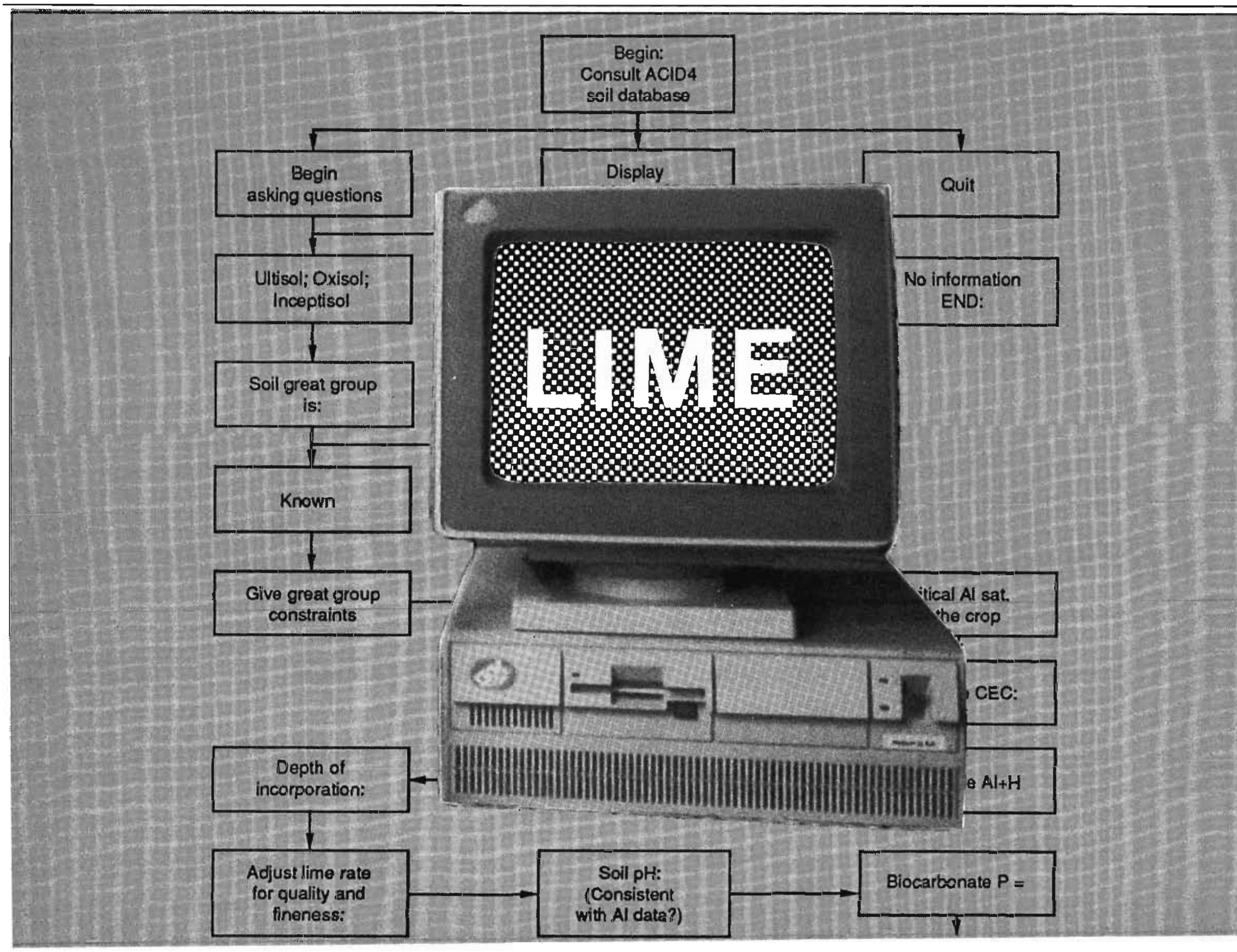
630 US ISSN 0271-9916 March 1988 RESEARCH EXTENSION SERIES 089

# Expert Systems in Agriculture: Determining Lime Recommendations for Soils of the Humid Tropics

Russell Yost, Goro Uehara, Michael Wade, M. Sudjadi, I P. G. Widjaja-adhi, and Zhi-Cheng Li

HITAHR · COLLEGE OF TROPICAL AGRICULTURE AND HUMAN RESOURCES · UNIVERSITY OF HAWAII



The Library of Congress has catalogued this serial publication as follows:

Research extension series / Hawaii Institute of Tropical Agriculture and Human Resources.–001––[Honolulu, Hawaii]:
The Institute, [1980–
v. : ill. ; 22 cm.
Irregular.
Title from cover.
Separately catalogued and classified in LC before and including no. 044.
ISSN 0271-9916 = Research extension series - Hawaii Institute of Tropical Agriculture and Human Resources.
1. Agriculture–Hawaii–Collected works. 2. Agriculture–Research–Hawaii–Collected works. I. Hawaii Institute of Tropical Agriculture and Human Resources. II. Title: Research extension series - Hawaii Institute of Tropical Agriculture and Human Resources
S52.5.R47 630'.5–dc19 85-645281
AACR 2 MARC-S
Library of Congress [8506]

## THE AUTHORS

**Russell Yost** is an associate researcher, Department of Agronomy and Soil Science, College of Tropical Agriculture and Human Resources, University of Hawaii.

**Goro Uehara** is a soil scientist, Department of Agronomy and Soil Science, College of Tropical Agriculture and Human Resources, University of Hawaii.

**Michael Wade** is a soil scientist, formerly with the Department of Soil Science, North Carolina State University.

**M. Sudjadi** is the director, Centre for Soils Research, Bogor, Indonesia.

**I P. G. Widjaja-adhi** is the coordinator, Tropsoils Research Program, and a soil scientist, Centre for Soils Research, Bogor, Indonesia.

**Zhi-Cheng Li** is a knowledge engineer, Tropsoils Project, Department of Agronomy and Soil Science, College of Tropical Agriculture and Human Resources, University of Hawaii.

This work was done under the auspices of the Tropsoils Project, comprising the Centre for Soils Research, Bogor, Indonesia; the University of Hawaii; and North Carolina State University.

## CONTENTS

# EXPERT SYSTEMS IN AGRICULTURE: DETERMINING LIME RECOMMENDATIONS FOR SOILS OF THE HUMID TROPICS

**Russell Yost, Goro Uehara, Michael Wade, M. Sudjadi, I P. G. Widjaja-adhi, and Zhi-Cheng Li**

## INTRODUCTION

Expert systems have recently attracted the attention of agricultural scientists for application in a variety of information development and transfer situations. These computer software systems are designed to simulate one or more of the ways that a human expert uses his or her knowledge and experience in making a diagnosis or a recommendation. While original applications included the diagnosis of bacterial diseases (Hayes-Roth et al., 1983), useful applications in agriculture include soybean disease diagnosis (Michalski et al., 1980, 1982), management systems for apples, and the taxonomic identification of turfgrass.

We have developed a prototype expert system to make lime recommendations in the humid tropics. The objectives were to:

1. Document current methods of determining lime requirements for highly weathered soils of the tropics. This objective was developed as part of the Tropsoils/Indonesia project, which is adapting and developing lime recommendation technology for the highly weathered acid uplands of Sumatra, Indonesia.
2. Provide a way of transferring current Tropsoils research within Indonesia for use by extension workers and others with limited agronomic training.
3. Provide an exploratory learning exercise for ourselves about how an expert system is built and what the potential applications might be.

## EXPERT SYSTEMS

To exploit the potential of expert systems, we must review what experts do. This includes (Michaelson et al., 1985):

1. Applying their expertise to solve problems in an efficient manner.
2. Explaining and justifying what they do.
3. Communicating with other experts and acquiring new knowledge.
4. Restructuring and reorganizing knowledge. Some individuals cannot accommodate massive changes in their knowledge. However, experts should be able to restructure information based on new data and concepts.
5. Breaking rules. In certain fields of science there are almost as many exceptions as there are rules. Experts understand both the spirit and the letter of the rule and are not bound by strict, literal interpretations of the concepts.
6. Determining relevance. They know when a problem is clearly outside of their expertise and that it should be referred to another expert.
7. At the boundary of their expertise, indicating whether their information is not likely to be the best available, and providing their information together with probable sources of better information.

Current expert systems partially achieve only functions 1 and 2. It is quite likely, however, that several of the other functions soon will appear in newer expert system development tools.

Computer-based fertilizer recommendations have been used successfully for many years. Users of such programs had to accept program recommendations on faith or persevere in reading arcane FORTRAN code. Checking the program's rationale for soil samples that were given unreasonable recommendations was very difficult, if not impossible, for those who didn't read FORTRAN. An expert system-based fertilizer recommendation would offer an alternative to this difficulty. The user would be able to examine the rationale at any part in the program. This is because an expert system is designed not only to provide a recommendation, but to explain how the recommendation was developed and, depending on the implementation, to support the recommendation with literature citations. This means there is usually an opportunity for the nonexpert to learn the rationale. The emphasis of expert systems is to apply knowledge and information and to share that knowledge with others.

To adequately develop expert systems, one must also learn techniques of knowledge acquisition (Hayes-Roth et al., 1983). This requires extracting information from the experts and representing it in a data base.

### Extracting Information from the Experts

It is widely recognized that knowledge extraction is one of the more difficult problems in developing expert systems. One technique is to have someone pose the questions and the situations as realistically as possible so that the experts can respond. It is well known that experts are better able to apply knowledge and expertise than to explain and teach it. Knowledge extraction efforts might benefit from some of the experience and techniques described by Kadane et al. (1980) in eliciting the prior information for Bayesian decision analysis.

**Representing Knowledge in a Data Base or Knowledge Base**

Here there are many approaches, such as rule-based systems, logic-based systems, and frame-based systems (ACM, 1985).

*Rule-based systems.* The most popular, rule-based systems use a sequence or chain of rules. These rules generally have the form:

IF
1.
2.
.
.
.
.
THEN
1.
2.
3.
or
Conclusion 1
Conclusion 2

It is possible for the conclusion of one rule to serve as an IF condition for a subsequent rule. In this way rules are linked in a logical sequence that simulates reasoning.

There appear to be three types of rules with which the system "reasons" or performs a logical sequence of questions and answers (Clancey, 1983):

1. Strategy rules, used to represent the plan for ordering the questioning or the presentation of the hypothesis and goals.

2. Structural rules, keys used to index the knowledge or as a way to reference a particular set of rules for a particular set of conclusions.

3. Support rules, those that supplement or add conditions to the main conclusions. These rules are easily changed or replaced because they do not have major structural implications.

*Logic-based systems.* The second type of knowledge representation is most fully developed in the programming language PROLOG. PROLOG represents a fifth generation approach to problem representation and solution. As is typical of fifth generation "declarative" languages, the user first states the problem. The problem-solving algorithms of predicate calculus then perform sophisticated matches and substitutions. The result is a very powerful logic-based derivation of conclusions. Languages such as PROLOG can prove mathematical theorems through their implementation of logic. It is also possible to develop rule-based expert systems in PROLOG that exploit the logic-based reasoning ability. Such languages also permit machine learning whereby a system can add rules to itself during execution. To do this in a useful manner, however, the system must have meta-rules with instructions on when and how to formulate the new rules.

*Frame-based systems.* The third type of knowledge representation has been available as expert systems development software costing $50,000 and upwards. Frame-based representation is explicitly developed to represent hierarchical knowledge. In this case information is passed or transferred to an object because it belongs to a larger class of objects with a standard set of attributes. A frame is the structure whereby attributes of an object are recorded, including its belonging to another class of objects. An example might be a soybean plant. The frame would be the name "soybean" and all the attributes and characteristics of the soybean, including the fact that it belongs to the class of legumes, flowering plants, and plants rather than animals. Because the soybean is a plant, we know that it requires nutrients, water, light, and other inputs for growth. Because it is a legume, we know that there are rhizobia requirements and other conditions for the rhizobia to be effective if soil N is low. Many things can be inferred by simply knowing that the object is a plant and that it is a soybean plant. This information can be used by a frame-based system to ask relevant questions or to develop patterns of reasoning. As suggested in the logic-based systems, hybrid systems can be developed that use frames as units of information from which rules can be formed.

**HOW WE CHOSE OUR EXAMPLE**

Ameliorating the effect of soil acidity was selected as an example from agronomy and soil science for three reasons. Determining lime requirements has been studied extensively and general guides are available, but the actual method of making a recommendation remains controversial. Secondly, this was an area of expertise with which the authors were relatively familiar. This meant that we did not have to learn the skills needed for knowledge and rule extraction at the same time that we were learning to represent the knowledge and rationale in the trial expert system. As time goes by and we gain more experience, it is becoming clear to us that this may be an alternative to hiring a knowledge engineer to extract and code the information. Finally, although there are important mathematical calculations in determining lime requirements, there are a large number of conditions that need to be attached to a numerical recommendation of the lime rate. This is a result of the highly complex soil–plant–climate–man system whose behavior we are attempting to simulate.

Clancey (1985) has suggested that expert systems are particularly appropriate for the solution of problems with several characteristics; he calls these characteristics the "heuristics of knowledge acquisition":

1. Problems amenable to solution with expert systems

    a. Are the solutions to the problems enumerable? Are there plans, diagnoses, typical configurations or syndromes?

    b. Can the problem be subdivided into smaller classification problems?

    c. What is observable? Does causality play a role in the problem?

2. Knowledge representation in a rule-based system

    a. List all possible solutions to the problem. Organize these solutions into classes, types, or hierarchies as appropriate.

    b. Identify relationships among the data: generalizations, definitions, and qualitative abstractions. Experts frequently leave out qualitative abstractions, stating associations instead in terms of numeric data.

    c. Identify and establish heuristics, or rules, that relate data to solutions after the solutions have been identified.

    d. Modeling the experts' thought processes can be difficult—they frequently tend to use a hypothesis generation-proof procedure that is difficult to implement with similar flexibility in the expert system.

3. Refinement of an expert system. Experience suggests that one should rapidly develop a prototype system and show it to the domain expert (subject matter expert), carefully noting his or her reaction (Waterman, 1986). With a sufficiently detailed prototype, the domain expert can identify with portions of the system rationale and will quickly see flaws and have the opportunity to suggest modifications.

Constructing an expert system requires learning concepts of organizing information and arranging rules and rule components so that questions are asked in an efficient and sensible manner. These include concepts based on the way the system searches the rules and determines what information to ask of the user. The way the system does this is determined by the structure of the "inference engine."

## OUR EXPERIENCE WITH EXSYS

### Introduction to EXSYS

EXSYS[1] (Hunington, 1985) is a rule-based expert system development shell designed to provide many of the common rule construction activities that form the substance of expert system development. The shell provides editing facilities to design output formats, run test data sets, and ensure that modifications have not disrupted the core logic flow of the system. The inference engine is mainly backward chaining and provides a switch that will enable the search to stop after the first valid rule or will cause the search to continue until all possible rules are evaluated. Only simple WHY capability is provided; it displays the rules that are being evaluated in the information input mode or provides the chain of fired rules in support of a recommendation. Programming effort is minimal with this software. There is a loss in flexibility for certain types of expert system construction. This software comes close to providing an expert system development system that computer-acquainted professionals should be able to learn with little effort.

In EXSYS the search procedure follows several simple rules. These search rules will be discussed in the sequence in which they operate.

*Choice selection.* The first search or "pattern matching" that is done on the knowledge base begins with the "choices." Choices in EXSYS are a list of all the potential conclusions from which the system can choose in presenting final results. None, one, or several choices are possible with any consultation or "run" of the system.

During run time, all choices in EXSYS will be checked by the inference engine to determine whether they are true. This checking procedure is sequential. The first choice on the list is selected first to determine if it can be proved true or false. Then the second choice is selected, and so on. The order of the choices is determined by the person developing the system.

The final results are selected and rated on the basis of the combination of the probabilities assigned to the choices in each of the supporting rules. The inference engine provides probability accumulation in dependent, independent, and averaging modes. Each choice must have at least one supporting rule that involves probabilities of the choice being correct.

*Rule selection.* The rule whose THEN part contains the choice currently being checked will be selected for analysis. If there is more than one choice, the rule with the smallest rule number will be chosen first; the rule with the larger number will follow. If two rules have exactly the same THEN parts (if mathematical evaluation is involved, see the relevant section, next page), the relationship between these two condition sets is OR, the same as that between the results of the analyses on these two rules. But within a rule all conditions in the IF part or in the THEN part have a relationship AND. For example:

[1]Use of brand names does not mean that the authors endorse this particular software. The discussion would apply to most rule-based shells.

RULE 11
IF
You prefer to continue
The soil great group is Paleudults

THEN
No lime is recommended—probability (100/100) ←This is the first choice in the list of choices. This choice will cause RULE 11 to be selected first for analysis. (Explanatory comment added for this paper.)

*Condition selection.* Once a rule is selected, EXSYS proceeds to analyze components of the rule—the "conditions." In EXSYS a condition has two parts: the "qualifier" and the "value." After selecting which rule to analyze, EXSYS determines which condition to analyze. This selection is quite logical—the first condition in the IF part of the rule is selected for evaluation. The purpose of the evaluation is to determine if the condition is true or false. The system determines if the condition is true by first searching the file of facts or input already concluded to be true; if the condition is not in the list of facts, the system searches rules that have the condition in their THEN parts. If the system finds a rule with the condition in the THEN part, it determines whether the conditions in the IF part of that rule are true or can be concluded to be true from other rules by chaining. If our first condition can be determined to be true, the system will proceed. Otherwise it will, as a last resort, display the first condition in the rule that had our first condition in its THEN part. These conditions will be displayed in the form of a qualifier and its values, asking the user to indicate which ones are successive conditions. For example:

RULE 1

| IF (qualifier) | (value) | (search order) |
|---|---|---|
| You prefer to | continue | ←first searched |
| The soil great group is | Paleudults | ←second searched |

THEN
No lime is recommended —probability (100/100) ←This is the first choice in the list of choices. This choice caused this rule to be selected first for analysis.

RULE 22
IF
You have used this system before and you don't need to see details of this system ←This condition will be searched for and, if not found, will be displayed for user selection.

THEN
You prefer to continue ←This condition matches the condition in RULE 11 and is why RULE 22 was selected. (This relationship between rules is also known as chaining.)

*Mathematical evaluation.* While EXSYS allows numerical comparison in the IF part of any rule, it also allows the assignment of numerical values to mathematical variables in the THEN part of any rule. If more than one rule has the same variable evaluated in the THEN part, the rule with the smallest number will be evaluated first and the variable will get its first value. The next rule will then be evaluated and, if all of the conditions are satisfied, the variable will be assigned a new value based on the current calculation. For example, we have these rules:

12 IF condition 1
THEN [X] = 1

15 IF condition 2
THEN [X] = [X] + 1

20 IF [X] = 2
THEN choice 2

In order to test choice 2, the inference engine tries to evaluate [X] (RULE 20). If, in the whole knowledge base, only RULES 12 and 15 contain [X] in the THEN part, RULE 12 will be picked first for analysis. If both rules are evaluated, [X] will be initially assigned as 1 by RULE 12 and reassigned as 2 by RULE 15. This mechanism enables modification of a mathematical value through several rules and different considerations.

**Summary of EXSYS**

The search begins with the selection of a rule to analyze. The first choice in the list of choices is selected. A rule that has this choice in its THEN part is selected. If there is more than one rule with the choice in its THEN part, the rule that has the smallest rule number will be selected.

The IF part of the selected rule is looked at. The first condition is selected and is checked to see whether it can be proved true or false from information already determined to be true. If the condition cannot be determined to be true or false based on information already in the system, the system will put the condition on screen and ask the user which combination of qualifiers and values is true.

The order of the conditions in the first selected rule will determine the order of the questions asked of the user. For example, one would prefer that the most likely conditions be asked first. This can be done by placing the most commonly selected choice as the first in the choice list (choice 1). This order should match the "directed graph" or decision tree that we recommend be constructed first to document the logical organization of the expert system. In other words, the first condition in the rule should ask for the most general information. This ensures that the system will reduce the number of rules to be searched in subsequent steps. If a very specific condition were placed first, it might ask for information that was irrelevant to most of the system.

The ideal expert system asks the simple questions first and uses its rules to infer the more difficult, specialized knowledge. The system would be self-defeating if, instead of asking the simple questions first, it asked the specialized questions that required expert knowledge. The condition sequence within a rule is thus crucial in establishing a search sequence within the expert system that will develop information from the general to the specific as it progresses through the system.

**The ACID4 System**

The ACID4 knowledge base was developed from existing information and research experience. Because the primary objective has been to address soil acidity problems in the transmigration area of Indonesia, we have focused on extractable acidity (mostly exchangeable Al) as the primary cause of yield reduction. The reference for the knowledge base is a review paper by Kamprath (1984). The main concepts in the data base are these:

1. Growth-limiting effects are due primarily to exchangeable Al + H (exchangeable acidity), although, if all cations are present in very small quantities, some lime is probably needed to provide Ca. It is assumed that toxicity to exchangeable acidity is closely related to Al + H saturation so that Al + H saturation is a satisfactory measure for diagnosis.
2. Crops vary considerably in their tolerance to exchangeable acidity; extremes are represented by mung bean (very intolerant, tolerating no more than 0 percent Al saturation) and cassava (very tolerant, tolerating about 75 percent Al + H saturation).
3. Organic material seems to reduce lime requirements. The current approximation is that 10 tons/ha of fresh organic material reduces the lime requirement by 1 ton/ha.
4. Lime requirements are based on soil analyses in order to accurately reflect the soil conditions.
5. Although data are sparse, an attempt is made to determine the approximate effects of lime quality on the lime requirement. Included are the neutralization value relative to calcium carbonate and an estimate of physical reactivity as related to the particle size. The estimate of neutralization value is a well-defined laboratory procedure in which an excess of acid is added to the lime and allowed to fully react. The excess acid is back-titrated to determine the unreacted acid for the calculation.

Particle size fractions have been used to estimate the physical reactivity of the limestone. Many factors have been studied to estimate the time required after application before crops can be planted. One of the simpler measurements of lime quality, as affected by particle size, is given by the measure of the amount of lime of various particle sizes needed to give approximately equivalent yields. The equation we used was developed from Figure 4 in Barber (1984):

| Fraction passing a 60-mesh sieve | Tons of lime required to attain 80% relative yield | Fraction increase |
|---|---|---|
| 0.90 | 3.7 | 1.00 |
| 0.70 | 4.0 | 1.08 |
| 0.55 | 4.4 | 1.19 |
| 0.45 | 5.1 | 1.38 |
| 0.35 | 6.2 | 1.68 |
| 0.25 | 8.0 | 2.16 |

The calculation of lime requirement is based on the need to neutralize sufficient Al to reduce aluminum saturation to the "critical aluminum saturation" that has been established for the various crops (Cochrane et al., 1980). Our modified form of the equation is:

Lime requirement (t/ha) = 1.4(exchangeable acidity - (CAS*ECEC/100))

where: — exchangeable acidity is the 1N KCl extractable Al + H
— CAS is the critical aluminum saturation of the crop
— ECEC is the "effective cation exchange capacity"
— the value 1.4 represents the relation of the cmol of $CaCO_3$ required to neutralize 1 cmol of Al + H in field studies adjusted for both bulk density and depth of incorporation. In this case 1.9 cmol of Ca was required for each cmol of Al + H, the bulk density was assumed to be 1.0, and the depth of incorporation was assumed to be 15 cm.

Preliminary data suggest approximately 0.53 cmol KCl-extractable acidity is neutralized for each cmol of Ca added as $CaCO_3$ (Wade et al., 1985). This corresponds to a relationship of 1.9 cmol of $CaCO_3$ being required for each cmol of extractable acidity, a value that is similar to the results reported elsewhere (Kamprath, 1984). This reference points out the need to consider the effectiveness of lime in neutralizing the extractable acidity. Such data should to be obtained in field studies, if possible, because of the need to ensure that one is testing the liming material and soil reactivity under conditions that are representative of the situation or for a group of farms for which the eventual recommendation is intended.

Other data and results from the Tropsoils work in Sitiung, Indonesia, are incorporated, such as minimum requirements of P and K for soybean, rice, cowpea, and peanut.

A directed graph of ACID4 is shown in Figure 1. The system is designed to apply to the humid tropics with soils of the Ultisol, Oxisol, and Inceptisol orders. The system has additional information pertinent to the Sitiung region. The general recommendations are based on other relationships, such as a general reactivity of 2 cmol of $CaCO_3$ for each cmol of extractable acidity. Levels of critical aluminum saturation are, so far, the same for the general recommendation as for the specific location in Sitiung.

At present the soil great group is incorporated for the aquic- and fragi- subgroups. We expect to expand this to access a much larger data base such as that being developed by our collaborators for their extensive collection of soils data from various surveys and inventories. One possible use of such a data base would be to request the town or geographic location to obtain a summary of the soil characteristics or specific problems that might be a problem for crop production or soil management in the area.

## FUTURE APPLICATIONS OF EXPERT SYSTEMS

We believe that knowledge-based systems offer considerable potential to help us organize and transmit problem-solving expertise. This should foster and stimulate application of agronomic knowledge in concepts rather than as simple facts or observations as in the past.

Expert systems are useful for us in agronomy and soil science and probably in agriculture and biological science in general for four reasons:

1. Agronomy and soil science deal with a highly complex, descriptive soil-plant-climate-human system. Usually a large amount of information is necessary to understand and predict any particular phenomenon—it is not usually possible to reduce this large amount of information to a single rule, theorem, or axiom. Some scientists, however, have succeeded in condensing their information to some extent, although it took them many years and at times their entire career. They have developed rules of thumb or heuristic guidelines that may not always work, but usually do. In some cases this information may be all there is, or this may be the best way to represent the state of knowledge of the system. It may be that we have in some cases attempted to fit round pegs into square holes in attempting to attach numbers to such ill-defined phenomena. Certain types of knowledge representation—for example, fuzzy systems (Negoita, 1985) and symbolic representation (Chandrasekaran, 1983)—offer a way to represent this approximate information in a more precise way than is possible with a single number. Expert systems permit capturing this expertise and knowledge so that it need not be learned all over again nor duplicated by following generations.

2. Potential applications of expert systems in agriculture include potential benefits to research, extension, and instruction.

Development of problem-solving protocol and procedure aids in identifying information gaps. In this fashion, research becomes more efficient and becomes part of a larger management strategy. Expert systems can serve as an important aid in remembering logical segments or procedures that eventually can be linked into a larger rationale. At various stages of development, expert systems can serve as memory or procedure aids, "assistants," "associates," or ultimately as "experts," depending on the level and quality of knowledge and skill attained.

A well-designed expert system offers a wide range of possible applications in extension. Repetitive questions by clients might be handled by a system that patiently addresses popular problems or queries. An incredible amount of information and problem-solving skill could be at the county agent's or extension specialist's disposal if even a small fraction of the agricultural expertise were recorded in this form. New information could be quickly and accurately disseminated.

It is clear that agricultural graduates must be equipped to manage, evaluate, and develop information to a greater extent than ever before. Acquaintance and skill with knowledge-based systems would permit improved problem-solving ability as one additional information management tool. Concepts of machine learning and intelligence stimulate thought and reflection on improving human skills in this area. Inclusion of knowledge-engineering concepts in instruction and graduate programs promotes awareness of information technology skills and their value in managing information.

3. If expert systems technology were widely implemented in agriculture, we should see a rapid advance in agricultural science from an essentially phenomenological stage to one in which the knowledge is more highly structured and organized. This should lead to a more advanced stage of development of the science, which, in turn, should lead to more emphasis on principles. Developments in other areas of science suggest this would pave the way for more theory development with a consequent increase in the number and significance of research breakthroughs.

4. From the nature of fifth generation research it is apparent that expert systems are the first of many innovations that we can expect from the application of microprocessors to information technology development. In many respects we have been using microcomputers to

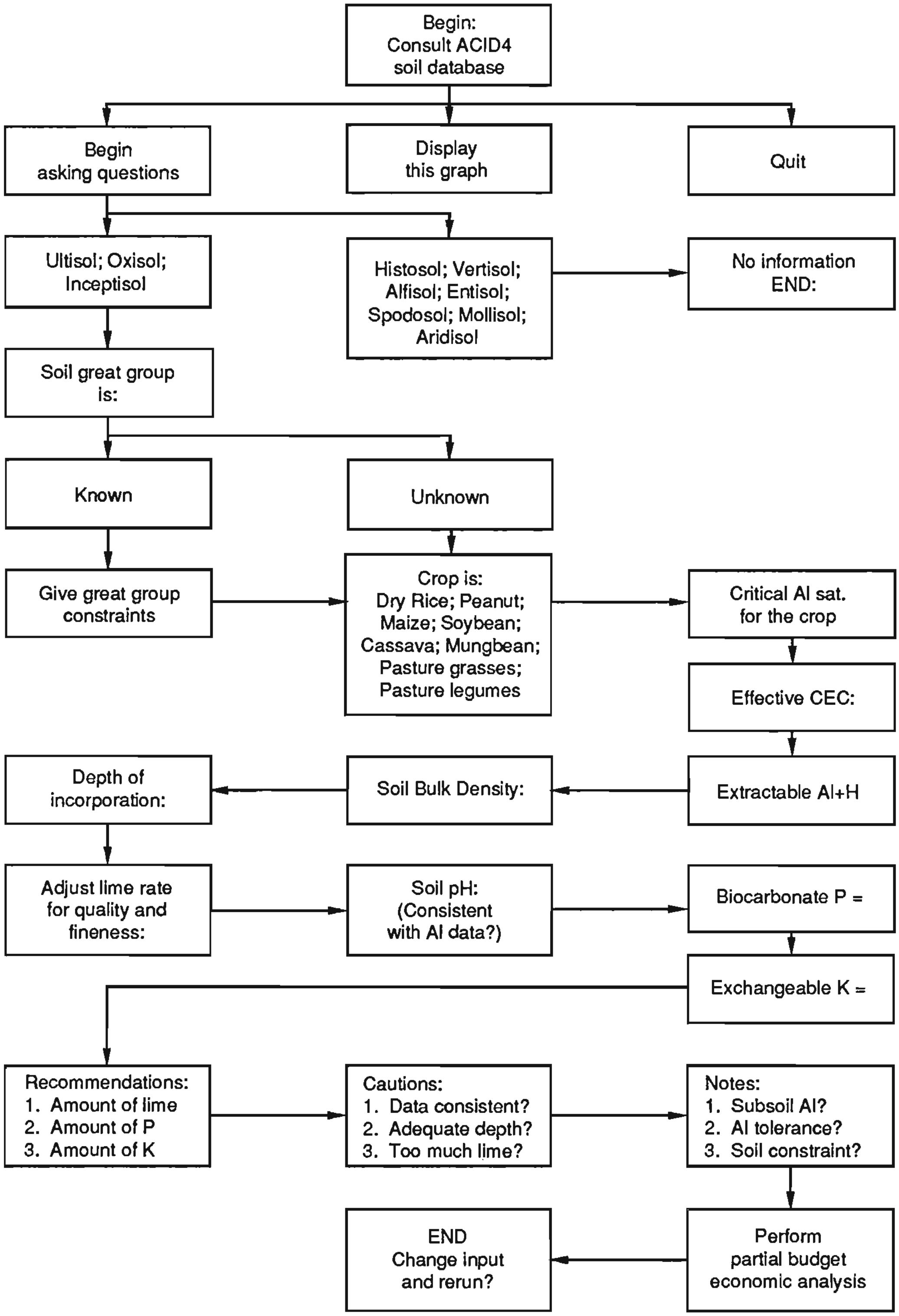



**Figure 1. Directed graph of ACID4 expert system.**

do the same things that we have been doing for many years—only faster and more conveniently. The maturing of this technology will lead to conceptual innovations. Almost certain to come soon will be powerful reasoning and learning capability beyond that currently provided by languages such as PROLOG. Agriculture should be in a position to benefit much more from such technology than the already highly structured sciences such as physics and chemistry.

## LITERATURE CITED


ACM. 1985. Special section on architectures for knowledge-based systems. I. The role of frame-based representation in reasoning, R. Fikes and T. Kehler; II. Rule-based systems, F. Hayes-Roth; III. Logic programming, M. R. Genesereth and M. L. Ginsberg. Communications of the ACM, September 1985, 28:903-941.

Barber, S. A. 1984. Liming materials and practices. *In* F. Adams (ed.), Soil acidity and liming, 2nd ed., Amer. Soc. Agron., Madison, Wisconsin.

Barr, A., and E. A. Feigenbaum. 1981. The handbook of artificial intelligence. Kaufmann, Los Altos, California.

Chandrasekaran, B. 1983. Expert systems: Matching techniques to tasks. Presentation at the New York University Symposium on Artificial Intelligence Applications for Business, May 18-20, 1983.

Clancey, W. R. 1983. The epistemology of rule-based expert systems—a framework for explanation. Artif. Intell. 20:215-251.

Clancey, W. R. 1985. Knowledge acquisition for classification expert systems. Proceedings ACM 1984 Annual Conference: The Fifth Generation Challenge. San Francisco, California.

Clocksin, W. F., and C. S. Mellish. 1981. Programming in PROLOG. Springer-Verlag, New York.

Cochrane, T. T., J. G. Salinas, and P. A. Sanchez. 1980. An equation for liming acid mineral soils to compensate crop aluminum tolerance. Trop. Agr. 57:133-140.

Hayes-Roth, F., D. A. Waterman, and D. B. Lenat. 1983. Building expert systems. Addison-Wesley Pub. Co., Reading, Massachusetts.

Hunington, D. 1985. EXSYS, version 3.0. Expert System Development, Albuquerque, New Mexico.

Kadane, J. B., J. M. Dickey, R. L. Winkler, W. S. Smith, and S. C. Peters. 1980. Interactive elicitation of opinion for a normal linear model. J. Amer. Statis. Assoc. 75:845-854.

Kamprath, E. J. 1984. Liming acid soils of the humid tropics. *In* F. Adams (ed.), Soil acidity and aiming, 2nd ed., Amer. Soc. Agron., Madison, Wisconsin.

Michaelson, R. H., D. Michie, and A. Boulanger. 1985. The technology of expert systems. BYTE Magazine, April 1985.

Michalski, R. S., and R. L. Chilausky. 1980. Learning by being told and learning from examples: An experimental comparison of the two methods of knowledge acquisition in the context of developing an expert system for soybean disease diagnosis. Intern. J. Policy Anal. and Info. Systems 4:125-161.

Michalski, R. S., J. H. Davis, V. S. Bicht, and J. R. Sinclair. 1982. PLANT/ds: An expert system consulting system for the diagnosis of soybean diseases. Proceedings 1982 European Conference on Artificial Intelligence. Pp. 133-138.

Negoita, C. V. 1985. Expert systems and fuzzy systems. Benjamin Cummings Pub., Menlo Park, California.

Wade, M. K., Heryadi, Aljabri, F. Agus, and E. Joniarta. 1985. Liming in transmigration areas. Report submitted for the Tropsoils Annual Report, 1985. Tropsoils/Indonesia.

Waterman, D. A. 1986. A guide to expert systems. Addison-Wesley Pub. Co., New York.

**DISCLAIMER**

Hawaii Agricultural Experiment Station
HITAHR, College of Tropical Agriculture and Human Resources, University of Hawaii at Manoa
Noel P. Kefford, Director and Dean

RESEARCH EXTENSION SERIES 089—03.88 (2M)