Evaluating a Precision Agriculture Herbicide Decision Model for Winter Wheat

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Abstract. A user-friendly computerized decision model has been developed for selecting profitable site-specific herbicide applications in winter wheat. The model is based on six years of field research in southeastern Washington State, USA. The model calibrates herbicide applications to management unit weed densities, soil organic matter, soil moisture, and preceding management, as well as to expected input and output prices. The model increased broadleaf herbicide rates by an average of 0.65 label rates compared to the recommendations by farmers and weed science professionals, but cut the more expensive grass herbicides by an average of 0.56 label rates. The model increased average projected profitability, excluding model application costs, by 65 percent compared to four other criteria for determining application rates. The profitability increase relative to local farmers was 19%. Both the model and the cooperating farmers properly chose no grass herbicides for the study sites, but weed science experts chose up to 1.0 label rates. The estimated payoff from using the model substantially exceeded the cost of weed scouting and other information collection. Determining economically optimal sampling and management units is an important challenge for adoption of precision agriculture models like the one developed in this study.

Introduction

Despite the fact that weed populations vary enormously across space and time (Wiles et al., 1992, Johnson, Mortensen and Gotway, 1996), growers and custom applicators frequently apply the same rate of herbicide over an entire field or several fields. However, bioeconomic models based on field data often show large potential increases in profit and, in some cases, reductions in chemical deposition to the environment by calibrating the types and rates of herbicides to observed weed populations and other site characteristics (Lybecker, Schweizer, and King, 1991; Swinton and King, 1994). Chemical weed control decisions provide a fruitful area for precision agriculture decision models. The need for spatially specific decision support in weed control has grown because many farmers have encountered increased weed competition with adoption of no-till and minimum tillage methods which substitute chemical for mechanical weed control (Young, Kwon and Young, 1994). The switch to increased chemical weed control places immediate pressure on cash flow margins as herbicides are an out of pocket expense while tillage is often performed with the farmer's own equipment and labor.

The precision agriculture herbicide decision model reported in this paper is based on six years of field experiment data (Boerboom et al., 1993; Young et al., 1994). The experiment was located 6 km northwest of Pullman, Washington, USA in a 450- to 550-mm annual precipitation zone. Weather and weed populations experienced a representative range of variation during the experiment. Winter wheat (*Triticum aestivum*) was the dominant crop within two rotations: winter wheat-winter wheat-spring wheat and winter wheat-spring barley (*Hordeum vulgare*)- spring pea (P*isum sativum*). Each crop in every rotation was grown every year and there were four replications of each treatment. The relatively large 12- by 46-m plots permitted use of field-size machinery. The experiment included three levels of chemical weed control and both conservation and conventional tillage. Because transition to no-till and minimum tillage in this region generally fosters weed growth, scientists and farmers desired to achieve the soil conserving benefits of conservation tillage with a profitable, but not excessive, level of herbicides.

The first objective in this paper will be to describe a computerized decision model for selecting profitable site-specific herbicide applications in winter wheat. The second objective will be to report changes in projected profitability and chemical use when the model's recommendations are compared to farmers' and professionals' recommendations. A third objective will be to compare the cost of collecting site-specific information to use the model to the payoff from using it.

Model Description and Estimation

The computer model recommends rates of postemergence grass and postemergence broadleaf herbicides for spring application to winter wheat. The model is based on statistically estimated control (or weed survival) functions, which show the effects of initial weed seedling populations, herbicide rates, and other conditions on the survival of weeds into the summer growing season (Kwon et al., 1998). Once surviving weeds, which affect crop growth throughout the growing season, are estimated, these surviving weed densities are employed as variables, along with other factors, to predict winter wheat yield. Finally, the yield predictions are joined with costs to predict profit per unit area.

The weed survival functions are specified for each of three weed types as negative exponential functions:

$$\mathrm{WD}_{\mathrm{i}} = SWD_{\mathrm{i}}\mathrm{e}^{-\mathrm{b}_{\mathrm{ij}}H_j} + \mathrm{d}DH_1 + \sum_{\mathrm{k-1}}^{2} \mathrm{a}_{\mathrm{k}}\ TIL_k + \sum_{\mathrm{m-1}}^{2} \mathrm{c}_{\mathrm{m}}CR_m \qquad \mathrm{i=1,2,3} \tag{1}$$

WD_{i} is preharvest weed density (plants m^{-2}) of the i^{th} weed subgroup, which survives herbicides and natural mortality. The three weed subgroups are summer annual grasses (WD_1), winter annual grasses (WD_2), and broadleaves (WD_3). SWD_{i} is spring weed seedling density (plants m^{-2}) of the i^{th} subgroup. H_j's are application rate (proportion of maximum labeled rate) of the j^{th} herbicide type (H_1 = preplant nonselective for i = 1, 2,3; H_2 = post emergence broadleaf for i = 3; and H_3 = post emergence grass for i = 1 and 2). TIL_k's are binary 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 plow, and $TIL_1 = TIL_2 = 0$ for moldboard plow). CR_m's are discrete variables for preceding 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). The symbol, “e”, denotes the exponential function. DH_1 equals one if a nonselective herbicide had been applied prior to planting winter wheat the preceding fall and equals zero if not applied. The symbols b_{ij}, d, a_{k}, and c_{m} are estimated coefficients. To accommodate the dependency in the error structure of the three weed survival equations, the seemingly unrelated regression (SUR) technique was utilized to estimate these equations (Judge et al. 1985). The data were from experimental plots (12m x 46m). Weed densities were random sample averages within the plots. Spatial data on weed populations within the plots were not recorded.

Weed control decisions are also dependent on estimated functions showing the effect of soil moisture, soil organic matter, surviving weeds, and other factors on wheat yield. The winter wheat yield response functional form which best fit our field data was a Mitscherlich-Baule response to soil moisture and soil organic matter combined with a rectangular hyperbolic weed damage (Kwon et al., 1998):

$$Y = b_1\left(1 - e^{-b_2 SM}\right)\left(1 - e^{-b_3 OM}\right)\left[1 - \frac{i_1 GWD + i_2 BWD}{100\left(1 + \left(i_1 GWD + i_2 BWD\right)/j\right)}\right] \qquad (2)$$
$$+ a_1 TIL_1 + a_2 TIL_2 + c_1 CR_1 + c_2 CR_2.$$

Previously defined variables remain as defined above. *Y* is expected winter wheat yield. *GWD* and *BWD* are aggregate biomass weighted densities of grass and broadleaf weeds. For wheat after peas, $GWD = 0.14 * WD_3$ and $BWD = 0.81 * WD_1 + 1.0 * WD_3$. These two variables account for competitive differences among weeds within each group by using the weed biomass as an indicator of competitiveness. *SM* is spring soil moisture (%) of the top 30 cm and *OM* is soil organic matter (%) of the top 30 cm. The symbols i_1, i_2, j, a_1, a_2, b_1, b_2, b_3, c_1, and c_2 are estimated regression coefficients. SHAZAM (White, 1997) nonlinear least squares was used to estimate the yield response functions. Coefficient j is the maximum percentage yield loss as weed density approaches infinity. Estimates for i_1, i_2 and j were expected to be positive to generate the characteristic rectangular hyperbolic shape of the damage function (Cousens, 1985). 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. Soil moisture is a primary determinant of crop yield potential in dryland crops. Soil organic matter is closely correlated to moisture absorption capacity and root penetration. No prior signs were hypothesized for tillage and preceding crop coefficients.

Profit ha^{-1}, as a function of postemergence broadleaf and grass herbicide (H) rates and the supplied site-specific variables, is a function of the predicted yield (Y) based on equations (1) and (2), output price (P), herbicide prices (P_h), and other production costs (OC).

$$\text{Profit} = PY - \Sigma P_h H - OC \tag{3}$$

Functions (1) through (3) compare the current year benefits of weed control to the current year costs. This approach is based on the earlier statistical work by Wei (1996) with the same data set which failed to find any dynamic or carry over benefits of weed control by herbicides for crop rotations involving winter wheat. This research suggested that weather, or other uncontrolled factors, dominated any dynamic effects of weed populations for this environment.

For the examples in this paper, the winter wheat price was a forecasted five-year average from Kwon et al. 1998, the price for each herbicide type was based on a frequency-weighted average of the prices of herbicides used within that subgroup in the six-year experiment, and production costs were based on production practices in the experiment (Kwon et al., 1998). To apply the decision model to their own situations, growers would supply their own price and cost estimates. Also the model recommends rates of generic postemergence grass and broadleaf herbicides leaving to the grower to select the precise herbicide within these groups, and specify the corresponding prices. Given the weed and environmental diversity, especially for broadleaf weeds, that can be present in this region, permitting flexibility in choosing the exact herbicide is desirable.

Numerical estimates are reported for the weed density (Table 1) and the yield equation for wheat after peas (Table 2). More detail on these statistical results is found in Kwon et al., 1998. The preceding crop variables (CR_m) were insignificant in initial regressions for the weed survival functions and were dropped from the final model. The signs and magnitudes of estimated coefficients agreed with agronomic theory and production experience in the study region. Both broadleaf and grass herbicides (H_2 and H_3) had expected positive signs and were significant at the 1% level which indicates significant suppression of target weeds in this six-year data set (Table 1). Preplant nonselective herbicide (DH_1) was highly significant in reducing survival of broadleaf weeds, but less so for winter annual grass weeds (WD_2) (Table 1). No-till (TIL_1) significantly increased surviving midsummer weed populations in winter wheat. This suggests tillage reduced weed population, other factors constant. Statistical significance of the overall equations and individual coefficients was acceptable for this type of cross sectional-time series agronomic data where weather and other uncontrolled factors also strongly influence weed survival.

The regression results in Table 2 show all yield response coefficients have theoretically expected signs and all are significant at the 1% to 10% levels except for the secondary weed response coefficient j. The estimate of j was retained as the best point estimate of this coefficient in order to preserve the rectangular hyperbolic function which was found statistically superior to other functions in representing weed yield damage for this data set (Kwon, 1998). The intercept term of 8,439 kg ha^{-1} indicate**s** strong yield potential in this region when soil moisture, soil organic matter, and weeds do not limit winter wheat growth.

While the estimated coefficient for BWD of 2.57 is ten times that for GWD (Table 2), the competiveness indices for GWD listed under equation (2) indicate that summer and winter grass weeds have competitiveness indices of 5.79 and 7.14 that of broadleaf weeds. Consequently, the yield impact of actual weed density (WD_i) for broadleaves and grassy weeds are roughly similar for this site. No-till boosted winter wheat yields significantly by 665 kg ha^{-1}. Chisel plow and preceding crop did not significantly affect crop yield. The adjusted R^2 of 48% is reasonable for combined cross sectional and time series experimental data of this type when weather and other uncontrolled factors strongly influence year-to-year yields. Yield response to weed competition tends to be more difficult to model than responses to direct inputs like fertilizer and water.

The computer model is programmed in Visual Basic with user-friendly input screens which elicit the grower's broadleaf and grass weed seedling densities prior to spraying, the site's average percentage soil moisture and organic matter content, whether a nonselective herbicide was used in the previous fall, the crop rotation, the tillage system (conventional, minimum, or no-till), herbicide prices and expected wheat price, and other production costs. Input screens also elicit whether the user wishes to use a model only for winter wheat after peas or a model that permits winter wheat after peas, after spring barley or wheat, or after winter wheat. In this study we illustrate the model for winter wheat after peas. The user specifies the field location and name. Users may select either U.S. or metric units and the choice is used for all input and output.

The model selects the projected profit maximizing combination of broadleaf and grass herbicide rates over a grid search of either 0.1 or 0.25 increments of proportions of manufacturer's label rate, as selected by the user. The wide dispersion of rates used in the experiment permitted estimation of herbicide effectiveness over a fine grid of rates (Boerboom et al., 1993). While it is possible to solve with rate increments as low as 0.1 of label rate, producers have indicated they would likely use increments of 0.25 for reasons of convenience. An output screen for an example field is displayed in Figure 1. The output screen reports the projected most profitable grass and broadleaf herbicide rates, surviving densities of grass and broadleaf weeds, the winter wheat yield, and profit. As shown in Figure 1, the output screen also lists the input data supplied by the user. The computerized model has two other output options not shown in Figure 1. One option displays the projected profit, winter wheat yields, and broadleaf and grass herbicide rates for the ten most profitable herbicide combinations. Another output option permits the user to specify the herbicide rates and the program displays projected winter wheat yield, profit, and midsummer surviving weed densities.

Results and Discussion

This computer model is evaluated in this paper for the weed densities, soil properties, and management conditions in six on-farm winter wheat fields that are considered as management units (Table 3). Four randomized replications were selected for each treatment within each management unit (Boerboom, 1993). The entire fields ranged from 60 ha to 200 ha in size. These fields were used to test an earlier herbicide decision model (Kwon et al., 1995) against the control criteria and recommendations of the farmer, a farm extension consultant, and a weed scientist (Hall, 1995). Grass weed densities were relatively low with a maximum of 26 plants $m^{-2.}$ However, broadleaf weeds were prolific ranging from 22 to 1020 plants m^{-2} (Table 3).

In this study, the current computer model's profit maximizing postemergence broadleaf and grass herbicide recommendations were compared to the same recommendations of the farmer, the weed scientist, and the extension consultant, as indicated above, plus the manufacturer's label rate for the same six management units (Table 4). The farmer's applications were those actually applied to the field surrounding the experiment. The weed scientist's recommendations were intended to achieve "good weed control" based on his visual inspection of field weed composition and density. The extension recommendation was intended to provide economically optimal weed control based on his visual inspection. The manufacturer's label rate was set exactly at the label rates for winter wheat. While label rates, or weed science recommendations for "good weed control," may not always be justified by weed densities, these recommendations are included as useful benchmarks against which to test the model recommendations. Also label rates are frequently used by custom applicators. The model recommendations are based on the field-data-based equations reported above, recent average prices and the measured management unit conditions listed in Table 3. If desired, readers can determine the model's absolute recommendations from Table 4 by adding 1.0 to the entries in the "Model vs. Label Rates" column because label rates were always equal to 1.0.

The model increased broadleaf herbicide rates averaged over all management units by 0.45 to 0.91 label rates compared to the other four recommendations listed in Table 4, but cut the more expensive grass herbicides by an average of 0 to 1.0 label rates. Rates greater than 1.0 label are either mixtures to increase the spectrum of control or multiple applications. Only on management unit D did the model recommend applying less postemergence broadleaf herbicide, by 0.20-label rate, than had been applied by the farmer (Table 4). Both the model and the cooperating farmers chose no grass herbicides for the study fields, which had sparse populations of grass weeds, but the extension and weed science personnel chose up to 1.0 label rates of grass herbicides. However, the extension consultant recommended less grass herbicide than the weed scientist. On management units C, D, and E the extension consultant recommended the same zero level of grass herbicides as the model. The costs of weed control using the model were higher than for the farmer and extension recommendations because of high broadleaf rates, but much lower than for weed scientist and label rate recommendations. The model's weed control costs exceeded the farmer's by \$14.49 ha^{-1} but the model's costs were \$39.46 ha^{-1} below the cost of the weed scientist's recommendations (Table 4). Postemergence grass herbicides in this study were slightly over twice as expensive as broadleaf herbicides per label rate, so the liberal use of grass herbicides elevated weed control costs.

The average projected profit increase from using the model compared to using the other four recommendations was \$130.57 ha^{-1}, equivalent to a 65% average increase in profit (Table 5). As in the Table 4 results, actual herbicide recommendations were used for the other four alternatives, but the model selected profit-maximizing levels based on the experimental plot data-based equations. The model was used to project yield and corresponding profit levels for the model and the four comparisons. Consequently, one would expect the model to improve projected (simulated) profitability as it searched all herbicide combinations over a 0.1 and 0.25 label rate grid to identify the highest profit rates. The farmers' recommendations most closely approached the computer model in projected profitability with only a \$38.55 ha^{-1} average difference. Indeed farmer applications on management units B and D essentially equaled the model in projected profitability. One tentative hypothesis for explaining this result may be that the local farmers had internalized some of the same relative weed damage information which was incorporated in the six-year plot information used in the model. Projected profit for the extension and weed scientist recommendations suffered both from model-projected unneeded expenditure on costly grass herbicides and from projected yield damage from inadequately controlled broadleaf weeds. Extension and weed scientist herbicide recommendations caused projected profit to fall short of the model by \$184.92 ha^{-1} and \$177.81 ha^{-1}. Interestingly, the extension recommendation incurred about \$46 ha^{-1} less weed control cost than the weed scientist recommendation, but the dollar value of reduced yields from inadequate broadleaf control on some management units more than offset the cost savings. Extension and weed science recommendations encountered the greatest projected profit loss where broadleaf weed infestations were massive as in management unit E with 1020 m^{-2} broadleaf seedlings. Applying manufacturer's label rates of postemergence broadleaf and grass herbicides also fell short of the model's projected profit maximizing rates by an average of \$120.98 ha^{-1}.

The model's profit projections in Table 5 do not include the cost of counting weeds, measuring soil properties, and adjusting herbicides to potentially smaller management units. Because it was developed at a public university, the model itself would be free to farmers. However, collecting the information to use the model could be costly. No commercial scouting services exist for quantitative weed scouting in the region. Consequently, we estimated some preliminary costs for this activity based on experience during our field tests of the first model. Our field tests indicated that a supervisor and three crew members could complete 5 to 6 weed counts or soil samples per hour including travel time. Local wage rates of \$9 hr^{-1} for workers and \$22 hr^{-1} for the supervisor and prevailing employee benefits, transport and equipment costs were used. To keep the model affordable and practical for the relative homogeneous soils and large farms of the study region, it is assumed that weed densities are counted on a six ha sampling unit, soil tests are taken on a 30 ha sampling unit, and herbicide rates are adjusted to 60 ha management units. While the 60 ha management units may seem large for smaller farms in many areas of the world, farmers in the test area typically farm 500 ha to 2000 and generally considered site specific adjustments of herbicide rates to less than 60 ha units as impractical. Based on this sampling intensity, the costs of implementing the model came to about \$6 ha^{-1}, or about 55 percent of the typical labor and machine cost of applying herbicides in this region. These costs are split about equally between the costs of collecting the weed and soil information and the increased cost of adjusting herbicide regimes to 60 ha management units compared to the 200 or 300 ha fields that are common in the study area. Adjusting to 60 ha management units was estimated to increase herbicide application costs by 26% over the standard \$11.12 ha^{-1} application cost in the region. The \$6 ha^{-1} total cost could be easily absorbed by the projected profitability advantages reported in Table 5, which range from \$39 to \$185 ha^{-1}.

The \$6 ha^{-1} estimated cost for implementing the model would absorb only 15% of the projected \$39 ha^{-1} average gain in profits over the farmers' weed control practices. However, this cost estimate for model application may be low. Determining the boundaries, size, and number of sampling and management units will present one of the larger challenges to field application of models like this one. Farmers point out that in many PNW regions irregularly shaped field border areas, valleys, hilltops, and traffic areas often possess very different weed densities and mixes. The 6 ha and 30 ha sampling unit procedure for weed densities and soil properties, and the 60 ha management units assumed in our cost estimates may be inadequate for many of the actual fields in the region. The model's profitability advantage could easily narrow if it were necessary to adjust site-specific weed control to smaller irregular management units. Determination of economically appropriate sampling and management units, possibly using geostatistical tools, represents an important future research area for precision agriculture decision models (Fleming et al., 2000). These formally determined units could be compared economically to management units determined subjectively and at less cost by farmers "from the tractor seat."

Summary and Conclusions

The computerized site-specific herbicide decision model for winter wheat reported here was based on six years of large-plot experimental data in the Palouse region of eastern Washington State, USA (Kwon et al. 1998). The computer model proved easy to use and showed potential to substantially increase profit while reducing postemergence grass, but not broadleaf, herbicides in the study region. The model increased broadleaf herbicide rates by an average of 0.45 to 0.91 label rates compared to competing recommendations, but reduced the more expensive grass herbicides by an average of 0 to 1.0 label rates. The projected costs of weed control using the model were slightly higher than for the farmer and extension recommendations, but much lower than the weed scientist and label rate recommendations. On average, the model recommendations boosted projected profitability (which accounted for yield and revenue increases as well as cost changes) by 65% compared to the farmer, extension consultant, weed scientist and label rate recommendations. The estimated \$6 ha^{-1} cost for using the weed decision model could be easily absorbed by the model's projected profitability advantages which ranged from \$39 to \$185 ha^{-1}, but the costs of weed monitoring and adjusting herbicide application to irregular subfields might be higher in real world conditions. More research is needed on cost effective monitoring of weed densities and other site characteristics and for adjusting herbicides to subfield management units.

Determination of optimal rate of herbicides is critical if site specific management for weed control. The computer model presented offers the potential to quickly determine a pesticide strategy for management units within a field. An application of the model to specific field conditions illustrated that there were economic benefits to adjusting the rate of herbicide application based on the weeds and density of weeds present. Blanket field applications can either over or under apply herbicides for the more unique management units within the field. Future research will need to examine cost effective procedures for defining the size of management and sampling units. Field validation of the model determined the returns were higher with the site specific management. The affordability of new technologies and models remains as an essential step in promoting precision agriculture tools.

Footnotes

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Table 1. Estimated coefficients of exponential preharvest weed survival functions for three weed subgroups in winter wheat after peas[a].

Variable[b]	WD_1[c]	WD_2	WD_3
H_2	[d]		2.787**[e] (0.137)[f]
H_3	1.078** (0.202)	0.281** (0.030)	
DH_1	-19.475+ (11.425)	-0.621 (0.398)	-15.230** (4.908)
TIL_1	22.152** (6.946)	0.041 (0.240)	12.943** (2.935)
TIL_2			
Root MSE[4]	44.83	1.56	19.58
Adj-R[4]	0.353	0.933	0.314

[a]Models were also estimated for winter wheat after spring barley, spring wheat and winter wheat, but these results are not presented here.

[b] H_2 = post emergence broadleaf herbicide, H_3 = post emergence grass herbicide, DH_1 = binary variable for preplant nonselective herbicide ($DH_1 = 1$ for application, $DH_1 = 0$ for none), TIL_i = binary variables for tillage ($TIL_1 = 1$ and $TIL_2 = 0$ for no-till, $TIL_1 = 0$ and $TIL_2 = 1$ for chisel plow, $TIL_1 = TIL_2 = 0$ for conventional tillage).

[c]Preharvest weed densities (plants m^{-2}) were categorized for summer annual grasses (WD_1), winter annual grasses (WD_2), and annual broadleaves (WD_3).

[d]Blank entries indicate that the variable was excluded because a herbicide was not relevant for the particular weed category or because a tillage practice was not used for that data set.

[e] +, *, and ** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[f]Standard errors are in parentheses.

Table 2. Estimated coefficients of yield response function for winter wheat after peas.

	Estimate[b]	Std. error
Intercept	8438.620**	644.169
SM	0.174**	0.022
OM	0.826**	0.235
GWD	0.257+	0.155
BWD	2.570*	1.174
J	278.080	794.514
TIL_1	665.249**	241.032
Root MSE	1216.43	
Adj - R^2	0.477	
Sample size (n)	144	

[a]Variables are defined in text following equations 1 and 2.
[b]+, *, ** indicate significance at the 10, 5, and 1% levels, respectively.

Table 3. Soil organic matter, soil moisture, and average pre-herbicide weed densities for six management units of wheat after peas, eastern Whitman County, Washington, USA

Management Unit	Tillage	Soil Organic Matter(%)	Soil Moisture Content(%)	Average Weed Densities (plants m^{-2})		
				Spring Grasses	Winter Grasses	Broadleaves
A	No-till	4.44	20.70	12.5	0.5	408.0
B	No-till	3.32	18.20	13.8	0.3	133.3
C	Conv.	2.96	17.80	7.2	4.0	303.1
D	Conv.	3.55	17.00	0.7	0.9	22.2
E	No-till	4.16	22.80	2.4	1.1	1020.2
F	Conv.	3.67	22.40	16.4	9.4	807.0

Table 4. Changes in recommended postemergence broadleaf (BL) and grass (Gr) herbicides (proportions of label rate) at six management units: model versus four other criteria[a]

Management Unit	Model vs Farmer		Model vs Extension		Model vs Weed Sci.		Model vs Label Rates	
	BL	Gr	BL	Gr	BL	Gr	BL	Gr
A	0.59	0.00	1.14	-0.75	0.64	-1.00	0.80	-1.00
B	0.01	0.00	0.50	-0.75	-0.16	-1.00	0.00	-1.00
C	0.70	0.00	1.04	0.00	1.04	-1.00	0.70	-1.00
D	-0.20	0.00	0.42	0.00	0.30	-0.75	-0.20	-1.00
E	0.69	0.00	1.34	0.00	1.34	-0.75	1.00	-1.00
F	0.91	0.00	1.04	-0.63	1.01	-0.75	1.00	-1.00
Av.	0.45	0.00	0.91	-0.36	0.70	-0.88	0.55	-1.00
Av. Cost Change ($/ha)	14.49		6.58		-39.46		-47.19	

[a]The difference was determined by subtracting the farmer, extension, weed scientist, and label rate recommendations from the model recommendation (a positive indicates the model rate is greater than the alternative).

Table 5. Projected increases in profit ($/ha) using model herbicide rate recommendations relative to those of the farmer, extension, weed science, and label rate applications[a]

	Model versus			
Management Unit	Farmer	Extension	Weed Sci.	Label Rate
A	26.16	219.93	84.45	102.43
B	0.55	112.38	55.80	50.92
C	28.41	121.84	180.18	85.86
D	1.58	9.04	57.87	70.00
E	66.04	464.69	517.51	240.46
F	108.59	181.62	171.08	176.21
Field Av.	38.55	184.92	177.81	120.98

[a]The difference was determined by subtracting the farmer, extension, weed scientist, and label rate profit from the model profit. Profit is net of all costs except those for measuring weed densities and soil properties as required for operation of the model.

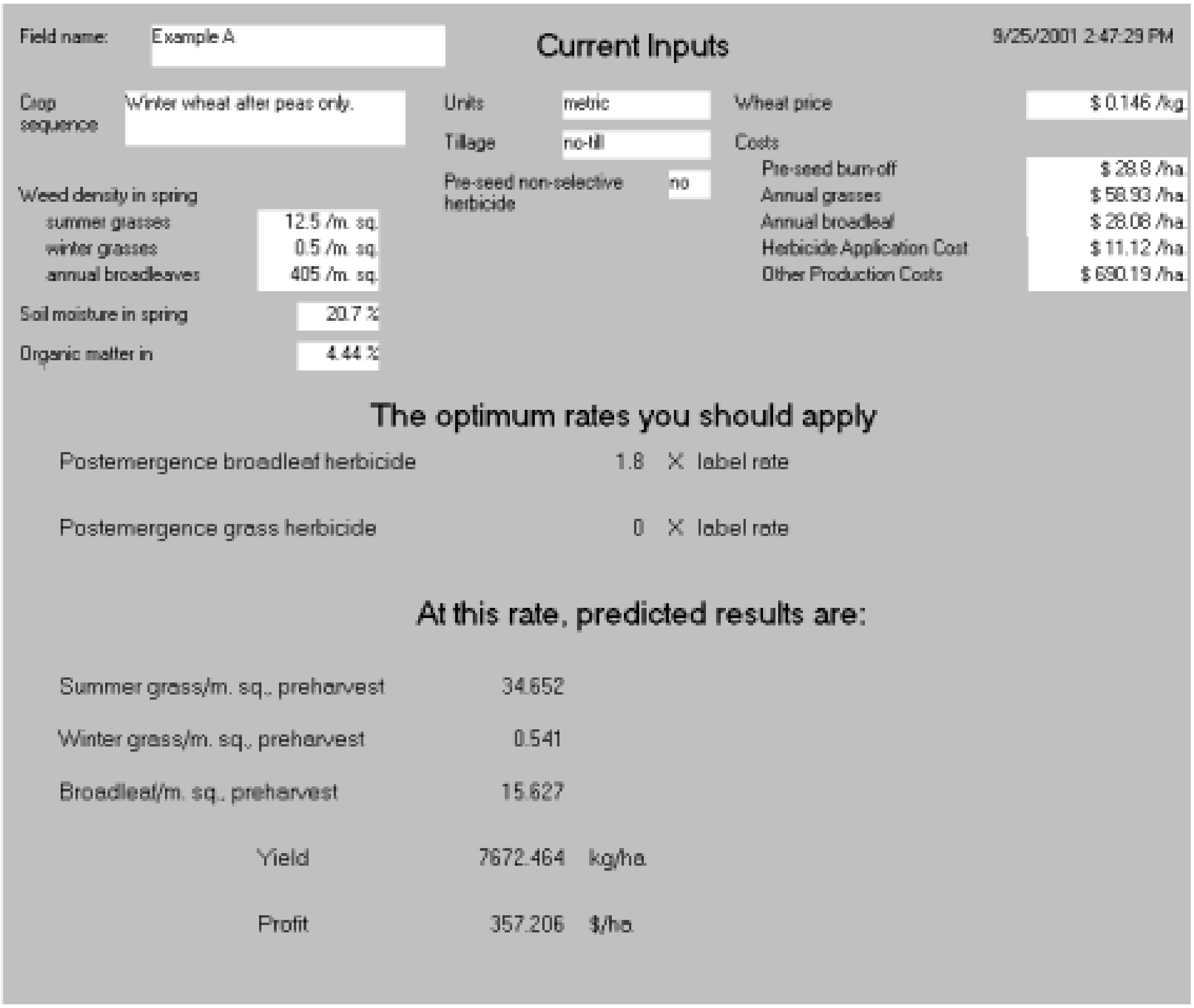

Fig. 1. Example output of herbicide decision model

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