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REGULATING PESTICIDE DISCHARGE INTO SURFACE AND GROUNDWATER UNDER CERTAINTY*

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ABSTRACT

The presence of contaminants such as agricultural pesticides in environmental media as well as the desire to maintain a high level of economic activity presents a difficult decision-making problem for all concerned parties. It has been difficult to identify the appropriate responses aimed at resolving the potential health risks associated with pesticides in surface and groundwater sources because of the high degree of uncertainty surrounding them and the processes generating them. Public decision makers must not only make decisions on how to manage risk, but also on how to manage risk compounded by uncertainty. Further complications include the high degree of public sensitivity to the notion that these risks are small but indeed costly.

The current policy used by the EPA to regulate pesticides is based on a mixture of policy instruments that are implemented within the context of a registration requirement. In general, this policy requires that pesticides be registered to be marketed. It has been concluded from an evaluation of this system that the policy decision is dominated by a cancellation decision. It has also been concluded that the current framework does not possess mechanisms

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for inducing marginal changes in pesticide use to give protection from health risks compounded by uncertainty as well as preventing runoff into surface waters or leaching into groundwater.

The limited flexibility of the current regulatory framework can be improved by supplementing it with a tax. Traditionally, the process of setting the "optimal tax" for each chemical is viewed as problematic. This can be done using the "standards and charges" approach, which involves two steps. First, standards or targets for environmental quality are set that reflect a relevant set of criteria; second, a set of taxes (charges) is designed and put in place to achieve these standards or targets. This process requires various types of information such as the productivity of and demand for classes of pesticides. In addition, the stochastic nature of pesticides must be taken into account. It is generally concluded that the information on which to base a tax on pesticides, even to achieve a certain level of health risk standards, is not readily available.

This article develops a protocol that uses simulation and mathematical programming techniques to compute the tax for a standards and charges approach for regulating pesticides under uncertainty. The Kuhn-Tucker conditions are used as a basis to develop the appropriate tax rates. It is shown that the tax rate is imposed on pesticides used as inputs and varies according to soil type. It is also shown that the tax rate can be expressed as a function of risk and uncertainty as well as the preferred level of safety.

INTRODUCTION

The presence of contaminants in environmental media as well as the desire to maintain a high level of economic activity presents an interesting and difficult decision-making problem for public policy decision makers as well as the general public. On the one hand, all parties are concerned about the potential health risks posed by the presence of contaminants and the need to formulate/implement policies for their mitigation and/or removal. But at the same time, these same parties are also concerned about the policy costs. These costs can be measured in terms of the losses in economic activity that occur when a policy is adopted.

The appropriate responses aimed at resolving the potential health risks associated with the contaminants in environmental media, especially with respect to the health risks, have been difficult to identify because of the high degree of uncertainty surrounding them and the processes that generate them. Lichtenberg and Zilberman argue that public decision makers must not only make decisions on how to manage risk, but also on how to manage risk compounded by uncertainty [1]. Further complications include the high degree of public sensitivity to the notion that these risks are small but indeed costly.

The definitions of risk are sometimes varied and confusing. Lichtenberg and Zilberman have adopted definitions of risk and uncertainty that will be used throughout this article [1]. "Risk" or "health risk" is defined as the probability that an individual selected randomly from a population contracts an adverse health effect. Thus health risk is concerned with the probability of mortality or morbidity. In contrast, it must be recognized that the relationship between health risk and the variables that generate it are not known with certainty. Thus risk estimates used for public policy evaluation are themselves subject to error. The magnitude of this error is defined as uncertainty. In general, Lichtenberg and Zilberman argue that policy analysis relating to environmental health problems must deal with risk compounded by uncertainty [1].

Agricultural pesticides are an important example of contaminants in environmental media which are thought to pose serious health risks. The current policy used by EPA to regulate pesticides is based on a mixture of policy instruments that are implemented within the context of a registration requirement. This policy requires that pesticides be registered in order to be marketed. The registration conditions for a chemical specify 1) the crops on which it can be used, 2) the areas (usually states or counties) in which it can be used for each crop, 3) the specific pests for which it can be used on each crop in each area, 4) maximum allowable application rates by pest, crop, and area, 5) required safety precautions, and 6) specific restrictions on crop rotations, times, etc. Lichtenberg concludes in an evaluation of this system that policy solutions are dominated by "corner solutions" [2]. That is to say, the policy solution in pesticide regulation is dominated by a cancellation decision. It is also concluded that the current framework does not possess mechanisms for inducing marginal changes in pesticide use to give protection from health risks compounded by uncertainty as well as preventing runoff into surface waters or leaching into groundwater.

The limited flexibility of the current regulatory framework can be improved by supplementing it with additional instruments. Lichtenberg examines liability, provision of information, and taxes as possible candidates and concludes that taxes may be the most useful instrument [2]. This conclusion is based on a number of appealing features of taxes, which include the following. First, taxes can affect whether a chemical will be used at all as well as the application rate. (This includes the prospect of fine-tuning at the farm level.) Second, taxes allow the regulator to influence application rates at a continuous level rather than as an "all-or-nothing" type of decision. Third, regulators can vary taxes according to indicators of environmental risk such as leachability and acute or chronic toxicity. The last feature allows regulations to influence farmers' decisions about the choice of pesticides.

The process of setting the "optimal" tax for each chemical remains a problem as a practical matter. One approach is to compute optimal Pigouvian taxes, which requires that the tax be set equal to the expected value of marginal damages at the optimal level of pesticide use. But the expected value of marginal damages is difficult to quantify; this fact has led some researchers to conclude that such optimal taxes are infeasible [3].

A second option is to use the "standard and charges" approach advocated by Baumol and Oates [4]. There are two steps to this process. First, standards or targets for environmental quality are set; second, a set of taxes (charges) is designed and put in place to achieve these standards or targets. Thus the policy problem for setting taxes on pesticides is to identify a tax or set of taxes aimed at reducing the total amount of pesticide to a predetermined level believed to involve acceptably low risk to human health (and the environment). This requires various types of information such as the productivity of and demand for classes of pesticides. In addition, the stochastic nature of pesticides must also be taken into account. Lichtenberg concludes that the information on which to base a tax on pesticides, even to achieve a certain level of health risk standards is not available [2]. Wu and Segerson also note that incorporating detailed site data into policy formulations can be problematic [5].

Given the fact that pesticides as a form of nonpoint pollution are stochastic in nature and information on the productivity of and demand for classes of pesticides is not available, empirical researchers have increasingly turned to simulation and/or mathematical programming techniques to evaluate the field-level impacts of alternative policies. A number of economic studies of water pollution have included the hydrological/biological aspects of nonpoint pollution. Crowder and Young investigated the tradeoffs between the costs of soil conservation practices and water quality and discussed the economic implications of such tradeoffs [6]. The authors used the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model to assess pollutant losses from agricultural cropland to surface and groundwater. Milon evaluated the economic implications of environmental reliability criteria and multiple effluent controls [7]. An integrated PRZM and STREAM simulation model was used to generate probability distributions for critical agrichemical effluents (loads and concentrations) in surface and groundwater. These probability distributions were then combined in a chance constrained programming model. Johnson et al. integrated plant simulation, hydrologic and economic models of farm-level processes to evaluate the on-farm economic effects of strategies to reduce nitrate groundwater pollution in the Columbia River [8]. Taylor et al. examined economic incentives and other mechanisms to offset nonpoint source pollution for representative farms in the Willamette Valley of Oregon [9]. This research linked a biophysical simulator and farm-level linear programming models to determine profit maximizing plans under alternative policies.

The purpose of this article is to explore the application of a standards and charges policy framework for regulating pesticides in surface and groundwater under uncertainty using simulation and mathematical programming techniques. That is to say, a protocol that uses simulation and mathematical programming techniques to compute the tax for a standards and charges framework for regulating pesticides in surface and groundwater under uncertainty is developed. This protocol allows the tax rate to be determined on the basis of information on the productivity of and demand for pesticides. The tax rate determined from this protocol also reflects the stochastic nature of pesticides as well as the achievement of a certain level of risk standard. The modeling framework is based on a safety rule structure. The model development begins with establishment of target concentration levels for pesticides in surface and groundwater. These target levels are then used to form a safety rule framework. It is assumed that a distributed parameter simulation model of water contamination under uncertainty is used to generate a set of response matrix coefficients, which are then embedded in the safety rule structure. These coefficients provide the main linkages and are assumed to be stochastic in nature. The safety rule model is then used to show the optimality properties of the standards and charges approach. The optimal tax is derived, and it is shown how information on parameter uncertainty and margins of safety can be used in developing the tax rate. The last section presents a summary of the article's finding along with a brief discussion of issues relating to implementation of the proposed protocol.

THE SAFETY RULE MODEL

The purpose of this section is to develop a standards and charges policy framework for regulating pesticides in surface and ground water under uncertainty. This is accomplished within the context of a safety rule modeling structure as initially suggested by Lichtenberg and Zilberman [1]. Let the index I ($I = 1, \ldots, I$) denote the type of crop produced and k ($k = 1, \ldots, K$) the type of land. (Land cn be defined according to fertility, climate, irrigation, or cropping history.) The index n ($n = 1, \ldots, N$) is used to denote the type of pesticide used, while s ($s = 1, \ldots, S$) is used to denote the type of farming practice. In addition, the following notation is used:

L_{iks} ≡ acres of land type k used to produce crop I with farming practice s,
Z_{nk} ≡ amount of pesticide n used on land type k,
Y_{iks} ≡ yield per acre for crop I on land type k with farming practice s,
P_i ≡ price of crop I,
c_{iks} ≡ variable cost per acre for crop I on land type k with farming practice s (excludes pesticide and irrigation costs),
w_{nk} ≡ cost of pesticide n applied to land class or type k,
e_{nk} ≡ response matrix coefficient for pesticide type n applied to land class or type k in the groundwater source,
g_{nk} ≡ response matrix coefficient for pesticide type n applied to land class or type k in the surface water source,
a_{niks} ≡ amount of pesticide n used for crop I on soil type k with farming practice s per acre,
b_{iks} ≡ amount of water applied to crop I on soil type k with farming practice s per acre of land,

D_{iks} ≡ total amount of water used for crop I on soil type k with farming practice type s,

$\overline{L}_k$ ≡ amount of land type k available for crop production,

$\overline{M}_n$ ≡ maximum permissible loading (concentration rate) of pesticide type n in the groundwater source,

$\overline{X}_n$ ≡ maximum permissible loading (concentration rate) of pesticide type n in the surface water source,

$1 - \alpha_n$ ≡ exceedance probability for pesticide n in the groundwater source $(0 < \alpha_n < 1)$,

$1 = \beta_n$ ≡ exceedance probability for pesticide n in the surface water source, and

d_{iks} ≡ per unit cost of water used for crop I on soil type k with farming practice s per acre.

The safety rule model is designed to reflect a number of important characteristics. First, the major agricultural activity is assumed to be crop production that takes place with various amounts of inputs using various types of farming practices. (In general, any particular type of farming practice may include irrigation as well.) Second, agricultural activity is assumed to be undertaken with exogenously determined prices. Third, crop yield can be expressed as a function of several factors, including water and pesticide applications. Finally, the initial model specification is assumed to be one year.

The safety rule model for crop production and pesticide application decisions is as follows:

$$\max \Pi = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{s=1}^{S} (P_i Y_{iks} L_{iks} - c_{iks} L_{iks}) - \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{s=1}^{S} d_{iks} D_{iks} - \sum_{n=1}^{N} \sum_{k=1}^{K} w_{nk} Z_{nk} \quad (1)$$

subject to

$$\sum_{i=1}^{I} \sum_{s=1}^{S} L_{iks} \le \overline{L}_k \quad (2)$$

$$(k = 1, \ldots, K)$$

$$\sum_{i=1}^{I} \sum_{s=1}^{S} \alpha_{niks} L_{iks} = Z_{nk} \quad (3)$$

$$(n = 1, \ldots, N)$$

$$(k = 1, \ldots, K)$$

$$b_{iks} L_{iks} = D_{iks} \tag{4}$$

$$(I = 1, \ldots, I)$$

$$(k = 1, \ldots, K)$$

$$(s = 1, \ldots, S)$$

$$Pr\left\{\sum_{k=1}^{K} e_{nk}\, Z_{nk} \leq \overline{M}_n\right\} \geq 1 - \alpha_n \tag{5}$$

$$(n - 1, \ldots, N)$$

$$Pr\left\{\sum_{k=1}^{K} g_{nk} Z_{nk} \leq \overline{X}_n\right\} \geq 1 - \beta_n \tag{6}$$

$$(n = 1, \ldots, N)$$

The objective function equation (1) for the safety rule model is defined as farm profits where the decision variables are land use activities, water application levels, and types and amounts of pesticides used for the various crops. Soil types or classes based on, for example, productivity levels along with specific tillage practices are explicitly represented in this model structure. The constraint set includes restrictions on land availability, equation (2) as well as chemical capacity in environmental media, equations (5) and (6). Equation (3) is a balance equation showing the amount of each pesticide used while equation (4) is a balance equation showing the amount of water applied to crops in each situation. The latter is extremely important in the selection of those farming practices utilizing an irrigation alternative. Equations (1) through (4) play an important role in determining the demand for pesticides, reflecting productivity and profitability considerations. Equations (5) through (6), in contrast, reflect the relevant factors, including the stochastic nature of agricultural pesticides, in limiting the presence of these substances in surface and groundwater media.

The presence of agricultural chemical releases to receiving water bodies is modeled in a stochastic manner as shown by equations (5) and (6). These equations are called "chance constraints." Note that $1 - \alpha_n$ is defined as an exceedance probability for pesticide n in the groundwater source ($0 < \alpha_n < 1$). The stochastic specifications include the generation of pollution as well. Distributed parameters simulation models for surface and groundwater can be combined to estimate the expected values and probability distributions of the pollution loadings [10, 11]. These are the e_{nk} in equations (5) and the g_{nk} in equation (6). Note that these are stochastic parameters and are sometimes referred to as "response matrix coefficients." It is assumed that these coefficients are constant. (In reality these are probably nonlinear in nature. The constancy assumption is sometimes based on a "steady-state" situation. See Gorelick [12] for more in-depth discussions.)

A number of perspectives may be advanced to rationalize these formulations, but the one most relevant to this research is the regulation of health risk under uncertainty. This perspective is advanced by Harper and Zilberman [13]. Begin by defining health risk as the probability that an individual selected randomly from a population contracts an adverse health effect (probability of morbidity or mortality). The relationship between health risk and the variables that generate it are not known with certainty. Thus the health risks used for policy evaluation are subject to error, the magnitude of which is measured by the term uncertainty. Constraints (5) and (6) incorporate both the probabilistic health risk assessment with a safety rule mechanism. The safety rule mechanism is stated as a condition that risk might be constrained to remain below a given maximum level (or risk standard) with a given probability.

The nature of this is examined by focusing on constraint (5). Consider the expression inside the brackets. The terms on the left-hand side of the inequality sign show the total amount of pesticide type n from all sources that may be transported to the groundwater source. The term $\overline{M}_n$ on the right-hand side of the inequality sign shows the maximum allowable limit of this type of pesticide that is permitted to be in the groundwater source. It is assumed that $\overline{M}_n$ is established using health risk procedures as described in Harper and Zilberman [13]. This constraint requires that the concentration of pesticide n in the groundwater cannot exceed the health-based standard 100 (1 - α_n) percent of the time. Alternatively, the constraint can be violated 100α_n percent of the time. A similar set of interpretations apply to constraint (6).

Constraints (5) and (6) must be converted to a form that is more convenient for solving as a mathematical programming problem. (Recall that the e_{nk} in constraint (6) and the g_{nk} in constraint (7) are assumed to be stochastic in nature and are the main focus of this discussion.) This is done using procedures outlined by Charnes and Cooper [14]. The following assumptions are used in this process. Each of the $\overline{M}_n$ and e_{nk} are normally distributed with means $\hat{M}_n$, $\hat{e}_{nk}$ and variances var ($\overline{M}_n$) and var (e_{nk}). Each of the $\overline{X}_n$ and g_{nk} are assumed to be normally distributed with means $\hat{X}_n$, $\hat{g}_{nk}$ and variances var ($\overline{X}_n$) and var (g_{nk}). The $\overline{M}_n$ and all of the e_{nk} are assumed to be statistically independent of each other. In addition, the $\overline{X}_n$ and all of the g_{nk} are assumed to be statistically independent of each other.

The assumptions outlined above are used to restate constraints (5) and 6) as follows:

$$\sum_{k=1}^{K} \hat{e}_{nk} Z_{nk} + \varphi_{\alpha n} \left[\sum_{k=1}^{K} Z_{nk}^2 \operatorname{var}(e_{nk}) + \operatorname{var}(\overline{M}_n) \right]^{0.5} \leq \hat{M}_n \tag{7}$$

$$(n = 1, \ldots, N)$$

$$\sum_{k=1}^{K} \hat{g}_{nk} Z_{nk} + \theta_{\beta n} \left[\sum_{k=1}^{K} Z_{nk}^2 \operatorname{var}(g_{nk}) + \operatorname{var}(\overline{X}_n) \right]^{0.5} \leq \hat{X}_n \tag{8}$$

$$(n = 1, \ldots, N).$$

The parameters ϕ_{an} in constraint (7) and $\theta_{\beta n}$ in constraint (8) are critical values of the standard normal distributions exceeded only with probabilities 1 - α_n and 1 = β_n, respectively.

The safety first model now consists of maximizing equation (1) subject to constraints (2), (3), (4), (7), and (8). Constraints (7) and (8) lend themselves to some interesting interpretations concerning risk and uncertainty. These discussions are carried out in terms of (7), but are equally applicable to (8) as well. First define the following:

$$h_n = \sum_{k=1}^{K} e_{nk} Z_{nk} - \overline{M}_n. \tag{9}$$

It is assumed that h_n is a normally distributed variable with mean

$$\mu(h_n) = \sum_{k=1}^{K} \hat{e}_{nk} Z_{nk} - \hat{M}_n \tag{10a}$$

and variance

$$\operatorname{var}(h_n) = \sum_{k=1}^{K} Z_{nk}^2 \operatorname{var}(e_{nk}) + \operatorname{var}(\overline{M}_n). \tag{10b}$$

It can be concluded that the value of $\mu(h_n)$ is related to the decisions derived from the optimization model while ϕ_{an} in (7) is a critical value of the standard normal distribution exceeded only with the probability $1 - \alpha_n$. This formulation raises two important points. First, regulatory decisions are based on two parameters: maximum allowable risk as implied by $\overline{M}_n$ (recall that this parameter is assumed to be based on health-risk considerations) and the margin of safety, $1 - \alpha_n$. Second, the constraint formulation expresses the health risk standard as a combination of mean risk and a weighted value for uncertainty. The notion of mean risk is represented by equation (10a), while weighted uncertainty is given as:

$$\varphi_{\alpha n}\,[\text{var}\,(h_n)]^{0.5} = \varphi_{\alpha n}\left[\sum_{k=1}^{K} Z_{nk}^2\,\text{var}\,(e_{nk}) + \text{var}\,(\overline{M}_n)\right]^{0.5} \tag{11}$$

$$(n = 1, \ldots, N)$$

Equation (11) shows the regulator's aversion to uncertainty, which is similar to the notion of risk aversion. The expressions in brackets on the right-hand-side of equation (11) show the uncertainty inherent in estimating the value of the response matrix coefficients as well as the uncertainty in determining the health-risk based target level of pesticide concentrations in groundwater. As the probability of exceeding a given risk level is lowered, the larger is the value of $\phi_{\alpha n}$, which implies that a higher weight is placed on uncertainty by the regulator.

IMPLICATIONS OF THE MODEL

Derivations of the optimality conditions and a corresponding set of decision rules are deduced from the Kuhn-Tucker conditions, which are derived from the appropriately defined Lagrangean function for the constrained optimization model defined in the previous section. The decision variables in this model are L_{iks}, D_{iks}, and Z_{nk}. The Kuhn-Tucker conditions for these decision variables are

$$P_i Y_{iks} - c_{iks} - \pi_k - \sum_{n=1}^{N} \lambda_{nk} a_{niks} - \Delta_{iks} b_{iks} \leq 0 \tag{12a}$$

$$\left(P_i Y_{iks} - c_{iks} - \pi_k - \sum_{n=1}^{N} \lambda_{nk} a_{niks} - \Delta_{iks} b_{iks}\right) L_{iks} = 0 \tag{12b}$$

for all

$$I = 1, \ldots, I$$
$$k = 1, \ldots, K$$
$$s = 1, \ldots, S$$

$$-d_{iks} + \Delta_{iks} \leq 0 \tag{13a}$$

$$(-d_{iks} + \Delta_{iks}) D_{iks} = 0 \tag{13b}$$

for all

$$I = 1, \ldots, I$$
$$k = 1, \ldots, K$$
$$s = 1, \ldots, S$$

$$\left\{- w_{nk} + \lambda_{nk} - \varepsilon_n \left\{\hat{e}_{nk} + \varphi_{\alpha n} \left[\sum_{k=1}^{K} Z_{nk}^2 \text{ var } (e_{nk})\right]^{-0.5} Z_{nk} \text{ var } (e_{nk})\right\}\right. \tag{14a}$$

$$\left. - \rho_n \left\{\hat{g}_{nk} + \theta_{\beta n} \left[\sum_{k=1}^{K} Z_{nk}^2 \text{ var } (g_{nk})\right]^{-0.5} Z_{nk} \text{ var } (g_{nk})\right\}\right\} Z_{nk} = 0.$$

$$- w_{nk} + \lambda_{nk} - \varepsilon_n \left\{\hat{g}_{nk} + \varphi_{\alpha n} \left[\sum_{k=1}^{K} Z_{nk}^2 \text{ var } (e_{nk})\right]^{-0.5} Z_{nk} \text{ var } (e_{nk})\right\} \tag{14b}$$

$$- \rho_n \left\{\hat{g}_{nk} + \theta_{\beta n} \left[\sum_{k=1}^{K} Z_{nk}^2 \text{ var } (g_{nk})\right]^{-0.5} Z_{nk} \text{ var } (g_{nk})\right\} \leq 0$$

for all

$$n = 1, \ldots, N$$
$$k = 1, \ldots, K.$$

The variables π_k, Δ_{iks}, and λ_{nk} are Lagrangean multipliers for the land availability constraint, water balance, and pesticide balance equations, respectively. In addition, the variables ε_n and ρ_n are the Lagrangean multipliers for the pesticide level constraints for the ground and surface water sources, respectively.

Consider first the marginal decision rule for optional land use decisions. If for any i, k, and s, $L_{iks} > 0$ and positive amounts of water are used, then (12a) and (13a) hold as strict equalities and (12a) can be rewritten as

$$P_i Y_{iks} = c_{iks} + b_{iks} d_{iks} + \pi_k + \sum_{n=1}^{N} \lambda_{nk} a_{niks} = 0. \tag{15}$$

The left-hand side of equation (15) represents the marginal revenue generated if crop i is produced with farming practice s on land type k. Notice that this marginal revenue is the product of the crop price and the crop yield.

The right-hand side of equation (15) represents the marginal opportunity cost of producing crop i on soil type k with farming practice s and consists of several components. The first term, c_{iks}, represents the marginal opportunity costs of the variable inputs used with farming practice on soil type k and excludes the opportunity costs of water use and pesticide use. The second term represents the marginal opportunity cost of a binding land constraint. If the land constraint is nonbinding, then $\pi = 0$. The last expression on the right-hand side of equation (15) represents the marginal opportunity cost of pesticide usage adjusted for differences in productivity levels by soil type. Land use decisions by crop, soil type, and farming practice are thus carried to the point where the marginal revenue equals marginal opportunity cost.

The optimization model also includes pesticide use as a decision variable along with a corresponding set of marginal returns and marginal opportunity cost expressions. Suppose that crop i is produced on soil type k with farming practice s and using pesticide n so that $Z_{nk} > 0$. Equation (15) can be used to express the marginal return for pesticide n as

$$\lambda_{nk} = \frac{P_i Y_{iks} - c_{iks} - b_{iks} d_{iks} - \pi_k}{a_{niks}} \tag{16}$$

In addition, equation (14a) holds as a strict equality so that

$$\lambda_{nk} = w_{nk} + A_{1nk} + A_{2nk} \tag{17}$$

where

$$A_{1nk} = \hat{e}_{nk}\varepsilon_{nk} + \varphi_{\alpha n}\varepsilon_n \left[\sum_{k=1}^{K} Z_{nk}^2 \text{ var } (e_{nk}) \right]^{-0.5} Z_{nk} \text{ var } (e_{nk}) \tag{18a}$$

$$A_{2nk} = \hat{g}_{nk}\rho_n + \theta_{\beta n}\rho_n \left[\sum_{k=1}^{K} Z_{nk}^2 \text{ var } (g_{nk}) \right]^{-0.5} Z_{nk} \text{ var } (g_{nk}). \tag{18b}$$

The right-hand side of equation (17) represents the marginal opportunity cost of pesticide n used on soil type k.

The marginal opportunity cost of using pesticide n consists of several components. The term w_{nk} is defined as the marginal variable cost of a unit of pesticide n purchased. Typically this will be a market price which is assumed to reflect the opportunity cost of producing the nth pesticide. The second and third components are concerned with restrictions imposed on the presence of pesticides in the ground and surface water sources. To facilitate an understanding of these opportunity costs, recall the following. The presence of pesticides in ground and surface water sources is assumed to be regulated from the perspective of health risk under uncertainty. Health risk is defined as the probability that an individual randomly selected from a population contracts an adverse health effect. Clearly the relationship between health risk and the variables that generate it are not known with certainty. Thus the health risk used to establish the target levels of pesticide concentrations in surface and groundwater is subject to error the magnitude of which is measured by uncertainty. This uncertainty is addressed by specifying a safety level or probability level of exceeding the given level of risk. Ideally, these elements should be included in the measure of marginal opportunity cost.

Equation (18a) measures the marginal opportunity cost of the health risk based limit imposed on the presence of pesticide n in the groundwater source as well as the uncertainty of this limit along with the uncertainty inherent in the estimates of the values of the response matrix coefficients. The variable ε_n is the shadow price of the health-risk based target concentration level of the pesticide in the groundwater as well as the uncertainty of this target concentration level. If the allowable concentration level of pesticide n is reduced by one unit, given a particular level of uncertainty as represented by var $(\overline{M}_n)$, then the level of farm profits is reduced by an amount equal to $\hat{e}_{nk}\ \varepsilon_n$. If, on the other hand for a given value of $\overline{M}_n$, there is an increase in var $(\overline{M}_n)$, the marginal opportunity cost of this increase in the uncertainty of the error in health risks is measured by $\hat{e}_{nk}\varepsilon_n$.

The marginal opportunity cost of the uncertainty inherent in the estimates of the response matrix coefficients is represented by the second expression on the right-hand side of the equation (18a). This uncertainty is represented by var (e_{nk}). Notice that as the size of var (e_{nk}) increases, there is a corresponding increase in this marginal opportunity cost. A similar set of interpretations can be made for equation (18b), which reflects the marginal opportunity cost of the health-risk based limit imposed on the presence of pesticide n in the surface water source.

In summary, combining equations (16) through (18) yields the marginal decision for optimal use of pesticide n. Thus optimal application of pesticide n requires that the marginal returns be equal to the marginal opportunity costs, including an accounting of the opportunity cost of regulating pesticides in the surface and ground water sources as well as the ways in which the pesticides enter and disseminate through the environmental media. The latter costs include mean health risk considerations as well as the opportunity cost of the uncertainty about this risk and the fate and transport of the pesticides.

The marginal opportunity cost of the uncertainty about the estimates of the response matrix coefficients includes a weighting factor $\phi_{\alpha n}$ in equation (18a) and $\theta_{\beta n}$ in equation (18b), which reflect a margin of safety. If the regulator is interested in increasing the safety level, then $\phi_{\alpha n}$ and $\theta_{\beta n}$ are increased by the appropriate amount with corresponding increases in the marginal opportunity cost of the nth pesticide. These expressions show directly how such decisions are brought to bear on the marginal opportunity costs of using the nth pesticide.

The relationship between health risk and the variables that generate it are not known with certainty, as noted previously. These sources of uncertainty include the fundamental mechanisms underlying physiological responses as well as the ways in which contaminants enter and disseminate through the environment. Estimates of the former are presumed to be reflected in estimates of $\overline{M}_n$ and $\overline{X}_n$, while estimates of the latter are summarized by the response matrix coefficients $\hat{e}_{nk}$ and $\hat{g}_{nk}$. The magnitude of the variance var (e_{nk}) and var (g_{nk}) reflect the degree of uncertainty in the estimates of these linkages. Equations (16) through (18) show how decisions on pesticide use are affected by these uncertainties.

Assume that estimates for $\hat{e}_{nk}$ and $\hat{g}_{nk}$ are improved and are manifested in the form of lower values for var (e_{nk}) and var (g_{nk}). This implies that the marginal cost of uncertainty about risk has been lowered and it is now possible to use more units of pesticide n as implied by equations (16) through (18).

THE OPTIMAL TAX

The optimal tax for the standards and charges approach advocated by Baumol and Oates [4] is derived in this section. There are a number of important factors that must be borne in mind in the derivation of this tax rate. Recall that with nonpoint sources it is impossible to observe (without excessive cost) the level of abatement or discharge of any suspected polluter or to infer individual levels from observable ambient levels. Nonpoint source pollution has proved much more difficult to encompass within the system of standards and charges. The inability to observe emissions seems to undercut the use of emission taxes.

Nichols argues that if the unobservable level of emissions is highly correlated with some observable part of farm production or pollution process such as inputs, policy options can still be exercised [15]. Pesticide contamination is closely associated with the way pesticides are used, the amount of pesticide purchased, and crops being planted. To some extent these are physical circumstances that can be determined by a regulatory agency, but there are also important unobservable inputs as well, such as soil and topographic characteristics where pesticides are applied. These unobservable factors can be approximated to a large extent in the modeling structure being utilized.

The optimal tax rate for the standards and charges approach is applied on the basis of the level of fertilizer application, following the arguments advanced by Nichols [15]. The decision problem in this case is given as follows:

$$\max \Pi = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{s=1}^{S} (P_i Y_{iks} - c_{iks}) L_{iks} - \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{s=1}^{S} d_{iks} D_{iks} \tag{19}$$

$$- \sum_{n=1}^{N} \sum_{k=1}^{K} (w_{nk} + t_{nk}) Z_{nk}$$

subject to

$$\sum_{i=1}^{I} \sum_{s=1}^{S} L_{iks} \leq \bar{L}_k \tag{20}$$

$$(k = 1, \ldots, K)$$

$$\sum_{i=1}^{I}\sum_{s=1}^{S} a_{iks}L_{iks} = Z_{nk} \tag{21}$$

$$(n = 1, \ldots, N)$$
$$(k = 1, \ldots, K)$$

$$b_{iks}L_{iks} = D_{iks} \tag{22}$$

$$(I = 1, \ldots, I)$$
$$(k = 1, \ldots, K)$$
$$(s = 1, \ldots, S)$$

The last component in the objective function, equation [19] represents the total cost for pesticides, including the total amount of tax revenues paid.

The decision variables in this model are L_{iks}, D_{iks}, and Z_{nk}. The Kuhn-Tucker conditions for these decision variables are:

$$P_iY_{iks} - c_{iks} - \pi_k - \sum_{n=1}^{N} \lambda_{nk}a_{niks} - \Delta_{iks}b_{iks} \leq 0. \tag{23a}$$

$$\left(P_iY_{iks} - c_{iks} - \pi_k - \sum_{k=1}^{N} \lambda_{nk}a_{niks} - \Delta_{iks}b_{iks}\right)L_{iks} = 0 \tag{23b}$$

for all

$$I = 1, \ldots, I$$
$$k = 1, \ldots, K$$
$$s = 1, \ldots, S$$

$$-d_{iks} + \Delta_{iks} \leq 0 \tag{24a}$$

$$(-d_{iks} + \Delta_{iks})D_{iks} = 0 \tag{24b}$$

for all

$$I = 1, \ldots, I$$
$$k = 1, \ldots, K$$
$$s = 1, \ldots, S$$

$$-(w_{nk} + t_{nk}) + \lambda_{nk} \leq 0 \tag{25a}$$

$$\left[-\left(w_{nk} + t_{nk}\right) + \lambda_{nk}\right] Z_{nk} = 0 \tag{25b}$$

for all

$$n = 1, \ldots, N$$
$$k = 1, \ldots, K$$

The variables π_k, Δ_{iks}, and λ_{nk} are Lagrangean multipliers for the land availability constraint, water balance, and pesticide balance equations, respectively.

Optimal land use and water use decisions are based on equations (23) and (24). If $L_{iks} > 0$ and $D_{iks} > 0$, then these equations can be combined to derive a marginal decision rule that is analogous to equation (15). The interpretations are the same as before and will not be discussed here.

The optimal use of pesticide n on soil type k is determined from equations (25). If $Z_{nk} > 0$, then (25a) hold as a strict equality and

$$\lambda_{nk} = w_{nk} + t_{nk}. \tag{26}$$

for all

$$n = 1, \ldots, N$$
$$k = 1, \ldots, K$$

The left-hand side of equation (26) represents the marginal return to pesticide n applied to soil type k with interpretations that are similar to those provided in equation (16).

The right-hand side of equation (26) represents the marginal opportunity cost of using pesticide type n on soil type k and includes the optimal tax rate. The regulator's objective is to motivate a level of pesticide use that is consistent with that implied from a cost minimizing solution as outlined in the previous section. The tax rate consistent with this objective can be determined by comparing equation (26) with equation (17). The cost-minimizing level of pesticide n on soil type k will be chosen if

$$t_{nk} = A_{1nk} + A_{2nk} \tag{27}$$

where

$$A_{1nk} = \hat{e}_{nk}\varepsilon_{nk} + \varphi_{\alpha n}\varepsilon_n \left[\sum_{k=1}^{K} \hat{Z}_{nk}^2 \operatorname{var}(e_{nk}) \right]^{-0.5} \hat{Z}_{nk} \operatorname{var}(e_{nk}) \tag{28a}$$

for all

$$n = 1, \ldots, N$$
$$k = 1, \ldots, K$$

$$A_{2nk} = \hat{g}_{nk}\rho_n + \theta_{\beta n}\rho_n \left[\sum_{k=1}^{K} \hat{Z}_{nk}^2 \operatorname{var}(g_{nk}) \right]^{-0.5} \hat{Z}_{nk} \operatorname{var}(g_{nk}) \tag{28b}$$

for all

$$n = 1, \ldots, N$$
$$k = 1, \ldots, K$$

where Z_{nk} is the cost minimizing level of pesticide use derived from the safety first model which consists of maximizing equation (1) subject to constraints (2), (3), (4), (7), and (8).

The optimal tax rate as shown by equations (27) and (28) reflects an accounting of the marginal opportunity cost of the pesticide in both surface and ground water, including the notions of risk and uncertainty. The marginal opportunity cost of the uncertainty, in turn, includes a weighting factor $\phi_{\alpha n}$ in equation (28a) and $\theta_{\beta n}$ in equation (28b), which reflects the margin of safety. If the regulator is interested in increasing the safety level, then $\phi_{\alpha n}$ and $\theta_{\beta n}$ are increased by the appropriate amount with corresponding increases in the optimal tax rate. It is also important to emphasize that the determination of a tax rate in this framework is based on the objective of motivating to make certain types of decisions in the use of pesticides. In contrast, the tax rate is not set with a revenue objective or goal in mind.

It has been emphasized throughout this article that the relationship between health risk and the variables that generate it are not known with certainty. These sources of uncertainty include the fundamental mechanisms underlying physiological responses as well as ways in which contaminants enter and disseminate through the environment. Estimates of the latter are summarized by the response matrix coefficients $\hat{e}_{nk}$ and $\hat{g}_{nk}$. The magnitude of the variances var (e_{nk}) and var (g_{nk}) reflect the degree of uncertainty in the estimates of these linkages. Equations (27) and (28) show how the optimal tax rate is affected by these uncertainties.

Assume that estimates for $\hat{e}_{nk}$ and $\hat{g}_{nk}$ are improved and are manifested in the form of lower value for var $(e_{nk}$ and var (g_{nk}). This implies that the marginal cost uncertainty about risk has been lowered and it is now possible to lower the optimal tax rate.

SUMMARY AND CONCLUSIONS

The presence of contaminants such as agricultural pesticides in environmental media as well as the desire to maintain a high level of economic activity presents a difficult decision-making problem for all concerned parties. It has been difficult to identify the appropriate responses aimed at resolving the potential health risks associated with pesticides in surface and groundwater sources because of the high degree of uncertainty surrounding them and the processes generating them. Public decision makers must not only make decisions on how to manage risk, but also on how to manage risk compounded by uncertainty. Further complications include the high degree of public sensitivity to the notion that these risks are small, but indeed costly.

The current policy used by the EPA to regulate pesticides is based on a mixture of policy instruments that are implemented within the context of a registration requirement. In general, this policy requires that pesticides be registered to be marketed. It has been concluded from an evaluation of this system that the policy decision is dominated by a cancellation decision. It has also been concluded that the current framework does not possess mechanisms for inducing marginal changes in pesticide use to give protection from health risks compounded by uncertainty as well as preventing runoff into surface waters or leaching into groundwater.

The limited flexibility of the current regulatory framework can be improved by supplementing it with a tax which has a number of appealing features. The first feature is that taxes can affect whether a chemical will be used at all as well as the application rate. Second, taxes allow the regulator to influence application rates at a continuous level rather than as an "all-or-nothing" type of decision. A third feature is that regulators can vary taxes according to indicators of environmental risk such as leachability and acute or chronic toxicity. The last feature allows regulators to influence farmers' decisions about the choice of pesticides.

Traditionally, the process of setting the "optimal" tax for each chemical is viewed as problematic. This can be done using the "standard and charges" approach which involves two steps. First, standards or targets for environmental quality are set; second, a set of taxes (charges) is designed and put in place to achieve these standards or targets. Thus, the policy problem for setting taxes on pesticides is to identify a tax or set of taxes aimed at reducing the total amount of pesticide to a predetermined level believed to involve acceptably low risk to human health (and the environment). This process requires various types of information such as the productivity of and demand for classes of pesticides. In addition, the stochastic nature of pesticides must also be taken into account. But it is generally concluded that the information on which to base a tax on pesticides, even to achieve a certain level of health risk standards, is not readily available.

Given the fact that pesticides as a form of nonpoint pollution are stochastic in nature and information on the productivity of and demand for classes of pesticides is not available, empirical researchers have increasingly turned to simulation and/or mathematical programming techniques for policy-making considerations. This article explored the application of a standards and charges policy framework for regulating pesticides in surface and groundwater under uncertainty using simulation and mathematical programming techniques. That is, a protocol that uses simulation and mathematical programming techniques to compute the tax for a standards and charges framework for regulating pesticides under uncertainty was developed. This protocol allowed the tax rate to be determined on the basis of information on the productivity of and demand for pesticides. The tax rate determined from this protocol also reflected the stochastic nature of pesticides as well as the achievement of a certain level of risk standard.

As shown, the Kuhn-Tucker conditions were used as a basis to develop the appropriate tax rates. It was shown that the tax rate was imposed on pesticides as inputs and varied according to soil type. It was also shown that the tax rate could be expressed as a function of risk and uncertainty as well as the preferred level of safety.

The chief advantage of the combined use of simulation/mathematical programming models as proposed here is that they allow the analyst the opportunity to examine counterfactual situations. That is to say, various kinds of situations can be represented with the modeling structure outlined in this article. But these types of modeling structures also have their drawbacks, the chief one being that they deal with idealized situations. Nevertheless, it is believed that the framework proposed in this article has a great deal of promise as a policy-making tool in the regulation of pesticides.

APPENDIX

The derivations for constraints (7) and (8) are verified in this appendix. This demonstration is done only for constraint (7) but can also be applied to constraint (8) as well. Recall first that the $\overline{M}_n$ are assumed to be determined on the basis of a health risk assessment procedure as outlined in Harper and Zilberman [13]. It is assumed that each $\overline{M}_n$ and e_{nk} are normally distributed with means $\hat{M}_n$, $\hat{e}_{nk}$ and variances var $(\overline{M}_n)$ and var (e_{nk}). The $\overline{M}_n$ and all of the e_{nk} are assumed to be statistically independent of each other.

Begin by defining the following:

$$h_n = \sum_{k=1}^{K} e_{nk} Z_{nk} - \overline{M}_n. \tag{A.1}$$

Now consider the following chance constraint:

$$Pr\{h_n \leq 0\} \geq 1 - \alpha_n \tag{A.2}$$

Assume that h_n is a normally distributed variable with mean

$$\mu(h_n) = \sum_{k=1}^{K} \hat{e}_{nk} Z_{nk} - \hat{M}_n \tag{A.3a}$$

and variance

$$\text{var}\,(h_n) = \sum_{k=1}^{K} Z_{nk}^2 \,\text{var}\,(e_{nk}) + \text{var}\,(\overline{M}_n). \tag{A.3b}$$

Note that (A.2) can be restated as follows:

$$Pr\{h_n \leq 0\} = Pr\left\{\frac{h_n - \mu(h_n)}{[\text{var}\ (h_n)]^{0.5}} \leq \frac{-\mu(h_n)}{[\text{var}\ (h_n)]^{0.5}}\right\} \geq 1 - \alpha_i \tag{A.4}$$

where $\left\{\frac{h_n - \mu(h_n)}{[\text{var}\ (h_n)]^{0.5}}\right\}$ is a standard normal variable with mean zero and variance equal to one.

The result shown in (A.4) means that

$$Pr\{h_n \leq 0\} \leq F\left[\frac{-\mu(h_n)}{[\text{var}\ (h_n)]^{0.5}}\right] \tag{A.5}$$

where F denotes the cumulative density function of the standard normal distribution.

Let $\phi_{\alpha n}$ be the standard normal value such that

$$F(\varphi_{\alpha n}) = 1 - \alpha_n. \tag{A.6}$$

Then the statement

$$Pr\{h_n < 0\} \geq 1 - \alpha_n \tag{A.7}$$

is realized if and only if the following holds true:

$$\frac{-\mu(h_n)}{[\text{var}\ (h_n)]^{0.5}} \geq \varphi_{\alpha n}. \tag{A.8}$$

Now rearrange (A.8) to yield the following:

$$\mu(h_n) + \varphi_{\alpha n}\ [\text{var}\ (h_n)]^{0.5} \leq 0. \tag{A.9}$$

Equation (3) can be used to rewrite (A.9) as follows:

$$\sum_{k=1}^{K} \hat{e}_{nk} Z_{nk} + \varphi_{\alpha n}\left\{\sum_{k=1}^{K} Z_{nk}^2\ \text{var}\ (e_{nk}) + \text{var}\ (\overline{M}_n)\right\}^{0.5} \leq \hat{M}_n \tag{A.10}$$

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