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AN EMPIRICAL TEST OF ALTERNATIVE PEST DAMAGE CONTROL MODELS

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I. Introduction

Recently, a great deal of concern is expressed about the negative effect of pesticides although relatively few results are reported on the quantitative estimation of adverse effect of pesticides. A number of studies suggest that earlier studies overestimated the productivity of pesticides. For example, Headly estimated that marginal product of one dollar's pesticides was \$3.90 - \$5.66 which is higher than any other input. Campbell indicated that the marginal dollar's worth of pesticides yields around \$12 worth of output.

Lichtenberg and Zilberman demonstrated that overestimates of pesticide productivity is due to the misspecification of production function. Overestimates of the marginal productivity of pesticides are possible whenever model specification renders decreasing marginal effectiveness of pesticides. These biases occur when pesticides are directly incorporated with yield function like conventional input. Carrasco-Tauber and Moffitt argued that the magnitude of the pesticide productivity estimate obtained by Headly is not relevant to the problem of funtional specification. Fox and Weersink argued increasing returns to pesticides are possible for the case of typically assumed concave control and damage functions. The productivity of increasing returns increases when the relative curvature of the control function is less than that of the damage function. Besides Lichtenberg and Zilberman, Fox and Weersink, several recent studies on pesticide productivity have shown that pesticide productivity depends on the

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functional forms of control and damage functions(Carrasco-Tauber and Moffitt, Cousens, Pannell, Swinton).

Regarding appropriate model specification, Carrasco-Tauber and Moffitt used the information criterion (AIC) suggested by Akaike. The main purpose was model selection rather than hypothesis test. Frank, Beattie, and Embleton used nonnested hypotheis tests to evaluate several competing models. Cousens compared several competing functional forms for damage function using the residual sums of squares. Few studies on bioeconomic model used statistical method to show appropriate functional forms for control and damage function based on real data.

The purpose of this paper is to use a large winter wheat data set to test for increasing returns to herbicide with common control and damage functional forms, and to compare the statistical performance of alterantive weed damage functions for winter wheat.

II. Conceptual Framework for Pest Control and Damage Functions

Lichtenberg and Zilberman argued that the contribution of herbicides to production of wheat differs from that of standard input like labor, machinery, and fertilizer. The productivity of herbicides is overestimated when herbicides are directly entered into yield function as an argument. A two-step procedure was suggested to determine the optimal level of pesticides. At the first step, profit maximizing abatement level is determined through a profit function. A damage abatement function has to be defined by herbicides and it is incorporated in the yield function. A profit function is defined by the damage abatement function and yield function. The damage abatement function is defined as the proportion of the yield loss capacity of weeds eliminated by the application of herbicides. In this case, a yield function is defined as eqation (2.1):

$$Y=f(X, G(H)) \tag{2.1}$$

where Y is yield, X is a standard input vector, G(H) is damage abatement function, and H is the level of herbicide application. G(H) is defined as the proportion of the destructive capacity of weeds eliminated by the application of a level of herbicide H. A damage abatement function is defined on (0, 1) interval with G=1 denoting complete control of weeds, and G=0 denoting completely ineffective control of weeds. In the second step, an optimal level of herbicide (H) is obtained by minimizing abatement cost. Blackwell and Pagolatos agrued that Lichtenberg and Zilberman did not consider state variables in the model specification. They also argued that a control function rather than a damage abatement function should be entered in the yield function. A control function is defined as the proportion of weeds remaining after herbicide application. Hence, the yield function suggested by Lichtenberg and Zilberman is modified as equation (2.2):

$$Y=f(X, Z(\cdot)) \tag{2.2}$$

where $Z(\cdot)$ is a weed density function which is defined by weed density before herbicide application, and the level of herbicides.

Let's narrow down our scope to the relationship between the yield and weed density function. According to Blackwell and Pagolatos, the weed density function is defined as:

$$Z=Z_0[1-C(H)] \tag{2.3}$$

where Z is weed density after herbicide application, Z_0 is initial weed density before herbicide application, and C(H) is a control function. The control function is defined by the level of herbicides. It is constrained by the (0, 1) interval. When C(H)=0, herbicides have no effect on the control of weeds. When C(H)=1, herbicides have complete control on weeds. Now weed density is incorporated in the yield function through a damage function:

$$Y=Y_0[1-D(Z)] \tag{2.4}$$

where Y_0 is weed-free yield, and D(Z) is a damage function which represents the proportion of yield loss by weed density Z in the yield function. The damage function is constrained by the (0, 1) interval as the control function because damage cannot exceed weed-free yield.

III. Empirical Models

The empirical models are based on six years of data from field experiment in the Palouse region, Washington, U.S.A. The USDA-ARS Integrated Pest Management(IPM) project was developed to assess the appropriate level of chemical weed control for conservation and conventional tillage systems in the area. A brief summary of the experiment follows. The IPM experiment compared 12 complete farming systems: (2 rotations) x (2 tillage levels) x (3 weed management levels). The experiment was a randomized complete block, split-plot design with four replications. It was repeated for six years over 1986 through 1991 yielding 432 observations for winter wheat. Three levels of chemical weed management were chosen to correspond roughly to 90%, 70%, and 50% of the recommended level rate of utilized herbicides in the area. Exact rates and combinations of herbicides within these levels were determined annually by the project's weed scientists. The experiment attempted to reflect current farm production methods by using full-size farm machinery, and to utilize larger plots than is normal in research situations.

The density for all weed species was counted two times each year. Spring weed counts were recorded before postemergence herbicide applications, and summer weed counts were taken before crop harvest. Every weed species was counted in three one-square meter quadrates per subplot in both periods. Weed biomass of every species was measured from the same three one-square meter areas where weed species were counted prior to crop harvest each year.

A bioeconomic model links biological relationships to an optimizing economic model. In this study, the bioeconomic model was developed in a three stage process. First, preharvest weed density functions were specified to determine weed density levels after herbicide applications. Second, a yield response function was specified to describe the relationship between winter wheat yield, aggregated surviving weed density, and other variables. Finally, the estimated results were incorporated into a profit function to determine profit maximizing rates for three herbicide classes. Optimal herbicide rates are conditional upon the state variables included in the biological and economic relationships. These state variables include spring weed densities, soil moisture, soil organic matter, tillage type, preceding crop, preplant nonselective herbicide use (in conservation tillage only), herbicide prices, herbicide application costs, and expected crop prices. If the decision model is to be used by farmers, all state variables must be known or have formulated expectations at the time the POST herbicide weed control decision is made.

Several functional forms are suggested for control function in the literature. Fox and Weersink suggested seven alternative functional forms--Pareto, Exponential, Logistic, Weibull, Rectangular hyperbola, Linear, and Square root-- for control and damage functions. An exponential function is often used for a control function(Auld et al., Cousens, Feder, Moffitt, Weersink et al.). Exponential control function was selected from the seven proposed functional forms because its estimates have expected signs and relatively higher R^2 in the nonlinear least square estimation[1]. When an exponential control function is adapted, the weed density functions are specified as:

$$WD_i = SWD_i e^{-b_j H_j} + dDH_1 + \sum_{k=1}^{a} a_k TIL_k + \sum_{l=1}^{2} c_l CR_l \qquad (3.1)$$

$$i=1, 2, 3;\ j=2, 3$$

where WD_i is preharvest (surviving) weed density (no. m^{-2}) of the i^{th} weed subgroup. More than 50 weed species were identified in the IPM experiment over 6 years, but many species had relatively low populations. In this study, weeds were classified into three subgroups: summer annual grasses (WD_1), winter annual grasses (WD_2), and broadleaves (WD_3). SWD_i is spring weed seedling density(no. m^{-2}) of i^{th} subgroup, H_j's are application rate (proportion of maximum labeled rate) of j^{th} herbicide type (H_2=POST broadleaf, and H_3=POST grass), DH_1 is a discrete variable for preplant nonselective herbicide application(DH_1 = 1 for application, and DH_1 = 0 for no application), TIL_k's are discrete variables (0 or 1) for tillage system (TIL_1=1 and TIL_2=0 for no-till, TIL_1=0 and TIL_2=1 for chisel, and TIL_1=TIL_2=0 for conventional tillage), CR_l's are discrete variables

[1] Unreported results showed that a number of observations were missing with Pareto and Weibull functions, several incorrect signs with Logistic functions, low R^2's with Linear and Square-root functions, and non-convergence with Rectangular hyperbolic model.

for previous crop (CR_1 = 1 and CR_2 = 0 for spring wheat, CR_1 = 0 and CR_2 = 1 for spring pea, and CR_1 = CR_2 = 0 for winter wheat), and a's, b's, c's, and d are estimated coefficients. Coefficient d is hypothesized to be negative under the expectation that application of nonselective herbicide decreases preharvest density of weed type i, other factors equal. Coefficients b_1, and b_2 are expected to be positive for herbicides intended to control weed type i. Coefficients a_1 and a_2 are expected to be positive indicating that conservation tillage increases weed competition relative to conventional tillage (Young F. L. et al.). No prior signs are hypothesized for c_1 and c_2, which indicate the influence of preceding crop on the surviving weed density in winter wheat.

A total of 15 herbicides were applied to winter wheat over the 6 years of the experiment. These herbicides were categorized into three subgroups: nonselective preplant, POST broadleaf, and POST grass[2]. An index of "effective application rate" was developed to aggregate different herbicide types. An index value of 1.0 was given to the manufacturer's label rate for all herbicides in each subgroup. Applications below the label rate received an index of k equal to the proportion of the label rate so that $0 < k < 1$. Then each herbicide was weighted by an "efficacy index" (EI_h), $0 \leq EI_h \leq 1$, within the subgroup. The "efficacy index" was assigned based on the rated relative performance of a herbicide within the subgroup (Boerboom et al.). The index of "effective application rate" for a specific herbicide in a subgroup equaled k times EI_h. These effective application rates were summed to obtain the aggregate application rate for a herbicide subgroup.

Each weed subgroup competes not only with the crop but with the other weed subgroups. All the weed subgroups are also affected by the same weather and other external influences within a given year. It is supposed in the models that the statistical error terms in the different preharvest weed density functions for a crop are correlated

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[2] The aggregation of 15 herbicides into 3 subgroups was statistically necessary given that some products were used only 1 or 2 years and/or over a narrow range of rates. We also believe the added flexibility of permitting growers to select exact herbicides from a general herbicide subgroup recommendation is practical for on-farm use. Confronted with weed species shifts within weed types, with changing herbicide availabilities and prices, and emerging environmental regulations, growers are likely to welcome some flexibility in model recommendations.

with each other within the same time period, while they are uncorrelated in different time periods. To accommodate the dependency in the error structure, the Seemingly Unrelated Regression (SUR) technique was used to estimate density functions (Judge et al.). The Breusch-Pagan test results supported the use of SUR estimates rather than estimates from single equations.

A few alternative fuctional forms are introduced for a damage function in the literature. The rectangular hyperbolic model is most frequently used for damage function in the literature (Cousens, Pannell, Swinton). Logistic model is often used for damage function (Kwon et al.). Cousens compared several models in winter wheat with a single weed species, but not with multiple weed species. In this study, a modified Mitscherlich-Baule production function (Beattie and Taylor) was combined in turn with alternative damage functions. The specification of the yield response function with rectangular hyperbolic weed damage is defined as:

$$Y=b_1(1-e^{-b_2SM})(1-e^{-b_3OM})\left[1-\frac{iTWD}{100(1+iTWD/j)}\right] \tag{3.2}$$
$$+a_1TIL_1+a_2TIL_2+c_1CR_1+c_2CR_2$$

Common variables in equation (3.2) are defined as above. Y is crop yield (bu ac^{-1}), b_1 is maximum potential crop yield with nonlimiting soil moisture, nonlimiting organic matter, and no weed competition. SM is spring soil moisture (%) of the top 30cm, OM is soil organic matter (%) of top 30cm. Coefficient j is the maximum percentage yield loss as weed density approaches infinity. Estimates i and j were expected to be positive to generate the characteristic rectangular hyperbolic shape of the damage function (Cousens, Kwon). The symbols b_1, b_2, b_3, c_1, and c_2 are estimated regression coefficients. Parameter estimates for b_1, b_2, and b_3 were expected to be positive to reflect higher expected yield with higher soil moisture and organic matter. No prior signs were hypothesized for tillage and preceding crop coefficients. Alternative functional forms for the damage function are shown in (Table 1).

The weed competition index, TWD(weighted number of weeds m^{-2}), is calculated from weighted predicted preharvest weed density

TABLE 1 Alternative Damage Functions[a]

Functional form	Damage function		
	f(TWD)	f'(TWD)	f''(TWD)
Logistic	$\frac{m}{1+e^{-(i+jTWD)}}$	$\frac{jme^{-(i+jTWD)}}{(1+e^{-(i+jTWD)})2}$	$\frac{-j^2me^{-(i+jTWD)}(1-e^{-(i+jTWD)})}{(1+e^{-(i+jTWD)})^3}$
Rectangular hyperbolic	$\frac{iTWD}{100(1+iTWD/j)}$	$\frac{i}{100(1+iTWD/j)^2}$	$\frac{-2i^2/j}{100(1+iTWD/j)^3}$
Exponential	$1-e^{-iTWD}$	ie^{-iTWD}	$-i^2e^{-iTWD}$
Weibull	$1-e^{-TWD^i}$	-	$f'(TWD)\left[\frac{i-1}{TWD}-iTWD^{i-1}\right]$
Pareto	$1-\left[\frac{k}{TWD}\right]^i$	$\frac{i}{k}\left[\frac{k}{TWD}\right]^{i+1}$	$\frac{-i(i+1)}{k^2}\left[\frac{k}{TWD}\right]^{i+2}$
Linear	iTWD	i	0
Square-root	$i\sqrt{TWD}$	$\frac{i}{2\sqrt{TWD}}$	$-\frac{i}{4TWD\sqrt{TWD}}$

[a]TWD is the weed competition index.

levels over subgroups:

$$TWD=\sum_{i=1}^{3} w_i\hat{WD}_i, \qquad i=1, 2, 3 \tag{3.3}$$

where the weed competition index, TWD, represents the overall competitive capacity of multiple weeds with winter wheat, and w_i's are competition indices by weed type. A competition index of 1.0 was given to winter annual grasses as a standard for winter wheat. The weight assigned to the other three weed subgroups is proportional to the frequency weighted average biomass of weeds in that subgroup relative to the frequency weighted average biomass of winter annual grasses. Biomasses were based upon average preharvest dry weight of all weed species over 6 years. The weed competition indices assume that the competitive contribution of each weed type is proportional to its average preharvest biomass. The WD_i for each weed group is predicted from equation (3.1).

SHAZAM (White) nonlinear regression model was used to estimate the yield response functions. There is no guarantee that the estimation process for a nonlinear model will converge to a unique set of coefficients for a given set of starting values. If it converges, there is no way to identify whether it is a local or global optimum. Therefore, the model was reestimated with different starting points to verify that a global optimum had been achieved. All reported optima in this study were stable based on these tests.

Two measures of goodness of fit were used to select final yield response functions for each functional form: log-likelihood and MLE of sigma squared . Although higher log-likelihood and lower MLE of sigma squared, these values cannot be used to select a specification from several alternative nonnested models (Davidson and MacKinnon, 1993). Consequently, a P-test developed by Davidson and MacKinnon(1981) was used to test the seven yield model specifications.

The profit function for this problem can be written as a function of herbicide applications as:

$$\pi = PY(\dot{H}) - \dot{P}_h\dot{H} - AC(\dot{H}) - OC \tag{3.4}$$

where π is net returns over total costs (\$ ac^{-1}), Y(H) is the predicted yield (bu ac^{-1}) from equation(2.2), H is the vector of herbicide applications (proportion of label rate), P is crop price (\$ bu^{-1}), P_h is herbicide prices (\$ label rate^{-1} ac^{-1}), AC is herbicide application cost (\$ ac^{-1}) which is a function of the herbicides applied, and OC is other production costs (\$ ac^{-1}). Other costs include land and miscellaneous fixed costs, operator labor, fertilizer, machine operations, and seed, but exclude a charge for management (Kwon, Painter et al.).

The herbicide price for each herbicide subgroup was based on a frequency of use weighted average of the prices of herbicides within that subgroup used over the 6 year experiment. The use of weighted average prices for herbicide types decreases the precision of economic recommendations, but it is a necessary compromise given the infeasibility of incorporating all 15 utilized herbicides as decision variables. Average application cost ($ ac^{-1}) for herbicide types were computed on the same frequency-weighted basis as herbicide type prices.

IV. Empirical Results

Estimated coefficients for the three prehavest weed density functions (WD_i) are presented in (Table 2). Coefficients of herbicides (H_2 and H_3) have expected positive signs and are statistically significant at the 1% level. POST broadleaf herbicides (H_2) significantly reduced the winter annual broadleaf weed population. POST grass herbicides (H_3) helped control both winter and summer annual grass populations, but the coefficient was not so big as that of POST broadleaf herbicides. Compared to the coefficients of herbicides, coefficients of POST broadleaf herbicide(H_2) are relatively higher than those of POST grass herbicides(H_3) and very close in both models. This means that POST broadleaf herbicides are more efficient to control broadleaves than POST grass herbicides control grasses.

A binary variable for preplant nonselective herbicide(DH_1) has expected negative signs except for winter annual grasses in three wheat models. Nonselective preplant herbicides applied to no-till winter wheat after spring peas significantly suppressed summer annual grasses and broadleaves. DH_1 was not significant at the 10% level in predicting density of winter annual grasses in both models. The failure of H_1(nonselective preplant herbicides) to show significant control of winter annual grasses might be partially explained by the IPM experiment data. In only 2 out of 6 years (1987 and 1990), fall soil moisture was sufficient to germinate weeds and to warrant application of nonselective preplant herbicides (H_1) before planting no-till winter wheat (Young D.L., T.J.Kwon, and F.L.Young). Over all conservation tillage treatments, preplant nonselective herbicide was applied only to winter wheat harvested in 1987, 1989, and 1990.

TABLE 2 Estimated coefficients of preharvest weed density functions for three weed subgroups in winter wheat using seemingly unrelated regression

Variable[a]	WD_1[b]	WD_2	WD_3
H_2	[d]		2.659**
			(0.137)
H_3	0.670**[c]	2.986**	
	(6.75)	(20.34)	
DH_1	-2.451	0.560	-7.050**
	(-0.43)	(0.11)	(-4.31)
TIL_1	13.267**	9.325*	9.640**
	(3.05)	(2.46)	(7.24)
TIL_2	18.778**	16.269**	2.770*
	(4.25)	(4.16)	(2.37)
Log-likelihood function	-6080.93		
Number of observation	432		

[a]H_2 = POST broadleaf herbicide, H_3 = POST grass herbicide, DH_1 = discrete variable for preplant nonselective herbicide (DH_1 = 1 for application, DH_1 = 0 for not application), TIL_i = discrete variables for tillage (TIL_1 = 1 and TIL_2 = 0 no-till, TIL_1 = 0 and TIL_2 = 1 for chisel plow).
[b]Weeds (plants m^{-2}) were categorized as summer annual grasses (WD_1), winter annual grasses (WD_2), and broadleaves (WD_3).
[c]*, and ** indicate statistical significance at the 5%, and 1% levels, respectively. t-values are in parentheses.
[d]Blank entries indicate that the variable was excluded because it was not relevant to the particular weed type.

As hypothesized, mid-summer weed populations of all weed groups in winter wheat increased with no-till (TIL_1) and chisel plowing (TIL_2) relative to conventional tillage.

Nonlinear maximum likelihood estimates of seven damage-yield response functions are presented in (Table 3). All estimates have expected signs and most of estimates are statistically significant at the 1% level. Weed competition index (TWD) was estimated as follows:

$$TWD = 0.93WD_1 + WD_2 + 0.47WD_3 \tag{4.1}$$

TABLE 3 Estimated coefficients of yield response functions for alternative models

Coefficients[a]	Logistic[b] (m=0.4)	Rectangular hyperbolic	Exponen-tial	Weibull	Pareto	Linear	Square-root
b_1	95.196	95.880	91.711	238.19	87.133	89.418	97.216
	(15.29)[c]	(16.24)	(18.88)	(21.80)	(22.58)	(22.43)	(17.73)
b_2	0.156	0.154	0.154	0.156	0.154	0.153	0.156
	(10.51)	(10.66)	(11.20)	(10.57)	(10.41)	(10.80)	(10.66)
b_3	0.826	0.809	0.873	1.059	1.100	0.972	0.839
	(4.45)	(4.46)	(4.51)	(3.97)	(3.86)	(4.69)	(4.54)
i	-2.883	1.156	0.004	0.033	0.028	0.002	0.040
	(-0.24)	(3.04)	(4.74)	(4.58)	(4.24)	(7.03)	(8.96)
j	0.092	68.448					
	(2.45)	(5.81)					
a_1	20.679	22.922	17.451	16.577	15.240	14.513	21.072
	(8.82)	(7.67)	(7.23)	(6.47)	(6.51)	(7.42)	(8.67)
a_2	15.655	16.731	9.927	5.519	3.660	4.541	13.687
	(5.08)	(4.41)	(3.00)	(1.78)	(1.35)	(1.90)	(4.63)
c_1	9.111	9.676	9.555	8.784	8.656	9.150	9.562
	(4.15)	(4.25)	(4.24)	(3.65)	(3.73)	(4.04)	(4.19)
c_2	25.906	26.741	25.641	24.390	23.979	24.403	26.247
	(12.22)	(11.84)	(11.05)	(10.34)	(10.62)	(10.91)	(11.69)
Log-likelihood	-1820	-1819	-1823	-1839	-1841	-1828	-1818
MLE of σ^2	267.38	265.55	271.07	291.58	293.87	276.39	265.13

[a]Coefficients are defined in the Table 1 and text following equation (3.2).
[b]The MLE of σ^2 was lowest for m equal to 0.4 in the logistic damage-yield response function. This value for m was selected from the results of a search ranging over 0.1 to 0.7 in increments of 0.05. The m is a maximum damage level under high weed density.
[c]t-values are in the parentheses.

Nonnested hypothesis tests were conducted to compare alternative models. Versions of the J-test and P-test have been developed for nonlinear models. It is known that the P-test is more generally used than the J-test. The J-test cannot be used when all parameters of null hypothesis model are not linear (Davidson and MacKinnon, 1993, p. 382). The P-test was performed by temporarily holding each hypothesis as null and testing in a pairwise fashion with each temporary alternative. Each model was also tested against alternatives jointly. A t-value is used as test statistic for pairwise tests, while chi-square with 6 degrees of freedom is a correct test statistic for the joint hypothesis tests.

Test results are shown in (Table 4). The purpose of nonnested tests is not to choose one out of a fixed set of models as the "best"

TABLE 4 Nonnested Hypothesis Test Results

Alternative hypothesis	Null hypothesis[a]						
	Logistic	Rectangular hyperbolic	Exponen-tial	Weibull	Pareto	Linear	Square-root
Logistic		1.10	2.47**	6.48**	6.16**	4.23**	1.90+
Rectangular hyperbola	3.49**		2.45**	6.83**	6.41**	4.10**	0.79
Exponential	2.32*	1.04		6.06**	5.77**	3.01**	-0.75
Weibull	0.45	-1.18	1.29		8.25**	2.01*	-1.29
Pareto	-0.24	-1.40	0.98	-7.97**		1.83+	-1.45
Linear	2.01*	1.41	-0.24	5.48**	5.30**		-0.65
Square-root	3.69**	1.26	2.83**	6.93**	6.32**	4.16**	
Joint test[b]	64.93**	60.95**	68.03**	111.17**	106.73**	78.89**	59.98**

[a]Under the null hypothesis, test statistics for pairwise test are distributed as standard normal. A +indicates statistical significance at the 10% level. A single and double asterisks are at the 5% and 1% levels, respectively.
[b]Test statistics for joint test are distributed as chi-squared with 6 degrees of freedom.

one. Since nonnested hypothesis tests are specification tests, nonnested tests may tell us that neither model seems to be compatible with the data. The pairwise tests illustrate that a rectangular hyperbolic and square-root models are favored over the other models. When the rectangular hyperbolic model is compared to the other models, the null hypothesis cannot be rejected at a 5% significance level. The same results are obtained when the square-root model is compared to the other models. However, the joint P-test results did not answer the question of which is the superior model because all the null hypotheses rejected at the 1% significance level. When the square-root model is compared to the other models, the null hypothesis is rejected against the logistic model at the 10% significance level. The Exponential model is not rejected against Pareto, Weibull, and Linear Models, while it is rejected against Logistic, Rectangular hyperbolic, and Square-root models at the 5% significance level.

Let's figure out the possibility of increasing returns to herbicides. The marginal product of postemergence grass herbicide (H_3) is defined as:

$$\frac{\partial Y}{\partial H_3} = \frac{\partial Y}{\partial TWD}(-0.623SWD_1e^{-0.670H_3}-2.986SWD_2e^{-2.986H_3}) \quad (4.2)$$

which will be nonnegative for the three models. The change in marginal product of the same herbicide is defined as:

$$\frac{\partial^2 Y}{\partial H_3^2} = \frac{\partial^2 Y}{\partial TWD^2}(-0.623SWD_1e^{-0.670H_3}- 2.986SWD_2e^{-2.986H_3})^2 \quad (4.3)$$

$$= \frac{\partial Y}{\partial TWD}(0.417SWD_1e^{-0.670H_3}+ 8.916SWD_2e^{-2.986H_3})^2$$

which is equally expressed in all three models. Now, $\partial^2Y/\partial H_3^2$ is possible to be positive at high TWD, while $\partial^2Y/\partial H_3^2$ is negative at low TWD. The level of weed density (TWD) is decided by the magnitude of marginal yield loss from weed ($\partial Y/\partial TWD$) and the changing rate of marginal yield loss from weed ($\partial^2Y/\partial TWD^2$) in the three models. The marginal yield loss from weed and the changing rate of marginal yield loss are calculated by using (Table 1 and 3).

(Figure 1, 2, and 3) show the marginal product of postemergence

FIGURE 1 Yield Response and Returns to One Label Rate of H_3 in Logistic Damage Function

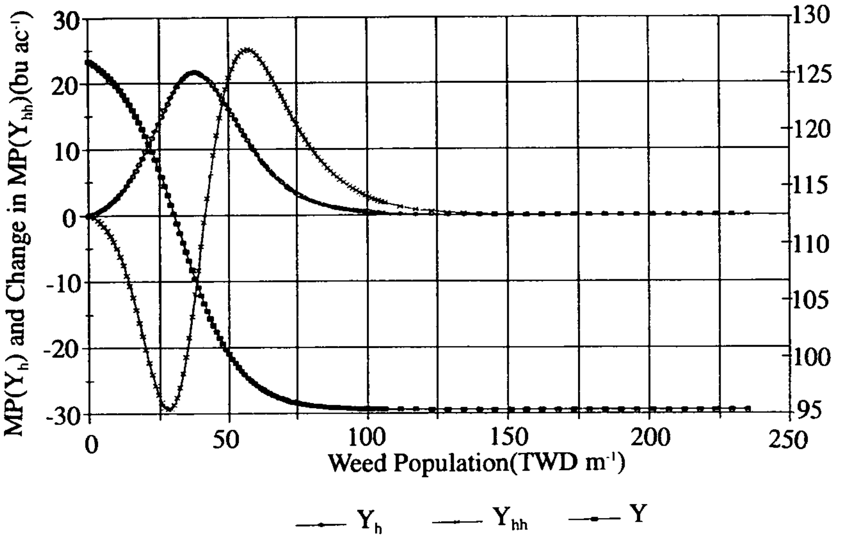


FIGURE 2 Yield Response and Returns to One Label Rate of H_3 in Rectangular Damage Function

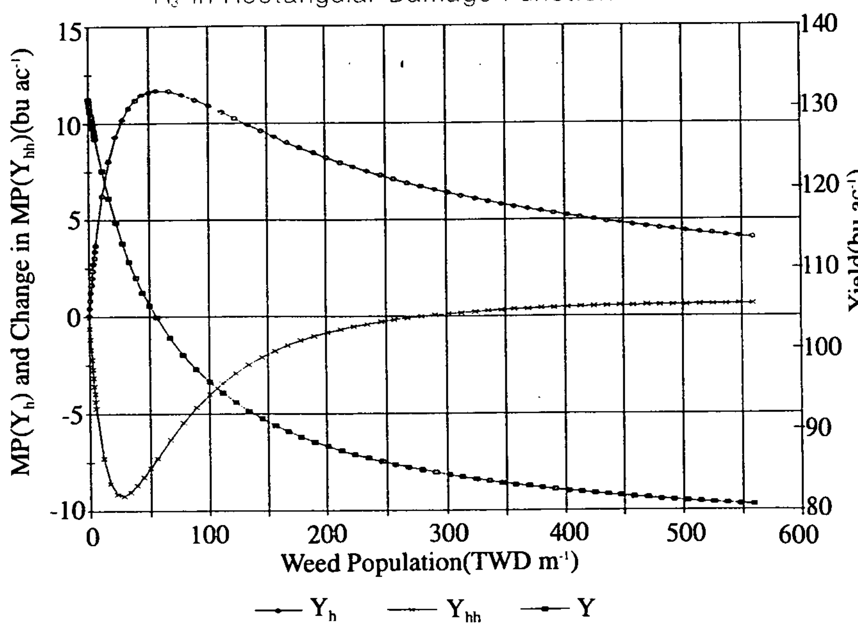
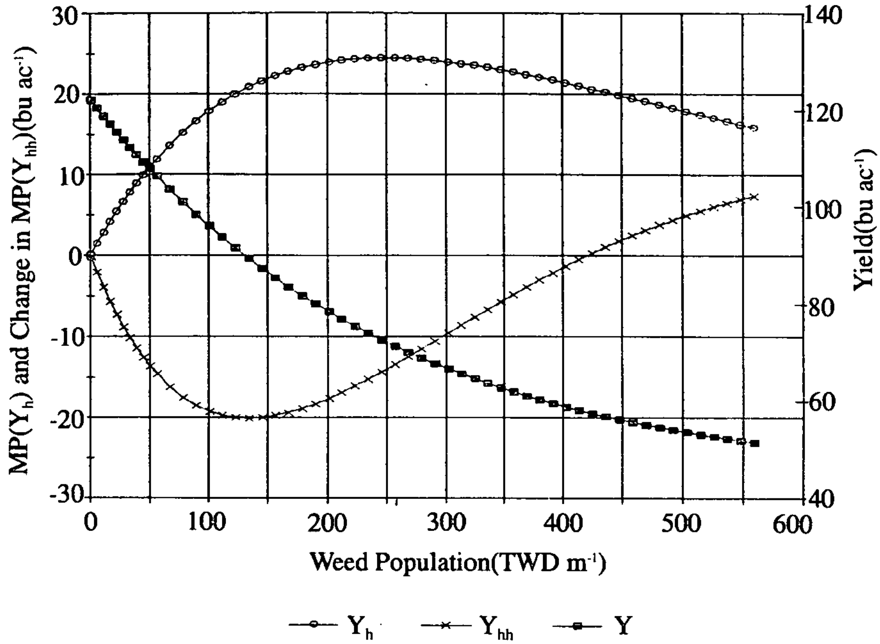


FIGURE 3 Yield Response and Returns to One Label Rate of H_3 in Exponential Damage Function



grass herbicide ($\partial Y/\partial H_3$), changing rate of marginal product ($\partial^2 Y/\partial H_3^2$), and wheat yield corresponding to weed density (TWD) for Logistic, Rectangular hyperbolic, and Exponential damage functions, respectively. Increasing returns to herbicide is always possible under high weed population for the three different models. It is possible whenever over 40 weeds per square meter were left after application of one label rate of postemergence grass herbicide in Logistic model. This means that applying over one label rate of postemergence grass herbicide generates higher profit than applying one label rate of herbicide application at high weed density as long as marginal value product (MVP) of herbicide is larger than marginal factor cost (MFC) of that herbicide. The marginal factor cost of postemergence grass herbicide is 7.1 bushel per acre. Therefore, more herbicide can be applied in addition if the number of weed density is expected to be left 20 to 70 per square meter after applying one label rate of postemergence grass herbicide.

In case of Rectangular hyperbolic model, increasing returns to herbicide is possible when weed density is higher than 300 per square meter after applying one label rate of postemergence grass herbicide. It is possible over 420 in case of Exponential model.

Compared to the three models, Exponential function is most conservative to reveal increasing returns to herbicide, while Logistic model has higher possibility to show increasing returns to herbicide than the other models. (Table 5) shows that the Logistic model recommends relatively higher rates of optimal herbicides than those of the other models. However, the predicted optimal herbicide rates are lower than actual application rates in the IPM experiment. Returns to herbicide are affected not only by functional forms of damage function but also by control function. If increasing returns to herbicide is possible under relatively lower weed density, wheat growers have more chance to apply higher rate of herbicide with that model. By economic theory, an optimal rate of herbicide is decided by marginal value product and marginal factor cost of herbicide under decreasing returns to herbicide. Given conventional concave profit functions, whenever MFC exceeds MVP, potentially small decrease in herbicide use will improve profit. The reason why every model recommends lower optimal rates of herbicide than actual application rates(H_2=1.00, H_3=0.67) is explained by relatively lower MVP's than MFC's. If increasing returns to herbicide is possible, the optimal rate of herbicides will be substantially on a higher level. However, it is almost impossible that those circumstances happen in wheat production under proposed three models.

V. Conclusions

Findings in this paper might serve as a caution to bioeconomic weed management modelers. Small changes in functional specification of crop yield and weed control functions cause large differences in profit maximizing recommendations for herbicides.

This paper confirms that an exponential control function reflects better results than the other alternative functional forms. The pairwise P-tests show that a rectangular hyperbolic and a square-root damage models are favored over the other models.

TABLE 5 Comparison of Estimated Managerial Performance of the Three Models for WinterWheat after Winter Wheat under Conservation Tillage[a]

Item	Logistic	Rectangular hyperbolic	Exponential
MVP's and MFC's			
MVP_{H_2}[b]($ l.r.$^{-1}$)	13.8	8.6	7.6
MVP_{H_3}[b]($ l.r.$^{-1}$)	28.4	17.7	15.8
MVP_{H_3}/MVP_{H_2}	2.1	2.1	2.1
MFC_{H_2}[c]($ l.r.$^{-1}$)	15.9	15.9	15.9
MFC_{H_3}[c]($ l.r.$^{-1}$)	28.4	28.4	28.4
Optimal herb. rate			
H_2(l.r.)	0.92	0.70	0.71
H_3(l.r.)	0.64	0.34	0.36
Yield[d](bu ac^{-1})	80.6	81.6	84.1
Profit[e]($ ac^{-1})	54.6	70.7	79.9

[a]H_2 = POST broadleaf herbicide, H_3 = POST grass herbicide, l.r. = label rate.
[b]MVP's = marginal value product for an additional application evaluated at the means of herbicide use (one label rate of POST broadleaf herbicide and 0.67 label rate of POST grass herbicide) and other variables in the experiment.
[c]MFC's = marginal factor cost for an additional herbicide application which include herbicide and application costs.
[d]Yield predicted by the model using the average state variables and optimal herbicide rates.
[e]Predicted profit by the model using expected wheat market price($3.98 bu^{-1}), herbicide costs(H_2=$11.37 l.r.$^{-1}$, H_3=$23.86 l.r.$^{-1}$), herbicide application cost($4.5 l.r.$^{-1}$), and the other costs($233 ac^{-1}).

Pesticide productivity depends on the functional forms of control and damage functions. Over several decades debate on the possibility of increasing returns to herbicide is being continued. It is possible to find increasing returns to herbicide under high weed population although the possibility is very low under the normal weather and field condition. Both a rectangular hyperbolic and an exponential control functions recommend lower rates of postemergence herbicide than conventional recommendation under moderate weed population. An exponential damage function recommends lower rates of postemergence herbicide than a Rectangular hyperbolic model under low weed population. However, more frugal herbicide recommendation is rendered under high weed population when a Rectangular hyperbolic damage function is adopted in the decision model. It is more appropriate to use well specified decision models than conventional conjecture for herbicide recommendation. With selected models, less herbicide and more profit are resulted than those of conventional recommendation. However, preferred models for farm use will require field comparisons.

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