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ASSESSING THE ECONOMIC VALUE OF SOIL INFORMATION USING DECISION ANALYSIS TECHNIQUES

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An important issue in the making of soil surveys is quantifying the value of the information generated and contained in the soil survey. This study uses decision trees, Bayes' Theorem, and map quality evaluation procedures to assess the economic value and economic efficiency of soil surveys. To develop this methodology, a case study is used that considers three different scenarios in which the level of information regarding soil changes. The three scenarios are: (i) site-specific soil information is unavailable, (ii) perfect site-specific soil information is available (not realistic), and (iii) imperfect site-specific soil information is available. The calculated economic value of this hypothetical soil survey was US$ 17.14 ha^{-1} year^{-1}, which is higher than the estimated soil survey cost of US$ 2.09 ha^{-1}. This simple comparison indicates that the soil survey is cost effective and that its costs would be paid off with the gain from the first year of its application. The combination of the calculated economic efficiency (55%) with the physical quality of the map (total percent correct in the map was 80%) allowed a better understanding of the actual value of the soil survey. The use of this method provided a means of calculating analytically a more complex and realistic value of soil surveys. (Soil Science 2000;165:971–978)

Key words: Soil, soil survey, decision analysis, decision tree, probability.

SOIL scientists have been trying to quantify the value of the information contained in soil resource inventories for many years. Although some governments have long-standing traditions of supporting soil survey efforts for the good of the general public, the value of these programs does not go unquestioned. Less affluent countries have been reluctant to support soil surveys, in part because they cannot assess the return on their investment either before or after the work is done. Additionally, private interests have funded or conducted soil surveys for the purpose of improving land management because of a perceived or determined return on their investment, but their methods for assessing soil survey value are either nonquantitative or are proprietary. For these and other reasons, there is a general need to quantify the value of soil information that is characteristically a time-consuming and costly venture. Methods that allow interested parties to quantify the environmental, social, or economic improvements brought by the acquisition of soil survey information are needed.

Several researchers have achieved the conceptualization and the development of soil survey quality indicators together with the evaluation of soil survey costs. Beckett and Burrough (1971) compared different soil maps and related them to map precision standards. Bie and Beckett (1971) evaluated the efficiency of soil maps by assessing their quality and production costs. Western (1978) defined survey value as "the balance between quality and cost," emphasizing that the term "quality" has different meanings for users of soil surveys than for makers of soil surveys. He stated further that if soil survey quality could be measured by its economic benefits, survey value could be expressed as a ratio between the cost to

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carry out the soil survey and the benefits it produces. However, he affirmed that "it is in fact extremely difficult to quantify the benefits of soil survey," and that these benefits depend on the useful life of the survey. Assuming that one could create a figure for soil survey quality expressed as a percentage, the effective cost of a soil survey of known quality on a per hectare basis could be calculated as shown in Eq. (1) (Western, 1978).

$$\text{Effective cost/ha} = 100 * [(\text{actual cost/ha})/(\text{\% quality})] \quad (1)$$

However, in his study, the percent quality was not quantified; he emphasized that survey value "is difficult to quantify because survey quality is rarely defined."

More recently, Dent and Young (1981) used a simplified example to illustrate methodologically that the economic benefit of a soil survey can be calculated by comparing the profitability from different management systems on each of a number of mapping units. In retrospect, several parameters have been used to measure the usefulness of a soil survey: value, utility, quality, and efficiency. Each of these terms has been used in different contexts and with different purposes. Sometimes the quality of soil surveys has been assessed in terms of the precision of the soil maps and soil survey reports. At other times, quality has been defined as the usefulness of survey outputs. The first aspect is certainly more important for surveyors, who want to maximize the precision and accuracy of the maps and survey reports. Although the users normally assume that the information contained in a survey is correct, they evaluate the quality of the information by the improvements that can be obtained and by the productive use of that information. The users will measure the success of a soil survey by the precision of the statements that can be made about the soil within each mapping unit.

In an open and competitive market, a good measurement of the quality of a soil survey would be the economic benefits generated by the use of the information. These benefits would depend on changes in the production system resulting from the use of the information, which in turn would depend on the accuracy and precision of the information.

In this study, we propose a method for using decision analysis techniques to derive a quantitative economic value of soil surveys. Although the method does not deal directly with the quantification or improvement of the quality of the information contained in a survey, it does take into account the accuracy of the information contained in a survey to evaluate its economic value. The method is based on the assumption that proper use and interpretation of soil surveys can reduce land management risks and increase quantifiable outputs. Therefore, a minimum soil survey value can be assessed through the quantification of these improvements. The case study defined and presented by Dent and Young (1981) will be used to illustrate the method and to introduce the decision analysis techniques and concepts.

MATERIALS AND METHODS

All decisions and associated uncertain events are analyzed and placed in the context of a decision tree (Clemen, 1999) that shows the structure of the decision-making process and quantifies the probabilities of the possible outcomes. Risks and/or outputs associated with the interactions of all considered land uses and all soil types are evaluated by including the probabilities of their occurrence. In situations requiring decisions among different options, the best decision will be the one with the highest or lowest payoff, depending on whether the objective is to maximize or to minimize the output variable being used for evaluation. An analysis may be repeated to represent several levels of accuracy of the available soil information and thereby determine the effects of the quality of the information on its value.

Hypothetical Soil Survey Area

We have applied our analysis to the example defined by Dent and Young (1981) updating it by converting economic values to January 2000 United States dollars. The hypothetical soil survey area is a 100-hectare farm, having 40 hectares of loamy soils, 40 hectares of sandy soils, and 20 hectares of shallow soils. Although this is a hypothetical site, it would be possible to find such soils occurring as an association of coarse-loamy, mixed, mesic Typic Dystrudepts; mixed, mesic Lamellic Udipsamments; and coarse-loamy, mixed, mesic Lithic Dystrudepts within landscapes comprising a small dairy farm in the Hudson River Valley in New York State. The management systems under consideration in this example include normal cropping, cropping under high fertilization, and pasture.

Decision Analysis Techniques

The decision analysis techniques described by Clemen (1999) and the accuracy assessment procedures of Congalton (1999) were used to assess the value of this specific purpose soil survey. Decision trees were produced by Data 3.0 (TreeAge, 1997). In the final analysis, the value of the soil survey was compared with its estimated costs (Bie and Beckett, 1971).

RESULTS AND DISCUSSION

The workings of decision tree analysis are best illustrated starting with the simplest scenario described by Dent and Young (1981), which assumes that there is no information about the types of soils in the farm, followed by examples that take into account soil survey information of increasing complexity.

Scenario 1: Site Specific Soil Information Is Unavailable

Assuming net returns under each management system as shown in Table 1, the best uniform management system, normal cropping, resulted in an annual net return for the farm of US$ 9264.00. However, by differentiating the three types of soil and applying the most profitable use to each soil type, they found an annual net return of US$ 12,352.00 for the entire farm [40 ha*(US$ 193.00 ha^{-1}) + 40 ha* (US$ 96.50 ha^{-1}) + 20 ha* (US$ 38.60 ha^{-1})]. Although this analysis is simple and can easily be displayed in table format, this situation can be schematized in a decision tree with the same results. Figure 1 illustrates the function of the decision tree. The soil proportions are termed prior probabilities and are defined as s_{lo} = 0.4 for the loamy soils, s_{sa} = 0.4 for the sandy soils, and s_{sh} = 0.2 for the shallow soils. The objective is to maximize the Expected Monetary Value (EMV) by choosing among three possible decisions with regard to land use, for which the output depends on the prior probabilities related to soils (s_{lo}, s_{sa}, and s_{sh}). Note that the EMV for each decision depends on the prior probability of each soil type and on the output that would be generated by it. In the case where we want to maximize net returns, the best decision is the one that has the highest EMV. By using EMV as payoff, it is assumed that there are no risk preferences in the decision-making process (risk neutral decision-maker).

In Fig. 1, decision nodes are represented by squares, probability nodes by circles, and output nodes by triangles. Under each probability branch the prior probability of each event is given. When read from left to right, the tree represents a decision regarding land use type first and occurrence of outputs from each soil type second.

The EMV can be calculated for each probability node by (Clemen, 1999)

$$\text{EMV} = \Sigma\ (p_i P_i) \tag{2}$$

where p_1 = the probability of each soil occurring and P_1 = payoff ($).

The solution of the decision tree is shown in Fig. 2. The EMV of each decision branch is shown in a box. If the entire 100 ha-farm was used for normal cropping, the EMV would be US$ 92.64 ha^{-1} year^{-1}, as previously determined by the simple table approach. Likewise, it would be US$ 69.48 ha^{-1} year^{-1} for use with heavy fertilization, and US$ 46.32 ha^{-1} year^{-1} for use with pasture. The EMV of the best decision for using the complete farm under one crop, in this scenario normal cropping, is shown in Fig. 2 in a box next to the main branch. The best decision is to crop the land with normal cropping because it has the highest EMV (US$ 92.64 US dollars ha^{-1} year^{-1}).

TABLE 1

Net returns for three land uses in each of the three soil types (adapted from Dent & Young, 1981)

Soil type	*Normal cropping*	*Heavy fertilization*	*Pasture*
	Management system		
	US dollars ha^{-1} year^{-1}		
Loam	193.00	154.40	57.90
Sand	77.20	96.50	38.60
Shallow	−77.20	−154.40	38.60
	US dollars year^{-1}		
Loam, 40 ha	*7,720.00*	6,176.00	2,316.00
Sand, 40 ha	3,088.00	*3,860.00*	1,544.00
Shallow, 20 ha	−1,544.00	−3,088.00	*772.00*
Total	9,264.00	6,948.00	4,632.00

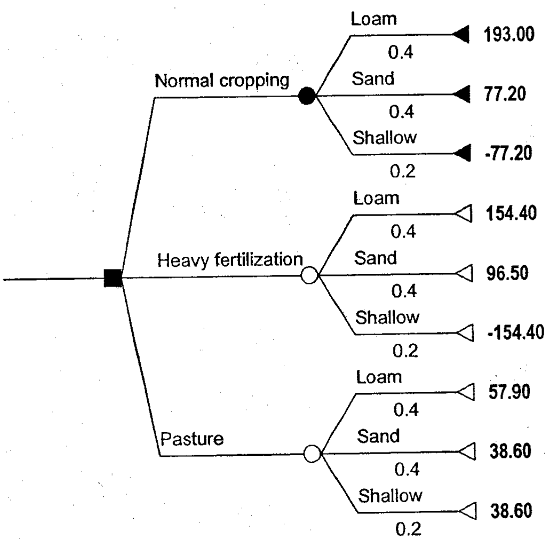

Fig. 1. Decision tree structure for selecting optimal land use type without site-specific soil information.

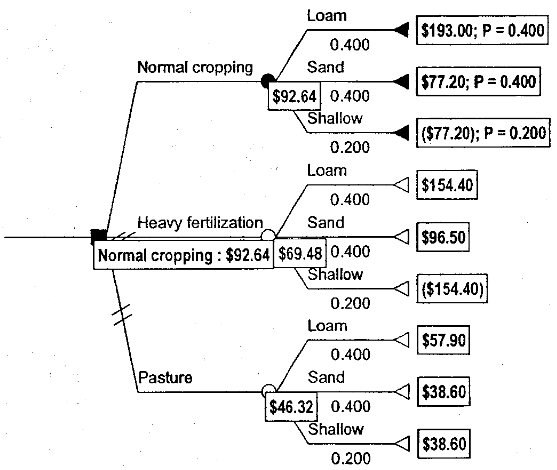

Fig. 2. Solved decision tree for selecting optimal land use type without site-specific soil information.

Scenario 2: Perfect Site Specific Soil Information

In this scenario, we assume that the soil distribution on the farm is known through a soil survey and that the information is perfect, i.e., soil performance in response to management is exactly as predicted by the soil survey. For each soil type, the user could select the most profitable land use type for that soil, thereby maximizing EMV for the whole farm. This analysis is performed by changing the sequential order on the decision tree (Fig. 3). The soil types are taken into account before the land use types. In this scenario, the best decision is to use the loam soils for normal cropping, the sandy soils for cropping with heavy fertilization, and the shallow soils for pastures. The EMV in this situation would be a net return of US\$ 123.52 ha^{-1} $year^{-1}$ or US \$ 12,352.00 for the whole farm. Again, this amount (US\$ 12,352.00) equals the value found by Dent and Young (1981) using the simple table approach.

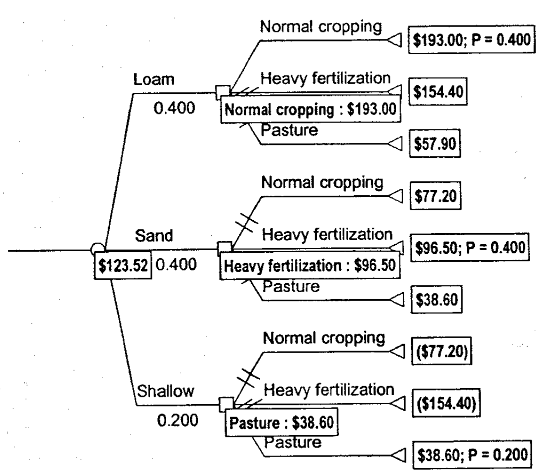

Fig. 3. Solved decision tree for optimizing land use across soil types assuming perfect site-specific soil information.

The difference between the EMVs for the two scenarios, with perfect site-specific soil information and without information, is called the Expected Value of the Perfect Information (EVPI), as calculated by Clemmen (1999) in Eq. (3).

$$\text{EVPI} = \text{EVwPI} - \text{EVwoPI} \qquad (3)$$

where: EVwPI = Expected Value with Perfect Information and EVwoPI = Expected Value without Perfect Information.

In this example, EVPI = 123.52 − 92.64 = US\$ 30.88 ha^{-1} $year^{-1}$, or US\$ 3088.00 for the whole farm per year. This means that if we have a soil survey with perfect site-specific soil information, and assuming that land management can be matched accordingly, the benefits derived from the soil survey would be US\$ 30.88 ha^{-1} $year^{-1}$.

This value for EVPI indicates a maximum potential value. It can be estimated for existing soil survey information, or it may be estimated in advance before making a soil survey. In the latter case it quantifies potential profits that may be derived from making the soil survey. In addition, soil information from existing soil surveys of similar landscapes located in adjacent areas could be used to obtain the prior probabilities.

Scenario 3: Optimizing Land Use in Each Soil Type Assuming Imperfect Site-Specific Soil Information

Although the Expected Value of the Perfect Information (EVPI) assumes that the information is precise, most of the time it is not. There are many sources of error inherent in the procedures of gathering and processing soil information. A more realistic value of the information is the Expected Value of the Sample Information (EVSI), which can be calculated using Bayes' Theorem. For estimating the real value of the soil survey, an assessment of the accuracy of the soil survey is needed. This accuracy assessment is used for generating conditional probabilities and can be obtained by sampling and field checking.

Confusion Matrices

Congalton (1999) suggested the use of confusion matrices for quantifying the uncertainties related to the information contained in a spatial database. The method is based on a comparison of the actual classification given by the soil survey with that obtained by field checking. It allows identification of the nature and the frequency of

TABLE 2

Hypothetical confusion matrix used for map accuracy assessment expressed in proportions

Mapped in the soil survey	Found in field checking sampling				
	Loam	Sand	Shallow	Total	User's accuracy
Loam	0.300	0.050	0.000	0.350	0.857
Sand	0.050	0.275	0.025	0.350	0.785
Shallow	0.025	0.050	0.225	0.300	0.750
Total	0.375	0.375	0.250	1.000	
Producer's accuracy	0.800	0.733	0.900		

the errors in the survey. Confusion matrices are tables where information on mapping units (as represented on the map) are entered in the rows and data on the same map units (as found to actually occur in the field) are represented in the columns. The table is generated in the field by collecting an adequate number of samples and placing the data in a confusion matrix. The data entries in the table are proportions between the number of observations that fall into a given slot in the table divided by the total number of observations. The proportions represent the correspondence between soils as shown on the map and actual soil occurrences as determined by field checking. Table 2 shows hypothetical proportion values for the example in this study. The use of this procedure before the execution of a soil survey could also be achieved by assessing subjective probabilities, using information from previous soil surveys and the experience of the survey team.

The information included in confusion matrices allows evaluating the quality of a soil survey. From Table 2, it can be seen that the overall percent of correct information is 80% [100(0.300+0.275+0.225) = 80%], and the soil surveyor's accuracy is 100(0.300/0.375) = 80% for loam, 100(0.275/0.375) = 73.3% for sandy soils, and 100(0.225/0.250) = 90% for shallow soils. The user's accuracy is 100(0.300/0.350) = 85.7% for loam, 100(0.275/0.350) = 78.6% for sand, and 100(0.225/0.300) = 75.0% for shallow soils.

In this method, the proportions between each mapping unit as shown in the map and its actual occurrence in the field are the information that is used to evaluate the quality of a soil survey. Conditional probabilities may be obtained from the matrix using Eq. (4).

$$p(I_i/s_j) = \frac{p(\text{soil is } i \text{ and the soil survey mapped it as } j)}{p(\text{soil is } j)} \quad (4)$$

where $p(I_i/s_j)$ is the probability of an area having soil type j when the soil survey says that the area has soil type i, with i and j considered to be loam, sandy, or shallow soils. Calculated conditional probabilities for our example are given in Table 3.

Using the prior and conditional probabilities, the marginal probabilities (I_i) that a soil can be mapped correctly as a specific soil type can be calculated, as follows

$p(I_{lo}) = p(s_{lo})p(I_{lo}/s_{lo}) + p(s_{sa})p(I_{lo}/s_{sa}) + p(s_{sh})p(I_{lo}/s_{sh}) = 0.4(0.80)+0.4(0.13)+0.2(0.00) = .372$

$p(I_{sa}) = p(s_{lo})p(I_{sa}/s_{lo}) + p(s_{sa})p(I_{sa}/s_{sa}) + p(s_{sh})p(I_{sa}/s_{sh}) = 0.4(0.13)+0.4(0.74)+0.2(0.10) = 0.368$

$p(I_{sh}) = p(s_{lo})p(I_{sh}/s_{lo}) + p(s_{sa})p(I_{sh}/s_{sa}) + p(s_{sh})p(I_{sh}/s_{sh}) = 0.4(0.07)+0.4(0.13)+0.2(0.90) = 0.260$

This information was included in the context of the land use decision in our example. The posterior probabilities ($p(s_i/I_j)$) that were calculated using Eq. (5) are shown in Table 4. They are the probabilities that the soil type indicated by the soil survey will really occur. For example, the probability that a site has soil loam because the soil survey mapped it as loam is:

$p(s_{lo}/I_{lo}) = p(s_{lo})\ p(I_{lo}/s_{lo})/p(I_{lo}) = 0.4(0.80)/0.372 = 0.860$ or

TABLE 3

Conditional probabilities calculated from the confusion matrix

Soil survey	*Field checking*		
	Loam	*Sand*	*Shallow*
Loan (I_{lo})	$p(I_{lo}/s_{lo}) = 0.300/0.375 = 0.80$	$P(I_{lo}/s_{sa}) = 0.050/0.375 = 0.13$	$p(I_{lo}/s_{sh}) = 0.000/0.250 = 0.00$
Sand (I_{sa})	$p(I_{sa}/s_{lo}) = 0.050/0.375 = 0.13$	$P(I_{sa}/s_{sa}) = 0.275/0.375 = 0.74$	$p(I_{sa}/s_{sh}) = 0.025/0.250 = 0.10$
Shallow (I_{sh})	$p(I_{sh}/s_{lo}) = 0.025/0.375 = 0.07$	$P(I_{sh}/s_{sa}) = 0.050/0.375 = 0.13$	$p(I_{sh}/s_{sh}) = 0.225/0.250 = 0.90$

TABLE 4

Posterior probabilities ($p(s_i/I_j)$)

	j		
i	*loam*	*sand*	*shallow*
loam	0.860	0.141	0.108
sand	0.140	0.804	0.200
shallow	0.000	0.055	0.692

$$p(s_{lo}/I_{lo}) = \frac{\text{p(it is a loam and the soil mapped as loam)}}{\text{p(soil survey mapped as loam)}} \quad (5)$$

Integrating Confusion Matrices with Decision Tree Analysis

A new decision tree can be generated using the probabilities of occurrence of each soil (I_i), and the posterior probabilities $p(s_i/I_j)$ (Fig. 4). This tree can be looked upon as having the following sequence: (i) the farmer examines the type of soil as predicted by the soil survey, (ii) the land use types are considered, and (iii) the payoffs are calculated by the tree for each actual soil type in the area. The posterior probabilities are used in each combination of land use, and actual soil types are used as the weights for the expected values (s_i). The results are specified for each combination of actual soil type and land use.

The maximum EMV of this new tree is defined as the Expected Value With Sample Information (EVwSI), and has a value of US$ 109.78 ha^{-1} year^{-1}. Subtracting this EVwSI from the original EMV, which now is called Expected Value Without Sample Information (EVwoSI), the Expected Value of the Sample Information (EVSI) can be determined. This is a measure of the real value of the soil survey. In this case, EVSI = EvwSI − EVwoSI = 109.78 − 92.64 = US$ 17.14 ha^{-1} year^{-1}, which represents the value of a soil survey with the hypothetical accuracy given in our example.

The economic efficiency (EE) of the soil survey is calculated by Eq. (6)

$$EE = 100\ (EVSI\ /\ EVPI) \quad (6)$$

In this example, the economic efficiency is 17.14/30.88 = 0.5550 or 55.50%. This percentage represents the value of the soil survey with the accuracy given in Table 3 relative to the value of a perfect soil inventory.

Comparing Economic Value and Costs

The value of a soil survey can be compared with its costs. If it is assumed that the three types of soils are distributed in several land segments and that the minimum legible delineation to separate the three soil types on the map is 0.4 cm^2, it is possible to calculate the map scale necessary to have an area of 10 ha on the field, represented in the map by a 0.4 cm^2 delineation (Forbes et al., 1987), by Eq. (7).

$$\text{Ground (ha)} = \text{map cm}^2\ /\ (RF^2 \times 10^8\ \text{cm}^2/\text{ha}) \quad (7)$$

In our case: 10 ha = 0.4/(RF^2 × 10^8 cm^2/ha), yielding a RF = 1/50,000, i.e., a map of scale 1:50,000.

The cost of this soil survey can be estimated by (Bie and Beckett, 1971)

$$\text{Log } C = 8.16 + 1.4 \log S \quad (8)$$

where C = cost in 1960, in 1960 US dollars per square kilometer, and S = map scale, expressed as a fraction

For a 1:50,000-scale map: C = 8.16 + 1.4 log (1/50,000) = US$ 38.14 per square kilometer in 1960. Considering the dollar deflation, we can calculate the cost of this soil survey in January 2000 United States dollars as US$ 2.09 per hectare.

Assuming that the area in our example is located in a region where the land use and the soil survey are extensive, the useful life of this survey is estimated to be 20 years, as suggested by Vink (1963). Therefore, with an estimated soil survey cost of US$ 2.09 per hectare (US$ 209.00 for the whole farm) and an economic added value of the soil survey of US$ 17.14 ha^{-1} year^{-1} (US$ 1,714 for the whole farm per year), the value of the soil survey would be equal to the profit generated by it over a 20-year period.

This simple comparison indicates that the soil survey is cost effective, and that the survey costs would be paid off during the first year of its application. This evaluation considers only one specific use of the soil survey, which is certainly an underestimation of all the possible uses that it could have in 20 years.

The combination of the map accuracy as an indicator of map physical quality, as assessed by the confusion matrix, and the soil survey economic efficiency shows that, although the physical accuracy of this survey was high (80% overall percent correct), its actual economic efficiency was low (55.5%).

CONCLUSION

The use of the decision tree and the consideration of the imperfections of the soil survey, along with the inclusion of a probabilistic assess-

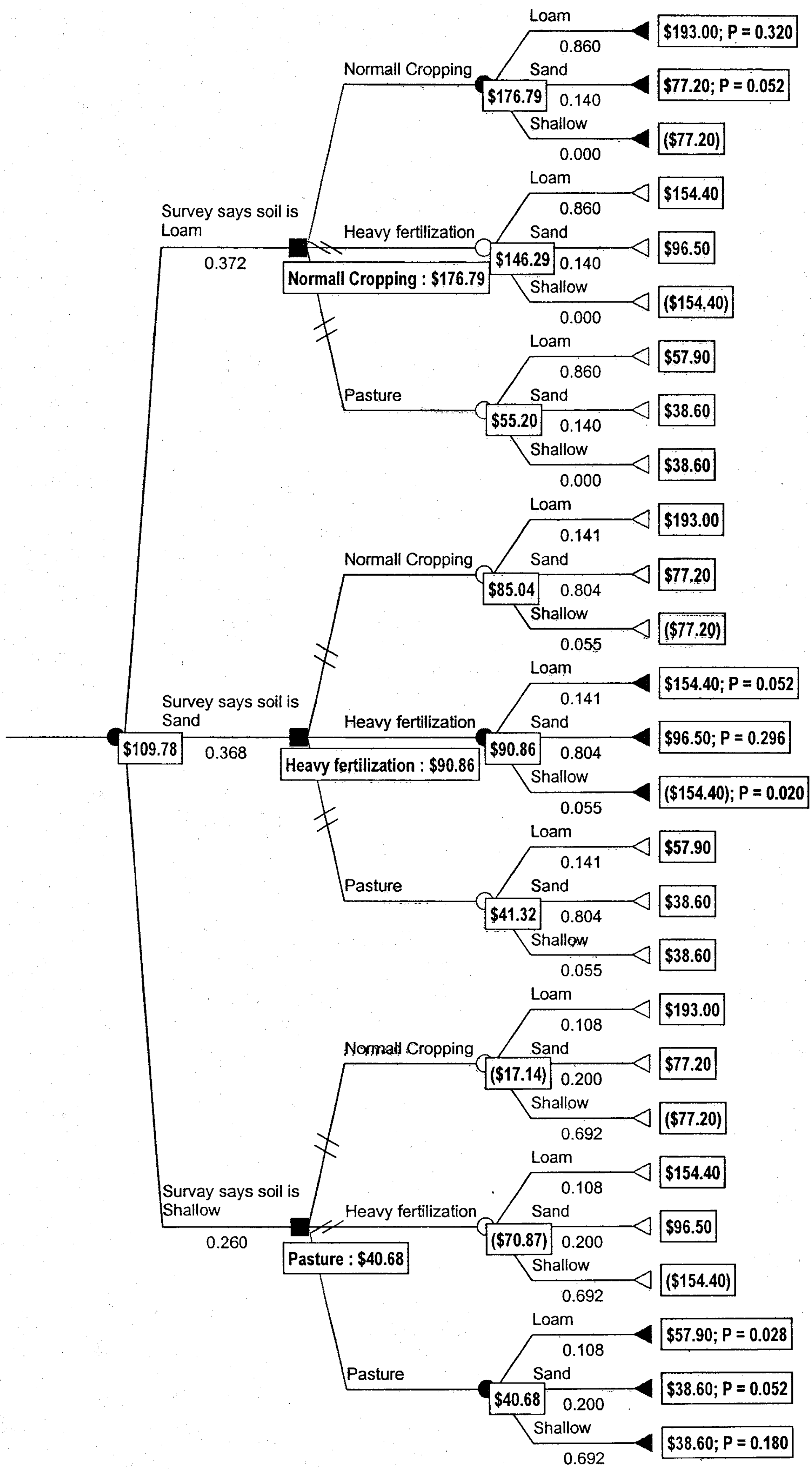

Fig. 4. Solved decision tree for optimizing land use across soil types assuming imperfect site-specific soil information.

ment of survey accuracy, provided a means of constructing and calculating a more realistic and more complex evaluation of the value of soil survey information. The use of a confusion matrix proved to be an effective way to obtain conditional probabilities.

Previous probabilities were obtained in this study by the actual soil distribution in the area. When applying this method in an area where there is no prior information about the soil distribution, one could use small-scale maps, expert knowledge, or information from adjacent similar areas to obtain these probabilities. Posterior probabilities were derived from the assessment of the accuracy of the map in the confusion matrix. The values would differ for different combinations of soils and among soil surveyors.

A sensitivity analysis could be used to structure the survey process. It can show which changes in the mapping will have changes in the economic result of the mapping process. The sensitivity analysis could show how the value of the soil survey changes, depending on the distribution of each soil map unit, productivity of each soil type, possible land uses on the region, net returns of each land use on each soil type, actual prices and costs. Changes in the confusion matrix would not only be a function of the reduction of the overall purity of the map but also of the distribution of the conditional probabilities within the confusion matrix, i.e., of the type of error happening on the map. A sensitivity analysis evaluating the changes in the final value of the information as a function of changes in specific aspects of map quality would indicate where the soil surveyor should focus efforts on collecting information. For example, the sensitivity analysis could show that the differentiation of two soil groups has a cost greater than the benefits it brings, indicating that the differentiation should not be done.

When applying these decision analysis techniques in real soil surveys, one could either be evaluating values and probabilities related to the differentiation of taxonomic classes or simply evaluating the value associated with the mapping of one soil or land characteristic or property. In both cases, this procedure is applicable. Soil taxonomic classes will define the overall value of the soil survey; considering just one soil characteristic will define the value of the inclusion of this characteristic in the survey.

The computation of economic parameters of soil survey information as presented here could be helpful in many situations: (i) for determining the value of gathering soil information; (ii) by government agencies to compare costs against benefits, possibly incorporating payoffs such as social utility; (iii) for specifying the degree of uncertainty associated with the information to be gathered, by using conditional probabilities; (iv) by soil survey contractors, for comparing prices and degrees of uncertainty linked to different soil surveyors; (v) by soil surveyors, to show to clients the value of the information to be gathered, comparing it with the cost of execution of the soil survey; (vi) when evaluating specific soil characteristics or processes, one could evaluate how much would be gained by using different and/or more detailed and expensive procedures to determine values of soil characteristics; (vii) for decisions regarding the comparison and selection of management practices; and (viii) for generating evaluations considering other types of payoffs, such as soil erosion, nutrient loading, or water quality.

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