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Pooling Data for Pest Management Analysis: A Stein-rule Approach

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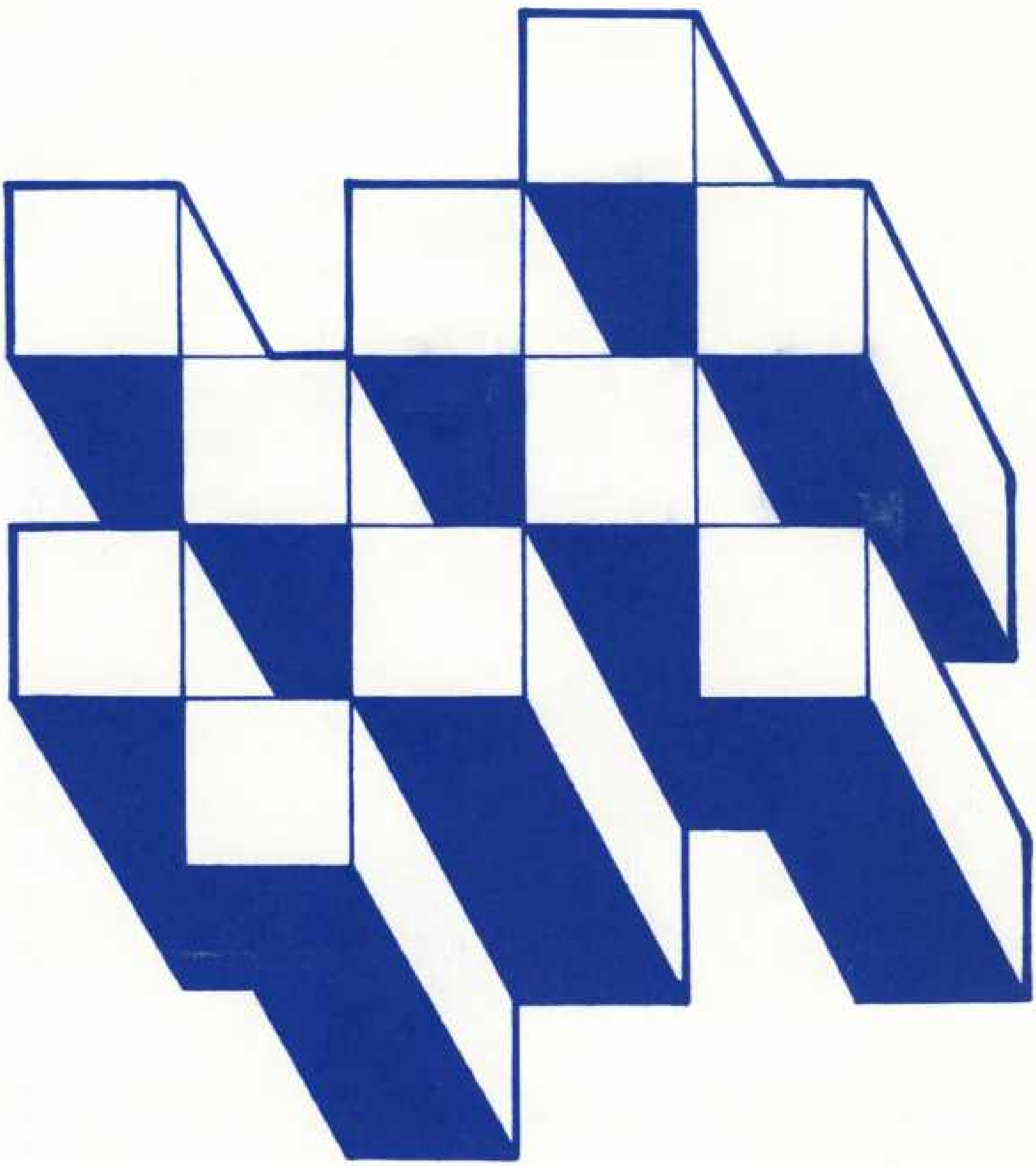

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ABSTRACT

Integrated pest management (IPM) researchers are often confronted with data of limited quantity and caliber. This study proposes a method to enrich prospective IPM data sets by pooling sample data originating from different experimental designs. Predictive risk performance of alternative estimation procedures are compared and a Stein-rule estimator is proposed as an alternative to traditional statistical approaches to pooling data. The Stein-rule estimator adjusts between ordinary least squares (OLS) estimates and restricted least squares (RLS) estimates based on the correctness of the restrictions. This type of analysis is required for any investigation of economic thresholds because the procedure will indicate whether the various restrictions associated with pooling conform to the data sets.

KEYWORDS: Pest management, Stein-rule, Restricted least squares, Pooling data, Ordinary least squares.

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INTRODUCTION

Integrated pest management (IPM) researchers are aware of the importance of comprehensive cross-sectional data. But required data often are not available, necessitating the design and implementation of experiments to provide the needed information. Applicability of available data is sometimes suspect due to design aberrations or regional differences in population dynamics and damage effects of particular species. Analyses carried out under these circumstances are apt to contribute to the uncertainty facing farmers confronting pest management problems. Uncertainty has been hypothesized as a major factor leading farmers to use pesticides to decrease the risk of crop damage from agricultural pests (11).1/ Increasing the efficiency with which data are evaluated and incorporated in pest management research may decrease uncertainty and lessen the environmental threat posed by unwarranted pesticide use.

This paper proposes a method for combining entomological and plant pathogen data originating from different experimental designs, along with theoretical considerations, to evaluate yield loss in soybean production. We employ a Stein-rule approach and compare relative estimator performance according to a number of statistical criteria. The methodology allows the researcher to determine at once the correctness of pooling to expand the available data set and also provides parameter estimates that derive from the restrictions imposed.

Early economic investigations of the economic threshold concept involved modeling production systems and imposing different aspects of IPM methods. Hall and Norgaard (2) considered both the timing and level of treatment when multiple pesticide applications were appropriate. Talpaz and Borosh (18) showed that for cotton insects, fewer treatments with higher dosages per application will maximize profits. These works provided significant improvement over the economic threshold developmental studies of Stern and others (16) and Headley (3). However, they were limited in scope and application since significant species interactions were ignored or other simplifying assumptions were adopted. Confining analyses to a single crop pest does not provide a sufficiently general approach to describe the multipest and beneficial insect environment. These limitations can be attributed to the lack of requisite data documenting the functional relationships between pests and predators, and their combined effects on crop damage and final yield.

1/ Underscored numbers in parentheses refer to literature cited in the References section.

A significant exception is the work of Reichelderfer and Bender (13) who analyzed the efficiency of alternative biological and chemical pest control strategies for reducing yield loss in soybean due to the Mexican bean beetle. In another study, Shoemaker (15) employed a dynamic programming model, incorporating prey-predator interaction as well as pesticide residues to obtain a numerical solution to a specific example. However, in both studies, species interaction remained restricted due to the limited scope of the experimental design underlying the data.

All of these models are generally driven by one set of data. However, little or no effort was directed toward investigating the validity of data sets employed. The lack of a valid data set may result in increasing rather than reducing the uncertainty of pest control decisions. In many cases, additional information about the phenology of each interacting organism may exist. This additional information may stem from theoretical relationships among certain components of the model or from a related experiment independent of the data under consideration. Incorporating the additional information into the modeling effort may not only enhance the data set by possibly incorporating additional prey-predator relationships, but may also provide an avenue for validation.

DESCRIPTION OF THE METHOD

Scientists have proposed numerous procedures for dealing with the question of pooling data, most involving an analysis of variance and covariance. The usual procedure involves statistically testing whether the parameter values of the model in question have changed over time, with the decision to pool depending on the chosen significance level of the test. We modify this approach by first considering the possibility of combining cross-sectional data originating from different experimental designs using a Stein-rule alternative to the traditional pooling techniques, and then evaluating relative estimator performance.

Consider the model:

$$y_{ij} = X_{ij}\beta_j + u_{ij}, \quad i = 1, \ldots, N, \quad j = 1, \ldots, J, \qquad [1]$$

where y_{ij} is a dependent variable observation representing yield for experimental plot i in data set j (J representing the number of possible data sets from differing experimental designs), X_{ij} is a (1xk) vector of observations on k pests and beneficials, β_j is a (kx1) parameter vector that is constant across plots but is allowed to vary between experimental designs, and u_{ij} is an error term in which all the classical assumptions hold (no autocorrelation, heteroskedasticity, or correlation with the design matrix X, normally distributed with mean zero and variance σ^2 for all $i = 1, \ldots, N$ and $j = 1, \ldots, J$). In estimating the parameters in equation [1], a primary consideration in the pooling decision is whether or not the parameter values are consistent over each data set, or in other words, whether or not the null hypothesis $H_o: \beta_1 = \beta_2 \ldots = \beta_J$ is true. More specifically, our concern focuses on whether coefficients associated with pests and beneficials common to the data sets in question are significantly different from one another.

A common estimation strategy is to pool or not to pool the total NJ sample observations on the basis of an F-test for the equality of the separate coefficient vectors $\beta_1, \beta_2, \ldots, \beta_J$ (8). To perform the F-test, one needs to compute the sum of squared residuals for both the restricted or pooled model in which the restrictions $\beta_1 = \beta_2 = \ldots \beta_J$ are imposed, and the unrestricted model in which the parameters of the model are allowed to vary between experimental designs. For the unrestricted model, equation [1] can be written:

$$y^* = X^* \beta^* + u^*, \text{ where} \qquad [2]$$

$$y^* = \begin{matrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_J \end{matrix} \qquad X^* = \begin{matrix} X_1 & & & \\ & X_2 & & \\ & & \ddots & \\ & & & X_J \end{matrix} \qquad \beta^* = \begin{matrix} \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \cdot \\ \beta_J \end{matrix} \qquad u^* = \begin{matrix} u_1 \\ u_2 \\ \cdot \\ \cdot \\ \cdot \\ u_j, \end{matrix}$$

so that each y_j is (Nx1), X_j is (Nxk), β_j is (kx1), and u_j is (Nx1)for j = 1, . . ., J. For this model, the maximum likelihood (OLS) estimator is $b = S^{-1}X^{*\prime}Y^*$ where $S = X^{*\prime}X^*$, and b is minimum variance unbiased. The pooled or restricted model is equivalent to equation [2] subject to the restrictions $R\beta^* = r$, where r is the null vector and

$$R = \begin{matrix} I_k & -I_k & & & \\ & I_k & -I_k & & \\ & & \ddots & & \\ & & & I_k & -I_k. \end{matrix}$$

I_k is a k order identity matrix so that R is a [(J-1)k x Jk] matrix. Consequently, (J-1)k is the number of linearly independent restrictions on the model. For the pooled model, the RLS estimator that combines the restrictions and the sample data is: $b^* = b - S^{-1}R'[RS^{-1}R']^{-1}Rb$. The RLS estimator b^* is biased unless the restrictions $R\beta^* = 0$ are true (that is, unless $\beta_1 = \beta_2 = \ldots = \beta_J$) but has covariance matrix no greater than that of the OLS estimator b.

The traditional pretest estimator chooses between b and b^* on the basis of the likelihood ratio statistic:

$$\delta = (Rb)' [RS^{-1}R']^{-1} (Rb)/(J-1)k\sigma^2, \qquad [3]$$

where $\sigma^2 = (y^*-X^*b)'(y^*-X^*b)/(NJ-JK)$ (7). The statistic δ has a central F distribution with (J-1)k and (NJ-JK) degrees of freedom if $R\beta^* = 0$. Therefore, the RLS estimator b^* is chosen if the null hypotheses $R\beta^* = 0$ are accepted and the OLS estimator b is chosen otherwise. In a repeated sampling context, the data, linear hypotheses, and level of significance all determine the combination of the two estimators that are chosen on the average. However, the cavalier way in which the significance level of the test is chosen in most applied work motivates a number of alternatives. Employing a random coefficients specification, implying the possibility that parameters may change for each observation,may be appropriate. Another specification alternative in this sampling context may be a switching regression regime in which the regression coefficients are allowed to be the same within subsets of observations but different across subsets (7). The method chosen here allows the estimator to provide parameter estimates closer to b^* or b depending on the correctness of the restrictions imposed.

We can compare the relative predictive performance of b, b^*, and the traditional pretest estimator using the following risk function:

$$E[(\bar{\beta} - \beta^*)' S(\bar{\beta} - \beta^*)], \qquad [4]$$

where $\bar{\beta}$ is an estimator of the true parameter vector β^*, and E is the expectation operator. Choosing β to minimize [4] will result in an estimator that minimizes the sum of squared errors in predicting y^*. Among b, b^*, and the traditional pretest estimator based on δ, only b is minimax, in terms of predictive risk as measured by [4]; that is, it minimizes the maximum expected loss over all possible parameter values. This motivates the Stein-rule estimator:

$$\theta = (1-c/\ \delta)(b-b^*) + b^*, \qquad [5]$$

where $c = [(J-1)k-2]/(NJ-JK + 2)$. The right hand side of [5] is minimax and has predictive risk less than or equal to that of the OLS estimator b (6, 10). Notice that the smaller the value of the test statistic δ, the further θ is moved from b toward b^*. This result is intuitively appealing since smaller values of δ are associated with acceptance that the restrictions $\beta_1 = \beta_2 \ldots = \beta_J$ are true, or equivalently, that pooling the data is desirable. A positive part version of [5] that has predictive risk less than or equal to θ is:

$$\theta^+ = I_{[c,\ \infty]}\ (\delta)(1-c/\ \delta)(b-b^*) + b^*, \qquad [6]$$

where the indicator function $I_{[c,\ \infty]}\ (\delta) = 1$ if $c \leq \delta \leq \infty$ but zero otherwise (7). Notice that if $I_{[c,\ \infty]} = 0$, $\theta^+ = b^*$.

The Stein-rule is based on the apparent statistical paradox that allows the overall average value of a number of related or unrelated means to be a better indicator of the true mean values than each mean taken individually. The essential process in the Stein-rule approach is the "shrinkage" of all individual averages toward the grand average. The procedure makes a preliminary "guess" that all the true and unobservable means are near the overall mean. If the data support this assumption, then the observed estimates are "shrunk" further toward the grand average. If the data contradict the assumption then little shrinkage occurs. In addition, the number of parameter values being estimated also influences the shrinkage factor. Estimation of a large number of means allows the shrinkage factor to be more extreme either toward or away from the grand mean since observed variations are less likely to represent random fluctuations. The reduction in risk as measured by mean square error can be substantial, particularly if the number of means is greater than five or six. In the present application, the Stein-rule provides significantly better estimates in terms of risk efficiency than the OLS estimates if the restrictions imposed upon the data sets are correct, that is, they correspond to the actual parameter values. If the restrictions are not correct, the Stein-rule estimates will closely correspond to the OLS results.

SAMPLING TECHNIQUES AND SOYBEAN PESTS

Entomologists generally employ two types of experimental methods for quantifying pest damage in field crops. Caged experiments are one method used to estimate damage activity of confined populations. Procedures include maintaining a constant number of pests over a portion of the plant for a specific period. Damage is then evaluated at the end of the period and projected yield reductions can be determined. A second method involves field plots. Experimental field plots provide the ability to assess the effectiveness of varying treatment regimes on pest populations and damages, symptomatic expression of disease vectors, and resultant final yield.

Sampling techniques that allow physical counts of above-ground insects include direct observation on the plant (in situ), shake-cloth samples, and sweep net techniques. Shake-cloth samples are generally taken by placing a large cloth ($1m^2$) or polyethylene film between 2 plant rows and shaking 30 cm of row from either side over the cloth for 30 seconds (9). Insects falling onto the cloth are then counted. For some pests of soybean, notably velvetbean (or other lepidopterous) caterpillars and stink bugs, this technique yields an approximation of the absolute numbers of insects in the length of row sampled. Sweep net samples involve the use of a 38 cm-diameter muslin net to sweep insects from the plant leaf canopy. Sweeps may be done along or across rows, with counts of insects in the net being taken at the end of a given number of sweeps. Data from this technique can be transformed to produce absolute estimates of insect numbers per linear measure of row (14, 12).

Total reliance on one sampling method reportedly influences results due to selective error (1); for instance, the collector searching more diligently at low than at high population levels. The ability to employ data originating from a number of different experiments in determining damage rates minimizes the effect of possible spurious observations and results, and underlies any attempts at validation. The principal pests of soybean in the Gulf Coast States and Georgia are the southern green stink bug (SGSB) *Nezara viridula* (L.), and the velvetbean caterpillar (VBC) *Anticarsia gemmatalis* (Hubner). These insects account for two-thirds of soybean dollar losses from insect pest damage in Georgia (17). The SGSB damages the soybean by feeding on pods and transmitting disease agents. Damaged seeds result in a reduction of grade and market value. The VBC, a defoliator of soybean usually during the later stages of plant maturity, can account for over 90 percent of total foliage damage (4). Another principal pest, the three-cornered alfalfa hopper (TCAH) *Spissistilus festinus* (Say), attacks soybeans and other legumes by egg laying and feeding punctures in seedling soybean stems. Girdling weakens the stem so that wind or rain may result in breakage and plant death. Later in the season, the insect may feed on tender petioles, causing new shoots to die (5). Spiders are among the first arthropods to invade newly planted soybean stands and are important beneficial predators during the production season.

Of the number of fungal diseases that affect the soybean plant, brown spot, *Septoria glycines* (Hemmi), is one of the earliest leaf diseases to appear on young plants. Severely affected leaves become yellow and drop, causing stunted growth and diminished yields.

TESTING THE PROCEDURE

Cage data were available documenting the yield reduction effects of the presence of VBC and SGSB on Bragg variety soybeans grown at the Coastal Plains Experiment Station, Tifton, Georgia. Todd et al. (20) collected data on the percentage of seeds with SGSB damage and total yield (bushel per acre) under constant levels of pest infestation. Fourth and fifth instar nymphs of SGSB and large larvae of VBC were infested in cage at the beginning of R5 (reproductive stage 5 in soybean plant development, representing beginning seed), R5.5 (mid pod-fill), and R6 (full seed). Reinfestation was made at 3-day intervals to replace dead or missing individuals. Each reproductive stage represents a 15-day period. Sixty observations were generated using this experimental approach.

A second data set was comprised of field plot data originating from an experiment conducted at the Coastal Plain Experiment Station during the 1983 growing season (21). Coker 237 soybean variety was grown under different types of treatment regimes. A Latin square experimental design was used, with plots 3 meters square, each containing four rows, 1 meter apart. Insect counts were made weekly over a 10-week period, using shake-cloth and sweep net techniques to document numbers of VBC, SGSB, TCAH, spiders, soybean looper (SBL) *Pseudoplusia includens*, and corn earworm (CEW) *Heliothis zea*. In addition, the final insect count also included a visual rating of the incidence of brown spot present in each plot according to the following scale: 1 = 0-10 percent involved, 2 = 11-30 percent, 3 = 31-50 percent, 4 = 51-70 percent, and 5 = 71-90 percent. The second experimental design yielded 150 sample observations.

SBL and CEW, both generally foliage feeders, infest soybean usually during the vegetative and early pod setting stages of development. This time period was designated as weeks 1 through 4 for modeling purposes. Their combined effects were aggregated into one variable designated as FOLG. SGSB were not included in the following field plot yield model since they were not present in numbers sufficient to cause yield loss. The incidence of SGSB in the Coastal Plain region had been significantly diminished during the 1983 and 1984 production seasons (19). Research entomologists attribute this reduction to periods of severe winter weather, which killed many of the insects overwintering in trees and decaying vegetative matter adjacent to production fields. SGSB repopulates a region at a very slow rate, often taking years to establish pre-kill numbers, which may account for the negligible field-plot sample populations.

List of Variables and Abbreviations

CEW	Corn earworm
D	Brown spot disease
FOLG	Combined effects of SBL and CEW during the vegetative and early pod setting stages of soybean development
SBL	Soybean looper
SGSB	Southern green stink bug
SPID1	Spiders in weeks 1 through 4
SPID2	Spiders in weeks 5 through 10
TCAH	Three-cornered alfalfa hopper
VBC	Velvetbean caterpillar

The two experimental designs result in the following two models predicting soybean yield.

$$Y_c = f_c(VBC, SGSB), \qquad [7]$$

$$Y_p = f_p(VBC, TCAH, FOLG, SPID1, SPID2, D), \qquad [8]$$

where the dependent variables Y_c and Y_p are soybean yield for caged and field plot experiments, respectively. SPID1 and SPID2 are variables accounting for the presence of spiders in weeks 1 through 4 and 5 through 10, indicating a first- and second-half season presence. D represents brown spot disease. The expectation is that all independent variables will exhibit an inverse relationship with yield, with the exception of beneficial variables SPID1 and SPID2, which could exhibit positive relationships. In addition to the two experimental designs, the field plot data included a regime in which a pesticide application was applied once per week in weeks 5 through 10. Thus, yield reduction should occur only as a result of pest infestation in weeks 1 through 4. Since foliage feeders and spiders are the only uncontrolled influences on yield within this period, the following yield model results:

$$Y_t = f_t(FOLG, SPID1). \qquad [9]$$

The pooling procedure outlined earlier is employed to investigate if the coefficients associated with VBC are consistent between data sets. OLS, RLS, and Stein-rule coefficients are estimated with the restriction that VBC coefficients are equal in [7] and [8] and coefficients associated with FOLG and SPID1 are equal in [8] and [9].

RESULTS AND DISCUSSION

Linear regression results and Stein-rule estimates for the caged experiment, 4-week, and full-season field plots are presented in tables 1, 2, and 3. Alternative model specifications such as logarithmic did not improve the summary statistics. In addition, there was no significant interaction among the independent variables. Dummy variables D1, D2, and D3 are associated with disease levels 1, 2, and 3. The fifth disease level did not occur in this sample and the fourth disease level was incorporated as the intercept. The Stein-rule estimates under the positive-part rule appear without comparable t-statistics since the sampling distribution of this estimator is not yet known (7).

All estimated coefficients are consistent in sign with *a priori* assumptions, although magnitudes of these variables appear to vary considerably between data sets in the unrestricted results. VBC damage effects were substantially greater when determined within the field plot experimental design than in the caged design. The damage coefficients associated with the full-season field plot regression model were larger by a factor of 12 (-0.261 versus -0.021). In addition, the effect of FOLG in the 4-week field plot was substantially greater than in the full-season field plot (-2.045 versus -0.011). The damage effect of TCAH during the latter portion of soybean reproductive growth was significant and unexpected, as these insects are considered to be principally a pest of seedling stands. These results indicate that the presence of TCAH in later growth stages inflicts considerable damage and contributes to diminished yields.

Table 1: Regression results describing the damage effects of caged velvetbean caterpillar and southern green stinkbug populations on Bragg soybean, Tifton, Georgia, 1981 1/

Variable	Unrestricted (OLS)	Restricted (RLS)	Stein-rule
Constant	62.422 2/	62.536 2/	62.430
	(33.74)	(32.15)	
VBC	-.021 2/	-.021 2/	.021
	(9.84)	(9.54)	
SGSB	-.075 2/	-.074 2/	.075
	(4.03)	(3.74)	

1/ t-statistic in parentheses.
2/ Significantly different from zero at 0.005 significance level.

Table 2: Regression results from field plot data describing the effects of soybean looper and corn earworm (FOLG) and spiders (SPID1) on Coker 237 soybean yield during the vegetative and early reproductive stages of growth, Tifton, Georgia, 1983 1/

Variable	Unrestricted (OLS)	Restricted (RLS)	Stein-rule
Constant	45.378 2/	44.032 2/	45.279
	(23.75)	(21.94)	
FOLG	-2.045 3/	-.011	-1.890
	(2.04)	(.01)	
SPID1	.758	.005	.702
	(1.02)	(.006)	

1/ t-statistic in parentheses.
2/ Significantly different from zero at 0.005 significance level.
3/ Significantly different from zero at 0.025 significance level.

Table 3: Regression results from full-season field plot data describing the yield influencing effects of insect pests, beneficials, and <u>Septoria Glycines</u> (Hemmi) on Coker 237 soybean, Tifton, Georgia, 1983 1/

Variable	Unrestricted (OLS)	Restricted (RLS)	Stein-rule
Constant	39.077 2/	33.579 2/	38.671
	(12.92)	(10.56)	
VBC	-.261 2/	-.021	-.243
	(5.07)	(.39)	
TCAH	-.651 3/	-.754 3/	-.658
	(2.48)	(2.73)	
FOLG	-.011 3/	-.011 3/	-.011
	(2.48)	(2.31)	
SPID1	.003	.005	.003
	(.88)	(1.45)	
SPID2	.442	.075	.415
	(1.20)	(.19)	
D1	14.197 2/	19.872 2/	14.616
	(3.87)	(5.15)	
D2	4.049	8.172 2/	4.353
	(1.45)	(2.79)	
D3	2.521	5.560 3/	2.746
	(.939)	(1.96)	
RMSE 4/	7.410	7.791	7.410

1/ t-statistic in parentheses.
2/ Significantly different from zero at 0.005 significance level.
3/ Significantly different from zero at 0.025 significance level.
4/ RMSE is Root Mean Squared Error.

By killing photosynthetic leaf surface and decreasing functional leaf area, the incidence and severity of brown spot were expected to significantly decrease final yields. The coefficients for D1-D3, which were interpreted as intercept shifters in this model, demonstrate the importance of including pathogen data when modeling pest damage. The statistical insignificance of the coefficients for D2 and D3 in the unrestricted full-season field plot results may be attributed to the limitations of using single-season data. IPM extension recommendations in Georgia have not included control of specific disease vectors. These results indicate that fungal diseases of soybean significantly lower yields, especially when considering the interaction of defoliating, and pod- and seed-damaging insects. Farmers should therefore consider controls specific to these disease agents.

The computed F-value $\delta = 8.9559$ from [3] was used for testing whether the parameter values in question remain virtually the same between the experimental designs. This value indicates that the restricted or pooled model would not be chosen from a pretest perspective given an $F_{[15,255]} = 2.04$ critical value at the .05 level of significance. Since the traditional likelihood ratio test yielded a value relatively far from the critical value, one would expect the Stein-rule to produce an estimator that gave substantial weight to the unrestricted OLS estimator. The Stein-rule estimates lie very close to those produced by the unrestricted model, indicating that pooling the data sets did not improve estimates substantially over the traditional OLS technique (see tables 1, 2, and 3). Root mean square error (RMSE) criteria based on actual and predicted soybean yields for the full-season data set were calculated. RMSE for the unrestricted model and the Stein-rule estimator were the same, while that for the restricted model was greater. These results indicate that incorporating additional information did not greatly enhance the data set. The lack of data set conformability or validity may be due to the influence of climate on both the soybean plant and insects. In addition, the different soybean varieties used in the experiments may have significant differences in insect and disease resistance. However, the Stein-rule provided the analytical ability to determine the appropriateness of considering the pooled data set. Failure to consider the additional information may lead to erroneous results and implications. Specifically, the OLS coefficient associated with VBC for the caged experiment was less than 8 percent of the corresponding VBC coefficient in the field plot experiment. Only considering the caged data set when determining economic thresholds may severely understate the influence VBC exerts on soybean and may lead to estimates of economic thresholds that are significantly above the actual threshold.

Incorporating additional information into the analysis provides a method for validating and modifying a particular data set. If the restrictions do not conform to the data sets, the Stein-rule estimates will not deviate from OLS estimates and predictive performance (RMSE) between the two estimates will not deviate significantly. Our results tend to fall in this category. Conversely, if the restrictions conform with the data sets then the Stein-rule estimates may result in improved predictive performance and lower RMSE compared with OLS and RLS estimates. This analysis is of central importance since economic threshold studies are totally dependent on experimental designs modeling pest damage.

SUMMARY AND CONCLUSION

IPM researchers are often confronted with the problem of limited quantity and caliber of data. The resultant limitations on model design and specification, given the intricacies of a dynamic production system, allow uncertainty to enter the modeling process. Considering the levels of uncertainty facing the farmer confronting pest management decisions, IPM recommendations based upon models developed from the narrow perspective of a single pest or single interactive insect relationship may contribute to uncertainty rather than alleviate it. In this study we have proposed a method to enrich prospective IPM data sets by pooling sample data originating from different experimental designs. A Stein-rule estimator was offered as an alternative to traditional approaches to pooling data, since it adjusts between OLS and RLS based on the correctness of the restrictions.

Results indicated that the restrictions imposed did not conform to the data sets. Thus, the validity of the data sets could not be confirmed and further investigation into relationships among the variables is required. In general, this type of analysis is necessary for any investigation of economic thresholds when data pooling is an option, since the procedure will indicate if the various restrictions do conform to the data sets. If they are conformable, this analysis may result in Stein-rule estimates with lower RMSE for incorporation into an economic threshold analysis. Finally, our approach in expanding data availability for the applied researcher should allow better agro-ecosystem modeling, and provide those in extension IPM greater confidence when providing the farmer with specific IPM recommendations.

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