Aggregate Analysis of Site-Specific Pollution Problems: The Case of Groundwater Contamination from Agriculture

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Control of nonpoint sources of pollution has traditionally been within the domain of local decision makers in recognition of the critical importance of site-specific issues. More recently attention has turned to the issue of what can and should be done at the regional or national level, while recognizing the importance of site-specific attributes. This paper describes and illustrates an approach for analysis of nonpoint pollution problems that focuses jointly at the aggregate and disaggregate levels of the problem. The approach is based on linking two tools of analysis, the microparameter distribution model and the Geographical Information Systems (GIS). Although there are significant challenges to be overcome in implementing such an approach, linkage of these two policy tools has considerable promise in dealing with site-specific issues within an aggregate framework. Furthermore, GIS is potentially an important source of data for economists to exploit, given the momentum of GIS systems throughout the nation and given the relatively disaggregate nature of the data.

Groundwater contamination from agriculture has been the focus of recent concern by both environmental and agricultural policy makers. This concern stems from reported contamination problems in some areas, the potential for contamination in others, and perceptions that the problem may be widespread.

Controlling agricultural sources of groundwater contamination poses a particular challenge to policy makers for at least two reasons. First, in many cases it is a nonpoint-source problem, where the point of entry of the pollutants is dispersed rather than concentrated. Nonpoint sources of pollution can be more difficult to control than point sources because of monitoring difficulties. Second, the impact of a given agricultural activity varies greatly with the characteristics of the site on which it is applied. For example, fertilizer applied to sandy soils over shallow aquifers is more likely to reach the groundwater and, thus, result in contamination than is fertilizer used in areas with deep water tables and thick, impermeable soil horizons. Likewise, contamination of an aquifer used as a source of drinking water for a large population is likely to result in greater social damage than contamination of a small aquifer located far from users.

The site-specific nature of groundwater contamination suggests that responses should be tailored to the characteristics of individual sites. However, because of the importance of the agricultural sector, policies governing those responses should be coordinated at the regional or national level. Thus, rather than simply leaving the design of an appropriate policy response to local officials who have traditionally had jurisdiction over site-specific land-use decisions, policy makers are asking what can and should be done at the state or federal level to control agricultural sources of groundwater pollution.

Economic analyses of the impact of alternative agricultural policies have generally taken one of two forms. The first is the use of aggregate regional or national models of the agricultural sector to predict the impacts of a given policy on aggregate input and output decisions, equilibrium prices, and international trade. These models do not, however,

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incorporate any information about the heterogeneity of site characteristics. Instead, they treat all farms within a given region as homogeneous with regard to the resource base. As such, aggregate models ignore the significance of variations in site characteristics in determining the input/output decisions, the resulting groundwater quality, and the ultimate impact on groundwater users. Omitting site characteristics from the model of production decisions will bias predicted levels of contamination unless the characteristics that influence production decisions are uncorrelated with those that determine pollution.[1] Since many characteristics, such as soil type, influence both production and pollution, the predictions of the aggregate models are likely to be biased. Thus, while this approach is very useful for policies not tied to the resource base, it may not be suitable for analyzing policies whose impacts depend crucially on site characteristics. For example, aggregate analysis cannot be applied in a straightforward manner to assess the full implications of policies targeting protection of vulnerable sole-source aquifers.

The second approach to evaluating groundwater policies links the economic and environmental effects of those policies by modeling individual farm-level decisions and their impacts at the field or watershed level. The predicted effects of policies are then conditional on the characteristics of the specific sites modeled. While such efforts are useful as case studies, by themselves they do not allow predictions of aggregate effects to be easily made. To make such predictions, information is needed about how "representative" the results of the case studies are.

The purpose of this paper is to explore the use and integration of two methods that may have potential for accommodating micro-level concerns into the analysis of aggregate-level policies aimed at groundwater contamination from agricultural activities. The first technique is the use of microparameter distribution models for capturing economic responses to policies. The second is the use of geographical information systems (GIS) for data collection, management, and characterization. Together these two tools show some promise for developing aggregate policy while maintaining a focus on the important site-specific aspects of groundwater contamination.

This paper is organized as follows. The next two sections provide overviews of the microparameter model and GIS, respectively, in the context of groundwater contamination from agriculture. The fourth section presents a method for linking the two tools and illustrates that method with a simple example. Some difficulties that are likely to arise in actual implementation of the method are discussed in the next section. The final section gives concluding remarks.

The Microparameter Distribution Model

The microparameter distribution model was pioneered by Johansen and applied to environmental issues by Hochman and Zilberman (1978, 1979) and more recently by Antle and Just, and Just and Antle.[2] Its purpose is to facilitate economic analysis with a joint focus on micro- and aggregate-level concerns. The distinction of the model is its reliance on joint probability distributions of micro-level parameters, such as parameters of firm-level production and pollution functions.[3]

Initial work with the microparameter model assumed a putty-clay technology, under which each individual firm had fixed-proportion production technologies determined at the time of the initial investment in capital equipment. However, although production by individual firms is in fixed proportions, aggregate-level production exhibits variable proportions, depending on the mixture of firms that are actively engaged in production at that point in time. Thus, as economic conditions change due either to market forces or to policy changes, firms with the most unfavorable proportions become unprofitable. As they drop out of the market or invest so as to change their input proportions, the aggregate input proportions change for the industry as a whole.

Under this original formulation of the model, the firm's production process uses a single input, say labor, and produces two outputs: a marketed output (y) and pollution (z). The fixed-proportions production function for firm i can then be represented by the labor/output ratio l_i, and the pollution/output ratio t_i. While these proportions are fixed for the individual firm, they vary across firms. Profit per unit of output for firm i is

$$(1) \qquad \pi_i = p - w\, l_i,$$

[1] A mathematical derivation of the bias is available from the authors upon request. The direction of the bias depends on whether the production and pollution-related characteristics are positively or negatively correlated.

[2] These studies develop the theoretical model. See Moffitt, Zilberman, and Just for an empirical application.

[3] More generally we could consider the technology of any "microunit." While the microunit could be a firm, it could alternatively be defined at the subfirm level, for example as a production process, a field, or as an acre of land. For expository convenience, we treat microunits as firms in this section. However, in the application in the fourth section, we treat a field as the microunit.

where p and w are the per unit prices for output and labor, respectively. Firms with nonnegative profits are assumed to continue to produce, while those with negative profits are assumed to drop out of the industry. Thus, for some given set of prices a "survival region" (A), identifying the firms that are able to produce profitably, can be defined as

(2) $$A = \{(l, t): l \leq p/w\}.$$

Given the survival region, we can define total output and total pollution for the industry. Following Johansen and Hochman and Zilberman (1978, 1979), let $g(t, l)$ be the "capacity distribution function" for firms in the industry. Then $g(t, l)\, dt\, dl$ is an approximation of the output capacity of all microunits whose parameters are contained in the interval $\{(t, l), (t + dt, l + dl)\}$ for small dt and dl. Thus, given a survival region, A, in the (t, l) plane, the total output capacity of all microunits within this region is

$$\iint_A g(l, t)\, dl\, dt$$

and the total level of pollution is

$$\iint_A t\, g(l, t)\, dl\, dt.$$

While the above model is cast in terms of a fixed-proportions technology, the microparameter distribution could correspond to the parameters of alternative production technologies (Antle and Just). For example, one could assume that each firm has a Cobb-Douglas production function where there is a probability distribution on parameters of the production function across firms. Similarly, each firm has a functional relationship between inputs and pollution. Combined, these two functions implicitly describe a joint relationship between inputs, outputs, and pollution.

Single-Crop Model

In the context of groundwater contamination from agricultural activities, we could describe a functional relationship between physical characteristics of a given field and the production and pollution from that field. Let those physical characteristics be divided into three sets: those that affect production only, c_y; those that affect pollution only, c_z, such as the underlying geological structure or depth to the water table; and those that affect both production and pollution, c_b, such as soil type, topography, and annual rainfall. We can then define production and pollution functions as follows:

(3) $$y = f(x, c_y, c_b)$$

and

(4) $$z = g(x, c_z, c_b),$$

where x is a vector of inputs.[4]

The objective of the firm is to choose x to

$$\max_x \pi = pf(x, c_y, c_b) - p_x'x,$$

where p is output price and p_x is a vector of per unit input prices. Maximizing this function with respect to x yields the first-order condition $p \cdot \partial f(x, c_y, c_b)/\partial x = p_x$.

If the second-order conditions are met, we could, in principle, solve the first-order conditions and define the firm's input demand functions:

(5) $$x^*(p, p_x, c_y, c_b).$$

The micro-level output and pollution supply functions are then

(6) $$y^*(p, p_x, c_y, c_b) = f(x^*(p, p_x, c_y, c_b), c_y, c_b)$$

and

(7) $$z^*(p, p_x, c_y, c_z, c_b) = g(x^*(p, p_x, c_y, c_b), c_z, c_b).$$

Under this formulation, the survival region can be defined as $A = \{(c_y, c_z, c_b): py^*(p, p_x, c_y, c_b) - p_x'x^*(p, p_x, c_y, c_b) \geq 0\}$.

Integrating over the characteristics of the firms in the survival region yields aggregate industry output:

(8) $$\iint_A y^*(p, p_x, c_y, c_b)\, dc_y\, dc_b.$$

Likewise, the total pollution of producing firms is given by[5]

(9) $$\iiint_A z^*(p, p_x, c_y, c_z, c_b)\, dc_y\, dc_z\, dc_b.$$

Consider now the impact of a policy designed to reduce pollution. Suppose, for example, that the government puts an upper limit, Z, on allowable pollution per firm. The firm's choice problem then becomes

(10) $$\text{maximize } \pi = pf(x, c_y, c_b) - p_x'x, \quad \text{subject to } g(x, c_z, c_b) \leq Z.$$

The corresponding input-demand, output-supply, and pollution functions are $x^*(p, p_x, c_y, c_z, c_b, Z)$, $y^*(p, p_x, c_y, c_z, c_b, Z)$, and $z^*(p, p_x, c_y, c_z, c_b, Z)$, where * indicates optimal choices under the rele-

[4] The relationship between input use and pollution could be determined in a number of ways. For example, site-specific process (fate-transport) models, such as the LEACHM model (see Wagenet and Hutson), could be run under a variety of parameter specifications to determine this relationship. Alternatively, a more reduced-form approach, such as that used by Anderson, Opaluch, and Sullivan, could be used.

[5] Note that for issues like groundwater pollution, the aggregate amount of pollution may be of less interest to policy makers than information about the spatial distribution of pollution since the distribution will play a key role in the determination of resulting damages. For further discussion, see the following section.

vant policy. Note that now the input demands and the output supply depend not only on the production-related microparameters, but also on those that directly influence pollution only (c_z). In addition, the survival region now also depends on the policy variable Z both directly and indirectly through the endogenous variables x^*, y^*, and z^*:

$$(11) \quad A(Z) = \{(c_y, c_z, c_b):py^* - p_x'x^* \geq 0\},$$

where $z^* \leq Z$, by (10). Thus, policy changes will affect aggregate production and pollution both at the intensive margin (through changes in x^* and thus y^* and z^*) and at the extensive margin (through changes in A).

The effect of a per unit pollution tax can be represented similarly. The firm's choice problem is then

$$(12) \quad \underset{x}{\text{maximize}}\ \pi = pf(x, c_y, c_b) - p_x'x - p_z g(x, c_z, c_b),$$

where p_z is the per unit charge for pollution (i.e., the pollution tax). As with the standards approach, input and output choices now depend on the pollution-related microparameters (c_z) as well as those related to production. In addition, all choice variables and the survival region depend on the level of the tax, with

$$(13) \quad A(p_z) = \{(c_y, c_z, c_b):py^* - p_x'x^* - p_z z^* \geq 0\}.$$

Thus, again policy changes affect production and pollution at both the intensive and the extensive margins.

Crop-Mix Effects

The above description of the farmer's choice problem focuses on a single crop and assumes that the alternative to producing that crop on the land is to leave the land idle, yielding a return of zero. In reality, of course, there are a number of alternative crops that can be feasibly grown on a given field and a farmer must choose which crop to grow as well as the optimal inputs for the given crop. In this case, choice at the extensive margin can be broadly thought of as the choice among alternative uses of the land, where different crops constitute different uses and one possible use is to leave the land idle.

When crop-mix choices are considered, the farmer's decision problem can be viewed as a two-step problem. In the first step, the farmer makes input-use decisions for each crop choice and the maximum profit is calculated for each. In the second step, the most profitable cropping pattern is chosen. The input-use decisions for a given crop and the resulting levels of output and pollution were described above. In particular, if we replace x, y, z, and p with x_j, y_j, z_j, and p_j in (3) through (9) above, the results can be interpreted as applying to crop j. The maximum profit obtainable if the land is used to grow crop j is then $\pi^*j(p_j, p_x, c_y, c_b) = p_j y_j^*(p_j, p_x, c_y, c_b) - p_x'x_j^*(p_j, p_x, c_y, c_b)$. Given the maximum profit levels for all crops, the crop choice becomes a discrete choice based on the π^*_j's (Lichtenberg). In particular, the farmer will choose to produce crop j if

$$(14) \quad \pi_j^*(p_j, p_x, c_y, c_b) > \pi_k^*(p_k, p_x, c_y, c_b) \text{ for all } k, \text{ and } \pi_j^* \geq 0.$$

Note that since π^*_j and π^*_k depend on c_y and c_b, the crop choice will depend on the characteristics of the land.

The crop-mix problem can be represented empirically using a qualitative choice model, such as a logit or probit model. These models recognize that discrete choice problems are subject to random or unobservable effects and, thus, that the choice of one option over another is probabilistic rather than certain. In our context, such a model would predict the probability that (14) would hold for a given land type or, correspondingly, the percentage of land with characteristics (c_y, c_b) that would be planted in crop j, given the other exogenous variables.

Since the choice of crop depends on relative profitabilities, the effects of alternative policies discussed in the context of a single crop can be easily extended to include crop-mix effects. In particular, π_j^*, and therefore the optimal choice in (14), would now be a function of both pollution-related characteristics (c_z) and the relevant policy variables. This is analogous to having the survival region depend on pollution parameters in the context of a single crop.

It is clear from the above discussion that land characteristics play a potentially important role in determining the impacts of alternative policies. Since those characteristics vary spatially and since the social costs of pollution may depend on the spatial distribution of activities, a methodology for analyzing spatial variability could enhance the usefulness of the microparameter approach. One such methodology is geographic information systems.

An Overview of GIS

A geographic information system (GIS) is a computerized information management system where data entries are tied to specific geographical locations, identified by latitude and longitude. It is designed to facilitate working with data that are ordered spatially. Theoretically, any data with a spatial dimension can be incorporated into a GIS. Obvious examples include physical land characteristics such as soils, topography, and underlying geology; land-use characteristics such as industrial land, residential land, cropland, and forest land; and the location of specific markers such as roads, rivers, historical sites, and political boundaries. These data are entered in one of three forms: (1) point data for characteristics keyed to a specific point such as the site of a monument or a drinking-water well; (2) linear data for characteristics with a linear dimension such as roads; and (3) area data for characteristics with two dimensions such as land use. The level of resolution, or the size of a discernible area, depends upon how the data were collected. For example, some satellite-generated data may have a minimum resolution size of about 30 square meters, so that anything smaller than that is not discernible. From other sources, the resolution may be 20 to 30 feet, about the size of a road.

The data in a GIS system can be viewed as a computerized version of the data normally presented on a map. These computerized versions have several advantages over the use of paper maps. First, by geo-referencing the data, data from different sources can be combined in a consistent manner and used for calculations. If observations in two different data sets are both tied to specific geographic locations, the observations can be matched to generate a single, larger data set. For example, soils data collected by the Soil Conservation Service can be combined with land-use data from the U.S. Geological Survey (USGS) to provide a richer data set for site characteristics. From such a data set, information about the joint distribution of site characteristics can be determined.

Second, unlike paper maps, use of the GIS creates digitized maps that can be easily overlaid. Thus, the geographical locations having a combination of several characteristics can be easily determined. This is equivalent to finding the intersection of several sets comprised of the locations with the individual characteristics. For example, if the GIS contains data on soil types, depth to groundwater, and land use, then the three maps—(1) the sites with soil type X, (2) the sites with a depth to groundwater of less than Y, and (3) the sites in agricultural land use—can be combined to produce a map of sites that have any combination of these characteristics.

Third, given that the data are digitized, they are readily available for performing a variety of calculations. For example, the computerized system could be used to calculate acreage in various land uses or the acreage of the intersection between various land uses and characteristics associated with susceptibility to groundwater contamination.

Federal and state agencies are increasingly recognizing the potential of GIS for both information presentation and policy analysis. For example, the USGS has several data sets/maps digitized. In many cases, coverage is not comprehensive but is instead limited to isolated locations or regions. The USGS has, however, compiled digital data on land use/land cover and hydrologic units for most of the U.S. The mapping units used for these data have a minimum size of 10 to 40 acres, depending upon the land-use category. Unfortunately, however, the current maps are based on 1972 data and there are no plans to update them systematically. In addition, the categories within "agricultural land" are defined broadly as crop land and pasture land; orchards, groves, etc.; confined feeding operations; and other agricultural land. Thus, the crop-specific information necessary to link farming practices with physical characteristics at a given site is not available in these data sets.

The Soil Conservation Service also has an extensive GIS effort underway. For example, detailed information from soil surveys has been aggregated across sites and the aggregates are being digitized for most of the U.S. in the STATSGO data set. However, the detailed data, which might be more useful than the aggregates for linking production decisions and groundwater quality with soil characteristics, have been digitized for only about 1% of the country. SCS also conducts the National Resources Inventory (NRI) survey every five years, which collects site-specific data regarding land use, soil and water characteristics, erosion, irrigation, etc. While the data collected for each site have been digitized, the site locations have not yet been geo-referenced. SCS plans to do this. Thus, the data from the NRI cannot yet be linked to other spatially ordered data. However, once the NRI sampling points are geo-referenced, they will provide a potentially useful data source for the joint distribution of site characteristics.

While the use of GIS has increased dramatically with improvements in computer technology, it is still in its infancy relative to its potential. The advances in computer technology have outpaced the time and resources necessary for data collection and conversion. Due to data limitations, policy analysts have not been able to take full advantage of the available technology. However, the up-front costs of data collection and conversion can be allocated over multiple applications. Because of the potential for economies of scale in the use of GIS data sets, the more the technology is used, the more it is likely to be extended, making it even more useful for other applications. Thus, one may expect accelerating progress in these data-collection efforts, given a critical mass of applications.

Linking Tools for Policy Analysis

Having identified two tools that are potentially useful in studying site-specific problems at an aggregate level, we turn now to how those tools might be linked together in a study of aggregate impacts of groundwater contamination from agriculture. Our purpose is to use a simple example to illustrate a methodology that seems to have some promise in this regard. Of course in a real-world application of these techniques, quantitative methods would replace many of the graphical depictions used for purposes of illustration.

The methodology is essentially an application of the microparameter modeling approach, coupled with the use of GIS for data collection and analysis. It involves several steps that lead to an assessment of the effects of policy changes designed to reduce groundwater contamination.

Step 1: Determining Pollution Potential

In the discussion of microparameter models above, the effects of policies depended on both the productivity and the pollution characteristics of the firm or other microunit such as a farm, field, or acre.[6] In the context of groundwater contamination from agriculture, the pollution potential of a given microunit depends not only on exogenous site characteristics (c_z),[7] but also on farming practices. For example, the pollution potential of production over shallow aquifers will generally depend on the type of crop grown, the chemicals applied, and the type of irrigation and tillage used. Thus, in order to rank sites according to pollution potential, we must first determine the pollution potential associated with any combination of site characteristics and farming practices.

Figure 1 presents a simplified graphical depiction of a two-dimensional version of the problem. Suppose that the physical characteristics affecting pollution potential can be summarized in a single statistic, such as a DRASTIC score.[8] The rows of the matrix in Figure 1 correspond to different scores, ranked here from high to low. Suppose also that we have identified K different field types or farming "practices," distinguished by crop and a set of management practices such as irrigation and tillage methods.[9] The columns correspond to the different farming practices. For example, the first column (farming practice 1) might correspond to irrigated corn produced with conventional tillage (ICC), while the second column could be nonirrigated corn or soybeans.

For any combination of farming practice and site characteristic, the corresponding cell in Figure 1 then indicates the pollution potential for that combination. For simplicity we have indicated only three possible levels, high (H), medium (M), and low (L).[10] As mentioned in footnote 4, the appropriate classification for any given combination or cell can be determined in a number of different ways. For example, structural or process models can be run using parameters corresponding to that combination (Wagenet and Hutson; Zeitouni and Opaluch). Alternatively, reduced-form or econometric models can be used (see, for example, Anderson, Opaluch, and Sullivan). Note that the pollution potentials vary across both rows and columns, indicating that the pollution associated with a given farming practice varies with site type, and vice versa. In addition, they will generally depend

[6] For simplicity, we will define microunits here as fields since site characteristics apply to particular fields, or even portions of fields, rather than whole farms. Individual fields or acres can come in and out of production of a specific crop in response to changes in economic conditions. Of course, production-related decisions are made jointly at the farm level rather than independently on an acre-by-acre basis. Thus, in the economic models of farm-level decisions, the decisions regarding several microunits will be interrelated.

[7] In the previous discussion, we distinguished between site characteristics that affect only pollution, c_z, and those that affect both pollution and productivity, c_b. For simplicity, we assume in this example that any characteristic affects productivity or pollution but not both (i.e., we ignore c_b). This could be addressed by including a single characteristic as both a pollution characteristic (c_z) and a production characteristic (c_y).

[8] Nielsen and Lee used DRASTIC scores to capture contamination potential attributable to site characteristics. These scores are convenient for this purpose since they are scalar-valued indices that reflect multiple site attributes. Of course, that convenience comes at the cost of precision. While we use DRASTIC scores as an illustration, our methodology is general enough to allow for other, possibly nonscalar representations of site vulnerability. If nonscalar measures are used, Figure 1 would, of course, have to be more than two dimensional. In practice this would not be an issue, since numerical methods would be used in this component of the analysis of any actual application.

[9] Ideally, the sensitivity of water quality effects to farming practices should determine the appropriate categorization of field types (i.e., types should be defined according to those characteristics deemed most important in determining the effect of farming activities on water quality). For example, if water quality effects depend crucially on whether or not the land is irrigated, then the categorization would have to distinguish between irrigated and nonirrigated fields. On the other hand, if heterogeneity across farming practices is not very important in determining water quality effects, then relatively few farming practices would have to be identified. If water quality effects are determined primarily by pesticide characteristics, then farm types should also be distinguished by the predominant pesticides used. In practice, data availability is also likely to determine the categorization that is used.

[10] Figure 1 is similar to the approach used in Goss, although under his approach, the columns of Figure 1 would refer to different pesticide-leaching potentials based on pesticide characteristics.

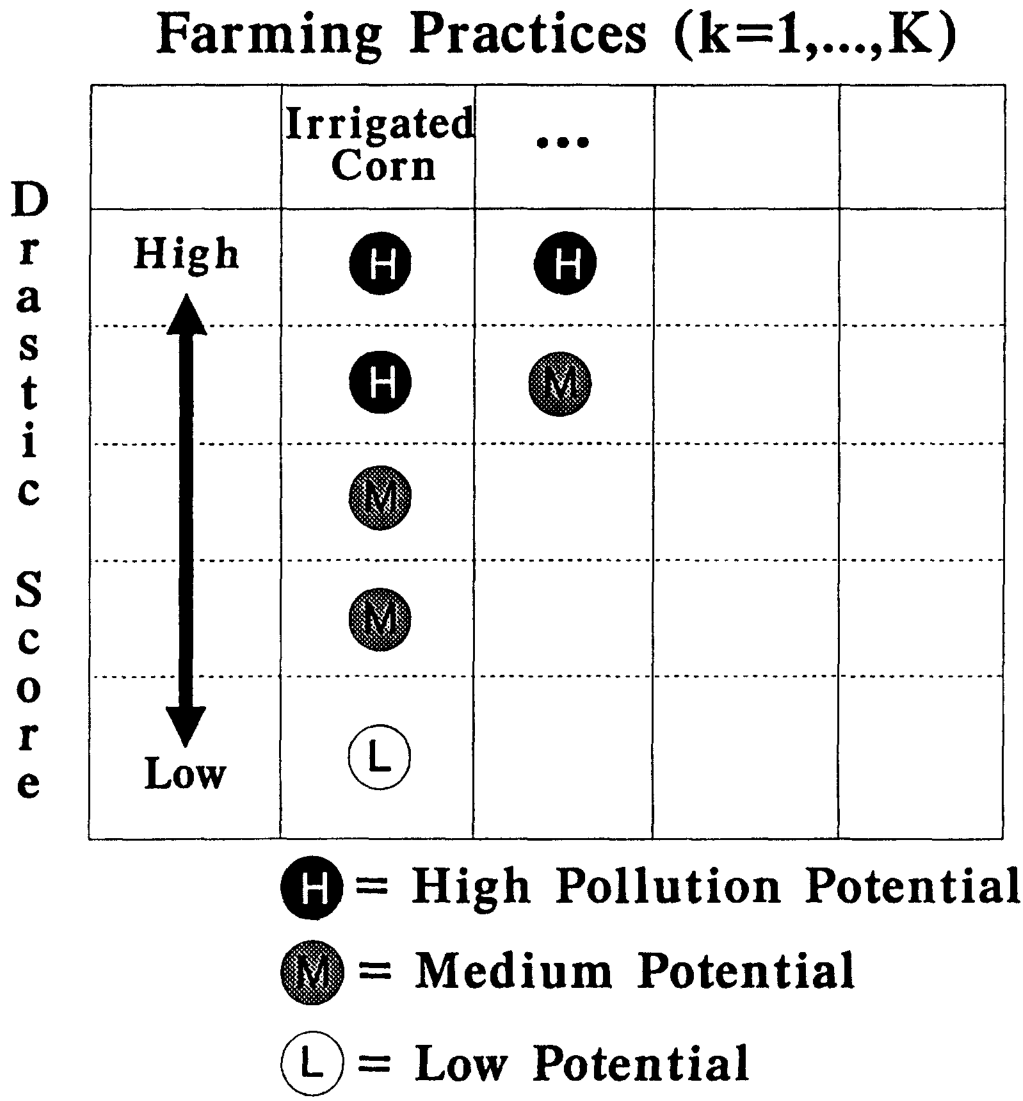

Figure 1. Determining Pollution Potential

on policy variables since those variables will affect decisions regarding input use.[11]

Step 2: Applying the Microparameter Model

Given the matrix in Figure 1, the standard microparameter approach with a one-dimensional measure of pollution potential can then be applied to each farming practice (column). Suppose, for example, that within the region of interest, there are 20 or 20,000 fields with irrigated corn with conventional tillage (ICC) corresponding to farming practice 1. The first step in applying the microparameter model to these units is to determine their distribution across site characteristics that influence pollution. If a DRASTIC score is being used as a proxy for these characteristics, then a score for each field should be determined or estimated. The necessary data could be collected and organized using a GIS system.

The distribution of fields across productivity-related characteristics must also be determined. Suppose, for example, that productivity is based solely on soil type and that soil types can be ranked from high to low in terms of productivity. Then the soil type for each field of ICC must be determined. Again, use of a GIS may be helpful in determining both the soil type for any given field and the distribution of fields across types.

Finally, the joint distribution of fields across pol-

[11] The role of policy variables in determining pollution potential is discussed in more detail under Step 2, where policy-induced changes at the intensive margin are discussed.

lution potential[12] and productivity must be determined. This distribution can be depicted graphically in the standard two-dimensional graph used in the microparameter model. For purposes of illustration, a possible microparameter distribution for a region comprised of twenty fields is shown in Figure 2, where each circled number corresponds to a given field, with the coordinates representing its productivity and pollution potential.[13] For example, field #17 in the southwest corner is a low pollution/high productivity field of ICC. Of course in a real application, information at this stage would be represented and manipulated mathematically, rather than graphically.

Given the joint distribution of ICC fields, we are now in a position to begin to analyze the effects of pollution-control policies. As discussed above and emphasized by Antle and Just, responses can occur at both the intensive and the extensive margins. Since the original microparameter model of Hochman and Zilberman assumed fixed proportions, their focus was on extensive-margin responses (i.e., changes in the survival region). Figure 2(a) depicts possible changes in the survival region induced by two alternative policies, A and B. In response to the new policy, all fields below the survival frontier continue to produce ICC after the policy is introduced while those above the line would either be idled or switched to an alternative practice, like a substitute crop. This is discussed in more detail below under Step 4. As discussed above, different policies have different effects on the survival region.

When substitutability exists, a policy-induced change at the intensive margin is expected as well. As examples, if the policy is a tax on fertilizer, farmers can respond by reducing use. If the policy is a ban on use of a specific pesticide, farmers can respond by switching to substitutes. Likewise, if the policy is liability for damages from contaminated water, they may alter the timing or method of application. These responses can be predicted by an economic model of decision making such as the one described above.

If responses at the intensive margin are substantial, they can change the pollution-potential classification of a given farming practice–site characteristic combination. For example, if pesticide use is reduced sufficiently, then irrigated corn on fields in the second-highest range of DRASTIC scores may switch from having a high pollution potential, as depicted in Figure 1, to a medium potential. Thus, changes at the intensive margin are represented by changes in the classification of the cells in Figure 1.

These changes in pollution potential, of course, cause changes in the joint distribution of pollution and productivity. Suppose, for example, that fields #4, #7, #8, and #10 are irrigated corn on land with the second-highest range for the DRASTIC score (row 2, column 1 in Figure 1). Without the policy, this combination yields high pollution potential. If policy response on the intensive margin reduces this potential to "medium," the joint distribution changes. Figure 2(b) illustrates these possible policy-induced adjustments. If the policy is targeted at pollution reduction, the moves that occur[14] should all be horizontal[15] and leftward. A comparison of the joint distributions before and after these moves provides an indication of the intensive effects of the policy change on ICC fields.[16]

Step 3: Determining the Spatial Distribution of Response

Figure 2 can be used to determine the aggregate effect of a policy on pollution from ICC fields, such as the acreage with "high" pollution potential with and without the policy. However, it does not provide any indication of the spatial distribution of the effect. For example, it does not allow us to determine where the remaining high-pollution fields are and whether they are dispersed or clustered. Yet, this spatial dimension of the impact may be important for policy design. A cluster of high-pollution fields located close to a population center for which the underlying aquifer is the source of drinking water would generally demand a different policy response than the same acreage widely dispersed or located far from population centers. Thus, to assess the desirability of a given policy change,

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[12] In Figure 2 we make no assumption about the correlation between the productivity and pollution potentials. However, if soil type influences both, then the two would clearly be correlated. See footnote 1 and the associated text, as well as Antle and Just, for related discussion.

[13] To keep the figure manageable, we consider here a very small (20-field) region. Clearly the approach could be applied to a much larger region, where these distributions would be represented numerically, rather than graphically. If there were more than one microunit with the same coordinates, they would be "stacked" on top of each other in a third dimension. We assume that this is not the case to avoid the need for a three-dimensional depiction of the joint distribution.

[14] The position of a field in Figure 2 will remain unchanged if the response is not sufficiently large to change the classification of its cell in Figure 1.

[15] The adjustment will have no effect on productivity as measured by exogenous site characteristics. It may, of course, affect output, which is determined by a combination of site characteristics and input decisions. In this case, the adjustments at the intensive and extensive margins are related since input adjustments will determine the parameter values for which profits equal zero. The determination of the survival frontier must reflect these adjustments.

[16] While here we are depicting the intensive-margin effects graphically, in an actual application they would be represented by change in predicted levels of inputs and, correspondingly, pollution potential.

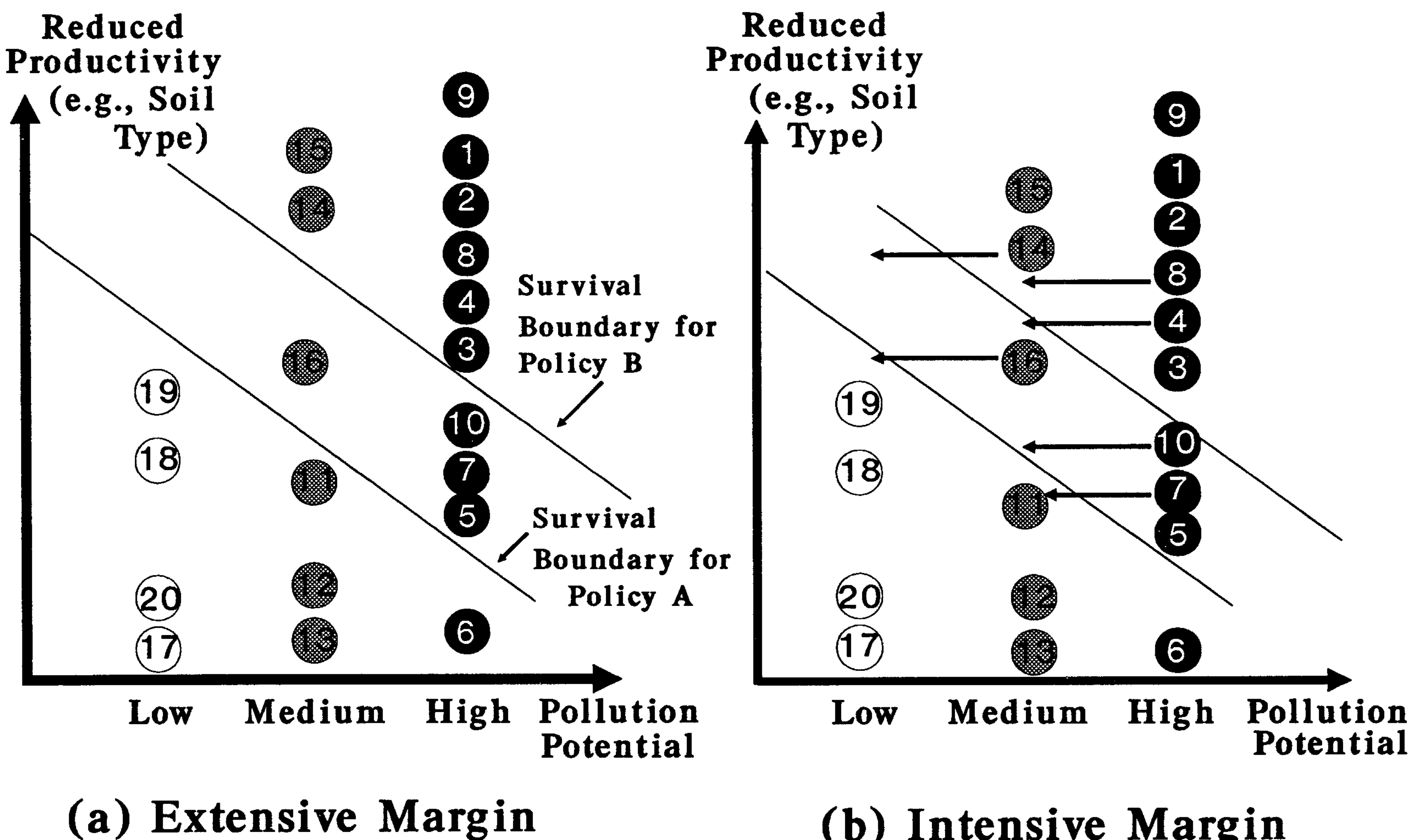

Figure 2. Effect of Policy on Farming Practice

information about the spatial distribution of responses is needed.

As discussed above, GIS is a useful tool for representing information spatially. With the help of a GIS, the fields in Figure 2 could be reordered spatially and represented on a map showing their geographic locations. In addition, information about their geographical locations could be coupled with other information amenable to inclusion in a GIS, such as nearby population densities, surrounding land uses, sole-source aquifers, and public wells.

The two "maps" in Figure 3 show the combined intensive- and extensive-margin effects of implementation of Policy B, as determined in Figure 2, for the case of dispersed contamination. Both before and after the policy change, the surviving fields with high or medium pollution potential (those of high concern) are dispersed geographically. It is possible, however, that these same surviving fields could have been clustered, as depicted in Figure 4. As noted above, knowing whether the distribution is dispersed or clustered could have important implications for policy design.

Step 4: Determining Crop-Mix Effects

Thus far the discussion has focused on a single farming practice such as ICC. A complete analysis of policy impacts requires, of course, that Steps 2 and 3 be applied to each of the *K* farming practices included in the columns of Figure 1. In addition, however, the possibility of switching farming practices in response to policy changes must be considered since this could also affect contamination levels.

In the original Hochman and Zilberman model, microunits that did not survive a policy change were assumed to become idle. In our context, however, "not surviving" could mean either that the land is no longer used for farming or that it is converted to an alternative farming practice. The choice between taking the land out of production all together and switching to an alternative farming practice is, of course, part of the farmer's economic decision problem. Thus, farm-level decision models could be used to predict these adjustments.[17]

Switching a field from one farming practice to another may or may not affect its pollution potential. For example, from Figure 1 it can be seen that switching a field of land within the highest range of DRASTIC scores from farming practice 1 to practice 2 will not change its pollution potential; under either farming practice, that potential would be high. Alternatively, switching any field with the second-highest range for DRASTIC scores from farming practice 1 to practice 2 would reduce its pollution potential from high to medium.

In terms of the geographical representation of policy effects, the role of switches in farming practices could be included as follows. A field that switches from, say, practice 1 to practice 2 in response to the policy would be shown on the before-policy GIS map for farming practice 1 but not on the after-policy map. For instance, if fields #2 and #8 change farming practice, they show up on the "before" map of Figure 3 but not on the "after" map. Instead, they are shown on the after-policy GIS map for farming practice 2, with the corresponding pollution potentials determined by column two of Figure 1. Likewise, any fields that switched to ICC would be included in the after-policy GIS map for farming practice 1.

The above procedure provides "before and after" maps of the fields in each of the *K* farming practices, which distinguish fields by pollution potential and reflect policy-induced switches among practices such as crop-mix changes. To determine the total effect of a given policy, the maps must be combined by overlaying them. Only then can the geographical distribution of the responses at both the intensive and the extensive margins be seen.

The overlaying could be easily accomplished with a GIS, providing a visual representation of the policy results. These results could also be expressed numerically by aggregating units within a geographic region of interest. For example, suppose that a policy was implemented to reduce total pollution inputs into an aquifer. The total pollution input, following implementation of the policy, could be determined by applying an appropriate numerical algorithm to the GIS system to aggregate the data resulting from the application of the microparameter model. If contaminant flow towards specific wells within the aquifer is of concern, a more complex algorithm could be developed that applies weights to pollution inputs according to distance to public wells, accounting for speed and direction of groundwater flow (see, for example, Zeitouni and Opaluch), assuming that appropriate data are available.

The microparameter distribution and GIS models appear to complement each other. Both models are particularly useful for retaining disaggregate information and for using the disaggregate information within a more aggregate decision environment. The microparameter model allows joint and

[17] Many existing models predict the effects of different types of policies on crop mix and total acreage. In most cases, however, they do not include information about site characteristics in their predictions. In reality, we would expect crop-mix decisions to depend on those characteristics.

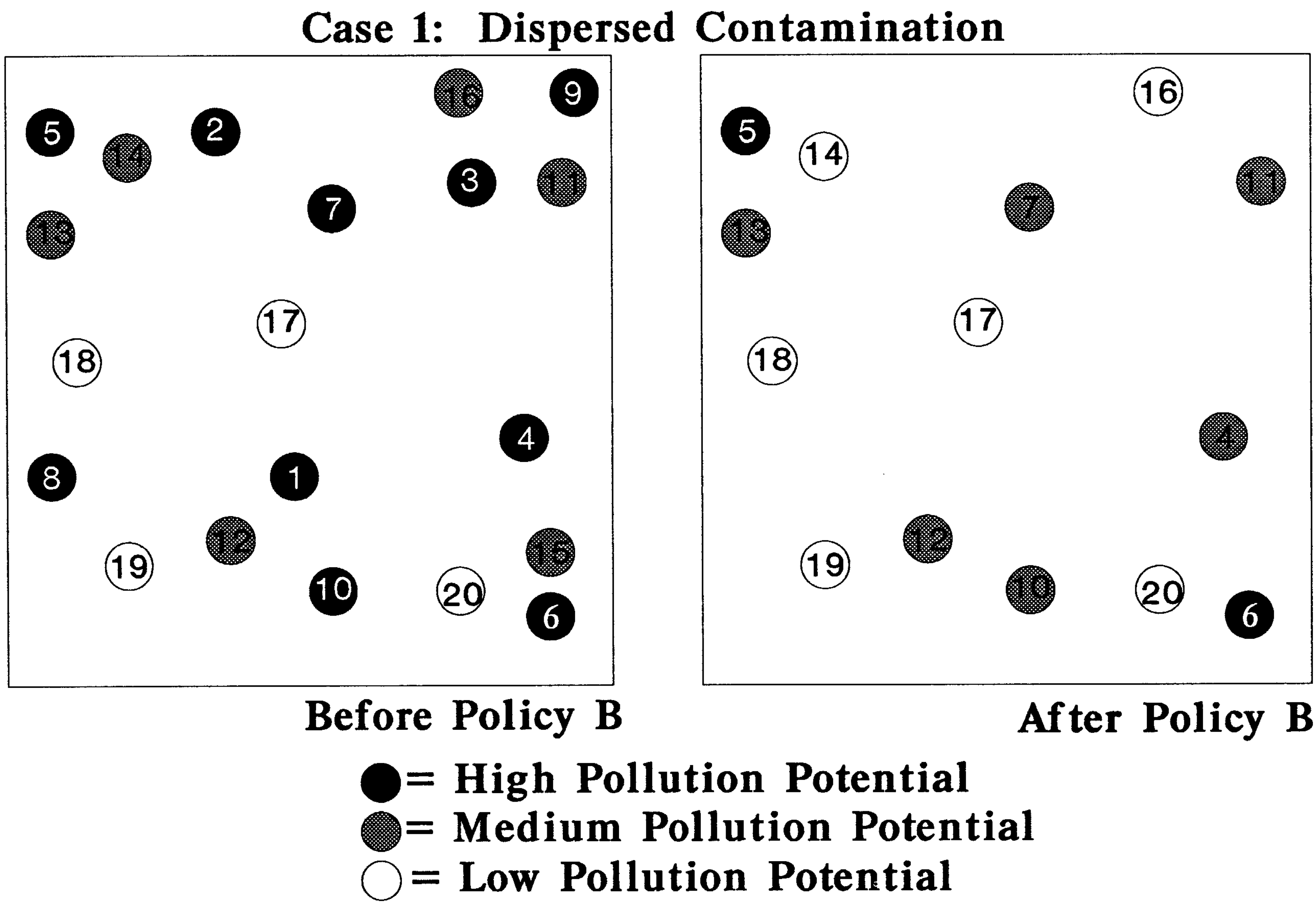

Figure 3. Spatial Distributions of Acres in Farming Practice 1

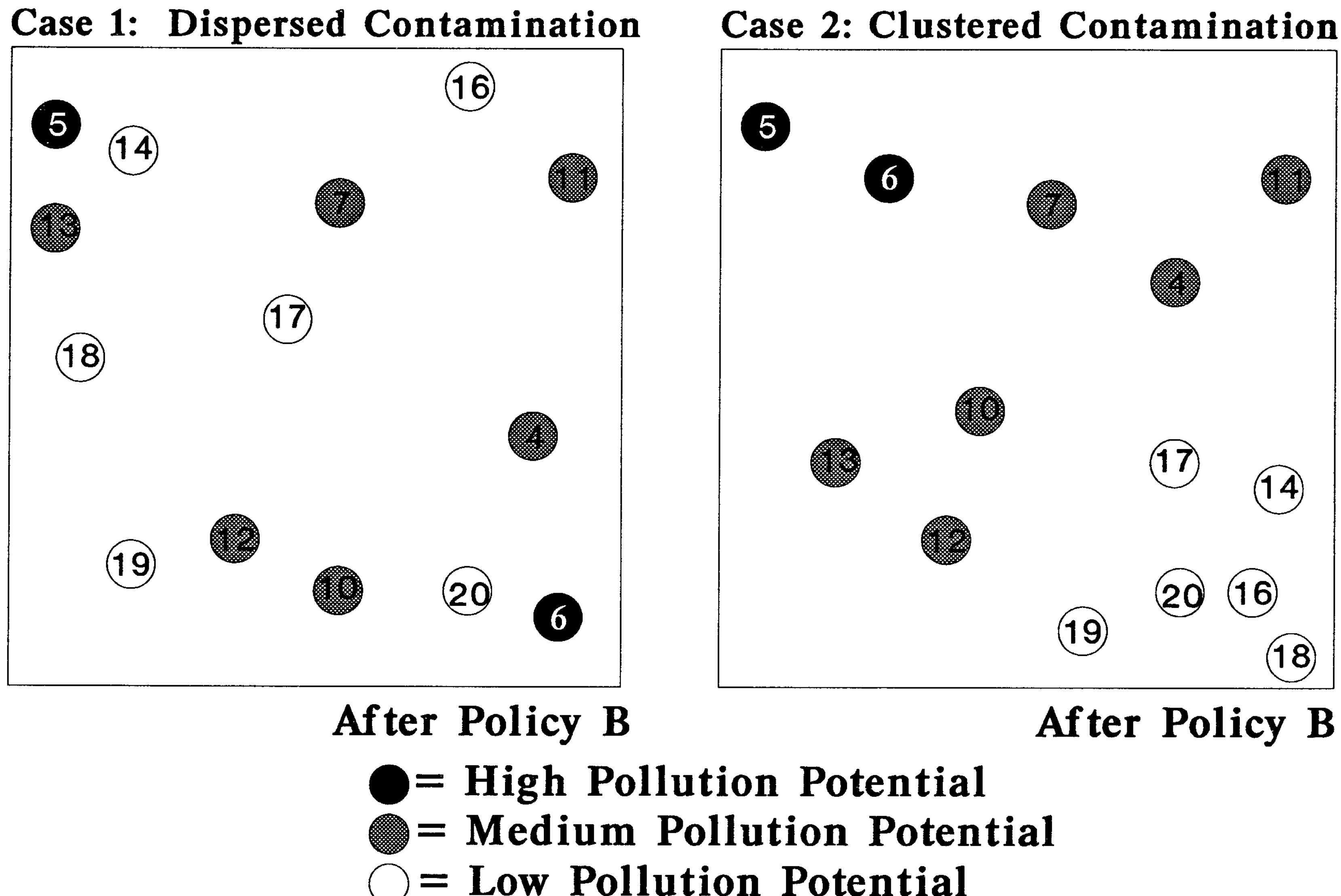

Figure 4. Spatial Distributions of Acres in Farming Practice 1

independent analysis of disaggregate and aggregate results. The GIS system adds a spatial dimension that may be critical for policy evaluation when geographic concentration of polluting activities or proximity of impacted systems, such as public wells, are an important policy concern. The GIS framework also simplifies data collection and organization for the microparameter model. The spatial dimension of GIS data facilitates combination of independently collected data sets. For example, independently collected GIS data maintain disaggregation and a spatial dimension that allows one to link the data sets to provide joint distributions for attributes such as land use, soil type, and depth to groundwater, as opposed to providing only independent marginal distributions on each, which greatly limit usefulness of the data.

Currently available or future GIS data could allow implementation of microparameter models that otherwise would require extensive and costly primary data collection. Furthermore, GIS data sets are rapidly gaining momentum, which can lead to significant improvements in data availability. The more extensive the data become, the more useful GIS systems will be and the more likely that the data sets will be maintained and extended, further increasing their usefulness. Thus, this represents a potentially rich and improving source of economic data, linked at a relatively disaggregate level.

Potential Problems with Implementation

While there appears to be considerable potential for linking microparameter economic models together with GIS to analyze the impacts of alternative policies, some major challenges would have to be overcome. Some of these are inherent in the GIS approach, while others stem from practical problems of implementation.

First is the problem of defining a microunit. In the above discussion, we defined each field to be a separate microunit. However, it is unlikely that field-level data will be available for the relevant variables. Thus, a more aggregate definition will probably have to be used, perhaps based on the resolution of the GIS that is used. Even in this case, however, the appropriate decision unit for the microparameter model of economic decisions is likely to differ from the scale used for the GIS data, creating a problem of matching the two grid sizes. If the GIS grid is larger than the decision unit, as is likely with more aggregate GIS data at a national or regional level, then the site characteristics within a GIS cell would simply be assumed to apply to all farms within that cell. For areas with considerable local diversity, this would obviously be problematic. Alternatively, if detailed site data are available, then the GIS grid is likely to be smaller than the size of the decision unit. In this case, two approaches are possible. One is simply to aggregate the GIS data to the farm level to determine a single representation of characteristics for a farm based on either predominant characteristics or a weighted average of the different characteristics within the farm. A second approach is to incorporate the entire distribution of characteristics into the economic decision model. While this latter approach is theoretically more correct, it complicates use of the microparameter model since farms would no longer be able to be ordered according to a single characteristic.

A second problem with linking a GIS and a microparameter model stems from the descriptive nature of GIS versus the predictive nature of the microparameter models. The strength of GIS is in providing a spatial description or map of sites with a particular combination of characteristics. To be useful for policy analysis, one would like a description of these sites with and without the policy change. This would require that for each individual cell within the GIS, we be able to predict the response of that cell to the policy change. However, our economic decision models are intended to predict the response of a representative farm with certain characteristics, not a particular farm with those characteristics. Thus, these models cannot reliably predict the response of any given cell within the GIS.

The prediction problem can be reduced somewhat through aggregation. For example, we could apply the microparameter model at the microunit level as described above (Step 2) but present the results at a more aggregate level, such as the county level, to increase reliability. Under this approach, the maps illustrated in Figure 3 would not show individual microunits; instead, the microunits within a county or other relevant region would be aggregated to determine a pollution potential for that county, which in turn would be depicted on the map. This provides an indication of how the pollution potential of the county as a whole would change, without requiring reliability for the predicted changes of each individual microunit.

While the above two problems in applying the proposed methodology are inherent in the GIS approach, a number of practical problems exist with the current state of the art of GIS use. For example, as noted above, the GIS gives a description of site characteristics and effectively presents a snapshot of a given area at a particular point in time. Unfortunately, the process of collecting and converting the data to construct this picture is expensive and time-consuming, thereby preventing frequent updating. As a result, the current data in a GIS may reflect some site characteristics as much as ten or twenty years ago. For characteristics that do not change rapidly, such as geology and topography, this time lag in collection and use of the data is unimportant. However, for characteristics that can change considerably over short periods of time, such as land use or cropping patterns, use of data collected over a decade ago can introduce significant errors into the analysis. Improvements over time in remote-sensing technology could help to alleviate this problem.

Finally, most applications of GIS to date have focused on relatively small areas such as a watershed. There are at least two reasons for this. The first is data availability. If data must be collected, the expense is generally related to the size of the area covered and thus applications to large areas may be prohibitively expensive. Second, depending on the cell size of interest, limitations regarding data storage may make such applications infeasible. Thus, if GIS is to be fruitfully used in the analysis of national/regional policies aimed at site-specific problems, some way must be found to overcome the dimensionality problem without sacrificing the site-specific information that is the advantage of the combined GIS/microparameter approach. Again, advances in the technology could help to resolve these problems.

Two possible approaches to the dimensionality problem exist. The first is to aggregate to reduce the number of cells (i.e., define larger microunits with characteristics that are representative of the units contained therein). While aggregation reduces the dimensionality problem, it does so at the cost of accurately capturing the role of site characteristics. Alternatively, the dimensions of the analysis could be reduced by working with a subset of cells. For example, we could identify specific regions on which to focus and work only with the cells in those regions. We would presumably want to target regions where policies are likely to have the largest impact on groundwater quality.

Summary and Conclusions

Control of groundwater contamination from agricultural sources poses a particularly challenging problem for national and regional policy makers because of the site-specific nature of most contamination problems. Methods are needed to analyze national or regional policies while still incorporating the role of site characteristics in determining policy impacts. To date, most studies either focus on aggregate conditions, completely ignoring site-specific conditions, or are so site-specific that the results cannot be easily used for aggregate analysis.

In this paper we have proposed a methodology for incorporating site characteristics into aggregate analysis. It builds on the microparameter approach originally proposed by Johansen and later extended by Hochman and Zilberman (1978, 1979) and Antle and Just. It goes beyond previous work, however, in suggesting how the basic microparameter model could be coupled with information about the spatial distribution of microunits to assess more fully the impacts of alternative policies. In addition, we illustrate how the methodology could actually be implemented through a simple example.

The microparameter model and GIS data systems appear to be strongly complementary. The GIS system appears to be a natural extension of the microparameter distribution model where the axes express location rather than values of microparameters. The spatial dimension of the GIS model allows for linkage of independently collected data sets that provide joint disaggregate distributions on these data rather than independent marginal distributions on each attribute or aggregate values. This may allow application of microparameter models without the need for extensive primary data collection. In addition, GIS data systems have obtained a momentum that, hopefully, will lead to maintenance and extension of these data sets. This implies that GIS systems may become a very valuable source of spatially oriented data such as land attributes. This is one type of data urgently needed for site-specific evaluation of various groundwater policies.

While implementation of the methodology involves some potential problems, these do not appear to be insurmountable. As is usually the case with empirical analysis, the actual application of the theoretical model to a specific problem will inevitably involve some compromises between what is theoretically correct and what is practical given data and other resource limitations.

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