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PROBABILISTIC COST EFFECTIVENESS IN AGRICULTURAL NONPOINT POLLUTION CONTROL

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Abstract

Conceptual weaknesses in the use of costs of average abatement as a measure of the cost effectiveness of agricultural nonpoint pollution control are examined. A probabilistic alternative is developed. The focus is on methods for evaluating whole-farm pollution control plans rather than individual practices. As a consequence, the analysis is presented in a chance-constrained activity analysis framework because activity analysis procedures are a practical and well developed device for screening farm plans. Reliability of control is shown to be as important as reduction targets in designing farm plans for pollution control. Furthermore, broad-axe prescriptions of technology in the form of Best Management Practices may perform poorly with respect to cost effectiveness.

Key words: nonpoint pollution, Best Management Practices, cost effectiveness.

Agricultural nonpoint pollution control is essential for the restoration and protection of acceptable levels of water quality in lakes and streams throughout the nation, including such water bodies as the Great Lakes and the Chesapeake Bay (U.S. Environmental Protection Agency). To alleviate agricultural and other nonpoint pollution problems, the 1987 Clean Water Act Amendments require state authorities to designate "Best Management Practices" (BMPs) that reduce pollution loads relative to conventional practices and implement regulatory or other programs to induce BMPs adoption. Title XII of the Food Security Act of 1985 explicitly links a farmer's access to Federal farm programs to erosion control practices on highly erodible land. It seems likely that future legislation will link a farmer's access to such programs to nutrient management as well as water quality protection activities.

Concern for minimizing the economic burden of pollution control in agriculture makes cost effectiveness an important consideration in designation of BMPs and the development and evaluation of farm plans for meeting water quality goals. Assessments of the cost effectiveness of pollution control are usually based on the general rule that efficiency is improved by reallocating abatement from sources with high marginal abatement costs to sources with low marginal costs. The welfare-theoretic foundation of this rule, appropriately modified when abatement by one source is not a perfect substitute for abatement by another, is well established for cases with nonstochastic emissions (e.g., Baumol and Oates). In situations where emissions are stochastic, which is clearly the case with nonpoint sources, pollution control properly defined involves improving the distribution of emissions rather than reducing a scaler value. It follows that a meaningful deterministic concept of marginal abatement cost does not exist for nonpoint sources. Nevertheless, certainly many, and probably most, analyses of cost effectiveness involving nonpoint sources sidestep formal consideration of the stochastic element by measuring pollution control on the basis of estimated changes in long-term average or expected flows (Milon). Correspondingly, control costs are also defined over long-term average or expected flows.

This paper examines conceptual weaknesses in the use of costs of average abatement as a measure of cost effectiveness and develops a probabilistic alternative. The focus is on methods for evaluating whole-farm pollution control plans rather than individual practices. This focus leads us to present the analysis in a chance-constrained activity analysis framework because activity analysis procedures are a practical and well developed device for screening farm plans. A numerical application is also presented to illustrate the framework and develop some implications for its use.

AVERAGE AND PROBABILISTIC COST EFFECTIVENESS

The case of a competitive, risk-neutral farm is considered to simplify the analysis. A single pollutant is assumed but the analysis could easily be generalized to multiple pollutants. Pollution runoff from the farm is a function of deterministic variables

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that the farmer controls in the production process and stochastic variables, such as rainfall. The runoff rate of the pollutant is expressed as

$$(1)\quad e = \sum_{j}^{n} (r_j + \varepsilon_j)\, x_j,$$

where e is the runoff rate, x_j is the level of the jth farm activity (e.g., acres of corn produced using a specific production system), r_j is the expected pollution runoff per unit of jth activity (e.g., expected nitrogen loss per acre of corn produced by a given production system), and $\varepsilon_j$is the stochastic variation of runoff per unit of the activity. The mean and variance of the runoff from the farm are:

$$(2)\quad E(e) = \sum_{j}^{n} r_j x_j$$

and

$$(3)\quad \mathrm{Var}(e) = \sum_{j}^{n} \sigma_j^2 x_j^2 + \sum_{j}^{n}\sum_{k}^{n} \sigma_{jk}\, x_j\, x_k,$$

where

$$(4)\quad \sigma_j^2 = \mathrm{Var}(\varepsilon_j)$$

and

$$(5)\quad \sigma_{jk} = \mathrm{COV}(\varepsilon_j, \varepsilon_k).$$

The farmer's expected cost of pollution control is the expected profit forgone due to changes in farm resource allocation. To analyze this cost and examine alternative concepts of cost effectiveness, assume that the farmer's decision problem in the absence of environmental regulations is to choose values of $x_1,\dots,x_n$ to maximize

$$(6)\quad \sum_{j}^{n} \pi_j x_j,$$

subject to expected resource use not exceeding expected resource availability, i.e.,

$$(7)\quad \sum_{j}^{n} a_{ij} x_j \le b_i,\ \ i = 1, 2, \dots, m,$$

where π_j is the expected profit per unit of activity j, a_{ij} is the expected use of the ith resource per unit of the jth activity, and b_i is the expected availability of the ith resource. The expected profit maximizing values of the x_j are denoted $x_j^*, i = 1, 2, \dots, n$. Accordingly, the expected values of farm profit and pollution runoff and the variance of runoff are, respectively,

$$(8)\quad \bar{\pi} = \sum_{j}^{n} \pi_j x_j^*,$$

$$(9)\quad \bar{e} = \sum_{j}^{n} r_j x_j^*,\ \text{ and}$$

$$(10)\quad \sigma_e^2 = \sum_{j}^{n} \sigma_j^2 x_j^* + \sum_{j}^{n} \sum_{k}^{n} \sigma_{jk} x_j^* x_k^*,\ \ j \ne k.$$

Now, consider measuring pollution control as the expected reduction in pollution runoff relative to the unconstrained case. In other words, control is measured as

$$(11)\quad \bar{z} = \bar{e} - \sum_{j}^{n} r_j x_j.$$

There may be any number of feasible farm plans that yield a specified value of $\bar{z}$. A plan, say $x_1', \dots, x_n'$, is more cost effective than another plan, say $x_1'', \dots, x_n''$, if the expected profit of the first plan exceeds the expected profit of the second. The least-cost plan is the feasible plan [i.e., it satisfies equation (7)] that maximizes expected profit in equation (6), subject to the expected reduction in pollution runoff being at least $\bar{z}$, i.e.,

$$(12)\quad \bar{e} - \sum_{j}^{n} r_j x_j \ge \bar{z}.$$

The farm pollution control cost function when control is measured as the expected reduction is

$$(13)\quad c(\bar{z}) = \bar{\pi} - \sum_{j=1}^{n} \pi_j \hat{x}_j(\bar{z}),$$

where $\hat{x}_j(\bar{z})$ is the value of x_j associated with the least-cost solution to equation (11) for any $\bar{z}$. Properties of linear programming imply that $c(\bar{z})$ will be piecewise continuous and increasing in $\bar{z}$ over the range of feasible expected reductions.

The obvious problem with using the costs of average abatement to evaluate cost effectiveness is that while one moment of the distribution of runoff is controlled, external damage costs may be influenced by the variability and other aspects of the distribution of runoff (Segerson; Shortle and Dunn). For example, suppose that a reduction in runoff of z* is needed to achieve water quality goals. This level might be achieved on average, but deviations from the average due to severe storms, structural failures, or other phenomena may still result in loadings substantially in excess of acceptable levels. Therefore, while two given farm plans may be equally cost effective in achieving z* on average, one may be preferred to the other because it has less variability. Indeed, a plan that is less cost effective in reducing the mean level of runoff may be preferred because of a desirable reduction in the variability of runoff.

Accordingly, consider measuring pollution control as the probability of reducing runoff at least to a specified target.[1] For the reduction target z^*, the measure of pollution control is

$$(14)\quad \mathrm{Prob}(z \geq z^*) = \alpha \quad (0 < \alpha < 1),$$

where z is the actual reduction in pollution runoff relative to $\bar{e}$. A plan x'_1 ,..., x'_n that achieves at least z^* with a probability of α is more cost effective than another plan, say x''_1 ,..., x''_n, that also achieves at least z^* with a probability of α if the former is more profitable. The least-cost plan for this measure is a feasible plan [i.e., it satisfies equation (7)] that maximizes expected profit of equation (6) subject to the probability of $z \geq z^*$ being at least α from equation (14). The farm's pollution control cost function when pollution control is measured in this probabilistic way is

$$(15)\quad c(\alpha, z^*) = \bar{\pi} - \sum_{j}^{n} \pi_j \tilde{x}_j(\alpha, z^*),$$

where the $\tilde{x}_j(\alpha,z^*)$ are the values of x_j in a least-cost plan for any α and z^*.

To compare implications of using this probabilistic concept of control, rather than average abatement, it is useful to work with the deterministic equivalent of (14) (Charnes and Cooper). Following Paris and Easter, the deterministic equivalent is written

$$(16)\quad \bar{e} - \sum_{j}^{n} r_j x_j + w_\alpha \left(\sum_{j}^{n} \sigma_j^2 x_j^2 + \sum_{j}^{n} \sum_{k}^{n} \sigma_{jk} x_j x_k \right)^{\frac{1}{2}} \geq z^*, \quad j \neq k,$$

where w_α is a number such that

$$(17)\quad \int_{w_\alpha}^{\infty} f(\theta)d\theta = \alpha,$$

θ is the standardized form of e, and $f(\theta)$ is the density function for θ. In the illustration that follows θ is assumed to be the standard normal random variable.

If it is desirable to achieve a reduction of z^* with a probability of more than 50 percent, then $w_\alpha < 0$ (Paris and Easter) and equation (16) implies a tighter constraint on the farm plan than equation (12), given $\bar{z} = z^*$. This can be seen easily using Figure 1 under the assumption that there are only two activities (i.e., n=2) and that the probabilistic constraint is convex. The line $c_1c'_1$ gives combinations of x_1 and x_2 such that the expected reduction is $\bar{e} - \bar{z}$ [i.e., the values of x_1 and x_2 that satisfy (12) as an equality given n=2]. Combinations to the north or east of this line are less effective while points to the south or west are more effective when effectiveness is measured by the expected or average reduction. The curve $c_2c'_2$ gives combinations of x_1 and x_2 such that the probability of reducing runoff by the amount of $\bar{e} - \bar{z}$ is at least (α x 100) percent [i.e., the combinations of x_1 and x_2 that satisfy (16) as an equality given $n = 2$ and $z^* = \bar{z}$]. The endpoints c_2 and c'_2 must lie below c_1 and c'_1 respectively because of the positive variance (no covariance effects at the endpoints) and the point on the density function corresponding to given α is positive. The curve will be everywhere concave to the origin if the variance-covariance matrix is positive semi-definite (Paris and Easter). Combinations to the north or east of this curve are less effective while combinations to the south or west are more effective in controlling runoff when effectiveness is defined probabilistically. The greater restrictiveness of the probabilistic measure for any given targeted reduction is evident in that $c_2c'_2$ must lie everywhere below $c_1c'_1$, given $z^* = \bar{z}$. Hence, more choices are available to the farmer to maximize expected profits when effectiveness is measured by the average reduction rather than probabilistically for a given reduction target. It follows that the cost of achieving a given reduction of pol-

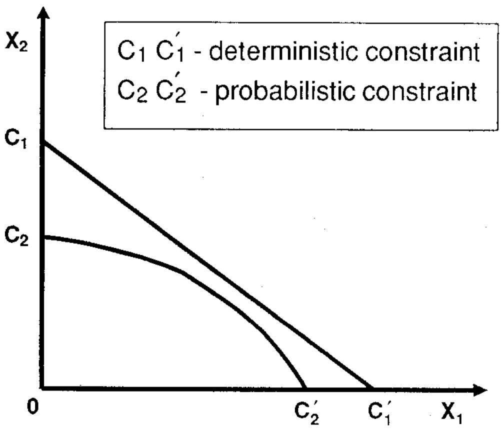

Figure 1. Feasible Region.

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[1] Probabilistic aggregate pollution control standards have been proposed and discussed by several authors, including Beavis and Walker, Burn and McBean, Maler, and Milon.

lution runoff from a farm will be greater with greater reliability of control.

ILLUSTRATION

The study area for this illustration of the framework and issues presented above are the Nansemond River and Chuckatuck Creek watersheds of the County of Isle of Wight and the City of Suffolk, situated contiguously in southeastern Virginia. These streams drain into the James River near its junction with the Chesapeake Bay, itself the recipient of recent attention concerning the levels of nonpoint source pollution found in its waters. The topography ranges from generally flat to gently rolling with steep slopes along streams. These watersheds were chosen for a Rural Clean Water Program because of their nonpoint source pollution problems.

An activity analysis model of the representative farm was developed to determine expected profit-maximizing farm plans with and without environmental constraints. The mathematical structure of the model was equivalent to maximizing (6) subject to (7) in the absence of environmental constraints. Two types of environmental constraints were considered. One type involved probabilistic restrictions. The mathematical form of the model then involved maximizing (6) subject to (7) and (16). The second type of constraint was nonprobabilistic and was considered to help examine the implications of the probabilistic measure of effectiveness in farm planning.

The model was solved using linear and nonlinear procedures of MINOS (Murtaugh and Saunders). The nonlinear procedures were needed to solve the model when (16) was imposed as a constraint.

The farm model reflected production practices and resource constraints considered typical of crop farms in the study area. The model consisted of 251 acres of cropland, the average size farm in the study area (U.S. Department of Commerce). In the absence of probabilistic constraints, the model was a linear programming model. The objective function was of the same form as equation (6) and was maximized subject to constraints having the same form as equation (7). It contained 139 activities and 42 constraints.

The farm model included four crops: corn, soybeans, wheat, and peanuts, which together accounted for over 90 percent of the harvested acreage in the study area in 1981 (U.S. Department of Commerce). The remaining activities in the model consisted of production and resource acquisition activities. Conventional tillage as well as no-till cultivation were permitted for all crops except peanuts. No-till was not used in the area. Conventional tillage was allowed with or without an over-winter cover crop for corn, soybeans, and peanuts. The cover crop was not allowed to be harvested. Wheat was allowed only as a double crop with late season soybeans. Additionally, all crops were permitted in combination with sod filter strips, which are structural practices that filter sediment out of runoff.

Because Agricultural Stabilization and Conservation Service (ASCS) cost shares are part of current policy for controlling soil loss under the Agricultural Conservation Program (ACP), they were incorporated in the objective function values of the various eligible conservation activities as reductions in production. The farm could have received up to $3,500 in cost-share funds.

The production activities were defined with several possible rotations and alternative primary and secondary tillage options to provide a range of substitution possibilities. Technical coefficients and production costs and returns for the various activities were determined using standard budgeting procedures, based on 1987 input and output prices, and Federal price and income support and conservation programs.

The mean nitrogen losses per unit of each activity in the environmental constraint (16) were based on a site study reported in Stavros. As with most site-specific hydrological modeling of nonpoint pollution flows, the Stavros study focused on providing good estimates of mean losses but ignored other parameters of the distribution. Accordingly, alternative values of the additional parameters of (16) were developed in a systematic way to illustrate the effects of the probabilistic constraints over a range of possible variances. The alternative variances were generated using the estimated means and alternative assumptions about the coefficient of variation of the unit nitrogen losses.[2] The assumed values of the coefficient of variation were 0.25 and 0.75. Covariances of the unit losses were obtained using the variances and assuming a correlation coefficient of unity between the unit losses from different activities. Under this assumption, the covariances are the square roots of products of paired variances.[3] Posi-

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[2] The definition of the coefficient of variation is used to solve for the variances given the mean and the assumed values of the coefficient of variation.

[3] This follows from the fact that the correlation coefficient for two random variables is their covariance divided by the product of their standard deviations.

tive covariance between unit losses is clearly the appropriate assumption to make given that alternative activities on a farm of the type considered here are exposed to the same exogenous stochastic influences. Unitary correlation coefficients are a reasonable approximation if the unit losses from different activities are approximately proportional to a common random variable.

Alternative values of the reduction target z* in (16) were considered. The values represent alternative percentage reductions relative to a baseline level of nitrogen loss. The baseline for the pollution reductions was the long-run average annual level of the field losses associated with the farm plan that would maximize the farm profit in the absence of environmental constraints. Nitrogen loss targets of 20, 40, and 60 percent relative to the benchline were considered with probabilities of 50, 75, and 95 percent.

In addition to these analyses, the cost and probabilistic effectiveness of three alternative restrictions that involve the prescribed use of specific control practices were considered. One was to prescribe use of no-till methods of planting on all cropland. This approach is interesting because widespread use of no-till has been advocated to protect the Chesapeake Bay from agricultural runoff. The second was to prescribe use of no-till methods of planting for all crops except peanuts, which are unsuited to no-till methods but are important in Virginia agriculture. This approach, however, required a cover crop for peanuts. The model was used to determine the practices that maximize farm profit subject to each of the stated restrictions on tillage practices.

Finally, the cost and probabilistic effectiveness of a conservation plan consistent with the highly erodible land requirement of the 1985 Farm Bill were examined. These requirements prohibit farmers who participate in various USDA programs from using practices with annual average soil loss rates in excess of soil tolerance (T) values on highly erodible land (Dicks). The conservation plan did not allow any activity with anticipated soil loss greater than T to enter the optimal solution. While the intent of such plans is primarily to reduce soil loss, nitrogen is carried along with soil particles in runoff. Therefore, reduction of soil loss will have an effect on edge-of-field nitrogen losses. The model was used to determine the practices that maximize farm profit subject to the conservation plan to analyze the environmental implications.

To facilitate discussion of the results, the farm plans generated by maximizing net returns subject to the probabilistic reduction targets are referred to as performance-restricted farm plans. The plans generated by maximizing net returns subject to restrictions on acceptable practices are referred to as practice-restricted farm plans.

RESULTS

Table 1 and Table 2 present the baseline results, as well as the cropping practices, that maximize net returns subject to the alternative nitrogen reductions discussed above, for each of the simulated distributions of nitrogen losses. The cost of the alternative environmental restrictions, in terms of foregone net returns relative to the baseline plan, also appear in Table 1 and Table 2. It is important to note that the changes in farm resource allocation between the environmentally unconstrained and the environmentally constrained solutions are influenced by both market incentives and government prices and income support, conservation, and tax programs. Hence, it is only appropriate to view the plans indicated here as private-cost-minimizing. It would also be interesting to examine divergences between the private and social costs of the plans, but that is beyond the scope and intent of this study. Tables 3 and 4 present results on the probabilistic cost effectiveness of the various farm plans.

Cropping activities in the baseline plan were approximately 126 acres of conventional tillage corn, 84 acres of conventional tillage soybeans, and 41 acres of conventional tillage peanuts. Note that for the wider distribution of nitrogen loss, Table 2 (c.v. = 0.75), many of the solutions were infeasible. The target reductions in expected losses could not be achieved with high probability when the distribution of nitrogen loss was relatively dispersed. Only one reduction/reliability combination proved infeasible for the much narrower distribution (see Table 1).

Changes in cropping practices to meet the probabilistic nutrient reduction targets at least cost did not involve simple additions of BMPs but instead entailed combinations of changes in rotation, tillage practices, and the addition of cover crops and/or sod filter strips. The combinations of measures varied significantly between the alternative cases. The no-till wheat-soybean rotation was added at the expense of conventional till soybeans in each case with the extent of the shift differing among the cases. With larger reliabilities and/or greater reduction targets, much of the corn land was shifted from conventional tillage to no-till methods. In addition, cover crops and sod filters were added to the no-till corn land with higher reliabilities and/or greater reduction targets. Finally, while the acreage in the corn/peanut rotation remained unchanged, sod filters were added to this land increasingly with higher reliabilities and/or nutrient reduction targets.

The results illustrate that more extensive changes in farm resource allocation are needed to meet any feasible reduction target as the reliability of control is increased (i.e., increasing reliability increases the restrictiveness of the farm plan). For example, in Table 1, increasing the reliability from 50 percent to 95 percent increased the cost of control for the 40 percent reduction target by a factor of seven and by a factor of about ten for the 20 percent reduction target. This is detailed more fully in Figure 2, which relates foregone income as a function of the percentage reduction in nitrogen loss, for α = (0.50, 0.75, 0.95) and c.v. = (0.25, 0.75). For any c.v., the costs of control were higher for higher levels of probability over all percentage reduction in nitrogen loss.

Costs also rose significantly for any reliability as the reduction target increased (Figure 2). It is interesting to note that in Table 1 the difference in the costs of a 20 percent reduction with 75 percent probability and a 60 percent reduction with 50 percent probability is not large. This, along with the foregoing discussion, suggests that if reliability is an important objective, then the implication of achieving reliability of control is certainly as important in analysis of appropriate changes in farming practices

Table 1. Cropping Practices And Costs, Coefficient Of Variation = 0.25.

Cropping Activities	Baseline	Nutrient Reduction Targets (t x 100) and Reliabilities (α x 100)									No-Till Only	No-Till Only Except Peanuts	Con-serv. Plan
		20%			40%			60%					
		50%	75%	95%	50%	75%	95%	50%	75%	95%			
	acres[a]												
Conventional Till Corn	125.88	121.65	24.49	125.88	62.93			18.23		INF			
With Sod Strips										INF			
With Cover Crop										INF			
No-Till Corn		4.23	101.38		62.94	125.88		107.65	109.94	INF	167.33	125.83	125.88
With Sod Strips							141.96		15.94	INF			
No-Till Wheat/ Beans		54.48	54.48	83.67	54.48	54.48	83.67	54.48	83.67	INF	83.67	83.67	83.67
Conventional Till Peanuts	41.45	41.45	41.45		41.45	14.20		41.45		INF			
With Sod Strip										INF			41.45
With Cover Crop				38.53						INF		41.45	
With Sod and Cover				2.92		27.25	25.37		41.45	INF			
Conventional Till Soy-beans	83.67	29.19			29.19					INF			
With Strip			29.19					29.19		INF			
With Cover						29.19				INF			
	$1000 [a]												
Cost ($1000s)	NA	0.587	3.415	5.066	2.011	4.311	14.996	3.593	7.181	21.866[b]	21.763	7.878	7.878

[a] INF means infeasible and NA means not applicable.

[b] Implied by the infeasibility.

and their direct and indirect costs as are the stated reduction targets.

The relative effectiveness of the performance-restricted farm plans discussed above and the practice-restricted plans can be evaluated by using information reported in Tables 2, 3, and 4. The expected level plus weighted standard deviation reported in Tables 3 and 4 is the left-hand side of equation (16) for the various practice-restricted farm plans for each value of α. In Table 3 each value of this sum corresponds to a farm plan that maximizes net returns subject to the various probabilistic constraints on nitrogen loss, that is, the performance restrictions. The changes in the sum reflect changes in the farm plan, the mean and standard deviation of the pollutant loss, and the weight on the standard deviation. The farm plans underlying Table 4 were not obtained by maximizing net returns subject to

Table 2. Cropping Practices And Costs, Coefficient Of Variation = 0.75.

		Nutrient Reduction Targets (t x 100) and Reliabilities (α x 100)											
		20%			40%			60%					
Cropping Activities	Baseline	50%	75%	95%	50%	75%	95%	50%	75%	95%	No-Till Only	No-Till Only Except Peanuts	Conserv. Plan
	acres[a]												
Conventional Till Corn	125.88	121.65		INF	62.93	INF	INF	18.23	INF	INF			
With Sod Strips				INF		INF	INF		INF	INF			
With Cover Crop				INF		INF	INF		INF	INF			
With Sod and Cover				INF		INF	INF		INF	INF			
No-Till Corn		4.23	125.88	INF	62.94	INF	INF	107.65	INF	INF	167.33	125.83	125.88
With Sod Strips				INF		INF	INF		INF	INF			
No-Till Wheat/ Beans		54.48	83.67	INF	54.48	INF	INF	54.48	INF	INF	83.67	83.67	83.67
Conventional Till Soybeans	83.67	29.19		INF	29.19	INF	INF		INF	INF			
With Sod Strips				INF		INF	INF	29.19	INF	INF			
With Cover Crop				INF		INF	INF		INF	INF			
With Sod and Cover				INF		INF	INF		INF	INF			
Conventional Till Peanuts	41.45	41.45		INF	41.45	INF	INF	41.45	INF	INF			
With Sod Strips				INF		INF	INF		INF	INF			41.45
With Cover Crop				INF		INF	INF		INF	INF		41.45	
With Sod And Cover			41.45	INF		INF	INF		INF	INF			
	$1000[a]												
Cost ($1000s)	NA	0.587	6.700	21.866[b]	2.011	21.866[b]	21.866[b]	3.593	21.866[b]	21.866[b]	21.763	7.878	7.878

[a] INF means infeasible and NA means not applicable.
[b] Implied by the infeasibility.

Table 3. Probabilistic Effectiveness: Performance-Restricted Farm Plans.

Nutrient Reduction Target	Reliability Factor	Expected Nitrogen Loss Level (lbs/year)		Expected Nitrogen Loss Level Plus Scaled Standard Deviation (lbs/year)	
(t x 100)	(α x 100)	C.V. = 0.25	C.V. = 0.75	C.V. = 0.25	C.V. = 0.75
20%	50%	234.86	234.86	234.86	234.86
	75%	123.69	63.55	234.86	234.86
	95%	73.55	INF[a]	234.86	—
40%	50%	176.15	176.15	176.15	176.15
	75%	92.77	INF	176.15	—
	95%	55.16	INF	176.15	—
60%	50%	117.43	117.43	117.43	117.43
	75%	61.84	INF	117.43	—
	95%	INF	INF	—	—

[a] INF means infeasible

the probabilistic constraint but were instead obtained by maximizing net returns subject to constraints on allowable practices. The sum of the mean and weighted standard deviation varies for a given farm plan only with changes in the reliability factor since the mean and standard deviation of pollutant loss are constant for the plan.

The expected nitrogen flows after 20, 40, and 60 percent reductions relative to the baseline were 234.86, 176.15, and 117.43 lbs./yr., respectively. These numbers are the upper bounds on the mean plus weighted standard deviations used to generate the optimal farm plans for meeting the probabilistic constraints. The sum of the mean losses plus weighted standard deviations in Table 3 are less than or equal to the corresponding bounds since the underlying plans satisfy the constraints by definition. The sums reported in Table 4 may be greater or less than these upper bounds. When less than or equal to the bounds, the implication is that the farm plan at least satisfied the probabilistic constraint. When the sum exceeds the bound, the implication is that the farm plan did not satisfy the probabilistic constraint.

Comparing the numbers in Table 4 to these upper bounds, it is apparent that the no-till-only restriction did not satisfy each reduction target for each reliability factor. For example, with c.v. = 0.25, the 60 percent reduction could be met with a probability of 0.75 (104.84 < 117.43), but not at a probability of 0.95 (176.33 > 117.43). If nitrogen losses occurred according to c.v. = 0.75 then the 60 percent reduction could not be met with even a 75 percent level of confidence (198.13 > 117.43).

Comparing the information across tables, it is evident that the practice-restricted farm plans did not provide cost effective control of nitrogen in comparison with the performance-restricted plans. The income penalty to the no-till-only farm plan was

Table 4. Probabilistic Effectiveness: Practice-Restricted Farm Plans.

Practice Restrictions	Reliability Factor (α x 100)	Expected Nitrogen Loss Level (lbs/year)	Expected Nitrogen Loss Level Plus Scaled Standard Deviation (lbs/year)	
			C.V. = 0.25	C.V.=0.75
No-Till Only	50%	55.22	55.22	55.22
	75%	55.82	104.84	198.13
	95%	55.22	176.33	418.56
No-Till Only Except Peanuts	50%	74.24	74.24	74.24
	75%	74.24	140.96	274.41
	95%	74.24	237.09	465.86
Conservation Plan	50%	69.73	69.73	69.73
	75%	69.73	132.38	250.18
	95%	69.73	222.66	528.53

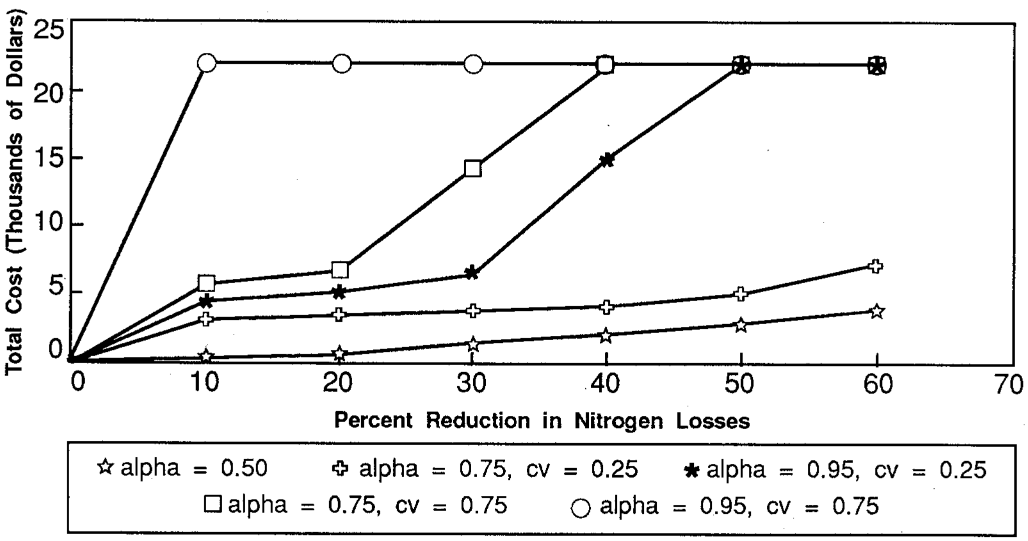

Figure 2. Foregone Farm Income.

almost 100 percent in Table 1, due largely to the loss of lucrative peanut acreage and the added expense of no-till cultivation over conventional tillage. The income penalties generated by the other practice-restricted plans were also substantial.

CONCLUSIONS

This paper examined a probabilistic concept for evaluating the cost effectiveness of whole-farm pollution control plans. A chance-constrained activity analysis framework was presented to implement the concept. An illustrative numerical application was presented. There are two main conclusions to be drawn from the numerical analysis here. First, reliability can be as important as reduction targets in designing farm plans for pollution control. The targets chosen for this analysis could be satisfied with widely varying degrees of reliability and the variations have important implications for cropping practices and the farm-level costs of control. For example, the farm plans needed to achieve relatively smaller reduction targets with high probability can require greater restrictions on farming practices and therefore higher costs than plans needed to achieve relatively greater reduction targets but with lesser reliability.

The second conclusion is that transaction costs aside, broad-axe prescriptions of "appropriate" technology in the form of Best Management Practices may perform poorly with respect to cost effectiveness. The case in point is the no-till restriction. This restriction is half again more costly than the most costly feasible performance-restricted farm plan considered here (40 percent reduction with a probability of 0.95) yet is not necessarily environmentally preferable. The implication of this conclusion is not necessarily that government should identify more cost effective plans and mandate them. Although this is a possibility, the transaction costs may outweigh the gains. Alternatively, standards could be imposed on means and weighted variances and farmers could determine least-cost plans for meeting them provided they receive technical assistance on the relationship between practices and the distribution of losses. Economic incentives offer another means for promoting cost effective planning at the farm level (Shortle and Dunn). Of course, standards or incentives involve transaction costs as well, and these costs must be considered in a complete economic evaluation of any policy approach.

A final note is in order regarding the usefulness of the farm-level approach used in this study. While useful in demonstrating the importance of designing controls in a probabilistic sense, as done here, a watershed model would provide more useful information to planners regarding trade offs across subsheds and tributaries. In such a model, differences in weather patterns could be incorporated that account for much of the variation in pollution losses.

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