Relative Importance of Environmental Attributes Using Logistic Regression

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Selected paper prepared for presentation at the
Southern Agricultural Economics Association Annual Meetings

Mobile, Alabama, February 4-7, 2007

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Abstract

We investigate the problem of determining the relative importance of attributes in the discrete choice setting. Four alternative methods of extracting the relative importance of attributes are considered. The empirical application involves the development of a risk index system for individual herbicides combining the information on the herbicides' different human and environmental risks. The values of the pesticide risk indices are found to be consistent across the different methods.

Introduction

The analysis of the relative importance of factors affecting agent's economic decisions is common in agricultural economics research. A quick search of the "AgEcon" agricultural economics on-line library displays 162 articles for the key words "relative importance". However, neither the concept nor the methods utilized by investigators to analyze the relative importance of explanatory variables are very clear (Kruskal and Majors, 1989).

In this study we consider the problem of determining the relative importance of attributes in a decision maker's choice of one out of several alternatives in the revealed preference setting. The determination of the relative importance of the attributes is required for the construction of an index summarizing the overall effect of a group of attributes. The calculated index can later be used to compare and rank the alternatives.

The empirical application involves the development of a risk index system for individual herbicides combining the information on the herbicides' different human and environmental risks. Using an empirical data on farmers' herbicide choices, we compare the performance of relative importance weights of different herbicide risk attributes constructed using: the unstandardized and standardized estimated coefficients of a conditional logit choice model, the relative importance indexes (RII) proposed by Soofi (1992), and a measure of attribute relative importance from the marketing literature (Green and Wind, 1975).

Relative Importance of Explanatory Variables

The determination of the relative importance of the explanatory variables is an important aspect of regression analysis. However, the literature is quite sporadic, and the concept of relative importance still remains ambiguous (Soofi et al., 2000). For example, Kruskal and Majors (1989) studied the concept of relative importance of explanatory variables in the scientific literature and found that 20 percent of the studies misused statistical significance (P values) as a measure of the relative importance of variables (Kruskal and Majors, 1989). As pointed our by Soofi et al. (2000) "a measure of statistical significance maps the analysts strength of confidence in making inferences about an unknown parameter based on a statistic, whereas relative importance refer to quantities that compare the contribution of individual explanatory variables to a response variable." (p.596)

Methods developed to analyze the relative importance of explanatory variables focus mainly on the linear regression model[1]. After reviewing the literature, we identified four measures of relative importance which can be used to gauge the relative importance of variables in the context of the conditional logit model: unstandardized and standardized estimated coefficients, the relative importance indexes (RII) proposed by Soofi (1992), and a measure of attribute relative importance from the marketing literature (Green and Wind, 1975).

Relative Importance Measures of Marginal Effects

The most commonly used measure of relative importance is the unstandardized coefficients. Statistically, the unstandardized coefficient indicates the impact of a "one-unit" difference in the independent variable on the dependent variable. In economics, since the conditional logit model is derived as the optimal solution to a random utility maximization problem, the parameter estimates represent the impact of a "one-unit" change in the independent variable on the value of the underlying indirect utility function.

An alternative to the unstandardized coefficients are the standardized coefficients. Menard (2004) argues in favor of standardized coefficients for two reasons. First, for variables with no natural metric (e.g. 1=strongly disagree, 2=disagree, 3=neutral, etc), a

[1] Johnston and Lebreton (2004) present a very detailed discussion on the history of relative importance indices and an evaluation of several alternative measures in the context of linear regression models.

"scale free" standardized coefficient may be more meaningful than unstandardized coefficient. Second, even for variables measured in a natural metric (e.g., dollars, pounds, etc.) it is not clear whether a one unit-change, or a 0.1 unit change, is "big" or "small" with respect to the scale. The use of the standardized coefficients transforms the independent variable into a variable measured in "standard deviation units." Menard (2004) compares five alternative approaches to constructing standardized logistic regression coefficients. Four out of the five proposed approaches are based on the original unstandardized coefficients. The first approach considered by Menard to calculate standardized coefficients (β_s) involves multiplying the understandardized coefficient (β) by the sample standard deviation of the predictor (s_x):

$$\beta_S = \beta s_x \,. \tag{1}$$

The other three standardized coefficients based on unstandardized coefficients are obtained by simple multiplication of β_s by some constant which results in standardized coefficients with different absolute values but unchanged relative values. Moreover, one of these approaches is only applicable to the bivariate logit model. Therefore, we do not consider these approaches. From our perspective, both unstandardized and standardized coefficients measure the relative importance of the marginal changes in the explanatory variables. Even though Menard (2004) also includes a relative importance measure derived from information theory as another approach to calculate standardized coefficients, we prefer to present it in the next section as a measure of aggregate relative importance of an explanatory variable.

One problem with the use of relative importance measures based on marginal changes is that these measures are conditional on the contribution of other variables. For example, the unstandardized coefficient represents the change in the value of the underlying utility function given one unit change in the explanatory variable, "all else being equal." In theory, this is a very relevant measure, however in practice this independent marginal change effect might be unattainable if the independent variables are correlated.

The most widely used measures of relative importance in economics are elasticity values. In the linear model $Y_j = \alpha_o + \sum_{i=1}^{k} \alpha_i x_{ij} + \varepsilon_j$, the elasticity $e_{ij} = \dfrac{\alpha_i x_{ij}}{Y_j}$ measures the contribution of each explanatory variable to the expected value of the dependent variable. The elasticity values for different variables are easy to compare since they are all measured in the same units. In the conditional logit model, elasticity values can be calculated with respect to the probability of choosing any alternative. This creates a set of elasticity values for each alternative, and therefore they are not very useful for the purpose of measuring the relative importance of the explanatory variables in the overall discrete decision process.

Aggregate Measures of Relative Importance of Explanatory Variables

The previous section presented measures of relative importance based on the marginal change in explanatory variables. In this section, we consider two measures that can be used to determine the overall effect of explanatory variables on the discrete choice decision. The first measure is derived from information theory, and the second measure is a measure commonly used in the marketing literature. Unlike the marginal measures of relative importance, aggregate measures of relative importance are not conditional on the effect of the other variables.

Using the concepts of information theoretic statistics, Soofi (1992) proposes a set of diagnostics for the evaluation of the relative importance of attributes in the logit model. These diagnostic are based on several information indexes. The joint importance of a set of M explanatory variables in a conditional logit model is given by the information index $I_{\pi^*}(1,..,M)$:

$$I_{\pi^*}(1,...,M) = \frac{H(\pi^*) - H(U)}{H(U)} = 1 - \frac{H(\pi^*)}{H(U)}, \tag{2}$$

where $H(\pi^*)$ is the negative of the log-likelihood function of the conditional logit model evaluated at the estimated maximum likelihood estimates, and $H(U)$ is the negative of the log-likelihood function of a conditional logit model with no covariates and no constant term.[2] Soofi et al. (2000) interpret this index as the contribution of the explanatory variables to the reduction in uncertainty (total entropy) about the prediction

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[2] $H(\pi^*) = -\sum_{j=1}^{N} \sum_{r=1}^{R} \delta_{ir} \ln \hat{\pi}_{ir}$, where N is the number of individuals in the sample, R is the number of alternatives, δ_{ir} =1 if individual n chooses alternative r, and 0 otherwise, and $\hat{\pi}_{ir}$ is given in equation 7. $H(U) = -N \ln R$.

of the alternatives. This information index corresponds to McFadden's likelihood ratio index, which is bounded between 0 and 1 and is used as a common measure of goodness of fit of the conditional logit model (Greene, 2003). Since maximum likelihood estimation attempts to minimize the likelihood function, this index can be seen as the proportional reduction in the -2 log-likelihood statistic (Menard, 2000).

Other information indexes defined by Soofi (1992) are the simple information index and the partial information index. The simple information index of an explanatory variable $I_{\pi^*}(m)$, m=1,..,M, measures the contribution in the reduction of uncertainty of each explanatory variable when there is only a single explanatory variable in the model. The partial information index measures the contribution to the uncertainty reduction of the attribute m over and above the other M-1 attributes. This can be expressed as:

$$I_{\pi^*}(m;1,...,m-1) = \frac{H[\pi^*(1,...,m-1)] - H[\pi^*(1,...,m)]}{H(U)}, \qquad (3)$$

where $H[\pi^*(1,...,m)]$ is the negative of the log-likelihood function of a model containing M explanatory variables. As pointed out by Soofi (1992), the information index, the simple information index and the partial information indexes are similar to the multiple, simple and partial correlation coefficients used in linear regression. The information index can be decomposed as the sum of simple and partial information indexes:

$$I_{\pi^*}(1,...,M) = I_{\pi^*}(1) + I_{\pi^*}(2;1) + I_{\pi^*}(3;1,2) + ... + I_{\pi^*}(M;1,...,M-1)\,. \qquad (4)$$

This decomposition can then be used to characterize the relative importance of the M explanatory variables if the order 1,..,M is the relevant order. However, since in most of the cases a relevant order for the explanatory variables is not present, Soofi (1992) proposes using the M! decompositions of type (4) (Kruskal,1987). The relative importance of each variable is measured using the average of the simple and partial information indexes over all possible M! decompositions.

Table 1 shows all the decompositions for a model with three explanatory variables (3! decompositions). Each row corresponds to one decomposition. The first column displays the ordering of the variables and the corresponding information index. The next three columns contain the simple and partial information indexes that make up the decomposition. The relative importance index for variable *j* (*j*=1,..,3) is obtained by calculating the average of the *j*th column.

There are two other features of Soofi's (1992) procedure to analyze the relative importance of explanatory variables in the conditional logit model. First, relative importance analysis can be performed not only for individual variables but also for groups of explanatory variables. Second, confidence intervals for the relative importance indexes can be obtained by using bootstrapping procedures.

The last measure of relative importance that we consider is widely used in the marketing literature (e.g.,Verlegh, Schiffertsein and Wittink; 2002) and was initially proposed by Green and Wind (1975). This measure is obtained by multiplying the range of the values of the attributes (highest minus lowest values of the explanatory variable) times the corresponding unstandardized coefficient. Green and Wind (1975) argues that this measure allow to compare utility ranges from attribute to attribute to get some idea of their relative importance.

A Theoretical Model of Herbicide Choice

In the empirical application, we evaluate these different methods to obtain relative importance of different herbicide attributes for farmers' herbicide choices. We use farmers' preference information for different herbicide attributes which they reveal by making their choices of herbicide products out of the sets of available alternatives. The relative importance information is later used to construct herbicide risk indices.

Herbicide choice by a farmer can be represented as a utility maximization problem. Herbicides are productive inputs affecting the farmer's profit, thus indirectly utility through consumption, that may also enter a farmer's utility directly by affecting environmental quality and health. Each herbicide product in the farmer's choice set is characterized by a stacked vector of attributes h consisting of h^{π}, a vector of attributes affecting profit, such as herbicide effectiveness in eliminating weeds, its product and application costs, and h^{e}, a vector of attributes affecting human health and the environment. We assume that a representative farmer is maximizing the one-period utility of consumption and safety, representing the human health and environmental factors important to the farmer, subject to the budget constraint:

$$\max_{c,h} U = U\left(c\ ,\ h^{e};\ g\right)$$
$$s.t.\quad c = \left(p\cdot y\left(h^{\pi};f\right) - r\left(h^{\pi}\right)\right)\times A, \tag{5}$$

where $c(\cdot)$ is farmer's consumption, g is a vector of structural preference parameters of the utility function, p is the price the farmer expects to receive for his crop, $y(\cdot)$ is expected yield per acre, f is a vector of other parameters affecting yield, r is per acre cost of production, which is also affected by herbicide choice, and A is the number of crop acres. The solution of this problem includes the optimal level of farmer's consumption and the herbicide choice with the optimal bundle of productive and risk attributes.

Data and Procedures

The herbicide use data were obtained from a national computer-aided telephone survey of soybean farmers in 2002 conducted by Doane's Market Research in cooperation with North Carolina State University. The survey explored the issues relevant to the comparative economic analysis of conventional and RR soybeans. In particular, it concentrated on differences in herbicide use.

There were 1,769 individual herbicide choices made by 610 farmers participating in the survey. These choices were used to estimate farmers' preferences for different herbicide production-related and risk attributes. The information on herbicide attributes was obtained from a variety of sources (herbicide Material Safety Data Sheets (MSDS), and labels; ExToxNet; U.S. Department of Agriculture, NASS 2002; Iowa State University Extension Service; University of Florida Cooperative Extension Service; University of Wisconsin) and is explained in the next section.

Herbicide Attributes

A number of herbicide attributes may affect the farmer's choice of herbicide product. Since herbicides are designed to control weeds, their effectiveness in dealing with weeds should be one of their most important attributes to the farmers. Herbicide effectiveness is measured as the percent of broadleaf and grass weed control calculated as an average percent control of a number of weeds within broadleaf and grass weed categories (calculations include all broadleaf or grass weeds for which information on percent control was available). The costs associated with herbicide application, including the crop stage-specific herbicide application cost and materials cost, determine the final profit and therefore affect the choice.

Herbicide risk attributes derive their relative importance through their impact on various arguments in farmers' utility functions. Their effect on farmers', farm families', and workers' health and on the quality of on-farm environmental resources, such as soil or water, may enter the utility function directly, as well as through the utility of profit (equation 5). Farmers may derive utility from fishing, hunting, swimming or some other recreational activities that may be affected by herbicides. Finally, farmers may have some altruistic concerns for environmental preservation. Herbicide risk attributes we consider in the choice model are acute human toxicity to eyes and skin, toxicity by ingestion and inhalation, chronic human toxicity, and the potential to contaminate ground and surface water.

Different herbicide risks are not measured in the same units. Therefore, the measures of different risks were rescaled to make them directly comparable. If certain herbicide presents a high risk in a certain risk category, it is assigned a value of 3 in this category, if it presents a moderate risk, it is assigned a value of 2, if it presents a low risk, it is assigned a value of 1, and if it presents no risk, it is assigned a zero value. A detailed explanation of the sources and procedures to calculate the indexes is available in Sydorovych (2005).

Table 2 provides the summary statistics of the characteristics of the forty six herbicides included in the herbicide choice set. The complete data on the characteristics of the herbicides is also presented in Appendix 1. The average cost for the herbicide application is around \$11/acre, however the application costs range from \$0.96/acre to \$20/acre. The average efficiency of the herbicides to control grass and broadleaf weeds is around 50 percent. The mean values for the human and environmental characteristics of the herbicides range from 1.2 to 2.4.

Estimation Procedures

Herbicide choices made by farmers were used to estimate their preferences for different herbicide attributes by applying the conditional logit procedure. The conditional logit choice probability is derived from utility-maximizing behavior. The utility function, U, of the farmer i (i: i=1,...,I) associated with the herbicide alternative j (j: j=1,…,J) is

$U_{ij} = \beta'_i \, x_{ij} + \varepsilon_{ij}$, where x_{ij} are observed attributes of the herbicide alternative *j* for farmer *i*, and β_i is a vector of coefficients for farmer *i*. Finally, ε_{ij} is an extreme value iid random term. The farmer observes all elements of the model and chooses herbicide alternative *j* if it maximizes his utility: $U_{ij} = Max\left(U_{i1}, U_{i2}, \ldots U_{iJ}\right)$. The researcher observes the x_{ij}'s, but not β_i and ε_{ij}'s. The conditional logit probability of choosing herbicide alternative *j* among *J* alternatives by farmer *i* is the integral of the conditional choice probability for the herbicide alternative *j* by farmer *i* over all possible values of β_i:

$$P_{ij} = \frac{exp\left(\beta' x_{ij}\right)}{\sum_{j=1}^{J} exp\left(\beta' x_{ij}\right)}. \qquad (6)$$

All the models were estimated using MATLAB 7.0. The computer codes are available from the authors upon request.

Development of a Pesticide Environmental Risk Index

As explained introduction, besides the relative importance of the cost of a herbicide, its efficiency, and environmental and human safety characteristics in farmers' decision to select an herbicide, the objective of this paper was to calculate a environmental risk index. The index is designed to combine information about various pesticide environmental and health risks with pesticide application information to give a more meaningful picture of pesticide impact. The form of the index is $\sum_{k=1}^{K} w_k r_k$, where w_k is the relative weight, or importance, placed on risk source r_k and $\sum_{k=1}^{K} w_k = 1$.

Results

Conditional logit estimation results (table 3) show that, in addition to the cost and production-related attributes, farmers consider herbicide safety when making their herbicide choices since the coefficients on all herbicide risk attributes, except for ground water risk, are statistically significantly different from zero at α=.01. The estimated parameters indicate that an increase in herbicide cost or an increase in the value of its human and environmental risk characteristics have a negative effect on the probability of choosing a herbicide. On the other hand, and increase in the efficiency of a herbicide to control grass and broadleaf weeds increases the probability that a herbicide will be selected by a farmer.

The four measures of relative importance of the herbicide attributes are shown in table 4. The unstandardized coefficients represent the marginal effect of a one unit change in attribute on the underlying indirect utility function. For example, the parameter corresponding to the application cost of the herbicide can be interpreted as indicating that a $1 dollar increase in the cost of the application of the herbicide decreases indirect utility by 0.11 units.

Using the unstandardized coefficients as measures of relative importance dermal toxicity appears the most important attribute. A one unit decrease in dermal toxicity increases the underlying utility function by 0.58 units. The second more important attribute using this criterion is surface water risk followed by ingestion and inhalation toxicity, chronic toxicity, eye toxicity and herbicide application cost. The small values of the unstandardized coefficients on herbicide efficiency measures make them appear as relatively less important. This result points to another drawback of unstandardized coefficients as measures of relative importance. Their values depend on the units in which the attribute is measured.

The marginal willingness to pay values for the attributes are closely related to the unstandardized coefficients. The marginal willingness to pay for any attribute is calculated by dividing its corresponding unstandardized coefficients by the price coefficients (application cost in our case). For example, the willingness to pay for a one unit reduction in dermal toxicity is $5.4. Even though the willingness to pay measures are easy to interpret, they are only rescaled versions of the unstandardized coefficients and therefore they also depend on the units in which the attribute is measured.

The values of the standardized coefficients show a different picture regarding the relative importance of the attributes. These coefficients represent the change in the underlying indirect utility function given a one standard deviation change in the explanatory variables (table 2). In other words, these coefficients represent the marginal change in the utility function caused by comparable changes in the range of the attribute values. Using these coefficients, the three most important variables are broadleaf weed efficiency, herbicide application costs, and dermal toxicity.

The fourth column in table 4 shows Soofi's relative importance measures. Intuitively, this measure can be interpreted as the average relative contribution of each explanatory variable to the loglikelihood value of models constructed using all the possible combinations of the remaining explanatory variables. This relative importance values indicate that dermal toxicity is the variable with most explanatory power, followed by broadleaf weed efficiency, herbicide application costs and surface water risk.

The last column shows the "marketing measure" of attribute relative importance. In our opinion, this measure is the hardest to interpret. The values represent the ranges in utility corresponding to each attribute but are difficult to relate to the choice decision process. Attributes with the largest ranges in utility were expected to have higher explanatory power but the relationship is not as direct as in the case of Soofis' relative importance index measures.

The pesticide risk indices weights (table 5) and the pesticides risk indices values (appendix 2) calculated using the different methods look very similar. Also, the rankings of the herbicides (appendix 2), in terms of their pesticide risk index value, are consistent across the methods. For example, Glyphosate is always ranked as one of the herbicides with the lowest pesticide risk index values.

Summary and Conclusions

In this study we considered the problem of determining the relative importance of attributes in a decision maker's choice of one out of several alternatives in a revealed preference setting. Our review of literature identified four measures of relative importance which can be used to gauge the relative importance of variables in the context of the conditional logit model: unstandardized and standardized estimated coefficients, the relative importance indexes proposed by Soofi (1992), and a measure of attribute relative importance from the marketing literature.

Using an empirical data on farmers' herbicide choices we compared the performance of the relative importance weights constructed using the four approaches. The different methods of estimating relative importance measures resulted in a different ranking of the relative importance of the variables. At the same time, the values of the pesticide risk indices were consistent across the different methods. The consistency of the results across different methods supports the value of the pesticide risk index developed in our study. However it is an open question if these results can be generalized to other data sets without additional empirical and/or theoretical comparison of the relative importance measures.

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Table 1. Decomposition of Information over All Orderings for a Model with Three Explanatory Variables.

Information Index	Variable 1	Variable 2	Variable 3
$I_{\pi^*}(1,2,3)$	$I_{\pi^*}(1)$	$I_{\pi^*}(2;1)$	$I_{\pi^*}(3;1,2)$
$I_{\pi^*}(1,3,2)$	$I_{\pi^*}(1)$	$I_{\pi^*}(2;1,3)$	$I_{\pi^*}(,3;1)$
$I_{\pi^*}(2,1,3)$	$I_{\pi^*}(1;2)$	$I_{\pi^*}(2)$	$I_{\pi^*}(3;2,1)$
$I_{\pi^*}(2,3,1)$	$I_{\pi^*}(1;2,3)$	$I_{\pi^*}(2)$	$I_{\pi^*}(3;2)$
$I_{\pi^*}(3,1,2)$	$I_{\pi^*}(1;3)$	$I_{\pi^*}(2;3,1)$	$I_{\pi^*}(3)$
$I_{\pi^*}(3,2,1)$	$I_{\pi^*}(1;3,2)$	$I_{\pi^*}(2;3)$	$I_{\pi^*}(3)$

Table 2. Summary statistics of herbicide characteristics

Herbicide Characteristics	Mean	Std. Deviation	Min	Max
Herbicide Application Costs	11.3602	4.7551	0.9600	20.4000
Grass Weed Efficiency	56.7391	23.2477	15.0000	91.0000
Broadleaf Weed Efficiency	52.8261	28.1705	15.0000	94.0000
Eye Toxicity	1.8261	0.8157	0	3.0000
Dermal Toxicity	1.2174	0.6225	0	3.0000
Ingestion and Inhalation Tox.	2.0000	0.9089	0	6.0000
Chronic Toxicity	1.5435	1.1365	0	3.0000
Surface Water Risk Toxicity	2.4130	0.7395	1.0000	3.0000
Ground Water Risk Toxicity	1.8696	0.8995	1.0000	3.0000

Table 3. Conditional Logit Estimation Results of the Herbicide Choice Model

Herbicide Characteristics	Unstandardized Coefficient	Std. Error
Herbicide Application Costs	-0.1078***	0.0069
Grass Weed Efficiency	0.0039***	0.0012
Broadleaf Weed Efficiency	0.0185***	0.0014
Eye Toxicity	-0.1353***	0.0429
Dermal Toxicity	-0.5751***	0.0578
Ingestion and Inhalation Tox.	-0.1542***	0.0273
Chronic Toxicity	-0.1362***	0.0320
Surface Water Risk Toxicity	-0.3107***	0.0304
Ground Water Risk Toxicity	0.0107	0.0427
Log-Likelihood Value	-5,9377	

[a] Significance levels of 0.01, 0.05 and 0.10 are indicated by ***, **, and *, respectively.

Table 4. Relative Importance Measures of Herbicide Attributes in the Farmer's Herbicide Choice Model

Herbicide Characteristics	**Unstandardized Coefficients**	**Standardized Coefficients**	**Soofi's Relative I.**	**Marketing Measure**
Herbicide Application	-0.1072	-0.5100	1.570	-2.0848
Grass Weed Efficiency	0.0038	0.0890	0.415	0.2910
Broadleaf Weed	0.0182	0.5136	2.865	1.4404
Eye Toxicity	-0.1324	-0.1080	0.125	-0.3971
Dermal Toxicity	-0.5781	-0.3599	3.295	-1.7343
Ingestion and Inhalation	-0.1524	-0.1385	0.930	-0.9142
Chronic Toxicity	-0.1374	-0.1562	0.820	-0.4123
Surface Water Risk	-0.3104	-0.2295	1.450	-0.6207

Table 5. Pesticide Risk Indices Weights

Herbicide Characteristics	**Unstandardized Coefficients**	**Standardized Coefficients**	**Soofi's Relative I.**	**Marketing Measure**
Eye Toxicity	0.101	0.109	0.019	0.097
Dermal Toxicity	0.441	0.363	0.498	0.425
Ingestion and Inhalation	0.116	0.140	0.140	0.224
Chronic Toxicity	0.105	0.157	0.124	0.101
Surface Water Risk	0.237	0.231	0.219	0.152

Appendix 1. Herbicide Characteristics

	GWE	BLE	COST	ET	DT	INGT	INHT	CHRT	GRWT	SUWT
2,4-D 6 Amine	15	85	1.76	3	2	1	1	3	2	1
Assure II	92	15	10.67	3	1	1	1	2	1	1
Authority	35	66	11.12	2	1	1	2	2	3	3
Canopy XL	45	79	17.17	2	1	1	2	2	3	3
Axiom DF	66	30	18.98	2	1	1	1	2	3	3
Backdraft	32	54	8.59	1	1	1	1	0	3	3
Basagram T/O	15	57	20.4	1	1	1	1	3	2	3
Ultra Blazer	25	78	12.34	3	1	1	1	2	1	2
Boundary 6.5 EC	66	30	12.02	2	1	1	1	0	2	2
Broadstrike+Dual	66	30	10.94	3	2	1	1	2	3	2
Broadstrike+Treflan	76	23	5.21	2	1	1	1	2	1	3
Canopy	45	79	13.55	1	1	1	1	2	3	3
Classic	17	72	6.41	1	1	1	2	0	3	3
Valor	15	80	14.85	1	1	1	1	3	1	2
Cobra	23	79	10.11	3	3	1	1	3	1	1
Command 4EC	77	65	20.2	2	1	1	1	1	2	2
Conclude Xtra G	94	80	12.4	2	2	1	1	1	1	3
Stellar	22	68	8.14	3	2	1	1	3	1	1
Dual II Magnum	66	30	17.86	1	1	1	1	0	3	2
Extreme	94	88	13.76	2	0	0	0	1	1	3
FirstRate	15	58	7.69	1	1	1	1	0	2	3
Storm	25	80	16.24	3	1	1	1	3	3	2
Lasso	66	33	14.58	3	3	1	0	2	3	2
Frontier 6.0	60	60	18.98	2	1	1	1	2	1	3
Fusilade DX	92	15	12.19	1	2	1	2	3	1	3
Fusion	92	15	9.08	1	2	1	2	3	1	3
Glyphosate	94	88	7.54	2	0	0	1	1	1	1
Gramoxone Extra	87	91	6.59	2	1	3	3	1	1	3
Harmony GT XP	15	59	0.96	2	2	1	1	3	3	2
Sencor DF	36	66	9.73	1	0	1	2	1	3	3
Lorox DF	50	49	11.59	2	1	1	1	0	2	2
Permit	40	62	9.77	1	1	1	0	1	2	1
Poast	93	15	14.72	2	2	1	1	1	1	3
Prowl 3.3 EC	76	23	9.73	1	1	1	1	0	1	2
Pursuit	72	55	15.87	1	1	1	0	0	1	3
Pursuit Plus EC	72	55	14.08	1	1	1	0	0	1	3
Python WDG	21	74	9.13	1	1	1	0	0	1	3
Raptor	68	73	15.39	0	1	0	1	0	1	1
Reflex	15	72	11.44	3	1	1	1	2	3	2
Resource	15	54	5.32	2	2	1	1	1	2	2
Steel	62	73	16.4	3	1	1	1	3	3	3
Trifluralin 4EC	76	23	5.21	2	1	1	1	2	1	3
Scepter 70 DG	32	54	5.6	1	1	1	1	0	3	3
Synchrony STS	17	82	2.39	1	1	1	1	3	1	3
Sonalan 10 G	76	25	11.8	2	1	0	0	3	1	3
Squadron	77	68	14.07	3	1	1	2	2	3	3

GWE=Grass weed efficiency; BLE= Broadleaf weed efficiency; ET=Eye toxicity; DT=Dermal toxicity; INGT= Ingestion toxicity; INHT=Inhalation toxicity; CHRT=Chronic toxicity; GRWT=Ground water toxicity; SUTW=Surface water toxicity.

Appendix 2. Pesticide Risk Indices (PRI) and Rankings of Herbicides (Lowest value and ranking indicate pesticides with lower environmental effects)

Herbicides	Unstandardized Coefficients		Standardized Coefficients		Marketing Measure		Soofi's Relative Importance	
	PRI	Ranking	PRI	Ranking	PRI	Ranking	PRI	Ranking
2,4-D 6 Amine	1.969	34	2.035	34	2.046	35	1.924	36
Assure II	1.423	13	1.515	17	1.520	18	1.302	10
Authority	1.912	32	2.008	32	1.951	33	1.862	31
Canopy XL	1.912	33	2.008	33	1.951	34	1.862	32
Axiom DF	1.796	25	1.869	25	1.727	24	1.721	25
Backdraft	1.485	15	1.445	13	1.427	14	1.455	15
Basagram T/O	1.800	29	1.917	30	1.731	28	1.826	29
Ultra Blazer	1.660	20	1.746	20	1.672	22	1.521	18
Boundary 6.5 EC	1.349	8	1.322	10	1.373	11	1.255	8
Broadstrike+Dual	2.101	38	2.109	38	2.097	40	2.019	38
Broadstrike+Treflan	1.796	26	1.869	26	1.727	25	1.721	26
Canopy	1.695	23	1.760	23	1.630	20	1.702	24
Classic	1.601	19	1.584	18	1.652	21	1.595	21
Valor	1.563	18	1.686	19	1.579	19	1.607	22
Cobra	2.410	45	2.398	44	2.471	45	2.421	44
Command 4EC	1.454	14	1.480	16	1.474	17	1.378	14
Conclude Xtra G	2.132	40	2.074	36	2.051	38	2.095	39
Stellar	1.969	35	2.035	35	2.046	36	1.924	37
Dual II Magnum	1.248	5	1.213	5	1.275	8	1.236	6
Extreme	1.017	4	1.069	4	0.752	2	0.819	2
FirstRate	1.485	16	1.445	14	1.427	15	1.455	16
Storm	1.765	24	1.904	29	1.773	30	1.645	23
Lasso	2.426	46	2.332	43	2.298	42	2.376	43
Frontier 6.0	1.796	27	1.869	27	1.727	26	1.721	27
Fusilade DX	2.357	43	2.420	45	2.380	43	2.465	45
Fusion	2.357	44	2.420	46	2.380	44	2.465	46
Glyphosate	0.660	1	0.746	2	0.672	1	0.521	1
Gramoxone Extra	2.156	42	2.270	42	2.522	46	2.159	42
Harmony GT XP	2.105	39	2.157	41	2.101	41	2.124	41
Sencor DF	1.265	7	1.379	12	1.327	10	1.221	5
Lorox DF	1.349	9	1.322	11	1.373	12	1.255	9
Permit	1.000	3	1.000	3	1.000	4	1.000	4
Poast	2.132	41	2.074	37	2.051	39	2.095	40
Prowl 3.3 EC	1.248	6	1.213	6	1.275	9	1.236	7
Pursuit	1.369	10	1.305	7	1.203	5	1.314	11
Pursuit Plus EC	1.369	11	1.305	8	1.203	6	1.314	12
Python WDG	1.369	12	1.305	9	1.203	7	1.314	13
Raptor	0.794	2	0.734	1	0.802	3	0.857	3
Reflex	1.660	21	1.746	21	1.672	23	1.521	19
Resource	1.895	31	1.843	24	1.899	31	1.876	34
Steel	2.002	36	2.135	40	1.925	32	1.864	33
Trifluralin 4EC	1.796	28	1.869	28	1.727	27	1.721	28
Scepter 70 DG	1.485	17	1.445	15	1.427	16	1.455	17
Synchrony STS	1.800	30	1.917	31	1.731	29	1.826	30
Sonalan 10 G	1.668	22	1.747	22	1.380	13	1.564	20
Squadron	2.013	37	2.117	39	2.048	37	1.881	35