# INTEGRATION OF A GENETIC ALGORITHM TO THE GOSSYM MODEL FOR IRRIGATION DECISION SUPPORT

**E. Jallas**
**CIRAD, USDA-ARS-CSRU**
**S. Turner and J.M. McKinion**
**USDA-ARS-CSRU**
**R. Sequeira**
**USDA-APHIS**
**G. Boggess**
**MSU**

## Abstract

Cotton was one of the first crops to be modeled with the objective of aiding profit-oriented commercial agribusiness. The GOSSYM-COMAX (Baker et al. 1983; McKinion et al. 1984; Sequeira and Jallas 1995) system is the only system currently being used in commercial agriculture. GOSSYM is a dynamic, daily simulation of the development and growth of the cotton plant. Baker et al. (1983), Jallas (1991) and Sequeira and Jallas (1995) published the descriptions of the theoretical background and most mathematical functions of GOSSYM. The model is divided into two daily, independent subsystems linked by a partitioning process. The first subsystem calculates the carbohydrate supply and the second subsystem calculates the carbohydrate demand. During each daily time step, the partitioning process –that drives the yield components and storage– balances the whole system. This explains the term "materials-balance" often used to describe this model.

By coupling an expert system (COMAX) with the simulation model GOSSYM, McKinion and Lemmon (1985) provided GOSSYM's users with expert decision support. COMAX uses an expert system rule base to determine the optimal actions to perform, given a projected or set of projected weather scenario. COMAX provides advice to irrigation, nitrogen, or plant growth regulator use. These algorithms have been described by Bridges et al. (in press) based on early designs by McKinion and Lemmon (1985) and Lemmon (1986).

Whereas COMAX has been used successfully for a number of years it has been proven sub-optimal. An alternative approach is proposed, in which a Genetic Algorithm (GA) is used to evolve an irrigation schedule. GA's are computer based optimization and search techniques that mimic natural selection to efficiently search very large solution spaces. They are based on the biological concepts of evolution through mechanisms such as selection and genetic crossover and mutation. The GA doesn't contain explicit representation of horticultural or botanical knowledge. Simply, it utilizes simulation results from the GOSSYM model to evolve "chromosomes" which represent (encodes) irrigation schedules similar to that produced by the expert system. A population of many chromosomes, which compete with one another in a "survival of the fittest" competition, evolves over time to produce better and better irrigation schedules. At the end of the evolutionary process, the population's best-fit irrigation schedule is displayed. A comparison with the irrigation schedules produced by the COMAX expert system indicate that the GA approach is able to produce better schedules, which increase the profitability of the cotton crop.

Reprinted from the *Proceedings of the Beltwide Cotton Conference*
Volume 1:422-428 (1998)
National Cotton Council, Memphis TN

## Introduction

The use of agricultural models (crops and insects) for prediction and management dates to the XVIII century when de Reaumur formulated the first temperature-dependent models to predict when a plant would reach a new phenological stage (cited by McFarland et al., 1992). Crop modeling based on computer-based simulation originated during the late 1960's and early 1970's with the application of quantitative methods developed in the area of the physical sciences to biology. Pioneering work in modeling and simulation in biology was conducted in England (Lokta 1932; Southwood 1966), France (Volterra 1931), the Netherlands (de Witt and Brouwer 1968), the United States (Duncan et al. 1967; Garfinkel 1962). After more than 25 years of research starting in the early 1970s, computer-based crop models migrated from research laboratories to farmers' "tool boxes".

Today, quantitative, mathematical computer-based simulation models are common in decision making. The decision-making process relies on using the model as a surrogate for real experimentation. Recently other modes of model-based decision-making have been investigated. Indeed, some of the early leading ideas in modern biology (the mechanisms underlying the processes of evolution, for example) are re-emerging in the bio-sciences and finding innovative applications in agriculture through the discipline of Artificial Intelligence. This is the case of evolutionary algorithms, such as the Genetic Algorithms technique.

Genetic Algorithms are computer based optimization and search techniques which mimic natural selection to efficiently search very large solution spaces. They are based on the biological concepts of evolution through mechanisms such as selection and genetic crossover and mutation. This basic biological metaphor has been formalized into the emerging discipline of Genetic Algorithms (or, more generally, Evolutionary Programming) as an effective method for search and as a key mechanism for machine learning.

Holland (1975) formulated the original ideas behind GAs. Even if GAs are part of the "weak" AI techniques (this is because no formal heuristics or other explicit "human-like knowledge" are used in a traditional GA) they are a good alternative to traditional optimization (Holland 1992) and discovery. They have been used efficiently in many different domains such as medicine (Fitzpatrick et al., cited in Goldberg 1989), industry (San Martin and Knight 1993), telecommunication (Davis et al. 1993) and crop modeling (Sequeira et al. 1994; Sequeira et al. 1995).

GAs are not currently used in agriculture to make recommendations or for decision-support. Another AI technique, rule-based Expert Systems (Olson and Sequeira 1995) is more commonly used in decision support, despite its constraints. Expert Systems are considered to be a more "intelligent" AI technique than GAs because they use an intensive knowledge approach (Luger and Stubblefield 1993). In Expert Systems, knowledge and search techniques are separate. Knowledge is stored in a database and the search technique, the 'inference engine', uses the knowledge to determine a solution for problems which are submitted to the expert system. Expert systems can be associated with crop models in order to make recommendations to the farmer. The GOSSYM-COMAX system is one example of such a link (Bridges et al., in press).

The sequence of farmer practices and the level of the input (e.g., amount of irrigation) can be seen as an adaptation problem. With this approach it becomes obvious that GAs may have a role in decision-making. Specifically, a farmer must adapt to different inputs, levels, soil substrates, weather, and plant behaviors, as well as interactions between these factors, in order to maintain a sustainable level of production. Several questions may be raised. Why use intensive knowledge approaches when adaptive techniques can be used? Do the latter represent a tangible improvement over the former or not? The main objective of this study was to integrate a GA to the GOSSYM model, representing the dynamic agent subject to adaptation, and compare results produced by this GA with results produced by the COMAX Expert Systems.

## Methods

### The Genetic Algorithm

Detailed theoretical descriptions of GAs and their mathematical foundations are well explained in Goldberg (1989), Holland (1992), Davis (1991), and Michalewicz (1992). Briefly described, GAs involve techniques called representation, selection, reproduction (including crossover, mutation, and inversion), and replacement. In GAs, possible solutions to a problem are often represented as bit strings (although many alternative representations are used). When the solution to a problem is the combination of a set of parameters, for example:

15 | .25 | blue | 1 | true

the solution may be represented in binary form, as:

1111 | 0000 | 1000 | 0001 | 1

The representation of a possible solution is called a "chromosome". The representation of a parameter is called a "gene". Each chromosome represents an approach to solving the problem. Since any proposed solution to a problem may be rated as better or worse than other solutions, each chromosome has a comparative rating. This rating, the value of an individual chromosome relative to others, is often referred to as the "fitness value" of the chromosome. GAs manipulate chromosomes with evolutionary operators (selection, crossover, mutation, inversion, and replacement) and "evolve", generation after generation, better solutions, tending towards improvement/adaptation as the evolutionary process continues (Goldberg 1989).

During the reproduction process, the crossover operation exchanges chromosome parts and the mutation operation changes the value of a gene (Figure 1). Selection is used to select the parents for the next generation (e.g., probabilistically, the "best" members of the population) (Koza 1992).

The code used for the GA was a modified version of the GENESIS code, which is a Genetic Algorithm (GENESIS © 1986, 1990 by John J. Grefenstette, in: Davis, 1991). This code, developed in C, has many useful options and allows the user to easily develop a specific fitness function. The key issue for this phase of our research was to link the GA to the GOSSYM model. Because of the modular structure of both GOSSYM and the GA, this procedure was straightforward.

Each chromosome was constructed with 200 genes that represented the amount of irrigation from day 1 after emergence until day 200. The daily amount irrigation was allowed to vary from 0 to 1.25 inches. This range was divided into 32 increments of 1.25/32. Thus we could code each gene on 5 bits. Each chromosome was thus composed of 1000 bits. For example, a gene of "00000" represented an amount of irrigation between 0 to 0.039 inches, 00001 any amount between 0.039 to 0.078, and so on. To avoid the effect of *Hamming cliffs* linked to the binary representation, the Gray code approach (Forrest 1993) was used. To illustrate this problem, consider the representations 01111 and 10000 that correspond to increments 15 and 16; they differ by only 0.039 inches of water but differ in 5 of their bits. The gray code represents mathematically adjacent values by bit patterns that differ by a single bit. For example here 15 will represented by 01000 and 16 by 11000.

In this study, the fitness function was determined by our specific problem, and simply corresponded to the economic value of a given irrigation schedule. This value was the difference between the cost of the irrigation and the direct gain procured by it. The fitness function was:

$$fitness = yield - \left( number\_irr\ igation * 3.5 + \sum_{i=1}^{end\ of\ season} H_2O(i) \right)$$

where *fitness* is the fitness value, *yield* is the simulated yield (in pounds of fiber per acre), *number_irrigation* is the number of irrigations scheduled, 3.5 is the cost per acre of one irrigation in pounds of fiber, and $H_2O(i)$, is the amount of water for the *i*th day in inches.

Different population sizes were tested, varying between 10 to 100 chromosomes per generation. The main limiting factor in carrying out this study appeared to be the use of the GOSSYM model that took about 15 seconds to simulate a complete growing season (less than 200 days). It thus takes 2.5 minutes to evaluate a generation composed of 10 chromosomes, 12.5 minutes for a generation of 50 chromosomes, and 25 minutes for a generation of 100 chromosomes. During the experiment the running time of the system varied between less than 2 hours to 20 days depending how fast the solution converged.

The selection method used was the roulette wheel method, which assigns a probability to a specific chromosome to be used for reproduction based on its fitness. We added to this selection method the elitist strategy that guarantees that the best structure always survives to the next generation (Beasley et al. 1993).

Different mutation rates were tested, varying from 0.001, which gives a chance to 1 genes per chromosome to be mutated at each generation, to 0.05 which a chance to 50 genes per chromosome to be mutated. Tested crossover rates varied from 0 to 80%. A lethal condition was added to take into account the irrigation constraint: if two irrigations or more were scheduled by the GA in a period less than the user-indicated minimum time between two irrigations, then the chromosome was destroyed and replaced by one valid. Different replications were conducted, starting with the same random population but with different random seed for selection, crossover and mutation processes.

When the GA was stopped, because the solutions converged or it run 10000 generations, the chromosome with the highest fitness value represented the "best" irrigation schedule for the environmental conditions of the experiment. This irrigation schedule was compared to the irrigation schedule obtained from the COMAX system running under the same environmental conditions.

## The GOSSYM-COMAX System

GOSSYM is a dynamic, daily simulation model of the development and growth of the cotton plant. Baker et al. (1983), Jallas (1991) and Sequeira and Jallas (1995) have published the descriptions of the theoretical background and most mathematical functions. The system is based on the 'mechanistic process' paradigm, which tries to maximize the number of causal relations present in the model and to minimize empiricism for a given level of observation. To achieve this, the model is divided into two daily, independent subsystems linked by a partitioning process. The first subsystem calculates the carbohydrate supply. The second subsystem calculates the carbohydrate demand. During each daily time step, the partitioning process – that drives the yield components and storage – balances the whole system. This explains the term "materials-balance" often used to describe this model. Thus the partitioning process balances the total supply and demand in the model. The model's structure includes developmental and morphogenetic rate equations for inter-nodes, leaves, fruits, etc.

COMAX is a decision support system coupled by McKinion and Lemmon (1985) with the simulation model GOSSYM. Bridges (personal communication) later reengineered this expert system and today provides users with expert decision support (Baulch et al. 1995). These algorithms have been described by Bridges et al. (in press) based on early designs by McKinion and Lemmon (1985) and Lemmon (1986). COMAX uses an expert system rule base to determine the optimal actions to perform, given a projected or set of projected weather scenario. If COMAX has been invoked, COMAX monitors the GOSSYM simulation in order to detect stress symptoms. If COMAX detects stresses, it may recommend different practices to solve the problems. GOSSYM output includes graphs of the daily mass accumulation and number of organs produced for different plant parts. Additionally, soil Nitrogen, soil water, stress factors, leaf area index, weather summaries, and other variables are also output. COMAX output includes recommendations for irrigation, nitrogen use, and for the application of plant growth regulators.

COMAX proposes three kinds of irrigation advisors:

- a short-term irrigation advisor which informs the user if his crop needs irrigation within the next two weeks,
- a long-term irrigation advisor which develops an irrigation schedule for all of the growing season, and
- a water conservation advisor which make its recommendations based on the evaporative demand of the crop.

Input requirements for these irrigation advisors are identical. The user must specify the maximum amount of water that can be applied per irrigation, the application method (furrow, sprinkler, or drip), the minimum number of days between irrigation applications, and start and stop criteria for irrigation. These start and stop criteria are examples of user-modified rules. The start criterion tells COMAX when to begin considering the possibility of scheduling irrigation. This does not schedule the first irrigation, but sets the earliest possible date for the first irrigation recommendation. There are four possible user-defined start criteria: a calendar date, the number of days after emergence, the number of days after the first square, or the number of days after the first bloom. The stop criterion tells COMAX when to stop considering the possibility of scheduling irrigation. There are four user-defined choices: a calendar date, the number of days after the first open boll, the percentage of open bolls, and the number of days before harvest.

The three irrigation advisory systems use an average value of -0.5 bars for soil water potential as a trigger for the initiation of irrigation. The rule for deciding whether to apply irrigation with all three advisors can be summarized as follows:

***If*** *today the current soil water potential is less than -0.5 bars and,*

> ***If*** *today's date is greater than or equal to the first day to consider irrigation, and today's date is less than or equal to the last day to consider irrigation, and the minimum number of days between irrigations has elapsed since the last irrigation,*

***Then***

> *make an irrigation application.*

Because the short-term irrigation advisor is meant to be used to know whether the crop will need to be irrigated within the next two weeks, it cannot be used in conjunction with any other advisors. The two other advisors running on a long-term period are often used in conjunction with other advisors (e.g., fertilizer and plant growth regulator).

The main difference between the long-term advisor and the water conservation advisor is that the long-term irrigation advisor will always apply the maximum application amount of water specified by the user. In contrast, the water conservation advisor will use the evaporative demand simulated from a first run of the model to determine the amount of irrigation that should be used for each application. This amount is the minimum of: (1) the demand simulated from "today" to the next scheduled irrigation, times 1.66 (it is assumed that the efficiency of the irrigation is only 60%), and (2) the maximum application amount.

Experiments were made with both long term and water conservation irrigation advisors.

## Experimental Conditions

In order to conduct a plant simulation, four main categories of external variables are needed: weather, soil, technical itineraries, and within-season plant sampling for "mid-season model adjustment" (plant mapping). The first three of these categories are required. In our experiments we did not use the fourth category. We used validated files provided with the software and corresponding to Mississippi conditions. We will describe here the first three categories of external variables needed for a GOSSYM simulation.

The soil, a Commerce type, is composed of three horizons with no water table. We considered that there is runoff with rain and irrigation. Table 1 shows the key characteristics of the soil used in the GOSSYM simulation. Characteristics may be variable at different soil depths as shown in the table. For this soil, layers become increasingly sandy. The "q" values, which are volumetric water contents at different matrix suction (see Hillel 1988), refer to the soil's ability to retain water. The initial soil conditions, prior to planting, are shown in Table 2 for different soil layers (soil depths). Residual nitrogen in all forms decreases with soil depth.

Table 3 summarizes the technical itinerary (cultural practices or agronomic management) for the simulated field. The variety (Cultivar) used represented "mid-season" cultivars, that is, cultivars with a season duration (planting to 50% open boll) of 140 days. The latitude is equivalent to that of Starkville, MS. The row spacing used was standard for mechanically cultivated cotton (around 120,000.00 plants/ha or 50,000 plants/acre). Fertilization was applied broadcast on three different dates using a urea-ammonium nitrate (UAN) formulation because the model simulates only the effect of nitrogen fertilizer.

Climatic variables are the basic driving data for all mechanistic growth models. The following weather information is input into the model:

- the daily solar radiation, which is the motor of photosynthesis;
- the minimum and maximum daily temperatures, which are mainly used to simulate soil processes, growth, and development;
- the daily precipitation, which is the first input for the water balance;
- the average wind speed (to which the model is not very sensitive).

Figures 2 to 5 summarize environmental conditions for the cotton-growing season simulated in this study. Figure 2 shows that temperatures peaked at 40°C and averaged 32°C during the growing season (05/09 to 11/22). Figure 3 shows the cumulative degree-days during the cropping season:

$$DD = \sum \left( \frac{Tmax - Tmin}{2} - Growth\_Threshold \right)$$

In the previous formula the Growth Threshold is 15°C. The maximum rate of DD accumulation occurred from 06/01 to 09/01. Figure 4 shows that solar radiation peaked during April to July ($\bar{x}$ = 25) and thereafter decreased. Figure 5 shows a bimodal rain distribution with a total rainfall during the growing season of 576 mm.

## Results and Discussion

The goal for both the GA and the COMAX expert system is to adjust irrigation scheduling, using the GOSSYM simulation, to optimize profit. This approach does not correspond necessarily to maximizing yield since there are irrigation costs and irrigation technical constraints (for example, it may not be possible to irrigate every single day due to equipment limitations).

### Regular Simulation

First the model was run to provide benchmark for comparisons with the schedules evolved by the GA and produced by COMAX. Figures 6 and 7 show the behavior of the model given the observed rainfall (with no supplemental irrigation). The rainfall during the season provides 576 mm of water but only 536.5mm are actually available for cotton growth (GOSSYM simulates 39.5 mm of runoff). The effects of water stresses are clear from figure (7) which show stress indices below 1 (1 = optimal) during long periods. The crop is stressed after about two months, when the flowering period starts. The simulation predicts water stress starting only after first bloom. The growth is sub-normal (26 nodes, 18 fruiting branches) and the yield is adequate (1031 kg of lint per ha).

### Results from the COMAX Expert System

Table 4 shows the results for the COMAX expert system. Each row in the table represents two outcomes for two COMAX consultations corresponding to the two water management strategies tested: long term (LT) and water conservation (WC). The irrigation amount was set to varying levels from 6.3 to 177.8 mm of water (0.25 to 7.00 inches) to be applied whenever the stress level of the plant justified irrigation as invoked by COMAX.

As expected, when the maximum possible amount of irrigation increased, the total number of irrigations decreased from 12 to 4 using the LT strategy and from 12 to 7 using the WC strategy. The WC strategy shows a relative reduction in number of irrigations when the amount of irrigation applied increases. Plant height reached its maximum value at 127 mm of water per irrigation for the LT irrigation strategy and around 25 mm for the WC irrigation strategy. In both water management strategies the yield increases from 6.3 to 30.5 mm per irrigation, then stays stable as the amount of water applied increases to the maximum of 177.8 mm per irrigation. The crop reaches its potential with 310 mm from irrigation in the WC strategy and with 302 mm from irrigation in the LT strategy. To these irrigation amounts must be added the 536 mm water from rainfall. Thus the total amount of water supplied to the system is between 838 to 846. The main interesting result is that the maximum yield was obtained in both strategies with the same number of irrigation (8) and about the same amount (300 mm). Figures 8 show the irrigation schedules recommended by COMAX where both strategies give the same schedule which start during the dry period.

### GA Results

GA experiments were run using input files as described for the "regular" simulation. Figure 9 shows the best irrigation schedules evolved by the GA. This graph is contrasted with Figure 8. In graph 9 the GA shows its overall better value for decision support compared to the COMAX expert system. Unlike COMAX, the GA proposed an irrigation schedule with large variations in amount of irrigation, number of irrigations, and timing. In Figure 9, the irrigation schedule planned important irrigations during critical growth stages; the blooming and boll filling periods which corresponds to the dry season. Like COMAX, it doesn't recommend irrigation at the beginning of the cropping season because there is enough residual water in the soil during this period of the crop. But unlike COMAX the GA recommended a small supply to complement rainfall just before the squaring and blooming periods.

In the experiments, as demonstrated by results in Table 5, the GA found a better solution than the expert system. This solution is not necessary the best solution in the space of all the possible solutions. Although it is a good enough solution, a human can still produce an even better solution once the GA results are obtained. The main limiting factor in the use of this technique is the time requirement needed to obtain a good solution. We made several experiments with different population sizes, mutation rates, crossover rates and random number seeds. It took between 2 hours to 20 days to run the GA on a Pentium 200. And the best solution was found in a run of 19 days which is obviously too long for a decision support system in agriculture. Table 5 shows that compared to the COMAX expert system, the evolved irrigation is better both in terms of total yield and in terms of optimality. That is, the schedule evolved resulted in reduced costs while manipulating the timing of irrigations such that the yield was not only maintained, but also increased.

## Conclusion

We conclude that this new approach to irrigation scheduling is an improvement over the existing expert-system method. Importantly, the GA-approach is generic in the sense that it is applicable to any conditions and to any cropping situation. This is not the case with the expert system approach. The knowledge base developed for the expert system is applicable only to the conditions considered by the experts. The adaptive, dynamic, and evolving nature of genetic algorithms are the key to their robustness.

The second conclusion is that if the GA is a very good optimization tool, it is also, in connection with a simulation model, a very good knowledge discovery tool. For example in our case we can now evolve new rules for our expert system. In automating this process we can build a learning machine. This result is possible because we are using a simulation model which represents deep knowledge. The GA gives us the possibility of exploiting the value of this knowledge. In GOSSYM, there are more than 300 original equations describing all biological cotton processes. It is very difficult, or even impossible, for a human being to follow all the interactions in the represented system (a cotton crop and its environment). But with the GA, it is possible to search the "right" part of the space of solutions for a given question and obtain a good solution. Then we can go back to the model to better understand and explain the result. This feature gives to the present tool, represented by the integration of a GA and a mechanistic model, a power previously unavailable.

## **References**


Baker, D., McKinion, J. M., and Lambert, J. R. (1983). "GOSSYM: a Simulator of Cotton Crop Growth and Yield." S.C. Agric. Exp. Stn.

Baulch, P. W., McCarter, K., Staggenborg, S., and Lambert, J. R. (1995). "GOSSYM-COMAX, User's Manual." AGBIT, Inc., Starkville, MS.

Beasley, D., Bull, D. R., and Martin, R. R. (1993). "An Overview of Genetic Algorithms: Part 1, Fundamentals." 15(2), 58-69.

Davis, L. (1991). "Handbook of Genetic Algorithms." VNR Computer Library, Van Nostrand Reinhold, New York, 385.

Davis, L., Orvosh, D., Cox, A., and Qiu, Y. (1993). "A Genetic Algorithm for Survivable Network Design." *Fifth International Conference on Genetic Algorithms*, Urbana, Illinois, 408-415.

de Witt, C. T., and Brouwer, R. (1968). "A Dynamic Model of the Vegetative Growth of Crops." *Das Zietschrift Fur Angewandte Botanik.*

Duncan, W. G., Loomis, R. S., Williams, W. A., and Hanau, R. (1967). "A model for Simulating Photosynthesis in Plant Communities." *Hilgardia, Journal of agriculture and Science*, 38, 181-205.

Forrest, S. (1993). "A Genetic Algorithm: Principles of Natural Selection Applied to Computation." *Science*, 261(13 August 1993), 872-878.

Garfinkel, D. (1962). "Digital Computer Simulation of an Ecological System Based on a Modified Mass Action Law." *Ecology*, 45, 502-507.

Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*, Adddison-Wesley Publishing Company.

Hillel, D. (1988). *L'eau et le sol. Principes et processus physiques.*, de Backer, L.W., translator, ACADEMIA. Edition et Diffusion, Louvain.

Holland, J. H. (1992). *Adaptation in Natural and Artificial Systems: an Introductory Analysis with Applications to Biology, Contrl, and Artificial Intelligence.*, The MIT Press, Cambridge, Massachusetts.

Jallas, E. (1991). "Modélisation de Développement et de la Croissance du Cotonnier," Mémoire de DEA, INA-PG, Paris.

Koza, J. R. (1992). *Genetic Programming: on the programming of computers by means of natural selection*, MIT Press, Cambridge, MA.

Lemmon, H. (1986). "Comax: an expert system for cotton crop management." *Science*, 233, 29-33.

Lokta, A. J. (1932). "The Growth of Mixed Population: Two Species Competing for a Common Food Supply." *Journal Washington Academy of Sciences*, 22, 461-469.

Luger, G. F., and Stubblefield, W. A. (1993). *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*, The Benjamin Publishing Compagny, Inc., Redwood City, CA.

McFarland, M. J., McCann, I. R., and Kline, K. S. (1992). "Synthesis and Measurement of Temperature for Insect Models." Basics of Insect Modeling, J. L. Goodenough and J. M. McKinion, eds., A.S.A.E., 75-92.

McKinion, J., and Lemmon, H. (1985). "Expert Systems for Agriculture." *Comp. Electr. Agric*(1), 31-40.

McKinion, J. M., Baker, D. N., Lambert, J. R., and Whisler, F. D. "Cotton Crop Management Using Gossym and The IBM PC/XT." *The 1984 Winter Meeting of ASAE*, New Orleans, Louisiana, 19pp.

Michalewicz, Z. (1992). "Genetic Algorithms + Data Structures = Evolution Programs." A. Intelligence, ed., Springer-Verlag, New York, 250.

Olson, R., and Sequeira, R. A. (1995). "Emergent computation in the modeling and management of ecological systems." *Computers and Electronics in Agric.*, 12, 183-209.

San Martin, R., and Knight, J. P. "Genetic Algorithms for Optimization of Integrated Circuits Synthesis." *Fifth*

*International Conference on Genetic Algorithms*, Urbana, Illinois, 432-438.

Sequeira, R. A., and Jallas, E. (1995). “The Simulation Model GOSSYM and its Decision Support System, COMAX: its Applications in American Agriculture.” *Agriculture et Developpement*, 8, 25-34.

Sequeira, R. A., Olson, R. L., and Willers, J. L. (1994). “Automating the Parameterization of Simulation Models Using Genetic Algorithms.” *Computers and Electronics in Agric.*, 11, 265-290.

Sequeira, R. A., Olson, R. L., and Willers, J. L. (1995). “Validation of a Deterministic Model-Based Decision Support System.” *J. Artificial Intelligence App.*

Southwood, T. R. E. (1966). *Ecological Methods*, Methuen and Co Ltd, London.

Volterra, L. (1931). Leçons sur la théorie mathématique de la lutte pour la vie, Gauthier -Villars, Paris.

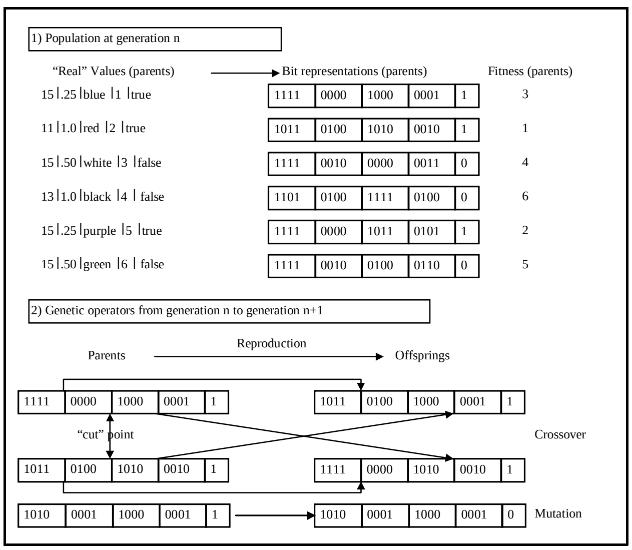


Figure 1

Table 1. Main Hydrological Soil Characteristics.

| Hor. NO. | Depth (cm) | θat Sat. | θ at F.C | θ at P.W.P | B.D. | % Sand | % Clay |
|---|---|---|---|---|---|---|---|
| 1 | 23 | 0.569 | 0.263 | 0.141 | 0.98 | 37 | 12 |
| 2 | 48 | 0.425 | 0.286 | 0.194 | 1.40 | 24 | 24 |
| 3 | 200 | 0.465 | 0.288 | 0.205 | 1.28 | 44 | 13 |

Table 2. Soil Initial Conditions.

| | Residual N | | | |
|---|---|---|---|---|
| depth (cm) | nitrate kg/ha | ammonia kg/ha | organic matter (%) | H2O content % of the F.C. |
| 0 | 12.3 | 1.2 | 0.74 | 100 |
| 15-30 | 6 | 0.6 | 0.72 | 100 |
| 30-45 | 4.6 | 0.4 | 0.67 | 100 |
| 45-60 | 3.4 | 0.3 | 0.43 | 100 |
| 60-75 | 3.4 | 0.3 | 0.37 | 100 |
| 75-90 | 3.4 | 0.3 | 0.30 | 100 |
| 90-+ | 2.2 | 2.2 | 0.00 | 100 |

Table 3. Technical Itinerary and Simulation Conditions.

| | | | | |
|---|---|---|---|---|
| *Simulation Conditions* | | | | |
| Start Simulation | | | | 05/09/92 |
| Stop Simulation | | | | 12/20/92 |
| *General Crop Conditions* | | | | |
| Emergence | | | | 05/13/92 |
| Season Length | | | | 226 |
| Variety | | | | Mid season |
| Latitude | | | | 34° |
| *Density Conditions* | | | | |
| Row Spacing (cm) | | | | 96 |
| Plant Spacing (cm) | | | | 3.5 |
| Plants per Ha | | | | 118700 |
| *Fertilization Conditions* | | | | |
| Date | Description | Rate | Units | Method |
| 278 | UAN | 447.7 | kg/ha | Broadcast |
| 06/15 | UAN | 6.7 | kg/ha | Broadcast |
| 06/30 | UAN | 167.9 | kg/ha | Broadcast |

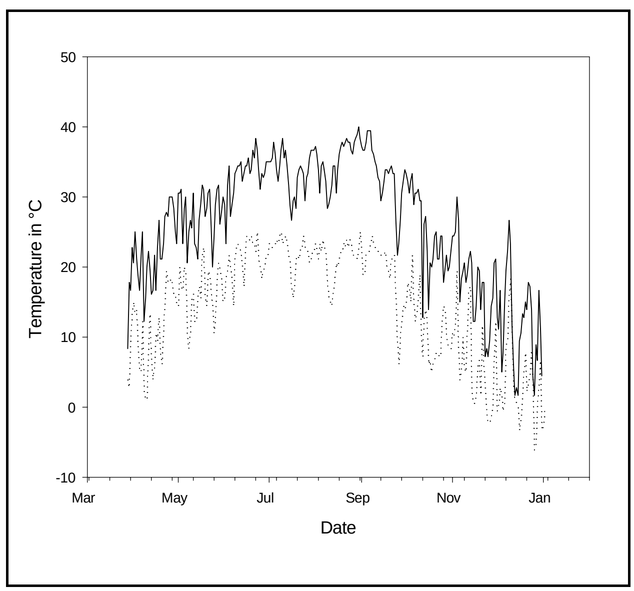


Figure 2. Temperature maximal and minimal in °C. 1992

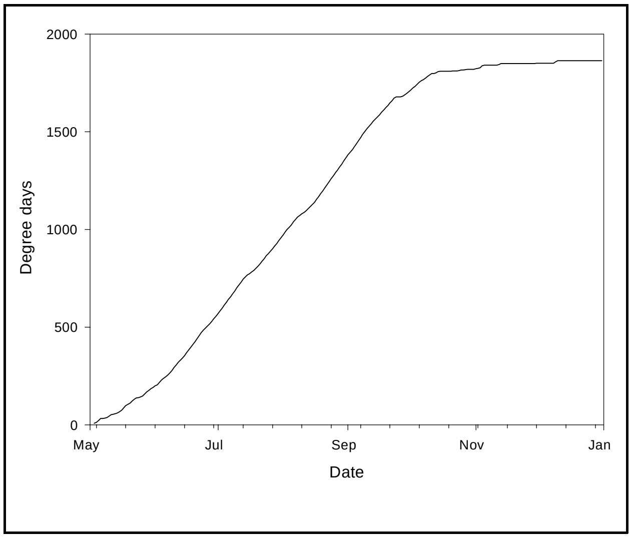


Figure 3. Sum of degree days (base 15°C)

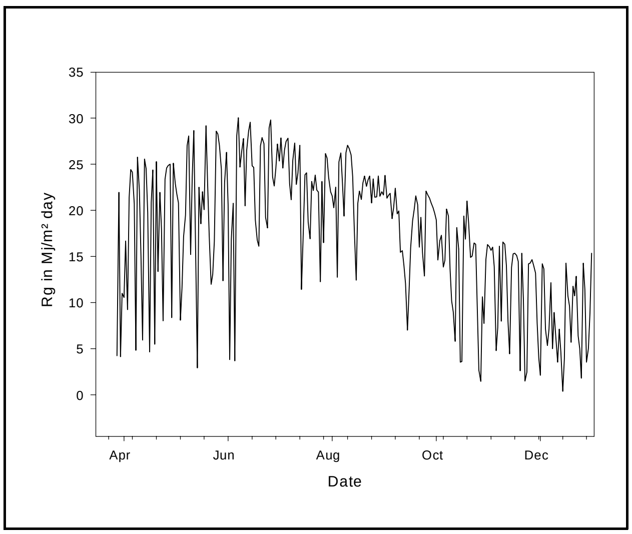


Figure 4. Global Radiation during 1992

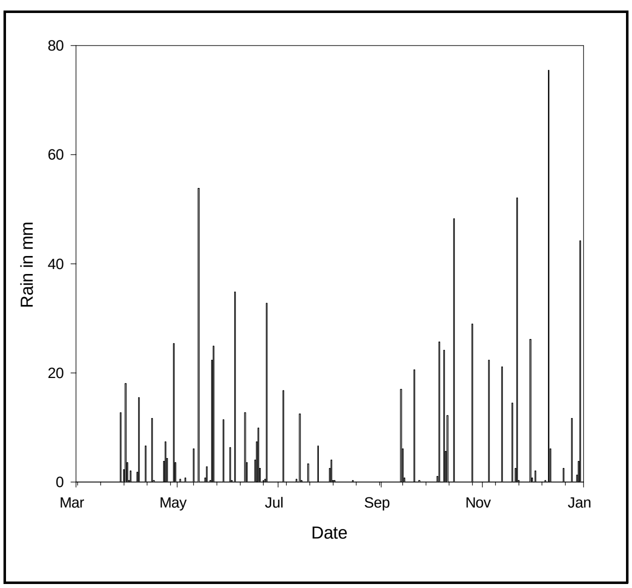


Figure 5. Rain pattern

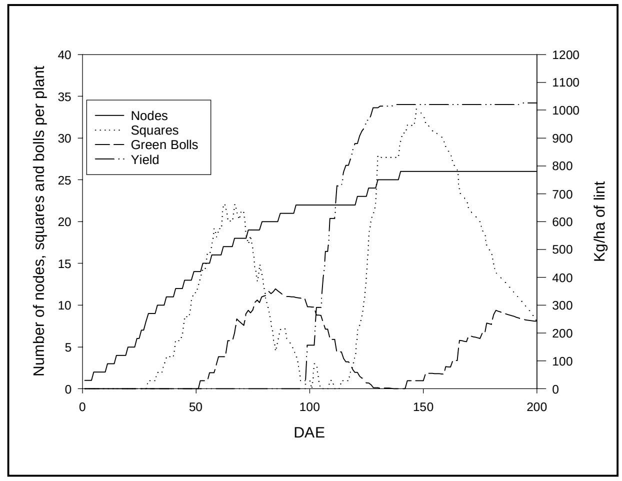


Figure 6. Yield components

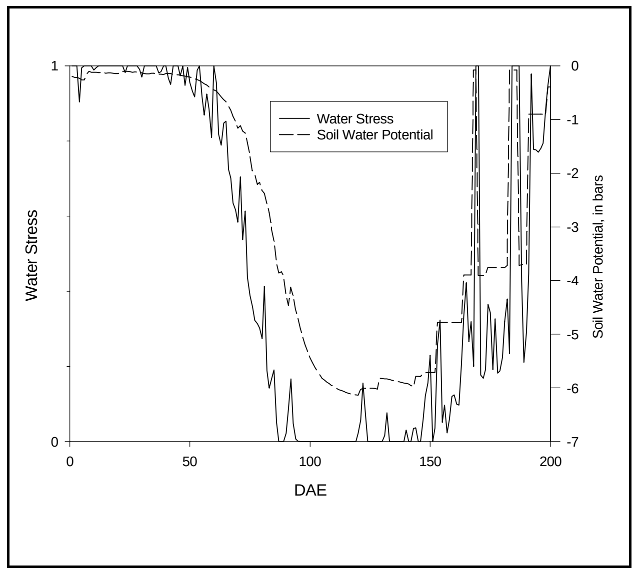


Figure 7. Soil water components

Table 4. Responses of Long Term and Water Conservation COMAX advisors.

| Max. Amount | No. of irr. | | Qt. of irr. in mm | | Yield kg/ha | | Plant height in m | |
|---|---|---|---|---|---|---|---|---|
| | LT | W | LT | WC | LT | WC | LT | WC |
| 6.3 | 12 | 12 | 68.5 | 68.5 | 1283.5 | 1283. | 0.94 | 0.94 |
| 12.7 | 12 | 12 | 144.7 | 144. | 1440.4 | 1440. | 0.94 | 0.94 |
| 19 | 12 | 12 | 220.9 | 220. | 1507.7 | 1507. | 0.97 | 0.97 |
| 25.4 | 12 | 12 | 297.1 | 297. | 1647.8 | 1647. | 1.02 | 1.02 |
| 30.5 | 10 | 10 | 304.8 | 294. | 1687.0 | 1692. | 1.02 | 1.02 |
| 31.7 | 9 | 9 | 285.7 | 285. | 1687.0 | 1687. | 1.02 | 1.02 |
| 33 | 9 | 9 | 297.1 | 294. | 1687.0 | 1687. | 1.02 | 1.02 |
| 38.1 | 8 | 8 | 302.2 | 294. | 1698.3 | 1698. | 1.02 | 1.02 |
| 44.5 | 7 | 8 | 309.8 | 307. | 1698.3 | 1692. | 1.02 | 1.02 |
| 50.8 | 7 | 8 | 355.6 | 309. | 1698.3 | 1698. | 1.02 | 1.02 |
| 63.5 | 6 | 8 | 381.0 | 309. | 1698.3 | 1703. | 1.02 | 1.02 |
| 88.9 | 5 | 8 | 444.5 | 304. | 1687.0 | 1698. | 1.02 | 1.02 |
| 127 | 4 | 7 | 505.4 | 289. | 1681.4 | 1698. | 1.04 | 1.02 |
| 178 | 4 | 7 | 711.2 | 292. | 1687.0 | 1698. | 1.04 | 1.02 |

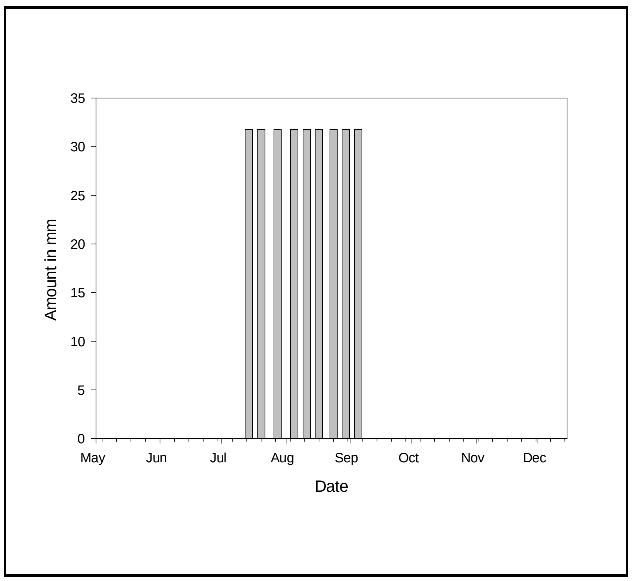


Figure 8. COMAX water conservation and long term irrigation schedule

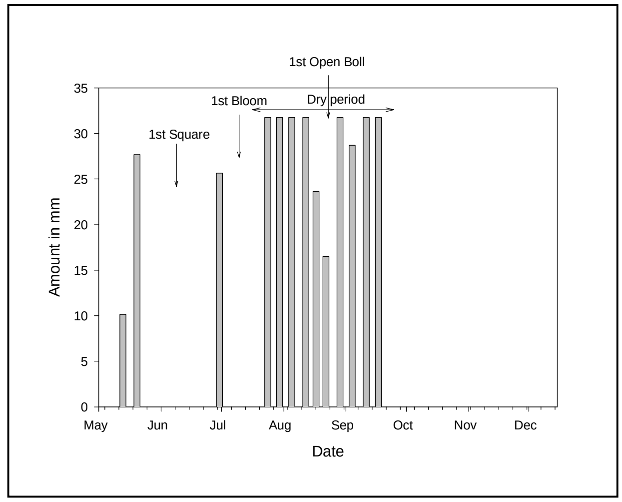


Figure 9. Best GA's evolved schedule

Table 5. Comparison of "best" schedules proposed by COMAX and the GA, for a maximum amount of irrigation of 31.7 mm (1.25 inches per irrigation application).

| Treatment | Number of Irrigation | Amount of Irrigation | Yield | Fitness |
|---|---|---|---|---|
| COMAX | 9 | 285.75 | 1687.09 | 1462.25 |
| GA | 13 | 354.37 | 1714.70 | 1470.19 |