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Estimation of Crop Yield Loss Due to Interference by Multiple Weed Species[1]

SCOTT M. SWINTON, DOUGLAS D. BUHLER, FRANK FORCELLA, JEFFREY L. GUNSOLUS, and ROBERT P. KING[2]

Abstract. **Previous efforts to model crop yield loss from multiple weed species constructed competitive indices based on yield loss from individual weed species. Our model uses a multispecies modification of Cousens' rectangular hyperbolic yield function to estimate a nonlinear competitive index for weed-crop interference. Results from 13 Minnesota and Wisconsin data sets provide measures of the relative competitiveness of mixed green and yellow foxtails, common lambsquarters, redroot pigweed, velvetleaf, and several other weed species. Competition coefficient estimates are stable over years, but not locations. Nomenclature: Corn, *Zea mays* L.; soybean, *Glycine max* Merr.; green foxtail, *Setaria viridis* (L.) Beauv. #[3] SETVI; yellow foxtail *S. glauca* (L.) Beauv. # SETLU; common lambsquarters, *Chenopodium album* L. # CHEAL; redroot pigweed, *Amaranthus retroflexus* L. # AMARE; velvetleaf *Abutilon theophrasti* Medik. # ABUTH; barnyardgrass, *Echinochloa crus-galli* L. Beauv. # ECHCG; common ragweed, *Ambrosia artemisiifolia* L. # AMBEL; Eastern black nightshade, *Solanum ptycanthum* Dun. # SOLPT.**

Additional index words. **Bioeconomic model, competition, competitive index.**

INTRODUCTION

Among U.S. crops, corn and soybean suffer the greatest aggregate production loss due to weeds and receive the largest total quantity of herbicide (4, 23). Bioeconomic decision-support models provide a tool to improve farmer profits while reducing herbicide use in the long run (15, 18, 33). True bioeconomic models incorporate a mechanism for estimating crop yield losses due to weeds. However, prior weed-crop interference research has been poorly suited to this application. Some has not measured interference in terms of marketable crop yield (22, 31). Other efforts have focused narrowly on competition between a single weed and a single crop. This has been done empirically in corn (2, 16, 26) and soybean (27), as well as via simulation modeling (1, 7, 9, 19, 20, 21, 30). Although farmers typically face multispecies weed populations, few competition studies have been published (27).

The primary information available for managing multiple-species weed infestations is herbicide efficacy ratings from state extension services. In several instances, these have been incorporated into herbicide efficacy decision support models (12, 14, 24). However, new decision aids are becoming available which incorporate yield functions (18, 28, 33). Further development of such software will require improvements in the means of predicting crop yield with various means of weed control.

Prior efforts at estimating the competitive effect of multiple weeds on a crop have employed a competitive index (CI)[4]. The CI approach assumes that weed-weed interference is negligible. Based upon estimates of crop yield loss from individual weed species, a ratio is constructed that relates yield loss from a given species to the most competitive weed in the system (5, 8, 18). Indices have been developed based both upon expert opinion (18) and statistical analyses. Not all of the latter are useful for bioeconomic models, however, as some calculate the CI from equations that use crop dry weight rather than yield of marketable product as the dependent variable (22, 31, 34). The Coble (5) CI was originally calculated from linear regressions of biomass of a single weed species on soybean biomass at 10 wk; however, subsequent verification of the indices established the link with crop grain yield, at least at the 10% yield loss level. For implementation of a bioeconomic weed control decision aid, the Coble CI is incorporated into a yield function constructed by splicing a linear segment to a hyperbolic asymptote (5, 33).

A potential flaw of competitive indices is that they exaggerate predicted yield loss when significant interspecies weed competition occurs. Exaggerated competition coefficients can be avoided by estimating multispecies yield loss equations directly from data. Availability of nonlinear statistical estimation software for microcomputers now puts such techniques within reach of researchers.

This paper introduces a statistical model of crop yield response to interference by multiple weed species, adapted from Cousens' density-dependent model (6). Empirical results from the "best" function are reported for seven corn and six soybean data sets from Minnesota and Wisconsin. Coefficient stability is examined across time and location.

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[2]Asst. Prof., Dep. Agric. Econ., Michigan State Univ., E. Lansing, MI 48824-1039; Res. Agron., Plant Sci. Res. Unit, U.S. Dep. Agric., Agric. Res. Serv. and Assoc. Prof., Dep. Agron. and Plant Genet., Univ. Minnesota, St. Paul, MN 55108; Res. Agron., U.S. Dep. Agric., Agric. Res. Serv., North Cent. Soil Conserv. Res. Lab., Morris, MN 56267; Assoc. Prof., Dep. Agron. and Plant Genet., Univ. Minnesota, St. Paul, MN 55108; and Prof., Dep. Agric. and Appl. Econ., Univ. Minnesota, St. Paul, MN 55108.

[3]Letters following this symbol are a WSSA-approved computer code from Composite List of Weeds, Revised 1989. Available from WSSA, 1508 West University Ave., Champaign, IL 61821-3133.

[4]Abbreviations: A, maximum percentage yield loss in the rectangular hyperbolic yield response function; CI, competitive index; I_i, hyperbolic competition coefficient for weed species i specifying crop yield loss predicted from first unit of weed density; LR, likelihood ratio; PDMECH, data set from study of planting date effect on mechanical weed control at Rosemount, MN (2); SE, coefficient standard error; TILLAGE, data set from study of tillage method effect on weed seed movement and emergence at Morris, MN, 1985–86 (9); VICM, data set from study on variable input crop management at Lamberton, MN, 1989–91 (10).

METHODS

Of the existing crop yield response functions to single-species weed density, Cousens' (6) rectangular hyperbolic form has become widely accepted. Cousens found this functional form to outperform 18 others from previously published studies. While none of the forms he reviewed was a sigmoid, subsequent research has found the rectangular hyperbola to be superior to one sigmoidal form, the logistic (29). Apart from its statistical strengths, the rectangular hyperbola is an attractive functional form for modeling yield loss due to weeds for two additional reasons. First, by having a lower asymptote, it brings prior knowledge about plant ecology to an otherwise unconstrained statistical estimation problem. Second, its coefficients have a clear biological interpretation. Cousens stated the original model as

$$Y = Y_0\left[1 - \frac{Iw}{100(1 + Iw/A)}\right] \tag{1}$$

where Y_0, I, and A are parameters to be estimated from data, and w is weed density. Y_0 represents weed-free yield, while I represents percentage loss in crop yield per unit of weed density as density approaches zero, and A^4 represents the maximum percentage crop yield loss asymptote as weed density approaches infinity. The hyperbolic form is approximately linear at low weed densities. At high densities it becomes asymptotic to the minimum yield level (Y_{min}) given by $Y_0(1 - A/100)$.

The rectangular hyperbola in equation 1 can be reformulated as a multiple regression. Using w_i to denote the density of weed species i (i=1 to n, for n weed species), this can be written

$$Y = Y_0\left[1 - \frac{\sum_i I_i w_i}{100\left(1 + \sum_i I_i w_i / A\right)}\right] \tag{2}$$

The competitive effect of an additional weed of species n is given by the derivative

$$\frac{\partial Y}{\partial w_n} = I_n\left[\frac{-Y_0 A^2}{100\left(A + \sum_i I_i w_i\right)^2}\right] \tag{3}$$

This implies that as the combined density of all weed species in a field increases, crop yield declines monotonically, but at a diminishing rate. The individual coefficients $(I_i)^4$ implicitly serve as competitive indices for each weed species. Yet these competition coefficients are calculated jointly, unlike the sequential approach used by Coble (5) and Wilkerson et al. (33) in which single-species linear regression results are used to calculate a competitive index, and then that index is used to fit a hyperbola. Note that interspecific weed competition is implicit in equation 3, since the competitive effect of an additional weed of one species depends in part on the density of the other species.

In order to test for temporal stability of the yield function parameter estimates, five multiyear data sets were used to test the null hypothesis H_0: that all parameters vary, versus the alternative hypothesis H_1: that only the weed-free yield Y-axis intercept varies, and H_2: that all coefficients are stable across years. The "full" model for the null hypothesis (H_0) is

$$Y = (Y_0 + D_1 yr_1)\left[1 - \frac{\sum_i (I_{0i}w_i + I_{1i}w_i yr_1)}{100\left(1 + \sum_i \frac{I_{0i}w_i + I_{1i}w_i yr_1}{A_0 + A_1 yr_1}\right)}\right] \tag{4}$$

where yr_1 is a dummy variable for year 1, the 0 subscripts denote parameters for year 0, and the 1 subscripts denote the deviation of year 1 from year 0. Thus, the D_1 variable indicates the change in weed-free yield in year 1 relative to year 0. Alternative hypothesis H_1 reduces equation 4 to

$$Y = (Y_0 + D_1 yr_1)\left[1 - \frac{\sum_i I_i w_i}{100\left(1 + \sum_i I_i w_i / A\right)}\right] \tag{5}$$

which implies that while annual variability in climate affects potential weed-free yield, it does not affect the proportion of potential yield that is lost due to weed interference. Alternative hypothesis H_2 is simply the basic multispecies model introduced in equation 2, implying that no parameters are influenced by year-to-year variability.

The equations in this study were estimated statistically by nonlinear maximum likelihood regression (32), assuming an additive error term that is independently and identically distributed normal $(0,\sigma^2)$.

Thirteen sets of weed density-crop yield data were used to evaluate the stability and significance of weed competition coefficients in rain-fed corn and soybean. Weed density and yield data were obtained from seven sets of rain-fed corn field trials. These included a 1989 experiment on cultivation and rotary hoe for weed control at Lamberton, Morris, and Waseca, MN (11); a 1989–91 study on variable input crop management (VICM)[4] at Lamberton, MN (11); 1989 studies of cultivation effects on no-till and chisel-plowed corn at Arlington, WI (3); and a 1985–86 study on effects of tillage method (TILLAGE)[4] on weed seed movement and emergence in corn and soybean at Morris, MN (10). The six soybean yield-weed density data sets included 1989 studies of rotary hoe use at Waseca, MN, and reduced herbicide rates at Waseca, MN, and Lamberton, MN (11); and a 1989–90 study of planting date effect on mechanical weed control (PDMECH)[4] at Rosemount, MN (3); as well as sets of soybean data from the 1989–91 VICM study at Lamberton (11) and the 1985–86 TILLAGE study at Morris (10).

Table 1. Temporal stability of multispecies hyperbolic yield model.

	Likelihood ratios (LR)					
	Intercept vs. full model			No year effect vs. intercept model		
Crop and experiment[a]	d.f.[b]	LR[c]	$\chi^2_{.05}$	d.f.[b]	LR[c]	$\chi^2_{.05}$
Corn:						
VICM	6	6.48	12.59	5	33.19	11.07
TILLAGE	4	4.15	9.49	1	31.66	3.84
Soybean:						
VICM	6	5.51	12.59	4	38.29	9.49
TILLAGE	4	8.54	9.49	1	8.89	3.84
PDMECH	6	0.56	12.59	1	37.65	3.84

[a]VICM = Lamberton, MN; TILLAGE = Morris, MN; PDMECH = Rosemount, MN.

[b]Degrees of freedom for likelihood ratio test.

[c]Likelihood ratio.

RESULTS AND DISCUSSION

Tests of the hypotheses concerning year-to-year parameter stability are presented in Table 1. The tests are based on multiyear data sets, three for soybean and two for corn from the VICM, PDMECH, and TILLAGE studies. Since the model is a nonlinear one, a likelihood ratio (LR)[4] test is applied to the nested models (13). The LR statistic is asymptotically distributed χ^2 with degrees of freedom equal to the number of restrictions imposed. A "restriction," in this instance, occurs in each case where a coefficient in the full model (H_0) is assumed to be zero.

To illustrate how the LR test is used, consider line 2 of Table 1, which displays comparisons of paired regressions using the 2-yr TILLAGE corn data set. The first compares the model in equation 5 with that in equation 4, asking the question, "Is there a significant interaction between year and weed competition coefficients?". Because the TILLAGE data set includes four weed species, four year X competition interaction coefficients must be restricted to zero in the "intercept only model" of equation 5, so there are four degrees of freedom to the associated χ^2 test. The second half of Table 2 compares the model in equation 2 with that in equation 5, asking, "Do weed-free yields vary significantly from year to year?" Since the TILLAGE data set includes 2 yr, using equation 2 is equivalent to imposing the restriction on equation 5 that the D_1 coefficient signifying year 2 change in weed-free yield is equal to zero. Hence, in this case, the χ^2 test has just one degree of freedom.

The rest of Table 1 makes similar comparisons for the four other data sets. The "intercept only vs. full model" results test alternative hypothesis H_1 against the null. In each of the five cases, the likelihood ratio is less than the $\chi^2_{.05}$ test statistic, signifying that the intercept model is not significantly different from the full model. The "no year effect vs. intercept only model" results test alternative hypothesis H_2 against alternative H_1. In every one of these cases, the likelihood ratio statistic exceeds the $\chi^2_{.05}$ threshold, indicating the significant explanatory power is lost if the year X intercept interaction is suppressed. Results support the model presented in equation 5. While the weed-free yield intercept varies from year to year, the weed interference coefficients appear to be stable.

The next questions concern plausibility and spatial stability of the coefficient estimates. Initial parameter estimates for the hyperbolic corn yield function based on equation 5 are presented in Table 2. Those for the hyperbolic soybean yield function are presented in Table 3. Since coefficient estimates reached by nonlinear maximum likelihood estimation are asymptotically normally distributed (13), asymptotic t-values are reported in parentheses for hypothesis tests.

While estimates of weed-free yield and competition coefficients (I_i in equation 5) fall into plausible ranges, estimates of maximum yield loss (A)[4] in Tables 2 and 3 reveal a flaw in this formulation of the model. To begin with, five of the A estimates could not be determined by the regression algorithm, as indicated by their unboundedly high values and asymptotic t-statistics of 0.0. Further, of the seven A values that are significantly different from zero at the 5% level, four exceed 100, impossibly signifying maximum yield losses over 100%. Even the median values for both corn and soybean exceed 100. The A parameter estimates offer no obvious candidate for a "typical" yield loss level to impose. As weed density approaches infinity, yield loss can be expected to become quite high. Soybean interference studies have found individual weed species to cause yield loss up to 80% (27). Since the median initial estimates here exceeded 100%, a reasonable hypothesis for both corn and soybean is A = 90%.

In Table 4, the hypothesis that the A coefficient can be parameterized at 90 is tested against the null that it must be estimated from data. In 11 of the 13 equations, the alternative hypothesis that A = 90 cannot be rejected with 95% confidence, based on the likelihood ratio χ^2 test. The two cases where the alternative hypothesis is rejected are both soybean trials, where the unrestricted estimates of maximum yield loss exceed 100%. Since it is not surprising to find one or two false rejections in a set of 13, and correct prior biological information (about maximum yield loss) should improve other parameter estimates, all 13 equations were reestimated with A set parametrically at 90. Results are presented in Tables 5 and 6.

Table 2. Corn yield as an unrestricted hyperbolic function of weed density in seven Minnesota and Wisconsin research trials.

Equation	Site[b]	d.f.	Standard error of estimate	Coefficient estimate[a]					
				Weed-free yield	A[c]	SETSP	CHEAL	AMARE	ABUTH
C1	L[d]	33	500	7700 (39.6)**	45 (1.59)	0.0 (0.52)			
C2	L	44	690	8500 (60.0)**	38 (2.74)**	0.4 (1.68)	–0.1 (–0.20)		
C3	M	43	890	7700 (36.6)**	8.5E9 (0.00)	0.1 (2.77)**	0.1 (0.34)	0.2 (1.10)	
C4	W	89	1250	8700 (28.3)**	133 (3.53)**	0.1 (3.83)**	0.7 (1.51)	–1.2 (–0.41)	0.7 (1.57)
C5	A	57	1180	6900 (11.5)**	85 (4.18)**	–0.3 (–0.39)	10.9 (1.82)*	18.3 (1.38)	3.6 (2.25)**
C6	A	60	990	7400 (25.8)**	127 (3.52)**		5.4 (3.46)**		2.9 (4.12)**
C7	M[e]	40	700	5100 (28.9)**	1.0E14 (0.00)	0.1 (0.73)	0.2 (0.27)	–0.0 (0.02)	

[a]The interpretation of these coefficient estimates follows equation 5. For example, equation C7 is interpreted as follows:

$$\text{Yield} = (5100_{1985\text{base}} + 1800_{\text{in}1986})\left[1 - \frac{0.1\text{SETSP} + 0.2\text{CHEAL} - 0.0\text{AMARE} + 1.1\text{OTHER}}{100\left(1 + \dfrac{0.1\text{SETSP} + 0.2\text{CHEAL} - 0.0\text{AMARE} + 1.1\text{OTHER}}{1.0\text{E}14}\right)}\right]$$

Note that the "dummy" variable for 1986 yield (1800 kg ha^{-1}) implies that 1986 yield is that much higher than the 1985 base yield. Other deviations from base yields are reported in footnotes.

Asymptotic t-values are presented in parentheses. One and two asterisks denote significance at the 10 and 5% probability levels of Type II error, respectively. Large numbers are presented in scientific notation, where "En" denotes $\times * 10^n$.

The following equations contained other broadleaf weeds with I coefficient estimates as follows:

C1:	Mixed annual broadleaves	3.4	(0.33)
	Mixed perennial broadleaves	3.9	(1.41)
	IECHCG	37.4	(0.74)
C4:	IAMBEL	–0.8	(–1.84)*
C5:	Other broadleaves	2.4	(0.79)
C7:	Other weeds	1.1	(1.02)

Equations C1 and C7 included dummy variables for low-input management practices and waterlogged plots, respectively, in order to remove these yield effects from the results presented here.

[b]Site refers to the year 1989 unless otherwise indicated. Sites are: A—Arlington, WI, M—Morris, MN, W—Waseca, MN, L—Lamberton, MN, and R—Rosemount, MN.

[c]A = maximum percentage yield loss in the rectangular hyperbolic function.

[d]Years 1989–91 in pooled sample. YWF represents 1989 yield; coefficient estimates for 1990 and 1991 dummy variables at –100 (–0.58) and 300 (1.60).

[e]Years 1985–86 in pooled sample. YWF represents 1985 yield; coefficient estimate for 1986 dummy variable is 1800 (8.26**).

A final test was made for heterogeneity of variance, since this has been reported in some yield-weed density functions in the form of decreasing variance (25). If present, it should be compensated for in order to obtain efficient parameter estimates. In order to test the hypothesis that yield models have constant variance, the hyperbolic yield function was linearized (29) and ordinary least squares regressions were run on the absolute residuals of equations C7 and S6.

To test for nonconstant variance, residuals from estimation of the linearized version of equation 5 were saved, and their absolute values regressed on the weed density independent variables. Corn and soybean residuals regressions had F-statistics with related degrees of freedom of $F(3,65) = 1.29$ and $F(3,29) = 1.69$, respectively. Since both are far below the associated 5% critical values, the null hypothesis of constant variance could not be rejected, and therefore a weighted estimation was not necessary.

The final sets of yield equation coefficients are presented in Table 5 for corn and Table 6 for soybean. Setting maximum yield loss parametrically at 90% had little effect on standard errors of estimate (SEE). Only for equation S3 does the SEE increase by more than 5%. Nor does parameterizing A have much effect on the number of significant competition coefficients.

The weed-free yield estimates for corn range from 5100 to 8800 kg ha^{-1} (Table 5). Those for soybean range from 1700 to 2700 kg ha^{-1} (Table 6). Both intervals are consistent with field observations of weed-free plots in the experiments used (3, 10, 11).

The competition coefficients (I_i)[4] in Tables 5 and 6 can be interpreted as percentage yield loss associated with the first weed per square meter. In corn two of six and in soybean three of six foxtail competition coefficient estimates were significantly different from zero based on asymptotic t-statistics at a 10% critical value. Significant values ranged up to 0.2 in corn and up to 2.3 in soybean. Common lambsquarters competition coefficient estimates were significant at the 10% level in two corn and two soybean equations, ranging up to 9.9 and 6.8, respectively. Redroot pigweed competition coefficient estimates were not significant at the 10% level in the four corn equations but were significantly greater than zero in two soybean equations, ranging up to 11.6. However, in one instance (equation S5), the redroot pigweed coefficient estimate was significant and negative.

Table 3. Soybean yield as an unrestricted hyperbolic function of weed density in six Minnesota and Wisconsin research trials.

Equation	Site	d.f.	Standard error of estimate	Coefficient estimate[a]					
				Weed-free yield	A[b]	SETSP	CHEAL	AMARE	ABUTH
S1	L[c]	34	260	2300 (25.9)**	3.7E14 (0.00)	0.0 (0.98)			
S2	W	24	380	2700 (5.95)**	91 (7.63)**	0.2 (1.57)	6.6 (1.60)	−1.5 (−0.29)	0.2 (0.26)
S3	W	138	340	2100 (17.5)**	127 (15.1)**	0.7[f] (5.24)**	−2.7 (−0.98)	3.9 (5.05)**	6.0 (3.45)**
S4	L	33	630	2400 (17.7)**	2.4E11 (0.00)	0.4 (3.70)**			
S5	R[d]	120	220	1600 (39.2)**	105 (20.53)**	1.8 (7.06)**	3.0 (1.78)*	−0.6 (−1.91)*	−1.5 (−0.63)
S6	M[e]	16	150	2100 (36.8)**	1.7E15 (0.00)	3.4 (2.00)	7.1 (1.60)	7.9 (2.48)**	

[a]The following equations contained other broadleaf weeds with I coefficient estimates as follows:

S1:	Mixed annual broadleaves	−48.9	(−2.19)**
	Mixed perennial broadleaves	18.2	(2.60)
	IECHCG	1.0	(3.08)
S5:	ISOLPT	1.3	(1.47)
S6:	Other weeds	−0.2	(−0.16)

Equations S1 and S6 included dummy variables for low-input management practices and waterlogged plots, respectively.

[b]A = maximum percentage yield loss in the rectangular hyperbolic function.

[c]Years 1989–91 in pooled sample. Weed-free yield represents 1989 yield; coefficient estimates for 1990 and 1991 dummy variables are 300 (3.17)** and −50 (−0.51).

[d]Years 1989–90 in pooled sample. Weed-free yield represents 1989 yield; coefficient estimate for 1990 dummy variable is 400 (6.53)**.

[e]Years 1985–86 in pooled sample. Weed-free yield represents 1985 yield; coefficient estimate for 1986 dummy variable is 270 (3.14)**.

[f]Foxtails were measured in dry weight units (gm^2), which are not directly comparable with density units. A regression of foxtail density on dry weight using 1989 Lamberton data found considerable unexplained variability ($R^2 = 0.12$).

Velvetleaf competition coefficient estimates were significantly different from zero at the 5% level in two of three corn equations (ranging up to 3.5) and one of three soybean equations (at 15.4).

Variability of competition coefficient estimates across data sets was less among grass than among broadleaf weeds. The entire range of foxtail competition coefficients in corn is only 0.5, and the median of 0.1 is significantly different from zero and lies among similar values. By contrast, the range of foxtail competition coefficients in soybean is 3.7, and the median is 1.1. This median figure implies that one foxtail plant per square meter reduces soybean yield at a rate ten times greater than the same foxtail plant in corn.

The variability across data sets is much greater among broadleaf weeds. The range of common lambsquarters competition coefficient estimates is 10 in corn and 21.7 in soybean. Median values of 0.9 and 5.1 may be broadly indicative but do not appear highly reliable. The same is true of redroot pigweed (range: 18.2 in corn and 13.2 in soybean; medians 0.1 and 3.3, including the one "significant" negative coefficient estimate). The velvetleaf results in corn have a narrower range of 2.7 (median of 3.4). This may be merely an artifact of the smaller number of data sets containing velvetleaf infestations, since in soybean the velvetleaf coefficients span a range of 18.3 (median at 0.2).

Overall, competition coefficient estimates indicate that weeds have a much more competitive effect on yields in soybean than in corn. Since the I_i coefficients signify the percentage yield loss due to the first weed, these results suggest that yield loss curves for soybean are more steeply sloped than those for corn, even though the lower asymptote ($Y_0[1 - A/100]$) may be 10% of weed-free yield in both cases. Velvetleaf is an exception, but it is also the weed for which the fewest observations are available.

Competition coefficient estimates appear unstable across locations. They result in a competitiveness ranking from least to greatest in corn of redroot pigweed followed by mixed foxtails, common lambsquarters, and velvetleaf. For soybean, the ranking was mixed foxtails, velvetleaf, redroot pigweed, and common lambsquarters. These are at odds with expressed expert opinions

Table 4. Results of hypothesis test that maximum yield loss coefficient A=90 for corn and soybean yield equations.

Equation	d.f.	Coefficient estimate A	Likelihood ratio[a]
C1	57	45	0.73
C2	44	38	2.03
C3	43	8.5E9	1.71
C4	89	133	2.75
C5	57	85	0.04
C6	60	127	2.14
C7	40	1.0E14	0.09
S1	57	3.7E14	1.25
S2	24	91	0.00
S3	138	127	48.61**
S4	33	2.4E11	1.18
S5	120	105	9.91**
S6	16	1.7E15	1.52

[a]Likelihood ratio = $2(LLR^r - LLR^u)$ where LLR^r is log likelihood for restricted model (A=90) and LLR^u is for unrestricted model. Critical value at 0.05 Type II error tolerance is $\chi^2_{(0.05,1)} = 3.84$.

Table 5. Corn yield as a hyperbolic function of weed density setting A = 90.

Equation	Site[b]	d.f.	Standard error of estimate	Coefficient estimate[a]				
				Weed-free yield	SETSP	CHEAL	AMARE	ABUTH
C1	L[b]	34	500	7700 (40.7)**	0.0 (0.51)			
C2	L	45	700	8400 (65.5)**	0.2 (2.80)**	0.1 (0.26)		
C3	M	44	900	7800 (30.7)**	0.1 (1.89)*	–0.1 (–0.11)	0.2 (0.82)	
C4	W	90	1270	8800 (29.2)**	0.1 (5.43)**	1.0 (1.52)	–1.2 (–0.31)	0.8 (1.38)
C5	A	58	1180	6800 (13.2)**	–0.3 (–0.40)	9.9 (3.20)**	17.0 (1.66)	3.4 (3.25)**
C6	A	61	1010	7600 (25.7)**		7.9 (5.38)**		3.5 (4.12)**
C7	M[c]	41	700	5100 (33.6)**	0.1 (0.66)	0.2 (0.23)	–0.1 (–0.03)	

[a]The following equations contained other broadleaf weeds with I coefficient estimates as follows:

C1:	Mixed annual broadleaves	3.1	(0.33)
	Mixed perennial broadleaves	3.4	(1.59)
	ECHCG	15.3	(2.06)**
C4:	AMBEL	–1.0	(–1.85)*
C5:	Other broadleaves	2.3	(0.97)
C7:	Other weeds	1.1	(0.91)

Equations C1 and C7 included dummy variables for low-input management practices and waterlogged plots, respectively.

[b]Weed-free yield represents 1989 yield. Coefficient estimates for 1990 and 1991 dummy variables are –100 (–0.60) and 300 (1.63).

[c]Years 1985–86 in pooled sample. Weed-free yield represents 1985 yield; coefficient estimate for 1986 dummy variable is 1800 (8.06)**.

on weed competitiveness in corn (18). Those surveyed ranked redroot pigweed on par with lambsquarters. By the same token, in soybean many weed scientists would rank velvetleaf as the most competitive of the three broadleaf weeds discussed here.

It remains unclear whether the apparent instability across locations of the competition coefficient estimates is due to confounding among the different experimental designs underlying the various data sets used. Coefficient estimates are much more stable among the three cultivation/rotary hoe corn experimental sites (equations C2, C3, C4 in Table 5) (11) and among the two reduced herbicide soybean experimental sites (equations S3 and S4) (11). Both of these experiments had just a single year of data available.

The question of coefficient stability is central to establishing the usefulness of this approach for bioeconomic models, and the geographic area within which a given set of coefficients is suitable. This raises three levels of challenge for future research. At the first and simplest level, a formal test of coefficient stability

Table 6. Soybean yield as a hyperbolic function of weed density setting A=90.

Equation	Site	d.f.	Standard error of estimate	Coefficient estimate[a]				
				Weed-free yield	SETSP	CHEAL	AMARE	ABUTH
S1	L[b]	35	270	2300 (23.4)**	0.0 (0.77)			
S2	W	25	380	2700 (6.00)**	0.2 (1.59)	6.8 (2.32)**	–1.6 (–0.30)	0.2 (0.28)
S3	W	139	400	2100 (14.2)**	1.7[e] (4.04)**	–14.0 (–1.55)	7.2 (3.17)**	15.4 (1.98)**
S4	L	34	640	2400 (14.7)**	0.5 (2.24)**			
S5	R[c]	121	970	1700 (36.9)**	2.3 (9.56)**	3.5 (1.66)*	–0.7 (–2.14)**	–2.9 (–1.22)
S6	M[d]	17	160	2100 (33.8)**	3.7 (1.27)	7.7 (1.28)	11.6 (2.37)**	

[a]The following equations contained other broadleaf weeds with I coefficient estimates as follows:

S1:	Mixed annual broadleaves	–41.3	(–1.95)**
	Mixed perennial broadleaves	19.2	(2.04)**
	ECHCG	1.7	(1.82)
S5:	SOLPT	1.4	(1.29)
S6:	Other weeds	–0.3	(–0.16)

Equations S1 and S6 included dummy variables for low-input management practices and waterlogged plots, respectively.

[b]Weed-free yield represents 1989 yield; coefficient estimate for 1990 and 1991 dummy variables are 300 (3.08)** and –40 (–0.37).

[c]Weed-free yield represents 1989 yield. coefficient estimate for 1990 dummy variable is 400 (5.79)**.

[d]Weed-free yield represents 1985 yield; coefficient estimate for 1986 dummy variable is 270 (3.01)**.

[e]Foxtails were measured in dry weight units (gm^2), as noted in Table 3.

across locations could be conducted by pooling data sets with a dummy variable assigned to each location. This approach would parallel the test reported in Table 1 for stability across years. In order to avoid confounding my major differences in experimental design, such a test should be based upon a multiyear experiment implemented over multiple locations.

At a higher level of complexity, this test could be based on an experimental design that controlled the densities of multiple weed species so as to insure a wide range of densities, including very high ones. Incorporation of high densities contradicts prevailing wisdom that low-density interference research is more important (27). However, high densities are necessary to estimate the maximum yield loss asymptote, A.

The greatest challenge to improving estimates of multispecies weed interference with crop yields is to improve our understanding of the underlying biological processes. It may be that density-dependent yield models are too simplistic in overlooking such attributes as weed size, health, relative time of emergence, and herbicide damage. For the purpose of improving weed management decision aids, future research should focus on variables that are known or predictable before weed management decisions must be made. For soil-applied weed controls, the key variable is likely to remain weed density (in the form of seed density in the soil or weed density the previous season), perhaps complemented by predicted time of emergence. For postemergence decisions, simulation models of weed-crop interference may be required to predict competition indices based on relative leaf area (17).

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