OPTIMUM USE OF HERBICIDES IN SPRING PEAS (PISUM SATIVUM)*

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I. Introduction

While dry edible peas and lentils are a relatively minor crop nationally, they are an important economic and rotational crop in the inland Pacific Northwest of the United States. Dry peas and lentils grossed Washington and Idaho growers $56 million in 1991 (11, 18). From a grower's perspective, dry peas and lentils are crucial rotational crops in sustaining high winter wheat yields in the Pacific Northwest. Continuous winter wheat is plagued with root diseases and winter annual grass weeds, which are both suppressed in legume rotations. In a recent 6-year field trial, winter wheat grown after dry peas, under conservation tillage conditions, out yielded winter wheat after spring wheat under similar conservation tillage conditions by 21% (22).

Although peas and lentils are extremely beneficial to the rotation, effective and affordable weed management in these crops is the greatest challenge to the success of this rotation. The difficulty relates to herbicide availability, efficacy, and cost. In 1988, growers lost the use of dinoseb, an effective, broad spectrum, low cost broadleaf herbicide, which was widely used by pea and lentil growers. Dinoseb replacements are few in number, of limited spectrum, and

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generally more costly. As a result, growers often need to use three or more herbicides to control the spectrum of weeds encounted.

The ideal herbicide regime would be excessively expensive, given the relatively low value of the pea crop (2). Even with a modest herbicide program, these inputs cost \$36/ac or 24% of the total variable costs for the production of a pea crop that has netted an average of -\$88/ac for the past six years. However, survey data from the region indicate that yield losses would range from 35 to 62% if no herbicides were used. Even with current herbicide use, yield losses from herbicide injury range from 7 to 13% and 4 to 9% is lost from swathing to dry weeds for harvest.[2]

Despite the challenges faced in developing effective weed management in peas and lentils, little work on weed control in dry peas and lentils has been published. Exceptions include Boerboom (3), Miller et al. (14), Stephens and Ogg (17), Prather et al. (16), Whitesides and Swan (20), Hornford and Drew (9), and Wilkins et al. (21). No economic analysis on weed management for dry peas or lentils has been reported since 1970, but growers would benefit from a decision model that optimizes profits through use of appropriate herbicide inputs. However, several unique challenges are associated with developing a bioeconomic model for weed management in dry peas that are often avoided in other models.

First, the primary herbicides used are soil active, applied either pre-plant incorporated or preemergence. These herbicides cannot be effectively replaced with postemergence herbicides. Therefore, applications made in early spring are before the eventual weed pressure in known and are prophylactic in nature. Growers are unable to use observed weed pressures as an indicator of profitable herbicide rates. Several classifications of herbicides must also be handled with such a model. Although there are relatively few herbicides labeled for peas, they are applied as pre-plant nonselective herbicides, pre-plant incorporated broadleaf herbicides, pre-plant incorporated grass herbicides, premergence broadleaf herbicides, postemergence broadleaf herbicides and postemergence grass herbicides. In addition, many of these herbicides have marginal efficacy on some key weed species in peas, such as mayweed chamomile (16). Thus, model

[2] Personal communication, Fuerst, P., May 1993.

design will require careful consideration of tank mixes and sequential treatments to provide control of the broadleaf spectrum of weeds.

As a minor crop, peas and lentils are not a major target for new herbicide development by chemical companies. Consequently, research to enhance effective and profitable use of available herbicides is particularly important to growers. The urgency of effective weed control for dry peas and lentils in the Pacific Northwest has increased with the approaching deadline, by the end of 1994, for phasing in soil conserving farm plans in the highly erodible Pacific Northwest croplands where these crops are grown. Transition to conservation tillage to implement these farm plans generally increases weed management requirements in the inland Pacific Northwest production region (12).

The objectives of this paper are to develop a bioeconomic decision model for weed management in dry edible peas and to find profit maximizing herbicide rates under both conventional and conservation tillage. Nonlinear multiple regression method and nonlinear programming algorithm were used to analyze the models.

II. Data

The bioeconomic weed management model is based upon six years of data from field experiment in the Washington-Idaho Palouse at a site near Pullman, Washington. The USDA-ARS Integrated Pest Management (IPM) project in the Washington-Idaho Palouse region was developed to assess the appropriate level of chemical weed control for conservation and conventional tillage systems in the area. Complete descriminations of the design, procedures, and selected spring peas results of the IPM experiment are presented in Boerboom et al. (4) and Young et al. (22). A brief summary of the experiment follows. Two crop rotations were examined, one containing two years of winter wheat and one year of spring wheat, and the other one year each of winter wheat, spring barley, and spring peas. Each crop in each rotational sequence was grown every year of the experiment. Three levels of chemical weed management were chosen to correspond roughly to 90%, 70%, and 50% of the recommended label rates of utilized herbicides. 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 on relatively large subplots measuring 12.2 m by 45.7 m. The research site was located five km northwest of Pullman, WA and had been farmed nine years previously in no-till small grains.[3]

The density (plants/m^2) 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 1-m^2 quadrates per subplot in both periods. Weed biomass of every species was measured from the same three 1-m^2 areas where weed species were counted prior to crop harvest each year.

All yield data were adjusted to reflect the typical 5% level of chaff and moisture for marketed dry peas in the region.

III. Modeling

A bioeconomic model links biological relationships to an optimizing economic model. In this study, the bioeconomic model is developed in three steps (13). First a system of weed survival functions is specified to determine weed density levels after herbicide applications. Second, a yield response function is specified to describe the relationship between spring pea yield and aggregated surviving weed density and content of organic matter, and tillage type. Finally, the estimated results are incorporated into a profit function to determine profit maximizing rates for six herbicide types. Optimal herbicide rates are conditional upon the state variables included in the biological and economic relationships. These state variables include such factors as spring weed densities, soil moisture, tillage type, preceding crop, herbicide prices, and expected crop prices. If the decision model is to be operational, all state variables must be known or have formulated expectations at the time the weed control decision is made.

The weed survival functions are specified as:

$$WD_i = b_0+b_1SWD_i+b_2WD_{i,t-1}+b_3SM+\sum_{j=1}^{6} c_jH_j+aTIL \quad i=1, 2, 3 \qquad (1)$$

[3] Refer to Journal of Rural Development, vol. 16(2) on the IPM experimental design.

where WD_i is weed density (no./m^2) of i-th weed subgroup in July, SWD_i is spring weed seedling density (no./m^2) of i-th subgroup, $WD_{i,t-1}$ is weed density (no./m^2) of i-th weed subgroup in the July of previous season, SM is spring soil moisture of the top 12 inches (%), H_j's are application rate (proportion of maximum label rate) of j-th herbicide type (H_1 = pre-plant nonselective herbicides, H_2 = pre- plant incorporated broadleaf herbicides, H_3 = pre-plant incorporated grass herbicides, H_4 = preemergence grass herbicides, H_5 = postemergence broadleaf herbicides, and H_6 = postemergence grass herbicides), TIL is a binary variable (0 or 1) for tillage system (TIL = 1 for chisel plow, TIL = 0 for moldboard plow), and a, b's, and c's are estimated coefficients. Over 40 weed species recorded in the IPM experiment over six years were classified into three subgroups: summer annual grasses (WD_1), winter annual grasses (WD_2), and summer annual broadleaves (WD_3) as listed in Table 1. Coefficients b_1 and b_2 are expected to be positive. Higher spring seedling densities of weed type i should increase mid-summer density of weed type i, other factors equal. And higher mid-summer densities of weed type i in the previous season should increase weed density in the following season, other factors equal. Coefficients c_j's are expectd to be negative for herbicides intended to control weed type i. Coefficient a is expected to be positive indicating that conservation tillage favors weed growth

TABLE 1 Major Weed Species in the Spring Peas

Common name	Scientific name	Average spring weed density	
		plants/m^2 [a]	Percentage[b]
Summer Annual Grass			
Wild oat	Avena fatua	20.5	98.7
Summer Annual Broadleaf			
Henbit	Lamium amplexicaule	26.4	55.6
Lambsquarter	Chemopodium album	12.1	25.5
Field penny cress	Thlaspi arvense	3.6	7.5
Gromwell	Lithospermum arvense	2.2	4.5
Winter Annual Grass			
Voluntary wheat	Triticum aestivum	1.0	97.1

[a] Average of mean density (plants/m^2) over six years and 24 subplots.
[b] Percent of weed density within each subgroup

relative to conventional tillage. No prior signs are hypothesized for b_3 which indicate the influence of soil organic matter on mid- summer weed density in spring peas.

A total of eight herbicides were used on spring peas over the six years of the IPM experiment. These herbicides were categorized into six subgroups as listed in Table 2. An index of "effective application rate" was developed to aggregate different type of herbicides for H_4 and H_6. An index of 1.0 was given to the manufacturer's label for all herbicides in each subgroup. Accordingly, applications below the label rate, received an index of k equal to the proportion of the label rate so that $0 \leq k \leq 1$. Then each herbicide was weighted by an "efficacy index" (EI_h), $0 \leq EI_h \leq 1$, within the subgroup (see Table 2). The "efficacy index" was assinged based on the relative performance of the particular herbicide within the subgroup. The index of "effective application rate" for a specific herbicide in a subgroup equaled k x EI_h. These effective application rates were summed to obtain the aggregate application rate (H_j) 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. This means that the statistical error terms in the different weed survival functions for a crop are correlated with each other within the same time period, while they are uncorrelated in different time

TABLE 2 Classification of IPM Herbicides in Spring Peas

Crop/Herb. type[a]	Herbicide name	Years used	Label rate (per acre)	Weed mgt. costs ($/ac) Herb.	Appl.	Total	Efficacy Index
H_1 (Non-selective)	Glyphosate	1987-90	0.38 lb ae	6.15	4.50	10.65	1.0
H_2 (PPI BL)	Ethalfluralin	1988-91	0.75 lb ai	9.01	2.25	11.26	1.0
H_3 (PPI GR)	Triallate	1988-91	1.25 lb ai	12.33	2.25	14.58	1.0
H_4 (Preemer. BL)	Dinoseb	1986	3.00 lb ai	16.71	4.50	21.21	1.0
	Metribuzin	1987-91	0.38 lb ai	13.65	4.50	18.15	1.0
H_5 (Postemer. BL)	MCPA	1988-90	0.25 lb ae	1.03	4.50	5.53	1.0
H_6 (Postemer. GR)	Barban	1987	0.38 lb ai	7.92	4.50	12.42	0.6
	Diclofop	1986-87	1.00 lb ai	20.77	4.50	25.27	1.0

[a] BL = Broadleaf weeds, GR = Grass weeds

periods. To test the dependency in the error stucture, the Breusch-Pagan Lagrange Multiplier test (5) was used.[4] As a test result, the alternative hypothesis was not accepted at the 5% significance level, consequently, contemporaneous correlation does not exist. Thus, least squares estimator is fully efficient and there is no need to employ the seemingly unrelated regression estimator (10).

Two "damage functions" have been used to represent the effect of weed density on crop yield: logistic and hyperbolic functions. Cousens (7) compared these models in winter wheat with a single weed species, but not with multiple weed species. A Mitscherlich-Baule yield response function is favored over other generally used functional types to show the technical relationship between crop yield and soil fertility (Frank, Beattie, and Embleton). The function has sufficient flexibility to accomodate factor substitution and imposes plateau growth. In this study, a modified Mitscherlich-Baule production function was combined with both logistic and rectangular hyperbolic damage functions. The yield function with logistic damage was specified as:

$$Y = b_1(1-e^{-b_2 OM})\left[1-\frac{m}{1+e^{-(i+jTWD)}}\right]+aTIL. \tag{2}$$

Variables shared with the survival functions in equation (1) are as defined above. Y is crop yield (kg/ha), OM is content of organic matter in the soil (%), b_1 is maximum potential crop yield with nonlimiting organic matter, and no weeds. The parameter m is maximum proportionate yield damage at infinite weed density and j is a weed competition coefficient. Parameters i, j, b_1, b_2, a, and m are regression coefficients to be estimated. The parameter m was restricted to 0.5 by prior information. The maxium yield loss with no herbicide is known 50% in the study area.[5] Parameter estimates for b_1, and b_2 are expected to be positive consistent with a positive expected

[4] The null hypothesis (H_0) is $\sigma_{12} = \sigma_{13} = \sigma_{23} = 0$, and the alternative hypothesis (H_1) is "at least one covariance is nonzero". Under H_0, the Lagrange multipier statistic(λ) has an asymptotic χ^2 - distiribution with 3 degrees of freedom in this case. The $\lambda = 0.724$ was smaller than the critical value from a $\chi^2_{(3)}$ - distribution for the 5% significance level.

[5] Personal communication, Pat Fuerst, May 1993.

yield correlated with a positive expected yield correlated with higher organic matter. Estimates i and j are expected to be negative and positive, respectively, to generate the characteristic reverse sigmoidal shape of the logistic damage function (12). No prior sign was hypothesized for the tillage coefficient.

The total weed competition index, TWD (weighted no. weeds/m^2), is calculated from weighted predicted weed survival levels over subgroups:

$$TWD = 2.37(\hat{WD}_1) + 3.19(\hat{WD}_2) + 1.00(\hat{WD}_3) \qquad (3)$$

in spring peas. The total weed competition index represents the overall competitive ability of all weed species with the host crop. A competitive index, 1.0, is given to a summer annual broadleaf weed as a standard weed unit for spring peas. In this study, the weight assigned to other weed subgroups is proportional to the average biomass of weeds in that subgroup relative to the average biomass of summer annual broadleaves. The biomasses were based upon biomass measurements of all weeds by species prior to harvest over the six years of the IPM experiment. The $\hat{WD}_i$ for each weed group are predicted from equation (1). Survey-based subjective weights were also examined for use in equation (2). Twelve local weed scientists and fieldmen were asked to assign competitive capacities on a positive scale centered at 1.0 for a common benchmark weed for a subjective weights in terms of goodness of fit and significance of weed competition coefficients in equation (2) and (4). Consequently only the results based on the objective weighting in equations (2) and (4) as used in the subsequent analysis.

The specification of the yield response function with rectangular hyperbolic weed damage is:

$$Y = b_1(1-e^{-b_2OM}) \left[1- \frac{iTWD}{100(1+iTWD/j)}\right]+aTIL. \qquad (4)$$

where common variables with (2) are defined as above, j is the maximum percentage yield loss as weed survival approaches infinity, and i is the proportionate yield loss as weed survival approaches zero.

The symbols b_1, b_2, and c are estimated regression coefficients. Parameter estimates for b_1, and b_2 are expected to be positive consistent with a positive expected yield correlated with higher organic matter. Both estimates i and j are expected to be positive to generate the characteristic rectangular hyperbolic shape of the damage function (12). No prior sign is hypothesized for the tillage coefficient.

SHAZAM (19) was used to estimate the nonlinear yield response functions. There is no guarantee that the estimation process for a nonlinear model will converge to a set of coefficients with 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 optima had been achieved. All optima were stable based on these procedutes.

A nonnested hypothesis testing procedure is required to find appropriate model specification, since these are not nested. A P-test (8) was used to test these nonlinear yield models.

The profit functions for this problem can be written as:

$$\pi = P\hat{Y}(\vec{H}) - \vec{P}_h\vec{H} - AC(\vec{H}) - OC \qquad (5)$$

where π is net returns over total costs ($/ha), $\hat{Y}(\vec{H})$ is the predicted yield (kg/ha) from equation (4), $\vec{H}$ is the vector of herbicide applications (proportion of label rate), P is crop price ($/kg), $\vec{P}_h$ is herbicide prices ($/label rate/ha), $AC(\vec{H})$ is herbicide application cost ($/ha) which is a function of the herbicides applied, and OC is other costs ($/ha). Other costs include land and miscellaneous fixed costs, operator labor, fertilizer, machine operations, and seed, but exclude a charge for management (12, 15).

The herbicide price ($/label rate/ha) for each herbicide subgroup was based on a frequency-weighted average of the prices of herbicides within that subgroup used over the six years of the IPM experiment. Average application cost ($/ha) for herbicide types were computed on the same frequency-weighted basis as used for herbicide type products.

An objective of this study was to find profit maximizing herbicide rates subject to specified on WD_i's, TWD, OM, and H_j's. The MINOS nonlinear programming algorithm within the GAMS software package (6) was used to solve this problem involving maximization of a nonlinear profit function subject to inequality constraints.

IV. Results and Discussion

Table 3 presents the three estimated weed survival functions.

TABLE 3 Estimated Weed Survival Coefficients for Four Weed Subgroups in the Spring Peas

Variables[c]	Weed Subgroup[a,b]		
	WD_1	WD_2	WD_3
Constant	23.57*	- 0.32+	21.79**
	(9.19)	(0.17)	(5.30)
SWD_i	0.66**	-[d]	0.08**
	(0.04)		(0.02)
$HWD_{i,t-1}$	0.06	0.05**	0.35*
	(0.06)	(0.01)	(0.14)
SM	-	0.02*	-
		(0.01)	
H_1	-	- 0.32**	-
		(0.12)	-
H_3	- 27.01**	-	
	(9.67)		
H_4			- 27.65**
			(7.48)
H_6	- 33.83**	-	
	(10.90)		
TIL	8.08*	0.31**	-
	(3.09)	(0.13)	
Log of Likelihood	- 502.94	- 88.36	- 546.59
Adj. R^2	0.86	0.18	0.30

[a] Weeds were categorized as summer annual grasses (WD_1), winter annual grasses (WD_2), and summer annual broadleaves (WD_3).

[b] +, *, and ** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses. Variables are defined in the text.

[c] SWD_i = weed seedling density (plants/m^2) in the spring of weed subgroup in the corresponding column, H_1 = pre-plant nonselective herbicide, H_3 = pre-plant incorporated grass herbicide, H_4 = premergence broadleaf herbicide, H_6 = postemergence grass herbicide, TIL = binary variable for tillage (TIL = 1 for chisel plow).

[d] A dash indicates the variable was excluded because estimated coefficient had low t-value (less than 1) in earlier models which included all relevant variables. Blank entries indicate that the variable was excluded because it was not relevant to the particular weed type.

Spring weed density (SWD_i) coefficients for summer annual weeds have expected positive signs and are statistically significant at the 1% level, while not significant for winter annual weeds. Clearly, spring weed seedling counts appear to be a good indicator for summer annual weeds, other factors equal, of mid-summer weed survival of summer annual grasses (WD_1) and summer annual broadleaves (WD_3) for spring peas in the region. Lagged mid-summer weed density ($HWD_{i,t-1}$) coefficients have expected sings and are statistically significant for winter annual grasses (WD_2) and summer annual broadleaves (WD_3), while not significant for summer annual grasses (WD_1). Compared to three weed types, spring weed density is more important indicator for WD_1, while lagged mid-summer weed density is more important for WD_2 and WD_3. Soil moisture has positive sign for winter annual grasses, but it is not significant for summer annual weeds. Pre-plant nonselective herbicide (H_1) were significant at the 1% level in predicting survival of WD_2, but were not significant for WD_1 and WD_3. H_1 significantly suppressed winter annual grasses. Pre-plant incorporated broadleaf herbicide (H_2) were not significant for WD_3. Pre-plant incorporated grass herbicide (H_3) helped control WD_1, but not WD_2. Preemergence broadleaf herbicide (H_4) were significant for summer annual broadleaves. Postemergence broadleaf herbicide (H_5) were not effective to control summer annual broadleaves. Postemergence grass herbicide (H_6) significantly reduced the summer annual grass population, but not winter annual grass weeds. As expected, chisel plowing (TIL=1) increased (relative to conventional tillage) mid-summer weed populations of grass weeds, but not broadleaf weeds.

Table 4 compares maximum likelihood estimates (MLE) of logistic and rectangular hyperbolic spring pea yield response functions as specified in (2) and (4). The value of m was restricted to 0.5 in this study. This value for m was found from the survey results of maximum pea yield losses in the study area.[6] Both logistic damage-yield response model and rectangular hyperbolic

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[6] Personal communication, Pat Fuerst, May 1993.

TABLE 4 Estimated Yield Response Functions in Spring Pea

	Logistic Model (m = 0.5)		Rectangular Hyperbolic Model	
Parameter[a]	Estimate	t-ratio	Estimate	t-ratio
b_1	3392.40	5.73	2886.90	8.31
b_2	0.71	2.59	0.73	2.61
i	- 0.91	- 0.82	0.14	1.74
j	0.01	2.24	104.93	0.98
a	258.86	2.30	257.88	2.41
Log of Likelihood	- 735.93		- 736.01	
Total obs.[b]	96		96	

[a] Parameters are defined in text following equations (2) and (3).

[b] Total 24 observations of 1990 were not included in the estimation of yield response function because severe yield losses were caused by disease.

model were not rejected at the 5% level by the P-test (8). All estimates of the logistic function have expected signs and are statistically significant at the 1% level except i. Estimates of the rectangular hyperbolic funcion have expected signs and statistically insignificant at the 5% level for i and j. Maximum predicted yield with logistic model at nonlimiting organic matter and weed-free conditions is 3392 kg/ha for spring peas with conventional tillage. This potential yield exceeds the average yield of six years of conventional tillage spring peas in the IPM experiment by 40%. Chisel plow spring peas had predicted potential yields of 3651 kg/ha or 8% higher than under conventional tillage.

In accordance with economic theory, profit is maximized where all marginal value products (MVP's) equal their marginal factor costs (MFC's). In this problem, the MVP represents the change in profit per hectare attributable to using one additional lebel rate of a herbicide type, other factors constant. The MVP is conditional upon the "starting value" or current herbicide use rate. The MFC represents the addition to costs per hectare, namely the constant price and application cost per unit, of using one additional label rate of a herbicide type. The estimated MVP and MFC of herbicides evaluated at the IPM experiment average herbicide rates are shown in Table 5. The MVP of pre-plant nonselective herbicides (H_1) and preemergence broadleaf herbicide (H_4) are lower than their prices (or MFC's), but those of pre-plant incorporated grass herbicide (H_3) and postemergence grass herbicide (H_6) exceed their prices (or MFC). The results indicate increasing H_3 and H_6 herbicide rates above those used in the IPM experiment would boost profit assuming current costs, specified crop prices, and weed densities and other state variables at their means. Pea price would have to be increase from $0.20/kg ($9.16/cwt) to $0.36/kg ($16.34/cwt) to justify the average rate of premergence broadleaf herbicide (H_4) applied in the IPM experiment. On average, broadleaf herbicides appear to have been used at economically excessive rates, but economically lower rates for grass herbicides in the IPM experiment.

Pre-plant nonselective herbicide (H_1), pre-plant incorporated broadleaf herbicide (H_2), preemergence broadleaf herbicide (H_4), and postemergence broadleaf herbicide (H_5) were not recommended for spring peas grown under conservation tillage. Instead, higher rates of pre-plant incorporated grass herbicide (H_3) and postemergence grass herbicide (H_6) were recommended to maximize profit. With optimal herbicide rates, net revenues over total costs are significantly increased compared to those

TABLE 5 Comparison of Estimated Marginal Value Product (MVP) and Marginal Factor Cost (MFC) for an Additional Herbicide Application at Label Rate, Evaluated Using the Means of Herbicide Use and Other Variables in the IPM Experiment

	Herbicide Subgroup			
MVP/MFC	H_1	H_3	H_4	H_6
MVP[a]	0.36	45.68	25.13	57.21
MFC[b]	26.32	36.03	44.85	53.08
Minimum Required Pea Price ($/kg) for Additional Herb.[c]	14.59	0.16	0.36	0.19

[a] MVP assuming market price of spring pea is $0.20/kg ($9.16/cwt).

[b] MFC is the weighted average local price of herbicide and application costs per acre in herbicide group Hj as of 1991.

[c] Minimum pea price required to make an additional application of a full labeled rate profitable beyond IPM average application.

from using average IPM experiment rates in the Table 6.

The bioeconomic weed management models were tested by simulating how optimal herbicide rates responded to changes in spring weed seedling densities, crop prices, herbicide prices, and herbicide application constraints. State variables vary according to

TABLE 6 Comparison between Optimal and IPM Average Herbicide Application Rates and Profit for Winter Wheat Affected by Preceding Crop and Tillage Systema

Herb.(l.r.)/ Yield (kg/ha)/ Profit ($/ha)	Conservation tillage	Conventional tillage
Optimal Hi's: Modeled		
H_1	0.0	0.0
H_3	1.0	1.0
H_4	0.0	0.0
H_6	0.7	0.1
Pred. yield	2727.5	2445.0
Pred. profit[b]	- 93.1	- 142.7
IPM Avg. Hi's: Simulated with Model		
H_1	0.7	0.0
H_3	0.8	0.8
H_4	0.6	0.6
H_6	0.2	0.2
Pred. yield[c]	2592.2	2432.6
Pred. profit[c]	- 145.8	- 176.1
Actual yield[d]	2275.5	2100.4
Actual profit[d]	- 209.7	- 243.1

[a] The optimal Hi's were obtained under the constraints of Hi $\leq$ 1.0. l.r. = label rate; H_1 = pre-plant nonselective herbicides; H_3 = pre-plant incorporated grass herbicides; H_4 = preemergence broadleaf herbicides; H_6 = postemergence grass herbicides.

[b] Expected market price ($0.20/kg) was used for spring peas.

[c] Simulated yield by the model using the average IPM results of state variables and herbicide rates over 6 years.

[d] Actual average yield and calculated profit over 6 year results.

the rotation and tillage. Table 7 demonstrates these sensitivity results for spring peas under conservation tillage. The specified benchmark values are the average of the IPM experiment over six

TABLE 7 Sensitivity Tests of Bioeconomic Model for Spring Peas under Conservation Tillage

			Sensitivity Test Number[a]				
Variable	Unit[b]	Bench-mark	1	2	3	4	5
SWD_1	weeds/m^2	23.6		50.0			50.0
SWD_2	weeds/m^2	0.3					
SWD_3	weeds/m^2	15.2			50.0	50.0	50.0
LWD_1	weeds/m^2	31.4		50.0			50.0
LWD_2	weeds/m^2	2.2					
LWD_3	weeds/m^2	8.3			50.0	50.0	50.0
P	$/kg	0.20					0.30
P_{h1}	$/l.r/ha	15.20					
P_{h3}	$/l.r/ha	30.47					
P_{h4}	$/l.r/ha	33.73				16.87	16.87
P_{h6}	$/l.r/ha	41.96					
<u>Constraint</u>							
H_i	l.r.		≤ 1	≤ 1	≤ 1	≤ 1	≤ 1
<u>Solution</u>							
WD_1	weeds/m^2	0.0	0.0	6.8	0.0	0.0	6.8
WD_2	weeds/m^2	0.1	0.1	0.1	0.1	0.1	0.1
WD_3	weeds/m^2	25.9	25.9	25.9	43.3	43.3	15.6
TWD	index/m^2	26.2	26.2	42.4	43.6	43.6	32.1
H_1	l.r	0.0	0.0	0.0	0.0	0.0	0.0
H_3	l.r	1.8	1.0	1.0	1.0	1.0	1.0
H_4	l.r	0.0	0.0	0.0	0.0	0.0	1.0
H_6	l.r	0.0	0.7	1.0	0.7	0.7	1.0
Y	kg/ha	2727.5	2727.5	2672.0	2667.6	2667.6	2707.6
π^c	$/ha	- 85.2	- 93.1	- 118.7	- 105.1	- 105.1	131.2

[a] Unspecified blanks are same as the benchmarks.
[b] Abbreviations used: l.r. = label rate, others as previously specified.
[c] OC = $564/ha, SM = 17.10%, and OM = 2.97%.

years. The sensitivity results shows that the bioeconomic models recommend only pre-plant incorporated grass herbicide (H_3) under no constraint, but they recommed pre- plant incorporated grass herbicides and postemergence grass herbicide (H_6) under the constraint of limiting herbicide application rates. The sensitivity test results generally show that the bioeconomic models behave as expected according to economic and agronomic theory. For example, increasing pea price from \$0.20/kg (\$9.16/cwt) to \$0.30/kg (\$13.74/cwt) in test 5 increase additional herbicide use. Increasing spring weed densities in tests 2 and 3 increases profit maximizing herbicide rates to sustain yield but profits fall. Reducing herbicide price in test 4 increases herbicide use.

V. Conclusions

On the whole, profit maximizing weed management recommendations from the bioeconomic models for spring peas suggested more frugal and more targeted use of herbicides than is typical for grower practices in the region. If validated profits to growers could be boosted by eliminating excessive herbicides through greater use of weed counts and other information collected early in the season. This model may serve as the frame of a decision aid to predict economically justified herbicide rates for pea growers' fields if weed seedling counts and other field conditions are measurable at modest cost in early spring and mid-summer. The model was structured to utilize readily available and relatively inexpensive information including spring weed seedling counts, mid-summer weed density in the previous season, soil properties, tillage system, and crop and herbicide prices. It will benefit the growers to employ the model whenever the predicted profit gain relative to the prvious strategy exceeds the cost of collecting the field data and using the model.

This bioeconomic model for use in spring peas in the presence of multiple weed species requires the grower or weed management consultant to select the appropriate herbicides consistent with the general recommended rates by herbicide type. While this need to combine judgement with objective recommendations increases management demands, it is probably realistic in a multiple weed context to permit some annual change in herbicide products as the mix of weed species varies within and among weed subgroups.

Two years of replicated testing of the bioeconomic model on farmers' fields is planned . The agronomic and economic performance of the model's recommendations will be compared statistically to the farmer's weed control treatment, to weed scientists' subjective recommendations, and a zero cotrol check. These results will be used to validate and/or further calibrate the model. More research is needed for developing a decision model for spring peas.

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