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A MODEL OF WHEAT YIELD RESPONSE TO  
APPLICATION OF DICLOFOP-METHYL  
TO CONTROL RYEGRASS (LOLUM RIGIDUM)

DAVID J PANNELL

Discussion Paper 11/89

Nedlands, Western Australia 6009

SOCIOECONOMIC



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**A MODEL OF WHEAT YIELD RESPONSE TO APPLICATION OF DICLOFOP-METHYL  
TO CONTROL RYEGRASS (*LOLIUM RIGIDUM*)**

**Abstract**

A general model of crop yield response to herbicide application is proposed. The model includes three components: the effect of herbicide dosage on weed density, the effect of surviving weed density on crop yield and the effect of herbicide directly on the crop. The model is used to estimate the response of wheat yield to application of diclofop-methyl to control ryegrass (*Lolium rigidum*) in Australia. It is found that the competitiveness of ryegrass plants surviving treatment is reduced by the treatment and that the proportion of yield lost at a given ryegrass density is not independent of the absolute weed-free yield. The response function is used to calculate economic thresholds and optimal herbicide dosages for ryegrass control in wheat by diclofop-methyl.

**Introduction**

In order to determine economically optimal herbicide dosages (Pannell 1987) or economic thresholds for herbicide application (Auld et al 1987) it is important to estimate the relationship between the level of herbicide application and the crop yield (the "production function"). This type of relationship has been illustrated in theoretical discussions by Auld et al (1987) and Davidson (1974) but they did not discuss the issues involved in estimating such a production function and neither included an empirical example.

Some production functions have been estimated for pesticides in the United States (eg, Headley 1968, Fischer 1970, Campbell 1976, Neal 1983). In each of these cases, the models involved simple single equation forms commonly employed by agricultural economists for analysis of response. However Lichtenberg and Zilberman (1986) showed that accurate representation and estimation of the production function requires the use of functional forms consistent with the technology and biology of damage control. In particular the effect of pesticides should be represented as occurring through their effect on pest levels. Two equations are required: one describing the effect of pesticide on the pest level and the other giving the effect of surviving pests on crop yield. In the case of herbicides there may be an additional direct effect of the herbicide on the crop (eg, Bowran et al 1987).

In this paper the appropriate form of a yield response model to herbicide application is considered in more detail. The proposed model is consistent with Lichtenberg and Zilberman's call for biologically realistic functions. The general form of the model is presented in the next section together with more specific discussions of the effect of herbicides on weed survival and the effect on crop yield of the number of weeds surviving treatment. The parameters of the model are estimated for post-emergent application of diclofop-methyl (as Hoegrass<sup>R</sup>) for control of ryegrass (*Lolium rigidum*) in wheat.

**The Production Function for Herbicide**

In this study, the general functional forms used are

$$Y = Y_0 \cdot [1 - D(W)] \cdot N(H) \quad (1)$$

and

$$W = W_0 \cdot [1 - K(H)] \quad (2)$$

where  $Y$  is crop yield,

$Y_0$  is yield obtained with no weeds present and no herbicide applied (hereafter termed the "weed-free yield"),

$W$  is post-treatment weed density,

$D(W)$  is the damage function giving the proportion of yield lost at weed density  $W$ ,

$H$  is herbicide dosage,

$N(H)$  is one minus the proportion of yield lost through phytotoxicity of the herbicide to the crop.

$W_0$  is initial or pre-treatment weed density, and

$K(H)$  is the kill function giving the proportion of weeds killed at herbicide rate  $H$ .

Now consider the specific functional forms for components of this model.

#### Weed survival function

In this section the specific form of the kill function,  $K(H)$  is considered. Pest mortality from application of pesticides is an example of a quantal response: a response which "permit[s] of no graduation and can be expressed only as 'occurring' or 'not-occurring'" (Finney 1971, p.1). There exists an extensive literature on statistical considerations in the estimation of all-or-nothing or quantal responses (eg, see reference lists in Finney 1971 or Hewlett and Plackett 1979). Although there have been a few economic studies in which the relationship between pesticides and pest kill has been considered, the relationship has often been approximated by an exponential function (eg, Auld et al 1987, Doyle et al 1984, Feder 1979, Moffitt et al 1984). Only occasionally has the relevant statistical theory and its implications for appropriate functional forms been mentioned in the literature on pest control economics (eg, Talpaz and Borosh 1974, Talpaz et al 1978, Moffitt and Farnsworth 1981) and never for weed economics.

The two most common approaches to modelling quantal responses are the probit and logit models. The probit model is based on the normal cumulative distribution function (CDF) while the logit model is based on the logistic CDF. In practice the two models leads to almost identical fitted values and predictions. However it has some analytical and computational advantages due to the simplicity of the logistic CDF relative to the normal CDF. For this reason the logistic CDF will be used as the basis of the model estimated here. The functional form used is

$$p = 1/[1 + \exp(-\beta H)] \quad (3)$$

where  $p$  is the proportion of individuals which respond,

$H$  is herbicide rate, and

$\beta$  is the parameter to be estimated.

An important consideration for herbicide applications to weeds is that mortality at a particular input level may depend on a range of factors other than the herbicide rate. For example environmental conditions such as temperature, humidity and soil moisture may influence herbicide effectiveness (Casely 1987). In addition the proportion of weeds killed may be dependent on the absolute weed density. At very high densities, overtopping might occur, reducing the probability of an individual weed receiving a lethal dose. On the other hand, intraspecific competition at high weed densities may act to reduce tolerances to herbicides. In these circumstances an appropriate model may be

$$K(H) = 1/(1 + \exp[-(\alpha + \gamma G)H]) \quad (4)$$

where  $G$  is a variable which affects herbicide efficacy and  $\alpha$  and  $\gamma$  are the parameters to be estimated. In this function,  $G$  only affects  $K(H)$  via its influence on the parameter  $\beta$  from (3).  $\beta$  is assumed in this example to depend linearly on  $G$

$$\beta = \alpha + \gamma G \quad (5)$$

but other forms of the relationship could be investigated.

#### Crop yield function

The general form of the crop yield functions used in this paper is given in equation (1). In contrast to the weed kill function, there has been discussion in the weed economics literature of the form of the relationship between weed density and production loss. Various functional forms have been proposed and used in the literature including exponential (Auld and Tisdell 1986, Auld et al 1987, Poole and Gill 1987a, 1987b), hyperbolic (Chisaka 1977, Cousens 1986, Cousens et al 1985, 1986, Lapham 1987) and sigmoidal functions (Taylor and Burt 1984, King et al 1986). A linear function has occasionally been used to approximate crop damage in studies of pest and disease control (eg, Feder 1979, Moffitt et al 1984, Walker 1987, Lichtenberg and Zilberman 1986).

Cousens (1985) conducted tests of a wide range of functional forms to see how well they could be fitted to published data on crop damage under weed competition, concluding that hyperbolic forms gave the best results. He was particularly critical of sigmoidal forms claiming that empirical evidence does not support their use. Cousens (1985) provided both empirical and theoretical justification for the use of strictly concave crop damage functions such as the hyperbolic and exponential forms.

Damage functions used in this study will be of the following hyperbolic form:

$$D(W) = bW/(1 + bW/a) \quad (6)$$

This is the form which gave best fit in Cousens' analysis. It also has the advantage of readily interpretable parameters;  $a$  is the maximum yield loss at high weed densities and  $b$  is the marginal yield loss as weed density tends to zero.

Kropff (1988) commented that:

"although the hyperbolic yield-density equation fits very well with data of additive experiments where only the weed density is varied, model parameters may vary strongly among experiments, due to the effects of other factors on competition processes" (p.466).

Proportional yield loss resulting from a particular weed density is likely to be influenced by a number of factors. This could be allowed for by estimating  $a$  and/or  $b$  as functions of other variables. Such variables might include the weed-free crop yield, climatic variables, the date of weed emergence relative to the crop and the amount of herbicide applied to the weeds.

Herbicides may also enter the crop damage function in another way: by directly affecting crop yield. This possibility was raised by Hillebrant (1960) in the context of pest control and has been widely studied (eg, Bowran et al 1987) but there appears to have been no attempt to include this factor in a response function for any pesticide. Resistance to herbicides is rarely absolute, so that the weed-free yield is effectively

changed by the addition of herbicides to a crop. The term  $N(H)$  in equation (1) captures this effect.

#### Production Function for Diclofop-methyl

This section covers statistical estimation of the production function for post-emergent application of diclofop-methyl to control ryegrass in wheat. Farmers in Western Australia consider ryegrass to be one of their most important crop weeds (Roberts et al 1988) and diclofop-methyl is the chemical most commonly used for its control. Details of data obtained, statistical problems encountered, procedures used and resulting parameter estimates are presented.

Fortunately there is no problem with simultaneous equations bias in the model since causality flows sequentially from herbicide rate to weed density to crop yield. This means that the two functions can be estimated separately without bias and combined to give the overall response function. The following two sections provide estimation details for weed survival and crop yield respectively.

#### Weed survival function

Data. Data from numerous field trials of ryegrass control by diclofop-methyl at sites throughout Australia over several years were obtained from Hoechst Australia Ltd, the manufacturers of Hoegrass<sup>R</sup>. Unfortunately the weed density prior to herbicide application was frequently not recorded. Since this variable constitutes the information about weed density available to farmers at the time when spraying decisions are made, it was considered crucial for this study. However excluding trials in which pre-treatment weed densities were not estimated reduced the data set to only four trials.

There were 96 observations in the data set. Variables used in the estimation were herbicide rate, pre-treatment weed density and post-treatment weed density. Weed-free crop yield was estimated separately for each trial by fitting a hyperbolic model like equation (1) and extrapolating to zero weed density. Herbicide rate was measured as kg active ingredient (a.i.) per hectare. Six herbicide rates from zero to 0.9 kg a.i./ha were represented in the sample.

Estimation procedure. If the logistic CDF is expressed as a function of a linear predictor it can be estimated using Generalised Linear Modelling (GLM) (Nelder and Wedderburn 1972, Baker and Nelder 1986). The standard assumption in probit or logit analysis is that the error term is binomially distributed (eg, Finney 1971). However the assumption is not appropriate for this data set since the data displays variance increasing monotonically with weed survival. The reason for the difference is that in standard logit analysis, the number of organisms treated is known (or assumed to be known) exactly, whereas in this study the pre-treatment density has to be estimated by sampling. (For a similar problem see Wadley 1949). It was found that the error was almost exactly Poisson distributed. The microcomputer version of GLIM was used for the estimation.

It is usual in logit analysis to use the logarithm of the treatment variable (in this case herbicide rate) as the independent variable due to the common occurrence of a right skew in the distribution of tolerance to control inputs. This appears to be the case for diclofop-methyl application to ryegrass, so the logarithmic form of the model is used here. Unfortunately, use of the log form precludes the inclusion of zero herbicide rates in the estimation. Rather than leave these points out of the estimation, it was assumed that they were associated with a very low herbicide rate (0.001 kg a.i./ha).

A similar problem occurred with observations in which 100% weed kill was achieved, resulting in zero survival. The estimation algorithm involves taking logarithms of post-treatment density, so it was assumed that in all cases at least one weed per square metre survived treatment.

Results and discussion. Table 1 shows descriptions of the variables used in the following discussion. The first criterion used for including a variable in the model was that it should pass a t test for difference from zero at  $p=0.05$ . The second criterion used to evaluate a particular set of independent variables was their ability to give sensible predictions of weed survival for situations not encompassed by the trial results used in the estimation. This test was necessary because of the small number of trials used (four) so that only a few of the possible combinations of independent variables were included. To illustrate, there were two trials with weed-free yields of less than  $1500 \text{ kg ha}^{-1}$  and both of these had high soil moisture levels at the time of treatment. Although a model with all independent variables included fit these trials well, it gave unrealistic predictions for low or medium soil moisture levels at this weed-free yield.

Table 1: Variable descriptions and units

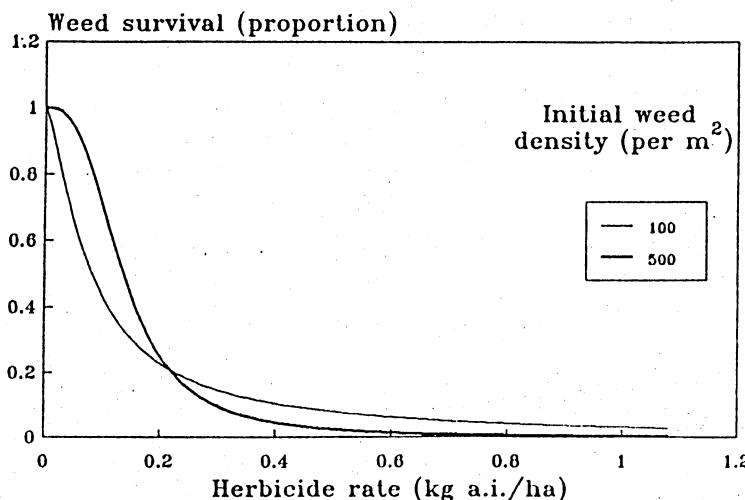
Variable	Description	Unit
H	Herbicide rate	kg a.i. ha <sup>-1</sup>
W	Post-treatment weed density	plants m <sup>-2</sup>
W <sub>0</sub>	Pre-treatment weed density	plants m <sup>-2</sup>
Y	Actual crop grain yield	tonnes ha <sup>-1</sup>
Y <sub>0</sub>	Weed-free crop grain yield	tonnes ha <sup>-1</sup>

Table 2: Parameter estimates for weed survival model

Variable	Parameter estimate	Standard error
Constant	-2.848	0.5187
ln(H)	-0.9948	0.4042
W <sub>0</sub>	-0.005588	0.001751
ln(H)•W <sub>0</sub>	-0.00361	0.001289

It was found that a model including  $\ln(H)$ ,  $W_0$  and  $\ln(H) \cdot W_0$  as independent variables passed both tests and fitted the data well. Estimated parameters for the model are shown in Table 2. Each parameter in Table 2 is significantly different from zero at  $p = 0.05$  and the value of  $r^2$  (calculated as  $1 - \sum(\hat{\phi} - \phi)^2 / \sum[\phi - E(\phi)]^2$  where  $\phi = W/W_0$ ) is high at 0.86. The sign of the parameter on  $\ln(H)$  is negative, as expected, implying that higher herbicide rates result in lower weed survival.

The significance of the parameters for terms including  $W_0$  indicates that the proportion of weeds killed at a particular herbicide rate is not independent of the pre-treatment weed density. Rather, there is a complex interplay between herbicide rate and weed density in determining the level of weed mortality. The parameter for  $W_0$  is negative, indicating that higher pre-treatment weed densities result in higher weed survival. However there is also an interaction between herbicide rate and initial weed density such that at higher herbicide rates, increasing initial weed density reduces weed survival. It appears that at higher weed densities, competition for light and nutrients acts to increase herbicide effectiveness. The combined effect of these two terms can be seen in Figure 1. At low herbicide rates, weed survival is greatest at high weed densities. As herbicide rate increases, weeds surviving the herbicide application are much weakened and are made more susceptible to competition. At herbicide rates above 0.2 kg a.i./ha the effect of competition dominates and higher weed densities result in lower proportional survival.



**Figure 1:** Effect of initial weed density on relationship between herbicide dosage and weed survival

It should be stressed that these results are based on just four trials so they should be interpreted tentatively. Further trials are needed to test the finding and to investigate the influence of weed-free yield on weed mortality for other herbicides and other weeds.

#### Crop yield function

Data. Data used to estimate the crop yield function were obtained from the same set of trials described above. Variables measured were herbicide rate, post-treatment weed density, weed-free crop yield and actual crop yield. The data set used included 339 observations from 14

trials in Western Australia, New South Wales and Victoria from 1975 to 1981.

Estimation procedure. Parameters of the crop yield function were estimated by non-linear regression using the microcomputer package Shazam (White 1978).

The estimation procedure in Shazam is maximum likelihood on the assumption of homoscedasticity. However a Goldfeld-Quandt test (Judge et al 1982) led to rejection of the null hypothesis of homoscedasticity at  $p = 0.01$ , so a weighted estimation was performed using the approach described by Taylor and Burt (1984).

Initially it was assumed that  $a$  and  $b$  are linear functions of  $Y_0$  and  $H$  and that the direct effect of herbicide on the crop is a linear function

$$a = a_1 + a_2 \cdot Y_0 + a_3 \cdot H \quad (7)$$

$$b = b_1 + b_2 \cdot Y_0 + b_3 \cdot H \quad (8)$$

$$N(H) = 1 + cH \quad (9)$$

Although this model fit the sample data quite well, problems were encountered when attempting to apply the model. The cause of the problems was the assumption that  $a$  and  $b$  depend linearly on  $Y_0$  and  $H$ . At sufficiently high levels of  $Y_0$  and/or  $H$ , negative values were predicted for  $a$  and/or  $b$  implying that yield increased with weed density. If possible a functional form should be chosen to reflect the fact that as  $Y_0$  and  $H$  reach high levels,  $a$  and  $b$  may approach zero but cannot become negative. The forms chosen were as follows.

$$a = a_1 \cdot \exp(a_2 \cdot Y_0) \cdot \exp(a_3 \cdot H) \quad (10)$$

$$b = b_1 \cdot \exp(b_2 \cdot Y_0) \cdot \exp(b_3 \cdot H) \quad (11)$$

Results and discussion. It was found that  $a_2$ ,  $a_3$  and  $c$  were not significantly different from zero, so they were dropped from the equation leaving the final model as

$$Y = Y_0 \cdot \left[ 1 - \frac{a}{1 + a/[b_1 \cdot \exp(b_2 \cdot Y_0) \cdot \exp(b_3 \cdot H)]} \right] + \epsilon \quad (12)$$

Table 3: Parameter estimates for yield model

Parameter	Parameter estimate	Standard error
$a$	0.5436	0.07114
$b_1$	0.01722	0.008487
$b_2$	-0.8010	0.1934
$b_3$	-5.705	2.0308

Parameter estimates for this model are shown in Table 3. All parameter estimates pass a t test for significant difference from zero at  $p = 0.05$  and  $r^2$  (calculated as  $1 - \sum(Y - \hat{Y})^2 / \sum(Y - E(Y))^2$ ) is 0.90 indicating very good fit by the model. This model effectively overcomes the problem of negative values for  $b_2$ . Parameters for  $b_2$  and  $b_3$  are negative, indicating that marginal yield loss declines with increases in  $Y_0$  or  $H$ .

The estimated effect of weed-free yield on proportional yield loss is shown in Figure 2. In low yielding crops, the proportion of yield lost increases rapidly as weed density increases from zero to 100 plants  $m^{-2}$ , but then remains relatively stable at higher densities. The graph shows that in higher yielding crops, proportional yield loss increases less rapidly and is much less at a given weed density.

Note, however, that although proportional yield losses are less, absolute yield losses may still be greater. For example Table 4 shows proportional and absolute yield loss for an untreated weed density of 300  $m^{-2}$ . The fall in proportional yield loss with increasing yield is not sufficient to reduce absolute yield loss.

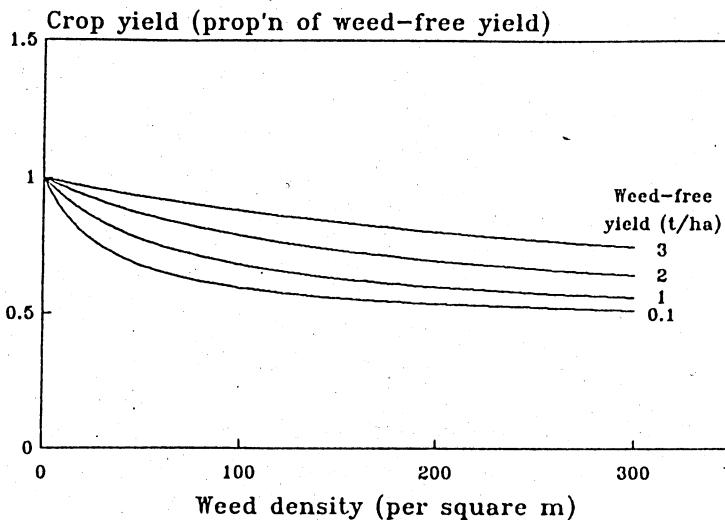


Figure 2: Effect of weed-free yield on relationship between weed density and crop yield if no herbicide applied

Table 4: Relative and absolute yield loss for various weed-free yields (weed density = 300  $m^{-2}$ ; herbicide rate = 0)

Weed-free yield ( $t \text{ ha}^{-1}$ )	0.1	1	2	3
Yield loss (%)	49	44	36	25
Yield lost ( $t \text{ ha}^{-1}$ )	0.05	0.44	0.71	0.75

Previously published relationships between weed density and crop yield have not included weed-free yield as a determinant of yield loss (eg, Poole and Gill 1987a, 1987b). The potential impact of this omission

on predicted yields is illustrated in Table 5. The table shows predicted yield losses for a model which is similar to equation (12) but excludes the  $\exp(b_2 \cdot Y_0)$  term. Model parameters were estimated using the same data

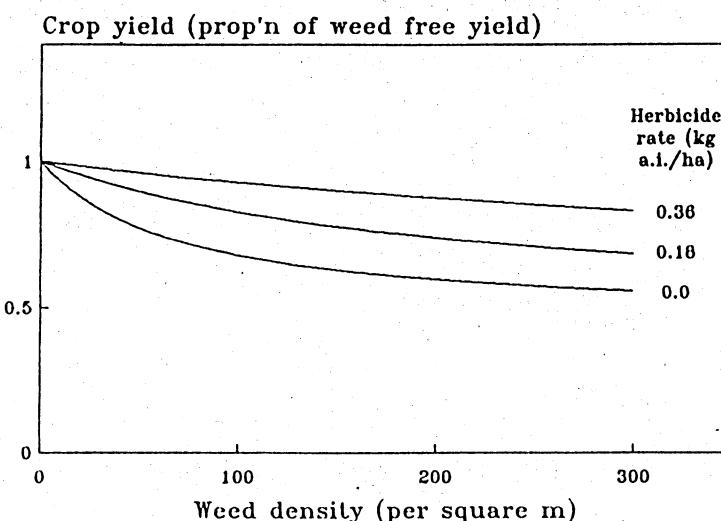
**Table 5:** Relative and absolute yield loss if relative yield loss not dependent on weed-free yield (weed density =  $300 \text{ m}^{-2}$ ; herbicide rate = 0)

Weed-free yield ( $\text{t ha}^{-1}$ )	0.1	1	2	3
Yield loss (%)	38	38	38	38
Yield lost ( $\text{t ha}^{-1}$ )	0.04	0.38	0.77	1.15

set as previously. A comparison of Tables 4 and 5 reveals that for weed-free yields up to  $2 \text{ t ha}^{-1}$ , errors resulting from the simpler model are less than  $100 \text{ kg ha}$  but at higher yields the prediction error may be quite substantial;  $400 \text{ kg ha}^{-1}$  if  $Y_0 = 3 \text{ t ha}^{-1}$ .

Figure 3 illustrates the way in which higher herbicide rates result in lower competitive abilities in those weeds which survive treatment.

Note that if weed density is reduced by applying herbicide, the shape of the yield function will depend on the level of herbicide applied. This means that two sites with the same weed density and the same yield potential can yield differently if different herbicide rates have been applied. For example, consider two sites with different pre-treatment weed densities (points A and C in Figure 4). If neither site is treated, the



**Figure 3:** Effect of herbicide rate on relationship between weed density and crop yield (weed-free yield =  $1 \text{ T ha}^{-1}$ )

relevant yield function is the same for each site (the darkest line on Figure 4). Imagine now that both sites are treated but that the high

density site receives a higher herbicide dose such that the final weed density is the same at each site (points B and D). At the site where a higher dose of herbicide is applied, weeds are less competitive and the relevant yield function is given by the dashed line in Figure 4. At the

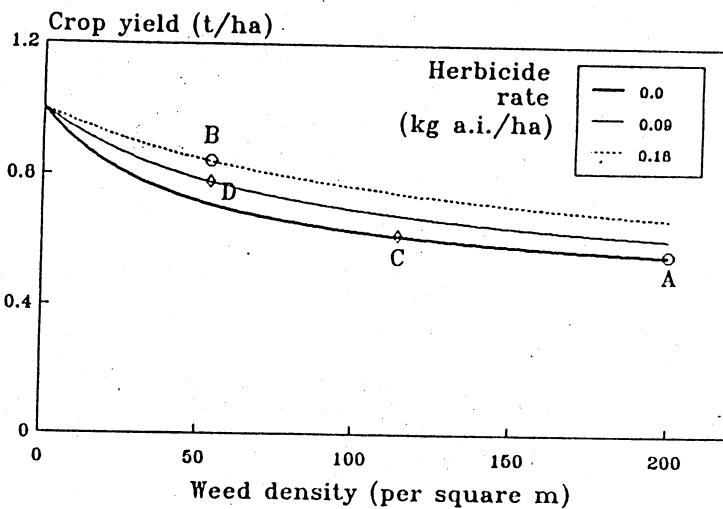


Figure 4: Crop yield versus weed density for different herbicide rates

other site weeds have not been so damaged and yield is given by the thin line passing through D. Thus although the weed density is the same at each site, yields differ.

Thus as herbicide rate is increased there is no movement along a given yield function. Rather there is movement across yield functions as illustrated in Figure 5. If an initial density of  $200 \text{ weeds m}^{-2}$  is not treated, yield is given by point A. As herbicide rate increases, weed density decreases and the yield function rises so that yield moves along the path ABCDE. This pattern of movement across functions is relevant to the yield response model being developed here, since the increase in yield resulting from herbicide application occurs only via a reduction in weed competition.

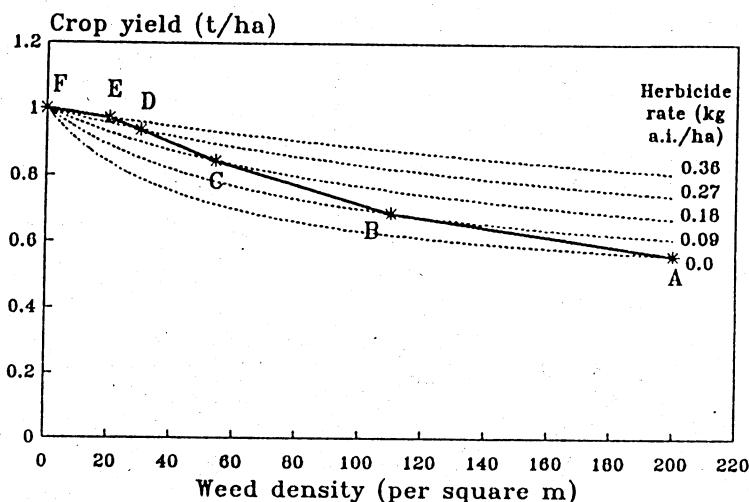


Figure 5: Relationship between weed density and crop yield obtained by applying herbicide

### Yield response to herbicide

In this section, the functions estimated above are combined to give the model of yield response to herbicide application. Figure 6 shows response functions for three situations with the same weed-free yield but different initial weed densities. If  $W_0$  is  $450 \text{ plants m}^{-2}$  the response model has a sigmoidal shape. As herbicide rate is increased from zero to  $0.1 \text{ kg a.i. ha}^{-1}$ , weed density is substantially reduced but not sufficiently to leave the relatively flat section of the function relating yield to weed density. Eventually, enough weeds are killed to reach the relatively steep part of the yield-weed density function so the response function rises more rapidly. Finally the response function flattens out again due to diminishing marginal weed kill and reductions in weed competitiveness at higher herbicide rates. Lower initial weed densities may already lie on the steep section of the yield-weed density function, in which case there is no section of the yield response curve with increasing marginal returns (eg, the dashed line in Figure 6).

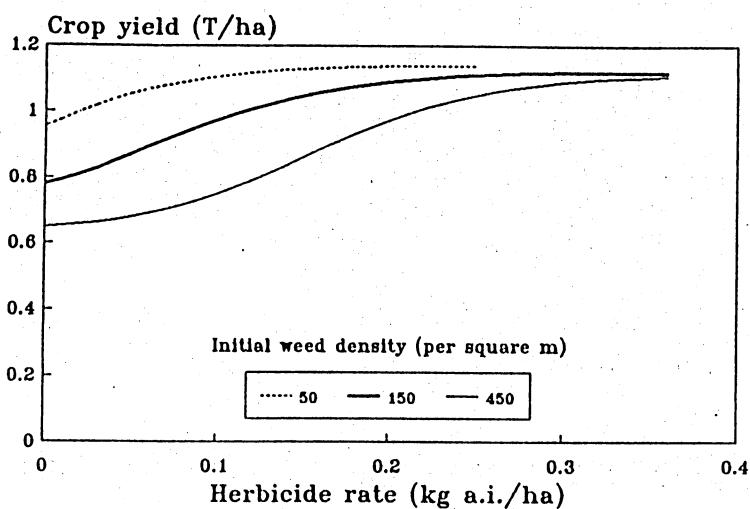


Figure 6: Production functions for various initial weed densities

### Economic Analysis

The response model derived above is useful for determining economically optimal weed management strategies. Two decision frameworks are considered here: the economic threshold approach and the optimal rate approach (Mumford and Norton 1984). In the traditional economic threshold approach the herbicide dosage is assumed to be fixed at the recommended or label rate. The decision maker simply has to calculate whether the recommended rate will be more profitable than no herbicide application. This calculation is usually summarised as a density threshold: a weed density above which treatment with the recommended dosage is more profitable than no treatment. It has been noted that the economic threshold is not a fixed value for a particular weed/herbicide combination (Cousens 1987). It depends on many variables in the system including the cost of herbicide, the price of crop output, the expected crop yield and the recommended herbicide rate. Figure 7 illustrates the way the threshold density is affected by the expected weed-free yield. The graph shows combinations of yield and weed density for which herbicide application is economic. The border of this region represents a multidimensional threshold. Assumptions underlying this graph are: wheat grain price,

\$160/tonne; recommended dosage of diclofop-methyl, 0.375 kg a.i.  $ha^{-1}$ ; herbicide price \$48 kg a.i.<sup>-1</sup>.

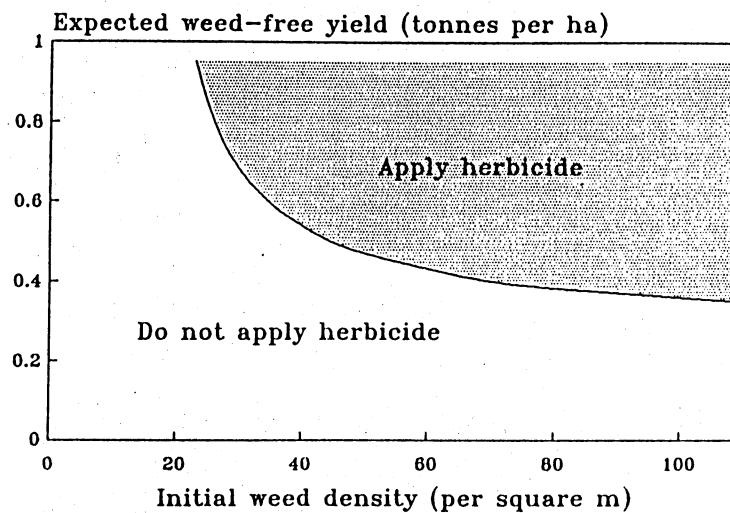


Figure 7: Multidimensional economic threshold based on weed density and expected weed-free crop yield.

Economists have noted that higher profits can be obtained if herbicide dosages are adjusted to suit particular circumstances rather than fixed at a recommended rate (eg, Pannell 1987, Moffitt 1988). Table 6 shows optimal rates of diclofop-methyl for ryegrass control for a range of weed densities, crop prices and weed-free yields.

Table 6: Optimal herbicide dosages

Weed-free yield ( $T ha^{-1}$ )	Grain price ( $\$ T^{-1}$ )	Initial weed density ( $m^{-2}$ )			
		100	200	300	400
1	120	0.22	0.29	0.32	0.34
	160	0.25	0.31	0.34	0.36
	200	0.27	0.33	0.36	0.38
1.5	120	0.23	0.29	0.32	0.34
	160	0.25	0.32	0.35	0.36
	200	0.28	0.34	0.37	0.38

The optimal dosage is quite insensitive to weed-free yield, moderately sensitive to grain price and relatively sensitive to initial weed density. It is notable that in many of the circumstances examined the economically optimal dosage is substantially less than the officially recommended dosage in Australia.

It should be acknowledged that these results are for a single season only. If benefits and costs in future years are considered when evaluating current weed control practices, the selected dosage or threshold may be

different. Pandey (1989) showed that if the area is to be cropped in subsequent years, there are net benefits from increasing the current level of control. On the other hand, Abadi Ghadim and Pannell (1989) showed that if the crop is part of a crop-pasture rotation, the optimal level of control in the crop may be reduced relative to what is optimal for a single year of crop. This is due to increased feed availability in the pasture if fewer weeds are killed in the crop.

The other issue not considered in calculating these results is resistance. Lower levels of control reduce the rate of resistance development (Gressel 1987). This means that it may be economically optimal to reduce the dosage or increase the threshold for treatment relative to a situation where resistance does not occur.

### Conclusion

A general model for representing yield response to herbicide application has been proposed. Parameters of the model were estimated for control of ryegrass in wheat by post-emergent application of diclofop-methyl in Australia. It was found that the proportion of weeds killed at a particular herbicide dose is not independent of the absolute number of weeds. The proportional yield loss at a particular weed density was decreased at higher weed-free yields. Competitiveness of weeds which survive herbicide treatment was found to be inversely related to the herbicide dose. Economic analysis showed that the optimal herbicide dosage is most sensitive to the initial weed density and relatively insensitive to the weed-free yield.

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### References

- Abadi Ghadim, A.K. and Pannell, D.J. (1989) Weed management in crop-pasture rotations. Paper presented to the 33rd Annual Conference of the Australian Agricultural Economics Society, Lincoln College, New Zealand, 7-9 February.
- Auld, B.A. and Tisdell, C.A. (1986) Economic threshold/critical density models in weed control. Proceedings of the European Weed Research Society Symposium on Economic Weed Control, EWRS, Wageningen, pp. 261-8.
- Auld, B.A., Menz, K.M. and Tisdell, C.A. (1987) Weed Control Economics, Academic Press, London.
- Baker, R.J. and Nelder, J.A. (1986) The Generalised Linear Interactive Modelling System, Users Guide, Appendix A, Numerical Algorithms Group, Oxford.
- Bowran, D.G., Porritt, S. and Madin, R. (1987) Chlorsulfuron and diclofop-methyl effects on the copper and zinc status and yield of wheat. In D. Lemerle and A.R. Leys (Eds) Proceedings of the Eighth Australian Weeds Conference, Weed Society of New South Wales, Sydney, pp. 404-6.
- Campbell, H.F. (1976) Estimating the marginal productivity of agricultural pesticides: the case of tree fruit farms in the Okanagan valley. Canadian Journal of Agricultural Economics 24(2):23-30.
- Casely, J.C. (1987) Effects of weather on herbicide activity. In D. Lemerle and A.R. Leys (Eds) Proceedings of the Eighth Australian Weeds Conference, Weed Society of New South Wales, Sydney, pp. 386-94.
- Chisaka, H. (1977) Weed damage to crops: yield loss due to weed competition. In J.D. Fryer and S. Matsunakaka (Eds) Integrated Control of Weeds, University of Tokyo Press, Tokyo, pp. 1-16.

Cousens, R. (1985) A simple model relating yield loss to weed density. *Annals of Applied Biology* 107, 239-252.

Cousens, R.D. (1986) The use of population models in the study of the economics of weed control. *Proceedings of the European Weed Research Society Symposium on Economic Weed Control*, EWRS, Wageningen, pp. 269-76.

Cousens, R. (1987) Theory and reality of weed control thresholds. *Plant Protection Quarterly* 2(1):13-20.

Cousens, R., Doyle, C.J., Wilson, B.J. and Cussans, G.W. (1986) Modelling the economics of controlling *Avena fatua* in winter wheat. *Pesticide Science* 17(1):1-12.

Cousens, R., Wilson, B.J. and Cussans, G.W. (1985) To spray or not to spray: the theory behind the practice. *1985 British Crop Protection Conference - Weeds*, pp. 671-78.

Davidson, B.R. (1974) Economic aspects of weed control. *Proceedings of the Weed Society of New South Wales* 6, 34-43.

Doyle, C.J., Oswald, A.K., Haggar, R.J. and Kirkham, F.W. (1984) A mathematical modelling approach to the study of the economics of controlling *Rumex obtusifolius* in grassland. *Weed Research* 24(3):83-93.

Feder, G. (1979) Pesticides, information, and pest management under uncertainty. *American Journal of Agricultural Economics* 61(1):97-13.

Finney, D.J. (1971) *Probit Analysis*, 3rd ed, Cambridge University Press, Cambridge.

Fischer, L.A. (1970) The economics of pest control in Canadian Apple production. *Canadian Journal of Agricultural Economics* 18(3):89-96.

Gressel, J. (1987) Strategies for prevention of herbicide resistance in weeds. In K.J. Brent and R.K. Atkin (eds) *Rational Pesticide Use*, Cambridge University Press, pp. 183-196.

Headley, J.C. (1968) Estimating the productivity of agricultural pesticides. *American Journal of Agricultural Economics* 50(1):13-23.

Hewlett, P.S. and Plackett, R.L. (1979) *An Introduction to the Interpretation of Quantal Responses in Biology*, Arnold, London.

Hillebrant, P.M. (1960) The economic theory of the use of pesticides, Part I. The dosage response curve, the rate of application and the area to be treated. *Journal of Agricultural Economics* 13(4):464-72.

Judge, G.G., Hill, R.C., Griffiths, W.E., Lutkepohl, H. and Lee, T.C. (1982) *Introduction to the Theory and Practice of Econometrics*, Wiley, New York.

King, R.P., Lybecker, D.W., Schweizer, E.E. and Zimdahl, R.L. (1986) Bioeconomic modeling to simulate weed control strategies for continuous corn (*Zea mays*). *Weed Science* 34(6):972-79.

Kropff, M.J. (1988) Modelling the effects of weeds on crop production. *Weed Research* 28(6):465-71.

Lapham, J. (1987) Population dynamics and competitive effects of *Cyperus esculentus* (yellow nutsedge) - prediction of cost-effective control strategies. In, *British Crop Protection Conference, Weeds*, Volume 3, BCPC Publications, Surrey, pp. 1043-50.

Lichtenberg, E. and Zilberman, D. (1986) The econometrics of damage control: why specification matters. *American Journal of Agricultural Economics* 68(2):261-73.

Moffitt, L.J. (1988) Incorporating environmental considerations in pest control advice for farmers. *American Journal of Agricultural Economics* 70(3):628-34.

Moffitt, L.J. and Farnsworth, R.L. (1981) Bioeconomic analysis of pesticide demand. *Agricultural Economics Research* 33(4):12-18.

Moffitt, L.J., Hall, D.C. and Osteen, C.D. (1984) Economic thresholds under uncertainty with application to corn nematode management. *Southern Journal of Agricultural Economics* 16(December):151-7.

Mumford, J.D. and Norton, G.A. (1984) Economics of decision making in pest management. *Annual Review of Entomology* 29, 157-74.

Neal, T.J. (1983) Optimal treatment rate for tebuthivion on rangeland infested with shimer oak. *American Journal of Agricultural Economics* 65(5):1198-1201.

Nelder, J.A. and Wedderburn, R.W.M. (1972) Generalized linear models. *Journal of the Royal Statistical Society, A*, 135, 370-84.

Pandey, S. (1989) Economics of wild oats control: an application of a stochastic dynamic programming model, paper presented to the 33rd Annual Conference of the Australian Agricultural Economics Society, Lincoln College, New Zealand, 7-9 February.

Pannell, D.J. (1987) Weed control economics research in Australia. In D. Lemerle and A.R. Leys (Eds) *Proceedings of the Eighth Australian Weeds Conference*, Weed Society of New South Wales, Sydney, pp. 1-11.

Poole, M.L. and Gill, G.S. (1987a) Competition between crops and weeds in southern Australia. *Plant Protection Quarterly* 2(2):86- 96.

Poole, M.L. and Gill, G.S. (1987b) The use of weed density - crop yield relationships for predicting yield losses in the field. In *British Crop Protection Conference, Weeds, Volume 3*, BCPC Publications, Surrey, pp. 945-54.

Roberts, E.J., Syme, G.J., Williams, K.D. and Hector, J.M. (1988) Farmers Attitudes to Weeds and Weed Control, Agriculture Protection Board, Discussion Paper 4/88.

Talpaz, H. and Borosh, I. (1974) Strategies for pesticide use: frequency and applications. *American Journal of Agricultural Economics* 56(4):769-75.

Talpaz, H., Curry, G.L., Sharpe, P.J., DeMichele, D.W. and Frisbie, R.E. (1978) Optimal pesticide application for controlling the boll weevil on cotton. *American Journal of Agricultural Economics* 60(3):469-75.

Taylor, C.R. and Burt, O.R. (1984) Near-optimal management strategies for controlling wild oats in spring wheat. *American Journal of Agricultural Economics* 66(1):50-60.

Wadley, F.M. (1949) Dosage mortality correlation with number treated estimated from a parallel sample. *Annals of Applied Biology* 36, 196- 202.

Walker, P.T. (1987) Quantifying the relationship between insect populations, damage, yield and economic thresholds. In P.S. Teng, (Ed) *Crop Loss Assessment and Pest Management*, American Phytopathological Society, St. Paul, pp. 114-125.

White, K.J. (1978) A general computer program for econometric methods - SHAZAM. *Econometrica* 46(1):239-40.

