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An Interdisciplinary Assessment of Regional-Scale Nonpoint Source Ground-Water Vunerability: Theory and Application

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U.S. Department of the Interior
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By Richard L. Bernknopf, Laura B. Dinitz, and Keith Loague

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FRONT COVER
Aerial photograph of Pearl Harbor basin, O‘ahu, Hawai‘i taken in 1977.

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Notation used in text and equations

a	action by a decisionmaker [$a = 1, \ldots, A$]
$[B_{\gamma_\theta}(Q)]$	expected present value of net benefits of agricultural production using γ_θ [$]
$[B_{\gamma_\theta}(\Delta Q)]$	expected present value of marginal net benefits of agricultural production from a refinement in γ_θ [$]
$\mathrm{C}(\theta)$	cost of regional-scale vulnerability assessment θ [$]
$\mathrm{C}_1(\theta)$	cost of improved understanding of physical process model [$]
$\mathrm{C}_2(\theta)$	cost of increased statistical accuracy [$]
C_j	cost of using pesticide j [$]
C_w	investment, operating, and maintenance costs for a wellhead treatment program [$]
d	distance to ground water (or some compliance depth) from the surface [m]
d_γ	admissible decisions based on γ [$d_\gamma = 0, \ldots, D$]
f_{oc}	soil organic carbon [0]
F_j	fraction of the total area treated with pesticide j [$0 \leq F_j \leq 1$]
$\mathrm{F}(P)$	critical value of the standard normal distribution exceeded only with probability $1 - P$ [0]
$\boldsymbol{G}$	vector of agricultural policy variables
h	number of planted hectares [$h = 0, \ldots, H$]
i	agricultural commodity [$i = 1, \ldots, I$]
j	pesticide type [$j = 0, \ldots, J$]
k	soil type [$k = 1, \ldots, K$]
K_{oc}	pesticide sorption coefficient [m^3/kg]
$\mathbb{N}$	set of natural numbers [$\mathbb{N} = \{1, 2, 3, \ldots\}$]
$NV(\theta)$	maximum net benefit of ESI [$]
P	confidence level of decisionmaker in applying a regional ground-water vulnerability assessment [$0 \leq P \leq 1$]
$p_{s(k)\gamma_\theta}$	conditional probability of γ_θ given that the true state of nature is $s(k)$ [$0 \leq p_{s(k)\gamma_\theta} \leq 1$]
q	net ground-water recharge [m/day]
Q	supply of agricultural commodity [tons]
R_0	regulatory standard for ground-water contamination based on a physical threshold [0]
s	state of the environment [$s = 1, \ldots, S$]
T	agricultural production time period [years]
$t_{1/2}$	pesticide half-life [years]
u	payoff or utility to the decisionmaker [0]
$V(\theta)$	benefit of regional-scale vulnerability assessment θ [$]
$V_1(\theta)$	benefit of improved understanding of physical process model [$]
$V_2(\theta)$	benefit of increased statistical accuracy [$]
Y	total yield per hectare [tons/hectare]
y_j	average yield per hectare when using pesticide j [tons/hectare]
γ	NPS vulnerability assessment, or information signal, based on ESI [$\gamma = 1, \ldots, \Gamma$]
θ	index of information uncertainty, or information structure [$\theta = 1, \ldots, \theta_I$]
θ_{FC}	soil-water content at field capacity [0]
Π_i	expected net revenue of crop i [$]
ρ	correlation of observed and predicted ground-water condition [$-1 \leq \rho \leq 1$]
ρ_b	soil bulk density [kg/m^3]

An Interdisciplinary Assessment of Regional-Scale Nonpoint Source Ground-Water Vulnerability: Theory and Application

By Richard L. Bernknopf[1], Laura B. Dinitz[2], and Keith Loague[3]

Abstract

The availability of potable ground-water supplies is a major environmental quality and human health concern throughout the United States. In the study reported here, a geographic information system (GIS) environment is used to apply an Integrated Earth Science–Economics Model (IESEM) that combines a regional-scale nonpoint source vulnerability assessment tool with a specific remediation measure to avoid unnecessary agricultural production costs related to the use of agrochemicals. Based on two screening indices that utilize earth science information, the vulnerability assessment tool functions in a spatial analysis to target areas vulnerable to ground-water contamination. This coordinated approach forms the core of a risk-based regulatory standard for the application of agrochemicals. The application of the IESEM in a cost-effectiveness analysis for 17 coordinated programs showed that 12 of the programs demonstrated substantial cost savings, ranging from \$8.0 million to \$244.0 million, that could accrue to producers if a regional vulnerability assessment were coordinated with a wellhead treatment program. The coordinated approach was not cost effective for the remaining five programs. The case study was conducted for the Pearl Harbor basin on the island of O‘ahu, Hawai‘i. The IESEM approach was developed as a spatial analysis tool to estimate the benefits of an information-based approach to decisionmaking.

Introduction

Governmental intervention in the U.S. agriculture industry results in a variety of policies and regulations. Some policies, such as the promotion and use of agrochemicals, are designed to enhance farm productivity, but others involve the regulation of chemical use to protect common property resources, such as ground water. These interventions appear contradictory, because although pesticide application can increase producers' crop yields, it can also create an unwanted byproduct of polluted ground water. There are several ways to approach this externality problem and act to reduce the adverse impacts of ground-water contamination. This study focuses on the analytical application of geographic information science for making policy choices in a decision framework. Two policy options are (1) to prevent contamination by restricting or eliminating agrochemical application using a screening model based on earth science information (ESI) (that is, an adaptation program) and (2) to remediate contaminated ground water with a granulated activated carbon wellhead treatment system in the agricultural producing region (that is, a mitigation program). Although each option has risks to both water consumers and decisionmakers, option 2 is the focus of this study. Separate regulatory policies that enhance farm production or reduce ground-water pollution could result in either an underestimate or overestimate of the benefits associated with agricultural productivity (crop yield) or environmental protection (contamination of the ground-water resource). Alternatively, using a geographic information system (GIS) with a coordinated agricultural and resource policy that combines a regulatory screen and a remediation program would provide a more socially beneficial framework by permitting the application of agrochemicals and implementing wellhead treatment in locations deemed appropriate by the screen.

The design of an efficient regional-scale ground-water quality protection program is contingent upon an accurate spatial representation of the hazard. Accurate scientific information is necessary to avoid resource allocation mistakes, such as inappropriately permitting or restricting agrochemical use or imposing additional production costs. Based upon a regional ground-water vulnerability assessment, the application of a decision rule provides a convenient mechanism to apportion the financial burden of the regulation to producers. This method distinguishes producers located in vulnerable areas who should incur the additional cost of a wellhead treatment program from those who should not. The framework provides a means to conduct a location-based comparison of alternative policy choices. Because the framework is integrated into the GIS, the benefits of a particular program can be evaluated.

The focus of this study was the estimation of an economic value for ESI to concurrently support agricultural production and protect ground-water resources. The analysis was conducted in a GIS environment to identify places that,

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depending on soil and chemical properties and their interactions, are vulnerable to ground-water contamination, require ground-water remediation, and are subject to increased farm production costs, and those that are not. In the latter case, there is potential for an improvement in resource allocation that can be exploited by reducing the uncertainty of information associated with the application of agrochemicals.

The remainder of this paper is divided into five sections: (1) development of an Integrated Earth Science–Economics Model (IESEM) that characterizes a regulatory decision framework, (2) a method for estimating the benefits of using ESI, at different levels of uncertainty, to make decisions regarding the use of agrochemicals, (3) a case study for pineapple production, in an area within the Pearl Harbor basin on the island of Oʻahu, Hawaiʻi, using alternative ESI information structures to support a coordinated agricultural and resource policy, (4) a discussion of the benefits and costs associated with using ESI for policy analysis and the inherent risks of scientific uncertainty, and (5) conclusions.

An Integrated Earth Science–Economics Framework

Agrochemicals have been used extensively in the United States for several decades. As a result, the economic consequences of nonpoint source (NPS) ground-water contamination, even at very low concentrations, cannot be ignored (Loague and others, 1998). Leon-Guerrero and others, (1994) reported on the occurrence of ground-water contamination in the Pearl Harbor basin of Oʻahu, Hawaiʻi. In response to this type of threat to a common property resource, public programs for mitigating losses associated with ground-water contamination have consisted of either safety rules that restrict or tax the use of hazardous chemicals (Wise and Johnson, 1991), or additional production costs for wellhead treatment (Leon-Guerrero and others,1994). The regulations that are promulgated to protect ground-water resources affect individual agricultural producers (Antle and Capalbo, 1993; Reicheldorfer and Kramer, 1993).

For the IESEM framework, the economic objective is to maximize agricultural output while maintaining a potable ground-water supply. The IESEM incorporates ESI directly into the constrained optimization problem:

$$\max_{Q} \; B(Q), \text{ subject to: } \gamma \le or \ge R_0 \qquad (1)$$

where $B(Q)$ is the economic benefit of agricultural production, Q is the supply (quantity produced) of an agricultural commodity, γ is an NPS vulnerability assessment based on ESI, and R_0 is a regulatory standard for ground-water contamination based on a physical threshold. The IESEM framework has four parts: (1) a regulatory model to characterize economic activities, (2) a risk assessment tool to identify the environmental hazard, (3) a risk management tool to choose a mitigation action, and (4) a valuation method to estimate the value-in-use of the scientific information.

Regulatory Model

Regulators attempt to maximize social welfare by imposing rules to achieve an optimal level of safety for the application of a pesticide j that could increase crop yield and so also increase income. The benefits of agricultural production $B(Q)$ are derived from the supply Q, total crop yield per hectare Y, and number of planted hectares h of H total available hectares of arable land. The optimal benefit, max $B(Q)$ where $Q = hY$ (Carlson and Wetzstein, 1993), is achieved when the greatest number of land parcels are permitted agrochemical application. Yield in the region is represented by $Y = \sum_j y_j F_j$, where y_j is the average yield per hectare and $F_j = h_j/H$ is the fraction of the total area treated with the j^{th} pesticide. Acreage is represented by $h = h(H,\Pi_i, \boldsymbol{G})$, where Π_i is the expected net revenue of crop i and $\boldsymbol{G}$ is a vector of agricultural policy variables. The vector $\boldsymbol{G}$ contains a regulatory standard, a regional ground-water vulnerability assessment, and, if necessary, the requirement of mitigation (for example, wellhead treatment).

The yield per hectare for a commodity varies according to the type and intensity of pesticide application. Many States use a regional-scale vulnerability assessment as the basis for determining whether a regulatory action would affect the use of specific chemicals (Barbash and Resek, 1996). Depending on the regulatory action, the number of chemicals used can alter Q. If the application of pesticide j is permitted, the benefit $B(\Delta Q)$ increases as a result of the increase in Q. The new supply will be:

$$(Q + \Delta Q) = (h + \Delta h)(Y + \Delta Y). \qquad (2)$$

Substituting for Y and h in equation 2 yields:

$$(Q + \Delta Q) = [h(H,\Pi_i,\boldsymbol{G}) + \Delta h(H,\Pi_i,\boldsymbol{G})] \cdot [\sum_j y_j F_j + \sum_j y_j \Delta F_j]. \qquad (3)$$

Equation 3 reveals that the quantity supplied depends on, among other things, the area F_j, the ESI, and the regulator risk associated with policy $\boldsymbol{G}$.

Risk Assessment

Risk to farmers and regulators is an outgrowth of the uncertainties related to maximizing agricultural output while sustaining a potable ground-water supply. In this context, the foundation for resource management actions is the translation of ESI into a ground-water vulnerability assessment. Assessments are made available in a variety of ways, ranging from site-specific evaluations to national assessments (National Research Council, 1993). These assessments combine hydrologic and chemical processes to produce a relative risk indicator of ground-water vulnerability that can be communicated using a map. For example, index-based methods used to estimate regional-scale ground-water vulnerability have been developed to determine, in a relative sense, if a specific agrochemical can be applied to a specific soil type on a particular tract of land without leaching to and subsequently contaminating ground water (see Khan and Liang, 1989).

Risk is a function of a regulatory standard and the information available from a ground-water vulnerability assessment:

$$1\text{-}P = f(R_0, \gamma) \qquad (4)$$

where 1-P is the risk of choosing the appropriate mitigation strategy. It should be noted that all of the currently available vulnerability assessment methods contain considerable uncertainty in targeting areas that are *more* vulnerable to contamination (National Research Council, 1993). The uncertainties inherent in these estimates can alter mitigation outcomes. The risk-averse decisionmaker invariably will choose the "safe way out" and either restrict chemical application or require wellhead treatment. In some cases, this approach could be suboptimal. To reduce risk, the decisionmaker's confidence level P about the information that supports a mitigation choice must increase (Lichtenberg and others, 1989; Bernknopf and others, 1997).

Consider the decisionmaker who has to choose among A actions as a means to ensure consumers of a potable water supply. There are two possible states of the environment s: (1) the agrochemical is mobile and is likely to contaminate ground water (s = 1), and (2) the agrochemical is immobile and is unlikely to contaminate ground water (s = 2). The payoff u depends on the true state of the environment s and the action a:

$$u = u(a, s). \qquad (5)$$

The true state of pesticide contamination in space and time at the regional scale is unknown. There exists some conditional probability distribution $p_{s\gamma}$, which is assumed to be known to the decisionmaker (Nelson and Winter, 1964) and consists of three elements (Phlips, 1988): (1) the set of possible states of the environment s, (2) the set of possible information signals γ, and (3) the probability p that a signal is observed, given that a particular state of the environment prevails.

Concerns have been expressed about the effectiveness and reliability of regulatory standards that are based on vulnerability assessments (National Research Council, 1993). The most obvious concern is the uncertainty of the ESI that supports γ. If γ were to be used to make regulatory decisions, it should correlate strongly with s. However, for a variety of reasons, it is extremely difficult to verify or validate the accuracy of γ (Konikow and Bredehoeft, 1992; Barbash and Resek, 1996). Although analyses show that reliance on γ is problematic, there is evidence of statistical correlation between an ESI prediction and observed values of ground-water contamination (Barbash and Resek, 1996).

The correlation coefficient is expressed as $\rho = Corr(\gamma, s)$, where the higher the ρ, the more closely γ correlates with s and hence, the more value accrues to γ. If $\rho = 1$, γ contains no noise and is a perfect predictor of s. However, because this is usually not the case, there is a risk in applying ESI in a regulatory decision. Let θ represent ρ (Radner and Stiglitz, 1984), where θ is an index of information uncertainty associated with γ.

Reductions in the ESI uncertainty and improvements in ρ result from a better understanding of the underlying physical processes and help reduce risk management uncertainty (Barbash and Resek, 1996). Refinements in ESI data collection (for example, greater sampling density) also reduce decisionmaking uncertainty (Bernknopf and others, 1999). A decrease in the uncertainty of the vulnerability assessment leads to a change in the area acceptable for agrochemical use. Any changes are benefits to the use of the regulatory standard and provide a means to measure the value of the improved ESI. However, less uncertainty resulting from a refined process model and/or from greater density of data collection comes at an increased cost.

There are Γ assessments of regional-scale ground-water vulnerability of increasing complexity in terms of both the physical processes and their data requirements (National Research Council, 1993). Among the various vulnerability-assessment methods, the process-based approach is, in theory, the best to apply. However, the regional-scale data requirements and costs for process-based simulations can be staggering (Loague and others, 1990). Another approach, the index method, is a calculation of the relative degree of vulnerability among different areas in a region, or the relative tendency for different compounds to contaminate ground water (Barbash and Resek, 1996).

A good vulnerability assessment attempts to characterize six physical processes associated with the leaching of organic chemicals. The first three, advection, dispersion, and diffusion, apply to the flux of contaminants through a subsurface environment. They account for the movement of a contaminant owing to the flow of water, the mixing of water caused by different flow paths through a porous medium, and the tendency for dissolved particles to disperse in an aqueous environment following the principles of Brownian motion. The latter three, decay, sorption, and volatilization, apply to the mass balance of contaminants in a subsurface environment. They account for the chemical or biochemical transformation of a contaminant into a different form, the attachment of a contaminant onto solid particles where it is no longer available in the aqueous solution, and the transformation of the contaminant from its dissolved or liquid form to a gaseous form. Several leaching indices (or screening models) that include some of these processes are currently used in regional-scale ground-water vulnerability assessments (for example, Diaz-Diaz and others, 1999; Jury and others, 1987; Rao and others, 1985).

Two indices of pesticide mobility are included in this study. The first index, the Retardation Factor (RF), is a linear measure of pesticide mobility with a numerical range between one and infinity. The RF index estimates pesticide mobility on the basis of only one of the six processes: sorption. The larger the RF value, the more likely it is that the pesticide will be sorbed by the soil. The second index, the Attenuation Factor (AF), is an exponential measure of pesticide leaching relative to a compliance depth, with a numerical range between zero and one. The AF index estimates pesticide mobility on the basis of three of the six processes listed above: advection, decay, and sorption. The larger the AF value, the more likely it is that the pesticide will leach. Because the AF index takes into account a greater number of physical processes, it is a more rigorous approach for estimating pesticide leaching than the RF index.

The AF index, originally proposed by Rao and others (1985), can be expressed as:

$$AF = \exp\left(\frac{-0.69\, d\, RF\, \theta_{FC}}{q\, t_{1/2}}\right) \tag{6}$$

where d is distance to ground water (or a compliance depth) from the surface, θ_{FC} is the soil-water content at field capacity, q is net ground-water recharge, and $t_{1/2}$ is pesticide half-life. The RF index is defined as:

$$RF = 1 + \frac{\rho_b f_{oc} K_{oc}}{\theta_{FC}} \tag{7}$$

where ρ_b is soil bulk density, f_{oc} is soil organic carbon, and K_{oc} is the pesticide sorption coefficient. The scales used to subdivide the AF and RF estimates into ranges are subjective. Khan and others (1986) adopted the schemes shown in table 1 for making relative assessments of pesticide mobility with the AF and RF indices.

Risk Management

For the application presented here, consider a population of K soil orders with varying degrees of vulnerability to J pesticides. Let h_k be the number of planted hectares of soil order k in the study area, and assume that the θ^{th} ESI signal is distributed as a uniform distribution; that is, $\gamma_\theta \sim U(\alpha, \beta)$ with mean $(\alpha + \beta) / 2$ and variance $(\beta - \alpha)^2 / 12$. For each soil order, vulnerability examination γ_θ is applied to each hectare that results in an expected value and a variance:

$$AF_\theta = (E(AF_\theta), \sigma^2(AF_\theta)) \tag{8}$$

and

$$RF_\theta = (E(RF_\theta), \sigma^2(RF_\theta)). \tag{9}$$

The first two moments of the AF distribution in a first-order uncertainty analysis (FOUA) have been used to characterize uncertainty for the AF and RF indices (Kleveno and others, 1992; Loague, 1991, 1994; Loague and Green, 1988, 1990a, b, c; Loague and others, 1989, 1990, 1996). The regulatory standard R_0 defines a threshold of contamination based on the AF and RF estimates. A standard R_0 is determined for confidence level P (Lichtenberg, 1991):

$$\text{Prob}[\gamma_\theta < \text{or} > R_0] > P. \tag{10}$$

The vulnerability assessment γ_θ is compared with R_0. In response, the decisionmaker associates the vulnerability index for soil order k with the admissibility of the application of pesticide j and chooses an action a from a decision function $d_\gamma \in D$ that relates the signal from γ_θ to $a \in A$. The decision rule states:

$$d_{\gamma jk} = \begin{cases} 1, & \text{if } \gamma_\theta \text{ meets the standard } R_0 \text{ for pesticide } j \text{ on soil type } k \text{ and is less than the margin of error; application is permitted} \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

The decision rule is illustrated for the RF in figure 1. To the right of R_0, the application of the j^{th} pesticide is permitted without treatment; to the left of R_0, treatment is necessary.

Assume there are existing data to estimate a *prior* probability $\varphi_s \in [0,1]$ of state s for pesticide j in soil k. Any refinement in γ suggests either an increase in the number of physical processes included in the vulnerability assessment or a decrease in its variance. The information structure $\theta \in [0, \theta_1]$, associated with γ, is a Markov matrix of the conditional probability $p_{s(k)\gamma_\theta}$ of ground-water contamination:

$$p_{s(k)\gamma_\theta} = \begin{bmatrix} p_{s(k)_1\gamma_1} & p_{s(k)_1\gamma_2} \\ p_{s(k)_2\gamma_1} & p_{s(k)_2\gamma_2} \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{12}$$

where p_{11} is the probability that γ_θ indicates that ground-water contamination will occur given that the agrochemical is mobile, p_{12} is the probability that γ_θ indicates that ground-water contamination will not occur given that the agrochemical is mobile, p_{21} is the probability that γ_θ indicates that ground-water contamination will occur given that the agrochemical is immobile, and p_{22} is the probability that γ_θ indicates that ground-water contamination will not occur given that the agrochemical is immobile.

The payoff to the decisionmaker is $u_s(a,\theta)$. The expected value of a decision rule d, given θ, is:

$$U(d,\theta) \equiv \sum_{s,\gamma} \varphi_s p_{s(k)\gamma_\theta} u_s(d_\gamma, \theta). \tag{13}$$

The value of a particular θ is the maximum expected utility that can be achieved using the d_γ, as defined by Radner and Stiglitz (1984), and is given by:

$$\max_\theta V(\theta) \equiv \sup\, [U(d,\theta) : d \in D(\theta)]. \tag{14}$$

$D(\theta)$ is the set of admissible decision functions, and its expected value achieves the supremum of $V(\theta)$. For the decision rule for θ to be optimal, d_γ must translate to an action that maximizes $\sum_s \varphi_s p_{s(k)\gamma_\theta} u_s(a, \theta)$ subject to $a \in A(\theta)$. This function establishes a relative value for different γ_θ in a risk-decision framework. To demonstrate the value of ESI, the Bayesian screening model is applied in the case study section.

The Value of ESI: $V(\theta)$

The relative value of a refinement in ESI is estimated as the difference in the expected payoffs of decisions for different θ. An increase in supply and hence in the value of agricultural production, without increasing the potential for ground-water contamination, accrues benefits to the ESI. Then, the benefit of θ is:

$$V(\theta) = U(d, \theta_{n+1}) - U(d, \theta_n) \geq 0, \text{ for any } n \in \mathbb{N}. \tag{15}$$

The benefits $V(\theta) = V_1(\theta) + V_2(\theta)$ and costs $C(\theta) = C_1(\theta) + C_2(\theta)$ associated with the implementation of a regional vulnerability assessment are composed of the benefits and costs from improved characterization of the physical processes, V_1 and C_1, and the benefits and costs from increased statistical accuracy, V_2 and C_2. It is assumed that the benefit of an improvement in θ meets the conditions $dV(\theta)/d\theta > 0$ and $d^2V(\theta)/d\theta^2 < 0$. The cost of supplying the information increases at an increasing rate, and therefore $dC(\theta)/d\theta > 0$ and $d^2C(\theta)/d\theta^2 > 0$. Although the benefits from ESI seem obvious, making decisions about "how much" ESI is less obvious. This decision involves estimating the benefits of each θ for a given P and then choosing the θ that maximizes the value of ESI. The maximum net benefit of ESI is defined as:

$$NV(\theta) = \max_{\theta} \left[(V_1(\theta) + V_2(\theta)) - (C_1(\theta) + C_2(\theta)) \right]. \quad (16)$$

A Method for Estimating ESI Benefits

The ESI is used to screen areas for ground-water vulnerability. To estimate $V(\theta)$, the location of vulnerable and "safe" areas must be identified. Improvements in the ESI may or may not have value in the decisionmaking process. Figure 1 shows the impact of changes in RF_θ. Because the information signal RF_1 crosses the threshold R_0, it is too uncertain to allow the use of pesticide *j* in soil *k* without the cost of wellhead treatment, and $V(\theta) = 0$. On the other hand, a refinement of RF_θ in the form of a reduction in the standard deviation $\sigma(RF_\theta)$ may yield an information signal RF_2, which does not cross R_0. Thus, the reduction in uncertainty allows the use of the pesticide without production costs for wellhead treatment, and $V(\theta) > 0$. This process yields ΔF_j (from equation 3), the change in the fraction of hectares that are permitted pesticide *j* without wellhead treatment:

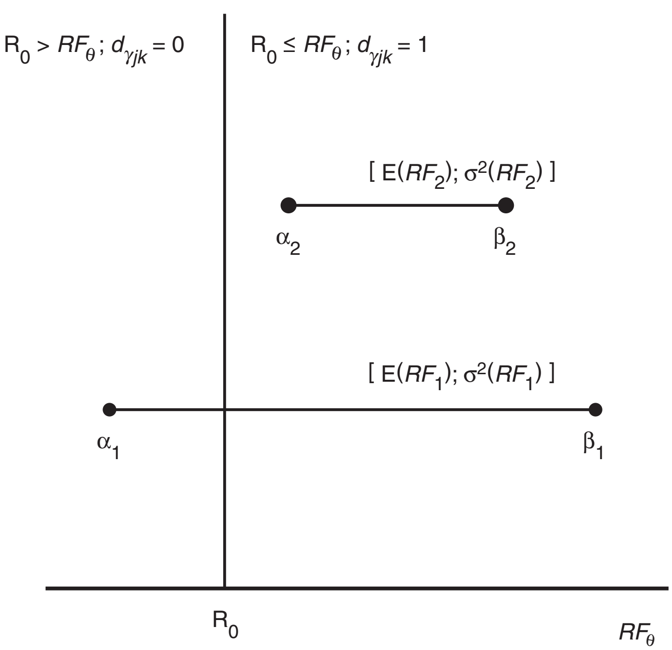

Figure 1.—Impact of reducing $\sigma(RF)$, the standard deviation of *RF*, and of using information structure RF_2 relative to information structure RF_1. The decision $d_{\gamma jk}$ is based on information signal γ, pesticide *j*, and soil type *k*. R_0 is the regulatory standard for ground-water contamination, and θ is an index of earth science information (ESI) uncertainty. It is assumed that $RF \sim U(\alpha, \beta)$.

$$\Delta F_j = \frac{h_j(\gamma_{\theta+1}) - h_j(\gamma_\theta)}{H}. \quad (17)$$

The ΔF_j bridges a gap between ESI and the regulatory model.

Cost-benefit analysis helps with the decision on whether the public should invest in the reduction of ESI uncertainty to potentially increase agricultural productivity. The value of ESI is estimated using the following three-step procedure:

Step 1.—Estimate the AF and RF Values and Uncertainties: Apply a regional leaching model γ_θ to estimate ground-water vulnerability, including uncertainty, in a GIS. This step incorporates a description of the physical environment and the interaction of chemicals, soils, and water recharge. Regional-scale ground-water vulnerability estimates and their associated uncertainties are assigned to each hectare of land that is available for agricultural production. The parameters that make up the *AF* and *RF* indices (see equations 6 and 7) generally can be divided into three groups: (1) soil properties (f_{oc}, θ_{FC}, and ρ_b), (2) hydrogeologic and climate characteristic parameters (d, q), and (3) chemical coefficients (K_{oc} and $t_{1/2}$). The soil database, at the order taxonomic category, and the recharge rates for the five major soil orders in the Pearl Harbor basin, Hawai‘i, have been reported by Loague and others (1990) and Loague (1991). For this study (following Loague and others, 1990), a very conservative estimate of the depth to the water table of 0.5 meter was used. The names and uses for the 10 pesticides included in this study, all of which are currently (or have been in the past) used in Hawai‘i, are listed in table 2. The statistical properties for the 10 pesticides have been reported in Diaz-Diaz and others (1998).

The E(*AF*) and E(*RF*) estimates for the 10 selected pesticides for the 5 major soil orders are calculated using equations 6 and 7. The associated uncertainties, $\sigma(AF)$ and $\sigma(RF)$, are estimated using the FOUA for each of the soil parameters and recharge rates. The resulting values for the means and standard deviations of the *AF* and *RF* are reported in tables 3 and 4. To examine the impact of a reduction in ESI uncertainty on decisionmaking, the standard deviations of the parameters that make up the *AF* and *RF* indices in equations 6 and 7 are artificially reduced by 10 percent and 90 percent. The revised $\sigma(AF)$ and $\sigma(RF)$ values are listed in tables 5 and 6. The values in tables 3, 4, 5, and 6 are used with the classification scheme in table 1 to illustrate the impact of increased statistical accuracy of the ESI in the application of the regulatory model described below.

Step 2.—Apply the Regulatory Model: Using a GIS, apply γ_θ in agricultural areas to decide which hectares of land should require wellhead treatment with pesticide use based on R_0. For a strategy to be efficient, the value of agricultural production $b_{ijk} = price_i \times Q_{ijk}$, or any additional benefits based on ΔQ_{ijk}, must offset the costs of either the collection of additional ESI or the wellhead treatment program. The standard R_0 is applied to determine the location of vulnerable and "safe" areas when pesticide *j* is applied to soil order *k*. For this demonstration, the standard for pesticide use to be considered safe is in the *very immobile* or *very unlikely* classification (see table 1). It is assumed that the decisionmaker is risk averse and only allows application of a pesticide without wellhead treatment if $E(\gamma_\theta) \pm F(P)\sigma(\gamma_\theta)$ meets R_0, where $F(P)$ is the critical value of the standard normal distribution exceeded only with probability 1 - *P* (Lichtenberg and others, 1989). Confidence levels of $P = 0.67$, 0.95, and 0.99 are evaluated to represent three levels of risk for the decisionmaker.

Step 3.—Adopt a Loss-Reduction Strategy: Apply a place-based Bayesian decision model to evaluate the costs and benefits of the societal impacts of using different γ_θ with a regulatory standard. Based on *Q* for commodity *i*, the expected present value of net benefits $B_{\gamma_\theta}(Q)$ over the production time period *T* are:

$$B_{\gamma_\theta}(Q) = \int_0^T [\sum_{i,j,k} (b_{ijk} - C_{ij}) - C_w - C(\theta)]e^{-rt}\, dt \qquad (18)$$

where C_{ij} is the cost of producing crop *i* using pesticide *j*, and C_w is the investment and operating costs of a wellhead treatment program. The expected present value of marginal net benefits $B_{\gamma_\theta}(\Delta Q)$ of a refinement in γ_θ is measured in terms of the additional number of hectares on which pesticide *j* is allowed without wellhead treatment. The value-in-use of ESI in terms of the benefits per hectare is the difference in the base level of $B_{\gamma_\theta}(Q)$ and the additional benefits that accrue with a refinement in the ESI, $[B_{\gamma_\theta}(\Delta Q)]$, where

$$b_{ijk} \cdot \Delta F_j = [B_{\gamma_\theta}(\Delta Q)] - B_{\gamma_\theta}(Q). \qquad (19)$$

The optimal benefit of a regional vulnerability assessment is achieved by using the θ that maximizes crop production while meeting the decision criterion:

$$NV(\theta) = \max_j\, (b_{ijk} \cdot \Delta F_j), \text{ subject to } d_{\gamma jk} = 1. \qquad (20)$$

Application of the IESEM, Pearl Harbor Basin, O‘ahu, Hawai‘i

To demonstrate the potential cost effectiveness of alternative strategies for mitigating ground-water contamination from pesticide use, the IESEM is applied to a hypothetical pineapple production example for the Pearl Harbor basin on the island of O‘ahu, Hawai‘i. In comparing these alternative strategies, it was assumed that ESI can be used to determine where ground-water contamination will not occur and therefore where the need for wellhead treatment can be eliminated. It was assumed that the application of a pesticide combination increases yield by 90 percent. The regulatory screen is applied to a 100-m × 100-m (1 hectare) grid in a GIS for the 5 soil orders found in the study area as shown in figure 2. There are 32,226 hectares in the Pearl Harbor basin study area. When this number is broken down by soil order, there are 4,606 ha for Inceptisols, 6,210 ha for Mollisols, 12,450 ha for Oxisols, 3,186 ha for Ultisols, and 5,774 ha for Vertisols.

For the Pearl Harbor case study, there are two alternatives for reducing the environmental hazard: Alternative A, conduct a regionwide wellhead treatment program over the productive lifetime of the resource to remove all pesticides from the ground water before consumption; Alternative B, target areas of vulnerability by increasing the amount of scientific information collected and decreasing the uncertainty of the components of γ_θ. Areas that meet the regulatory standard do not require wellhead treatment, whereas the remaining vulnerable areas do. It was assumed that maintaining a viable ground-water resource is of great value.

Alternative A

Wellhead treatment is an investment to remediate contaminated ground water that results from pesticides used in agricultural production. The expected payoffs of ground-water treatment result from the unrestricted application of pesticides to maximize agricultural output and having no restrictions on where pineapple can be planted. In the production scenarios that follow, pineapple is assumed to be produced on all 32,226 hectares and to have a 3-year production cycle (Leon-Guerrero and others, 1994). The wellhead treatment alternative is considered a noninformative information structure (that is, $\theta = 0$) because $p_{s(k)\gamma_0}$ is independent of *s(k)* for each γ. In this case, no regional vulnerability assessment is used to make decisions (that is, $C(\theta)$ is zero and $B(Q)$ is independent of γ_θ), and all ground water must be treated. For Alternative A, the benefits and costs of agricultural production are contained in table 7. The present value of the agricultural benefits b_{ijk} is estimated as $4.8 billion, and the production and wellhead treatment costs, C_{ij} and C_w, are estimated as $2.2 billion and $336 million, respectively. The expected present value of net benefits of using wellhead treatment over a production period of $T = 24$ years (or 8 production cycles) is calculated using equation 18 and is listed in column 5 of table 7. Alternative A has an expected present value of net benefits of $2.3 billion, or $11.7 million annually.

Alternative B

By determining locations that meet the regulatory standard, ESI is incorporated in the decision to permit pesticide application without wellhead treatment. As in Alternative A, pineapple is assumed to be produced on all 32,226 hectares. The expected payoffs of γ_θ result from the reduction in the uncertainty associated with decisions concerning the application of pesticides and the potential decrease in production costs (that is, a reduction in C_w from equation 18). For this alternative, $\theta = \rho$, and $p_{s(k)\gamma_\theta}$ is an informative information structure that depends on $s(k)$ for each γ (Radner and Stiglitz, 1984).

R_0 consists of an implementation protocol that relates γ_θ to a soil order. The risk of making the wrong decision is a strong motivation to be conservative in the application of the protocol. It is assumed that the decisionmaker applies γ_θ with confidence level P. For the protocol, based on the RF standard of 10.0 and a critical value of $F(P) = 1$, an action to require wellhead treatment occurs if $E(RF) - F(P)\sigma(RF) < 10.0$; this is referred to as the screen and is meant to be only illustrative. Initially, it is assumed that owing to pesticide application, ground water must be treated at all wellheads. However, if in some locations the RF signal meets the standard, that is, $E(RF) - F(P)\sigma(RF) \geq 10$, then production can occur without treatment in those locations. For each hectare, the RF value is compared with R_0 to identify which soil orders are potentially suitable for application of the j^{th} pesticide. Table 8 lists, for each pesticide combination and information structure, the number of hectares acceptable for pesticide use without wellhead treatment. The application of the standard for the chemical combinations in table 8 results in a range from 0 ha for the RF index to 32,226 ha for the AF index of areas that are acceptable for pesticide use without wellhead treatment . It was assumed that 8 of the 10 chemicals listed in table 2 were in use within the study area. The remaining two chemicals (DBCP and EDB), though no longer used, were included to examine whether banning them was a good policy decision.

An example illustrates how Alternative B works (following Bernknopf and others, 1997). Consider the following values: $E(RF) = 11.0$; $R_0 = 10.0$; $F(P) = 1$; $\sigma(RF) = 3.0$; $0.9\sigma(RF) = 2.7$; and $0.1\sigma(RF) = 0.3$. For the 0 percent reduction and 10 percent reduction cases, $E(RF) - F(P)\cdot 1\sigma(RF) = 11.0 - 3.0 = 8.0 < 10.0$, and $E(RF) - F(P)\cdot 0.9\sigma(RF) = 11.0 - 2.7 = 8.3 < 10.0$. Neither case meets the standard R_0, so $d_{\gamma jk} = 0$, and the application of pesticide j requires wellhead treatment and its associated production costs. This corresponds to the distribution $RF_1 \sim U[\alpha_1, \beta_1]$ in figure 1. On the other hand, for the 90 percent reduction case, $E(RF) - F(P)\cdot 0.1\sigma(RF) = 11.0 - 0.3 = 10.7 > 10.0$, as illustrated by the distribution $RF_2 \sim U[\alpha_2, \beta_2]$ in figure 1. R_0 is now met and $d_{\gamma jk} = 1$, so the application of pesticide j is permitted without requiring wellhead treatment. Because of the reduction in treatment costs in areas for which γ_θ meets the standard, the γ-based model yields an increase in net revenue from agricultural production. Fewer hectares require treatment in Alternative B than in Alternative A in nearly every case.

The 10 pesticides that can be or have been used in the study area are divided into 2 groups: herbicides (Ametryn, Atrazine, Bromacil, Diuron, Hexazinone, and Simazine) and insecticides (DBCP, EDB, Fenamiphos, and Oxamyl). It is assumed that production requires a combination of one chemical from each group. The success of a pesticide combination is measured by the number of hectares permitted

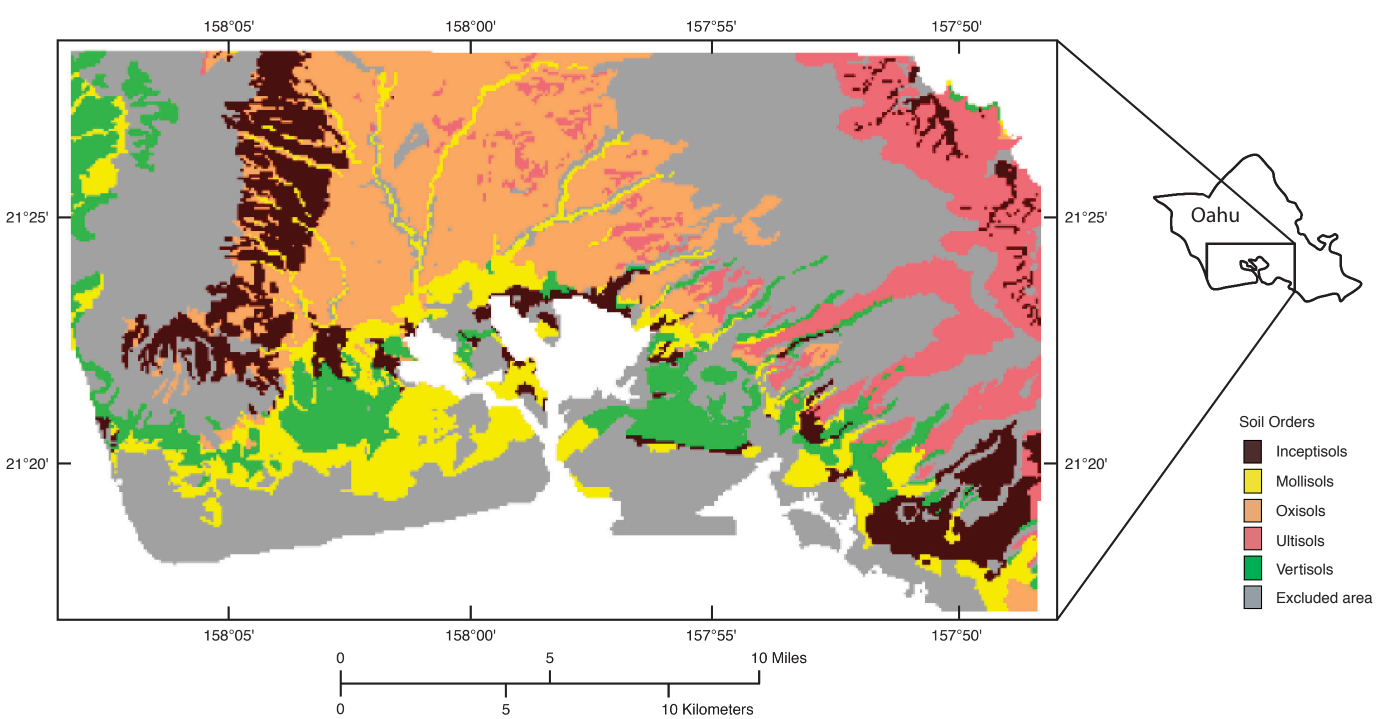

Figure 2.—Soil orders for the Pearl Harbor basin, Island of O'ahu, Hawai'i.

for pesticide application that do not require ground-water treatment (see table 8). For any AF_θ, without treatment, the application of any EDB combination is permitted on zero hectares, while the application of Fenamiphos or Oxamyl with Ametryn or Diuron is permitted on all 32,226 hectares. The agricultural benefits and the costs of production associated with γ_θ are estimated to be \$4.8 billion and \$2.2 billion, respectively. The costs of the screen and wellhead treatment for Alternative B range from \$92 million to \$403 million (see Leon-Guerrero and others, 1994, for details on monitoring and sampling costs for $C(\theta)$). Using equation 18, depending on the choice of γ_θ from Alternative B, the expected present value of net benefits $B_{\gamma_\theta}(Q)$ ranges from \$2.2 billion to \$2.5 billion as displayed in table 7.

Cost-Effectiveness Analysis

After the payoffs have been estimated for Alternatives A and B, the decisionmaker must decide which program is most cost effective. The GIS was used over the entire study area to compare Alternative B with Alternative A in a very straightforward manner. The difference between the expected present values of net benefits of the two alternatives represents the cost effectiveness of Alternative B. The regulatory program with the maximum positive expected present value of net benefits is the most efficient and should be implemented. Figure 3, a bar graph of the last column of table 7, shows, in ascending order, the difference between the expected present value of net benefits of each Alternative B program and the Alternative A program (the \$0 line). The most cost-efficient program (Alternative B, Program 17) was based on combinations of Fenamiphos or Oxamyl with Ametryn or Diuron. Over a 24-year period, its total savings amounted to \$244 million, or \$10.1 million annually. On the other hand, the least cost-efficient program (Alternative B, Program 1) was based on all six of the DBCP combinations. Over the same 24-year period, its total net loss was \$ -66.4 million, or \$ -2.8 million annually. Of course, these findings are meant only to demonstrate the cost effectiveness of the coordinated agricultural and resource programs and do not reflect economies of scale or the value of ground water lost.

Discussion

The number of hectares acceptable for pesticide use without wellhead treatment ranges from 0 ha for all chemical combinations using the *RF* index to 32,226 ha for combinations of Fenamiphos or Oxamyl with Ametryn or Diuron using the *AF* index (see table 8). For these combinations, the expected present values of net benefits $B(Q)$, listed in table 7, are \$2.2 billion (Alternative B, Program 2) and \$2.5 billion (Alternative B, Program 17). For each chemical combination, a reduction in the aleatory uncertainty changed the designation of at least 4,606 ha from vulnerable to “safe.”

A specific comparison of the benefits of improving the epistemic uncertainty for the Oxamyl/Bromocil combination is shown in figure 4. Figure 4*A* is a map of the application of *Step 1*, the method to determine the *AF* categories for the Pearl Harbor basin. The outline of an area of approximately 12,958 ha was sketched onto figure 4 as the active pineapple- and sugar-producing region in 1980 (Armstrong, 1983). On the basis of the outline, there were about 10,423 ha of pineapple production and about 1,709 ha of sugar production. The remaining 826 ha could not be classified. It should be noted that the following results illustrate an example based on historical cultivation and do not imply that this area would be planted exclusively with pineapple. Figure 4*B* is a map of the outcome of using the *AF* classification scheme in table 1, applying the decision rule from equation 11, and applying *Steps 1* and *2* of the method for estimating ESI benefits. The map shows that without treatment, 16,590 ha are acceptable and 15,636 ha are unacceptable for the application of the Oxamyl/Bromacil combination. A comparison of figures 4*B* and 4*C* illustrates the impact of a reduction in statistical uncertainty and the potential economic benefits described in *Step 3* of the method. With a 90 percent reduction in uncertainty, 12,450 ha are added to the acceptable category for a total of 29,040 ha as shown in figure 4*C*. Only 3,186 ha remain unacceptable.

The maps in figure 4 illustrate that the risk of using the Oxamyl/Bromacil chemical combination would have been real. Even though the “safe” areas increased from figure 4*B* to figure 4*C*, vulnerable areas remain and reduce the possibility of avoiding future NPS contamination. For the Oxamyl/Bromacil combination, using the *AF* index, the 90 percent reduction in uncertainty provides a potential decrease in income from pineapple production of \$36.5 million; that is, \$44.2 million (Alternative B, Program 9) - \$80.7 million (Alternative B, Program 11); thus, Alternative B, Program 11 would be preferred. On the other hand, for the combinations of Fenamiphos or Oxamyl with Ametryn or Diuron, for both the 1.0*AF* (Alternative B, Program 17) and 0.1*AF* (Alternative

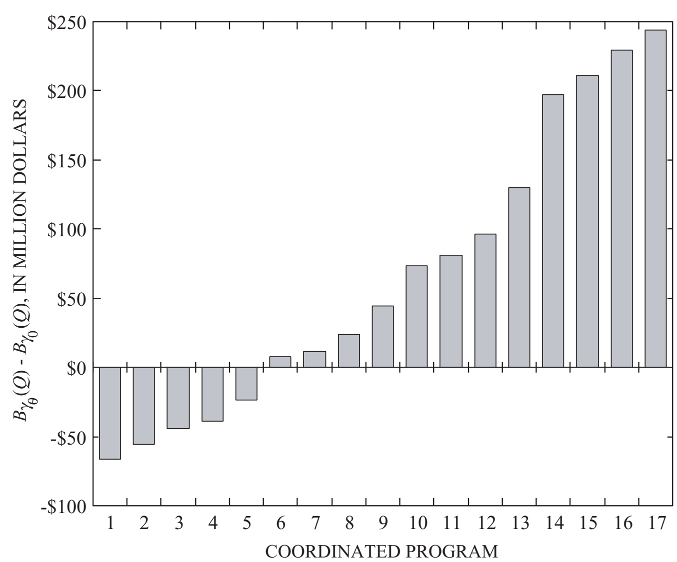

Figure 3.—Cost effectiveness of earth science information (ESI) in million dollars.

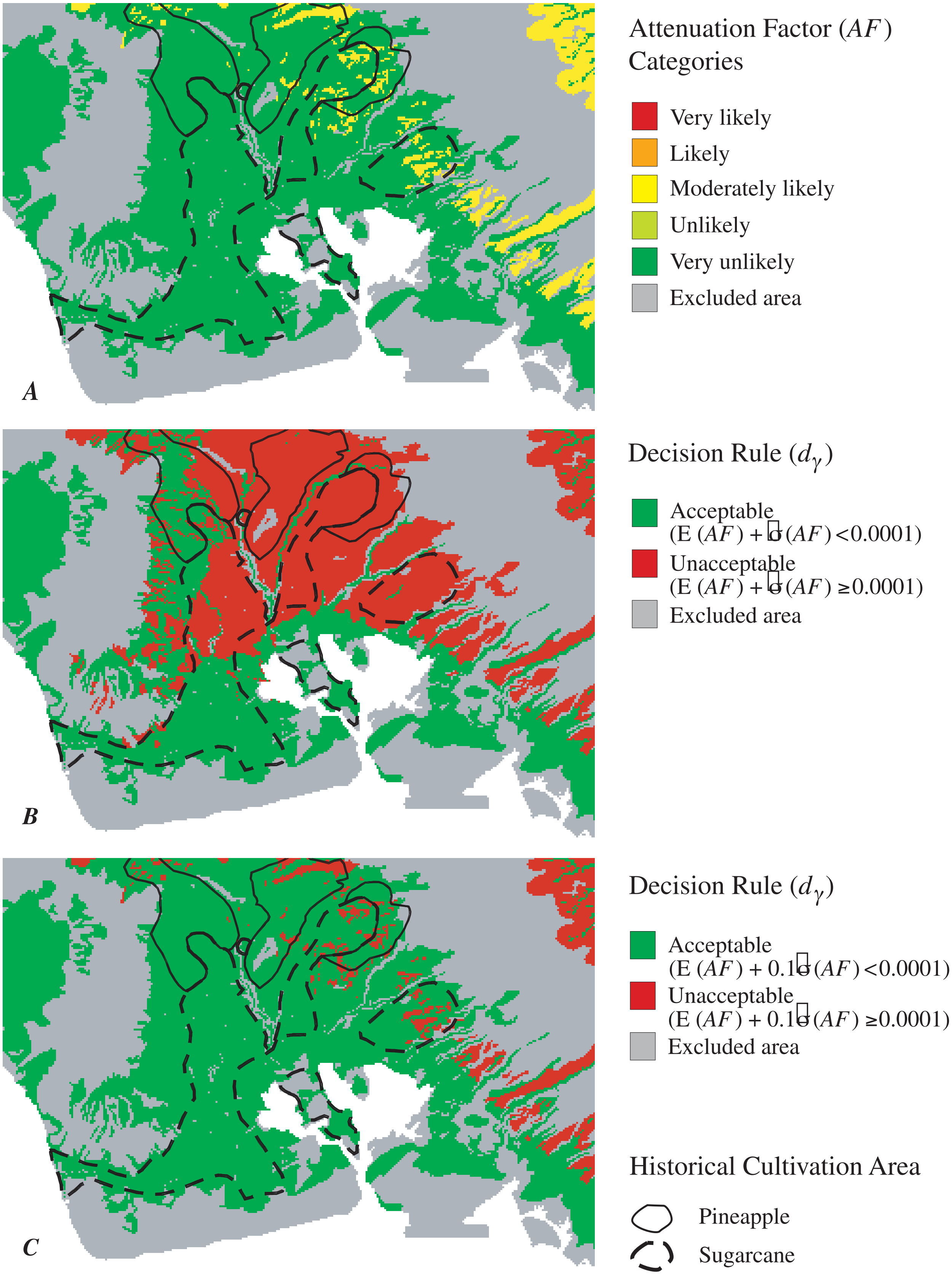

Figure 4.—Ground-water vulnerability maps for the Pearl Harbor basin, Island of O‘ahu, Hawai‘i, for the Oxamyl/Bromocil combination based upon the *AF*. *A*, spatial representation of the *AF* categories; *B*, decision rule (d_γ) to accept or reject the application of a pesticide without wellhead treatment based on the rule $E(AF) + \sigma(AF) < 0.0001$; *C*, decision rule ($d_\gamma$) to accept or reject the application of a pesticide without wellhead treatment based on the rule $E(AF) + 0.1\sigma(AF) < 0.0001$. Outlined areas represent active pineapple and sugar production in 1980 (Armstrong, 1983).

B, Program 12) cases, the expected present values of net benefits of $244.0 million and $96.1 million, respectively, are greater than those of Alternative B, Program 11. Furthermore, for all six of the DBCP combinations, Alternative A is more cost effective than Alternative B, Programs 1 and 3 (with expected present values of net benefits of $ -66.4 million and $ -44.3 million, respectively) and would be preferred; these are the only two programs for which Alternative A is more cost effective than Alternative B. Depending on the availability, effectiveness, and price of the chemicals, conclusions about the efficacy of their use can vary.

The application of the regulatory model demonstrated that the *RF* and *AF* indices behaved differently. The *RF* estimates were affected by changes in the levels of uncertainty far more than the *AF* estimates. However, in nearly every case, the *AF* estimates resulted in fewer hectares that would require wellhead treatment than did the *RF* estimates. This model indicates that the application of the *AF* consistently allows greater use of chemicals.

The regulator's level of risk aversion moderately affects the outcomes of the regulatory model and the actions to be taken. For the *RF* index, a change in the confidence level P from 0.67 (F(P) = 1) to 0.95 (F(P) = 2) decreases the number of hectares exempt from wellhead treatment from 4,606 ha to 0 ha for combinations of DBCP or Fenamiphos with Simazine. For the regulator who requires $P = 0.99$ (F(P) = 3), the number of hectares that do not require wellhead treatment decreases from 4,606 ha to 0 ha for combinations of DBCP with Ametryn, Atrazine, and Diuron, and from 26,452 ha to 14,002 ha for combinations of Fenamiphos with Ametryn, Diuron, and Simazine. An increase in P for the *AF* index results in only one change in farm productivity for pineapple production. When $P = 0.99$ for the 1.0*AF* case, the number of hectares exempt from wellhead treatment decreases from 16,590 ha to 10,816 ha for combinations of Fenamiphos or Oxamyl with Hexazinone, reducing the expected present value of net benefits from $80.7 million to $20.5 million. These results demonstrate that the IESEM is capable of representing changes in decisionmaker risk and in reductions of ESI uncertainty. Finally, the application of the IESEM showed that the policy to restrict the application of DBCP and EDB in areas of historical production was a wise decision. When the ESI for these two insecticides was used in the application of the implementation protocol, the model result was too uncertain to permit the use of these chemicals without wellhead treatment.

Conclusions

This study demonstrates that using an IESEM in a GIS framework provides an ability to assess, at a regional scale, the tradeoffs among pesticide use, crop yield, and ground-water treatment. The cost-effectiveness analysis described here allowed an assessment of alternative policy choices. The results indicated that a coordinated information-based screening and wellhead treatment program could be cost effective. Extensions to the method developed in this paper can be made to accommodate a physics-based model with more realistic delineations of known agricultural regions or recreational areas (for example, golf courses).

The IESEM has been developed to estimate the value of ESI in a decision framework using a GIS. The two contributions of the decision framework reported here are understanding the physical processes at work in the shallow soil subsurface and refining the accuracy of ESI predictions on the basis of regional-scale vulnerability assessments. However, the estimation of ρ remains problematic. Further research must improve the correlation between an ESI prediction and observed ground-water contamination to demonstrate the utility of the regional vulnerability measure as a regulatory tool. Before the application of regional models becomes routine, additional regional vulnerability assessment measures, including chemical concentrations, will be necessary for a successful regulatory program.

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TABLES 1–8

Table 1.—Classification scheme used for the *AF* and *RF* indices for pesticide movement in soils (Khan and others, 1986).

Attenuation Factor (*AF*)	Classification
≥ 0.0 and < 0.0001	very unlikely
≥ 0.0001 and < 0.01	unlikely
≥ 0.01 and < 0.1	moderately likely
≥ 0.1 and < 0.25	likely
≥ 0.25 and ≤ 1.0	very likely
Retardation Factor (*RF*)	**Classification**
$= 1.0$	very mobile
> 1.0 and < 2.0	mobile
≥ 2.0 and < 3.0	moderately mobile
≥ 3.0 and < 10.0	moderately immobile
≥ 10.0	very immobile

Table 2.—The 10 pesticides included in this study, which are (or have been) used in Hawai‘i for sugarcane and pineapple (after Kleveno and others, 1992).

Common and chemical names	Use in Hawai‘i
Ametryn 2-(ethylamino-4-(isopropylamino)-6-methylthio)-s-triazine	herbicide 1964–present
Atrazine 2-chloro-4-ethylamino-6-isopropylamino-s-triazine	herbicide 1958–present
Bromacil 5-bromo-3-sec-butyl-6-methyluracil	herbicide 1963–present
DBCP 1,2-dibromo-3-chloropropane	soil fumigant 1955–1984
Diuron 3-(3,4-dichlorophenyl)-1,1-dimethylurea	herbicide 1954–present
EDB ethylene dibromide	insecticidal fumigant 1946–1983
Fenamiphos ethyl 3-methyl-4-(methylthio) phenyl (1-methyl) phosphoramidate	nematicide 1969–present
Hexazinone 3-cyclohexyl-6-(dimethylamino)-1-methyl-s-triazine-2,4-(1H,3H)-dione	herbicide 1976–present
Oxamyl methyl N′, N′-dimethyl-N-[(methylcarbomoyl)-oxy]-1-thiooxamimidate	insecticide/nematicide 1969–present
Simazine 2-chloro-4,6-bis-(ethylamino)-s-triazine	herbicide 1956–present

Table 3.—The mean E(*AF*) and standard deviation σ(*AF*) of the Attenuation Factor for the 10 selected pesticides for the 5 major O‘ahu soil orders.

Chemicals	Soil orders				
	Inceptisols	Mollisols	Oxisols	Ultisols	Vertisols
	E(*AF*) σ(*AF*)	E(*AF*) σ(*AF*)	E(*AF*) σ(*AF*)	E(*AF*) σ*AF*)	E(*AF*) σ(*AF*)
Ametryn	$4.4x10^{-54}$ $4.1x10^{-52}$	$8.3x10^{-33}$ $3.4x10^{-31}$	$1.3x10^{-18}$ $3.3x10^{-17}$	$2.8x10^{-6}$ $1.8x10^{-5}$	$5.4x10^{-26}$ $1.8x10^{-24}$
Atrazine	$3.0x10^{-33}$ $1.7x10^{-31}$	$6.4x10^{-21}$ $1.6x10^{-19}$	$5.2x10^{-12}$ $8.3x10^{-11}$	$3.8x10^{-4}$ $1.4x10^{-3}$	$4.7x10^{-17}$ $9.9x10^{-16}$
Bromacil	$4.9x10^{-12}$ $1.3x10^{-10}$	$1.0x10^{-8}$ $1.4x10^{-7}$	$3.2x10^{-5}$ $2.6x10^{-4}$	$5.8x10^{-2}$ $1.4x10^{-1}$	$8.5x10^{-8}$ $9.2x10^{-7}$
DBCP	$3.3x10^{-8}$ $4.3x10^{-7}$	$1.5x10^{-5}$ $8.8x10^{-5}$	$2.0x10^{-3}$ $7.4x10^{-3}$	$1.6x10^{-1}$ $1.7x10^{-1}$	$9.5x10^{-5}$ $4.6x10^{-4}$
Diuron	$7.4x10^{-96}$ $1.4x10^{-93}$	$3.3x10^{-57}$ $3.1x10^{-55}$	$3.5x10^{-32}$ $2.0x10^{-30}$	$1.4x10^{-10}$ $2.2x10^{-9}$	$9.8x10^{-45}$ $7.4x10^{-43}$
EDB	$3.3x10^{-1}$ $4.5x10^{-1}$	$4.6x10^{-1}$ $2.7x10^{-1}$	$6.4x10^{-1}$ $3.6x10^{-1}$	$8.9x10^{-1}$ $3.0x10^{-1}$	$5.0x10^{-1}$ $2.4x10^{-1}$
Fenamiphos	$2.6x10^{-57}$ $2.8x10^{-55}$	$3.1x10^{-35}$ $1.6x10^{-33}$	$5.6x10^{-20}$ $1.7x10^{-18}$	$1.2x10^{-6}$ $1.0x10^{-5}$	$3.2x10^{-28}$ $1.3x10^{-26}$
Hexazinone	$3.3x10^{-9}$ $4.3x10^{-8}$	$1.3x10^{-6}$ $7.5x10^{-6}$	$4.9x10^{-4}$ $1.8x10^{-3}$	$1.2x10^{-1}$ $1.0x10^{-1}$	$6.9x10^{-6}$ $3.3x10^{-5}$
Oxamyl	$1.6x10^{-139}$ $3.2x10^{-137}$	$1.5x10^{-102}$ $1.3x10^{-100}$	$3.8x10^{-58}$ $2.1x10^{-56}$	$4.2x10^{-16}$ $4.9x10^{-15}$	$6.1x10^{-93}$ $4.4x10^{-91}$
Simazine	$9.0x10^{-41}$ $3.9x10^{-38}$	$1.7x10^{-25}$ $4.3x10^{-23}$	$1.5x10^{-14}$ $2.1x10^{-12}$	$6.3x10^{-5}$ $2.8x10^{-3}$	$1.1x10^{-20}$ $2.1x10^{-18}$

Table 4.—The mean E(*RF*) and standard deviation σ(*RF*) of the Retardation Factor for the 10 selected pesticides for the 5 major O'ahu soil orders.

Chemicals	Soil orders				
	Inceptisols	Mollisols	Oxisols	Ultisols	Vertisols
	E(RF) σ(RF)	E(RF) σ(RF)	E(RF) σ(RF)	E(RF) σ(RF)	E(RF) σ(RF)
Ametryn	41.7 29.6	19.2 10.1	18.6 11.1	31.0 12.3	13.3 7.5
Atrazine	19.4 14.0	9.3 4.9	9.0 5.3	14.6 6.3	6.6 3.6
Bromacil	5.9 5.7	3.2 2.3	3.1 2.3	4.6 3.6	2.5 1.6
DBCP	11.7 8.4	5.8 3.0	5.6 3.2	8.9 3.9	4.2 2.2
Diuron	74.3 63.5	33.8 23.8	32.6 24.9	55.0 33.6	23.1 17.1
EDB	6.2 5.8	3.3 2.4	3.2 2.4	4.8 3.6	2.6 1.6
Fenamiphos	27.8 22.2	13.0 8.2	12.6 8.6	20.7 11.2	9.1 5.9
Hexazinone	6.5 4.1	3.5 1.4	3.4 1.5	5.0 1.7	2.7 1.0
Oxamyl	4.8 2.8	2.7 1.0	2.6 1.1	3.8 1.2	2.2 0.7
Simazine	20.8 97.7	9.9 43.5	9.6 42.1	15.6 71.4	7.0 29.4

Table 5.—Reductions in the components of $\sigma(AF)$ by 10 percent to $0.9\sigma(AF)$ and by 90 percent to $0.1\sigma(AF)$ for the 10 selected pesticides for the 5 major O'ahu soil orders.

Chemicals	Soil orders				
	Inceptisols	Mollisols	Oxisols	Ultisols	Vertisols
	$0.9\sigma(AF)$ $0.1\sigma(AF)$	$0.9\sigma(AF)$ $0.1\sigma(AF)$	$0.9\sigma(AF)$ $0.1\sigma(AF)$	$0.9\sigma(AF)$ $0.1\sigma(AF)$	$0.9\sigma(AF)$ $0.1\sigma(AF)$
Ametryn	$3.7x10^{-52}$ $4.1x10^{-53}$	$3.0x10^{-31}$ $3.4x10^{-32}$	$3.0x10^{-17}$ $3.3x10^{-18}$	$1.7x10^{-5}$ $1.8x10^{-6}$	$1.6x10^{-24}$ $1.8x10^{-25}$
Atrazine	$1.5x10^{-31}$ $1.7x10^{-32}$	$1.5x10^{-19}$ $1.6x10^{-20}$	$7.5x10^{-11}$ $8.3x10^{-12}$	$1.3x10^{-3}$ $1.4x10^{-4}$	$8.9x10^{-16}$ $9.9x10^{-17}$
Bromacil	$1.2x10^{-10}$ $1.3x10^{-11}$	$1.3x10^{-7}$ $1.4x10^{-8}$	$2.3x10^{-4}$ $2.6x10^{-5}$	$1.3x10^{-1}$ $1.4x10^{-2}$	$8.3x10^{-7}$ $9.2x10^{-8}$
DBCP	$3.8x10^{-7}$ $4.3x10^{-8}$	$8.0x10^{-5}$ $8.8x10^{-6}$	$6.6x10^{-3}$ $7.4x10^{-4}$	$1.5x10^{-1}$ $1.7x10^{-2}$	$4.1x10^{-4}$ $4.6x10^{-5}$
Diuron	$1.3x10^{-93}$ $1.4x10^{-94}$	$2.8x10^{-55}$ $3.1x10^{-56}$	$1.8x10^{-30}$ $2.0x10^{-31}$	$2.0x10^{-9}$ $2.2x10^{-10}$	$6.6x10^{-43}$ $7.4x10^{-44}$
EDB	$4.0x10^{-1}$ $4.5x10^{-2}$	$2.4x10^{-1}$ $2.7x10^{-2}$	$3.2x10^{-1}$ $3.6x10^{-2}$	$2.7x10^{-1}$ $3.0x10^{-2}$	$2.1x10^{-1}$ $2.4x10^{-2}$
Fenamiphos	$2.6x10^{-55}$ $2.8x10^{-56}$	$1.4x10^{-33}$ $1.6x10^{-34}$	$1.6x10^{-18}$ $1.7x10^{-19}$	$9.1x10^{-6}$ $1.0x10^{-6}$	$1.2x10^{-26}$ $1.3x10^{-27}$
Hexazinone	$3.9x10^{-8}$ $4.3x10^{-9}$	$6.8x10^{-6}$ $7.5x10^{-7}$	$1.6x10^{-3}$ $1.8x10^{-4}$	$9.0x10^{-2}$ $1.0x10^{-2}$	$3.0x10^{-5}$ $3.3x10^{-6}$
Oxamyl	$2.8x10^{-137}$ $3.2x10^{-138}$	$1.2x10^{-100}$ $1.3x10^{-101}$	$1.9x10^{-56}$ $2.1x10^{-57}$	$4.4x10^{-15}$ $4.9x10^{-16}$	$4.0x10^{-91}$ $4.4x10^{-92}$
Simazine	$3.5x10^{-38}$ $3.9x10^{-39}$	$3.8x10^{-23}$ $4.3x10^{-24}$	$1.9x10^{-12}$ $2.1x10^{-13}$	$2.5x10^{-3}$ $2.8x10^{-4}$	$1.9x10^{-18}$ $2.1x10^{-19}$

Table 6.—Reductions in the components of $\sigma(RF)$ by 10 percent to $0.9\sigma(RF)$ and by 90 percent to $0.1\sigma(RF)$ for the 10 selected pesticides for the 5 major O'ahu soil orders.

Chemicals	Soil orders				
	Inceptisols	Mollisols	Oxisols	Ultisols	Vertisols
	0.9s(RF) 0.1s(RF)	0.9s(RF) 0.1s(RF)	0.9s(RF) 0.1s(RF)	0.9s(RF) 0.1s(RF)	0.9s(RF) 0.1s(RF)
Ametryn	26.7 3.0	9.1 1.0	0.0 1.1	11.0 1.2	6.8 0.7
Atrazine	12.6 1.4	4.4 0.5	4.8 0.5	5.7 0.6	3.3 0.4
Bromacil	5.1 0.6	2.1 0.2	2.1 0.2	3.2 0.4	1.5 0.2
DBCP	7.5 0.8	2.7 0.3	2.9 0.3	3.5 0.4	2.0 0.2
Diuron	57.1 6.3	21.4 2.4	22.4 2.5	30.2 3.4	15.4 1.7
EDB	5.2 0.6	2.1 0.2	2.1 0.2	3.2 0.4	1.5 0.2
Fenamiphos	20.0 2.2	7.4 0.8	7.8 0.9	10.1 1.1	5.3 0.6
Hexazinone	3.6 0.4	1.3 0.1	1.4 0.2	1.6 0.2	0.9 0.1
Oxamyl	2.5 0.3	0.9 0.1	0.9 0.1	1.1 0.1	0.6 0.1
Simazine	87.9 9.8	39.2 4.4	37.9 4.2	64.3 7.1	26.4 2.9

Table 7.—Expected present value of net benefits of agricultural production and cost effectiveness of the ESI in millions of dollars to produce pineapple[1] on 32,226 hectares in the Pearl Harbor basin, Island of O'ahu, Hawai'i.[2] Assume production area, estimated yields, and income (b_{ijk})[3] of $4,832.2 million at a production cost (C_{ij})[4] of $2,213.0 million.

Program		Number of ha permitted without treatment	C_w[5]	$C(\theta)$[6]	$B_{\gamma_\theta}(Q)$	$B_{\gamma_\theta}(Q) - B_{\gamma_0}(Q)$
Alternative A		0	$336.4	$0	$2,282.8	N/A
Alternative B						
1	0.1*AF*	10,816	$223.5	$179.2	$2,216.5	$–66.4
2	1.0*RF*	0	$336.4	$55.4	$2,227.4	$–55.4
3	1.0*AF*	4,606	$288.3	$92.4	$2,238.5	$–44.3
4	0.1*RF*	4,606	$288.3	$87.1	$2,243.7	$–39.1
5	0.9*RF*	3,186	$303.1	$56.5	$2,259.5	$–23.3
6	0.1*RF*	7,792	$255.0	$73.3	$2,290.8	$8.0
7	0.9*AF*	10,816	$223.5	$101.1	$2,294.6	$11.8
8	0.1*AF*	16,590	$163.2	$149.5	$2,306.5	$23.7
9	0.1*AF*	29,040	$33.3	$258.9	$2,327.0	$44.2
10	0.9*AF*	16,590	$163.2	$100.0	$2,355.9	$73.1
11	1.0*AF*	16,590	$163.2	$92.4	$2,363.6	$80.7
12	0.1*AF*	32,226	$0	$240.3	$2,378.9	$96.1
13	0.1*RF*	26,452	$60.3	$146.5	$2,412.4	$129.6
14	0.9*AF*	29,040	$33.3	$105.7	$2,480.2	$197.4
15	1.0*AF*	29,040	$33.3	$92.4	$2,493.5	$210.7
16	0.9*AF*	32,226	$0	$107.2	$2,512.0	$229.2
17	1.0*AF*	32,226	$0	$92.4	$2,526.8	$244.0

[1] A growing cycle is 3 years (Leon-Guerrero and others, 1994).

[2] All prices and costs are in 1999 dollars.

[3] Assumes benefits per hectare are $11,324 for pineapple (U.S. Department of Agriculture, 1999).

[4] Production costs are based on Philipp and Baker (1975).

[5] Present value of costs for Alternative A includes capital investment ($5,850/ha) and operating costs ($400/ha/yr) discounted at 7 percent annually.

[6] Present value of costs for Alternative B includes monitoring and sampling for the *RF* ($150/ha/yr), 0.9*RF* ($150/ha/yr + $10/*j*/ha/yr), 0.1*RF* ($150/ha/yr + $100/*j*/ha/yr), and for the *AF* ($250/ha/yr + $1,000/*j*), 0.9*AF* ($250/ha/yr + $10/ha/yr + $1,000/*j*), and 0.1*AF* ($250/ha/yr + $100/ha/yr + $1,000/*j*).

Table 8.—Number of hectares acceptable for pesticide use without wellhead treatment for insecticide–herbicide combinations at 3 levels of uncertainty for the 10 selected pesticides for the 5 major soil orders (h_j). The total number of hectares (H) in the study area is 32,226. There were no EDB combinations with positive acreage.

Combinations		1.0*RF*	0.9*RF*	0.1*RF*	1.0*AF*	0.9*AF*	0.1*AF*
Insecticide	Herbicide						
DBCP	Ametryn	0	0	4,606	4,606	10,816	10,816
DBCP	Atrazine	0	0	4,606	4,606	10,816	10,816
DBCP	Bromacil	0	0	0	4,606	10,816	10,816
DBCP	Diuron	0	0	4,606	4,606	10,816	10,816
DBCP	Hexazinone	0	0	0	4,606	10,816	10,816
DBCP	Simazine	0	0	4,606	4,606	10,816	10,816
Fenamiphos	Ametryn	0	3,186	26,452	32,226	32,226	32,226
Fenamiphos	Atrazine	0	0	7,792	29,040	29,040	29,040
Fenamiphos	Bromacil	0	0	0	16,590	16,590	29,040
Fenamiphos	Diuron	0	3,186	26,452	32,226	32,226	32,226
Fenamiphos	Hexazinone	0	0	0	16,590	16,590	16,590
Fenamiphos	Simazine	0	0	4,606	29,040	29,040	29,040
Oxamyl	Ametryn	0	0	0	32,226	32,226	32,226
Oxamyl	Atrazine	0	0	0	29,040	29,040	29,040
Oxamyl	Bromacil	0	0	0	16,590	16,590	29,040
Oxamyl	Diuron	0	0	0	32,226	32,226	32,226
Oxamyl	Hexazinone	0	0	0	16,590	16,590	16,590
Oxamyl	Simazine	0	0	0	29,040	29,040	29,040

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