 0$
D	—	Proportional yield loss due to weed competition
F	—	Parameter of logistic kill function
H	kg ha^{-1}	Herbicide dosage (in active ingredient terms)
K	—	Proportion of weeds killed at herbicide dose H
W	m^{-2}	Weed density in the crop
W_0	m^{-2}	Pretreatment weed density in the crop
Y	kg ha^{-1}	Actual crop yield
Y_0	kg ha^{-1}	Weed-free crop yield
Y_p	kg ha^{-1}	Weed- and herbicide-free crop yield

density and weed-free yield for the crop. Then, if this density exceeded the threshold value for that weed-free yield, the fixed recommended herbicide dose would be applied. For lower densities, no herbicide would be used. This binary "all-or-nothing" approach is the most commonly used decision rule in economic analyses of pesticide decisions, although usually only information about pest level is considered. Given its relative simplicity to calculate and use, it might be considered a manifestation of bounded rationality. However, simplicity has its price. Moffitt observed that "the very simple if-then-else decision rule common in pesticide treatment recommendations cannot be more profitable than the marginal decision rule" (p. 630).

Results and Discussion

Value of Information

The expected value of information is calculated as the difference between the certainty equivalent value of the distributions of income with and without use of the information. Figure 1 shows certainty equivalents for four different herbicide strategies: always applying zero herbicide (labeled "zero"), always applying the recommended label rate ("label"), a multidimensional threshold approach (similar to Pannell 1990a) using both yield and density information ("threshold"), and an optimal rate approach using both sources of information ("optimal"). The graph shows how certainty equivalents change in response to risk aversion given a mean weed density of 200m^{-2}. Increasing risk aversion reduces the certainty equivalent for all strategies (the welfare of a risk-averse decision maker is reduced by income variation and the greater the degree of risk aversion, the greater the reduction in welfare). At zero risk aversion, the order of preference (from highest to lowest) of the strategies is: optimal, threshold, label, and zero. As risk aversion increases, the margin between the optimal rate and economic threshold approaches is maintained. However, the strategy of using herbicide prophylactically (the "label" strategy) has greater income variability, so as risk aversion increases, the certainty equivalent falls more rapidly than for the other strategies. At levels of relative risk aversion above 1.7, the risk premium from blanket use of herbicides is so great that zero-use of herbicide is preferred despite its lower expected profit.

If herbicide dose is considered to be a binary variable (i.e., the threshold approach), the prior optimal act is either to apply the label rate or zero, whichever has the higher certainty equivalent. Thus, the expected value of information for the threshold approach is the difference between the "threshold" line in figure 1 and whichever is greater of the "label" and "zero" lines. The value of information for the optimal rate strategy is not

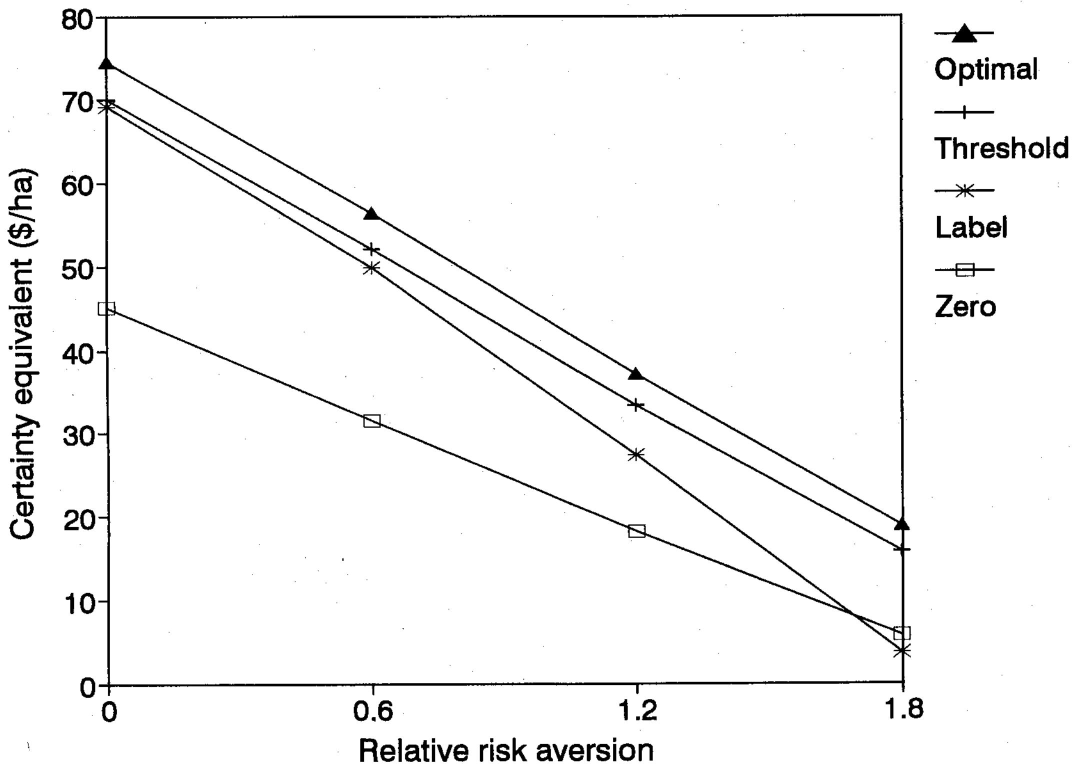

Figure 1. Certainty equivalent for different strategy types (weed density = 200m^{-2})

illustrated in figure 1 since the prior optimal act (use of an endogenously determined optimal dose) is not depicted.

Figure 2 shows the expected value of information in the optimal rate strategy for a mean initial weed density of 400m^{-2}. For risk-neutral decision makers (R_r = 0), the expected value of information about weed density exceeds that for weed-free yield. However, as risk aversion increases, two trends are apparent. The value of weed density information slowly declines so that under high risk aversion it is less than one-third of the value under risk neutrality. At the same time, the value of yield information increases dramatically with risk aversion to be more than 15 times as great if R_r = 1.8 than if R_r = 0. Yield information is worth more than weed density information for all non-zero levels of risk aversion examined. The value of combining both sources of information in the decision is not exactly, but approximately, equal to the sum of the values for individual information use. The magnitude of information value is low for risk-neutral decision makers: less than $1 per hectare of crop. For risk-averse decision makers, the value of yield information is more substantial: several dollars per hectare.

It is instructive to examine the reasons for the trends in figure 2. Table 2 shows expected profits and certainty equivalents under full information and no information. It is apparent from this table that the benefits of information use under risk aversion are primarily due to reductions in the cost of risk rather than increases in expected profit. Under risk neutrality, full information increases expected profit by $.76 ha^{-1}, whereas the optimal strategy under risk aversion produces expected profits which are $.86 ha^{-1} higher with information than without it. The effect of information on expected profit is increased only slightly by risk aversion. The trend of increasing information value is, then, almost entirely due to reduction in the risk premium. Of the $6.10 which is the expected value of full information under high risk aversion, $5.24 is due to reduction in the risk premium.

Figure 3 is equivalent to figure 2 except that figure 3 is for the threshold strategy. A

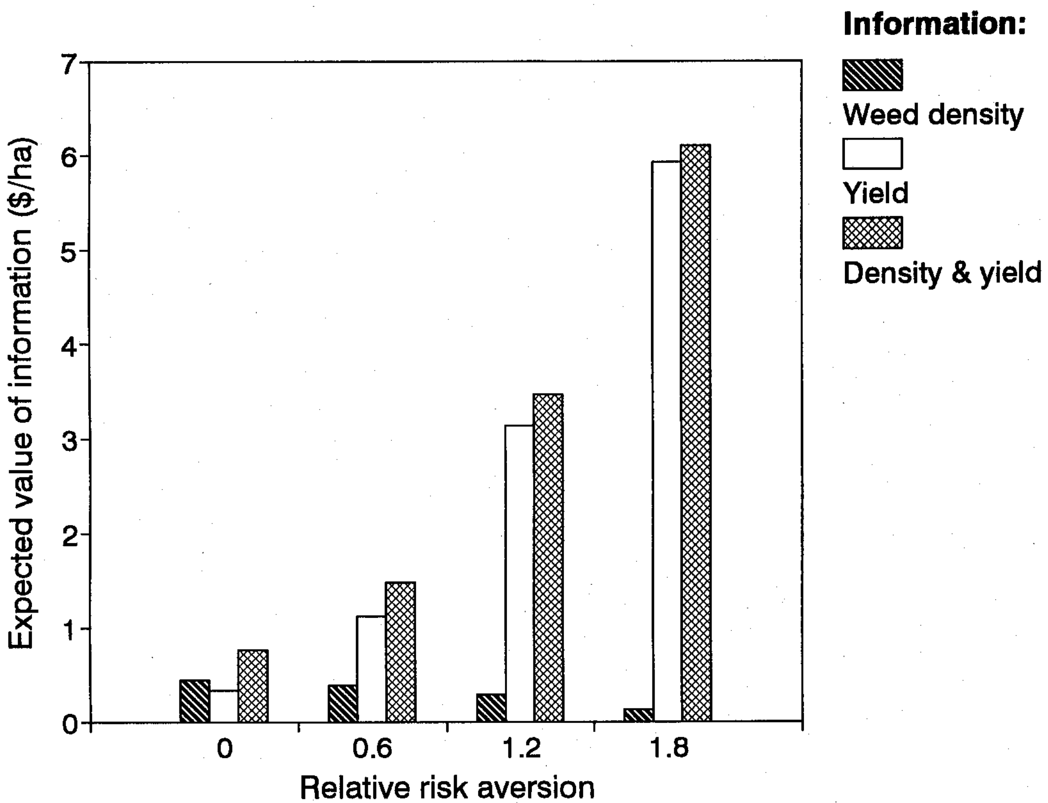

Figure 2. Expected value of information (optimal rate approach; 400 weeds m^{-2})

comparison of the two figures reveals that the value of yield information is substantially higher in the threshold strategy than in the optimal rate strategy. Yield information is worth up to \$11 ha^{-1} to a highly risk-averse decision maker using a threshold strategy, whereas a similar decision maker applying optimal herbicide rates would not be prepared to pay more than \$6 ha^{-1} for the information.

In contrast to the higher value of yield information, weed density information is worth less in the threshold approach. This is because there is less scope for flexibility in the threshold decision framework. With the assumed mean and variance of weed density in this example, there is only a small probability of a weed density being so small as to justify zero herbicide application. Consequently, in most years, weed density information does not change the control decision from the prior optimal act, i.e., apply the recom-

Table 2. Effect of Full Information on Expected Profit (\$ ha^{-1}) and Certainty Equivalents (\$ ha^{-1})

		Relative Risk Aversion	
	Information	.0	1.8
Expected Profit	None	70.43	69.91
	Full	71.19	70.77
	Value	.76	.86
Certainty Equivalent	None	70.43	9.45
	Full	71.19	15.55
	Value	.76	6.10

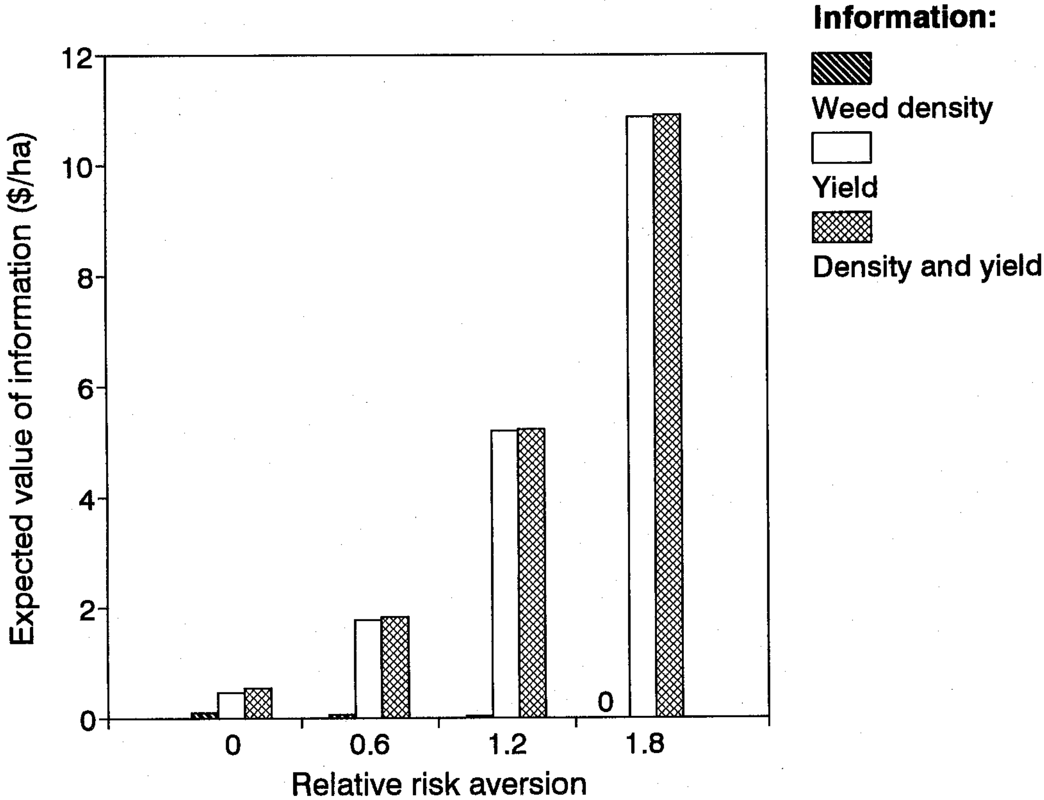

Figure 3. Expected value of information (threshold approach; 400 weeds m^{-2})

mended rate. However, if adjustments in herbicide dosage are allowed, information about weed density is very likely to affect the level of treatment and to improve profits.

It is interesting to compare the results presented in figure 3 with those from other studies which have investigated the impact of risk aversion on the value of information used in damage agent control decisions. Thornton and Dent (1984b) found that in a threshold decision framework, the value of information about disease level declined with increasing risk aversion. By contrast, Antle (1988), also using a threshold approach, found that the value of pest density information in an integrated pest management (IPM) program increased with risk aversion. The results in figure 3 are consistent with those of Thornton and Dent (1984b), with the value of weed density information being negatively related to degree of risk aversion. However, other results not presented here show that if yield is treated as a deterministic variable, the value of information about weed density increases with risk aversion, consistent with Antle (1988). These results suggest that Antle might have found a different result had he treated yield as a stochastic variable.

Another contrast is that results from Thornton and Dent (1984b) and the present study suggest that the value of information about damage agent density is relatively low, whereas Antle (1988) estimated large values of information, particularly under risk aversion. It is not apparent why this difference occurred.

Figures 4 through 7 illustrate the effects of weed density on the values of the different types of information. Under risk neutrality in an optimal rate approach, the value of information is very insensitive to the mean weed density (fig. 4). In other words, expected profit with and without information falls at almost the same rate with increasing weed density.

Under moderate risk aversion, however, a trend is readily apparent. Figure 5 shows

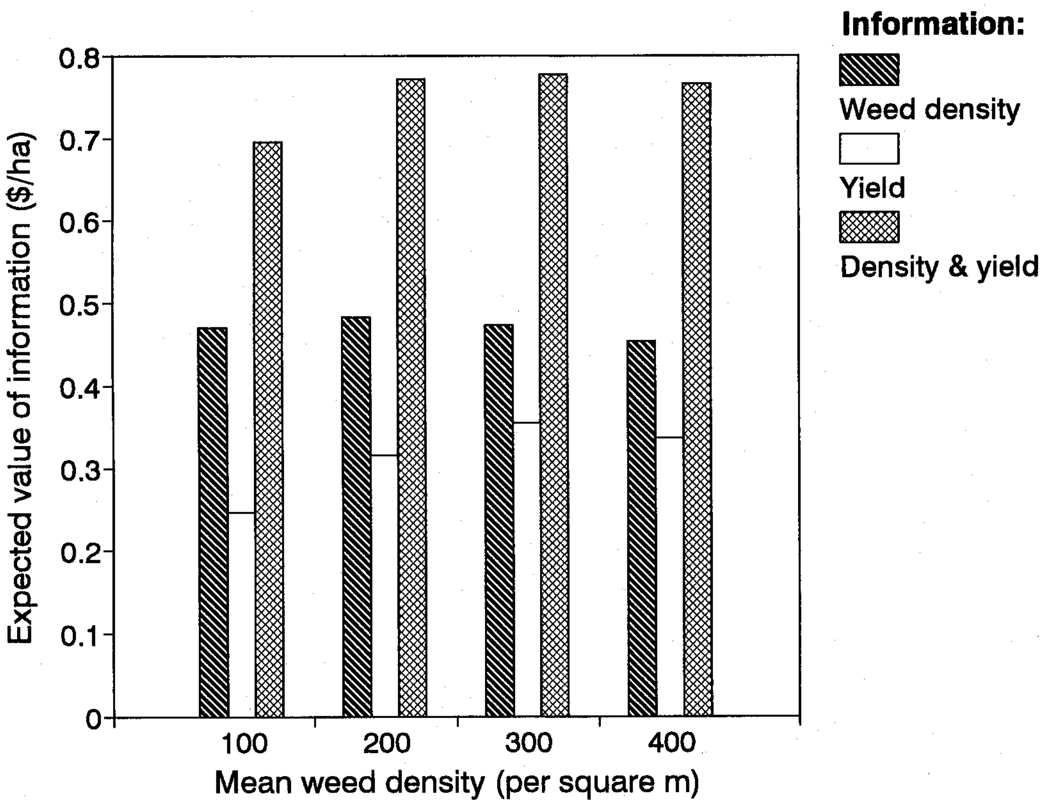

Figure 4. Expected value of information (optimal rate approach; relative risk aversion 0.0)

that if $R_r = 1.2$, the value of yield information increases with weed density when an optimal rate strategy is adopted. The value of weed density information is still unaffected by mean weed density. Because of the increase in yield information value, the value of joint information increases with weed density.

One factor contributing to the increased value of yield information is the increase in herbicide use which accompanies higher weed densities. Higher herbicide use means that there is potential to avoid grater herbicide costs by using yield information. This would be a benefit to risk-neutral as well as risk-averse decision makers. It is apparent from figure 4 that the extent of this benefit is not great. Therefore, the major reason for the trend in figure 5 is changes in the utility cost of risk. Table 3 shows that the certainty equivalent of the profit distribution falls with increasing weed density and that the fall is less rapid if yield information is used.

Figures 6 and 7 show the effect of weed density on information value if the threshold strategy is adopted. There are some striking differences between these results for the threshold approach and those just discussed for the optimal rate approach. Results for risk neutrality are shown in figure 6. In this figure, the value of information is more sensitive to weed density than it was in the equivalent figure for the optimal rate approach (fig. 4).

Whereas increasing weed density slightly increases the value of yield information in figure 4, the trend in figure 6 is for yield information value to decrease. Furthermore, whereas the value of weed density information was almost unaffected by weed density in figure 4, it declines markedly in figure 6. These two trends mean that the value of using both types of information declines with increasing weed density.

There are different reasons for the declines in values of the two types of information.

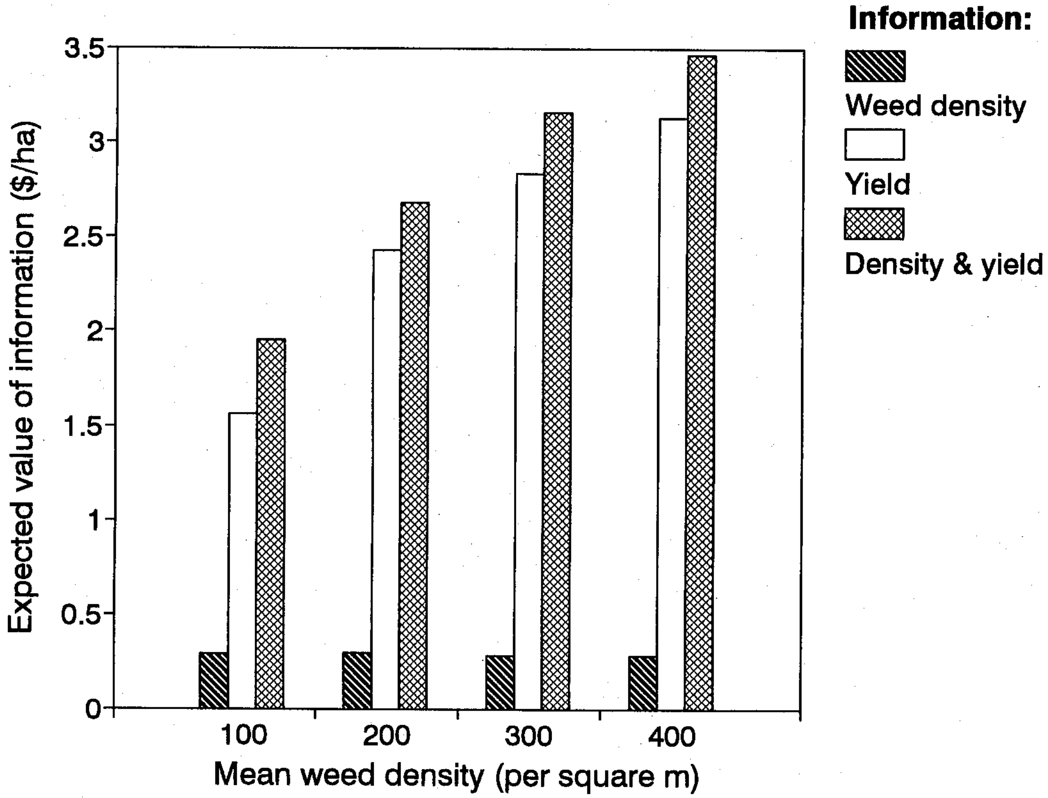

Figure 5. Expected value of information (optimal rate approach; relative risk aversion 1.2)

In the case of information about weed density, a higher mean weed density lowers the probability that the actual weed density will be below the threshold for herbicide use. Since the prior optimal act is to use herbicide, a rise in mean weed density reduces the probability of information changing the treatment decision and so reduces the expected value of the information. For yield information, a rise in mean weed density does not affect the distribution of weed-free yields, but it does reduce the threshold yield above which treatment is justified (e.g., see Pannell 1990a). Lowering the yield threshold reduces the probability of nontreatment being the optimal act. Again, this reduces the probability of information changing the treatment decision and so reduces the expected value of the information.

Figure 7, for risk-averse decision makers, shows similar trends to those in figure 6, but the value of yield information is much higher under risk aversion (as discussed earlier) and the value of information about weed density is even more sensitive to changes in mean weed density. This latter result is related to the effect of risk aversion reducing the

Table 3. Effect of Weed Density on Certainty Equivalents and Value of Information in Optimal Rate Approach (R_r = 1.2)

Weed Density	Certainty Equivalent ($ ha^{-1})		Value of Yield Information ($ ha^{-1})
	No Information	Yield Information	
100	19.76	22.55	2.79
200	14.23	18.61	4.38
300	11.25	16.60	5.35
400	9.45	15.38	5.93

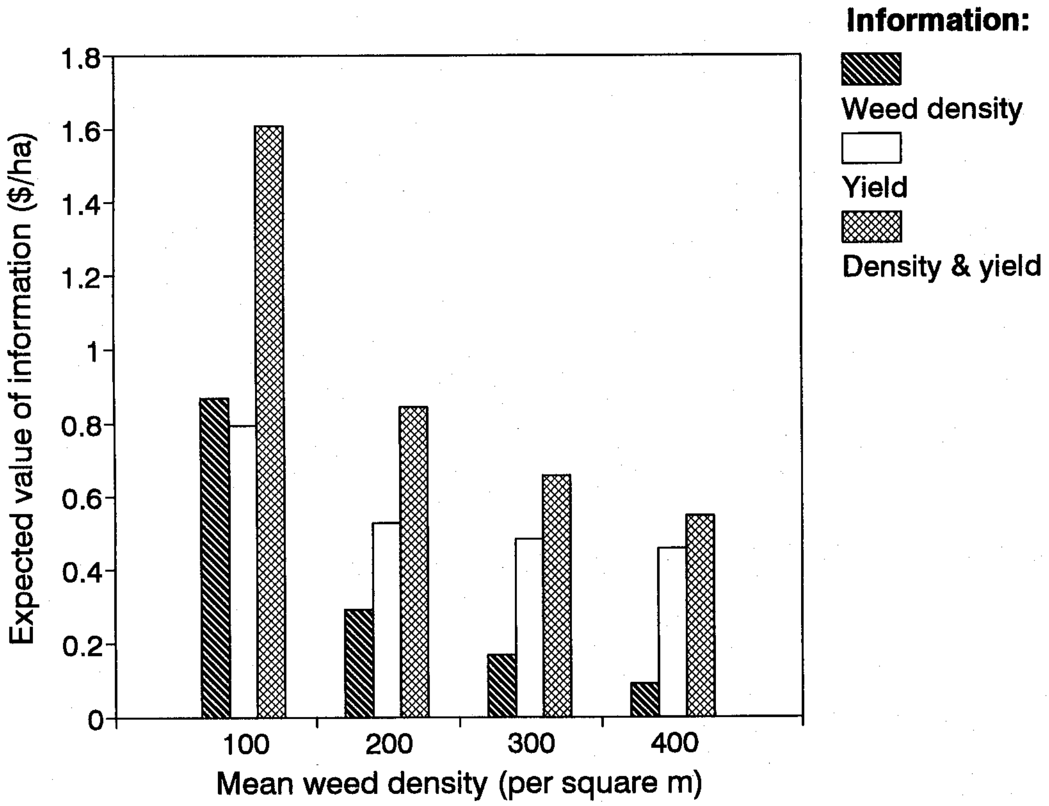

Figure 6. Expected value of information (threshold approach; relative risk aversion 0.0)

threshold density. This risk effect interacts with mean weed density to reduce the value of weed density information to very low levels at high weed densities.

On the basis of results by Menz and Webster, Webster assumed that the values of different types of information are independent and additive. This assumption was not made in the present study, but from figures 2 through 7, it appears reasonable.

Herbicide Usage

The effect on herbicide use of the inclusion of weed and yield information in the decisions is illustrated in figure 8 (assuming R_r = 1.2 and mean weed density = 200m^{-2}). The results are consistent with herbicide use in the study region where rates of diclofop-methyl range from .19 to .38 kg ha^{-1}, depending on circumstances. For each decision framework, herbicide use decreases with increasing information. The effect of yield information on herbicide use is greater than the effect of information about weed density. Information has a much greater impact on herbicide use in the threshold strategy.

However, even if no information is used in the optimal rate strategy, the resulting expected level of herbicide use is still lower than results from full information use in the threshold strategy.

Implications

The results presented in this article have some important practical implications for procedures used to select pest control strategies in general and herbicide strategies in particular. First, in most circumstances, the value of adjusting decisions on the basis of revised expectations about weed-free yield was found to exceed the value of adjusting for the

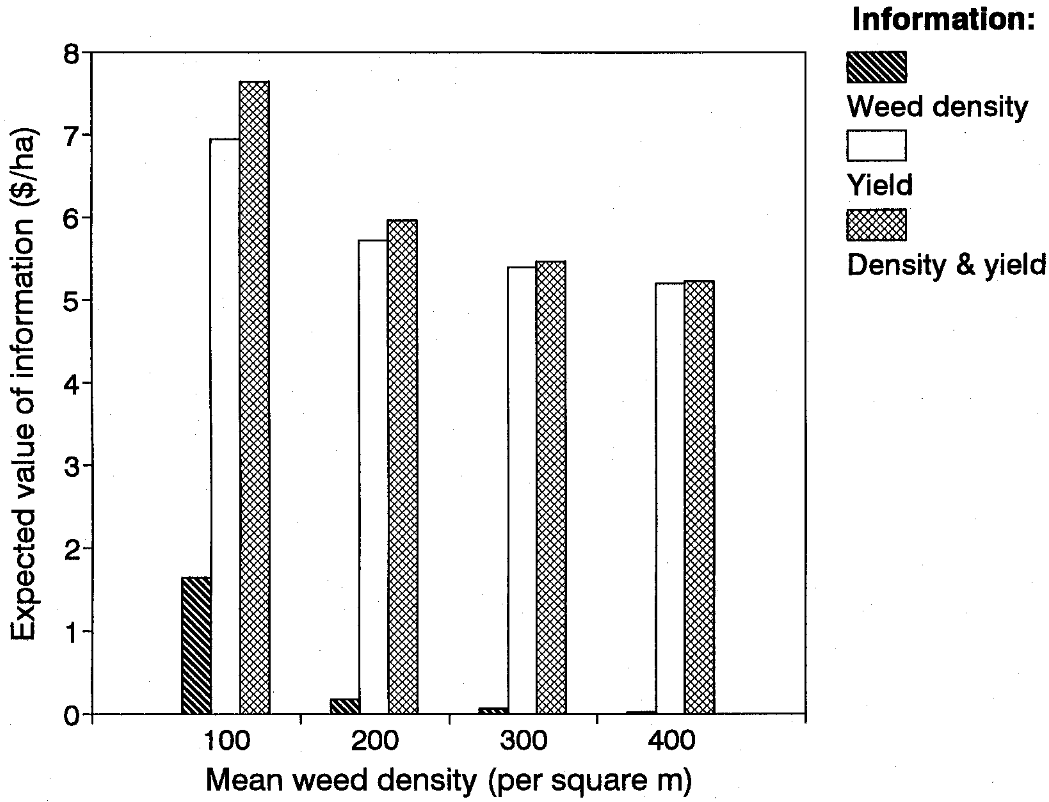

Figure 7. Expected value of information (threshold approach; relative risk aversion 1.2)

actual weed density. In many cases, the difference between these two values was substantial. This occurred even though the value of weed density information would have been slightly inflated by (*a*) the assumption that it was perfect information, and (*b*) the assumed variance of weed density being at the high end of what was considered the likely range. It is remarkable that the value of perfect information about weed density is often significantly less than the value of relatively imprecise information about weed-free yield.

Given this finding, the possibility of yield affecting pesticide decisions needs wider consideration than it has received in the past. Carlson reviewed eight studies of risk in pest control. In all cases, a traditional threshold based on pest level was used, with no option for updating decisions according to yield prospects. On investigation, it may be found that, in other environments or farming systems, yield is not as important a variable as damage agent density. However, this should not be presumed without good reason.

There is widespread concern about levels of pesticide use in agriculture. Results suggest that public provision of information and/or decision support may be an effective means of reducing external costs from pesticide use. The public sector is more likely to be able to provide useful information on climate/yield prospects than on pest densities due to the locational specificity of pest information. The yield information also may be subject to under-provision due to its public-good nature. At least in the example presented here, such under-provision would significantly increase herbicide use, especially by farmers who follow a threshold-type decision rule.

Concluding Comments

The value of information used in this weed control situation varies widely depending on the degree of risk aversion, the expected weed density, and the decision framework used.

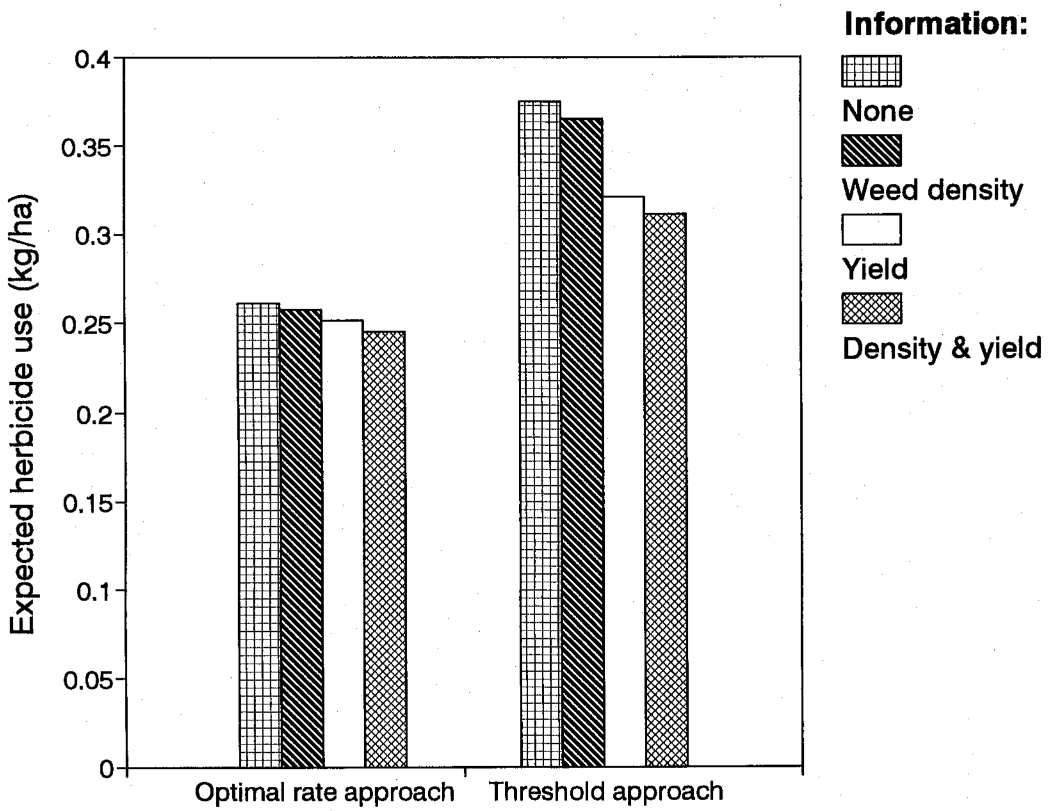

Figure 8. Expected herbicide use (relative risk aversion 1.2; 200 weeds m^{-2})

The value can be as much as \$11 per hectare for highly risk-averse decision makers using a threshold decision rule. This represents 15% of the expected gross margin from the crop.

Information about climatic effects on yield prospects does reduce income risks from weed control. This is reflected in higher values of yield information under higher risk aversion for both decision rules examined. On the other hand, information about weed density declines in value with increasing risk aversion.

The most striking result of the study is the high value to risk-averse farmers of information about crop yield prospects. Yield information is particularly important if a threshold decision rule is used (fig. 3). The high value of yield information was due primarily to avoidance of herbicide application in years of poor yield potential, preventing further reductions in profit in what are already unprofitable seasons. This is of particular significance to risk-averse decision makers.

Risk aversion and the mean weed density were found to be important in determining producers' willingness to pay for information. The value of information on weed density was generally less at higher levels of risk aversion, whereas the value of yield information can be very much higher. The effect of mean weed density on information value depends on which decision rule is used.

Expected use of herbicides is reduced by inclusion of these types of information in the decision process. The reduction in herbicide usage is greater under a threshold decision rule relative to a marginal analysis approach.

Although the results of this study are specific to a particular weed control problem in Australia, these results should encourage investigation of the value of yield information in other pest control situations. The probability of similar results being obtained is highest where yields are highly variable (e.g., in dryland situations) and where there is a reasonable correlation between prior rainfall and final crop yield.

The climatic information analyzed here is for the period prior to the treatment decision. Another possible avenue of investigation is the value for weed control purposes of long-range climatic forecasts. Several such forecasting services are provided by commercial operators in Australia.

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Notes

[1] Negative draws are assigned the value of zero.

[2] Refer to Pannell (1990b) for standard errors and goodness-of-fit statistics for parameters in this and later equations.

References

Abadi-Ghadim, A. K., and D. J. Pannell. "Economic Trade-Off Between Pasture Production and Crop Weed Control." *Agr. Systems* 36(1991):1–15.

Anderson, J. R., J. L. Dillon, and J. B. Hardaker. *Agricultural Decision Analysis.* Ames IA: Iowa State University Press, 1977.

Antle, J. M. "Econometric Estimation of Producers' Risk Attitudes." *Amer. J. Agr. Econ.* 69(1987):509–22.

———. *Pesticide Policy, Production Risk, and Producer Welfare: An Econometric Approach to Applied Welfare Economics.* Washington DC: Resources for the Future, 1988.

Arrow, K. J. *Essays in the Theory of Risk Bearing.* Amsterdam: North-Holland, 1971.

Auld, B. A., K. M. Menz, and C. A. Tisdell. *Weed Control Economics.* London: Academic Press, 1987.

Bardsley, P., and M. Harris. "An Approach to the Econometric Estimation of Attitudes to Risk in Agriculture." *Aust. J. Agr. Econ.* 31(1987):112–26.

Cammell, M. E., and M. J. Way. "Economics of Forecasting for Chemical Control of the Black Bean Aphid, *Aphis fabae,* on the Field Bean, *Vicia faba.*" *Ann. Appl. Biol.* 85(1977):333–43.

Carlson, G. A. "Risk Reducing Inputs Related to Agricultural Pests." In *Project Proceedings: Risk Analysis of Agricultural Firms: Concepts, Information Requirements, and Policy Issues,* pp. 164–75. Regional Research Project S-180, Dept. Agr. Econ., University of Illinois, Urbana, 1984.

Hamal, K. B., and J. R. Anderson. "A Note on Decreasing Absolute Risk Aversion Among Farmers in Nepal." *Aust. J. Agr. Econ.* 26(1982):220–25.

King, R. P., D. W. Lybecker, E. E. Schweizer, and R. L. Zimdahl. "Bioeconomic Modeling to Simulate Weed Control Strategies for Continuous Corn (*Zea mays*)." *Weed Sci.* 34(1986):972–79.

LeBaron, H. M., and J. Gressel. *Herbicide Resistance in Plants.* New York: Wiley-Interscience, 1982.

Lichtenberg, E., and D. Zilberman. "The Econometrics of Damage Control: Why Specification Matters." *Amer. J. Agr. Econ.* 68(1986):261–73.

Little, I. M. D., and J. A. Mirrlees. *Project Appraisal and Planning for Developing Countries.* London: Heinemann, 1974.

Lybecker, D. W., E. E. Schweizer, and R. P. King. "Economic Analysis of Four Weed Management Systems." *Weed Sci.* 36(1988):846–49.

Marra, M. C., T. D. Gould, and G. A. Porter. "A Computable Economic Threshold Model for Weeds in Field Crops with Multiple Pests, Quality Effects, and an Uncertain Spraying Period Length." *Northeast. J. Agr. and Resour. Econ.* 18(1989):12–17.

Menz, K. M., and J. P. G. Webster. "The Value of a Fungicide Advisory Programme for Cereals." *J. Agr. Econ.* 32(1981):21–30.

Moffitt, L. J. "Incorporating Environmental Considerations in Pest Control Advice for Farmers." *Amer. J. Agr. Econ.* 70(1988):628–34.

Moffitt, L. J., R. L. Farnsworth, L. R. Zavaleta, and M. Kogan. "Economic Impact of Public Pest Information: Soybean Insect Forecasts in Illinois." *Amer. J. Agr. Econ.* 68(1986):274–79.

Myers, R. J. "Econometric Testing for Risk Averse Behavior in Agriculture." *Appl. Econ.* 21(1989):541–52.

Newbery, D. M. G., and S. E. Stiglitz. *The Theory of Commodity Price Stabilization: A Study in the Economics of Risk.* Oxford: Clarendon Press, 1981.

Pandey, S., R. K. Lindner, and R. W. Medd. "Towards an Economic Framework for Evaluating Potential Benefits from Research into Weed Control." *J. Agr. Econ.* 44(1993):322–34.

Pandey, S., and R. W. Medd. "Integration of Seed and Plant Kill Tactics for Control of Wild Oats: An Economic Evaluation." *Agr. Systems* 34(1990):65–76.

Pannell, D. J. "An Economic Response Model of Herbicide Application for Weed Control." *Aust. J. Agr. Econ.* 34(1990a):223–41.

———. "Model of Wheat Yield Response to Application of Diclofop-Methyl to Control Ryegrass (*Lolium rigidum*)." *Crop Protection* 9(1990b):422–28.

———. "Pests and Pesticides, Risk and Risk Aversion." *Agr. Econ.* 5(1991):361–83.

———. "Responses to Risk in Weed Control Decisions Under Expected Profit Maximisation." *J. Agr. Econ.* 41(1990c):391–403.

Roberts, E. J., G. J. Syme, K. D. Williams, and J. M. Hector. "Farmers' Attitudes to Weeds and Weed Control." Discus. Pap. No. 4/88, Agriculture Protection Board, Perth, Australia, 1988.

Stefanou, S. E., M. Mangel, and J. E. Wilen. "Information in Agricultural Pest Control." *J. Agr. Econ.* 37(1986): 77–88.

Thornton, P. K., and J. B. Dent. "An Information System for the Control of *Puccinia hordei,* I: Design and Operation." *Agr. Systems* 15(1984a)209–24.

———. "An Information System for the Control of *Puccinia hordei,* II: Implementation." *Agr. Systems* 15(1984b): 225–43.

Thornton, P. K., R. H. Fawcett, J. B. Dent, and T. J. Perkins. "Spatial Weed Distribution and Economic Thresholds for Weed Control." *Crop Protection* 9(1990):337–42.

Webster, J. P. G. "The Value of Information in Crop Protection Decision Making." In *Decision Making in the Practice of Crop Protection,* ed., R. B. Austin, pp. 33–41. Croydon, England: British Crop Protection Council, 1982.