An Integrated Wheat Crop Management System Based on Generic Task Knowledge Based Systems and CERES Numerical Simulation[1]

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Abstract: In this report, we discuss the development of an integrated problem solving architecture to capture all relevant aspects of a crop management system within one working computer program. Specifically we discuss the development of a computer expert system to support the management of irrigated wheat in Egypt on a regional level. Our system will capture local expertise for the management of irrigated wheat production through the integration of expert system technology and one of the premier crop simulation models used in agriculture today. The system will address the various facets of management as follows: planting date selection; water utilization and management; pest monitoring, identification, and remediation; disease monitoring, identification, and remediation; and harvest management. The two major methodologies we integrate in our system are the Generic Task second generation expert systems methodology first developed by Chandrasekaran *et al (Chandrasekaran*, 1986), and the CERES crop simulation methodology pioneered by Ritchie *et al (Ritchie,Godwin*, & Otter-Nacke, 1985). The expected contributions of this research lie in two major areas. In agriculture, regional level management of cropping will allow better utilization of crop inputs, particularly water inputs. In knowledge-based systems, the major contributions of this research lie in proof of principle scale-up of a number of current problem solving templates and in the integration of expert system and quantitative simulation technologies.

1.0 Introduction

The development of a district-level wheat management consultation system is centrally important in Egypt. In 1990, total harvested wheat acreage in Egypt was 819,150 ha, while (from 1989 figures) total crop land in Egypt was approximately 2,585,000 ha. (statistics from CIMMYT, Mexico). Taken together, these statistics indicate that wheat is a central agronomic crop in the Egyptian economy, accounting for approximately 33% of all harvested acreage. Since the limiting factor for agricultural production in Egypt is water, any comprehensive management tool must place water management in a central position. In this paper, we focus on the development of a comprehensive irrigated wheat management system based on the integration of "second generation" expert systems technology and a quantitative crop simulation model.

Through the research discussed here, we address numerous problems related to both computer science and agriculture. From an expert systems/computer science viewpoint, the first problem we address is the "scale up" issue, which is common in knowledge-based systems. First generation expert system (ES) technology has proven difficult to scale to large-scope problems, such as developing a comprehensive agro-management consultant system for wheat. The difficulties are well documented and well understood. The second problem we will address in our research is the integration of numerical simulation models (specifically in our case, the CERES Wheat crop model) into a compiled level crop management system. CERES Wheat takes as input boundary conditions, such as planting date and irrigation regime, then predicts (among other items) grain output at harvest. Although quite accurate in its output, one difficulty is the level of expertise which must be employed to set the initial input parameters. Within our integrated system, we leverage compiled level expertise to "propose" a management scheme, CERES Wheat to test that scheme, and complied level expertise to (possibly) modify the suggested management in light of CERES results.

From a purely ES viewpoint, the problem we set to integrate compiled-level problem solving and numerical simulation is receiving wide spread current attention. The reason is largely due to the perceived "naturalness" of an interaction between "experience" to quickly center on a part of a large search space, and numerical methods to select the correct exact solution from the narrowed

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possibilities. This mode of interaction would utilize the best of both ES and simulation models, using the ES to quickly limit the search space, then using simulation-based methods to find the best candidate in the current focus.

As a starting point, in section 2 we present previous work in agricultural expert systems. Next, we begin discussion of our approach to building a regional wheat management system. In section 3 we give an overview of the Generic Task approach. We highlight two of the Generic Tasks which are relevant to the work related here: Routine Design in section 4 and Functional Reasoning/Functional Modeling (FR/FM) in section 5. In section 6, we discuss the features of the CERES family of crop simulation models, in particular CERES Wheat. The integration of the expert systems technology and the crop simulation tool is discussed in section 7. In section 8 we discuss the division of the management system into the modules which address the various facets of wheat crop management. Finally, in section 9 we close the paper with a discussion of future research.

2.0 Background on Expert Systems in Crop Management

Expert systems have found wide applicability in problems of crop management in agriculture. In the area of agronomically important crops, substantial programs have been produced in a number of areas. For example:

- in making fertilization recommendations (Armoni,Rakantalio, & Dominguez, 1988; Evans,Mondor, & Flaten, 1990; Goodrich & Kalbar, 1988),
- in diagnosing crop disease (Boulauger, 1983; Stone & Toman, 1989),
- in diagnosing and controlling pests (Batchelor & McClendon, 1989; Beck,Jones, & Jones, 1989; Pasqual & Mansfield, 1988; Ton,Sticklen, & Jain, 1991),
- weed control (Gonzales-Andujar,Rodreigues, & Navarrete, 1990; Linker,York, & Wilhite, 1990; Renner & Black, 1991),
- irrigation management (Thompson & Peart, 1986), and
- varietal selection (Morgan & et.al., 1989).

The great bulk of these systems have been aimed at narrow domain problems, and have typically been implemented under a rule-based approach. Those applications not written in a rule-based shell have been implemented in a variety of frame-based, blackboard-based or procedural approaches. These “first generation” expert systems were capable of performing analytical tasks with a high degree of expertise. However, experience has shown that these systems are not powerful enough to perform the synthesis task necessary to generate an agricultural commodity management plan (Chandrasekaran, 1987).

Additionally, one of the strongest perceived needs in the agro-management arena regarding expert systems is for integrated systems (Whittaker & Thiewe, 1988). These systems link simulation models and expert systems to facilitate the use of the proven models. The expert system is used to parameterize and/or interpret the results of simulation. There have been very few such “integrated systems” approaches taken to date for agricultural management problems, notable exceptions being (Durkin,Godine, & Lu, 1990; IBSNAT, 1986; Plant, 1989). The management system discussed here is designed to address the issues involved in creating an integrated system, and to overcome the problems of first generation expert systems.

3.0 Background on Second Generation Expert Systems

To overcome the problem associated with the first generation approaches, our integrated approach involves second generation expert system technology, specifically the *Generic Task* (GT) approach of Chandrasekaran and his colleagues. The assumption of the GT approach is that knowledge takes different forms depending on its intended function (Chandrasekaran, 1986; Chandrasekaran, 1987). Following the Generic Task view, a problem is analyzed according to the methods associated with solving it, where each method can be specified by the forms of knowledge and inference necessary to apply the method, and by the subproblems that must be solved to carry it out. These sub-problems can then be recursively decomposed in a similar fashion. The assumption of the GT approach is that there exist a number of ubiquitous combinations of method, knowledge structure, and inference structure (termed *generic tasks*) that serve as sub-problems for a variety of complex problem-solving tasks in a variety of domains.

One of the main intuitions underlying the Generic Task approach is the belief that there are a (small) finite number of very pervasive problem solving types. These problem solving types are the individual generic tasks (GT’s). For purposes here, the three most significant are:

- **Hierarchical Classification and Structured Matching** (Chandrasekaran & al, 1979; Gomez & Chandrasekaran, 1981; Mittal, 1980). Hierarchical classification is intuitively a knowledge organization and control technique for selecting among a number of hierarchically organized options. The abstract engine used for hierarchical classification, known as

CSRL, was the first TSA shell and is described in (Bylander & Mittal, 1986).

- **Routine Design** (Brown & Chandrasekaran, 1986; Chandrasekaran,Josephson,Keuneke, & Herman, 1989). Routine Design was proposed by Brown as an architecture for performing design and planning tasks in which substantial experience is available (not for design or planning in totally novel situations).
- **Functional Reasoning** (Sembugamoorthy & Chandrasekaran, 1986; Sticklen,Chandrasekaran, & Bond, 1989a). Functional reasoning was proposed by Sembugamoorthy and Chandrasekaran initially as a means of capturing the intuition that knowing what a device is used for (i.e., its purposes/functions) yields leverage in understanding the device (Sembugamoorthy & Chandrasekaran, 1986). Later, Sticklen and Chandrasekaran extended functional representational frameworks by adding a qualitative simulation component (Sticklen et al., 1989a).

Hierarchical classification, as a selection methodology, is readily understood, and will not be further described here. However Routine Design and Functional Modeling are not as intuitive, and will be described in more detail below.

4.0 Routine Design (Planning)

The research presented here is fundamentally a planning activity. The Routine Design GT is the high level planning template that is the cornerstone method on which we rely. Routine Design is used for the generation of plans for top level crop management, and for the remediation portions of the disease and insect modules of our approach.

Routine Design makes use of hierarchical structures of design specialists to perform design, each responsible for a particular part of the overall plan. Hierarchies are used because hierarchical decomposition is a typical means utilized to manage complexity. The input is a set of planning constraints, and the output should be a full set of specifications for the required plan.

A design problem solver consists of a collection of design specialists. Each specialist is responsible for accomplishing a small part of the overall design. A part of the decision making conducted by each specialist is to determine (locally) which of a number of plans to carry out. S1 in Figure 1 has two such plans from which to choose. Generally each specialist chooses just one of its plans. The actions that constitute a plan include doing a calculation for a local value, satisfying a local constraint, and requesting another specialist to refine the current plan. For example, the left plan in S1 invokes the S2 specialist. If a plan fails, then alternate plans are tried. If part of a plan fails then an attempt is made to redesign the part of the plan that caused the failure. Potential causes of failure (i.e., where to try to fix a plan) are precompiled into the specialist.

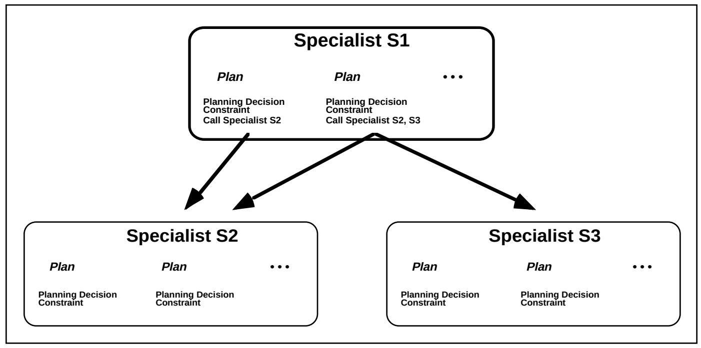

Figure 1: General structure of a Routine Design problem solver.

Of particular importance here is the selection functionality of the design specialist. Note, the specialist must choose among various plans (i.e., actions) to achieve the specialist's goals. But Routine Design does not make a commitment per se on how the selectors must operate. In most Routine Design applications to date, the selection operation has been pattern matching directed.

However, in the agricultural crop management area, decisions are made in ways that can be viewed as supplementing compiled-level experience. First, on the basis of qualitative simulation, a good agronomist can determine if a proposed management decision (that was arrived at on the basis of experience) will produce, in general, desirable results in a current environment. This "back of the envelope" type of computation is often based on causal understanding of a system, and is typically not capable of detailed, in depth results, but only of indicative results. A GT problem solving method referred to as Functional Reasoning/Functional Modeling (FR/FM) used to carry out such qualitative simulation activity is described below.

In addition, in agro-management, one very important tool is the numerical simulation models in general, and the CERES families of models in particular. Given boundary conditions, these models can accurately predict crop development and final harvest. The difficulty in using CERES-type models however, is in setting the initial parameters. Background on CERES-type models is described in section 6.

5.0 Functional Reasoning and Modeling (Causal Relationships)

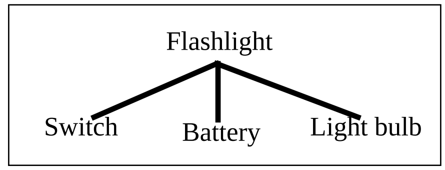

Figure 2: FR Device Decomposition

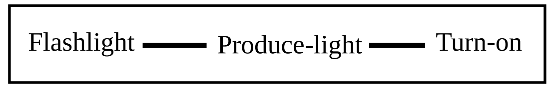

Figure 3: FR Device-Function-Behavior

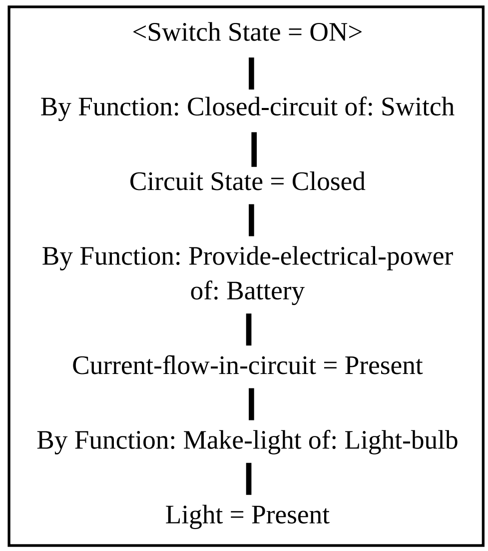

Figure 4: FR Behavior

The second Generic Task tool utilized is Functional Reasoning/Functional Modeling (FR/FM) which is based on the functional reasoning approach. Functional Reasoning (FR) is a methodology aimed at handling the staggering complexity of causal relationships in real world devices. The common intuition in all FR approaches is that provided the goals/purposes of a device are known, we may organize causal understanding by modularizing known causal relations and indexing the resultant modules by the known goals or purposes of the device.

The functional representation used by FR/FM originates from the work of Chandrasekaran and Sembugamoorthy (Sembugamoorthy & Chandrasekaran, 1986). Sticklen and Chandrasekaran developed a device simulation overlay to the earlier developed FR representation scheme which aimed at doing case specific consequence finding in domains of human body physiology (Sticklen et al., 1989a). FR/FM has since been applied to a diverse set of domains, including composite materials applications (Adegbite,Hawley,Sticklen, & Kamel, 1991; Kamel & Sticklen, 1990), high performance aerospace applications (Pegah,Bond, & Sticklen, 1993; Sticklen,-Bond, & St.Clair, 1988), and initial explorations in modeling landscape level ecological systems (Patzer & Sticklen, 1992; Sticklen,Robertson, & Tufankji-Attar, 1989b). The diversity of these domains demonstrates the wide applicability of the approach.

A functional representation uses four epistemic building blocks: devices, functions, behaviors, and state variables. Devices are the active components of the system being represented, and are usually represented in a component hierarchy. Functions represent abstractly stated capabilities of devices. Behaviors are implementations of functions; they describe how functions are achieved by showing the explicit state changes. State variables describe relevant aspects of the system.

Depictions showing a simple functional representation appear in Figures 2 through 4. Figure 2 shows a device decomposition of a flashlight. It has three components: a switch, a battery, and a light bulb. Figure 3 depicts a device-function-behavior viewpoint of the flashlight; it shows that “Produce-light” is a function of the flashlight, and that function is achieved using the behavior “Turn-on”. Finally, Figure 4 shows the behavior “Turn-on”. It starts with a test; the switch must be turned to the ON position for this behavior to be applicable. If the switch is on, then the circuit becomes closed, then current flows in the circuit, and finally light energy is produced. Notice that the behavior associated with a function of the flashlight references the functionality of the flashlight’s component devices.

A case-specific functional simulation is produced using a process analogous to “macro expansion.” Initially, the functionality of the top level device is examined. Any behaviors associated with its functionality whose tests are true are selected. Normally, these behaviors will describe partial state changes which reference a behavior or function of a subdevice. The information associated with the referenced behaviors or functions are then retrieved and replace the annotation. The process is similar to the expansion of a macro in software applications such as the preprocessor of a compiler. This process of macro expansion continues until all references to other behaviors and functions are expanded and only steps annotated with links pointing to “world knowledge” remain. A “By Knowledge” link describes a piece of the deepest knowledge (world knowledge) incorporated into the model. For example, a behavior associated with the function “Provide-electrical-power” of the battery might be two steps in length. The first step might reference the functionality of its components (a zinc and a copper rod and an electrolytic solution between them) to describe how a voltage drop potential is produced across its terminals. The second step might reference a By Knowledge link associated with “Kirchhoff’s Law”: if a voltage drop exists across a pair of terminals in a closed circuit then current will flow in the circuit.

The functional representation actually stores a large causal net in an organized and modular fashion, with the modules indexed by functions. When the simulator is run, only the relevant pieces of the causal net are retrieved. The functional viewpoint (as expressed in the FR/FM shell) is utilized to capture the gross causal relationships among the entire agricultural system under study. Results of simulation with the FR/FM model we will develop will be used to drive the CERES model for wheat growth.

6.0 Background on CERES and CERES Wheat

CERES Wheat (Ritchie et al., 1985) is one of a family of dynamic process-orientated models which simulate the growth, development, and yield of major cereals. Several of these models and supporting submodels are incorporated into a single software system, the Decision Support System for Agrotechnology Transfer (DSSAT), which provides users with common input/output and interface features (IBSNAT, 1990). Users of DSSAT can perform experiments on the computer to estimate what would happen under various input and management constraints. Users can modify the way a simulated crop is irrigated to predict changes in crop yield as well as other variables such as evapotranspiration and irrigation requirements. These computer experiments could involve any number of alternative ways to irrigate the crop and simulate them for a number of years to estimate long term average responses as well as year-to-year variability in these responses. These experiments could be repeated on the computer for different soils, varieties, planting dates, and nitrogen fertilizer management levels. It is also possible to combine crop model results with economic factors to compare profitability and risks associated with each strategy (Boggess & Ritchie, 1988).

DSSAT and CERES Wheat exploit several interrelated sub-routines which simulate the growth of various plant organs and the extraction of nitrogen from the soil profile. Fine tuned knowledge of the rates and magnitudes of the component processes as influenced by environment and previous crop circumstances enables precise prediction of both the timing of crop developmental events and final yield. The following gives a brief description of the subroutines used by CERES Wheat:

- **Development** Wheat growth is separated in CERES Wheat into two distinct but interdependent processes, phasic development and morphological development. Phasic development involves changes in the stages of growth and is generally associated with changes in biomass partitioning patterns. Morphological development represents the beginning and ending of plant development within the whole plant life cycle.
- **Yield Prediction** The most important simulation in the model is partitioning of biomass to the grains or economic yield. Calculation of sink size or the grain number is the most critical step in accurate yield prediction.
- **Soil Water Balance** The soil water balance model is a one-dimensional model, which predicts water content of each layer through time as it is changed by the processes of infiltration, redistribution, drainage, evaporation, and root water extraction for transpiration.
- **Soil Nitrogen Dynamics** The nitrogen (N) balance component of the CERES crop models simulates the processes of turnover of soil organic matter and crop residue, hydrolysis of urea, nitrification, losses of N, and the uptake and use of N by the crop.
- **Plant N Uptake** - The plant nitrogen (N) uptake is determined from the lesser of plant N demand and N supply.

The CERES-Wheat model has been extensively tested by Otter-Nacke et al. (Otter-Nacke,Godwin, & Ritchie, 1986). Our objective is to exploit the model’s simulation capabilities as a dynamic knowledge base for prediction of input demand and yield as influenced by farm and district-level management decisions. The model is sensitive to crop management decisions including choice of variety, date of planting, fertility levels, and irrigation amount and timing. With recently incorporated modifications, it can also simulate the impact of long-term climatic change on yield, crop duration, and nutrient losses. Modeling can thus be used to evaluate long-term agricultural productivity and sustainability in light of management decisions.

7.0 Integration

The regional wheat management system integrates three levels of problem solvers from the methodologies discussed above. The most experience-based level is the Routine Design planning agent. Problem solving is very direct and relatively straightforward once the experience-based knowledge necessary is embedded in a system. The knowledge for an instance of Routine Design is highly organized and tuned for one purpose and thus problem solving efficiency is very high.

The intermediate problem solving level is implemented using the FR/FM approach. At this level, the many causal relations about soil, fertilizer, irrigation effects, and so on are organized around the function each part plays in the development of the crop (e.g., soil tillage has one purpose of aerating the soil). Knowing these causal relationships, "back of the envelope" computations are performed to determine likely responses to proposed changes in management. These computations typically do not produce definitive results, only indicative results. They take a deeper level of expertise than the purely experience-based problem solving, and are typically more compute intensive.

At the deepest level, the CERES family of crop simulation models is utilized. Once several different proposals from the experience-based problem solver and qualitative causal-based simulation show similar benefits, detailed simulation modeling can be applied to discriminate between the candidate management changes.

In general, the problem solving method we follow can be viewed as a two phase computation for each growing unit (field). First, given boundary constraints on economic value of wheat, growing season length, available varieties, insect and disease problems from the last crop year, available fertilizer, and available irrigation water, a rough cut version of a "plan" for the coming crop year is developed. Then this rough plan is refined by the use of both a model-based functional reasoner, and by the CERES Wheat simulation model. The output of Phase 1 will be an elaborated, pre-planting plan for the coming crop year.

Phase 2 amounts to following the plan developed in Phase 1 in the face of additional, real time constraints set by conditions during the crop year. Most successful farmers, the world over, follow a version of this two step management strategy: before planting develop a plan; during the growing season try to follow the plan, but be ready to modify or augment it as conditions during the cropping year demand.

8.0 Wheat Crop Management Modules

The management of a wheat crop is modularized to address the various aspects of management as follows: planting date selection; water utilization and management; pest monitoring, identification, and remediation; disease monitoring, identification, and remediation; and harvest management. The following discussion gives an overview of the problem solving architectures used in each of the modules.

- **Varietal Selection**: Wheat varietal selection is a relatively straightforward selection task. The capability of Hierarchical Classification, augmented with experience-based matching will be used in this module.
- **Planting Date Calculation**: This module is likewise relatively easy in concept. Planting date selection is modeled by following a Routine Design problem solving method.
- **Fertilization Requirement and Timing, and Irrigation**: Fertilization and irrigation is handled in one module. Unlike planting date (which once fixed, must remain fixed), fertilization and irrigation plans can be altered during the growing season, and in an irrigated regime, changed on a regular basis. This module at the high level will be a routine designer, which will include both FR/FM and CERES Wheat modules interfaces.
- **Pest and Disease Identification**: The two modules which identify growing season problems (insects or diseases) will be simple classification systems. A picture database (on line) will be supplied to help with the identification of both insects and diseases.
- **Pest and Disease Remediation**: These two modules will be experience-based routine design systems. Taking as input the identification of a problem, and current cropping conditions, this module makes recommendations on plans of action to alleviate the problem.
- **Harvest Management**: This simple module concentrates on the timing of harvest.

9.0 Future Work

The work discussed above is just the starting point for many extensions to larger regions and to other countries. The following discussion outlines the long-term goals of our work and the applicability of the work beyond the management of wheat in Egypt.

In this paper we have presented what we envision as the first step in an Egypt-wide water distribution system. Since the wheat management system we develop can be considered prototypical for management of other crops in Egypt, the next step is the development of a management system for other major crops. Furthermore, since the limiting factor for agricultural production in Egypt is water, each cropping consultant will include a strong emphasis on water utilization and management. As each comes on line, it will be interfaced with a country-scoped water distribution consultant. Thus, we envision a cooperative problem solving unit in which each of the district-level crop management agents deals specifically with maximizing economic yield given local constraints, and the single water distribution agent deals with maximizing economic yield for a district-level (and eventually region-level and total country-level) basis by planning water distribution over all areas covered. Figures 5 and 6 below show the interaction between the regional district crop management systems and the water distribution consultant.

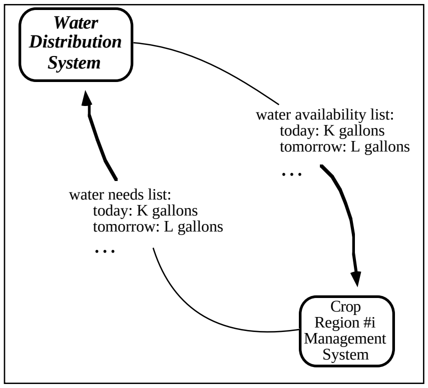

Figure 6: Interaction between water distribution agent, and each regional crop management specialist

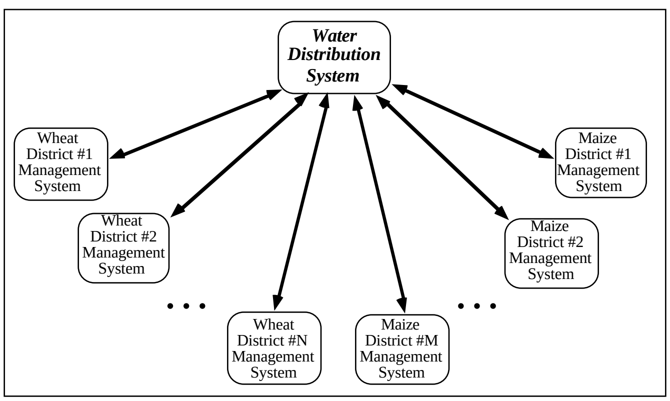

Figure 5: Conceptual long term goal - maximizing water utilization by cooperative problem solving

Although the present research focuses on agro-management in Egypt, applicability to the United States is also anticipated. Problems of water utilization and management directly affect sectors of US agriculture. In areas such as the Central Valley of California, water has always been a limiting factor. We observe agricultural interests increasingly being asked to justify water allotments. Thus, systematic, effective, and easily documented water management methods will become increasingly important.

In addition, although district-level expertise in wheat and other crops is not typically limiting in the U.S., the ability to quickly check the results of experience-based reasoning against a cropping simulation model (such as CERES) is not typically available. Thus, at the level of our specific problem, results of our research will also impact U.S. agriculture by providing a problem solving template for the integration of experience-based reasoning with the numerical simulation capability of CERES models.

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11.0 Bibliography

Adegbite, V.,Hawley, M.,Sticklen, J., & Kamel, A. (1991). Implementation of an Artificial Intelligence Technique for Real-Time Control of Microwave Processing of Composite Materials. In Seventh Annual ASM/ESD Advanced Composites Conference, (pp. 409-413). Detroit, Michigan.

Armoni, A.,Rakantalio, E., & Dominguez, A. (1988). Knowledge Systems and Farming. In Applications of Artificial Intelligence to Agricultural, Agrochemical, and Food Processing Industries,. Caen, France:

Batchelor, W. D., & McClendon, R. W. (1989). Evaluation of SMARTSOY: An Expert Simulation System for Insect Pest Management. Agricultural Systems, 31, 67-81.

Beck, H. W.,Jones, P., & Jones, J. W. (1989). SOYBUG: An Expert System for Soybean Insect Pest Management. Agriculture Systems, 30, 269-286.

Boggess, W. G., & Ritchie, J. T. (1988). Economic and Risk Analysis of Irrigation Decision in Humid Regions. Production Agriculture, 1, 116-122.

Boulauger, A. G. (1983) The Expert System PLANT/DS: A Case Study in Applying the General Purpose Inference Systems ADVISE to Predicting Black Cutworm Damage in Corn. University of Illinois at Champaign-Urbana.

Brown, D. C., & Chandrasekaran, B. (1986). Knowledge and Control for a Mechanical Design Expert System. IEEE Expert, 3(July), 92-100.

Bylander, T., & Mittal, S. (1986). CSRL: A Language for Classificatory Problem Solving and Uncertainty Handling. AI Magazine, 7(2), 66-77.

Chandrasekaran, B. (1986). Generic Tasks in Knowledge-Based Reasoning: High-Level Building Blocks for Expert System Design. IEEE Expert, 1(3), 23-30.

Chandrasekaran, B. (1987). Towards a Functional Architecture for Intelligence Based on Generic Information Processing Tasks. In IJCAI-87,. Milan:

Chandrasekaran, B., & al, e. (1979). An Approach to Medical Diagnosis Based on Conceptual Structures. In Proceedings of IJCAI 6,.

Chandrasekaran, B.,Josephson, J.,Keuneke, A., & Herman, D. (1989). An Approach to Routine Planning. International Journal of Man Machine Studies, 377-398.

Durkin, J.,Godine, J., & Lu, Y. C. (1990). Expert Systems for Specialty Crop Management. AI Applications in Natural Resource Management, 4(2), 48-56.

Evans, M.,Mondor, R., & Flaten, D. (1990). Using Expert Systems to Generate Fertilizer Recommendations. AI Applications in Natural Research Management, 4(2), 3-10.

Gomez, F., & Chandrasekaran, B. (1981). Knowledge Organization and Distribution for Medical Diagnosis. IEEE Transactions on Systems, Man, and Cybernetics, SMC-11(1), 34-42.

Gonzales-Andujar, J. L.,Rodreigues, J., & Navarrete, L. (1990). Development of a Prototype Expert System (SIEXMAL) for Identification of Weeds in Cereals. In ENRS Symposium,. Madrid, Spain:

Goodrich, P. R., & Kalbar, S. N. (1988). Manure Application Expert. In 2nd International DLG Congress for Computer Technology,. Frankfurt, Germany:

IBSNAT (1986). Decision Support Systems for Agrotechnology Transfer. Agrotechnology Transfer, 2, 1-5.

IBSNAT (1990). Documentation for IBSNAT crop model input and output files for the decision support system for agrotechnology transfer (DSSAT V2.1) No. Dept. of Agronomy and Soil Science, University of Hawaii.

Kamel, A., & Sticklen, J. (1990). An Artificial Intelligence-Based Design Tool for Thin Film Composite Materials. In The Fifth Technical Conference of The American Society for Composites, (pp. 375-381). East Lansing, Michigan:

Linker, H. M.,York, A. C., & Wilhite, D. R., J.r. (1990). WEEDS - A System for Developing a Computer-Based Herbicide Recommendation Program. Weed Technology, 4(2), 380-385.

Mittal, S. (1980) Design of a Distributed Medical Diagnosis and Data Base System. Computer and Information Science Department, Ohio State University.

Morgan, O. W., & et.al. (1989). SELECT: An Expert Systems Shell for Selecting Amongst Decision or Management Alternatives. Agricultural Systems, 31, 97-110.

Otter-Nacke, S.,Godwin, D. C., & Ritchie, J. T. (1986). Yield Model Development: Testing and Validating the CERES Wheat Model in Diverse Environments. Agristars.

Pasqual, G. M., & Mansfield, J. (1988). Development of a Prototype Expert System for Identification and Control of Insect Pests. Comput. Electron. Agric., 2(4), 263-276.

Patzer, K., & Sticklen, J. (1992). Causal Knowledge Sharing in Large Biological Projects: Leveraging the Functional Approach. In AAAI-92 Workshop on Communicating Scientific Knowledge,. San Jose, CA:

Pegah, M.,Bond, W. E., & Sticklen, J. (1993). Functional Representing and Reasoning About the F/A-18 Aircraft Fuel System. IEEE Expert, 4, 65-71.

Plant, R. E. (1989). An Integrated Expert Decision Support System for Agricultural Management. Agricultural Systems, 29, 49-66.

Renner, K. A., & Black, J. R. (1991). SOYHERB - A Computer Program for Soybean Herbicide Decision Making. Agronomy Journal, 83(5), 921-925.

Ritchie, J. T.,Godwin, D. C., & Otter-Nacke, S. (Ed.). (1985). CERES Wheat. A Simulation Model of Wheat Growth and Development. College Station, Texas: Texas A&M University Press.

Sembugamoorthy, V., & Chandrasekaran, B. (1986). Functional Representation of Devices and Compilation of Diagnostic Problem Solving Systems. In J. Kolodner & C. Reisbeck (Eds.), Experience, Memory, and Learning Hillsdale, N.J.: Lawrence Erlbaum Associates.

Sticklen, J.,Bond, W. E., & St.Clair, D. C. (1988). Introducing Functional Reasoning into the Aerospace Domain. In Proceedings of the 4th Conference o AI Applications for Space,. NASA:

Sticklen, J.,Chandrasekaran, B., & Bond, W. (1989a). Distributed Causal Reasoning. Knowledge Acquisition, 1, 139-162.

Sticklen, J.,Robertson, G. P., & Tufankji-Attar, R. T. (1989b). An Artificial Intelligence-Based Approach to Modeling an Ecological Problem: A Methodology to Capture and Extend Understanding of the Global N2O Cycle. In Proceedings of the Summer Computer Simulation Conference,.

Stone, N. D., & Toman, T. W. (1989). A Dynamically Linked Expert-Database System for Decision Support in Texas Cotton Production. Comput. Electron. Agric., 3(4), 139-148.

Thompson, S. J., & Peart, R. M. (1986). An Expert System for Soil Moisture-based Scheduling of Center Pivot Irrigation. In ASAE, (pp. 4518).

Ton, J.,Sticklen, J., & Jain, A. K. (1991). Knowledge Based Segmentation of Landsat Images. IEEE Transactions on Geoscience and Remote Sensing, 29(2), 222-232.

Whittaker, A. D., & Thiewe, R. H. (1988). Integration of Problem Solving Techniques in Agriculture. American Association for Artificial Intelligence (AAAI) & Knowledge Based Systems Area of American Society of Agriculture Engineers.