This is to certify that the

dissertation entitled

"Multicriteria Optimization Of Nondifferentiable Stochastic Biosystems: Technology Management Of Irrigated Maize"

presented by

James C. Schaper

has been accepted towards fulfillment of the requirements for

Ph.D. degree in Agricultural Technology & Systems Management

Major professor

Date 24 Sep 98

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MULTICRITERIA OPTIMIZATION OF NONDIFFERENTIABLE STOCHASTIC BIOSYSTEMS: TECHNOLOGY MANAGEMENT OF IRRIGATED MAIZE

By

James Carl Schäper

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of requirements
for the degree of

DOCTOR OF PHILOSOPHY

Agricultural Technology and Systems Management
Department of Agricultural Engineering

1998

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ABSTRACT

MULTICRITERIA OPTIMIZATION OF NONDIFFERENTIABLE STOCHASTIC BIOSYSTEMS: TECHNOLOGY MANAGEMENT OF IRRIGATED MAIZE

By

James Carl Schäper

A mathematical model of an irrigated maize enterprise, from preseason manure application to the transport of grain to market, is constructed and used to simulate crop production in southern Michigan under linguistically categorized climatic scenarios. The simulation deploys a multi-variable sequential-random-search algorithm that incorporates a simple adaptive evolution strategy to optimize both economic net return and nitrate leaching for a given soil type. The parameters of optimization describe the genetic coefficients of maize, irrigation technology, and agricultural practices. Net return is found to be greatest with cultivars adapted to the specific growing season. Scheduling irrigation in conjunction with a weather forecast reduces the amount of nitrate leached. Simultaneous scheduling of all controllable resources is found to be beneficial for an enterprise that is managed to achieve multiple criteria at a Pareto frontier.

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A methodology is developed which permits model-referenced optimal control in highly nonlinear (nondifferentiable) representations of biological production systems that are managed according to conflicting and environmentally-conditioned goals. The methodology also lends itself to parameter estimation on the enterprise model contained within a hierarchical ecological network structure which conformally maps economic performance to the mass-energy flows and transformations in the enterprise. Based on a definition for compromise, the optimization continuously seeks a more desirable multi-goal target while simultaneously searching for the management strategy which encompasses the stochastic influences of weather. The search evolves, subject to explicit and implicit constraints which are defined *a priori* by boundaries and rules.

The traditional method to accommodate an implicit constraint requires additional iterations of the model with a new trial solution vector each time the constraint is violated. The implicit constraints in the irrigated maize enterprise model that demanded this procedure were related to cumulative environmental measures and resulted in tedious nested optimizations. A subset of implicit constraints, characterized by the influence of weather on the scheduling of agricultural operations, was efficiently resolved with functional adjustments to the trial solution vector rather than with nested optimizations.

DEDICATION

In memoriam.

Michael Alan Schäper, my brother.

(1951-1986)

"All is process...there

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They are like the sha

EPIGRAPH

"All is process...there is no '*thing*' in the universe. '*Things*'...are abstractions of what is relatively constant from a process of movement and transformation. They are like the shapes that children like to see in the clouds."

D. Bohm in <u>Towards a Theoretical Biology</u>

Some were bad and so
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To faculty - the many

To family and friends.

To my gudance comm

To Dr. John B. Gerrish

To my parents, Carl a
measure.

Peace be with you.

ACKNOWLEDGEMENTS

Some were bad and some were good,
some did the best they could,
and some tried to ease my troubled mind.

From the song: *I can't help but wonder where I'm bound.*

To librarians everywhere, especially the librarians at Michigan State University and the University of Michigan, thank you.

To faculty - the many faculty- I have learned from, thank you.

To family and friends, thank you for the support.

To my guidance committee, thank you for the patience.

To Dr. John B. Gerrish, thank you for the understanding.

To my parents, Carl and Alberta Schäper, thank you for what is beyond words or measure.

Peace be with you.

James C. Schäper
East Lansing, September 1998

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CHAPTER ONE

INTRODUCTION

"Irrigation...is a social contract to sacrifice some environmental values...."

J. van Schilfgaarde

The sandy-loam soils of southern Michigan are sensitive to drought. Supplemental irrigation has made these soils highly productive for a number of field and vegetable crops. The porous and free-draining nature of these soils, however, causes them to be prone to nitrate leaching.

Supplemental irrigation measurably contributes to increased crop production and may improve overall profitability. The increase in productivity may come at the expense of the environment, or conversely, irrigation may possibly mitigate nitrate leaching by stimulating crop growth. It is reasonable to ask, therefore: "If, indeed, there is a trade-off between nitrate leaching and net return, how is a reasonable compromise to be achieved?"

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One suspects that the selection of a particular irrigation technology depends upon factors such as fertilization rates, tillage practices, crop protection practices, harvest residual management, and plant genetics. Soil fertility is critical for crop production and bears on nitrate leaching. Fertilizer amounts, timing, and chemical form all have quantifiable effects on both crop production and nitrate leaching. Animal wastes used as a nutrient source can be intelligently scheduled if the quantifiable effects are known.

Soils are complex resources, categorized according to their physical, chemical, and biological properties. Plants respond over time to multiple properties of both the soil and the microclimate. Microclimates are both complex functions of time and a primary "driving" force in any crop production enterprise. Farm production management is the conscious seeking of the "best" way to control the many factors of production over time throughout the entire growing and harvest seasons, taking advantage of "good" weather and alleviating the effects of "bad" weather. The value of a perfect weather forecast should be quantifiable through simulation; also it should be possible to determine the cost of assuming that the weather will be "normal."

The commodity markets, like the weather, are stochastic. Like weather, the market "drives" many of the decisions and outcomes of farm production. Thus, the economic stab[illegible]

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HYPOTHESIS

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harm.

OBJECTIVES

Specific objectives are

the economic stability of a farm enterprise is in principle, a complex function of many factors of production, some of which are clearly stochastic in nature.

HYPOTHESIS

"... when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind."

Lord Kelvin

On the basis of existing models of temperate-climate irrigated-maize production enterprises, I hypothesize that irrigation can be managed to lessen the impact of nitrate leaching to the environment while simultaneously contributing to a positive economic net return. I will show that on sandy loam soils, properly managed irrigation actually protects groundwater and I will present a method to quantify the tradeoffs between profit and environmental harm.

OBJECTIVES

Specific objectives are as follows:

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5. Quantify the econ
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1. Combine the “best” available simulation models of the various aspects of irrigated maize production into a comprehensive enterprise model that can predict the impact of various management alternatives on environmental and economic performance measures.
2. Develop procedures for identifying the “best” enterprise organization and time schedule of resources consistent with a given set of yield, economic, and environmental impact targets.
3. Identify from the model the extent to which irrigation can be used to reduce the negative impact of nitrate leaching at acceptable economic costs.
4. Articulate trade-offs between economic return and environmental damage, where possible.
5. Quantify the economic and environmental impacts of using animal waste as the major nitrogen and phosphorus source for irrigated maize production.

OVERVIEW OF APPROACH

An enterprise, in the context of this thesis, is defined as a network of synthetic and natural processes designed and managed to achieve a commercial goal. The enterprise operates within a dynamic environment which serves as the source of all resources and as the recipient of all residuals of the processing network. In general, the limitations of the environment also restrict the goals of the enterprise and, moreover, impose restrictions on how the goals are achieved. In the s

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achieved. In the sequel, a model-referencing and optimization scheme is developed for technology management describing how such enterprise goals can be achieved.

Typically, the goals of the enterprise are set so high and the environmental limitations are so restrictive that quantitatively articulated management strategies are required to meet them. Management strategies are quantified in terms of resource flows within the enterprise and between the enterprise and its environment. Furthermore, management strategies must be evaluated over the accounting period, or the production cycle of the enterprise. Characterizing the resource flows of the enterprise and their change over time is the substance of this thesis.

The enterprise is represented as an archipelago of linked processes with a multiplicity of inter-process resource flows. The loads imposed by the enterprise on its environment are quantified in terms of the material flow rates between the enterprise and its environment. Some of the resource flows are uncontrollable by human intervention, some are controllable. Uncontrolled flows may vary with time from "drought" to "flood," for example. Generally, both controlled and uncontrolled resources contribute to the achievement of the enterprise goal.

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Only a small fraction of all flows is controllable, and most flows are associated with noncommercial co-products and/or unintended by-products. Collectively, noncommercial co-products and unintended by-products are identified as "unproducts", the obverse of the desired product.

Unproduct flows are "un-natural" in the sense that they do not exist in pristine ecosystems. Unfortunately, unproduct flows are frequently toxic to organisms in natural ecosystems, including people. The toxicities of unproducts are frequently unknown and are undetectable until they concentrate over time and reach detectable levels sometimes evidenced by macro-level systemic consequences. Hence, management requires reliable methods which anticipate the risks of environmental degradation and provide acceptable countermeasures integrated with the overall management strategy.

The management problem is confounded by the unproduct stream because unproducts generally have no markets; consequently, the concept of price has little practical meaning. In this situation, management typically attempts to sustain economic returns of the enterprise above a minimum threshold and environmental impacts below a maximum tolerance level. Such a management strategy implicitly attempts to strike an acceptable balance among often-conflicting multiple goals. Such a management strategy, whatever the balance, is deemed "optimal." Thus an optimal management strategy is frequently a balance among dimensionally distinct performance measures, and a compromise amo

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a compromise among competing goals -- a "Goldilocks optimum." "Best" cannot usually be found at an extreme value of any one attribute, nor does only one attribute provide an adequate measure of performance.

The Traditional Approach to Resource Scheduling

Traditional methods of scheduling agricultural resources consider production practices in a piece-meal fashion; allocation decisions only indirectly consider the linkages among production activities. Irrigation scheduling, for example, assumes that crop growth proceeds according to a given norm, given that a reasonable soil moisture balance will support an acceptable yield. Scheduling of fertilizer applications likewise is based on crop growth according to historical norms, and assuming all other resource factors are maintained at appropriate levels. Cultivar selection is based on soil types, microclimate, and soil fertility. Irrigation, fertilization, and cultivar selection are based on achieving yield expectations.

Environmental concerns are usually handled by implementing "best management practices." Best management practices are stated in terms of tillage tools, soil water depletion allowances, and split fertilizer treatments, all based on soil descriptions and yield targets. Best management practices are supposed to achieve an acceptable level of environmental impact at an acceptable cost based on normative values. Over the long term, however, annual environm

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A Non-traditional Approach to Resource Scheduling

If environmental sustainability is a social necessity in the same sense that a positive economic net return is necessary to the individual commercial enterprise, then economic and environmental issues deserve equal treatment, if not equal priority. To be responsive and adaptable to "the way things are" as opposed to normative values, resources and technologies ideally should be organized into a management system directly linked to the economic and environmental goals of the crop production enterprise. For these reasons, a non-traditional, all-inclusive method of analysis appears warranted.

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CHAPTER TWO

LITERATURE REVIEW

The approach taken to the multicriteria optimization of the irrigated maize enterprise draws particularly from several sub-disciplines in numerical methods and the agricultural sciences. The first part of the literature review is devoted to the relevant numerical methodologies:

- Processing Networks
- Multidimensional Nonlinear Optimization
- Adaptive Control
- Evolutionary Algorithms

The relevant research from the agricultural sciences regarding maize production is presented in the last part of the literature review:

- Climatological Modeling
- Crop Modeling
- Irrigation
- Grain Drying
- Production Economics

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THE PROCESSING NETWORK

Economic enterprises, including irrigated maize production, can be characterized as networks of natural and engineered transformations on the structural state of matter. Network modeling techniques have broad applicability. No case was found while conducting the literature search where networks could not be applied to economic enterprises specifically, or to ecology in general. To quote one prominent researcher, "*Among the advances in...operations research,...the theories of networks are among the simplest, most elegant subjects which possess a wide variety of applications*" (Emaghraby, 1971).

As for the processing network approach, each transformation within the network is modeled as an unconstrained component process, according to the principles of material and energy balance. The component processes are then constrained according to the principles of conservation of matter and energy. The result is a model of the enterprise and its environment which shows the material (resource) flows and energy factors as explicit functions of the product flows at the boundary (H.E. Koenig and Cantlon, 1998).

All material flows and energy factors are measured in physical units. An economic model of the enterprise is established by multiplying each material flow and each ene

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flow and each energy factor in the boundary model by an economic price parameter. The network thus becomes an ecologically conformable accounting system (ibid.).

Ecological and economic measures of enterprise performance are expressed as explicit functions of the technological, ecological, and organizational parameters of the network and the economic prices at the boundary of the enterprise network. These networks thus provide a rigorous and tractable mathematical framework for technical design and management of agricultural production on the basis of "both" ecological and economic measures of performance, plus pricing alternatives. And, they provide a comprehensive accounting system for the management of operations that is isomorphic to the technical organization of the production network (B.E. Koenig, 1992; H.E. Koenig and Cantlon, 1998).

The changes in technical and economic performance are therefore mathematically linked to changes in specific financial performance measures. Since the component processes are modeled initially as unconstrained material transformation processes, various [disciplinary] perspectives are readily accommodated within one systemic structure. Hierarchies of multi-product processes are constructed in which the parameters at higher levels are rigorously computed from the parameters at the lower levels, starting with observable single-product processes. Changes in crop production technologies, for example, can b

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for example, can be mathematically mapped into changes in ecosystems; similarly observable parameters of elementary processes are mathematically mapped into parameters of a non-observable "hyper-processor(s)" with multiple products and their effects integrated on multiple performance measures.

Some applications of the processing network paradigm (ibid.) are found in Saama et al. (1994), Tummala and B.E. Koenig (1991), and B.E. Koenig (1992). Saama et al. (1994) demonstrate the application of hierarchical ecological networks in engineering design, strategic planning, and management for the prototype of an agricultural enterprise. Tummala and B.E. Koenig (1991) focused on manufacturing enterprises. The joint ecological and economical performance of alternative materials recycling networks were presented by B.E. Koenig (1992). Other applications of the network paradigm to agroecosystems (Alocilja, 1990) include the following:

1. The variation of water delivery to small farms from an earthen canal distribution system as typically constructed in Senegal (Barry, Schäper and Alocilja, 1990).
2. Nitrate leaching resulting from alternate cropping patterns and soils using farming practices typical of Michigan, (Dadoun and Alocilja, 1990).
3. Analysis of beef feedlots, (Saama, Schipull, and Alocilja, 1990).
4. Analysis of combined swine and crop production, (Tilma, Tilma, and Alocilja, 1990).

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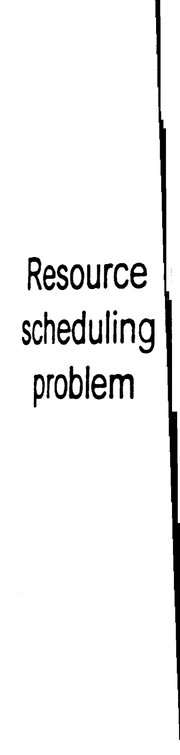
5. Phosphorous loading resulting from the application of dairy-cow manure to crop-land, (Alocilja, von Bernuth, and Beede, 1995).

Alocilja, von Bernuth, and Beede (1995) used the compromise programming approach of Romero and Rehman (1989) to minimize three competing factors: excess manure after fertilization, feed costs, and cropland. A similar approach was used by Dadoun and Alocilja (1990) to manage the impact of nitrate leaching under various cropping patterns.

MULTIDIMENSIONAL NONLINEAR OPTIMIZATION

The Process of Enterprise Optimization

The word "optimization" describes the general "process of improvement" (Box, Davies, and Swann, 1969). The logic and mathematics of optimization are independent of application (Beveridge and Schechter, 1970; Sawargi, Nakayama, and Tanino, 1985). In addressing the management task of the allocation of resources, the decisions on the control of resources may reference a sequence of models that mimic the essential features of the real world production enterprise (see Figure 2.1); this is an example of model-referenced control (Sawargi, Nakayama, and Tanino, 1985).



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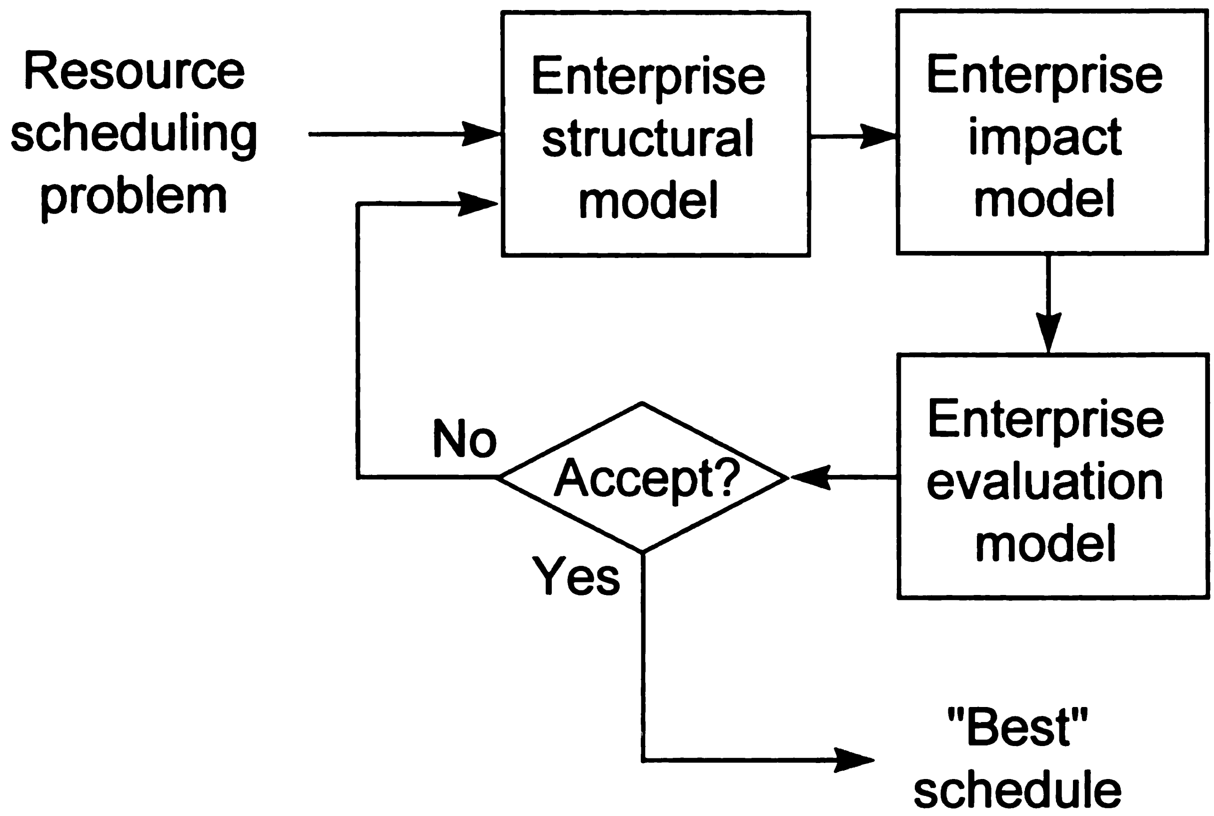

Figure 2.1. The general optimizing decision process (after Sawaragi, Nakayama, & Tanino, 1985).

Typically an initial proposed schedule of resources is processed through a structural model of the enterprise that characterizes all essential processes and their results in terms of mass, energy, and monetary flow. The results from the structural model are then processed through an impact model of the enterprise. The impact model translates information on the mass, energy, and monetary flow within the enterprise into performance indices. The performance indices are formulated from various perspectives such as physical, chemical, biological, social, and economical (ibid.). The various impact perspectives form

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The performance results of the proposed resource schedule emanating from the impact model are then processed by the enterprise evaluation model. In the evaluation model, the distinct impact measures are merged into a merit function of overall performance acceptability. The evaluation model is based on a value system that includes the acceptable ranges for both individual impact measures and any weighted combination of impact measures (ibid.).

The criteria to accept, or reject the proposed resource schedule need not be fixed *a priori*, but possibly may be negotiated once an interpretation of the impacts becomes possible. Indeed, the discovery process of assessing the meaning of impacts may display conflicts, trade-offs, and potential resolutions that could not be anticipated. The rules for revising the evaluation criteria (negotiation), however, may be established *a priori* (ibid.). Dynamic revision of evaluation criteria is achieved with hierarchical optimization methods such as Cultural Algorithms (CAs) described in sequel (Reynolds, 1994).

The results from the enterprise evaluation model lead to a decision to either accept the proposed resource schedule, or to reject it. Further decisions are warranted if the proposal is rejected. The ultimate decision has to be made as to whether the d

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to whether the decision process should be terminated, or another attempt should be made to improve the resource schedule economics (Sawargi, Nakayama, and Tanino, 1985).

Continuing attempts for improved resource schedules require the creation of alternatives to previous proposals. Alternatives may be generated totally at random; however, a strategy which extracts information arising from previous proposals may be used within an alternative generator to guide the formulation of further proposals. The proposal history may also provide information that may help in negotiating revised acceptance criteria. By this means, the search for an acceptable resource schedule may evolve and adapt to conditions (operating and environmental) which were not, or could not be described *a priori* (Bäck, 1996).

The optimization decision process may not necessarily find an acceptable resource schedule for highly constrained conditions. The termination criterion needs some means to accommodate this possibility; otherwise, the optimization process could continue indefinitely. If one acceptable resource schedule is discovered, other acceptable schedules will likely be discovered from the optimization process; the one which ranks highest may then be implemented as the "best management strategy" (Sawargi, Nakayama, and Tanino, 1985).

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Linear versus Nonlinear Optimization

Linear optimization methods tend to be mathematically sleek and computationally fast; therefore, linear approaches to resource allocation are often the methods of choice. Real world problems, however, must be simplified (linearized) to a form which can be accommodated by linear methods. Whether linear methods are appropriate for the problem at hand depends upon the tolerance to distortion produced by the linearizing process; in other words, the problem may become over-simplified. Nonlinear optimization methods may produce more realistic results; but, greater accuracy comes at the cost of greater computational effort.

The solution to a linear optimization problem is generally a "corner solution"; that is, the solution point, or solution vector is located at the intersection of constraints on the response surface of the modeled process which for linear methods is a plane, or hyperplane (ibid.). If the optimum is to "maximize" and the evaluation surface is canted from horizontal, the optimum is located at the top corner, or top edge. Conversely, if optimizing is to minimize, the optimum lies at the bottom corner, or edge. The top and bottom are defined by the limiting constraints.

One difficulty for linear methods is the identification of field optima which are optima residing within the interior of the response surface. If the evaluation is dead level, the optimu

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dead level, the optimum includes the entire evaluation surface within all the constraints. Given the limitations of computational precision, however, a "dead level" evaluation surface is almost impossible to obtain and a corner solution to a linear structure will be found. In practical terms, the evaluation plane could be "in the neighborhood" of dead level and the result from the linear optimization may be no more than one of many workable solutions (ibid.).

If the problem can be bounded by a set of constraints confining a small evaluation surface, the error in applying linear methods to nonlinear field problems can be reduced. This approach, however, requires experience specific to the problem in order to achieve convergence and essentially emulates nonlinear programming through successive approximation (Alocilja, 1995; Sawargi, Nakayama, and Tanino, 1985).

Nonlinear methods, on the other hand, are not restricted to planar evaluation surfaces. Many real world problems, especially those involving biological systems, cannot be reasonably solved by linear methods. The repertoire of nonlinear methods can accommodate evaluation surfaces that appear as either smooth or cratered hyper-spheres. Derivative methods work for situations with smooth-continuous solution vectors. Nondifferentiable methods apply where the variables in the solution vector are non-smooth or discontinuous (Lange, 1965) The choice of nonlinear method depends on the difficulty of the problem and the accur

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Multidimensional Numerical Methods

All numerical optimization methods share the common "sequence of logic steps" (as depicted in Figure 2.1) where trial vectors of input variables are evaluated against a performance criterion, the optimization being terminated once the criterion has been satisfied, or else the process is interrupted if no feasible region is apparent (Beveridge and Schechter, 1970).

All but two of the classical optimization procedures gradually improve the value of the input vector with each sequential (subsequent) iteration of the optimization process. The tabulation method and sequential random search do not improve the input vector with most sequential trial input vectors *per se*. Both tabulation and random search, however, are direct search methods (Box, Davies, and Swann, 1969).

Techniques that improve the value of the input vector with each iteration are referred to as "iterative techniques." Iterative techniques begin with an initial point and progress in an "efficient" manner toward the optimal value with each successive iteration. Efficient is defined in terms of the problem and the algorithm used to solve it (Buchner, 1975). Iterative techniques are divided into two classes: dire

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into two classes: direct search methods and gradient methods (Box, Davies, and Swann, 1969). Direct search methods do not require an explicit evaluation of the partial derivatives of the objective function; these are called "derivative free methods" (Kuester and Mize, 1973). The value of the performance criterion is added to the history of the iteration progression to "direct" the search efficiently toward the optimum. Some directed search methods use the information thus obtained to generate numerical approximations to the derivatives of the objective function. Some search methods fit low order polynomials or surfaces through selected points in the iteration history so that proxy partial derivatives may be processed by gradient search methods (Kuester and Mize, 1973; Press et al., 1986).

Gradient methods select a search path based on the values of the partial derivatives of the objective function with respect to the independent variables. Gradient methods generally use first derivatives only; depending on the problem and the solution algorithm; however, higher order derivatives may also be used (Buchner, 1975; Kuester and Mize, 1973).

Numerous multivariable nonlinear optimization methods have been developed since the introduction of the computer. Some methods are more appropriate for particular applications than others. The guidelines for selecting an optimization method depend firstly on the availability of derivatives from the objective function and secondly on the "quality" of the derivatives:

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1. If analytical derivatives are available, analytical methods should be considered, especially if high precision is required (Kuester and Mize, 1973).
2. If "smooth" numerical derivatives are available or easily generated, derivative methods and direct function evaluation methods have similar efficiencies (ibid.).
3. Gradient methods incorporating numerical derivatives can be expected to have convergence difficulties with high precision (ibid.).
4. Gradient methods tend to have trouble at boundaries and ridges but gradient methods are suited to locating field optima (Shoup and Mistree, 1987).
5. Direct search methods become relatively more efficient and accurate than gradient methods as the accuracy of numerically derived derivatives deteriorates (Box, Davies, and Swann, 1969).
6. If the response surface of the objective function is "smooth" (not "cratered"), direct linear search and pattern search methods are more efficient than grid tabulation and random search methods, (ibid.).
7. Grid tabulation and random search methods are not bothered by multimodal surfaces (more than one local optimum), cratered, and non-smooth response surfaces, (Shoup and Mistree, 1987).
8. Random search does not converge quickly and is very slow for high precision. If the response surface permits, random search can be used in combination with a rapidly converging method, (ibid.).

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9. Grid and random search methods will work with any response surface (cratered, ridged, or gullied) and solution vector (continuous, or discreet), success is not affected by the dimension of the space being considered, (ibid.).

The final selection of non-linear optimization method rests with prior knowledge of the type of problem and the behavior of the numerical model to be considered. Models with many embedded case selections, condition statements, and rule bases tend to produce rough response surfaces with numerous local optima that may deceive derivative methods (Box, Davies, and Swann, 1969; Shoup and Mistree, 1987). Similarly, optima that are hidden in "crevasses" and "caves" as depicted in Figure 2.2 require fastidious searches of the response surface (Gill and Murry, 1981). Both conditions imply the use of computationally

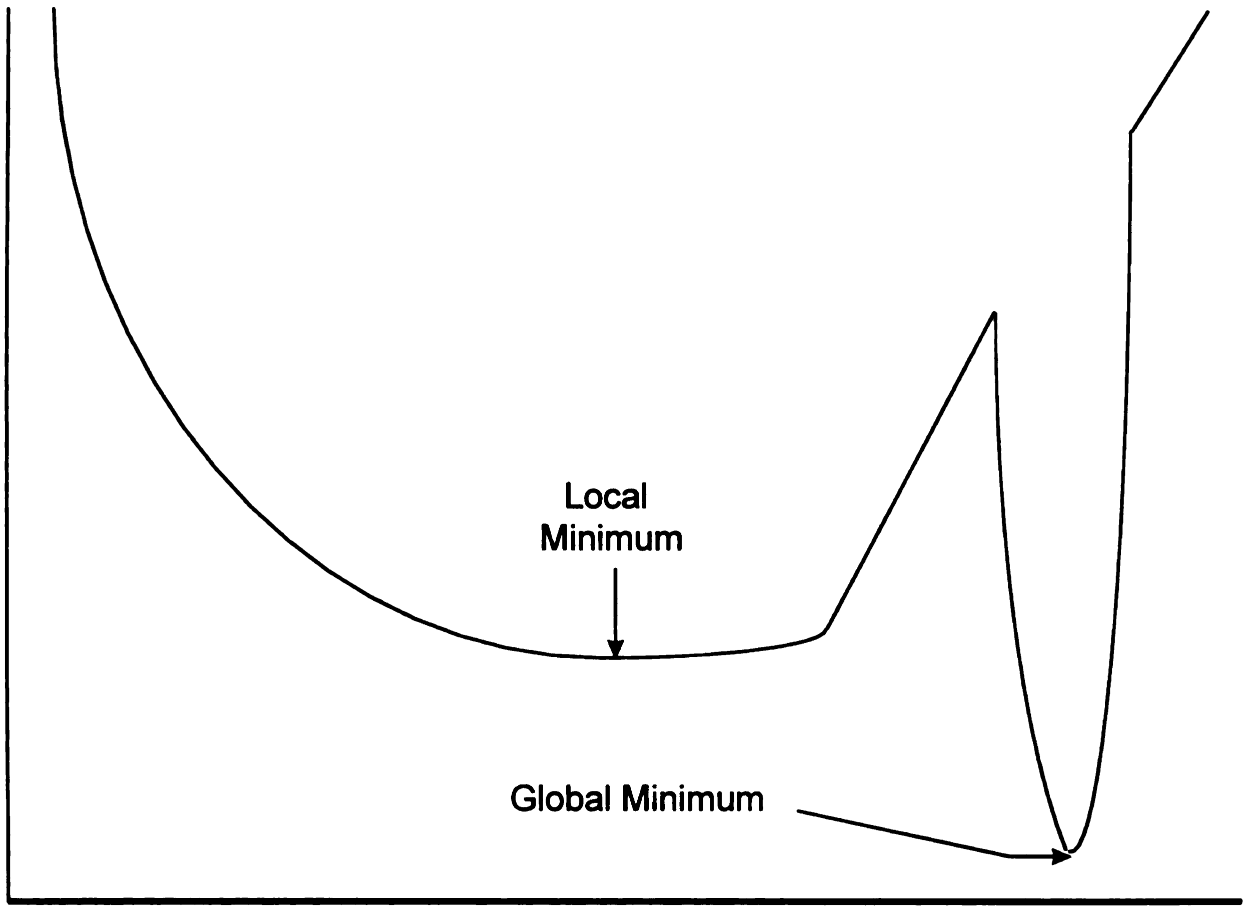

Figure 2.2: Example of a global minimum hidden in a crevasse. (after Gill and Murry, 1981).

slower methods to better guarantee that the "global optimum" is found. Appendix A gives an overview of the more widely known multivariable nonlinear optimization methods.

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Multidimensional Root Finding versus Multidimensional Optimization

Numerically, a nonlinear system is a set of related nonlinear equations. Why not, then, use a method such as Newton-Raphson to find the roots of the system equations? The answer depends on prior knowledge of the system behavior and the number of independent variables in the system. Having a good first guess for the solution is crucial for implementing root-finding methods that must iterate from a starting point. As the system to be solved becomes larger and increasingly nonlinear, the ability to propose an initial guess deteriorates (Press et al., 1986).

Root-finding methods do not guarantee the correct answer for optimization. Root-finding methods may converge to the wrong root. On the other hand, no roots may exist. In short, there are *"no good general root-finding methods for solving systems of more than one nonlinear equation"* (ibid.).

The notion that root-finding is the same as optimization is actually false for multidimensional systems. Optimization is not the same as finding a zero in a multidimensional gradient. In the one-dimensional problem, a minimum can always be found by "sliding-downhill." There is "no analogous conceptual procedure for finding a multidimensional root." In the multidimensional problem, "downhill" r

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problem, "downhill" must allow for marginal tradeoffs; how much is "downhill" in one dimension worth in terms of performance against the "downhills" in the remaining dimensions. Collapsing a multidimensional root-finding problem into a composite objective function does not guarantee that the global optimum will be found. Furthermore, in those special large systems where root-finding is successful, the global optimum need not have any nearby roots. Moreover, multidimensional optimization procedures have been found to be faster than root-finding methods, (ibid.).

Which multidimensional optimization procedure to choose depends on the nature of the system to be solved. Methods which "make no special assumptions" about the system and the objective function, which optimize based on direct function evaluation over the response surface can be extremely slow. For difficult response surfaces, however, they can be "extremely robust," (ibid.).

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ADAPTIVE CONTROL

Adaptive control refers to the control of systems for which the full behavior or state is only partially known in real time (Bellman, 1961; Narendra and Annaswamy, 1989). Adaptive control systems use "feedback" in a multi-tiered process. Feedback consists of the following:

1. Measurement of the operating system and its environment,
2. Comparison of the operating system performance against some performance standard, and
3. Correction toward the performance standard.

The adaptive control problem is one where the parameters of an operating system are known to a limited degree of accuracy by the system designer or operator. In adaptive control systems, the parameters (and possibly the structure as in evolutionary programming) of the system may change with time during the system's operation, (Bäck, 1996; Fogel, 1995; Narendra and Annaswamy, 1989; Lange, 1965).

In biological terms, "adaptation" refers to "an advantageous conformation of an organism to changes in its environment." The term "adaptive system" in control theory represents control systems that monitor their own performance and adjust their parameters toward better performance, (Drenick and

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Narendra and Annaswamy (1989) have brought together the concepts of various researchers as to what defines an adaptive system and what constitutes adaptive control. A selection of these are presented in Appendix B. The authors have struggled over time trying to achieve mathematical precision on-the-one-hand and inclusion on-the-other-hand to describe what is "adaptive."

Adaptive control involves solving the optimal control problem over time for a time dependent process (Kalaba and Spingarn, 1982; Narendra and Annaswamy, 1989). The determination of optimum system performance is a multistage process; that is, an estimate of optimum performance is evaluated and corrected during system operation. This is the concept underlying dynamic programming which is based on Bellman's Principle of Optimality, (Bellman, 1957). The trace of optimum system performance over time constitutes an envelope of tangents to the solutions of the optimal control problem at each evaluation, (Kalaba and Spingarn, 1982). By extension, one can deduce that adaptive control is Markovian (Agrawal and Heady, 1972).

Every adaptive system is merely a feedback system involving the estimation of the current state of the system and the subsequent control response. The complexity of adaptation increases as a parameter in a system is adjusted over time to cope with ne

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time to cope with new uncertainty; that is, the parameter becomes a state variable in evaluating the performance of the system, (Narendra and Annaswamy, 1989). Properties of adaptive systems are given in Appendix C.

The Stable Behavior of Plants in Biosystems and Agroecosystems

In terms of biomass accumulation, a plant is a biological integrator of solar flux in its environment (Schäper, 1976). Biomass accumulation is essentially linear with respect to absorbed solar energy provided that nutrients and water are not limiting. The change in the phenological development of plants for any time period can serve as an indicator of the weather (heat-units, solar radiation, effective rainfall) for that period, (Ritchie, 1993-1995). The growth of plants from one developmental stage to another is coupled to biochemical reactions. The rates of these biochemical reactions respond to temperature. Phenological development, therefore, proceeds according to the accumulation of heat units, (ibid.).

Biomass accumulation with respect to precipitation follows a general quadratic relationship provided light and other nutrients are not limiting, (Hexem and Heady, 1978). The ability of a plant to consume water from precipitation for biomass production is tied to the physics of water movement through the soil. The influence of soil media on water movement is analogous to a resistance-capacitance (RC) electrical circuit, (Campbell, 1985). Soil water movement is a first-

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movement is a first-order phenomenon for which the response to transient inputs diminishes with time (Coughanowr and Koppel, 1965; Del Toro, 1965).

Although the responses of soil and plants with respect to time are nonlinear, the response of each is none-the-less bounded. Bounded environmental and agronomic inputs yield bounded behavior.

EVOLUTIONARY ALGORITHMS

'Would you tell me, please, which way I ought to go from Here?'

'That depends a good deal on where you want to get to', said the Cat.

'I don't much care where...', said Alice.

'Then it doesn't matter which way you go', said the Cat.

'So long as I get somewhere', Alice added in explanation.

'Oh, you're sure to do that', said the Cat, 'If you only walk long enough.'

Lewis Carroll in Alice in Wonderland

Evolutionary Algorithms (EAs) have emerged over the past thirty years as a class of multivariable optimization methods particularly adapted to large-scale nonlinear parameter estimation problems. The feature common to all Evolutionary Algorithms is iterative adaptation or stepwise optimization of successive populations of trial solutions. The structure of the adaptation process draws, albe

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process draws, albeit somewhat crudely, from biological paradigms (Bäck and Schwefel, 1993; Schwefel and Rudolph, 1993).

Exploration of the search space proceeds on a *randomized selection* of trial solutions. The search process is initiated arbitrarily with a hunt for an initial feasible solution. The initial feasible solution can be very inferior to the goal(s) of the optimization. The search space is then explored by successive generations of trial solution populations. The results from individual trial solutions within each population generation is examined for their achievement of *fitness criteria*. The elite(s) that have the "best" fitness is (are) selected for the basis of the next generation of trial solutions. A random selection process is employed to generate the next generation. Evolutionary Algorithms make use of the concepts of *mutation*, and *recombination* (ibid.).

The theory of Evolutionary Algorithms is based on the multivariate statistics of experimental design (Schwefel and Rudolf, 1993; Box, 1957; Box and Wilson, 1951; Brooks, 1958; Fisher, 1935; and Fisher, 1941). Both Box and Brooks developed multidimensional optimization methods based on Fisher's earlier work in experimental design (Schwefel and Rudolf, 1993). Brooks studied the application of random methods for seeking maxima and compared these to the factorial, univariate, and steepest-ascent methods (Brooks, 1958). Brooks found that random methods may prove more efficient for larger, more complex experiments than th

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experiments than the other methods. Also, he noted that random methods need not be applied sequentially; trials may be conducted *simultaneously*. Brooks proposed further elaborations of random search which he termed the Stratified Random Method and the Creeping Random Method (ibid.).

In 1955, G. E. P. Box proposed the statistical method of Evolutionary Operations (EVOP) as a means to increase the productivity of chemical manufacturing processes following the completion of plant construction and maintenance, or in response to aging (Box, 1957; Box and Draper, 1969). Evolutionary Operations applies multivariate statistics to measurements of manufacturing processes to guide the successive readjustments of control parameters. EVOP assumes that normal distributions and a linearized model of the plant are reasonable. A practical consideration of the statistical correlations among the control parameters is used to search for a configuration which achieves the greatest productivity (ibid.). Under EVOP, the plant or manufacturing process is regarded as an evolving species. "The quality of the product advances through random mutations and selections as determined by the [managing] committee" (Fogel, 1995). EVOP was not instituted as an autonomous computer simulation. Random Search and Evolutionary Operations led directly to the development in Germany by Rechenberg of a multidimensional optimization method called *Evolutionsstrattegie* which he applied to the analysis of the complex fluid mechanics describing the performance of jet e

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performance of jet engines (Rechenberg, 1965; Fogel, 1995).

Three main categories of Evolutionary Algorithms that have been advanced over the past thirty years are Genetic Algorithms (GAs), Evolution Strategies (ESs), and Evolutionary Programs (EPs) (Bäck and Schwefel, 1993). A forth category has developed within the past ten years that is essentially a hierarchical coupling of Evolutionary Algorithms; these are referred to as Cultural Algorithms (CAs) (Reynolds, 1994). The main characteristics of Evolutionary Algorithms are given in Table 2.1.

Three multidimensional nonlinear search methods to network analysis were studied by Schneider, Schuchhardt, and Wrede (1994) for their applicability to optimization problems in biochemistry and biological processes:

- Gradient search as implemented in neural networks,
- Diffusive search which characterizes genetic algorithms, and
- Evolution strategy comprising adaptive sequential random search (Bäck, 1996).

Table 2-1: M

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Table 2-1: Main characteristics of evolutionary algorithms (after Bäck and Schwefel, 1993; Bäck, 1996).

Characteristic	ES Evolution Strategy	EP Evolutionary Programming	GA Genetic Algorithms
Representation	Real-valued	Real-valued	Binary-valued
Self-adaptation	Standard deviations and covariances	Variances (in meta-EP)	None
Fitness is	Objective function value	Scaled objective function value	Scaled objective function value
Mutation	Main operator	Only operator	Background operator
Recombination	Different variants, important for self-adaptation	None	Main operator
Selection	Deterministic, extinctive	Probabilistic, extinctive	Probabilistic, preservative
Constraints	Arbitrary inequality constraints	None	Simple bounds by encoding mechanisms

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Research by Ducho

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They concluded that gradient search as implemented currently in neural networks "is well suited for optimization in smooth fitness landscapes without local minima." Evolution strategy, adaptive sequential random search, "seems to be the method of choice for optimization in a high-dimensional multimodal search space." Diffusive search, genetic algorithms, apply to situations having intermediate difficulty (ibid.).

CLIMATIC SCENARIOS

Climatic scenarios in this research relate to running the irrigated maize enterprise model under a linguistically-described weather regime for the whole of the year; some scenarios may involve splicing a forecasted weather regime for a period into the weather for a reference year. Using scenarios, observations can assess the impact of a particular weather regime on the model performance. The following references provided the basis for techniques used in the methodology presented in the next chapter: Duchon (1986), Andresen and Stefanski (1991), and Richardson and Wright (1984).

Research by Duchon

The seminal research in the development of climatic scenarios was conducted for Peoria, Illinois (Duchon, 1986) using a total of 36 actual weather records. The year 1983 was used as the representative "low yielding" year and 1976 was used as the re

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was used as the representative "high yielding" year. Using the CeresMaize 1.0 crop growth model, different simulations were created by inserting the record of the portion of the growing season for each year into the record for the reference year in order to obtain forecast periods that sequenced from planting through crop maturity. Only rainfed maize production was considered; nitrogen was assumed adequate for all cases. Also, only one soil type and one cultivar were used for all runs for any location. The results depicted the yield variance versus the proportion of the growing season for which a "perfect" weather forecast was provided.

The objective of Duchon's work was to observe the impact of having a "perfect" weather forecast up to any given day in the growing season. Following the last day of the perfect forecast, a four-day transition was made from the reference year (1976, or 1983) to each of the remaining 35 years of weather history. The transition coefficients were based on a study of the correlation of maximum and minimum temperatures on a given day to the corresponding temperatures on succeeding days. Average autocorrelation coefficients were used as weighting factors to splice the reference weather year to each of the remaining weather records. The values used were 0.70, 0.35, 0.18, and 0.10 for the first to the fourth transitional day, respectively. No transition was applied to precipitation, however.

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As the change-over date was advanced through the growing season, the variance declined from its maximum value in a sigmoidal manner toward zero. From the sowing date until after tassel initiation, the variance remained at its maximum value which indicates that the weather regime and, hence, the weather forecast was not an important factor in predicting the crop yield for rainfed maize. Beginning from the development of the ear through to the early grain-filling period, the variance declined to zero; therefore, the weather forecast proved important during these stages of crop growth.

Except for frost, weather had no influence on yield at the end of the grain filling period. Additional observations from Duchon's research are as follows:

1. The yield variance in some cases increased from one forecast period to the next, reflecting the nonlinearity of the plant growth model, CeresMaize.
2. The effect of weather on the model at a given time depends on the antecedent weather.
3. The weather record must be considerably greater than 35 years to ensure reasonable stability of the yield prediction.
4. The accuracy of yield prediction depends on the "adequacy" of the crop model and the accuracy of the weather forecast.

Duchon attempted to assess the value of a perfect weather forecast by considering the reduction in the yield variance for three forecast periods leading up to the m

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leading up to the mid grain-filling period after which weather no longer had an effect on yield. The value of a 5, 15, and 30 day perfect forecast peaked at 0.8 T/ha, 2.1 T/ha, and 3.2 T/ha, respectively.

Duchon suggested the derivation of six or nine categories of the weather from local weather records for above average, below average, normal weather conditions would be useful to describe weather regimes . Additionally, the roles of fertilizer and irrigation on yield prediction were suggested for future investigation.

Research by Andresen and Stefanski

Andresen and Stefanski developed climatic scenario statistics over the growing season for eight sites throughout the U.S. cornbelt (Andresen and Stefinski, 1991, Stefinski and Andresen, 1991). They then applied CeresMaize 1.0 in the same manner as did Duchon. They validated CeresMaize against twenty years of data recorded at Washington, IA. The sites chosen for their research were:

Coldwater, Michigan (25 miles south of Kellogg Biological Station)
Columbus, Indiana
David City, Nebraska
Darlington, Wisconsin

Greenville, (

Morris, Minn

Urbana, Illin

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Andresen and Stefar
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Greenville, Ohio

Morris, Minnesota

Urbana, Illinois

Washington, Iowa

Andresen and Stefanski obtained monthly weather data for each of the sites from the National Climatic Data Center and then used the data to develop site parameters for the WGEN synthetic weather generator (Richardson and Wright, 1984). They next produced twenty synthetic weather years for each of nine weather scenarios for each location. The nine linguistically-described weather scenarios were:

Above average temperature, above average rainfall

Above average temperature, average rainfall

Above average temperature, below average rainfall

Average temperature, above average rainfall

Average temperature, average rainfall

Average temperature, below average rainfall

Below average temperature, above average rainfall

Below average temperature, average rainfall

Below average temperature, below average rainfall

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Average conditions were defined as the forty percent of temperature and rainfall observations about the midrange of all observations. Above and below average conditions were defined respectively as the thirty percent of the observations above and below the average conditions.

Andresen and Stefanski applied the climatic scenarios to three periods of varying durations within the growing season (June to August, July to August, and August) to twenty-one actual weather years spanning 1968 to 1988 for each location. The highest yields were found in cool-wet scenarios (below average temperature, above average rainfall). Conversely, the lowest yields were observed for warm-dry scenarios (above average temperature, below average rainfall.)

Andresen and Stefinski suggested that the 30- and 90-day extended weather outlooks from the Climate Analysis Center be used to anticipate electric power demand, and weather-dependent non-agricultural sales.

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THE RICHARDSON-WRIGHT WEATHER GENERATOR WGEN

The National Weather Service has extensive weather data on magnetic tape and CD-ROM. The data can be cumbersome to use; moreover, data are not available for all locations (Hanson et al., 1994). The WGEN model was developed to permit generation of realistic climatic information on micro-computers (Richardson and Wright, 1984).

The 1984 version of WGEN uses 12 parameters to characterize the weather for a particular location. The weather parameters for a location are interpolated from historic weather parameters (Hanson et al., 1994). The parameter set for Michigan's reporting stations was based on twenty years, or more, of weather observations (Nurnberger, 1995).

Considering the weather parameters for a location, WGEN simulates daily weather for the specified time period, giving the following measures: daily precipitation, daily maximum temperature, daily minimum temperature, and solar radiation. "Daily precipitation is described by a first-order Markov chain with precipitation amounts distributed as a mixed exponential. Additionally, data on daily maximum and minimum temperatures and on daily solar radiation are simulated using a weakly stationary generating process first described by Matalas (1967) and adapted to daily weather by Richardson (1981). The seasonal variations of parameters are described by Fourier series providing a very

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To generate daily weather, WGEN first examines the occurrence or nonoccurrence of precipitation based on "the dependence between wet and dry occurrences on successive days...." "Seasonal variations are accounted in the model by expressing the transition probabilities as a Fourier series..." (ibid.). The maximum temperature, minimum temperature, and solar radiation values are "conditioned on whether the day was dry or wet as determined by the Markov chain occurrence model" (ibid.).

Several accuracy problems were found with the 1984 version of WGEN for several North American locations. The first problem was noticed for stations east of the Rocky Mountains along the Canadian border and in the northern Great Plains (ibid.) which involved duplicating mean minimum temperatures less than zero degrees F. "Furthermore, the standard deviations of the generated temperature records [for these locations] were low during the summer and midwinter and very high during early spring and fall." (ibid.). The second problem involved solar radiation, daily values "did not represent actual conditions in northern latitudes. The upper limit on solar radiation was too restrictive for stations in the southwest generally and too restrictive for cloudy days in the northeast" (ibid.). The problems with the 1984 version of WGEN have been appreciated (Andresen, 1995; Nurnberger, 1995) and the 1994 version has been corrected for the problems mentioned. Unfortunately, very few stations in

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very few stations in Michigan appear in the 1994 version, for which reason the 1984 version remains in use.

MAIZE CROP GROWTH MODELS

CeresMaize and CORNSIM are maize crop growth models orientated toward solving particular agricultural problems; hence, they are not as detailed as models intended solely for research. The requirements for crop models of this type have been outlined by Whisler et al. (1986) and are listed in Appendix D.

The CORNSIM Model

CORNSIM was developed in the late 1970's for the particular purpose of simulating the expected flow of grain at the farm or community level during the harvest season (Van Ee and Kline, 1979). The data on grain flow at harvest were used for a study of corn drying and storage for conditions in Iowa. CORNSIM followed from a fifteen year succession of crop production models that focused on how best to manage machinery resources.

Maize growth in CORNSIM was based on crop histories in Iowa; as such, a number of simplifying empirical relationships were used (Van Ee, 1995-1996). Rather than including a detailed model of plant growth, CORNSIM focused on predicting the yield and moisture content at harvest, based on weather, maize variety, and planti

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CORNSIM enabled the direct consideration of planting several maize varieties with the intention of obtaining the sequential crop maturity dates across a farm or community. Harvesting and drying capacities could then be better utilized through linear programming and the community could achieve an economic advantage (ibid.). The model could accommodate thirty fields of maize with physiological maturity calculated for each. Maize development after planting was based on heat units (growing degree-days). Yield projections were based solely on data collected from research plots of the Iowa Crop Association; no photosynthesis submodel was included.

The subprogram inside CORNSIM for "dry-down" of mature maize in the field received special attention as crop-drying was a concern for the use of the model. The effect on machinery management subject to alternative planting plans could then be observed (Van Ee and Kline, 1979).

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The CeresMaize Model

CeresMaize is perhaps the best-documented and tested crop growth model. It has been used worldwide for more than ten years to predict maize growth and production for various plant genotypes, soil properties, climatic conditions, and nutrient sources. CeresMaize 1.0, CeresMaize 2.1, and CeresMaize 3.0 have been embedded in decision support programs such as DSSAT 2, DSSAT 3, WEPP and DAFOSYM, all of which include subprograms for chemical forms of nitrogen fertilizer (DAFOSYM, 1996; DSSAT, 1995; Rotz et al., 1989; Rotz et al., 1991; WEPP, 1997). None of these versions, however, includes animal waste within the CeresMaize model.

CeresMaize followed from a set of maize production models that focused on the variation of yields across locations and environments (Kiniry, 1991). As compared to CORNSIM, CeresMaize was designed to be portable; that is, CeresMaize has been used to simulate conditions for maize growth for numerous locations around the world (Ritchie, 1993-1995).

CeresMaize considers plant phenological development based on heat units. Photosynthesis and carbohydrate accumulation are based on solar energy. Root development, leaf number, and biomass accumulation by plant organ are also calculated in addition to a yield projection at 15.5 percent moisture (wet basis) (Kiniry, 1991).

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The program operates on a daily time-step. Likewise, only daily average weather measures are needed. Changes in the soil profile and within the plant can be recorded to output files on a daily basis. CeresMaize simulates much more of the plant's activity than CORNSIM; however, it does not track field dry-down. As opposed to research models which simulate plant processes throughout the day, CeresMaize uses some simplifying empirical relationships to permit use of the daily time-step in order to reduce computation time.

The photosynthetic activity and resultant distribution of biomass depend on the phenological stage of plant development (ibid.). CeresMaize divides maize development into seven growth stages:

Stage number	Stage description
7	Prior to sowing (fallow)
8	Sowing to germination
9	Germination to seedling emergence
1	Seedling emergence to end of juvenile stage
2	End of juvenile stage to tassel initiation (photoperiod-sensitive stage)
3	Tassel initiation stage
4	Silking to beginning of effective filling

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5	Effective filling period of grain
6	End of effective filling period to physiological maturity (black layer)

Shifting plant development from one stage to the next occurs when the appropriate number of heat units has accrued subject to the genetic coefficients for the cultivar in question. Therefore, weather and genetics control the development of a normally growing plant. The general flowchart of the CeresMaize program is given in Figure 2.3 (Kiniry, 1991). Numerous validation studies have been performed on CeresMaize (Kiniry, 1991; Ritchie, 1993-1995); CeresMaize may well be the most popular maize growth program in use in applied research in the United States.

The Inbred Maize Version of CeresMaize

Martin (1992) constructed a version of CeresMaize, CERES-IM, for inbred maize to simulate seed corn growth. He also conducted a two-year lysimeter study of nitrate movement from seed corn in sandy loam soils in St. Joseph County, Michigan. The lysimeter studies where used to validate CERES-IM. Martin used the validated CERES-IM to evaluate the effects of several fertilization strategies on nitrate leaching and enterprise profit. He considered 17 fertilizer management strategies including single fertilizer application. split

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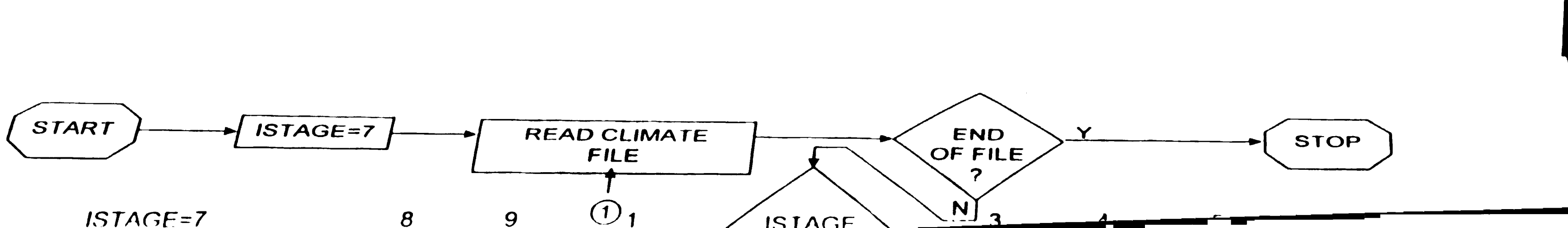
application, split nitrogen application, and plant response fertilization (PRF). Martin concluded that a split application of 30 kg/ha at planting and 80 kg/ha at cultivation (growth stage 6) gave optimal results. Irrigation in CERES-IM was performed with fixed schedules and by daily top-up.

The Animal Waste Management Version of CeresMaize

The Animal Waste Management version of CeresMaize (hereafter referred to as AMaize) was developed by Shayya and von Bernuth (1992) to include the various nitrogen transformations of animal manure in the soil. Swine, cattle, or mixed slurries are included in the original version. AMaize was constructed from CeresMaize 1.0, but includes features of later versions of CeresMaize. AMaize considered the land area per plant but not row spacing as does CeresMaize 2.1. AMaize does consider capillary rise and root die-back to a rising water table. None of these models consider phosphorous directly. Phosphorous dynamics will be included in the SALUS Model, which will succeed CeresMaize (Ritchie, 1993-1995).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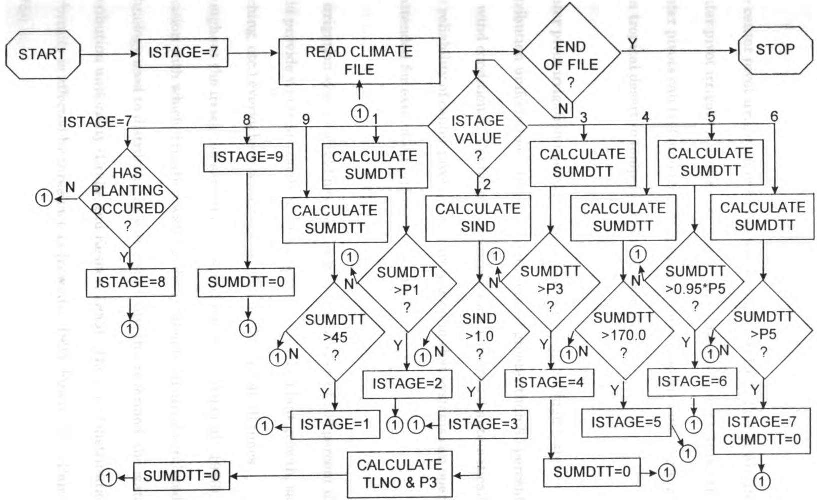

Figure 2-3: General flowchart of the CeresMaize crop model.

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CENTER PIVOT IRRIGATION SYSTEMS

The center pivot irrigation machine was patented in 1952 (Pair et al., 1975). Center pivot irrigation is now common on all continents except Antarctica. Center pivots can be found irrigating every type of crop in climates ranging from tropical desert to temperate humid regimes.

Center pivot irrigation machines are capable of relatively high water distribution uniformities (statistical uniformities greater than 85 percent in low wind conditions). Center pivots are commonly operated automatically. The reliability of center pivots is relatively good in that systems can operate unattended for extended periods (weeks) (ibid.).

An irrigation system would have an irrigation efficiency of 100 percent if it could provide water to exactly meet all beneficial needs (plant growth, salinity leaching, etc.) everywhere within the irrigated area and at all times throughout the irrigation season (Bralts and Wu, 1987; Wu et al., 1986). The precision with which irrigation water is distributed to all areas is related to the technology used to distribute the water spatially; this is termed the water distribution uniformity (Bralts and Kesner, 1983). The water distribution uniformity is affected by three factors (Elwadie, 1995; Fusco, 1995; Pair et al., 1975):

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- Hydraulic performance of the water supply, sprinklers, and lateral,
- Movement of the sprinkler lateral, and
- Wind distortion of the sprinkler/spray pattern.

The center pivot irrigation machine is peculiar in that the system distributes water by "sweeping" an arc about the pivot center as water is sprinkled or sprayed onto the soil beneath the lateral. The flow rate at which water is distributed increases linearly from the pivot center to the distal end of the sprinkler lateral. How well sprinklers and nozzles can be selected to match the required water distribution along the lateral is largely a function of the system's "hydraulic uniformity." The constancy of the sweeping movement about the pivot center is related to the machine's alignment and drive mechanisms. Alignment uniformity and drive uniformity degrade if the topography is undulating (Fusco, 1995).

Wind is a stochastic phenomenon. The orientation of wind to the sprinkler lateral, the variability of the wind, and the exposure of the sprinkler/spray pattern to the wind distorts the water distribution across the irrigated area. Accommodating the effect of wind involves compromises. Larger water droplet sizes are less affected by wind, but are more erosive to bare soils. Lowering the sprinklers nearer to the crop reduces wind distortion; however, the system generally must accommodate several crops which vary in height. Maize, for example, grows to

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example, grows to a height of 2.5 meters during the irrigation season (ibid.).

At least five manufacturers supply the North American market. Each offers a variety of sprinkler and nozzle packages, gearboxes, tires sizes, alignment systems, control systems, lateral diameters and overall length, truss designs, tower designs, etc. The reliability and longevity of the center pivot systems have increased as better designs and materials have become available. A properly maintained center pivot can operate for several decades, thus a market for used center pivots has developed. The performance of used systems is inferior and highly variable with respect to distribution uniformity (Barclay, 1994-1995; Graber, 1995; Krieger, 1995; Nemec, 1995).

The maxim "you get what you pay for" generally applies to center pivot performance with respect to overall irrigation efficiency and distribution uniformity (Graber, 1995). Technological advances in design and materials have made modern machines perform better than old machines. The water distribution uniformity of a center pivot irrigation machine derives from the design, installation, and maintenance of a particular system operating within a particular environment. The distribution uniformity of a system is the most critical factor determining irrigation efficiency, but it is only one factor. The other critical factor is the ability to "best" adapt the performance capabilities of a given system to the demands of crop production, both economical and environmental (Sammis and Wu, 1985). Determining how best to operate an irrigation system

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Irrigation Scheduling

The allocation of irrigation water, its timing and amounts, in accordance with the needs of crop production is called irrigation scheduling. The ability to schedule irrigation is constrained by the irrigation technology employed (Howell et al., 1986; Keller et al., 1981; Replogle and Merriam, 1981).

Spatial variability in the water distribution constrains the irrigation schedule to be based on an "average" or some "critical" irrigated condition within the irrigated area. The critical condition is typically to provide adequate irrigation to the least-watered area within the irrigation system. If the least-irrigated criterion is chosen, all other locations within the system are then over-irrigated. If scheduling is keyed to the average irrigated condition then part of the system is over-irrigated and another part is in deficit (Bralts, 1986; Wu et al., 1986).

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The concepts of over- and deficit-irrigation have to be referenced to crop needs over each scheduling period. Ideally the scheduling period is keyed to crop development, but in practice the scheduling period is frequently constrained by the irrigation technology. High frequency, or daily irrigation scheduling may be ideal for the crop; however, the irrigation system may have a minimum cycle time lasting several days. The minimum cycle time together with the water supply rate establish the minimum irrigation that may be applied for any scheduling period. The maximum irrigation is limited by the water supply. During extreme droughts for example, only deficit-irrigation may be possible because of the limited capacity of the irrigation system (Wallace, 1987). The irrigation technology employed, therefore, constrains the time step for scheduling the irrigation and sets limits on the upper and lower bounds of each irrigation event ((Howell et al., 1986; Keller et al., 1981; Replogle and Merriam, 1981).

Crop development is driven by the weather. Weather is stochastic (Ritchie, 1993-1995). Irrigation scheduling demands adaptive and stochastic optimization (Howell et al., 1986). The needs of crop production are economical and environmental (Hoffman, 1986; Young, 1981). Hence irrigation scheduling warrants multicriteria (conflicting criteria and compromise) optimization (Alocilja, 1995).

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Irrigation efficiency has traditionally been keyed to factors such as root development. Root development and stage of plant growth, while important, are merely intermediate measures of irrigation performance. The economical and environmental performance measures applied to a crop production enterprise also apply to the technology employed by the enterprise. Hence, direct economical and environmental impact measures are relevant to optimization of the irrigation schedule.

FIELD DRY-DOWN

The drying of maize in the field following maturity reduces the need for post-harvest mechanical drying and thus reduces the cost of production (Bakker-Arkema, 1995). Field drying requires both favorable weather and an adequate drying period between maturity and harvest (Van Ee, 1995-1996). Field dry-down is not included in the CeresMaize crop growth model. Field dry-down, however, influences the choice of cultivar to plant (Van Ee and Kline, 1979). Therefore, the field dry-down model from CORNSIM was adapted by this researcher to the Animal Waste Management version of CeresMaize. Schmidt and Hallaver (1966) first made a model to calculate daily field dry-down based on a system of four empirical relationships. The daily kernel moisture reduction from the "milky kernel" developmental stage (75 percent moisture content, wet basis) down to "average maturity" (30 percent MCWB) was described as two linear functions of average daily dry-bulb temperature. From

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30 percent to 20 percent, the daily kernel moisture reduction was described by two linear functions of average daily wet-bulb depression.

The Schmidt field dry-down model had three major problems. The transition points selected for shifting from one empirical relationship to the next were somewhat arbitrary and did not consider biological markers associated with drying grain (Van Ee and Kline, 1979). The Schmidt relationships were based on long-term averages of drying-rates over several years. Lastly, the Schmidt model did not consider rewetting on humid days.

Van Ee improved the field dry-down model by relating the transition from “complete dent” and “average maturity” to “black-layer development” at 37 percent moisture. Rewetting of mature kernels was also accommodated. Adjustment coefficients were appended to the relationships to accurately determine daily moisture change. Also a relationship was added to determine moisture loss for grain below 20 percent moisture (Van Ee and Kline, 1979). Both the Schmidt and Van Ee field dry-down models were developed on data from Iowa. The Van Ee model has been applied to Michigan (Brook, 1995; Van Ee, 1995-1996).

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A number of commercial seed producers note susceptibility to lodging, ear drop, and other factors which affect harvest losses; however, no standardized basis for comparison of genotypes is presently available. Therefore, factors affecting losses from mechanical grain harvesting were not considered in this research.

POST HARVEST GRAIN DRYING

The standard practice in the U.S. grain-marketing system assumes that considerable stress-cracking and kernel damage will occur from post-harvest mechanical grain-drying (Bakker-Arkema, 1995). For this reason, grain quality as affected by drying technology was not addressed in this research. The performance of typical commercial grain drying technology was assumed.

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IRRIGATED MAIZE ECONOMICS IN MICHIGAN

The effect on maize yield and gross margins from irrigation, nitrogen rate, and seeding rate was studied in field research conducted on medium- to fine-textured soils near Lansing and Saginaw, Michigan from 1987 to 1989 (Christenson, Bricker, and Murphy, 1992). The time period chosen to conduct the research was fortuitous since 1987 had near-normal rainfall, 1988 had below-normal rainfall, and 1989 had above-normal rainfall. In the study, scheduled irrigation was found in general to boost yields 40 bu/acre (2.5 T/ha) on loam and silty-clay soils. A yield increase of 58 bu/acre (3.6 T/ha), however, was needed to achieve the same gross margins as non-irrigated maize on the same soils after considering the technology and prices used in the study.

Nitrate leaching was not reported; however, the "best practices" for lessening environmental impacts from farming were used. The recommendations were based on field data, no crop modeling was attempted to simulate other soils, technologies, and farming practices. Christensen et al. (1992) cited other research which inferred that irrigation is rewarding in Michigan on coarse and sandy soils. Strommen, Van Den Brink, and Kidder (1969) "found that drought occurred one-third of the time during the growing season" over a 37-year period for which records were available. "There is less than a 20 percent probability of receiving more than one inch of moisture per week during June, July, and August in Michigan" (Baten, Eichmeier, and Kidder, 1959). In Michigan, "corn requires more th

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requires more than one inch per week during this period" (Christenson, Bricker, and Murphy, 1992). As coarse-textured soils such as sandy-loams have only two-thirds the moisture holding capacity of fine textured silt-loams, the risk of drought during critical growth stages increases the need for irrigation on sandy-loams (Pair et al., 1975).

GRAIN MARKETING

Grain marketing and price forecasting are beyond the scope of this thesis. The optimization of resource utilization as structured in this thesis assumes that a decision to produce maize has already been made by the farmer.

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CHAPTER THREE

APPROACH

Simulation and optimization are used here to schedule the resource inputs for irrigated maize production. The production process yields both desirable and undesirable products and byproducts. The objective is to find a resource management strategy that will provide a quantitative balance between desired and undesired results. Such resource management strategies are based on real-time models of maize development and production.

THE CERESMAIZE GROWTH MODEL

The Animal Waste Management version of CeresMaize is adopted here as the crop growth model because AMaize includes subprograms in which animal waste is used in addition to chemical nitrogen fertilizer (Shayya and von Bernuth, 1992). Since AMaize is derived from CeresMaize, cultivar genetic coefficients, soil properties, and micro-climate are also accessible for analysis.

Irrigation is included in CeresMaize and AMaize either by appending an irrigation schedule file to supplement rain from the weather file in the soil water balance subprogram, or by "topping-up" the soil profile. Different

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versions of CeresMaize schedule irrigation by simulating a daily top-up of the soil profile, by simulating in fixed amounts, or by simulating top-up at specified intervals.

I modified the irrigation subprogram in AMaize to include:

1. the spatial uniformity of irrigation as a measure used to defined a specific level of irrigation technology thus specifying parameter values describing the irrigation technology and operating characteristics of the irrigation system,
2. a soil water depletion parameter which established a minimum threshold to initiate irrigation,
3. minimum and maximum daily irrigation amounts defined by the selected level of irrigation technology,
4. average, minimum, and maximum daily irrigation amounts as a basis for relating crop response on a field-wide basis to the statistical uniformity of water application,
5. and cumulative monthly irrigation amounts, monthly electrical energy consumption, and monthly energy charges for irrigation as actually calculated by the power utility as a consequence of the level of irrigation technology.

Ammonium nitrate was used as a proxy for "generic" cattle manure to conduct a comparison of the subroutines for nitrogen from manure in AMaize and for nitrogen from fertilizer in CeresMaize. Target yields for various combinations of fertility, soils, cultivars, weather stereotypes, and irrigation with the two versions of the crop model were similar.

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On advice from J. Ritchie (1993-1995), the denitrification subprogram within AMaize was updated to reflect current estimates of denitrification thresholds for free draining sandy loam soils. The old routine set the threshold for denitrification too low. Denitrification occurs when the soil is near saturation, an infrequent event on free-draining sandy loams.

MODIFIED VANEE DRY-DOWN MODEL

AMaize like CeresMaize predicts the crop maturity date and the grain yield at 15.5 percent moisture content (wet basis). On the maturity date, the grain has a moisture content in the neighborhood of 33 percent. Post-harvest grain drying is required to reduce the grain moisture content to below 15.5 percent for safe storage. Post-harvest drying is expensive; field drying depends on the weather, but is essentially free. The preference is to dry the standing crop as much as possible in the field before harvesting to reduce the expense of post-harvest drying.

Cultivars which take full advantage of available heat and solar energy over the growing season achieve the greatest yields. Cultivars which mature very late, however, must be harvested at a high moisture level. Some of the revenue gained from a high yield is thus lost in the cost of drying. Also, long season cultivars give a stronger response to irrigation and fertilization. If animal manure is used as a fertilizer, then high yielding, long season culitvars potentially have an advantage that needs to be quantified.

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A model of maize field dry-down is needed to predict the harvest date because of the impact of the choice of cultivar on net return in combination with water and nutrient consumption. Water and nutrient uptake affect nitrate leaching. The VanEe Dry-Down Model for the in-field drying of standing corn was appended to AMaize so as to extend the crop management program from preplanting through to postharvest. The drying rate of field corn depends on the equilibrium moisture content of the corn grain at a given air temperature and humidity. To reduce computation time, relative humidity and equilibrium moisture content were appended to the to the weather files.

The VanEe Field Dry-Down Subprogram was originally incorporated into CornSim, a corn production model for central Iowa (Van Ee and Kline, 1979) and has been applied to other areas in the Midwest (Van Ee, 1995-1996; Brook, 1995). This model was chosen based on validation in a temperate, albeit drier-than-Michigan, portion of the American Corn Belt.

The VanEe Dry-Down Model uses relative humidity as an input to the "dry-down" (dehydration) equations. Relative humidity, however, is not provided by the Richardson and Wright Weather Generator used here. An estimate of the daily average humidity was constructed by assuming the dew point temperature to be at the daily minimum temperature (Merva and Fernandez, 1985). This method looses accuracy when the mean temperature drops below freezing in December and January, but this is after the normal harvest season.

The psychrometric submodels from SYCHART (Lerew, 1972; Bakker-Arkema, Lerew, and DeBoer, 1974; Brooker, Bakker-Arkema, and Hall, 1974) which are valid to -18 °C (

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valid to -18 °C (0 °F) were adapted here to the dry-down model. The subprogram for the equibrium moisture content of shelled corn in the VanEe Dry-Down Model was also replaced by the more accurate model at low temperatures (4 °C to 60 °C, 40 °F to 140° F mean temperature) from DeBoer (Bakker-Arkema, Lerew, and DeBoer, 1974). The average deviation from experimental data is 0.5 percent for the DeBoer model.

Simulated field drying was initiated the first day after crop maturity as calculated from AMaize. Every day with rainfall less than 3 mm was counted as a drying dry, the grain moisture contents were then adjusted for the maximum, minimum, and average irrigated conditions. No drying accrued on days with 3 mm or more of rainfall. Grain harvest was constrained to occur between the first day following crop maturity and Julian day 330, the 26th of November.

CENTER PIVOT IRRIGATION MODEL

The spatial distribution of the water delivered to the maize field by a center pivot irrigation system was quantified in terms of a symmetrical beta distribution (Hahn and Shapiro, 1967; Hastings and Peacock, 1974). Figure 3-1 depicts the flexibility of the density function for the beta distribution. This statistical measure of irrigation uniformity became the key parameter describing the irrigation technology used in any given simulation. The beta distribution of statistical irrigation uniformity formed the link between the irrigation technology and maize production performance measures such as yield variability, nitrate leaching variability, and economic net return. This

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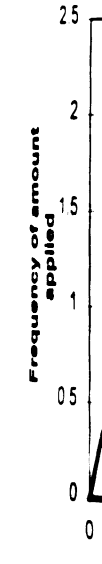
combined approach of linking irrigation uniformity with a comprehensive crop-enterprise model to find a "best" schedule for farming activities and a "best" selection of irrigation technology is a first.

Center pivot irrigation is the common mode of irrigation in southern Michigan. Center pivot costs and performance were based on nominal "quarter-section" center pivot designs (128 to 145 acres). Three center pivot designs were selected as references for performance (Barclay, 1995; Graber, 1995; Krieger, 1995; McDonald, 1995) and are described in Table 3.1.

Controls, gear-boxes, tires, etc. were specified in packages appropriate to the sprinkler and speed specification (ibid.). The maximum speed of rotation, area-of-coverage, and pump flow-rate establish the daily minimum irrigation. The pumping rate over a 24-hour rotation of the center pivot around the field together with the area-of-coverage establish the maximum daily irrigation.

The frequency of irrigation is taken as a management parameter. Daily irrigation is permitted only when the demand for irrigation water exceeds a threshold deficit in soil water, the objective being to minimize the potential for runoff and drainage resulting from the combination of irrigation and rainfall.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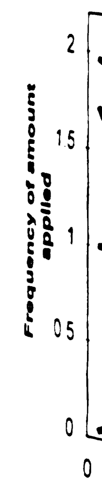
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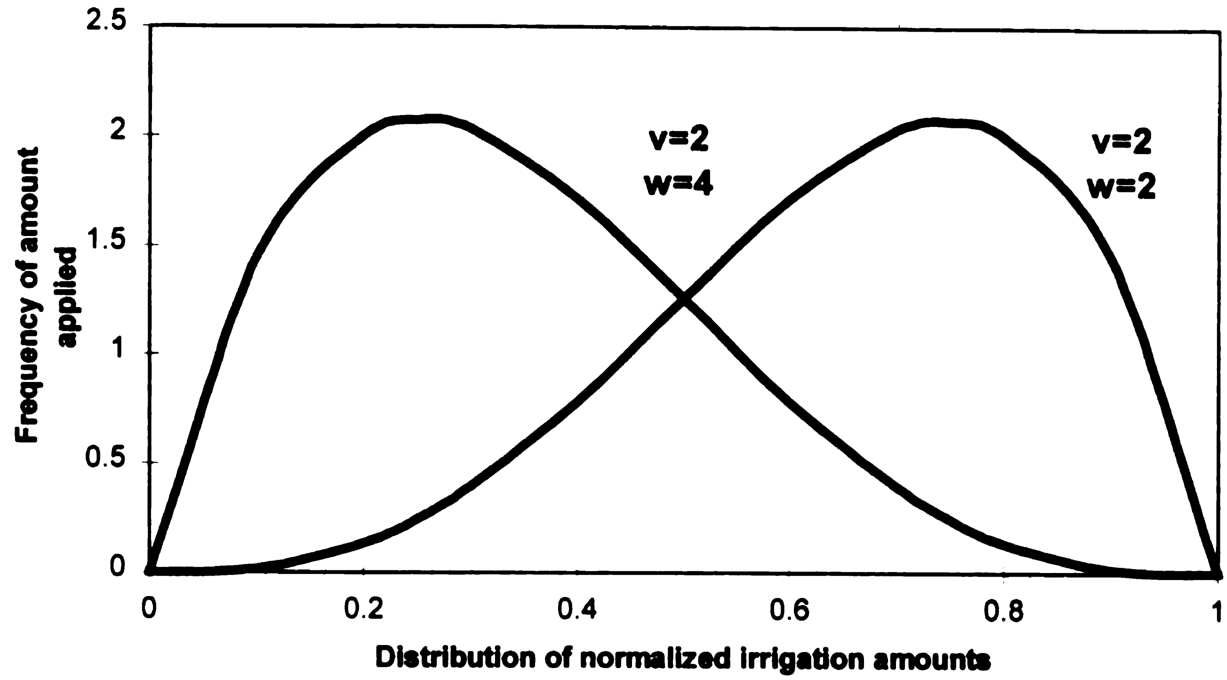

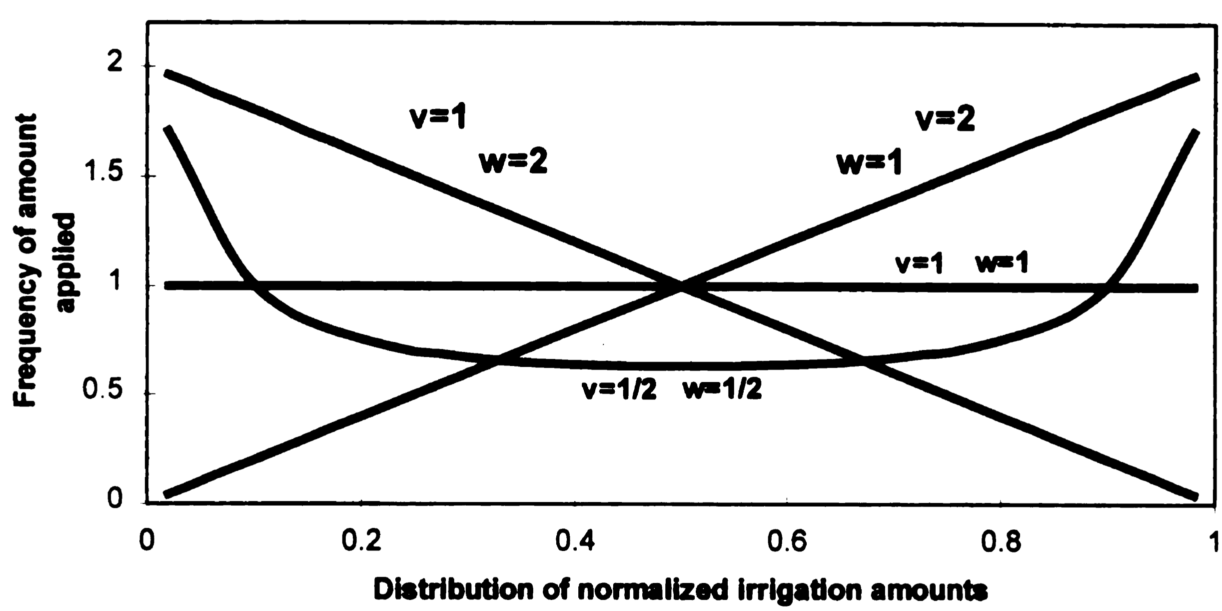

$$f(x) = \frac{x^{(v-1)} \cdot (1-x)^{(w-1)}}{\beta(v,w)}$$

Figure 3-1: Flexibility of the beta distribution density function for the beta variate β:v,w, after Hastings and Peacock (1974).

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Table 3-1. Reference center pivot specifications.

Low-tech:	a twenty-year-old used center pivot with old high pressure sprinklers
Mid-tech:	a modern high-rotation speed center pivot with low pressure sprinklers, end-gun and booster pump
High-tech:	a modern very-high-speed center pivot with low pressure sprinklers throughout

Variations in water well technology and cost were not considered. Rather, on advice from local well drilling companies and pump distributors, a single "good-quality" long-life water well design common in southern Michigan was used for pumping and cost calculations, with the pump discharge pressure and flow rate matched to the characteristics of the pivot (Barclay, 1995; Burrows, 1995; Hart, 1995; McDonald, 1995).

Electric power requirements were keyed to the area of coverage, sprinkler package, and drive package. The cost of electric energy was taken as a function of the monthly kilowatt-hours consumed based on the power utility (Indiana & Michigan Electric Company) rate schedules (Rodendeck, 1995).

Electric energy demand, minimum and maximum daily irrigation, combined capital, operating, and repair costs were each expressed as a functions of the statistical measure of uniformity.

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The twenty-year old "low-tech" pivot required the least capital investment, had the slowest rotation speed, and had the poorest measure of uniformity with the greatest runoff/leaching potential. The "high-tech" center-pivot had low-pressure sprinklers, high-flotation tires, a relatively high speed of rotation, the lowest minimum daily application rate and the highest measure of uniformity. The "mid-tech" center-pivot is equipped with low-pressure sprinklers and end-gun with booster pump. It was in the middle in terms of uniformity, cost and rotational speed.

The low-tech, mid-tech, and high-tech designs provided the references for machine specifications obtained through simulation. Technical and economic performance parameters for center-pivots between the low-tech, mid-tech, and high-tech machines were based on linear interpolation. A power function was used to extend the system cost beyond the low-tech and high-tech systems, based on previous experience and the assumption that the system cost is zero for a uniformity of zero and unbounded for perfect uniformity.

WEATHER STEREOTYPES

Inspired by recent work by Andresen and Stefanski (1991), I used the concept of climatic scenarios to identify ten stereotypical weather years within a sequence of 99 weather years of weather data obtained from the Richardson-Wright Weather Generator for the Kellogg Biological Station; this is a more rigorous test of the influence of weather on the farming enterprise than in previous research (Christenson, Bricker, and Murphy, 1992; Martin, 1992). The stereotypical weather years, characterized by monthly temperature and rainfall values.

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Table 3-2. Description of weather stereotypes.

Linguistic Description	Average Temperature °C	Total Rainfall mm
hot and dry	11.4	531
hot with moderate rainfall	11.4	970
hot and wet	11.4	1534
moderate temperature and dry	9.3	437
moderate temperature with moderate rainfall	9.3	755
moderate temperature and wet	9.3	1011
cold and dry	7.4	520
cold with moderate rainfall	7.4	940
cold and wet	7.4	1458
normal temperature with normal rainfall	9.5	1007

Moderate is defined as a year having monthly values for temperature, or rainfall spanning the center forty percent of the 99 weather years. Normal is defined as a year having the mean monthly temperature and rainfall of the 99 weather years.

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A stereotypical weather year of twelve consecutive hot/dry months is highly improbable. In southern Michigan for example, two consecutive hot/dry months have occurred during the summer only once in 50 years. Stereotypical weather years for a given location are used to forecast the impact of microclimates on crop production.

In the results reported here, short-term weather forecasts were either assumed to be perfect or, assuming no other knowledge of future weather, a normal temperature/normal rainfall stereotype was used. Long-range weather forecasts are expressed as monthly temperatures and rainfall above, or below normal.

The ten stereotypical weather years were constructed by sorting monthly temperature and rainfall summaries. Insertion-sort and heap-sort routines were modified to accommodate the large temperature and rainfall arrays of 99 years (1101 months) plus an annual summary. The heap sort routine performed fastest and was used for all of the sorts. The simpler but slower insertion-sort routine was used to spot-check the results.

The monthly sorts were used to compose monthly temperature and weather templates from which to knit the stereotypical weather years. The 99 years of weather data were first sorted by temperature into hot, moderate, and cold categories. The central 40 percent of the monthly summaries were classified as moderate, with the upper and lower 30 percent as hot and cold, respectively.

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The variation from hot to moderate and moderate to cold was on the order of 2 degrees Celsius.

The categories of temperature were then sorted according to dry, moderate, and wet rainfall, and mean values were calculated for each. The sort was performed and a representative month nearest to the mean value was selected. Frequently several months had mean rainfall values very near to the mean value. In these cases, the month with the "most" typical rainfall frequency was selected. Months with very large storms tended to be eliminated from the stereotypes.

A "knitting" program took the temperature and rainfall templates for each stereotypical weather year and made a weather file containing the following daily information: Julian day, solar radiation, daily maximum temperature, daily minimum temperature, and daily rainfall. Humidity and equilibrium grain moisture content were then added for each day to the weather file in the manner described previously in the section on the Van Ee Dry-down Model. The weather file was organized to begin on Julian day 111 (21 April) and end on Julian day 110 (20 April).

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THE PROCESSING NETWORK

The network formulation from graph theory and development of the matrix algebra for a simple processing network with cross-links is described in the Indonesian Post-Harvest Rice Processing Model posed by Handaka (1989), Appendix D. Appendix D demonstrates how elemental processes are merged into a network and formulated into the reduced matrix representation of the complete system. The alpha-numeric structure developed in the course of this research to facilitate debugging of source code is also presented in Appendix D.

The combined AMaize/VanEe DryDown model created a number of data files which were used to calculate the parameters for the maize production process in the enterprise network. The processing network was configured in two modes: the mode considering the average irrigated condition only and the mode considering beta-distributed statistical irrigation uniformity. A set of output files from the minimum, average, and maximum irrigated conditions were written, means and variances were calculated for crop model results.

The parameters of the maize production process were computed by the combination of the Amaize and Van Ee Drydown models for a given set of cultivars, soils, irrigation parameters, and weather. The model of the processing network was then used to simulate the ecological and economic performance of the enterprise for the network parameters. Statistical means and variations were calculated according to a beta-distribution. The simulation results were written to output files along with "what if" values for network parameters and resource inputs.

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Embedding Large Models in a Processing Network

As long as input data are available, AMaize and CeresMaize will run whenever called by a controlling program. In this research, the results from AMaize were central to the computations of the irrigated maize processing network.

In the solution structure, the design vector pertains to the combined Amaize/DryDown model. The optimization algorithm first created the trial design vector and then program control was chained to the average irrigated condition of Amaize/DryDown. After reading the initialization file, Amaize reads the design vector. Amaize and Dry-Down developed the output files based on computations performed for the entire weather year.

The reply (feedback with revisions from individualistic constraints discussed in the sequel) to the trial design vector was read in the optimization algorithm and the trail design vector was updated accordingly. An irrigation schedule file was written for the maximum and minimum irrigation versions of Amaize/DryDown to follow. The exchange files which communicated a summary of information on events of the entire year were created for reference by the process network program. Figure 3.1 gives the general linkage of the models to the optimization algorithm.

After the average irrigated condition was calculated, the maximum and minimum irrigated conditions were calculated in turn. The maximum and minimum irrigated Amaize/DryDown programs responded to the same initialization file, design vector, and weather files as the average irrigated condition. The maximum and minimum variants, however, did not independently

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I chose a symmetrical beta distribution to describe the statistical uniformity of the irrigation application in this research. Depending on the irrigation uniformity selected in the design vector, the maximum and minimum irrigations deviated from the average irrigation by a uniform deviation parameter. A symmetrical beta distribution does not exist for uniformities below 67 percent.

The maximum and minimum irrigation conditions were calculated, with crop and soil responses recorded in exchange files. The exchange files for each irrigated condition carried different field prefixes so that the process network program could collate the information.


Results:
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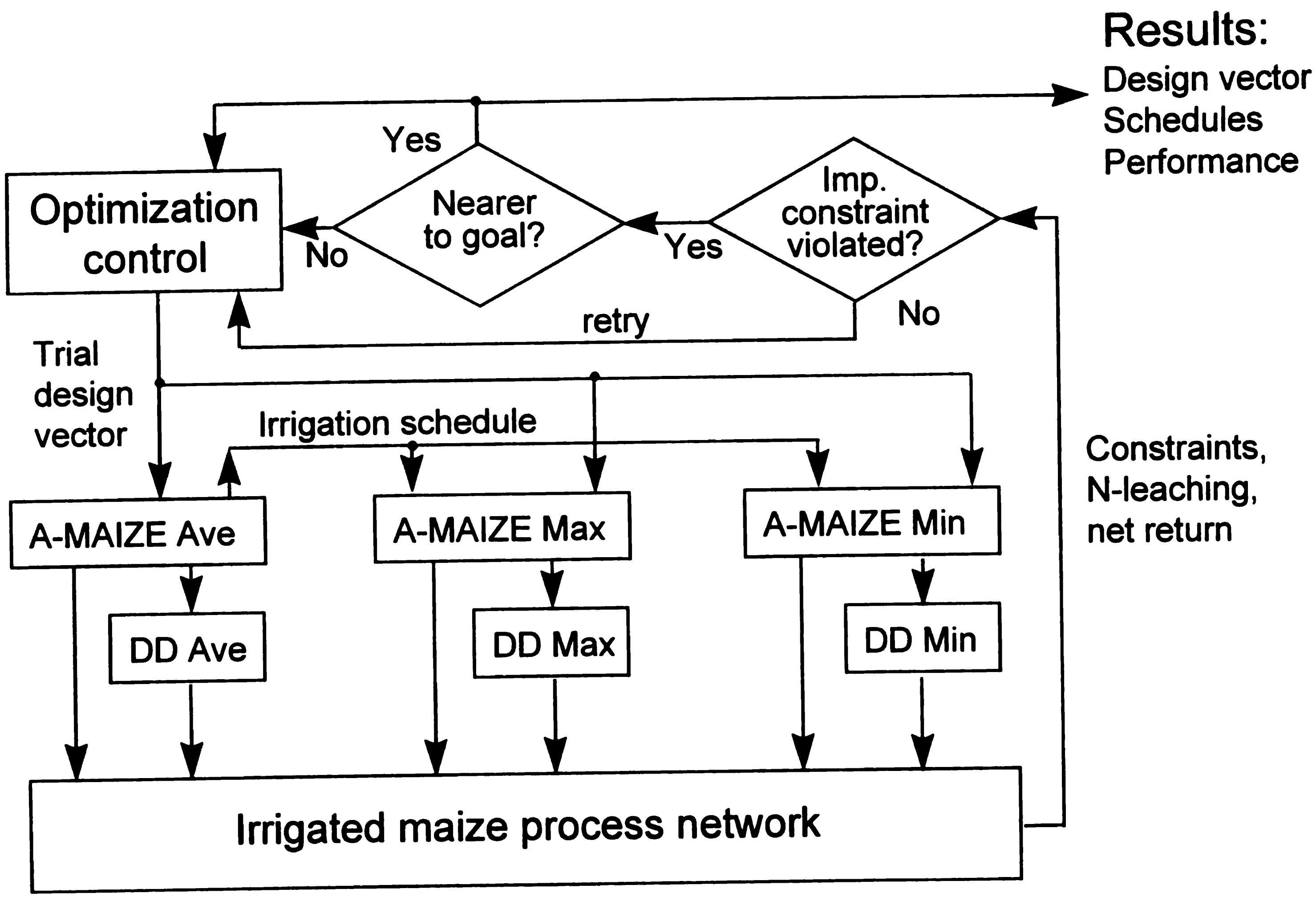

Figure 3-2: General linkage of the models to the optimization algorithm.

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Upon conclusion of Amaize/DryDown, the optimization algorithm then called the process network program. The variation in irrigation distribution had the potential to produce nonlinear effects throughout the enterprise model. Other factors affected were crop developmental stages, yields, biomass production, grain moisture at harvest, soil water and nitrogen levels. The consequence was that all could vary according to a *non-symmetrical* beta distribution. The process network processed information from the three irrigated conditions and then calculated mean values and variances for the flows through the network.

Three parallel computational paths representing the maximum, average, and minimum irrigated conditions comprised the process network. The inputs to the three paths originated from five groups of resources: the natural resource base, biomaterials/biochemicals, plants and nutrition, preharvest agricultural operations, and irrigation.

Natural resources included land, rain, solar radiation, growing degree-days, and drying degree-days. All calculations were based on an area of one hectare. The annualized price of land was a proxy cost for the use of all incident natural resources contained in the weather scenario. If the variability due to irrigation was being calculated, it is possible that the resultant maturity dates differed; the cumulative weather measures also may have differed.

Biomaterials included root biomass and stover biomass from the previous crop and post season from the present crop. Information was included for each stage of crop growth. Biochemicals included herbicides and insecticides. These biochemicals were not transformed into the crop, but represented part of the energy expended in preserving the enterprise. Current unit prices were

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multiplied by the amount used and added to the cost of production. Precise local application of chemicals was possible in the model.

Plants and nutrition included the seed, fertilizer and manure applied. Market prices for 1996 were used for seed and fertilizer. Manure carried no unit price, *per se*.

Preharvest agricultural operations included manure spreading, primary, secondary, and finish tillage, planting, cultivation, spraying, anhydrous ammonia injection, and field transport operations. All operations were considered "per treatment." The costs of all agricultural field operations were based on 1996 custom-hire charges for central southern Michigan (Schwab, 1995; Schwab and Siles, 1994).

Monthly cumulative irrigation and statistical uniformity were used to compute the annual cost of irrigation per hectare. The monthly cumulative irrigation of maximum, average, and minimum irrigation schedules were used to compute the monthly electric energy charge based on the technology level indicated by the statistical uniformity. The statistical uniformity also indicated values for fixed and variable costs (per hectare per year) of the center pivot irrigation system, including the water well, pump, and power supply.

From the inputs for crop production, results from the maximum, average, and minimum crop growth were read into the process network. These results included: runoff, evapotranspiration, drainage, growing season and post season nitrate leaching, volatilization, and denitrification. The changes in levels of root mass, stover mass, nitrogen, and phosphorous were also monitored.

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Figures 3-2 to 3-6 describe the maize enterprise model.

The grain moisture at maturity was assumed to be 33 percent for maximum, average, and minimum irrigated conditions. The maturity dates may have differed, however. Harvest was assumed to occur in a single day. Therefore, the amount of dry-down in the field may have differed among the maximum, average, and minimum irrigated conditions. If so, the cost of mechanical grain drying may have differed for the three irrigated conditions. The cost of harvesting was based on 1996 average custom hire rates. The cost of grain drying was based on a price schedule from a local grain elevator (Jorgenson Farm Elevator, 1994).

The effect of mechanical grain drying on grain quality could have been included in the process network; however, it was not used because U.S. grain markets assume that grain will be mechanically dried, and therefore the resulting stress-cracking and breakage is expected and do not affect the price of grain (Bakker, 1995). Although some food producers pay a small premium for grain with low stress-cracking, this was not modeled at this time.

The grain was assumed to be stored for five months before transport to a regional market. Monthly storage charges were accumulated until marketing. The three pathways of maximum, average, and minimum irrigated grain were merged for transport to market. The cost of transport reflected typical cartage distances to a regional grain elevator (Schwab, 1995; Schwab and Siles, 1994).

Output files from the process network program recorded costs; means and variances of energy and material flows, levels, and selected durations; and the values of tech

values of technology coefficients.

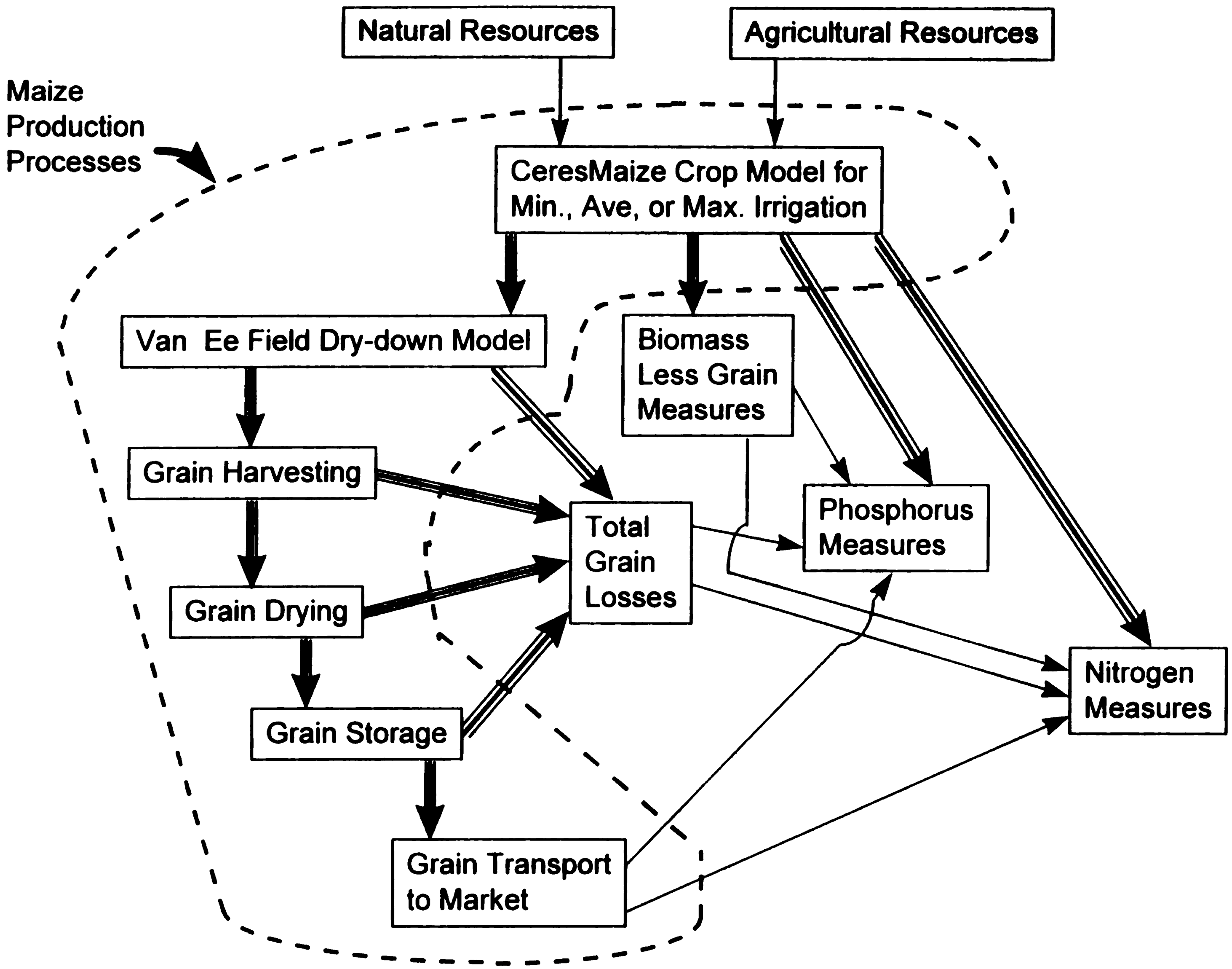

Figure 3-3: Overview of the irrigated maize enterprise model.

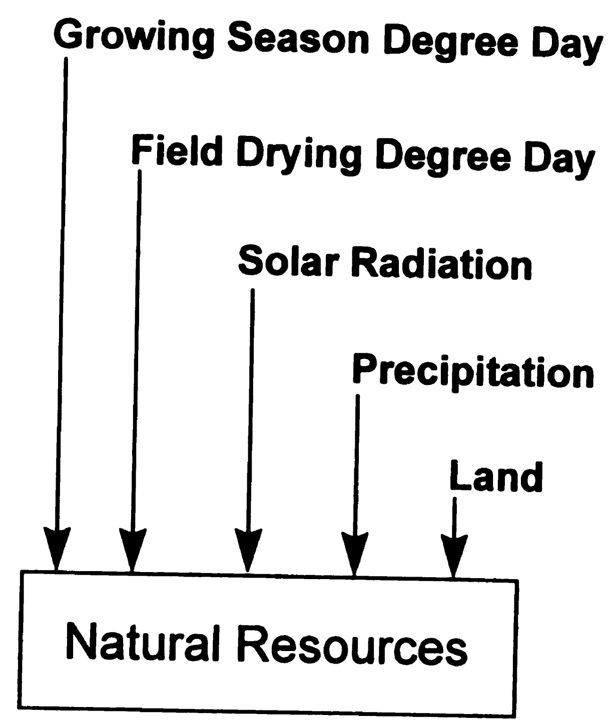

Figure 3-4 Natural resource input variables.

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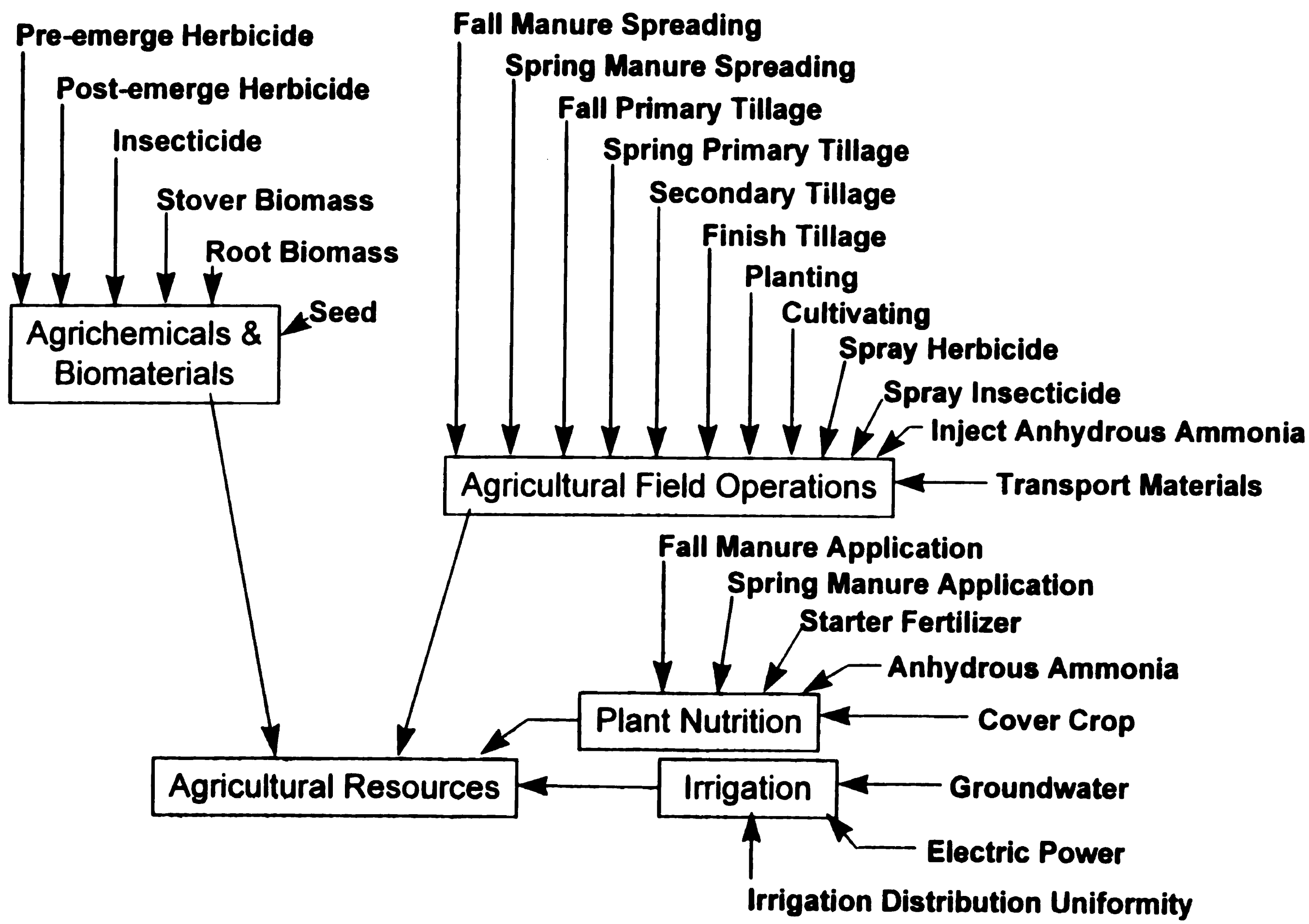

Figure 3-5: Agricultural resource input variables.

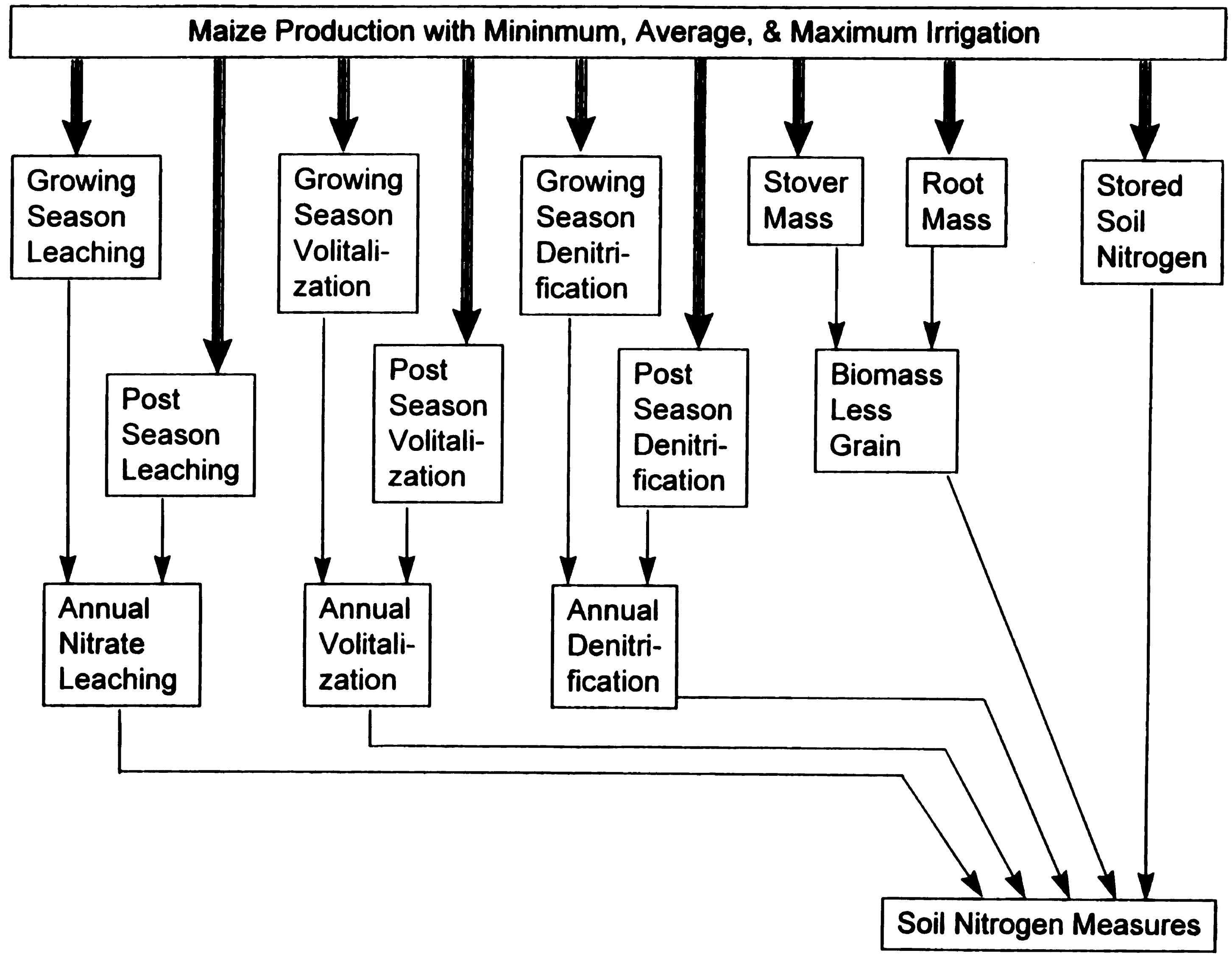

Figure 3-6: Soil nitrogen output measures.

Maize Production with Minimum, Average, & Maximum Irrigation

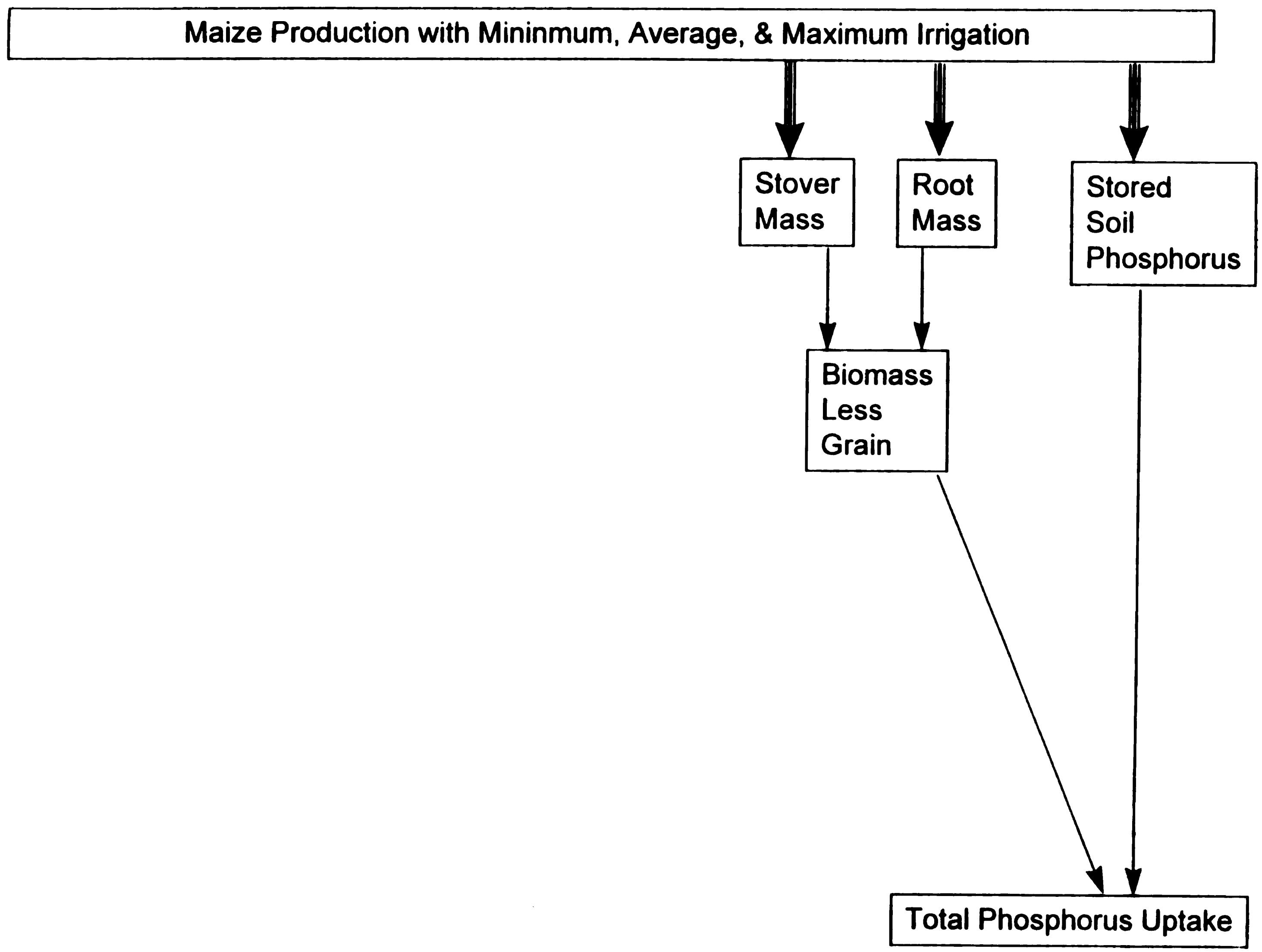

Figure 3-7: Phosphorus output measures.

OPTIMIZATION

The network parameters and resource inputs for successive simulations of the enterprise are determined by an optimization algorithm designed to interact directly with the processing model in the "search" for the "best" taken from three input data files as follows:

1. A program initialization file contains the initial and default values for printing output, soil properties, cultivar genetic coefficients, fertilizer schedules, manure application schedules, and preset irrigation schedules.
2. A weather file contains daily weather measures for solar radiation, maximum temperature, minimum temperature, precipitation, relative humidity, and the equilibrium moisture content for maize.
3. A file contains the trial solution vector network structural parameters and resource inputs parameters to be optimized. An optimization algorithm which evaluates each iteration of the solution vector against a given response-dependent objective function.

Figure 3.7 shows the model of the enterprise. Figure 3.8 shows the location of model reference decision support within the management of the enterprise.

The optimized solution vector identifies the network parameters and the schedule of resources required to "efficiently" produce maize under irrigation. The process network is "best" for a given environment as characterized by vectors of parameters taken from the initialization and weather files. Thus, any and all irrigation schedules depend on the fertilization schedule, tillage and

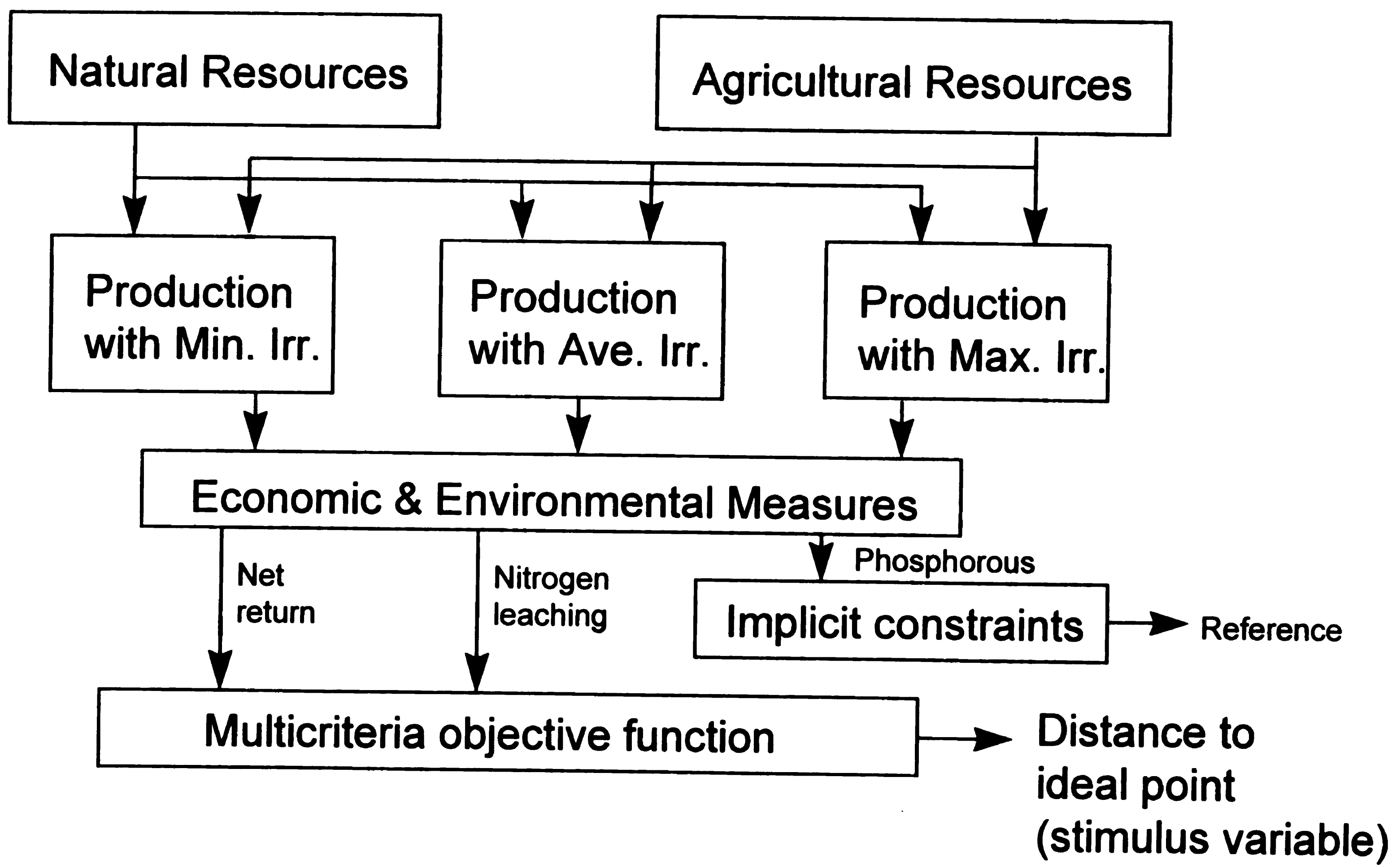

Figure 3-8: The irrigated maize enterprise model.

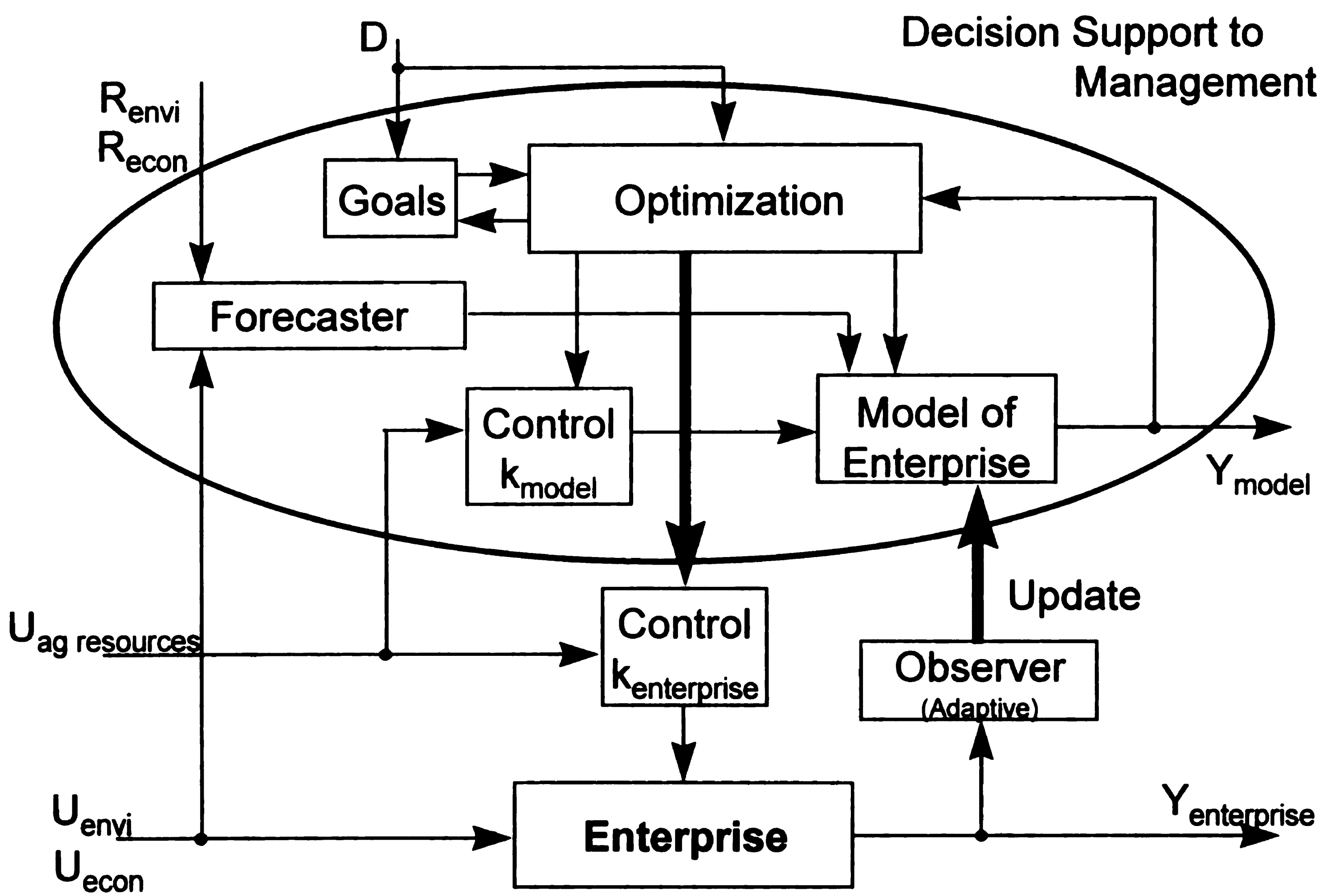

Figure 3-9: The linkage of model referenced decision support to the management of the irrigated maize enterprise.

planting schedule, harvest schedule, irrigation and other technologies, the miroclimate parameters, the genetics of the cultivar, explicit and implicit operational constraints, primary and secondary goals of system performance, both economical and ecological.

In practical and real senses, there is no such thing as a single optimal irrigation schedule, but rather, many optimal schedules, each dependent upon the structural parameters and resource inputs of the overall enterprise. In general, the solution vector is of large order and the performance criteria are few, hence, there are many optimal solutions. This leads to practical questions about the solution vector, for example: How sensitive is the irrigation schedule to perturbations in the solution vector?

The Solution Space

Maize production enterprises operate in both a natural and an economic environment. They are designed and managed to achieve a particular set of production goals within these environments, even though the parameters of these environments are sure to change over time, within limits. The natural environment is not subject to management and control, yet it certainly influences the performance of the production network. Micro-climate factors, though bounded, are described as cyclic, intermittent, and stochastic. Likewise, the economic environment, specifically the commodity markets, are generally unpredictable and uncontrollable even though the prices for agricultural inputs and the price of maize have been held constant in the optimization given here.

Commodity prices, for example, may influence the decision to allocate land to maize production. Once the decision has been made, the farm manager must select the best possible production parameters such as tillage and planting technologies, fertilization protocols, irrigation schedules, plant protection and harvesting technologies, all within the context of near-term uncertainties regarding the microclimate and economic parameters of environment.
If the optional irrigation schedule, for example, is essentially independent of these and other network parameters, the optimal solution is said to be global with respect to the parameter space. Otherwise it is characterized as a local optimal solution in the parametric space.

An objective of this research is to identify not only optimal solutions to the maize irrigation problem, but to identify the nature of the solution in the parameter space of the processing network. Indeed, an optimal that is relatively stable over the entire parameter space may be more desirable than a greater optimum that is stable over a highly restricted region of the parameter space.

The multiple performance measures used here to judge optimality are annual economic net return and annual nitrate leaching. In as much as net return and nitrate leaching conflict, optimality is a compromise between the two criteria. The goal of the optimization is, to the extent possible, to simultaneously maximize net return and minimize nitrate leaching. The envelope of the feasible solution space facing toward the goal is *pareto optimal*.

The analytical procedure of optimization involves both the real-time maize enterprise (RealME) and the simulation model of the maize enterprise (SimME) operating historically, in the same parametric space, including the microclimate to date. SimME is operated in simulated time in advance of RealME using projected forecasts of future microclimates. If the forecast of future micro-climates prove to be reasonable prognostications of actual natural parameters, then the performance of SimME and RealME should prove to be largely equivalent.

To get the "best" performance out of RealME, the "best" performance must first be obtained from SimME. Specifically, the optimization algorithm is used to find the "best" set of values in the space of controllable parameters and/or resources. The optimization algorithm need search only within the parameter space for parameters and resources not already committed. It is within this highly restricted space that yet uncommitted resources must be found.

The forecast of future micro-climate depend upon past climatic conditions. If the forecast departs radically from the past, then the utility of the forecast deteriorates. Catastrophic changes in microclimate are inherently excluded from the forecasts.

Traditionally crops are managed by monitoring plant development with a projection of yield based on the development to date; no attempt is made to close the gap between the present date of plant development and the end date of the production cycle. On the basis of the relationship between micro-climate forecasts and historical weather records, the complete production cycle can be simulated at any point in time by SimME. Thus, performance of the enterprise can be simulated at any point in time by SimME for any point in the parameter space, and for performance measures, such as economic net return and cumulative nitrate leaching evaluated for the production cycle.

Performance measures and decision rules for their use may be independent of time, or they change over time during the production cycle. In as much as the purpose of mathematical modeling and simulation are to explore risky situations without being exposed to hazard, only time-depended performance measures and decision criteria are considered in this thesis.

Prudent application of performance measures and decision criteria, however, require that the mathematical models upon which they are based be checked and updated against the performance of the production system they represent. Optimization procedures in themselves are sometimes useful to establish decision criteria. Decision criteria are necessary aspects of the optimization. Establishing decision criteria concurrently with performance measures and system optimization is called "adaptive goal setting" and is a feature of the optimization process used in this work.

Numerical Optimization Algorithms

The numerical optimization algorithms used here are selected primarily on the basis of numerical accuracy and iteration speed. The CeresMaize crop model proved awkward especially when in-field drying and economic parameters were added to the optimization. CeresMaize and AMaize are detailed plant models based on accumulated research on plant growth, soil physics, weather events, and nutrient transformations. If changes for these were computed second by second for example, then derivative optimization methods might apply. Since the time step for CeresMaize is one day, changes in system dynamics can be abrupt, hence, convergence of derivative optimization methods is not reliable.

Discontinuities are introduced by accurately portraying production costs and constraints on operations management. Some variables, such as electric power costs, are taken from price schedules that are nonlinear discontinuous functions of use rate. Planting is not permitted on rainy days; the optimization algorithm must choose a date before or after the rainy period for planting. Furthermore, field operations are scheduled to the nearest day. For these reasons algorithms are selected that are applicable to nonlinear, *nondifferentiable* methods which accommodate constrained solution variables and objective functions.

The two algorithms used for this research were the Box complex method and sequential random search. Multiple optimization runs with the Box complex method should be performed for response surfaces with multiple optima to verify that the search has terminated at the global optimum rather than at one of the local optima (Box, Davies and Swann, 1969). The number of confirming optimization runs needed is problem dependent. The initial values for the trial solution vector is generated randomly for the Box complex algorithm; hence, prudent application of the Box complex algorithm (and related methods) reduces to a random search strategy.

Classical Sequential Random Search

The classical sequential random search method evaluates the performance measure for 10 randomly selected trial values for each variable in the parameter space, starting with the midpoint of the allowable ranges for each parameter. After 10 random trial values have been completed for each parameter, the search space (which was originally the entire parameter range) is reduced by half (Shoup and Mistree, 1987).

The new search space is centered about the *elite* solution vector of parameter values obtained from the first sequence of trail values. If any parameter is less than one-quarter of its limited value, the search space is reduced to half of the interval between the previous best value and the end of the allowable range. Thus the search process continues to evolve until the termination criteria are achieved.

High Density Sequential Random Search

The classical sequential random search algorithm was found in the literature to be adequate for differentiable nonlinear problems. However, in the case of this discontinuous and nondifferentiable nonlinear model, the classical algorithm could also miss the neighborhood of the global optimum, and converge on a local optimum. To accommodate this situation, high density searches were appended to the sequential random search algorithm.

Increasing the density of the search (increasing the population of trial solutions) also increases the computation effort. Fortunately, four factors determine the total computational effort for acceptable convergence:

- the density of the search,
- the dispersion of the search about the elite solution vector that propagates the next search generations,
- the number of search generations to achieve an acceptable convergence within one optimization, and
- the number of optimizations to confirm that the global optimum has probably been discovered.

The balance among these four factors appears to be problem dependent. For the problem at hand, an inverse relationship was observed between the density of the search (the population of trial solutions per variable) and reduction of the search space (reduction of search dispersion) for each generation of searches. The combinations search densities and dispersions attempted are given in Table 3.3. The best balance of convergence with computational effort was found for the combination of

10*e	trials per variable and
1/e	search space dispersion

Three to five search generations gave an acceptable probability of convergence to an optimum. Likewise, three to five optimizations were adequate to confirm that the global optimum had been located. Confirming optimizations could and were performed simultaneously; hence, the total computation time to confirm the results was not extended substantially.

Implicit Constraints

The allowable ranges for searching the design parameter space are restricted by explicit and implicit constraints. Explicit constraints on parameter values are definable at the outset of a generation of random searches. On the other hand, implicit constraints cannot be defined *a priori*.

Traditionally, violations of implicit constraints are "discovered" following the "complete execution" of the simulation model. Violations are resolved by first generating new trial solution vectors and then reiterating the model simulation until a simulation is achieved without violating the implicit constraints, or until a higher level of optimization control discontinues the search. An example of this constraint resolution procedure can be found as in the complex algorithm by Box (1965). This approach, however, becomes a

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Table 3-3. Combinations of search densities and dispersions attempted.

Trials per variable	Search dispersion
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10*e	1/e
10*3	1/3
10*4	1/4
10*5	1/5
10*6	1/6

lengthy and tedious process when working with large simulation models.

A further examination into the particular nature of the implicit constraints in this model revealed that a considerable savings in execution time could be achieved by implementing logical adjustments to the trial solutions through specific adjustment functions consistent with random search that did not require aborting an iteration of the simulation model. Subprograms for adjusting the solution vector were appended to the optimization.

An example of a traditional implicit constraint is the balance of phosphorous imported in the fertilizer and exported in the harvested grain. The amount of phosphorous imported can be calculated from the trial design for fertilization.

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However, the amount of phosphorous exported cannot be determined until the grain harvested is known. In other words, the crop growth model has been run to completion before a violation of the implicit phosphorous constraint can be evaluated.

The other type of implicit constraint, for lack of a better term, shall be referred to as "individualistic constraints" in that particular knowledge of impact of the constraint on the simulation model leads to an individual remedy to the violation of the constraint such that computation time is less affected. Two examples referred to here involve the timing of agricultural operations.

Agricultural operations are affected by weather, for example, rainfall above a certain amount can preclude field operations. A trafficability subprogram could be evaluated, or a decision rule could be invoked to delay an operation if the rainfall is above a certain amount (Harrigan, 1995a; Harrigan, 1995b). The decision rule approach is a practical approach for sandy loam soils and, thus, was invoked in this research. If rainfall was found to exceed six mm for any spring time field operation, it was deferred to the next permissible day, with the date revision amended to the trail solution vector.

A second example of an individual implicit constraint regards the first feasible harvest date. Harvesting cannot commence until after the crop has reached maturity. Maturity is not known until the crop growth model has been run through the growing season up to calculated maturity. If the trial harvest date has been set before maturity, a simple function can delay the trial harvest date until the first allowable day following maturity. The crop growth model is not affected by this procedure. The field dry-down model requires the date of maturity an

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maturity and harvest date in order to compute the grain moisture at harvest. Therefore, the trial harvest date can be deferred to a feasible date without extending program run-time. Again, the adjusted value must be communicated to the optimizing algorithm to update the solution vector.

Equality and Inequality Constraints

Inequality constraints are much more easily satisfied than equality constraints. Equality constraints can be satisfied only if it is known that an exact value exists for the evaluation function; therefore, success depends on the model structure.

Inequality constraints can be written in several ways; the concept of deviational variables was found to be useful for this model. A measure X is established and is set equal to trial resultant X' plus an allowable margin of error E. E may be fixed according to prior knowledge, or it may be treated as another parameter to be minimized:

$$X = X' + E$$

For the final versions of this simulation model, the error minimization approach was used.

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MULTICRITERIA OBJECTIVE FUNCTIONS AND GOAL SETTING

The two measures of performance considered are (1) economic net return and (2) cumulative nitrate leaching over the calendar year. A high density sequential random search algorithm was used to find the neighborhood of the optimum for each of the two measures as separate goals, thereby defining a payoff matrix. Assuming a linear trade-off between nitrate leaching and net return, the payoff matrix established the bounds for the joint optimum.

If a joint optimum exists, it may or may not be unique with respect to the parameter space. If it is not unique, then additional measures of performance may be added. The added measures of performance are sometimes described as defining secondary or "adaptive" goals. Secondary or adaptive goals are entered into the optimization algorithm only after attainment of the primary goals has been demonstrated, thus prioritizing the goals and extending the search process. For example, a non-negative net financial return may be necessary to sustain the enterprise economically. Limitations on nitrate leaching may be necessary to sustain the enterprise ecologically. In practice, economic net return usually gets first priority, and nitrate leaching is secondary.

Equal weight can be given to economic net return and nitrate leaching by defining a joint objective function which for example, computes the square root of the sum of the squares of the deviations of the individual performance measures from the goal. In the work reported here, the nitrate leaching rate is multiplied by the sine function and the economic net return rate by the cosine. The relative emphasis given to either nitrate leaching, or economic net return is thus wei

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Adaptive Evolution Strategy

The numerical values describing the goals were unknown at the initiation of optimization of any enterprise configuration. The goals for minimum nitrate leaching and maximum net return were discovered from the results generated for any population of trial solutions. Improvement in the goals was handled as a secondary optimization. The improvement in the goals guided the evolution of successive search generations. Convergence toward the global optimum was affected by the size of the search population and the dispersion of the population within any generation of the search.

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CHAPTER FOUR

RESULTS

This chapter is organized into three parts:

- an introduction with an explanation of the common parameter settings used for the optimizations of the model,
- figures showing the results from a first series of optimizations based on stereotypical weather years and based on the average irrigated condition from a single level of irrigation technology, and
- figures showing the results from a second series of optimizations based on weather years composed of stereotypical summers coupled with normal winters and a choice of irrigation technology.

The same processing model structure for the irrigated maize enterprise and the multidimensional sequential random search algorithm were used in both series of optimizations.

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The first set of figures (Figures 4-1 to 4-4) shows the results for each iteration over the span of one optimization depicting the convergence behavior of the search algorithm. Figure 4-1 is a plot of net return versus nitrate leaching; the final goal and the optimum are labeled. Table 4.1 lists the initial trial solution and best values discovered for the control parameters at the optimum.

Table 4-1: Initial and final parameter values from optimization.

Parameter	Initial Value	Final Value
Plant Population, plants/m^2	6.5	6.88
Slurry Application Date	117	115
Plowing Date	121	116
Planting Date	131	122
Sidedress NH_4 Date	160	156
Sidedress Amount, kg/ha	105	131
Irrigation Depletion Parameter	0	0.72
Harvest Date	290	200

Optimum:	Nitrate Leaching	= 20.9 kg/ha/yr
	Net Return	= $540/ha/yr

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The optimization performed was a two-generation search with 30 trial solutions for each parameter, each search generation. The optimization terminated at 487 iterations. The optimum was discovered at iteration 463.

Figure 4-2 shows a trace of the distance from the best point discovered to the goal at each iteration. The discovery of an improved goal is indicated by a spike in the trace. The optimum was discovered just after the last improvement in the goal.

Figure 4-3 shows a plot of nitrate leaching for each iteration in the optimization. As this is a plot of minimization towards zero, the effect of the reduction in the search space about the elite vector from the first generation is dramatic. The optimum at iteration 463 is also noted.

Figure 4-4 shows a plot of net return for each iteration in the optimization. The effect of nitrate minimization is visible in the second generation of the search. The intermediate values for net return disappear; this leaves the higher values for net return, but also causes a string of very negative values to be generated as well.

The next set of figures (Figures 4-6 to 4-29) within the first series were constructed to verify that the crop-growth model and grain-drying model were correctly linked and embedded within the processing network program.

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Figures 4-6 to 4-29 give results for (1) a range of stereotypical weather years, (2) two commonly associated soils, and (3) three cultivars of maize grown in Michigan. The figures for the first series conclude with a summary figure (Figure 4-30) showing the effect of satisfying an increasing demand for irrigation on the dual criteria of nitrate leaching and the economic net return of the enterprise.

The second series of optimizations presents the results from a range of stereotypical summers followed by a normal winter. Also, the level of irrigation uniformity is included in the list of parameters to optimize. The second series begins with a set of figures (Figures 4-31 to 4-34) which demonstrates the consistency of the optimization algorithm. The next set of figures (Figures 4-36 to 4-61) shows the response of the maize enterprise for different levels of irrigation uniformity with one soil and one cultivar. The second series also concludes with a summary figure (Figure 4-62).

Common Parameter Settings

The following parameters were fixed for both series of optimizations:

- Seed depth: 5 cm
- Primary tillage and slurry incorporation depth: 20 cm

- Slurry
- Starter
- Starter
- Sidedre
- Sidedres

Parameter

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- Slurry ammonia fraction: 0.58
- Starter fertilizer type: Diammonium Phosphate
- Starter fertilizer depth: 10 cm
- Sidedress fertilizer type: Anhydrous Ammonia
- Sidedress fertilizer depth: 30 cm

Parameter Settings for the First Series of Optimizations

The following parameters were fixed in the first optimization series:

- The economics of the irrigation system were based on a distribution uniformity (U_s) of 0.73.
- Assessment of average irrigation condition only, beta distribution parameters v and w both equal 1.
- The amount of nitrogen from manure: 120 kg/ha.
- The amount of nitrogen in the starter fertilizer: 10 kg/ha.
- The harvest date: Julian day 290.

Manager

Stereotypi

- Hot Ter
- Normal
- Moderat
- Cold Ter

Sandy-loam

- Elston sar
- Oshtemo s

Genetic coeffi

Season length

Short

Medium

Long

Management Regime for the First Series of Optimizations

Stereotypical weather years:

- Hot Temperature and Dry Rainfall
- Normal Temperature and Normal Rainfall
- Moderate Temperature and Moderate Rainfall
- Cold Temperature and Wet Rainfall

Sandy-loam soils (Martin 1992):

- Elston sandy-loam, predominantly fine sand and little gravel
- Oshtemo sandy-loam with fine sand and some gravel.

Genetic coefficients of maize cultivars defined for CeresMaize:

Season length	Variety	P1	P2	P3	P4	P5
Short	Pioneer 3995	130	0.30	685	825	8.6
Medium	Pioneer 3780	200	0.76	685	725	9.6
Long	Pioneer 3147	255	0.76	685	834	10.0

Paramet

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  < 0 gives

Irrigation was r
values of 0.9. F

Parameters Estimated for the First Series of Optimizations

- Preseason soil nitrogen level: 1 percent to 100 percent of the original soil nitrogen level from preseason nitrate and ammonium concentrations in all soil layers.
- Plant population: 4 to 9 plants per square meter.
- Supplemental nitrogen application: 10 kg/ha to 200 kg/ha for N as anhydrous ammonia.
- Date for slurry application: Julian Days 112 to 122.
- Date for primary tillage: 1 to 8 days after slurry application.
- Date for planting: 1 to 20 days after primary tillage, latest possible planting date was Julian day 148.
- Date for anhydrous ammonia application: Julian Day 151 to 170.
- Deficit irrigation parameter: the values for this parameter range from -1 to 1. At a parameter value of 0, the amount of irrigation would "top-up" the soil to field capacity. As the value approached 1, irrigation would diminish; at a value in the near 0.9, irrigation would cease. A value approaching -1 would produce irrigation at double the top-up amount

    > 0 gives irrigation less than field capacity,

    < 0 gives irrigation greater than field capacity.

Irrigation was not scheduled when the deficit irrigation parameter exceeded values of 0.9. For irrigation to occur on any given day during the growing season, the product of the amount of the top-up depth and the value of the expression (1- deficit irrigation parameter) had to exceed the minimum daily application depth of the center pivot. The minimum daily application depth was a function of the distribution uniformity U_S.

Parameter Settings for the Second Series of Optimizations

- The preseason soil nitrogen level was fixed at 20 percent of the level measured by Martin (1996).
- The amount of nitrogen from manure was set to 80 kg/ha.
- The amount of nitrogen in the starter fertilizer was set to 3 kg/ha.

Management Regime for the Second Series of Optimizations

Weather years:

- Hot-Dry Summer and Normal Winter
- Normal Summer and Normal Winter
- Moderate Summer and Normal Winter
- Cold-Wet Summer and Normal Winter

The summer, or growing season spanned the range of Julian days 111 to 292. Winter, or the cold season, spanned Julian days 293 to 110.

Soil: Elston sandy-loam (Martin 1992).

Maize cultivars: long season Pioneer 3147.

Bounds on Parameters to be Estimated for the Second Series of Optimizations

- Plant population: 4 to 9 plants per square meter.
- Supplemental nitrogen application: 10 kg/ha to 200 kg/ha for N as anhydrous ammonia.
- Date for slurry application: Julian Days 112 to 122.
- Date for primary tillage and slurry incorporation: 1 to 8 days after slurry application.
- Date for planting: 1 to 20 days after primary tillage, latest possible planting date was Julian Day 148.
- Date for anhydrous ammonia application: Julian Day 151 to 170.
- Amount of anhydrous ammonia per application: 10 kg/ha to 200 kg/ha.
- Deficit irrigation parameter: -1 to 1.
- Irrigation distribution uniformity (U_S): 0.68 to 0.96.
- Date for harvest: Julian Days 250 to 330.

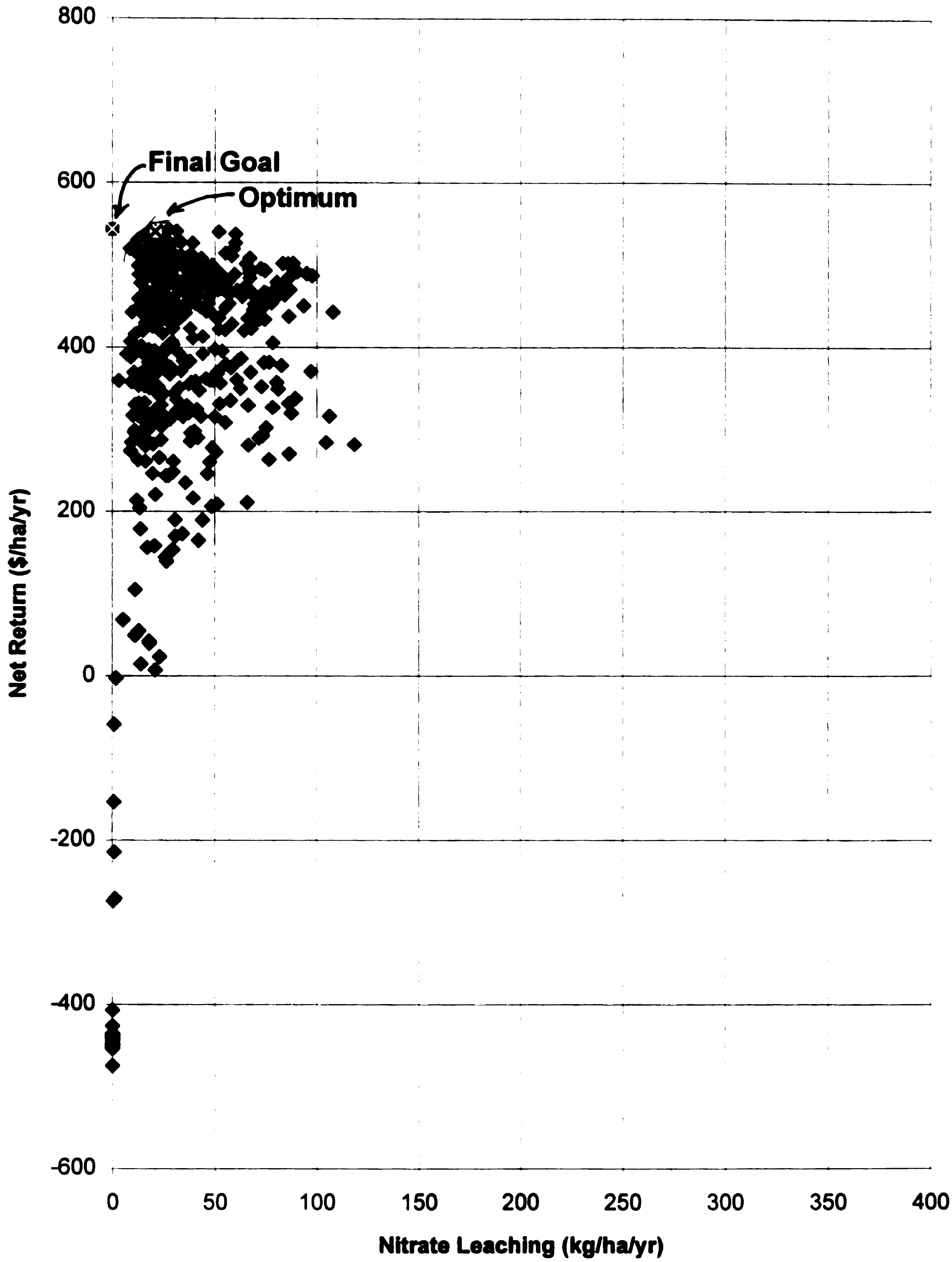


Figure 4-1: Two-generation search, Hot Temperature, Dry Rainfall, Elston Sandy Loam, Long Season Cultivar.

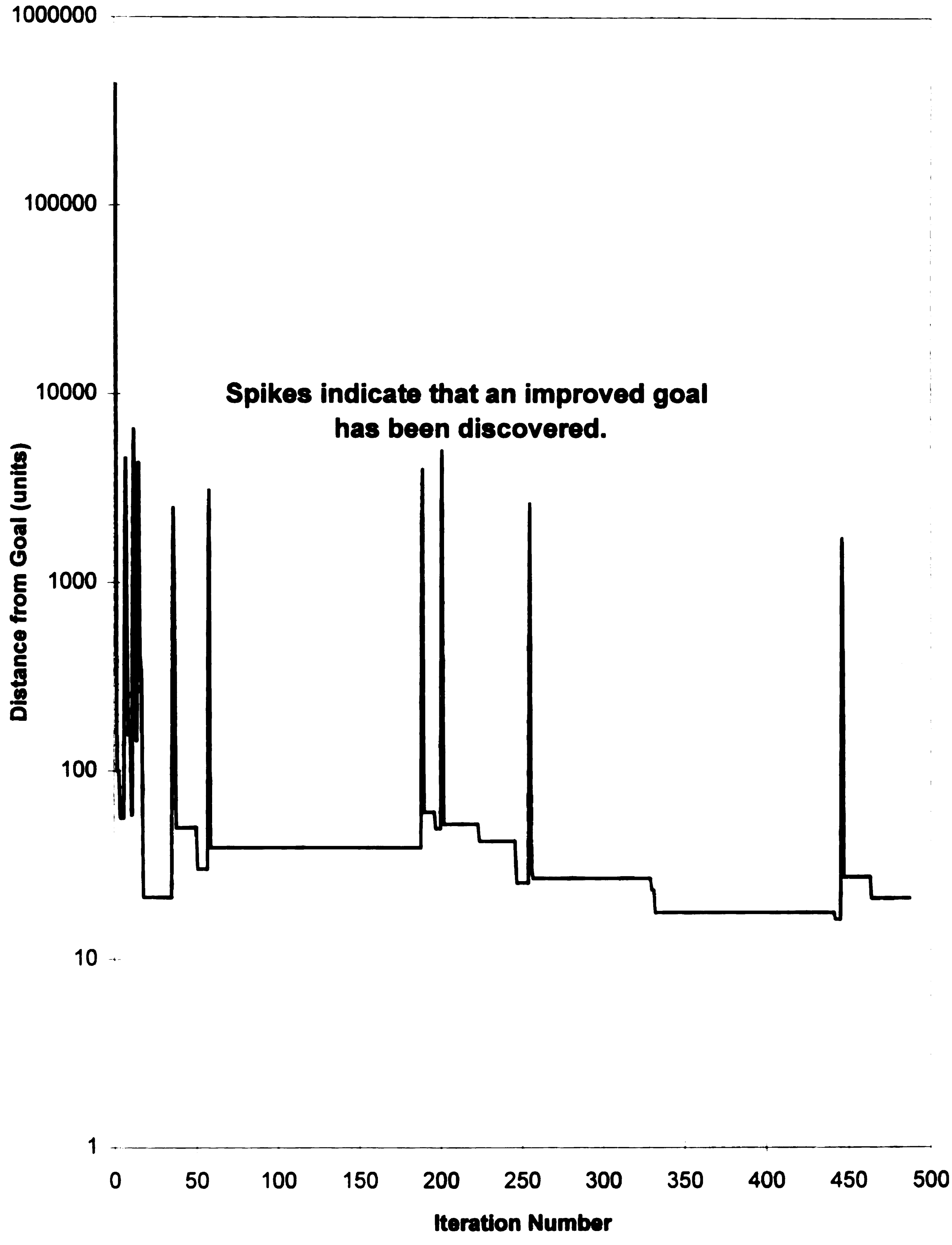


Figure 4-2: Trace of goal improvement for two-generation search, Hot Temperature, Dry Rainfall, Elston Sandy Loam, Long Season Cultivar.

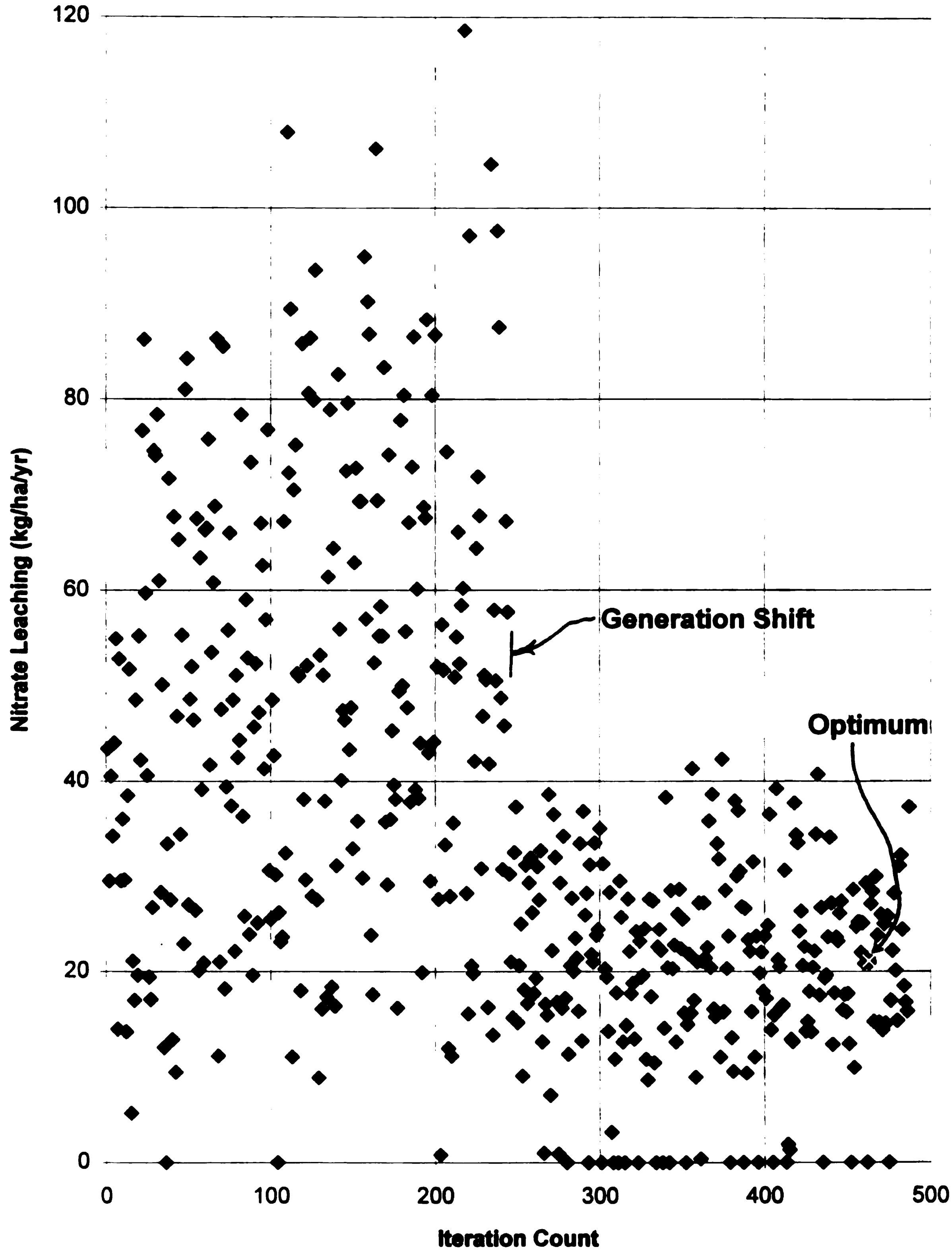


Figure 4-3: Plot of leaching results over a two-generation search, Hot Temperature and Dry Rainfall, Elston Sandy Loam, Long Season Cultivar.

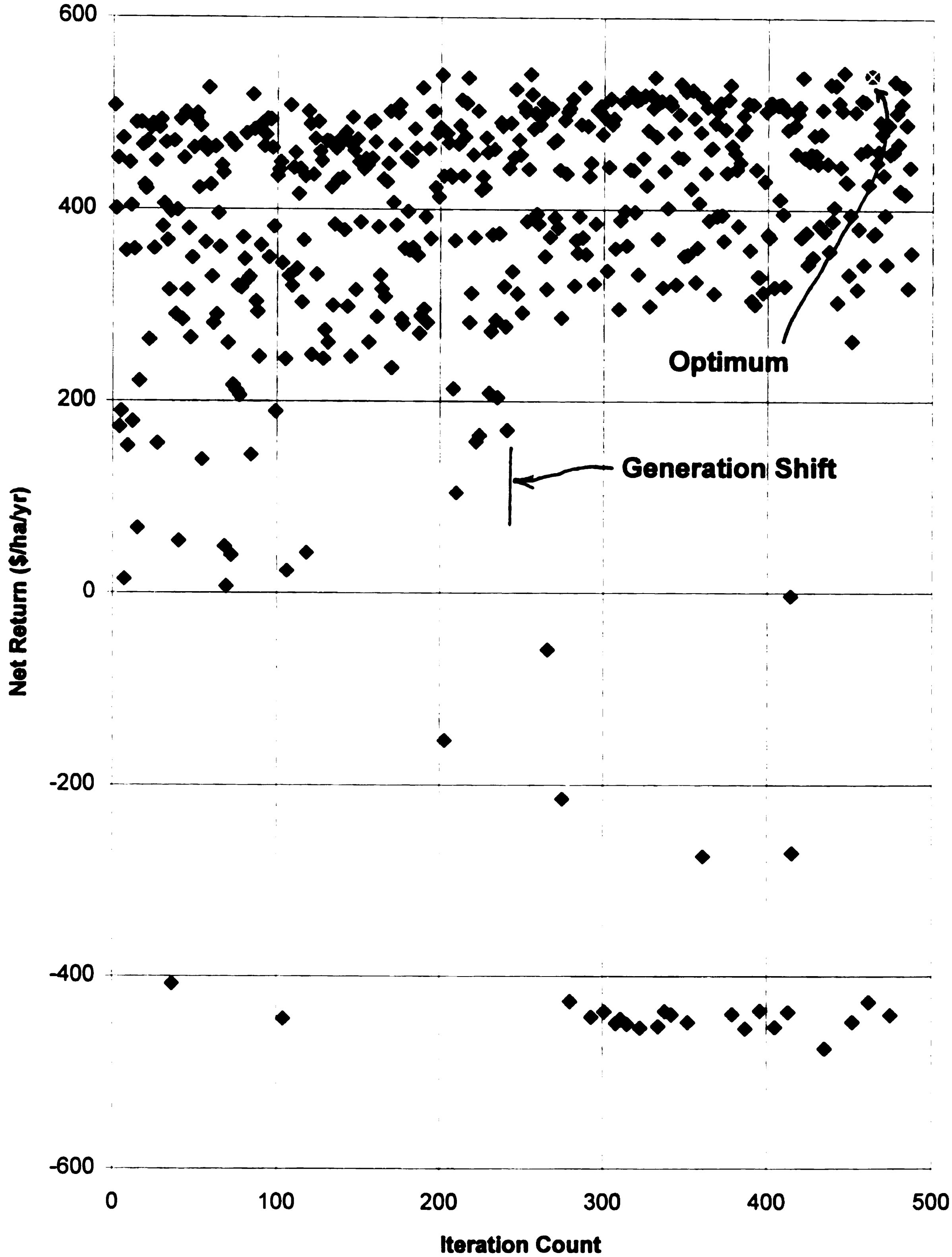


Figure 4-4: Plot of net return for a two-generation search, Hot Temperature and Dry Rainfall, Elston Sandy Loam, Long Season Cultivar.

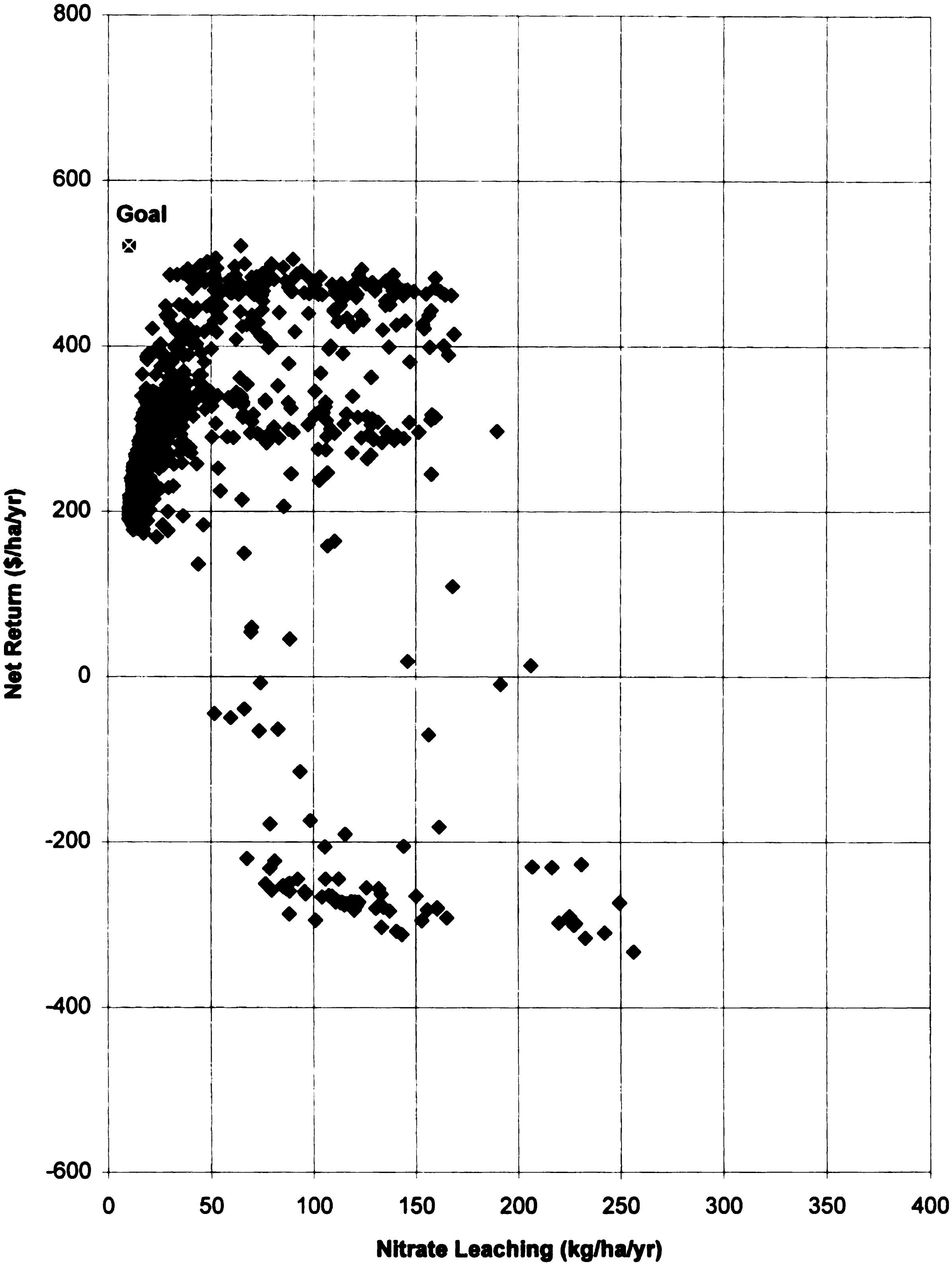


Figure 4-5: Normal Temperature, Normal Rainfall, Oshtemo Sandy Loam, Long Season Cultivar.

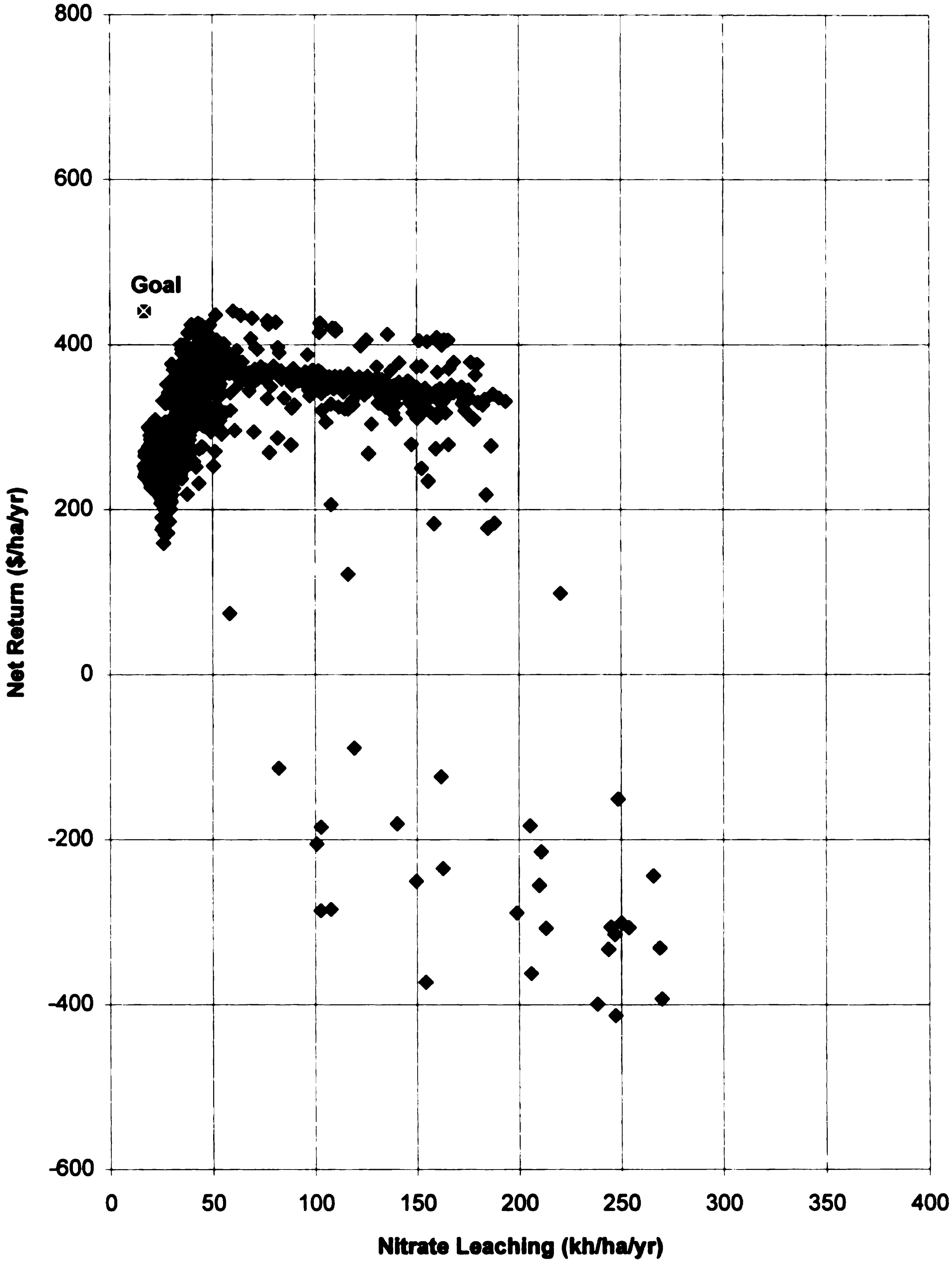


Figure 4-6: Normal Temperature, Normal Rainfall, Oshtemo Sandy Loam, Average Season Cultivar.

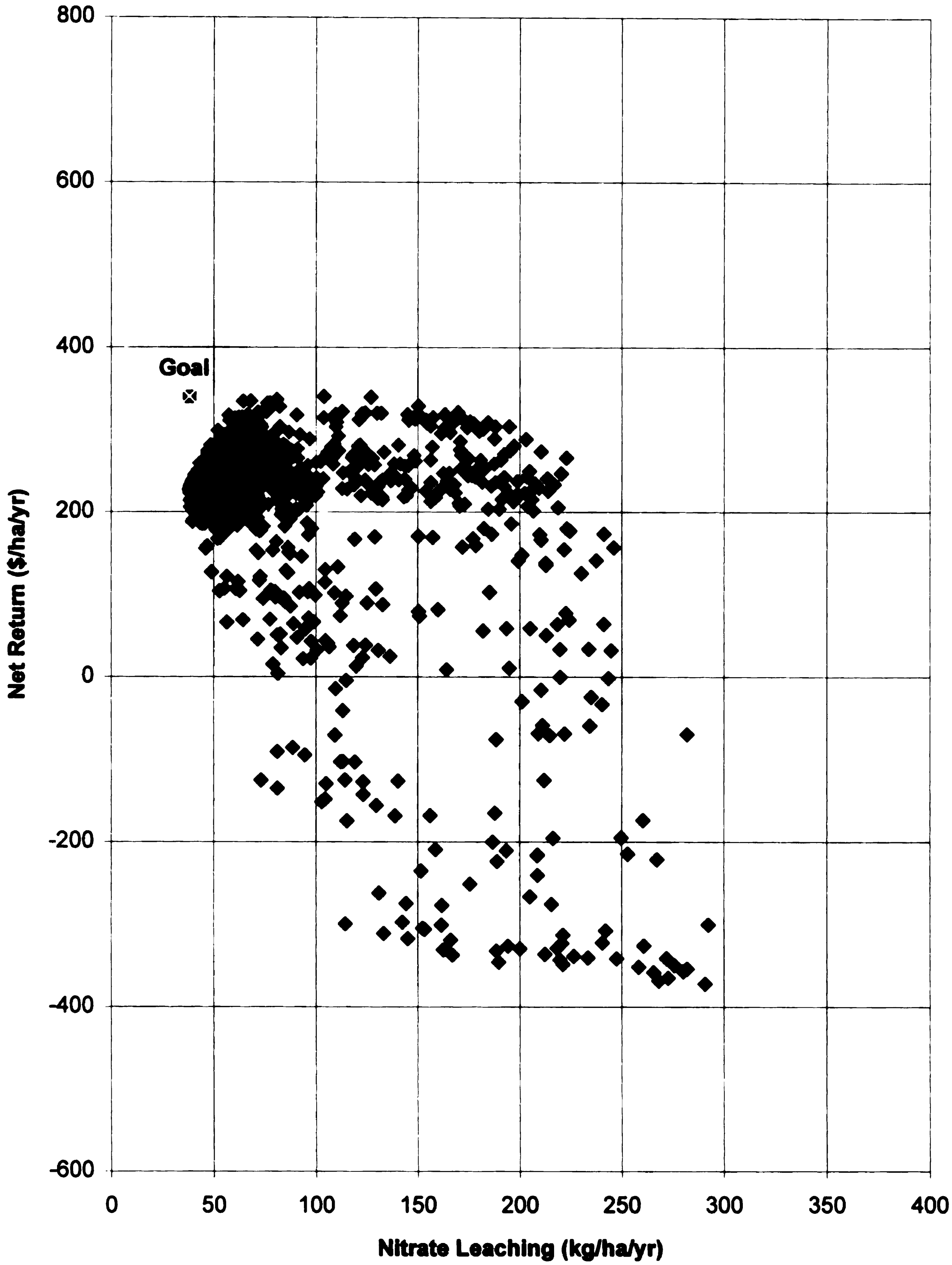


Figure 4-7: Normal Temperature, Normal Rainfall, Oshtemo Sandy Loam, Short Season Cultivar.

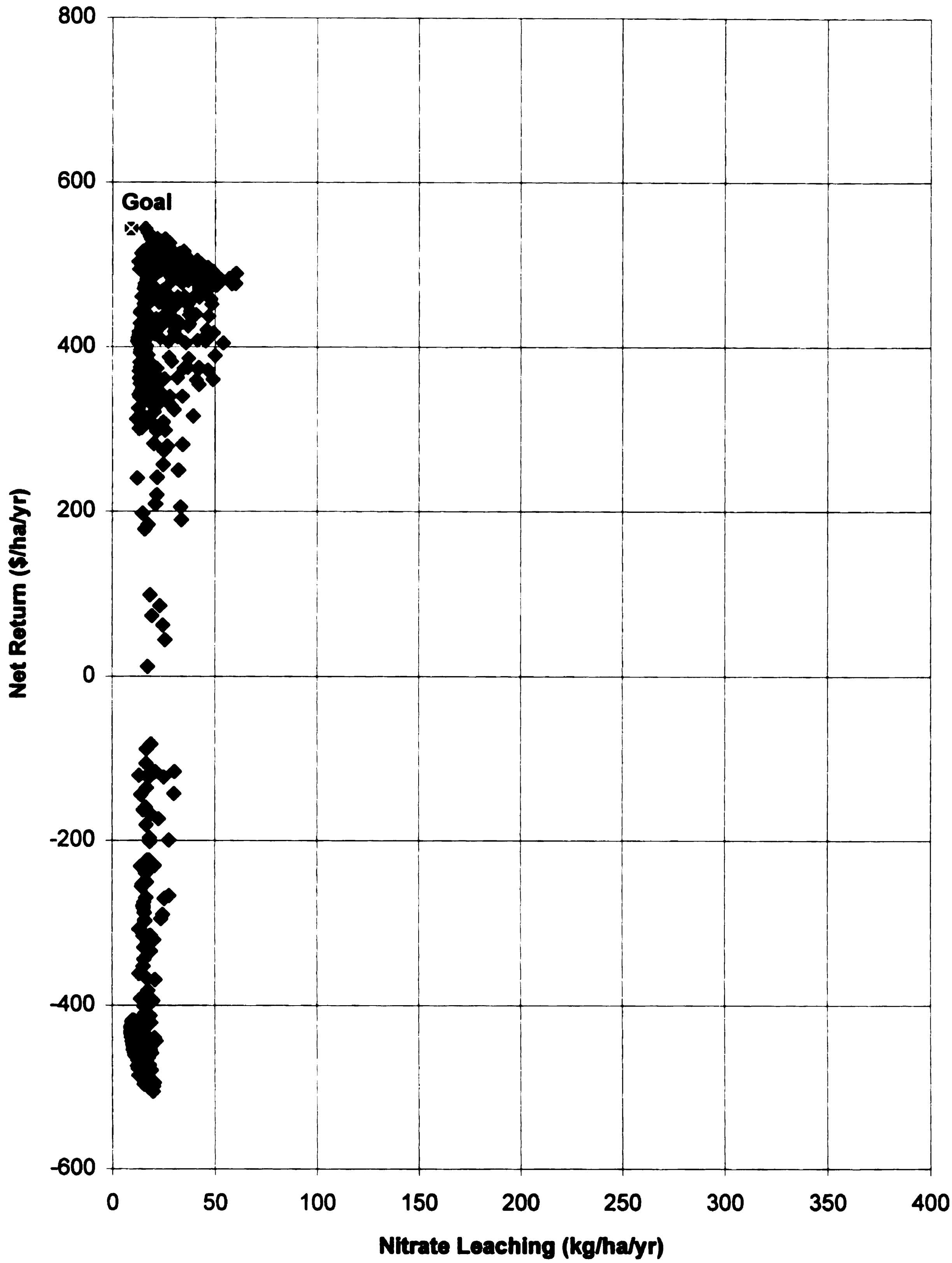


Figure 4-8: Hot Tempeature, Dry Rainfall, Oshtemo Sandy Loam, Long Season Cultivar.

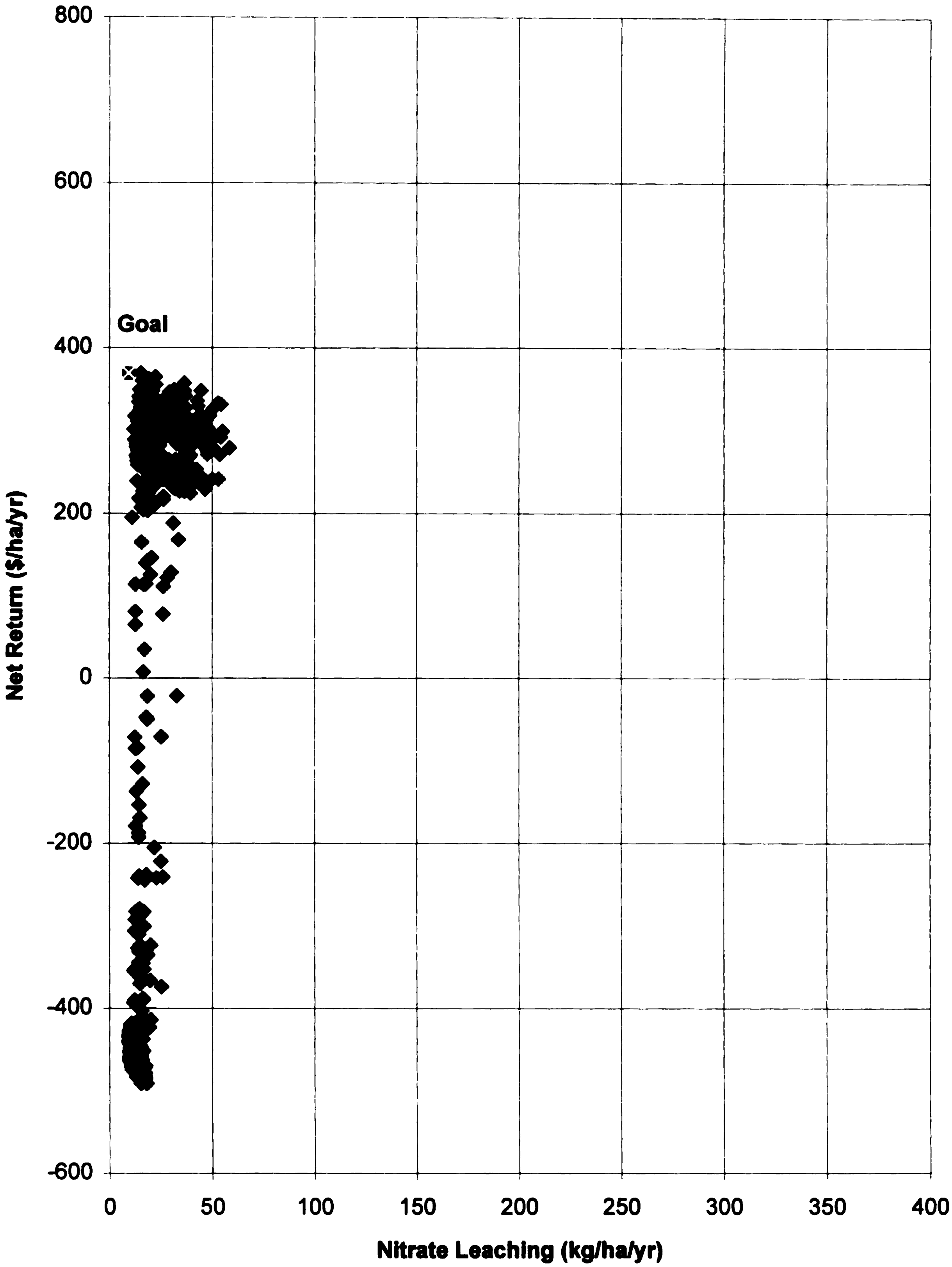


Figure 4-9: Hot Temperature, Dry Rainfall, Oshtemo Sandy Loam, Average Season Cultivar.

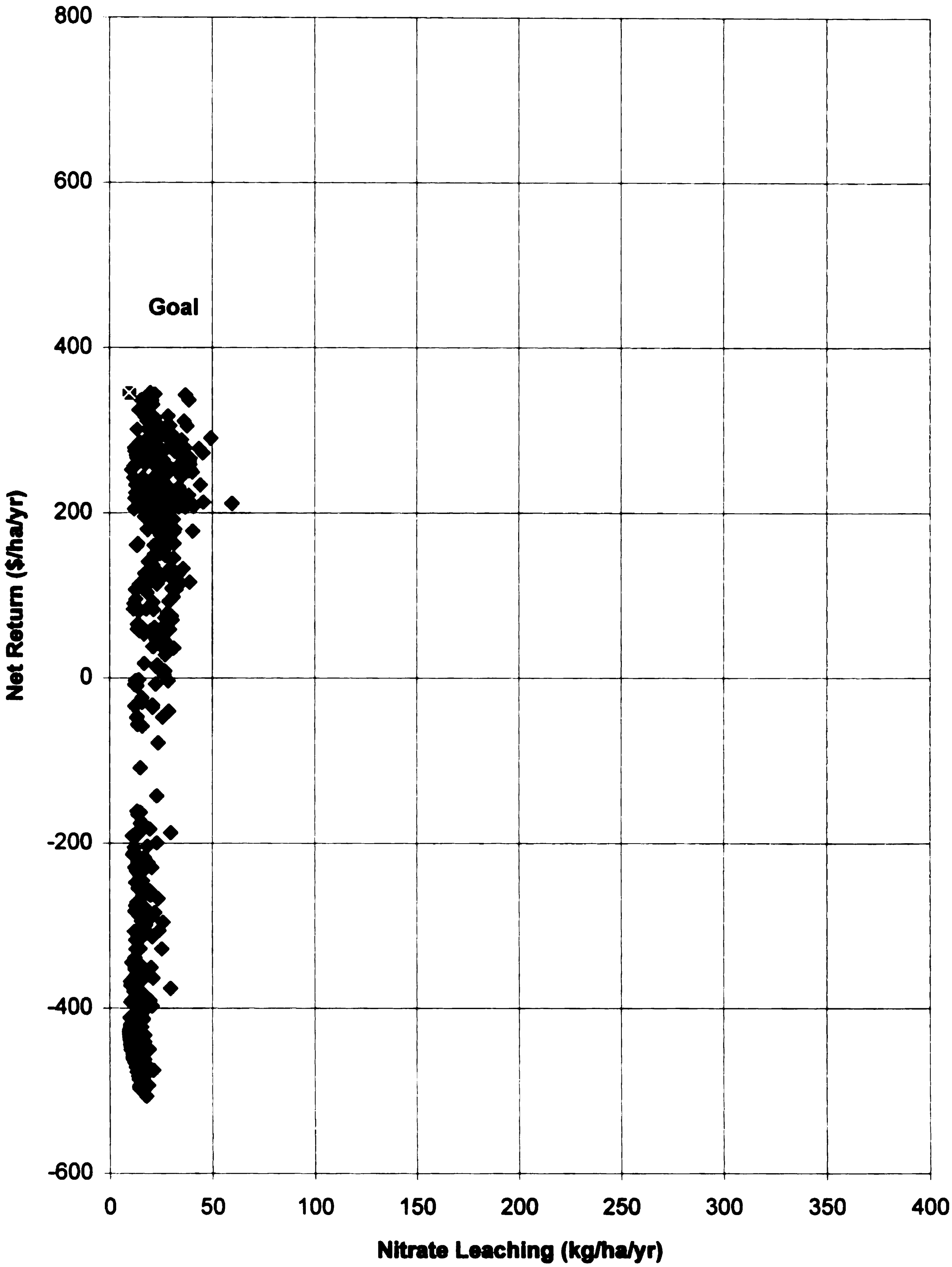


Figure 4-10: Hot Temperature, Dry Rainfall, Oshtemo Sandy Loam, Short Season Cultivar.

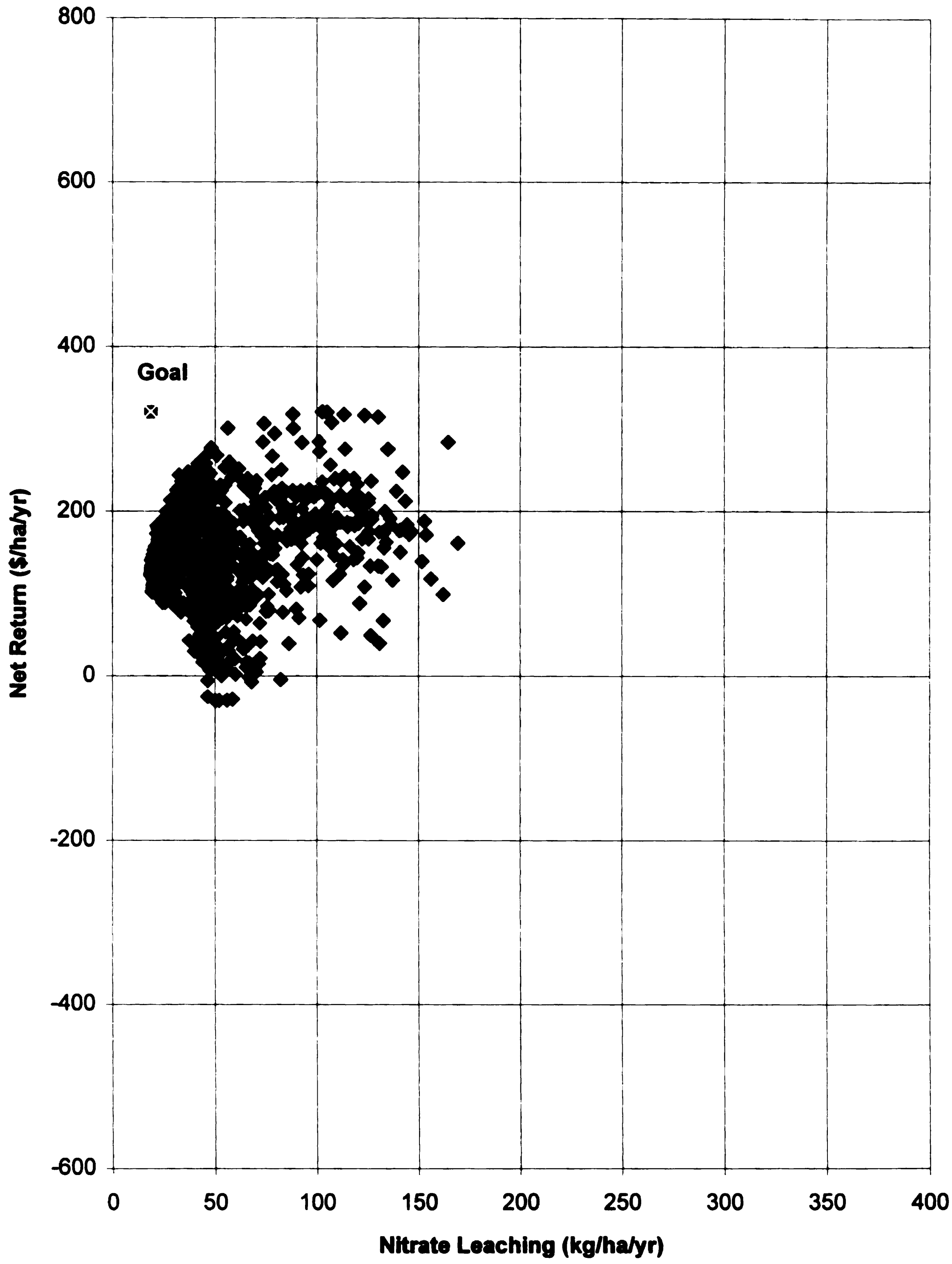


Figure 4-11: Cold Temperature, Wet Rainfall, Oshtemo Sandy Loam, Long Season Cultivar.

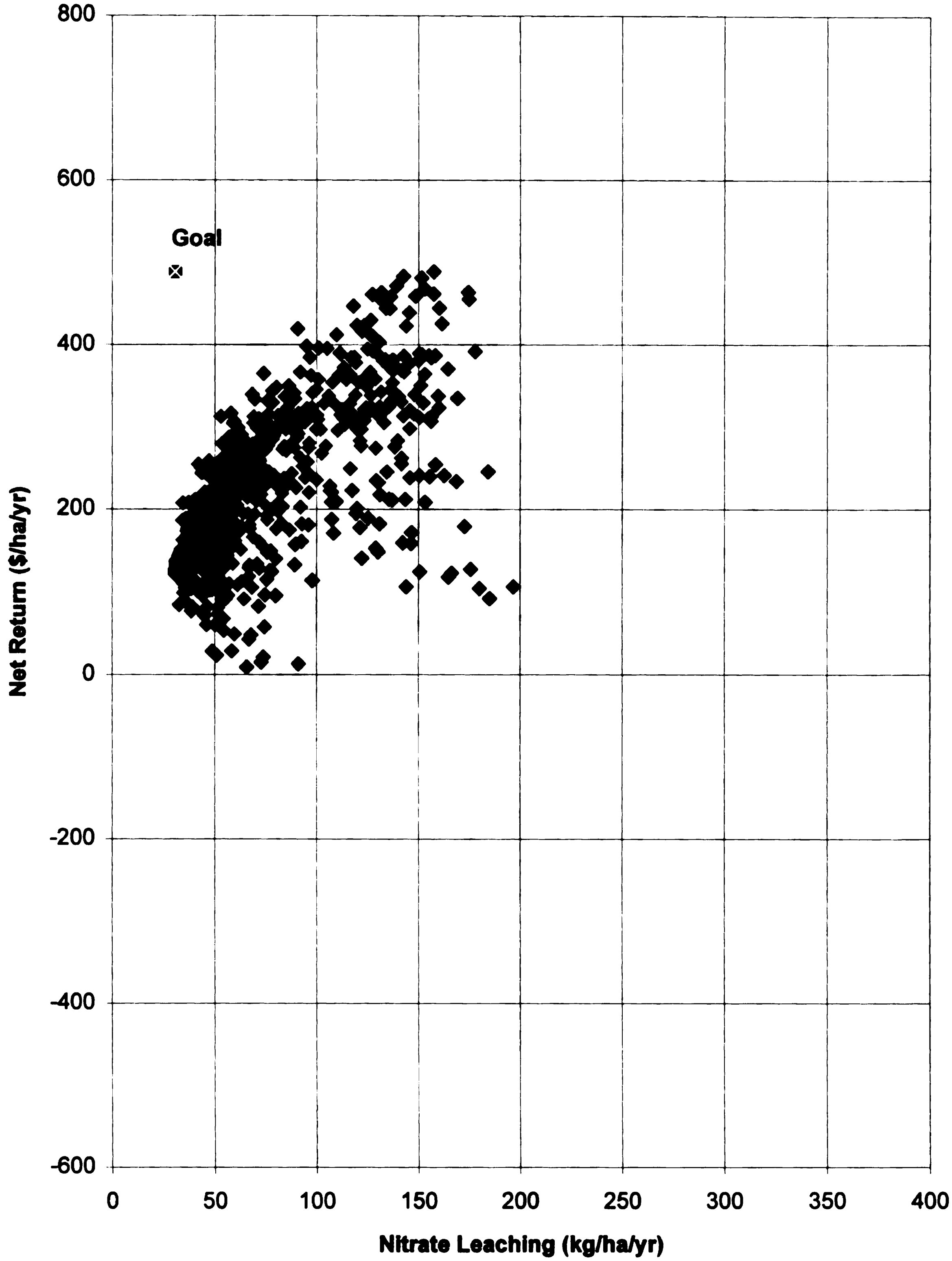


Figure 4-12: Cold Temperature, Wet Rainfall, Oshtemo Sandy Loam, Average Season Cultivar.

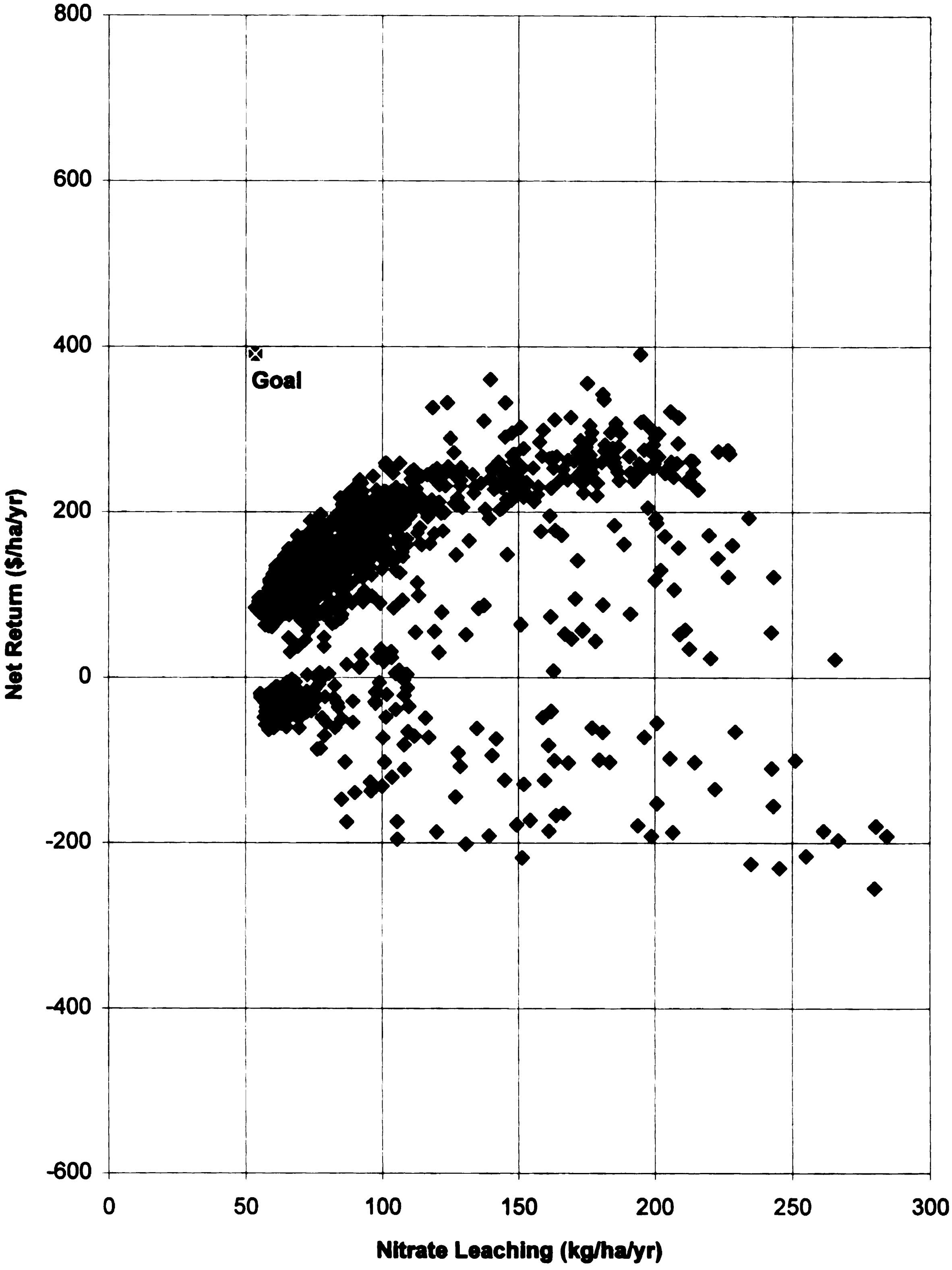


Figure 4-13: Cold Weather, Wet Rainfall, Osthemo Sandy Loam, Short Season Cultivar.

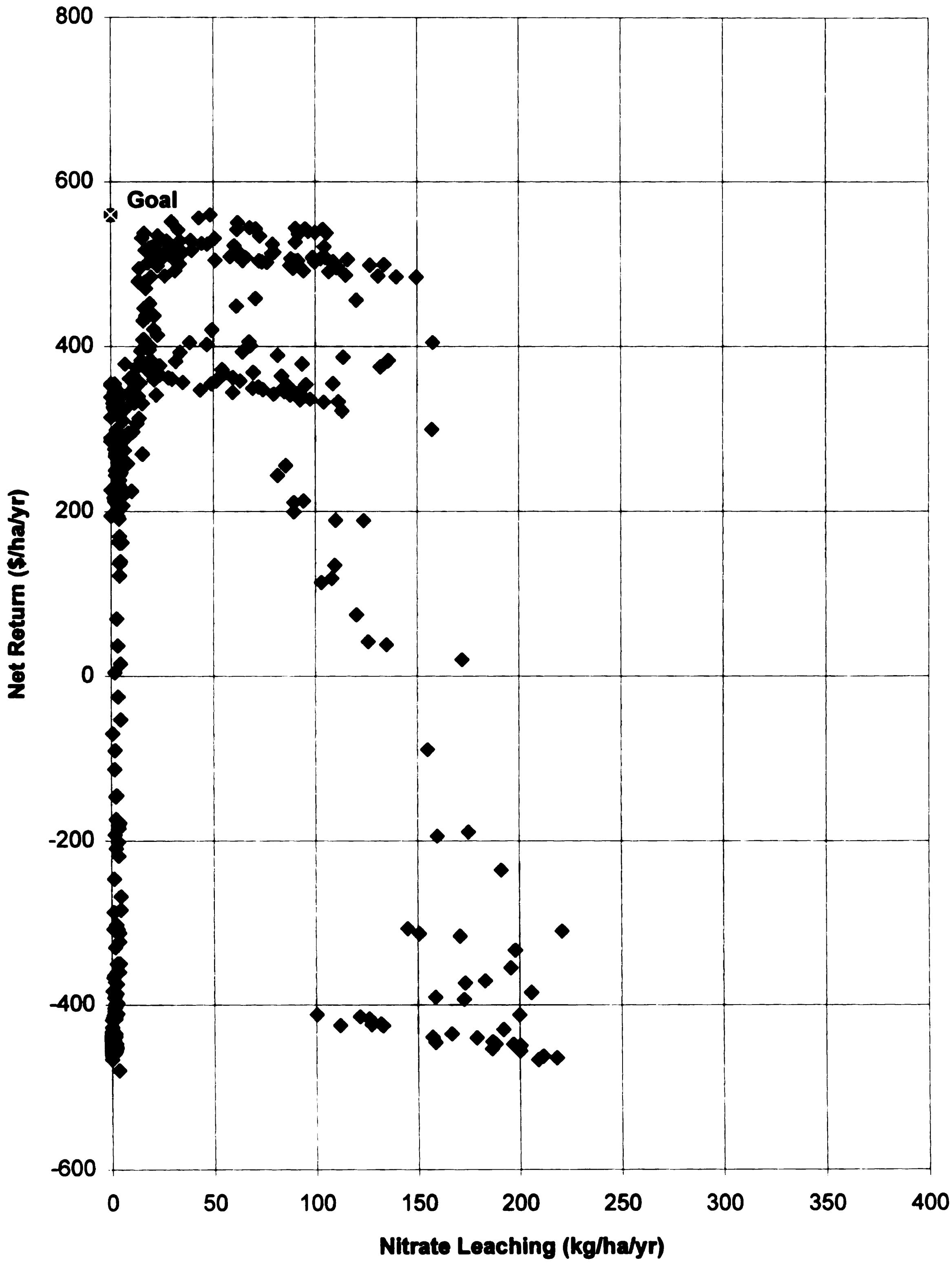


Figure 4-14: Moderate Temperature, Moderate Rainfall, Oshtemo Sandy Loam, Long Season Cultivar.

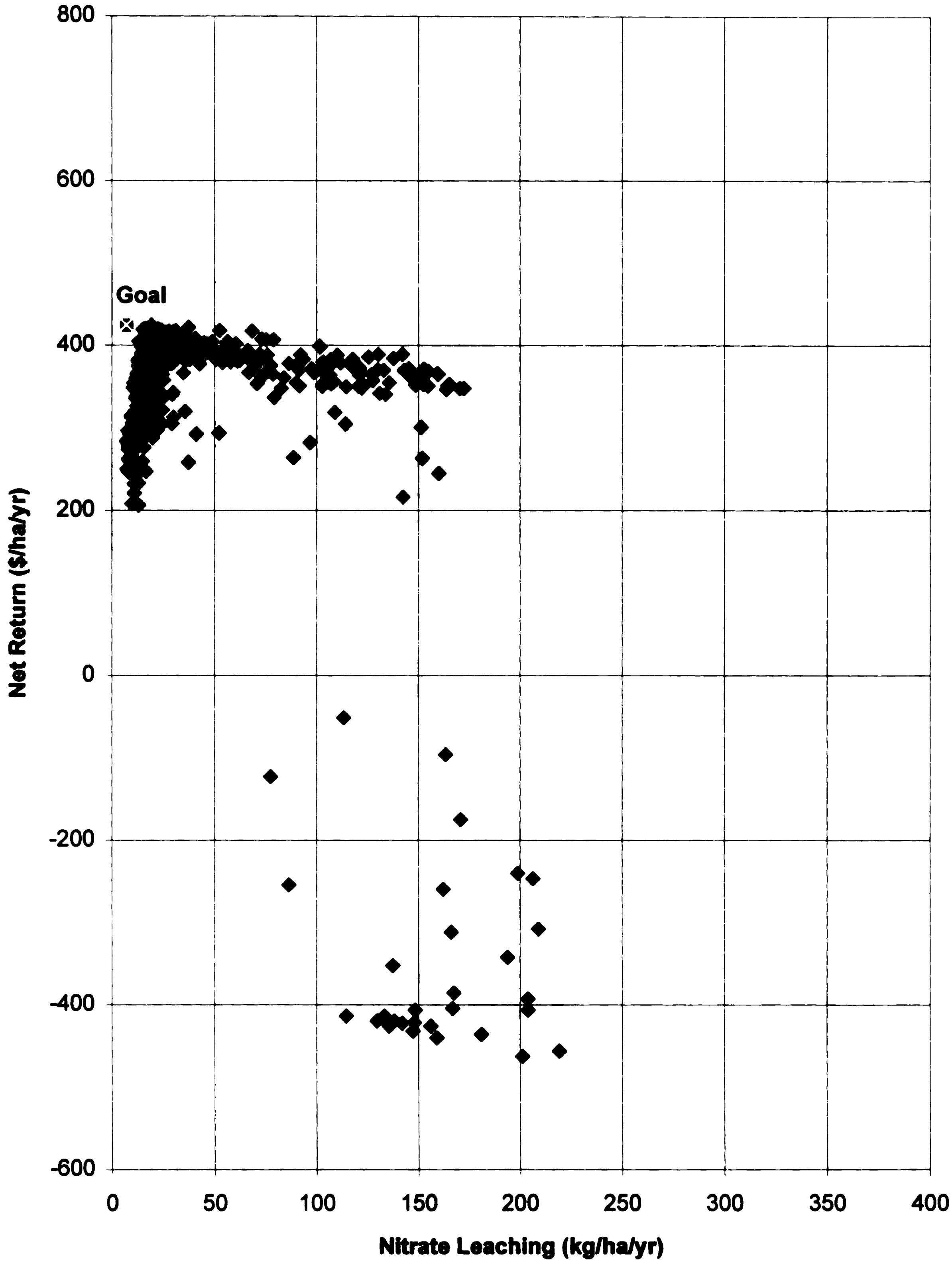


Figure 4-15: Moderate Temperature, Moderate Rainfall, Oshtemo Sandy Loam, Average Season Cultivar.

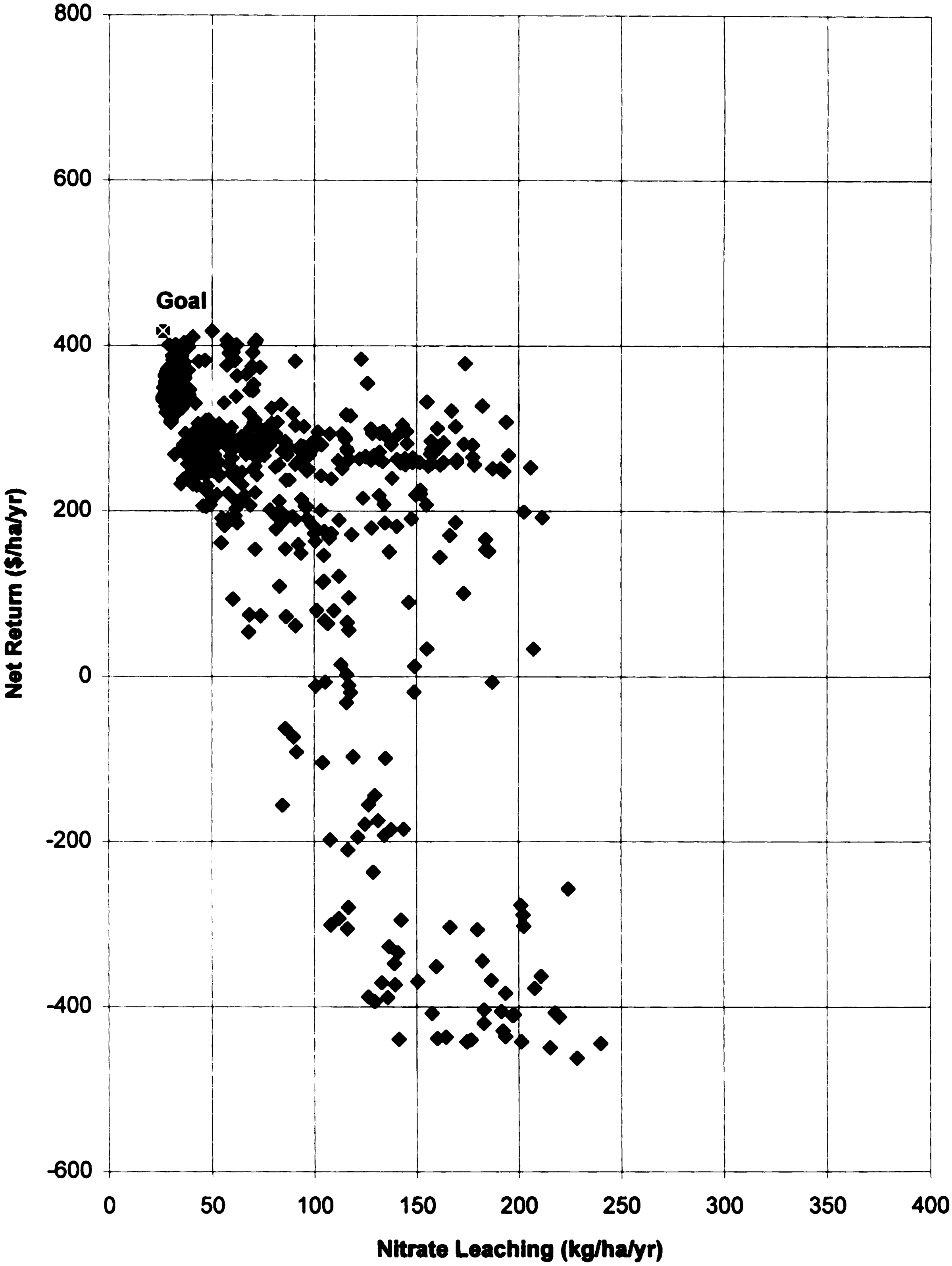


Figure 4-16: Moderate Temperature, Moderate Rainfall, Oshtemo Sandy Loam, Short Season Cultivar.

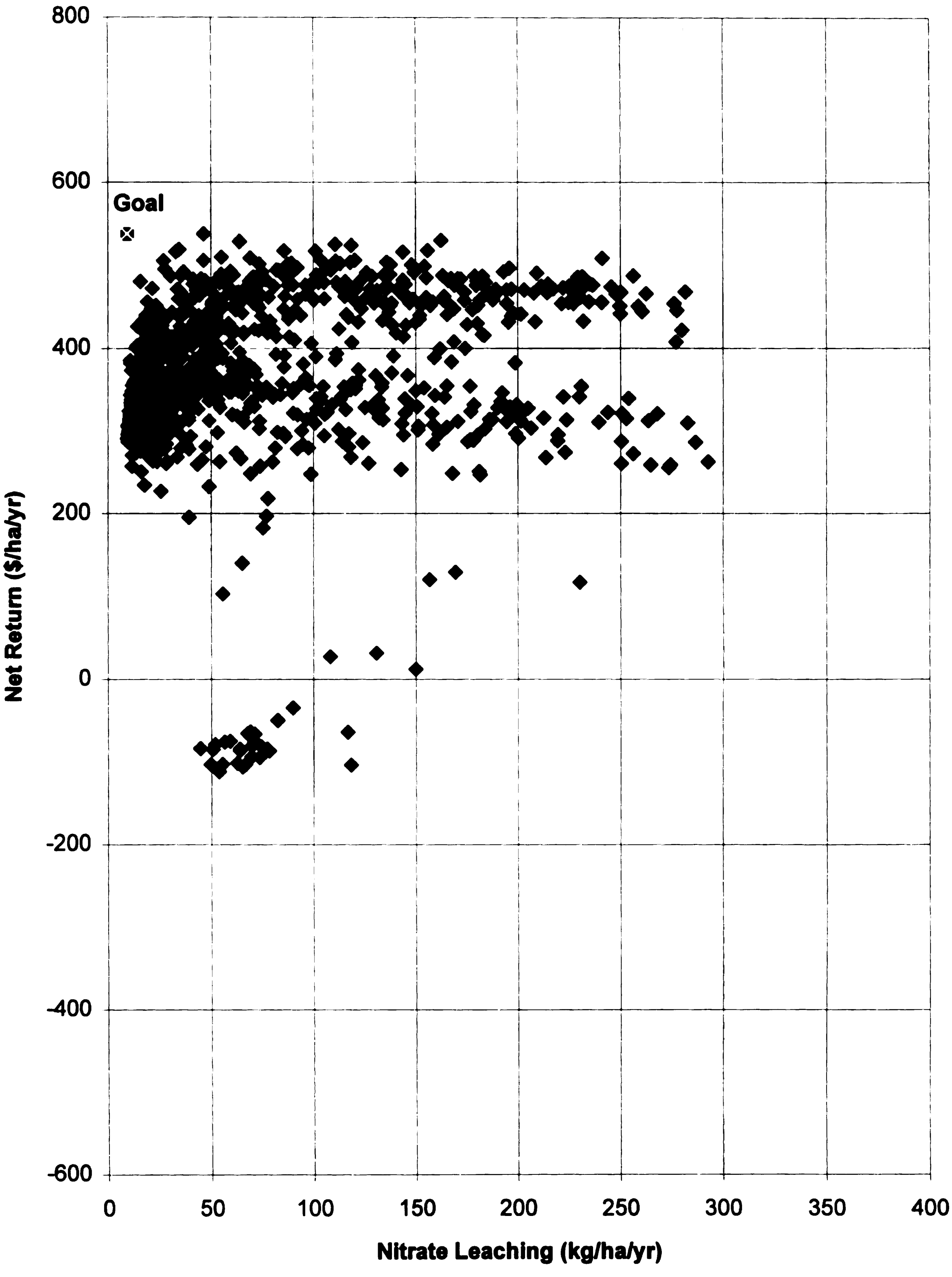


Figure 4-17: Normal Temperature, Normal Rainfall, Elston Sandy Loam, Long Season Cultivar.

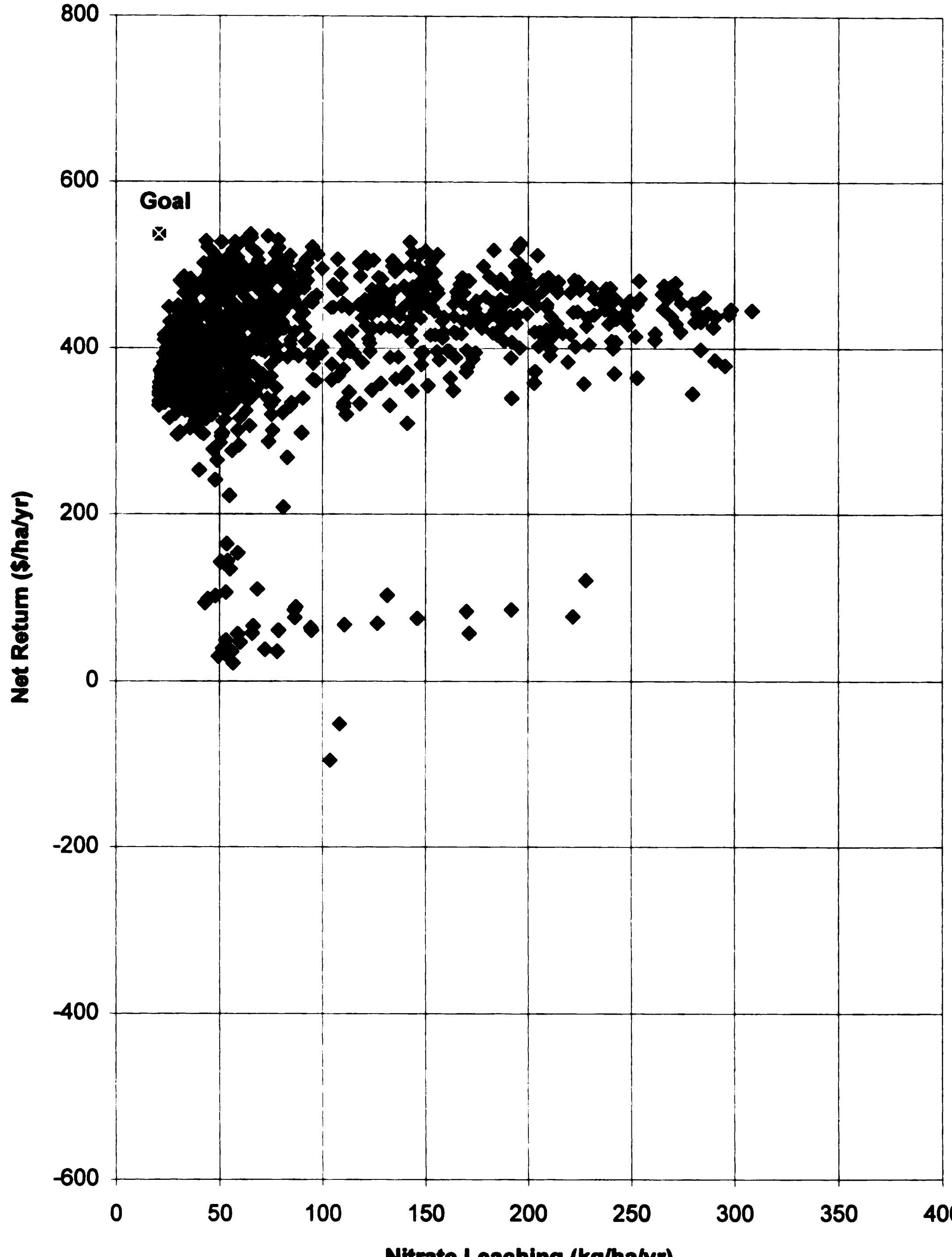


Figure 4-18: Normal Temperature, Normal Rainfall, Elston Sandy Loam, Average Season Cultivar.

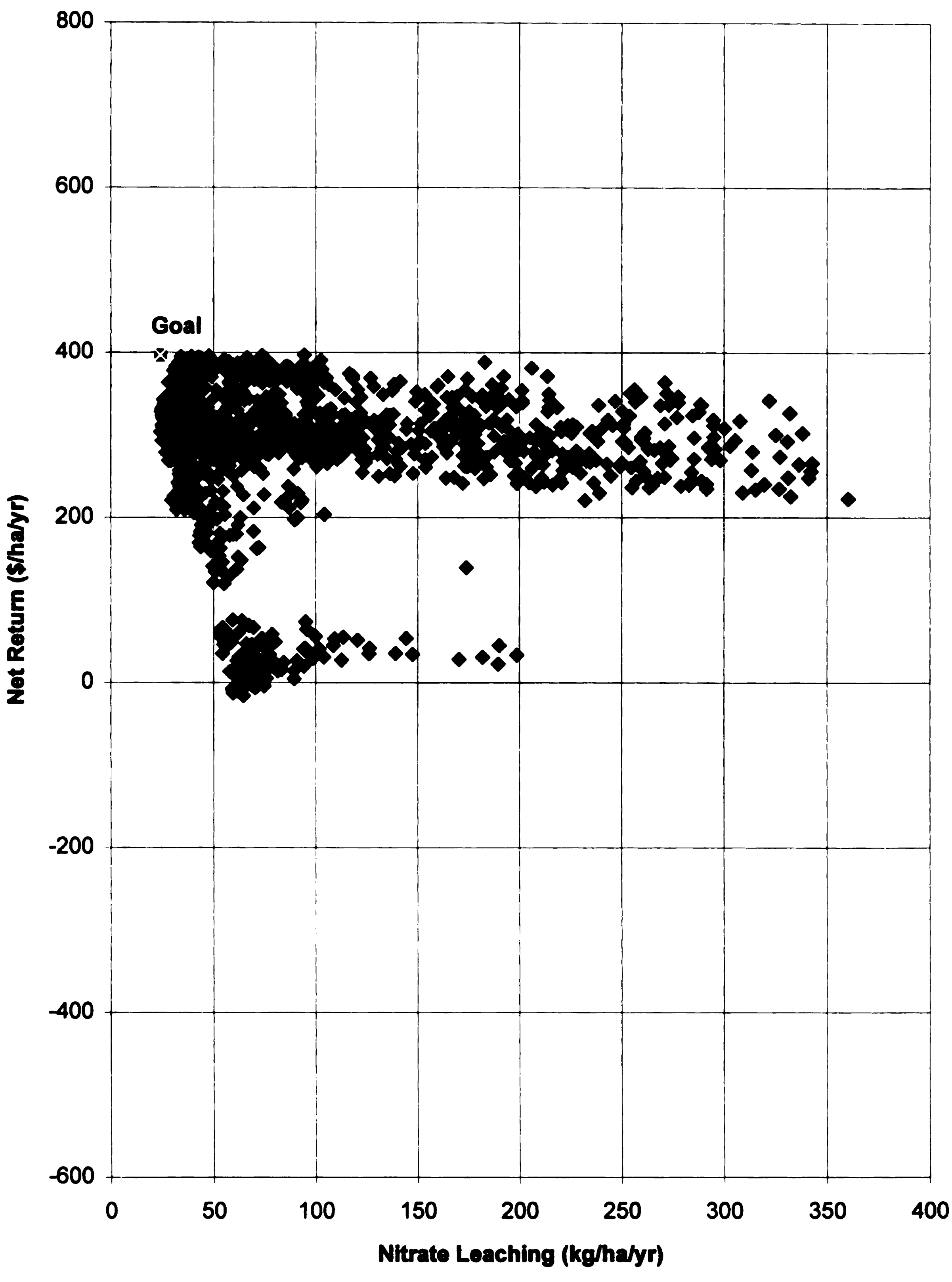


Figure 4-19: Normal Temperature, Normal Rainfall, Elston Sandy Loam, Short Season Cultivar.

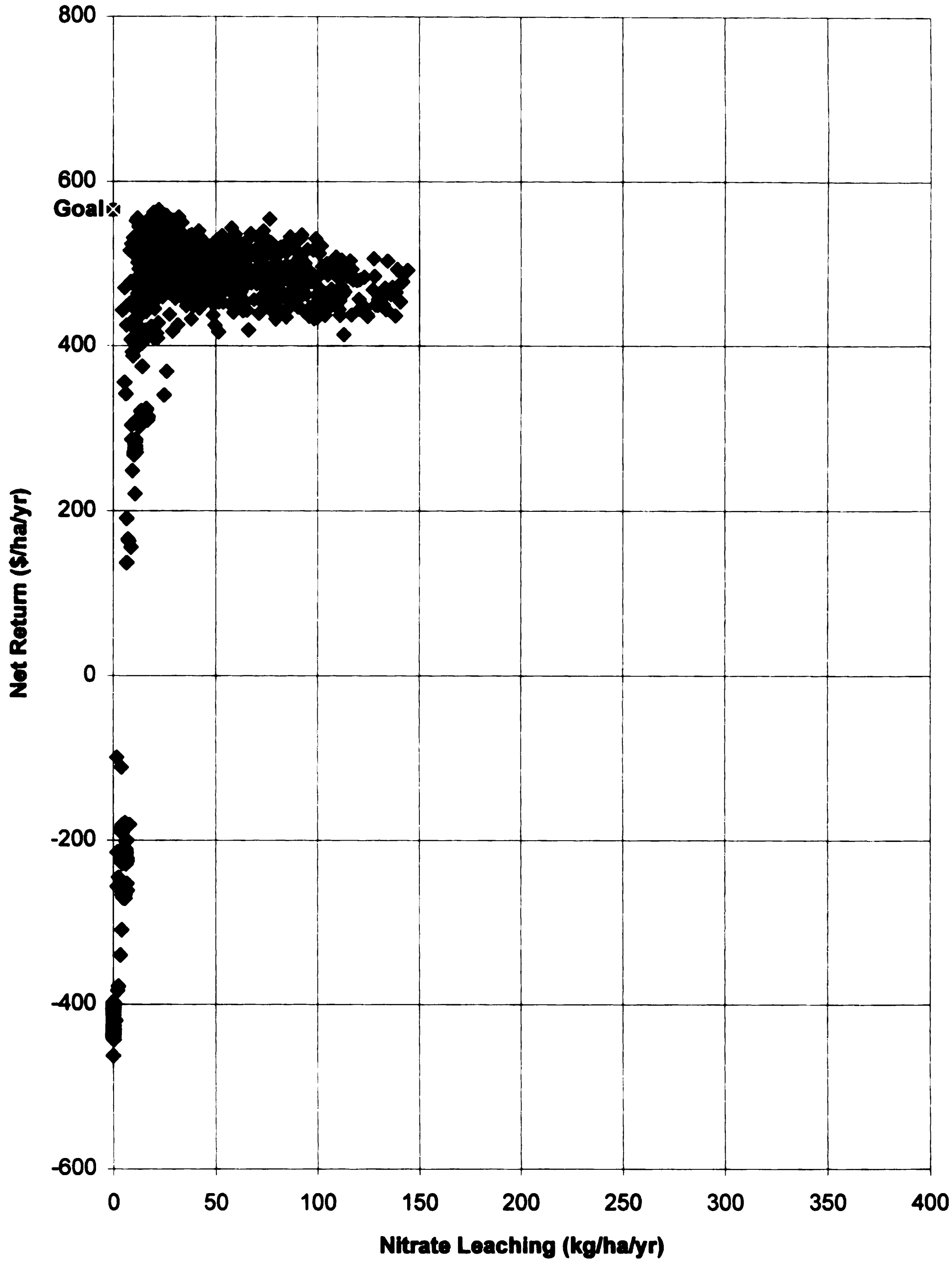


Figure 4-20: Hot Temperature, Dry Rainfall, Elston Sandy Loam, Long Season Cultivar.

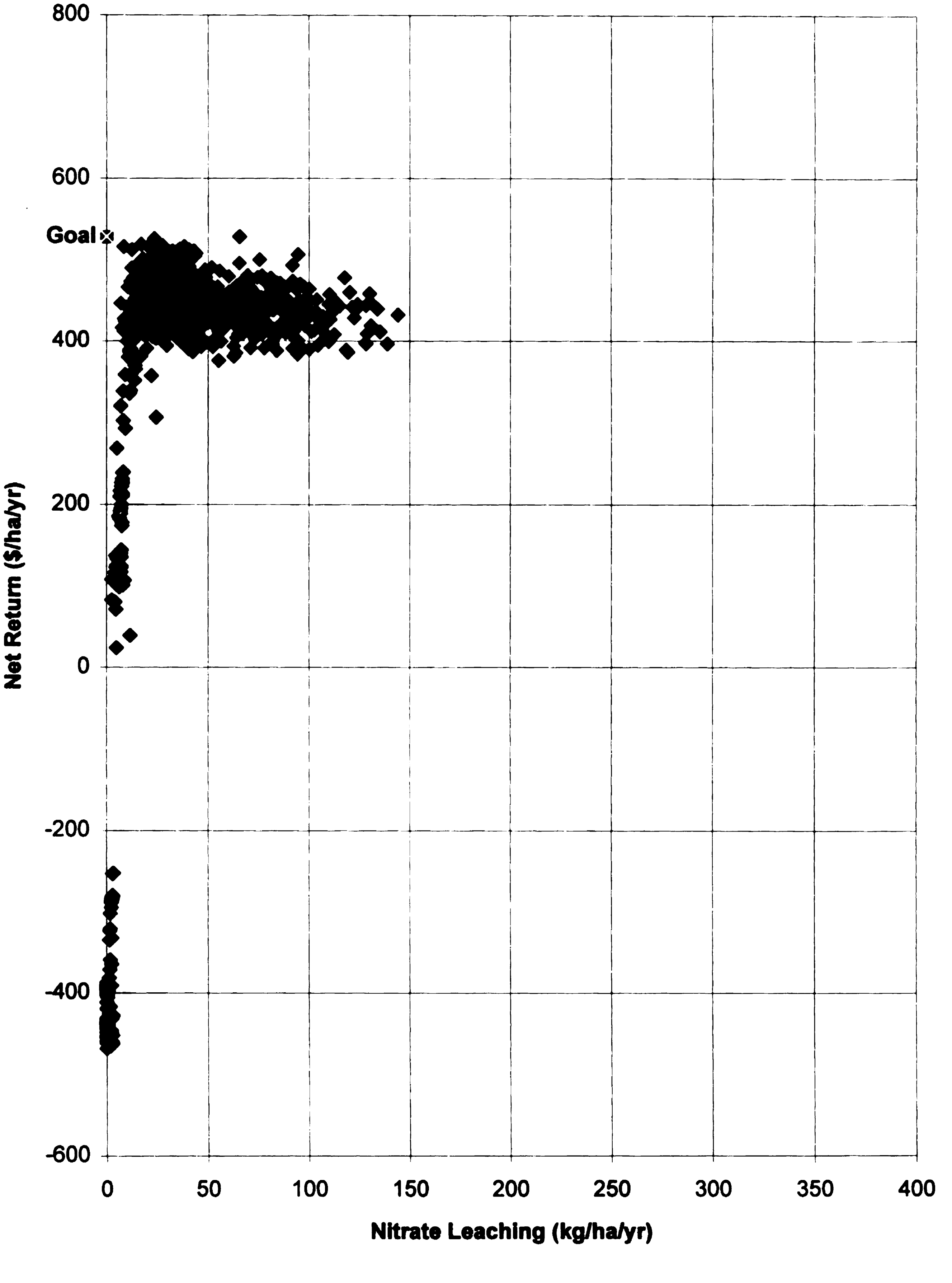


Figure 4-21: Hot Temperature, Dry Rainfall, Elston Sandy Loam, Average Season Cultivar.

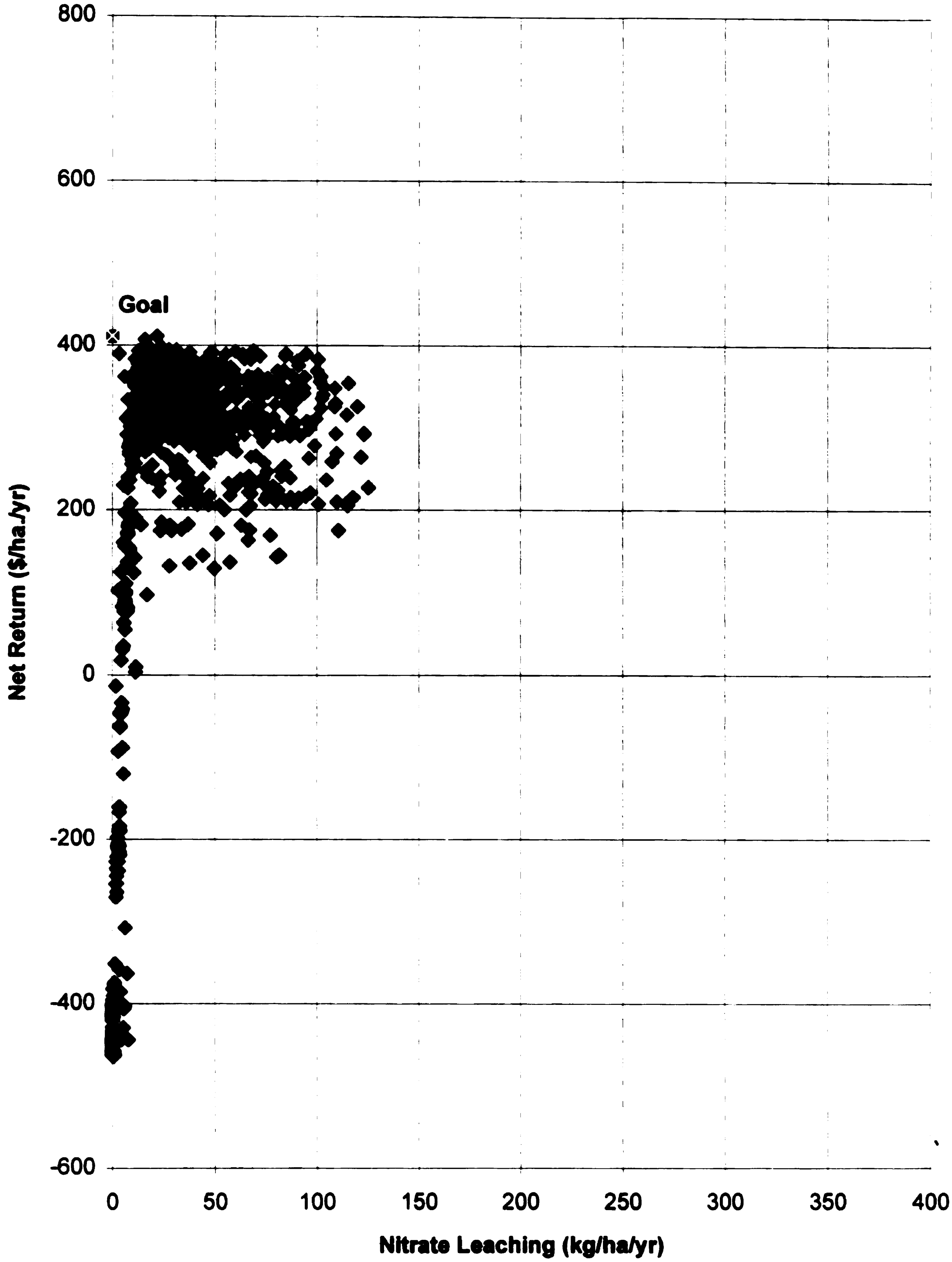


Figure 4-22: Hot Temperature, Dry Rainfall, Elston Sandy Loam, Short Season Cultivar.

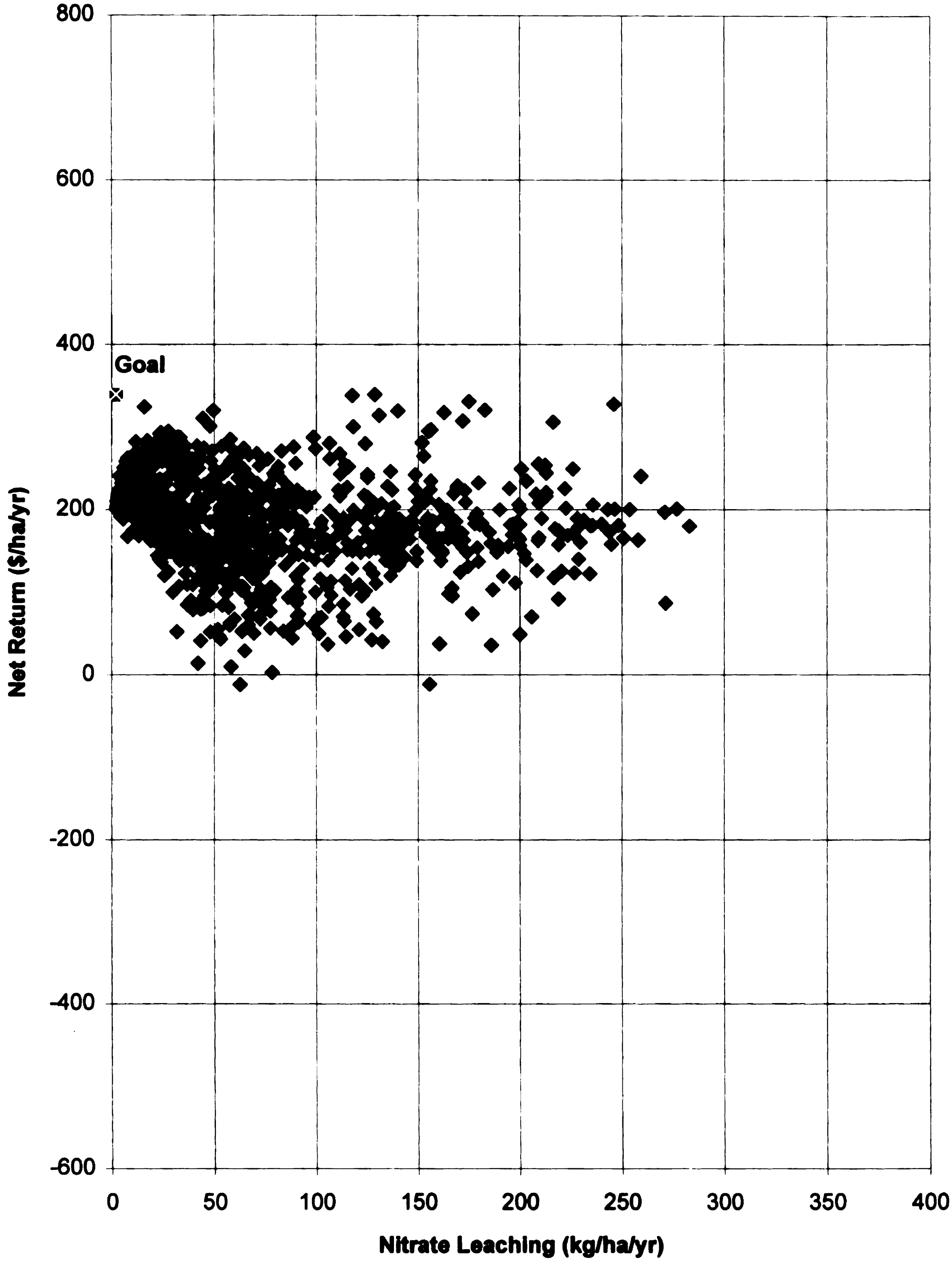


Figure 4-23: Cold Temperature, Wet Rainfall, Elston Sandy Loam, Long Season Cultivar.

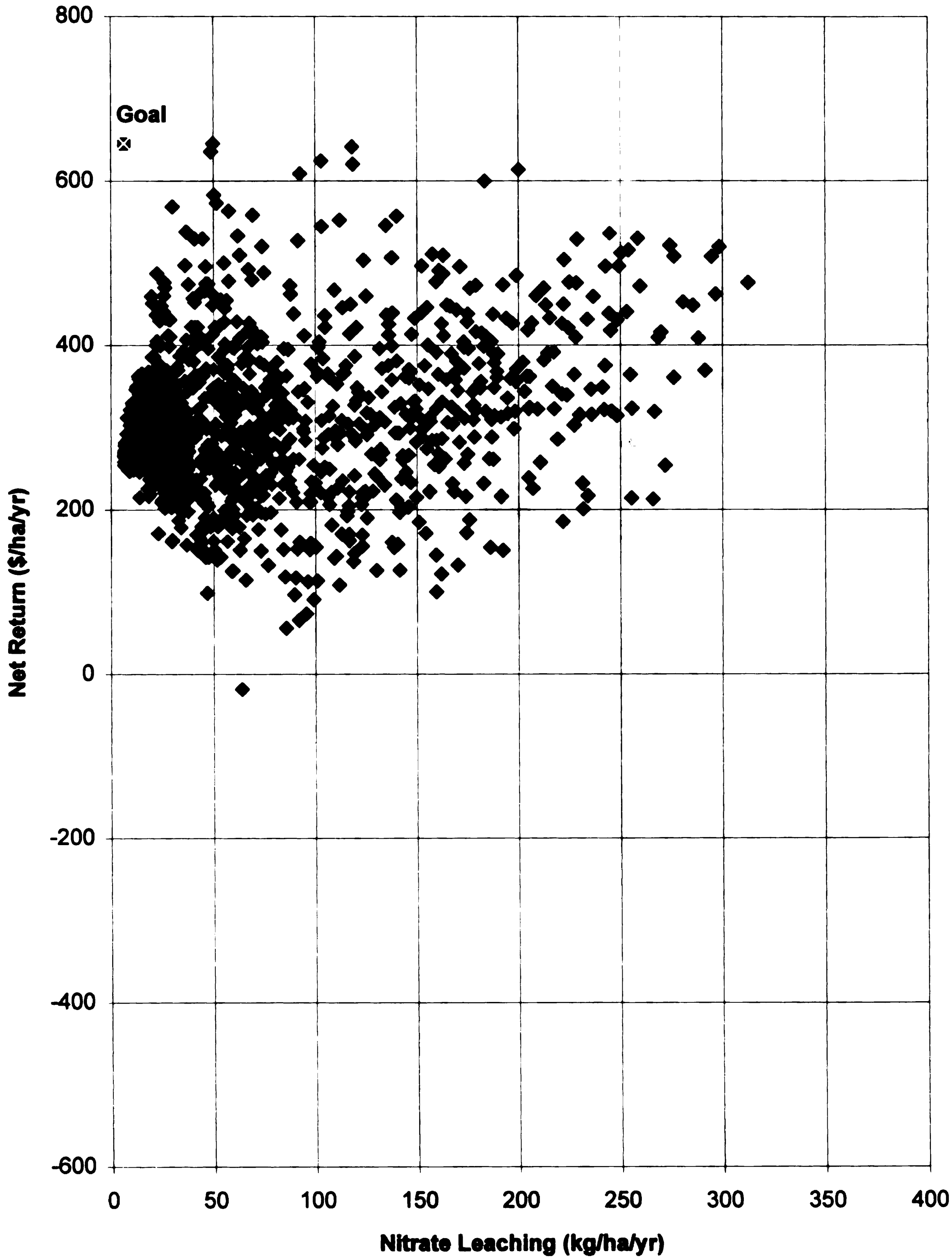


Figure 4-24: Cold Temperature, Wet Rainfall, Elston Sandy Loam, Average Season Cultivar.

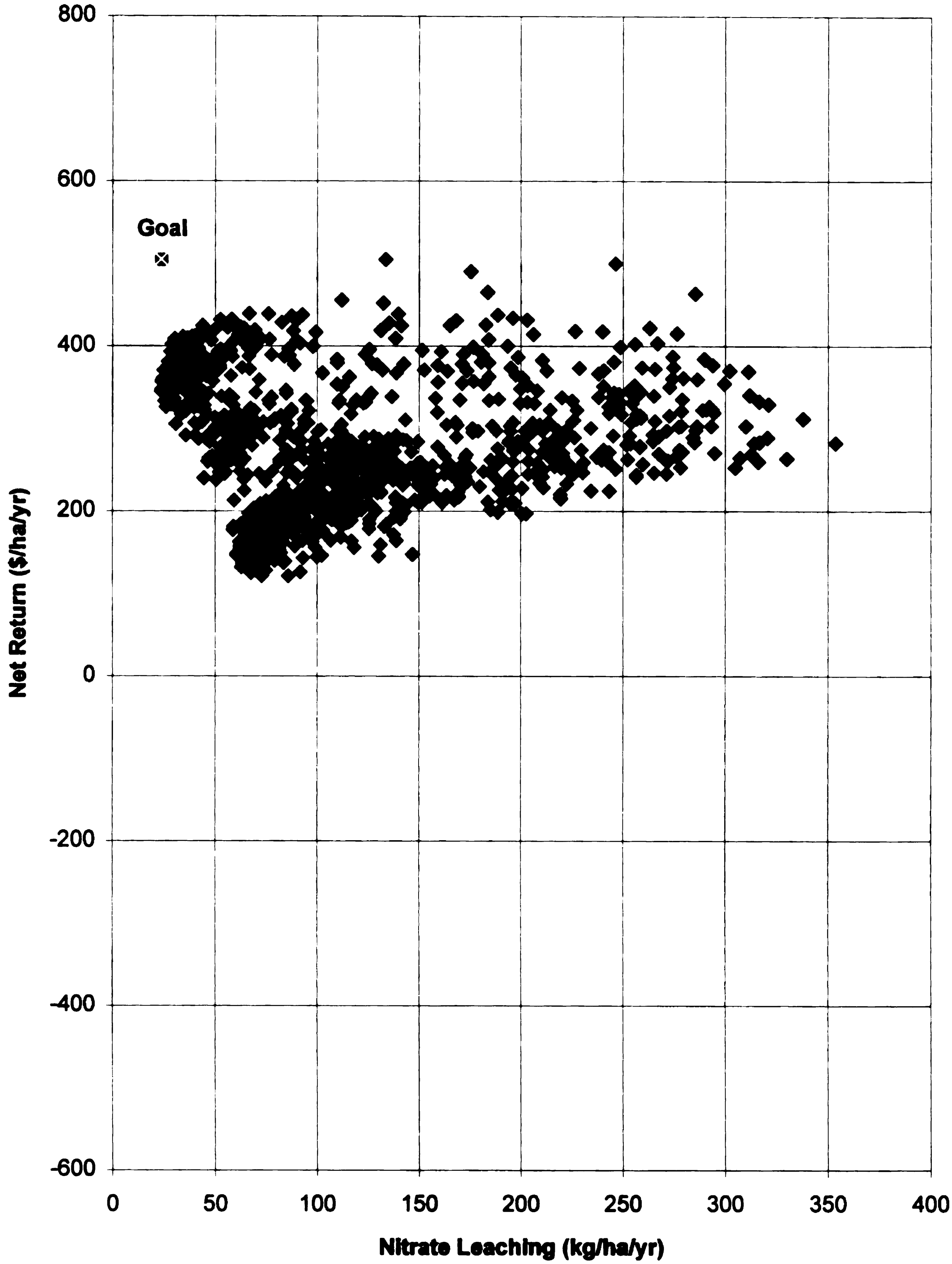


Figure 4-25: Cold Temperature, Wet Rainfall, Elston Sandy Loam, Short Season Cultivar.

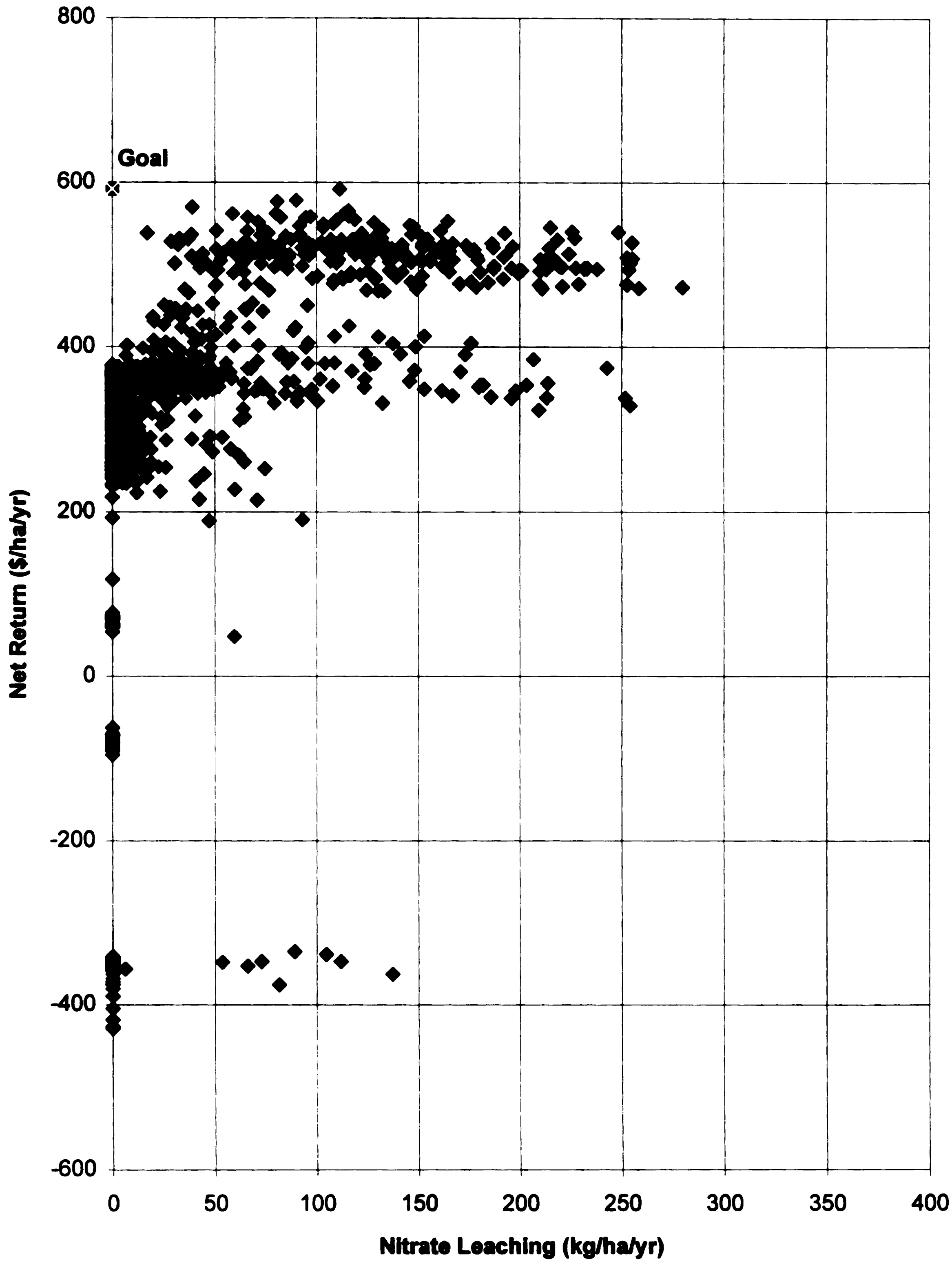


Figure 4-26: Moderate Temperature, Moderate Rainfall, Elston Sandy Loam, Long Season Cultivar.

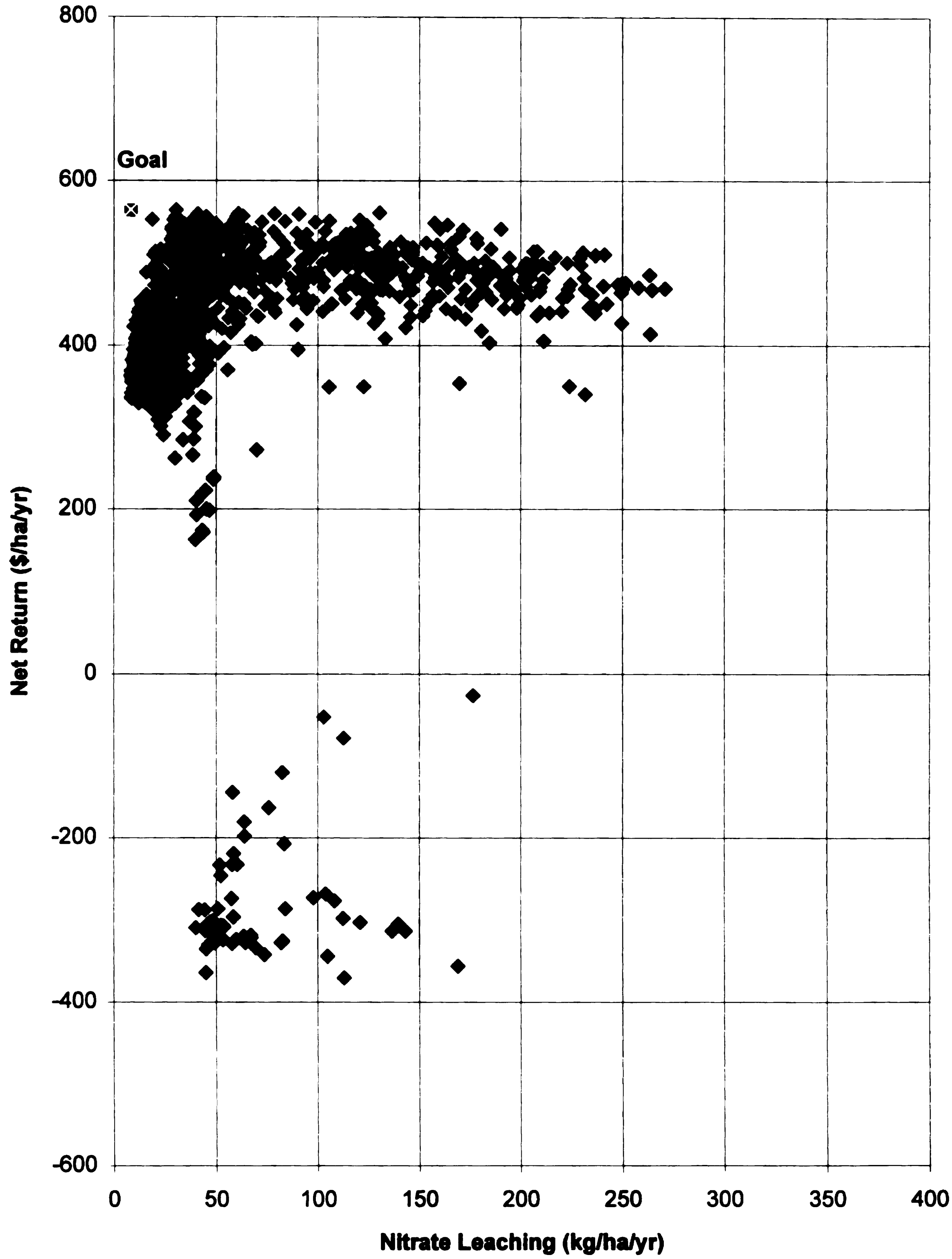


Figure 4-27: Moderate Temperature, Moderate Rainfall, Elston Sandy Loam, Average Season Cultivar.

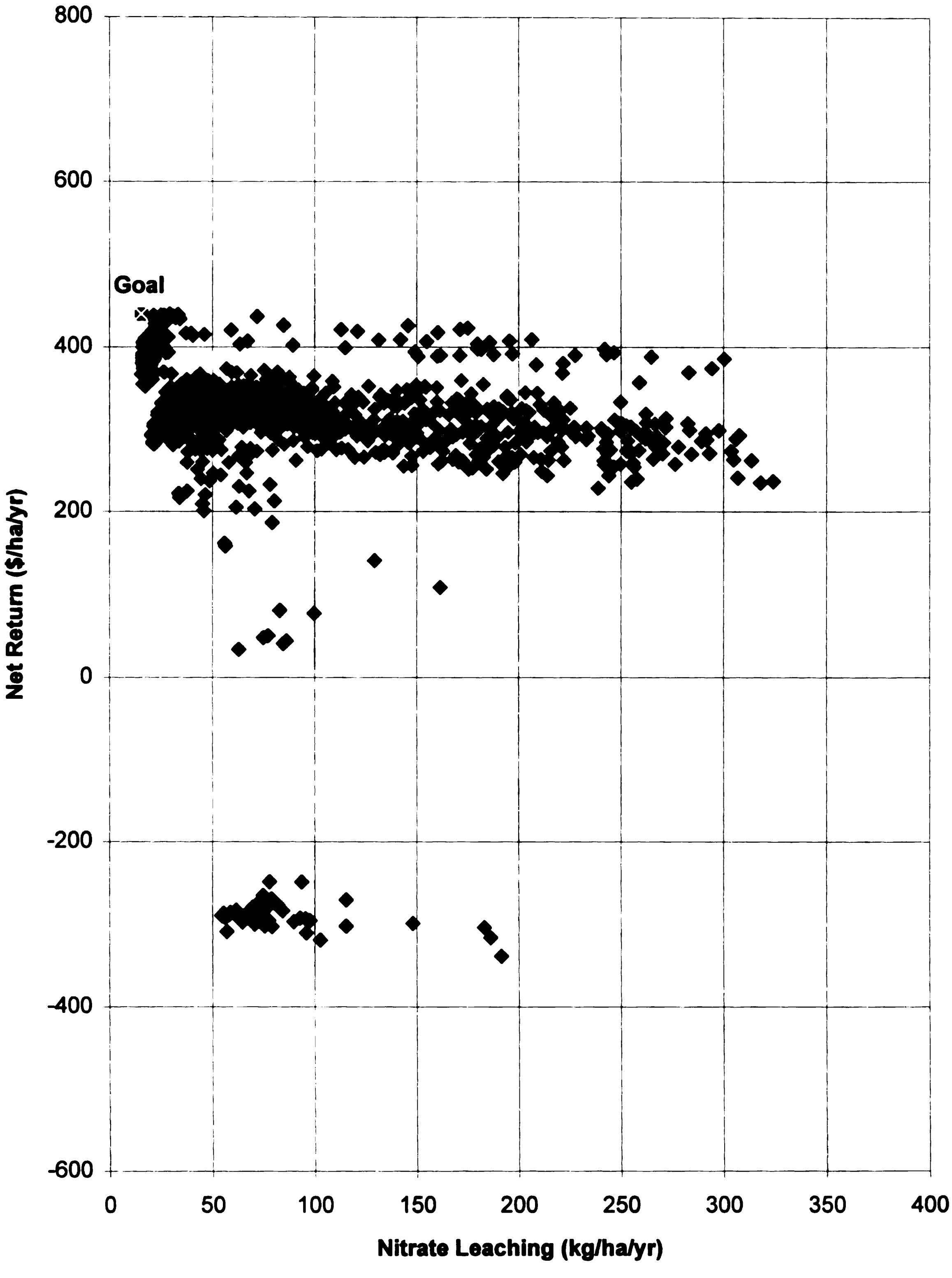


Figure 4-28: Moderate Temperature, Moderate Rainfall, Elston Sandy Loam, Short Seaon Cultivar.

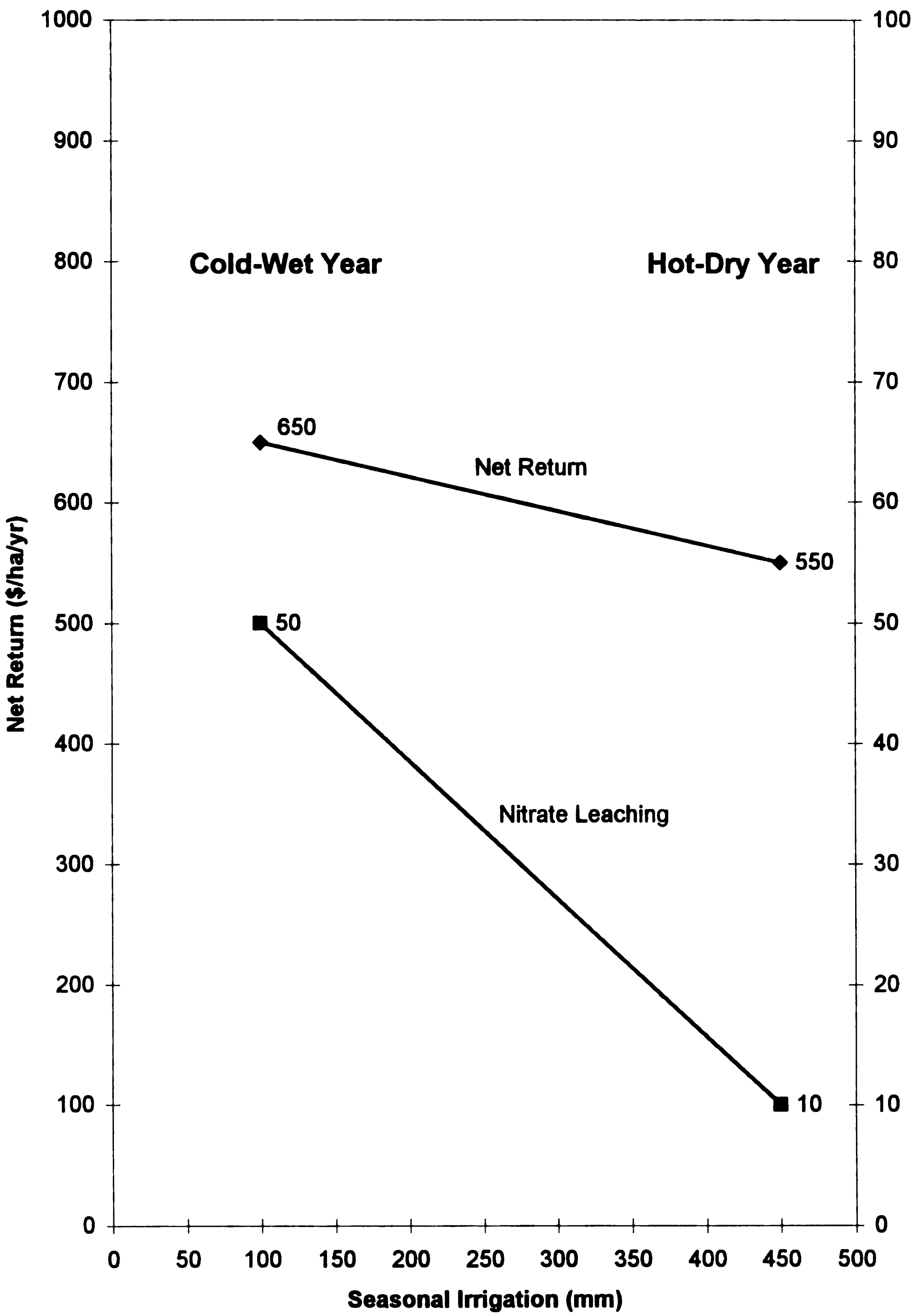


Figure 4-29: The effect of scheduled irrigation on nitrate leaching and economic net return.

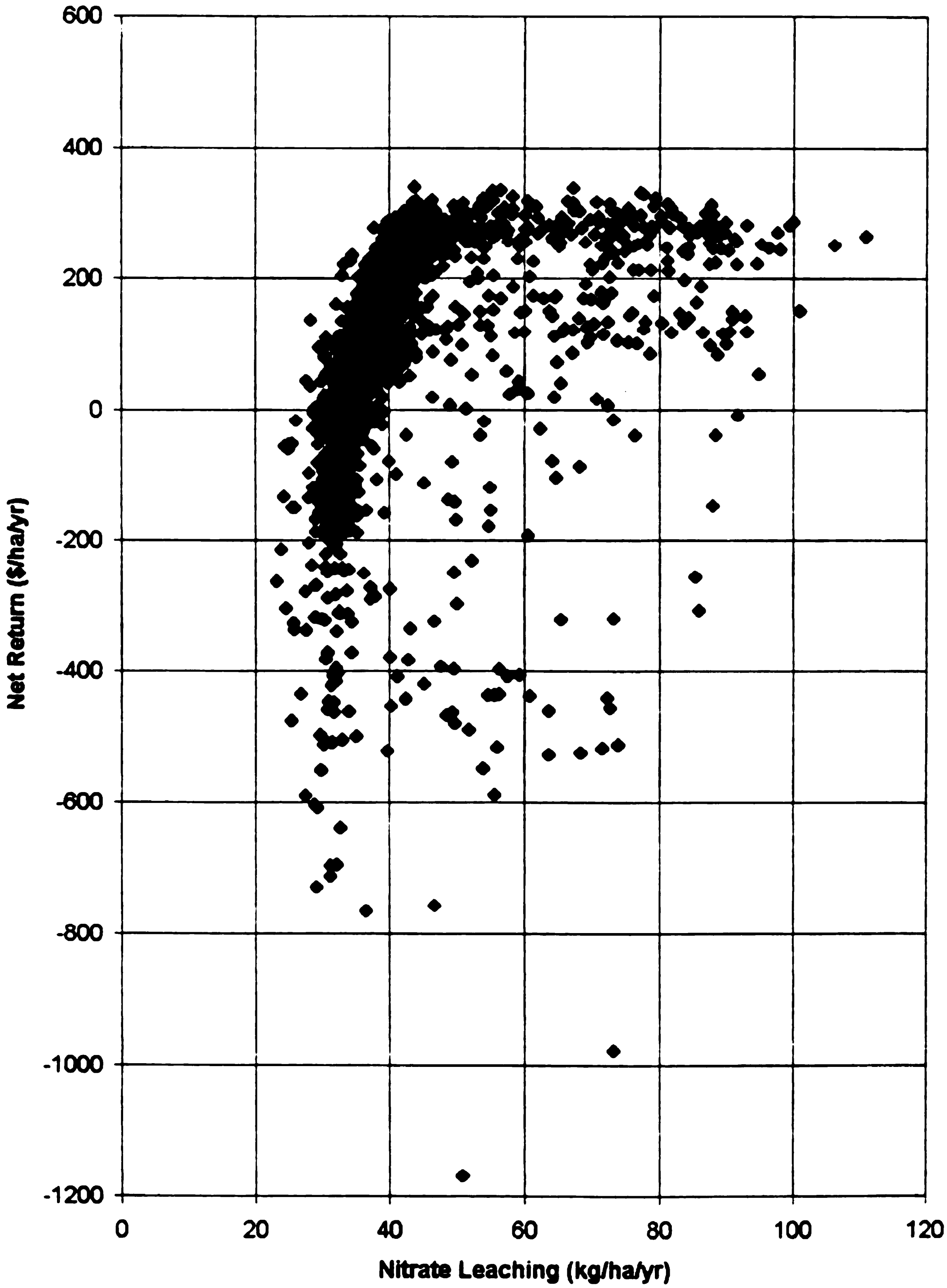
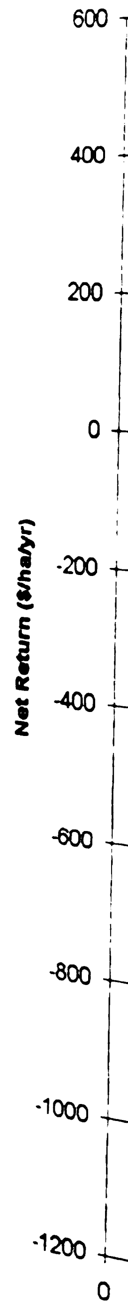


Figure 4-30: First set of 4000 points from 14 output files of optimizations for Hot-Dry Summer and Normal Winter Scenario.



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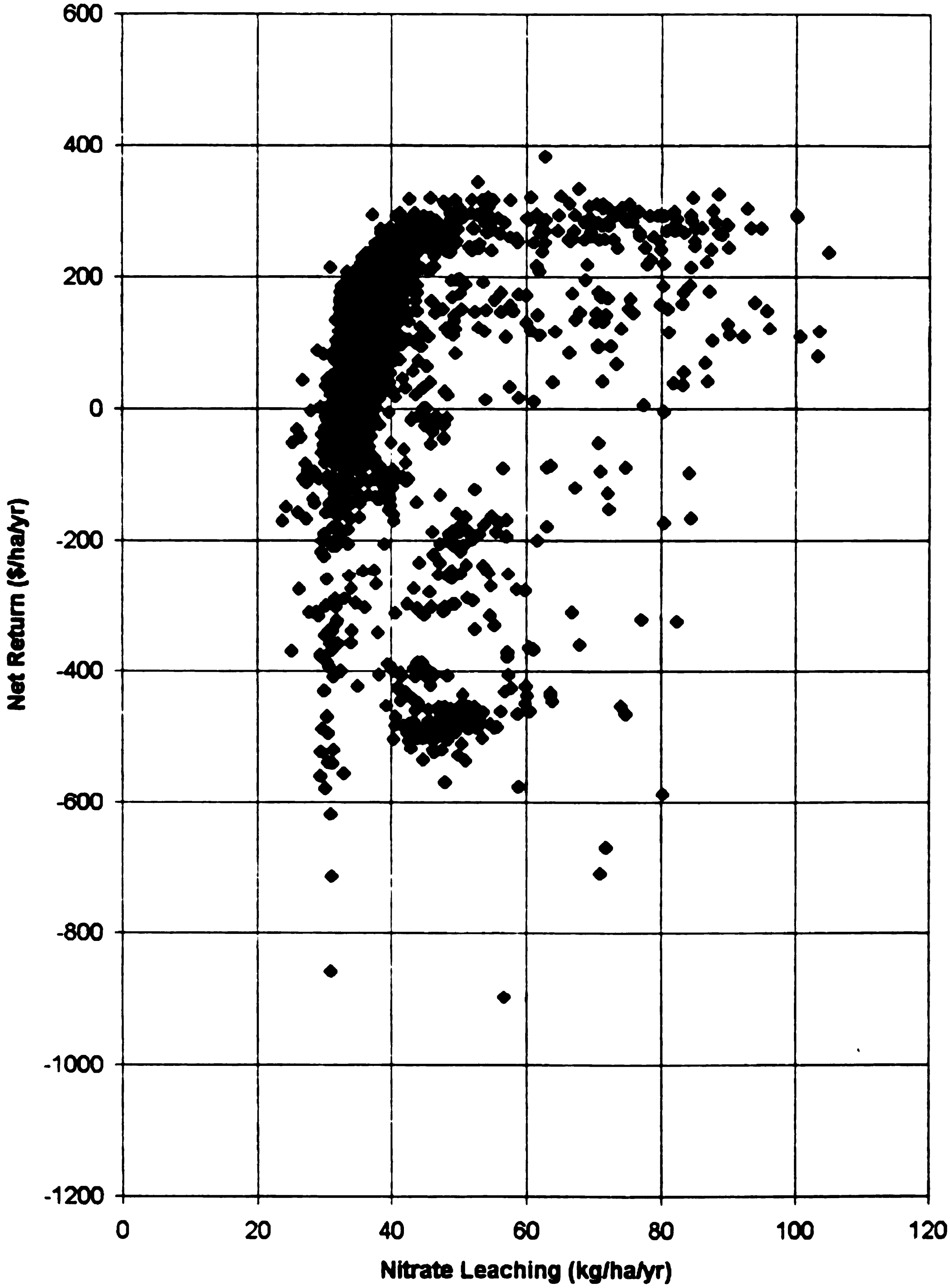
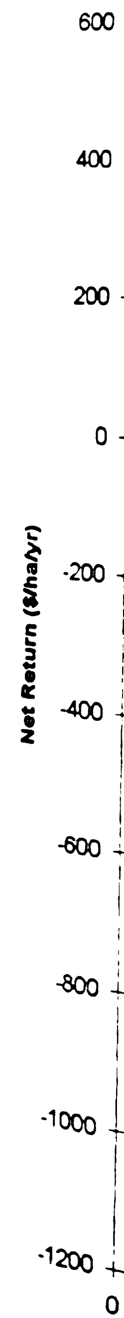


Figure 4-31: Second set of 4000 points from 14 output files of optimizations for Hot-Dry Summer and Normal Winter Scenario.



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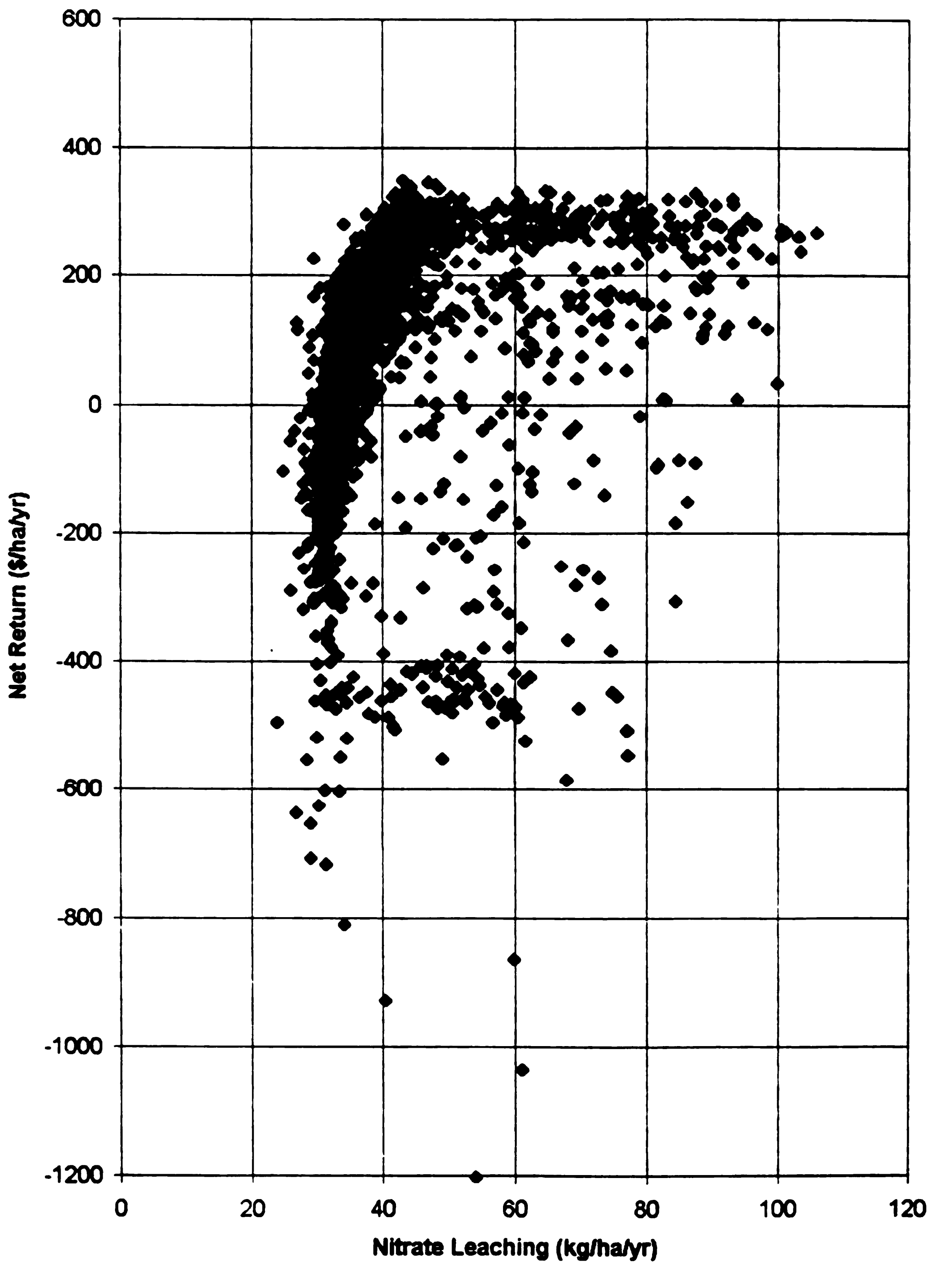
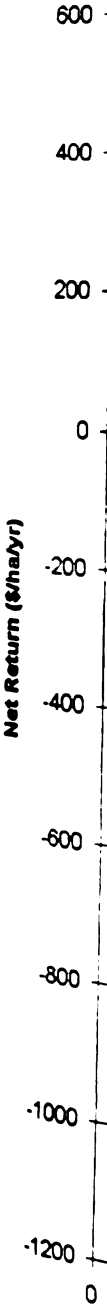


Figure 4-32: Third set of 4000 points from 14 output files of optimizations for Hot-Dry Summer and Normal Winter Scenario.



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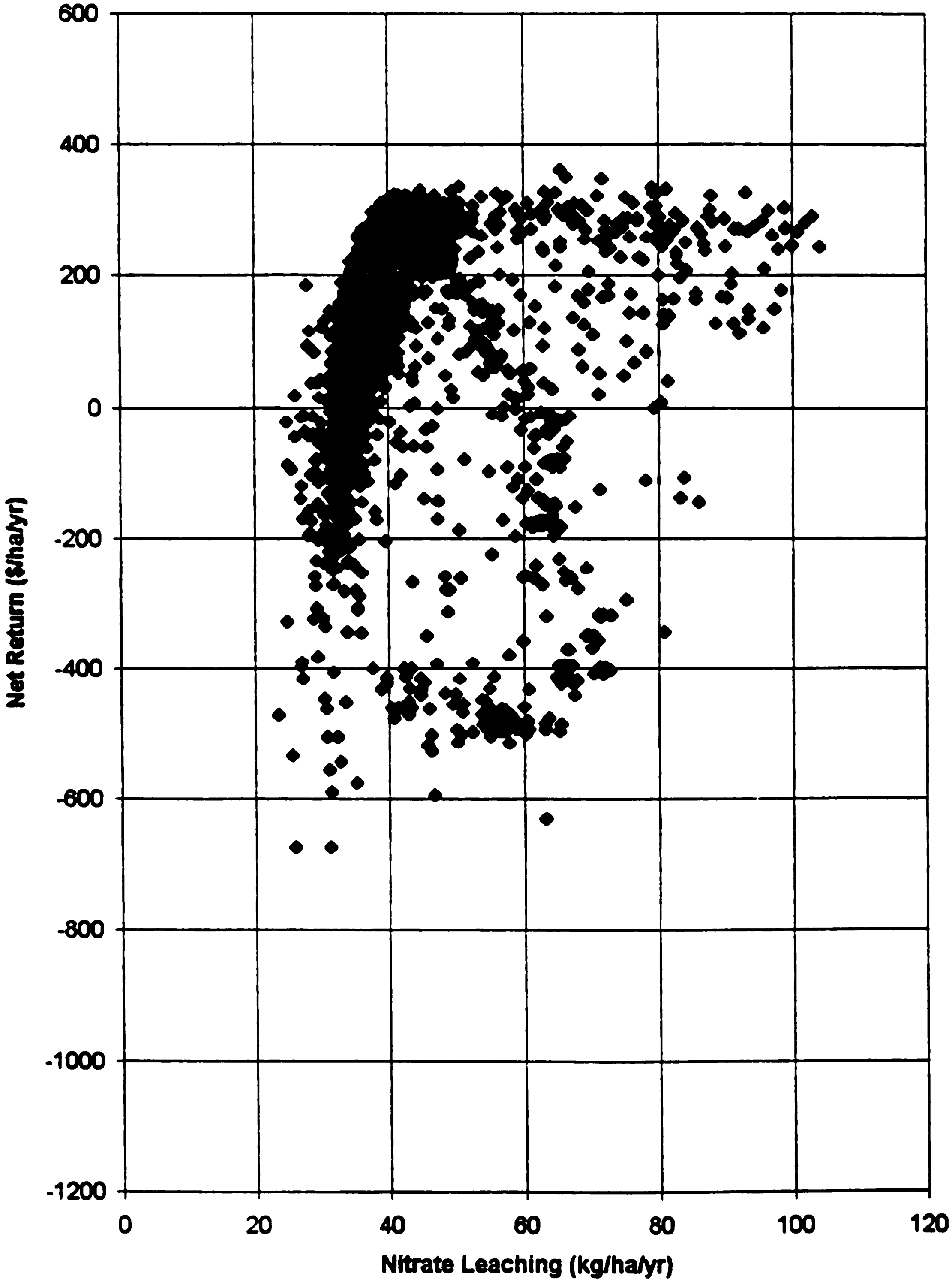
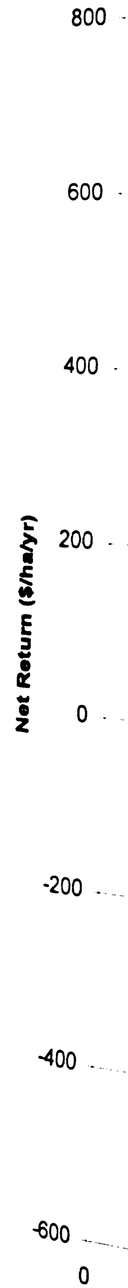


Figure 4-33: Fourth set of 4000 points from 14 output files of optimizations for Hot-Dry Summer and Normal Winter Scenario.



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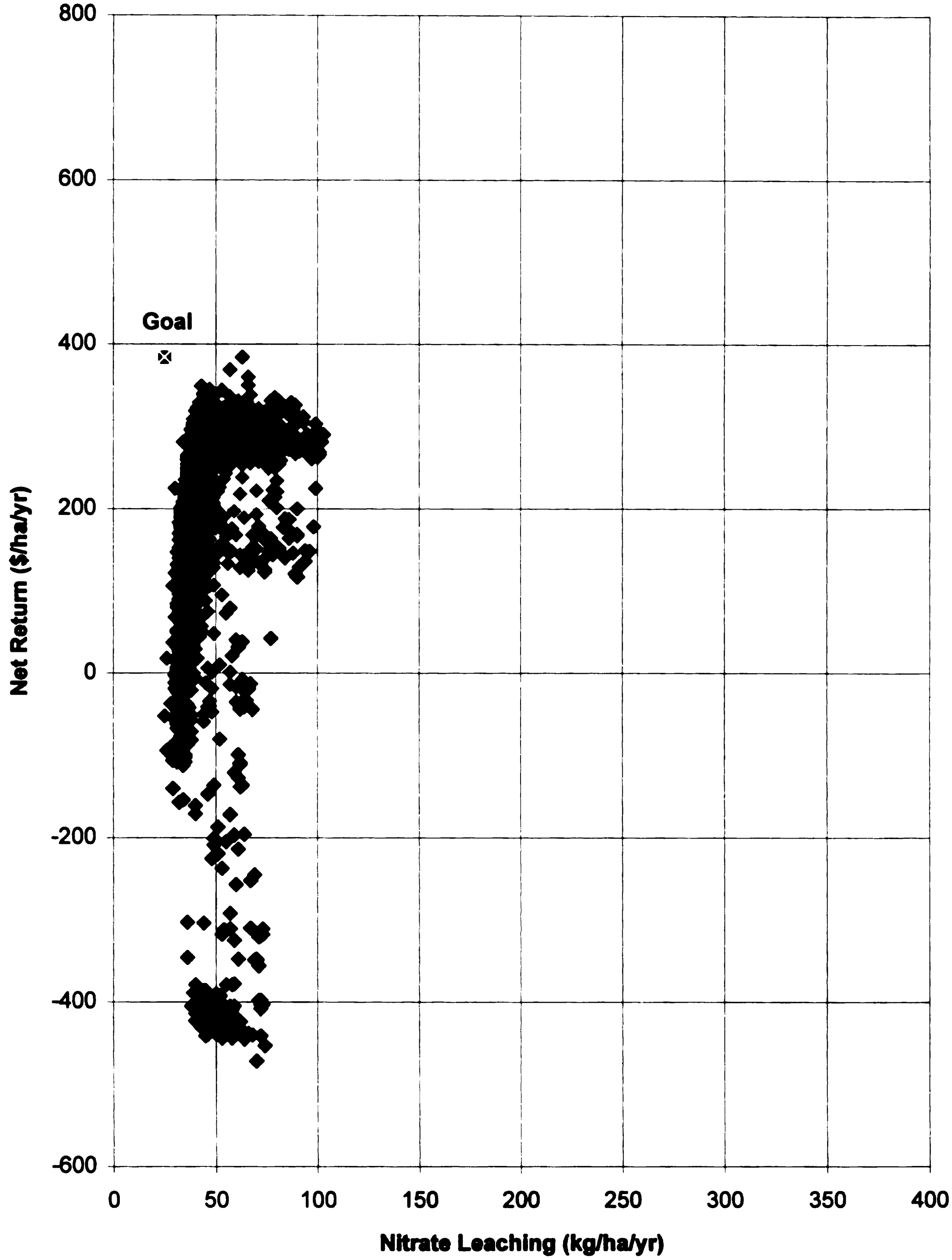
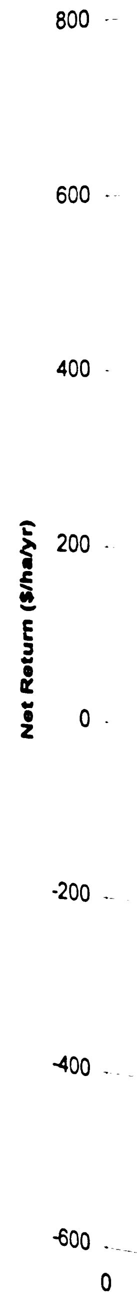


Figure 4-34: Irrigation Uniformity 68 to 74 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.



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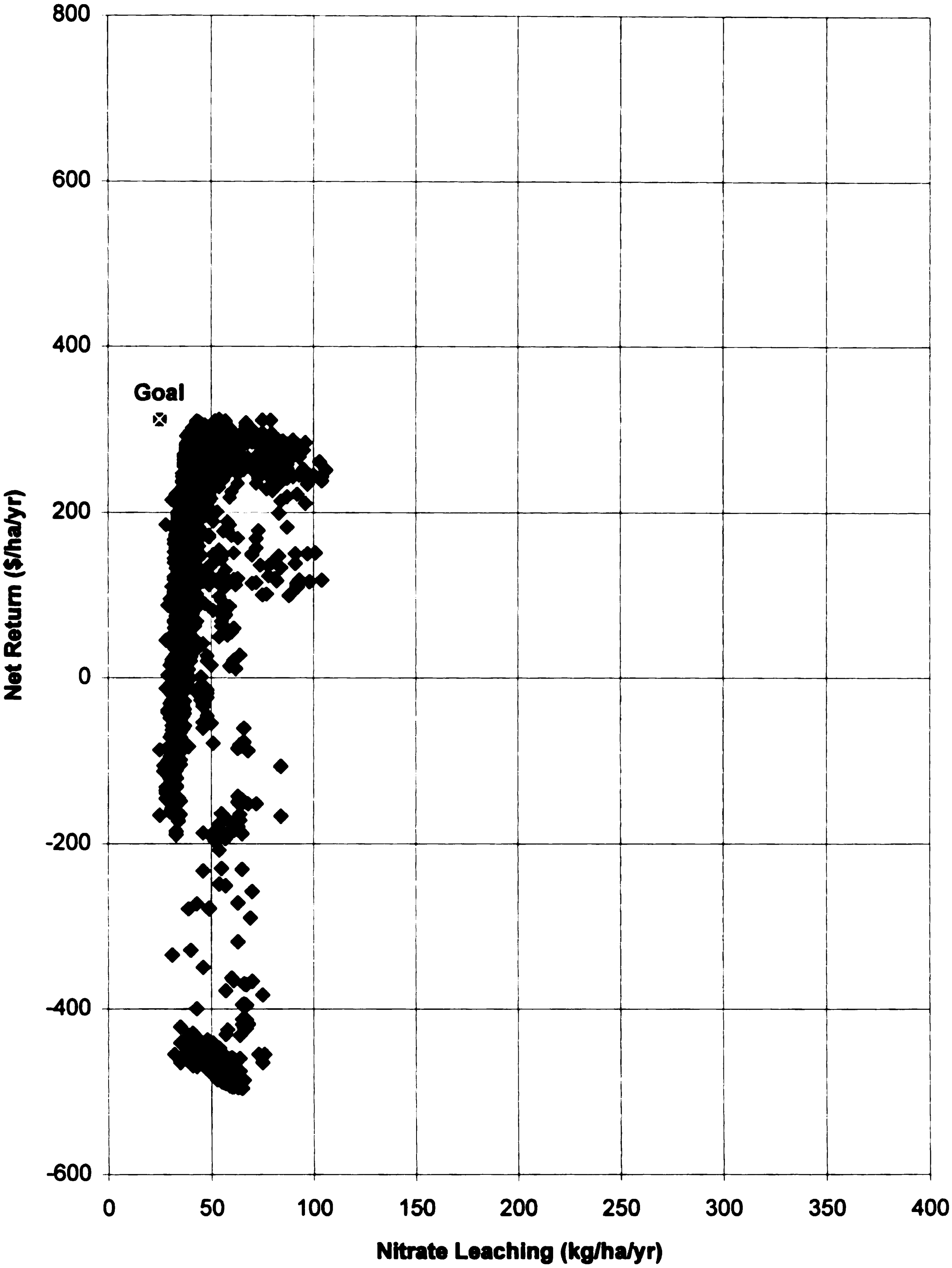
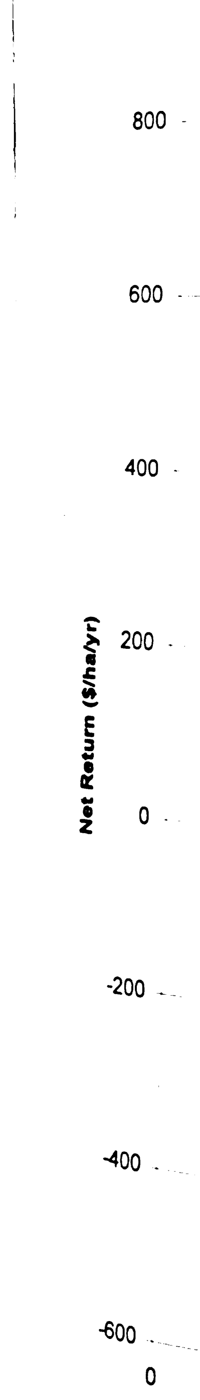


Figure 4-35: Irrigation Uniformity 74 to 79 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.



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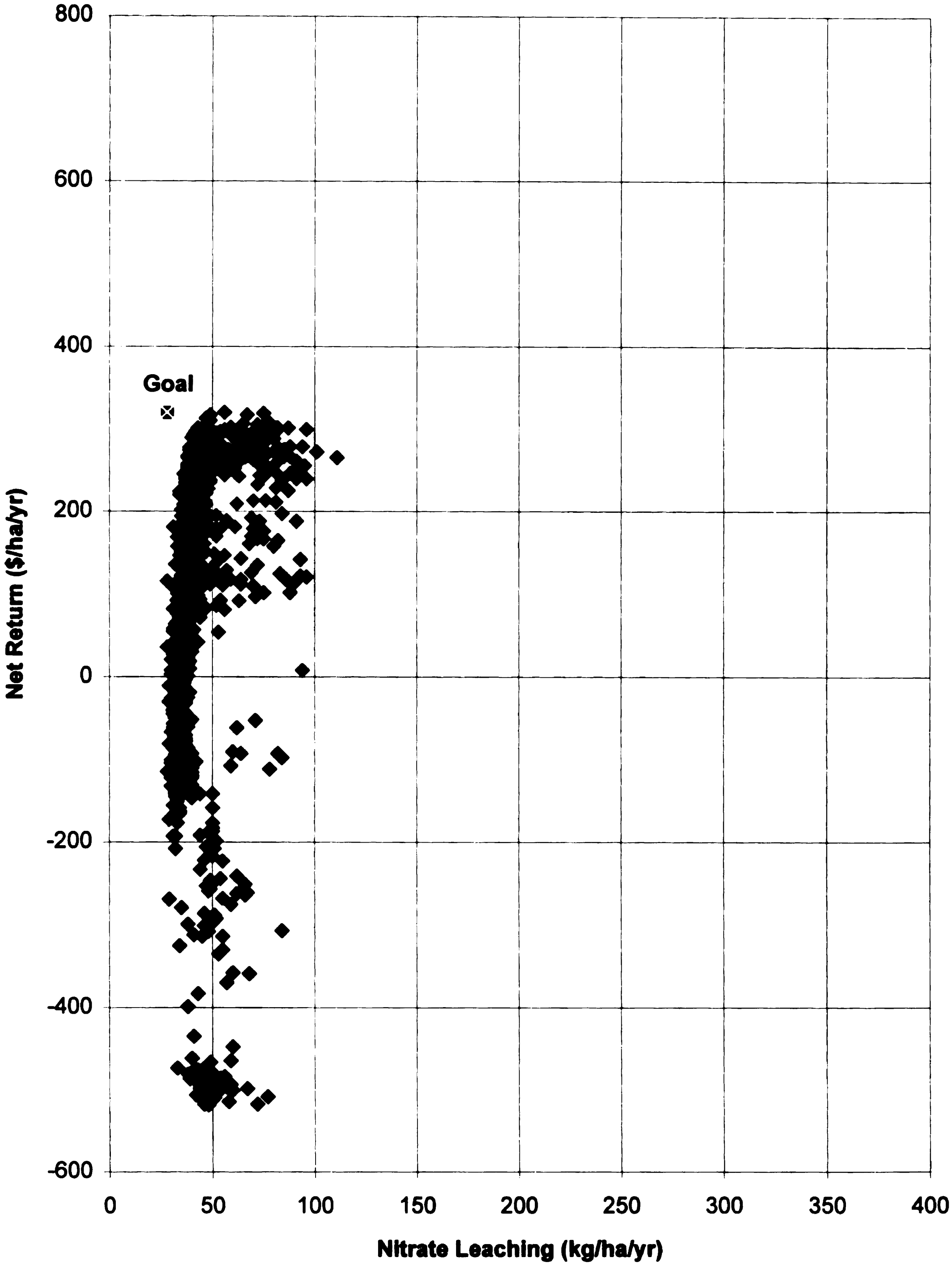
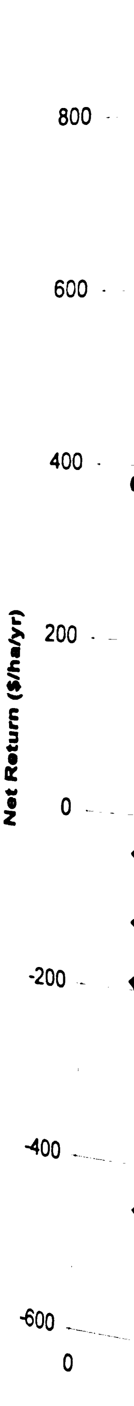


Figure 4-36: Irrigation Uniformity 79 to 83 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.



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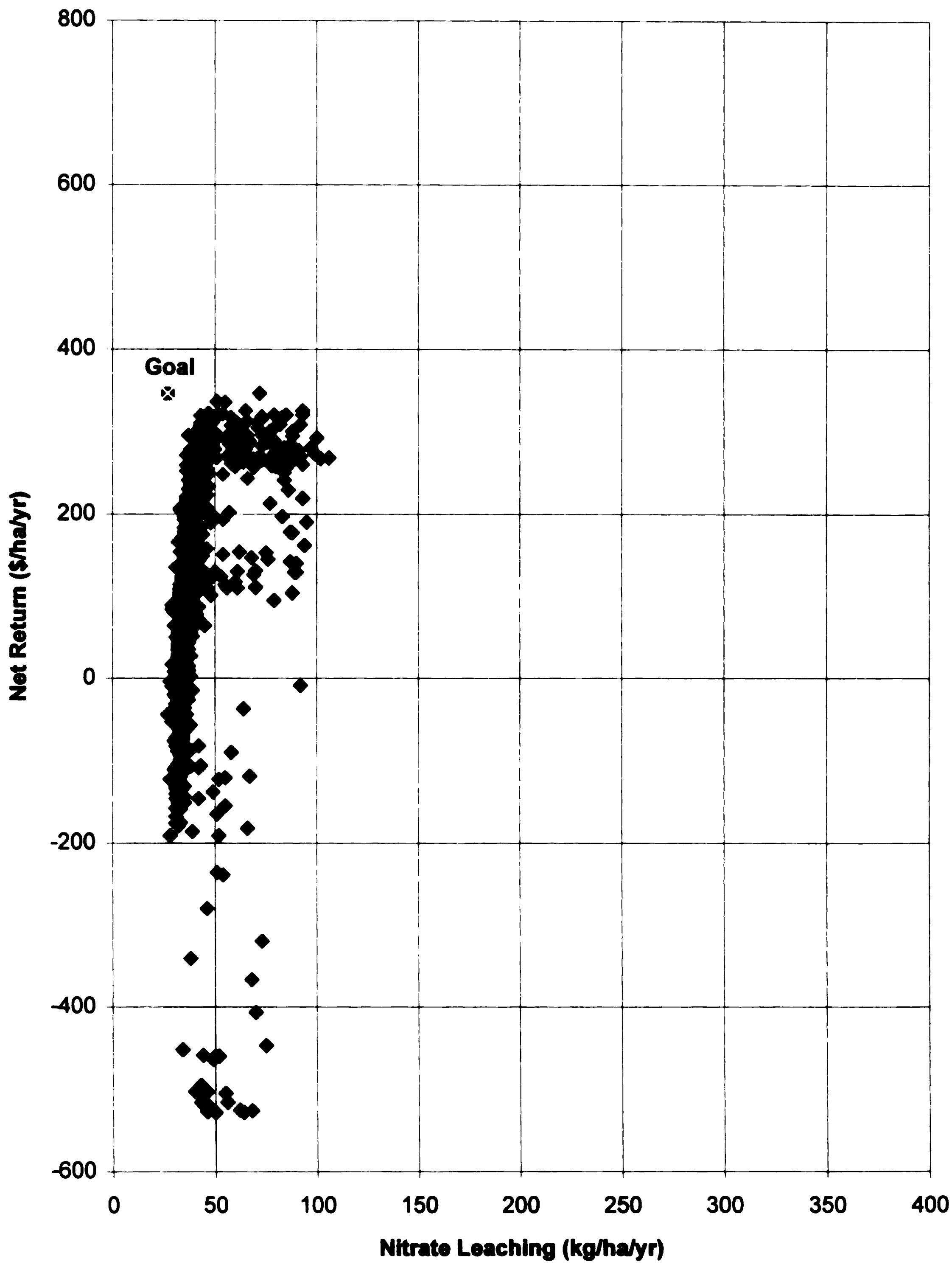

Figure 4-37: Irrigation Uniformity 83 to 86 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

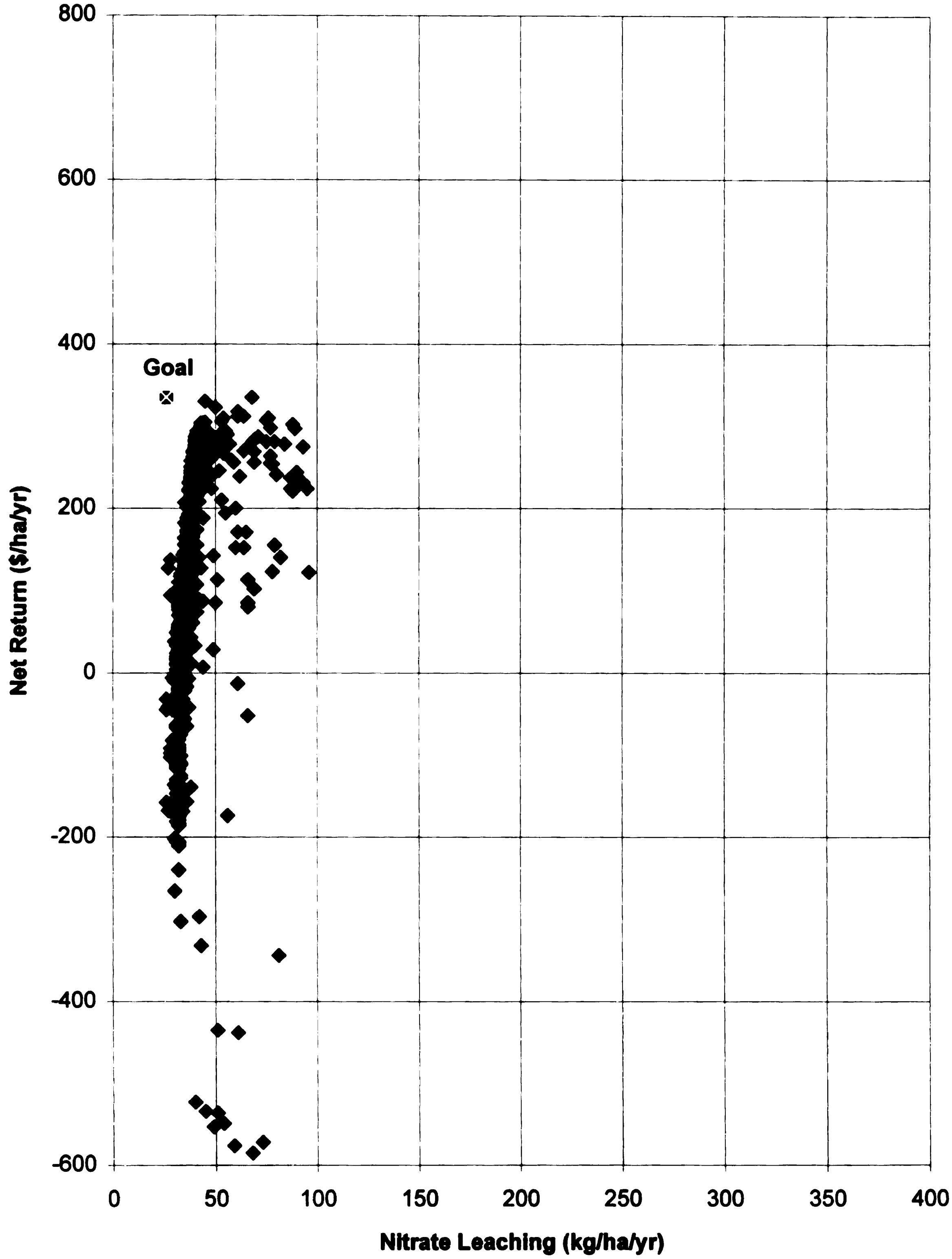

Figure 4-38: Irrigation Uniformity 86 to 88 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

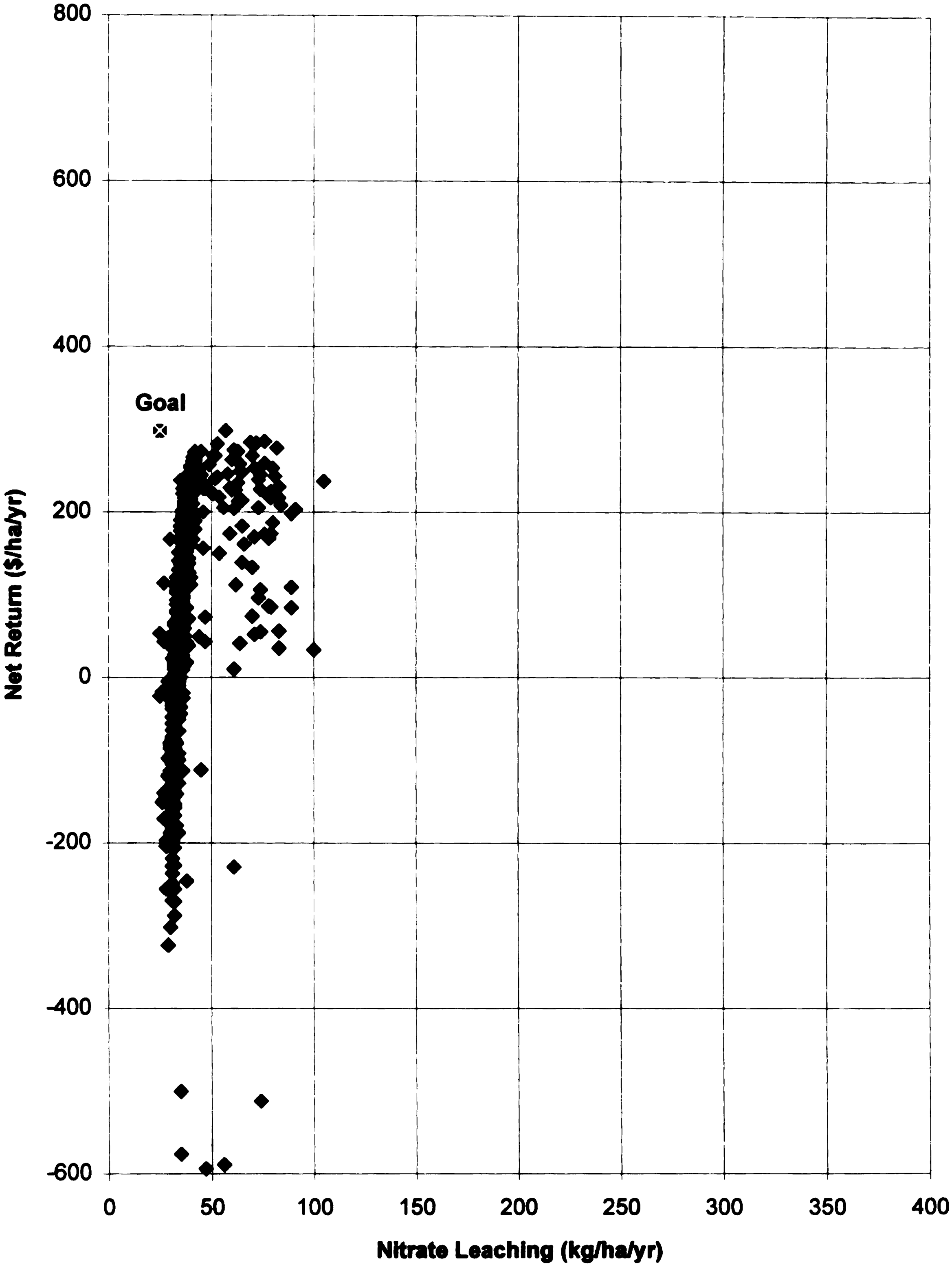

Figure 4-39: Irrigation Uniformity 88 to 90 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

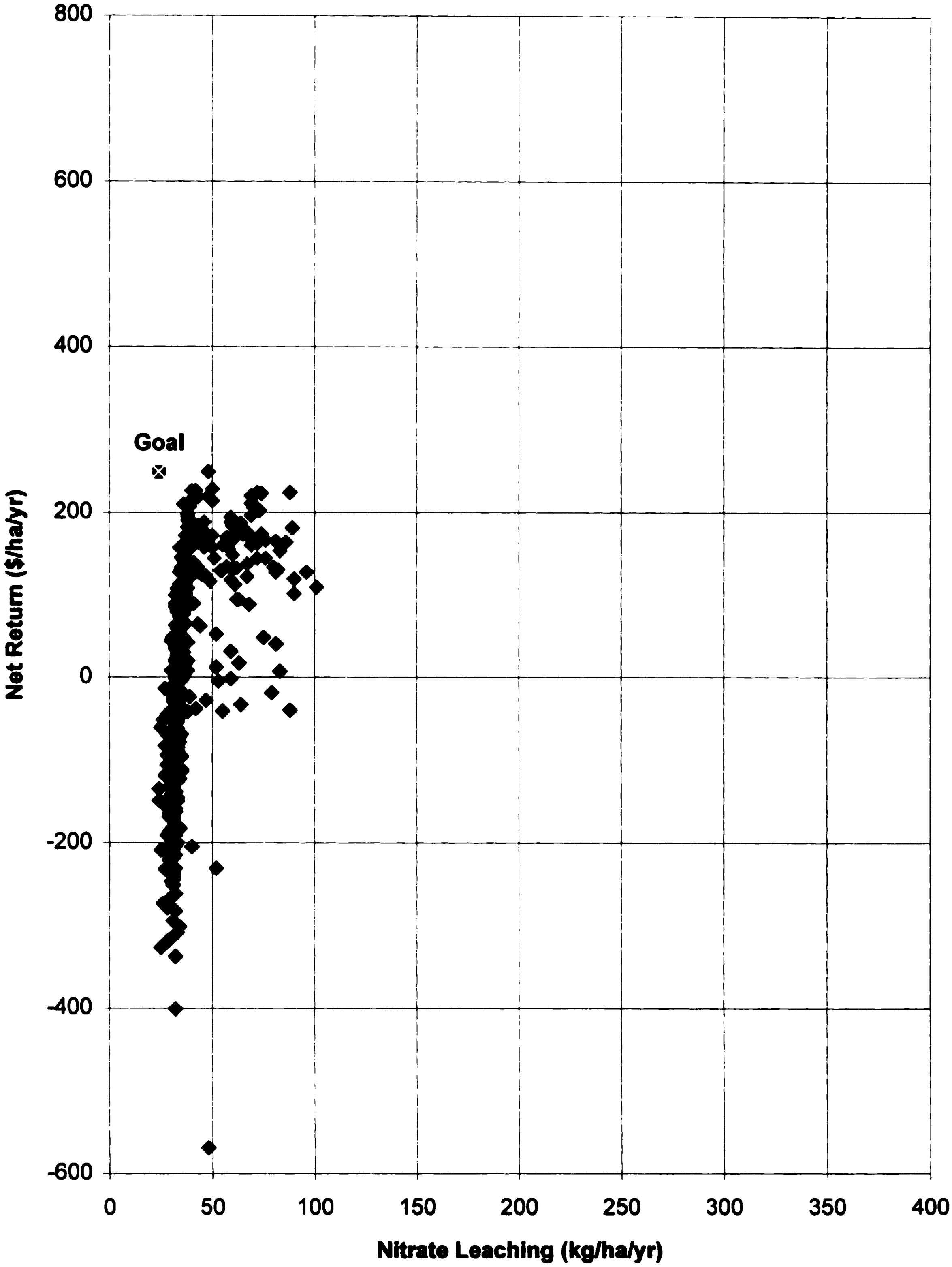

Figure 4-40: Irrigation Uniformity 90 to 92 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Laom, Long Season Cultivar.

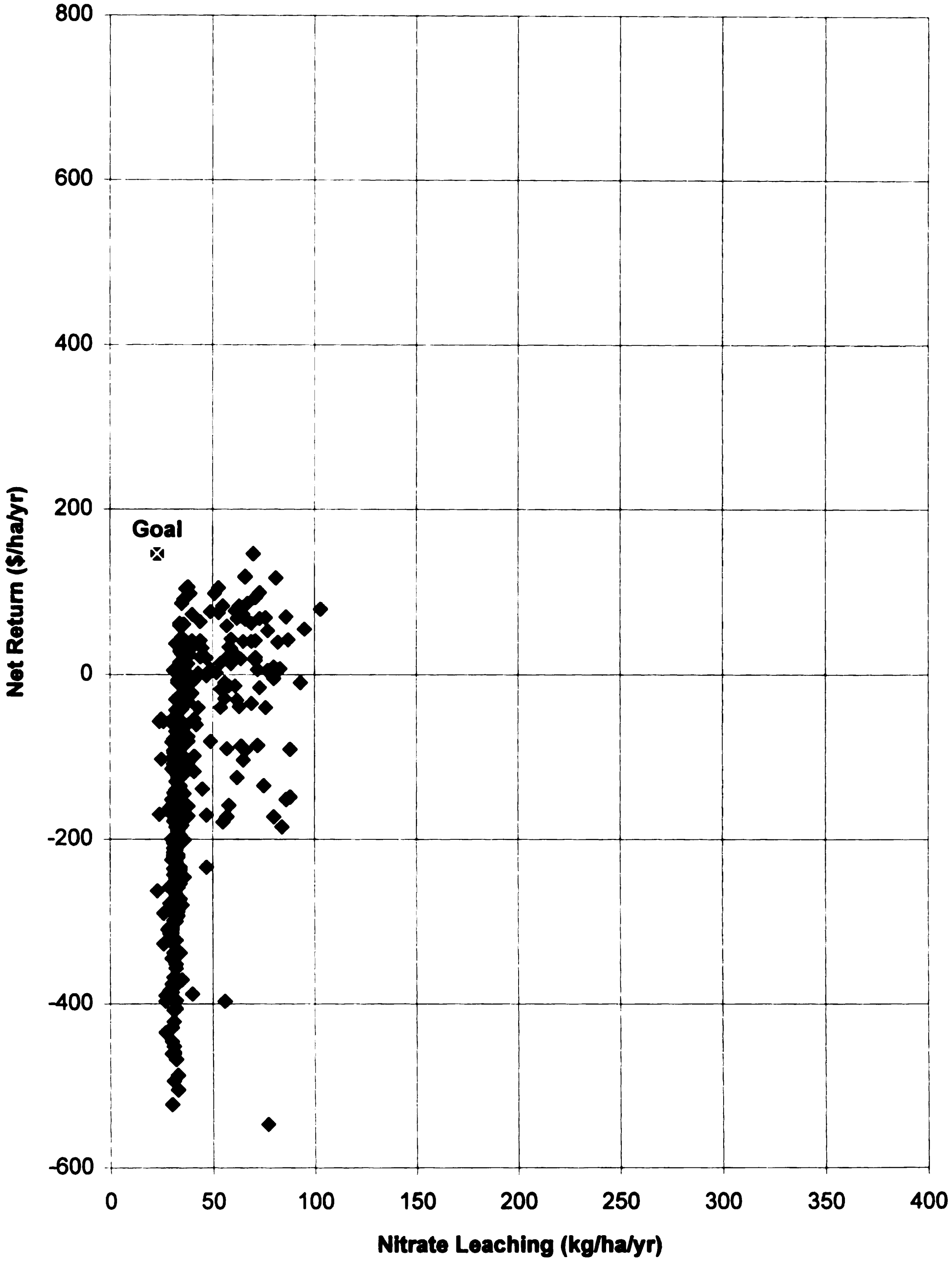

Figure 4-41: Irrigation Uniformity 92 to 94 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

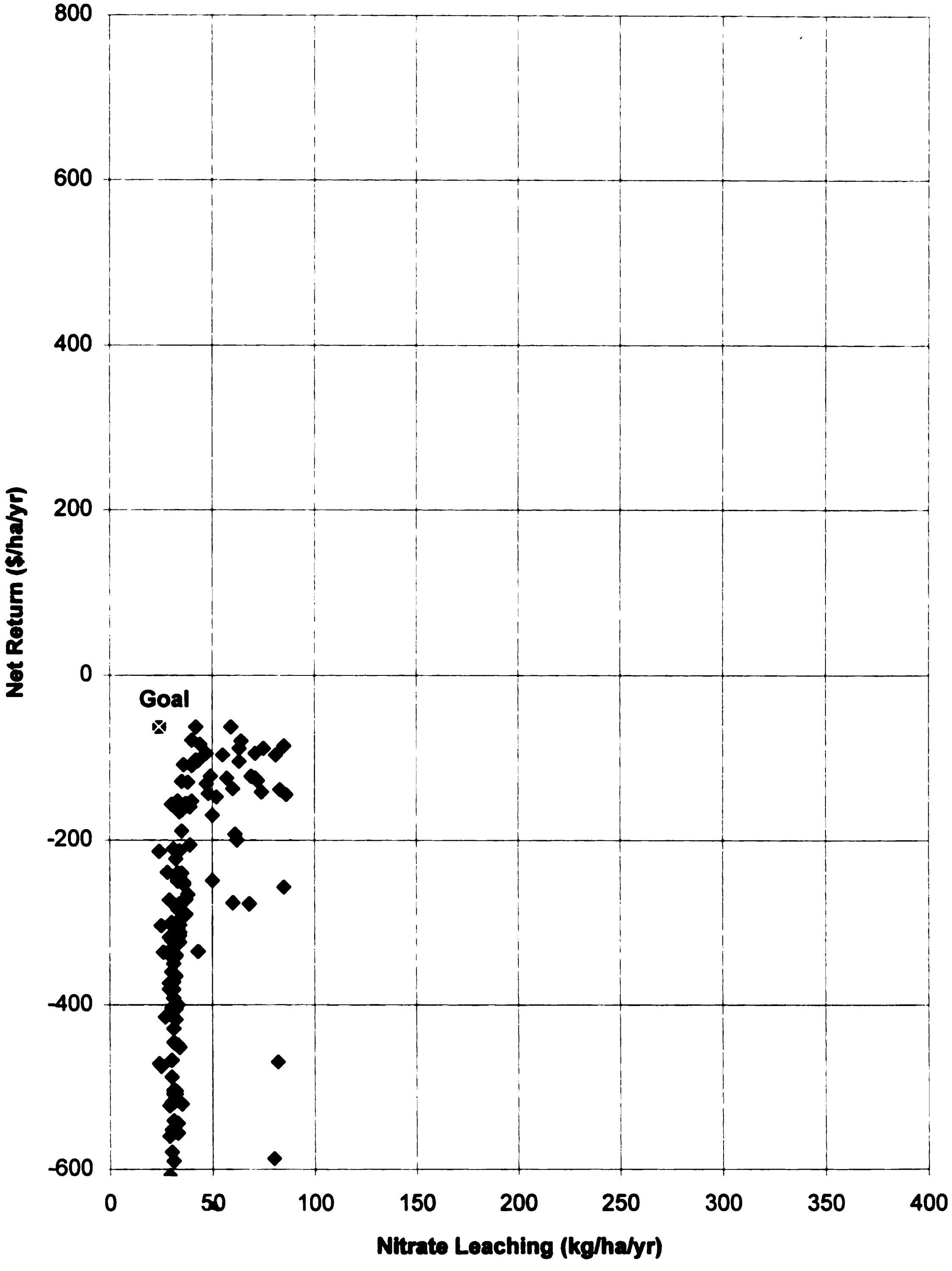

Figure 4-42: Irrigation Uniformity 94 to 95 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

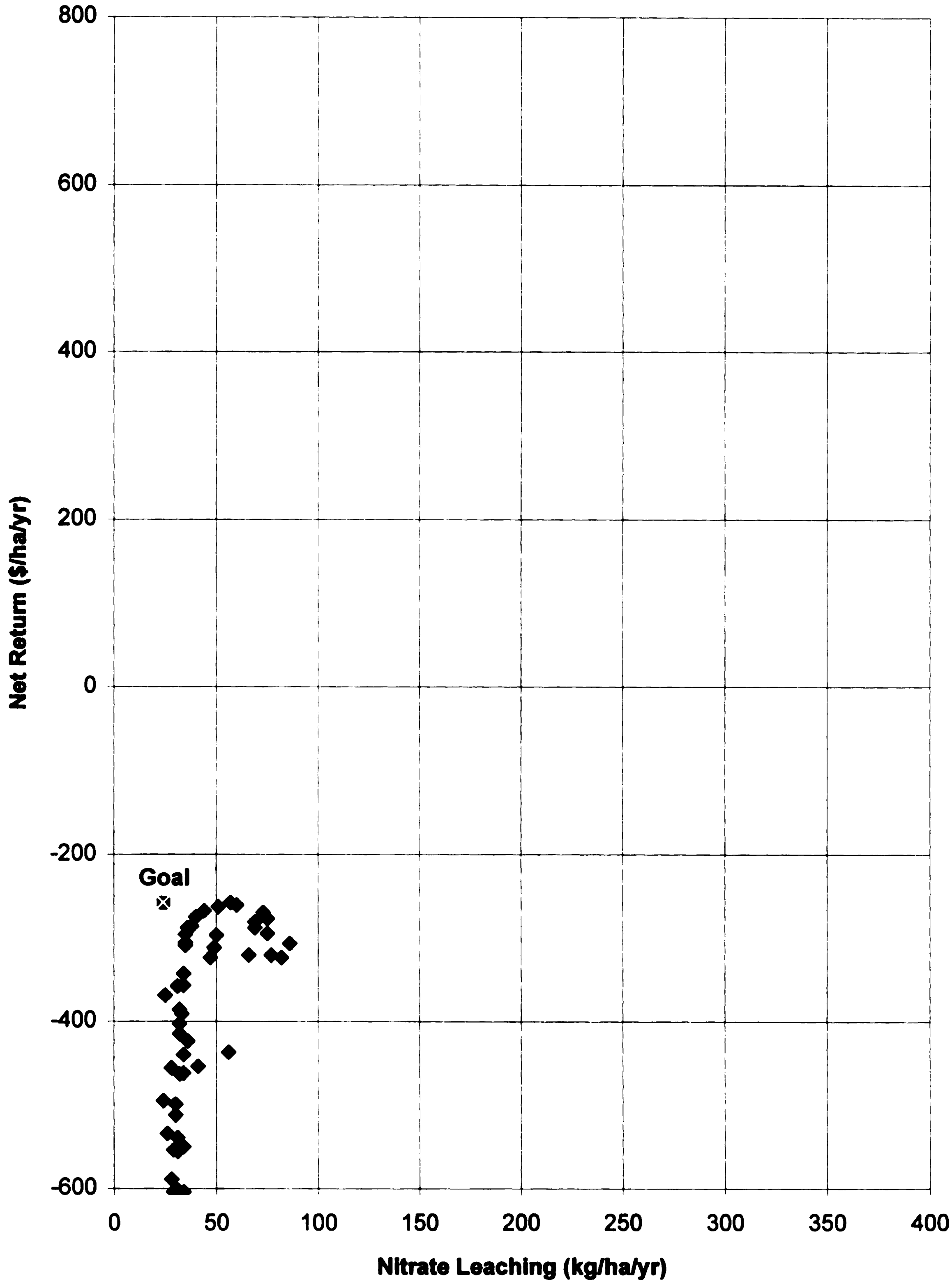

Figure 4-43: Irrigation Uniformity 95 to 96 Percent, Hot-Dry Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

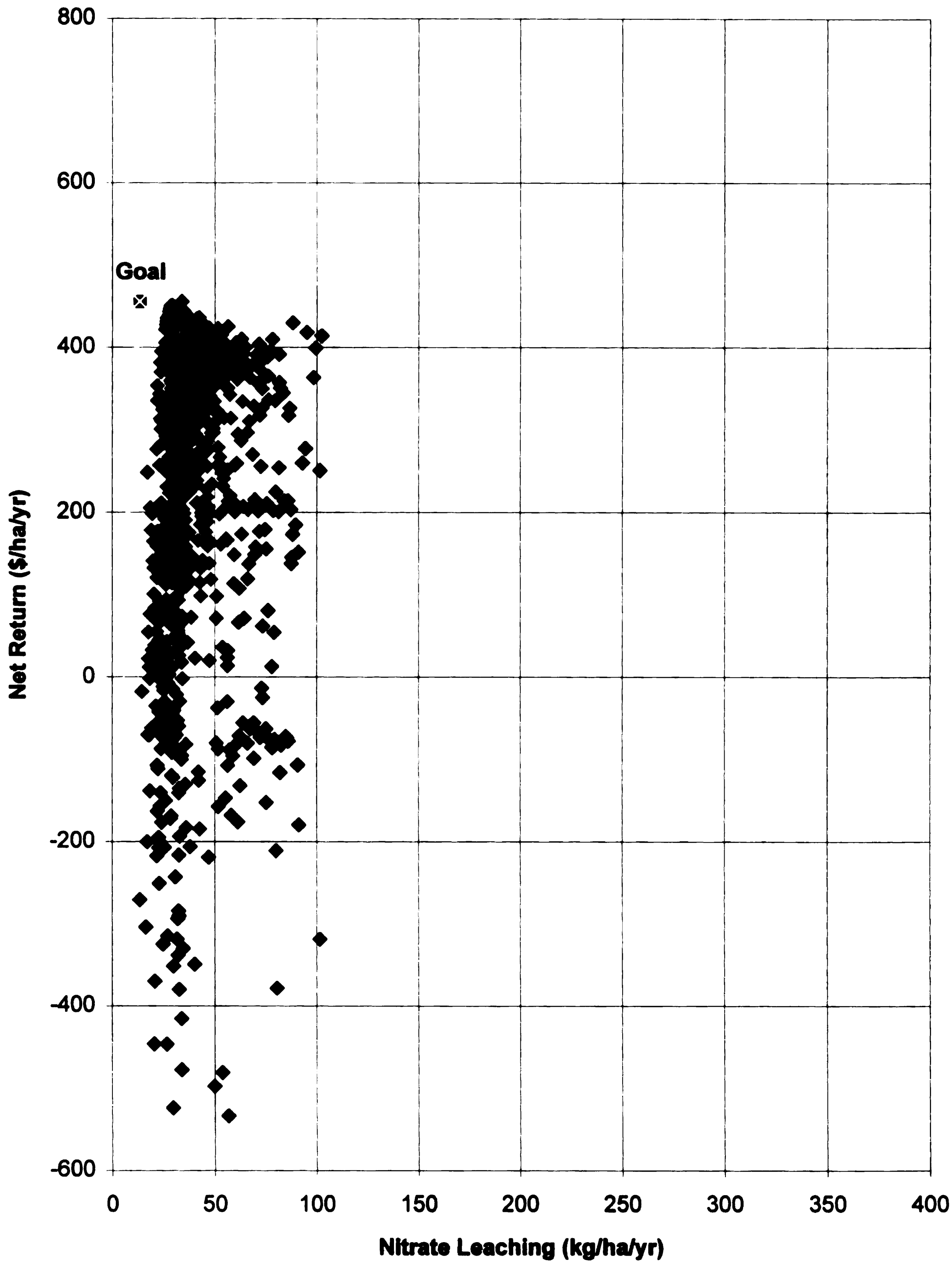

Figure 4-44: Irrigation Uniformity 68 to 96 Percent, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

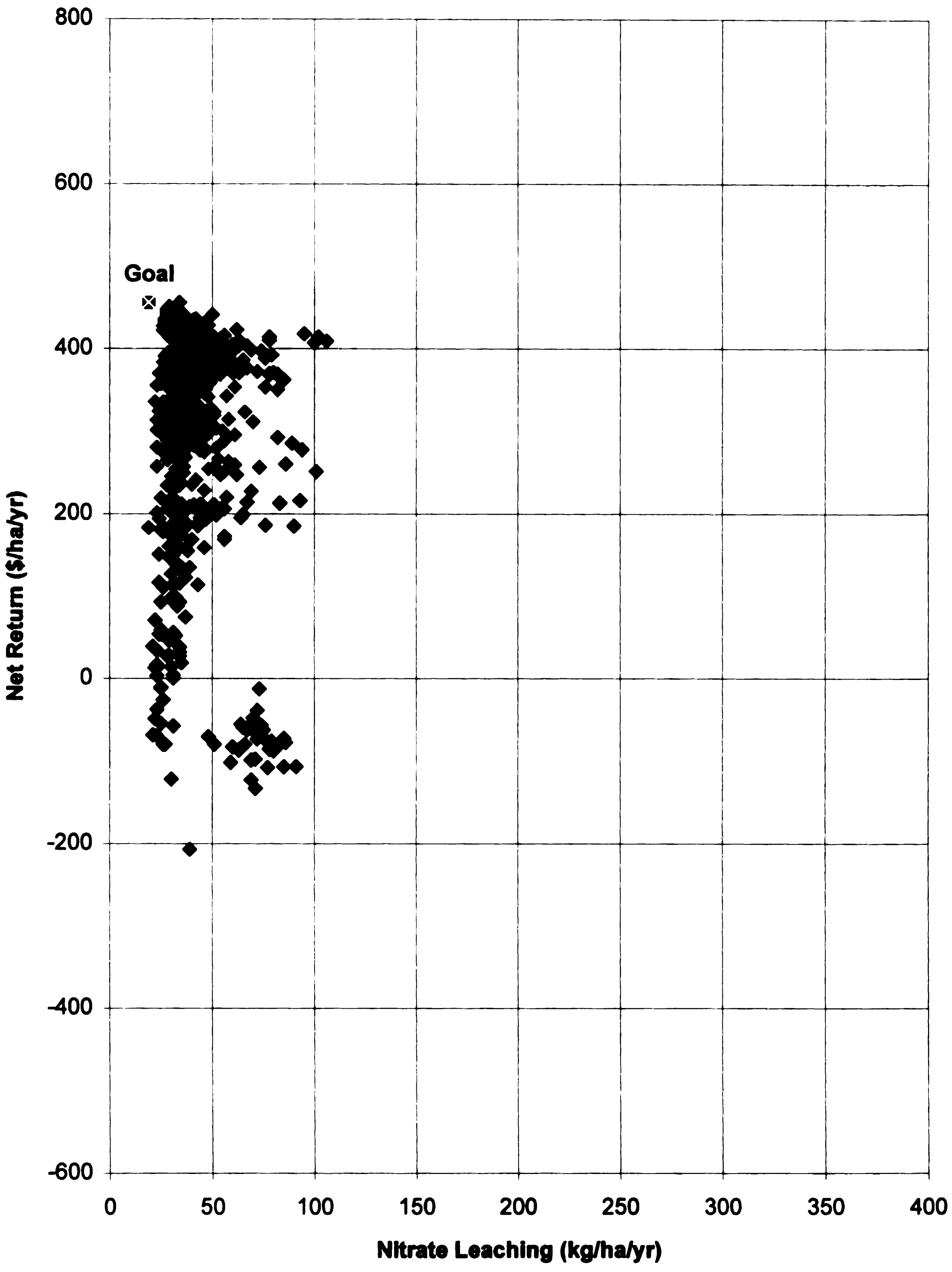

Figure 4-45: Irrigation Uniformity 68 to 72 Percent, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

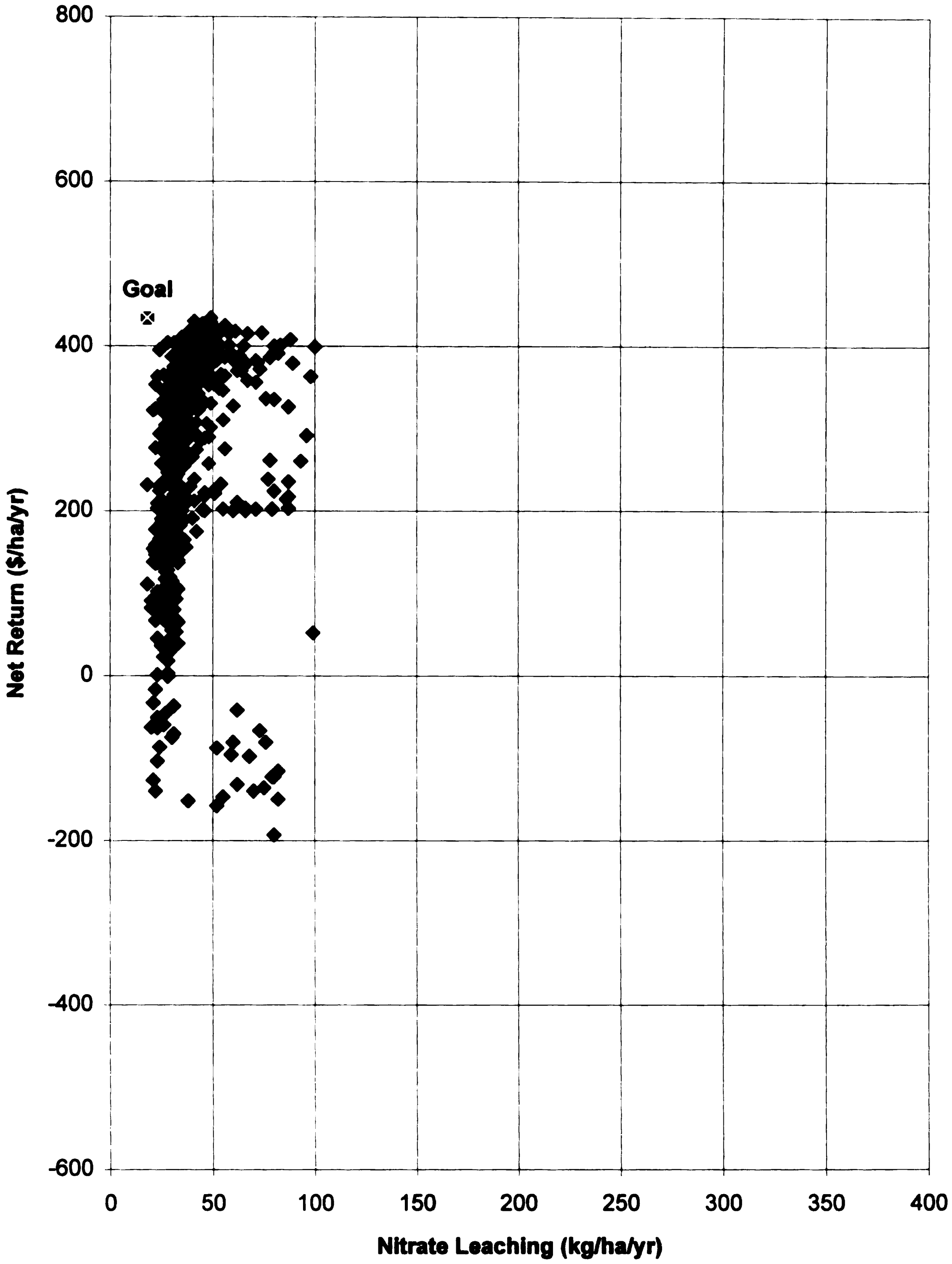

Figure 4-46: Irrigation Uniformity 72 to 76, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

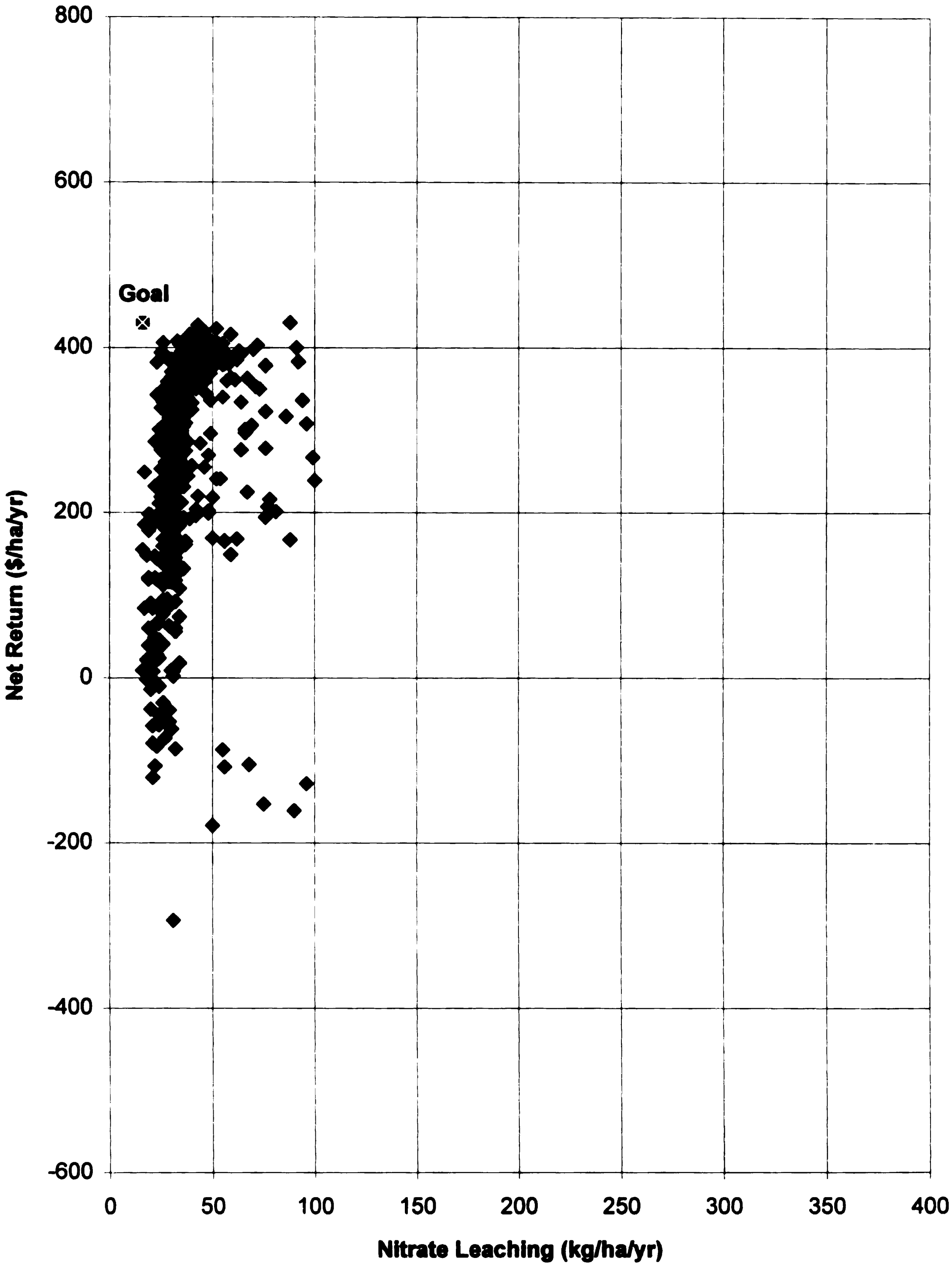

Figure 4-47: Irrigation Uniformity 76 to 80 Percent, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

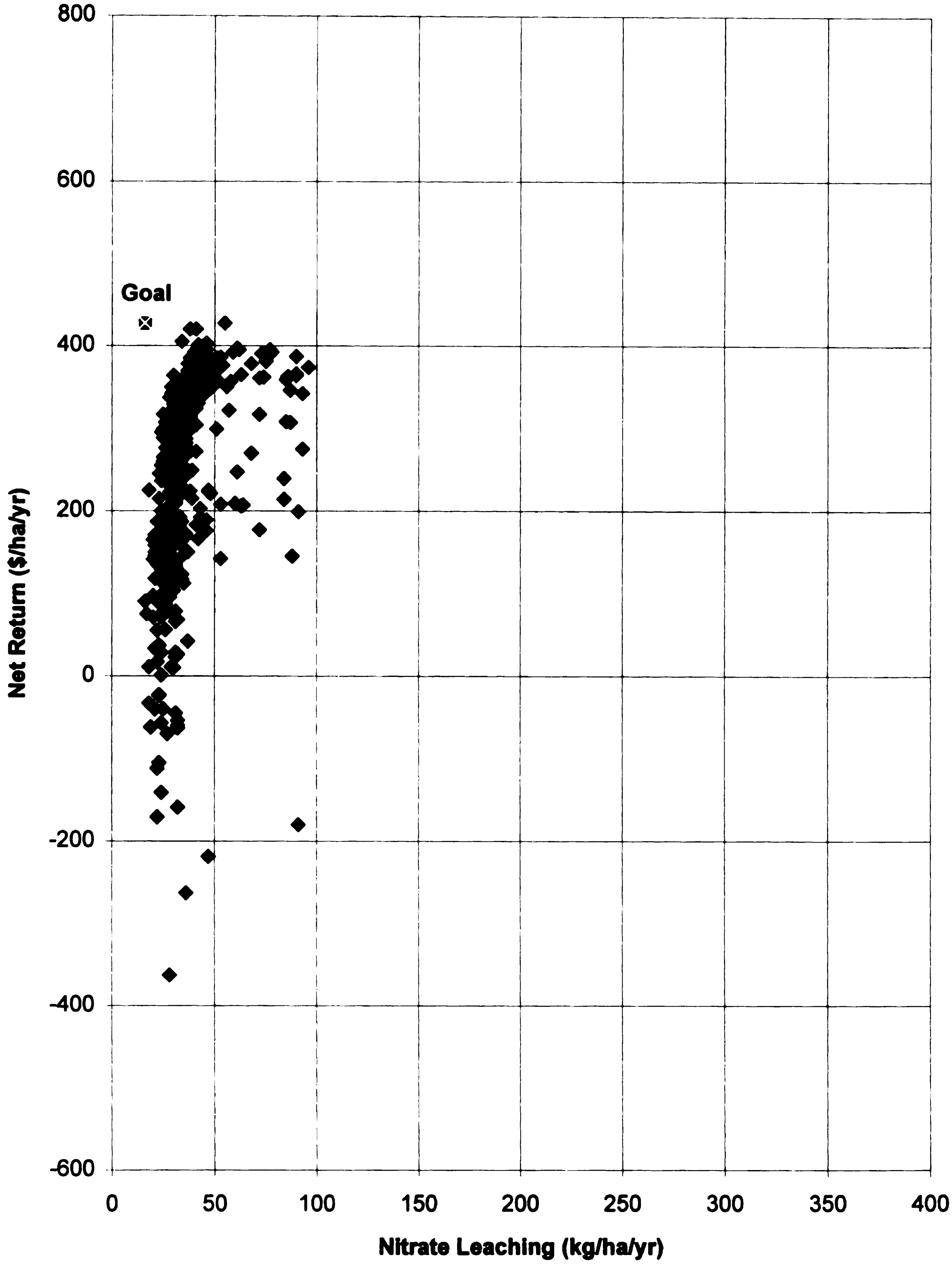

Figure 4-48: Irrigation Uniformity 80 to 84 Percent, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

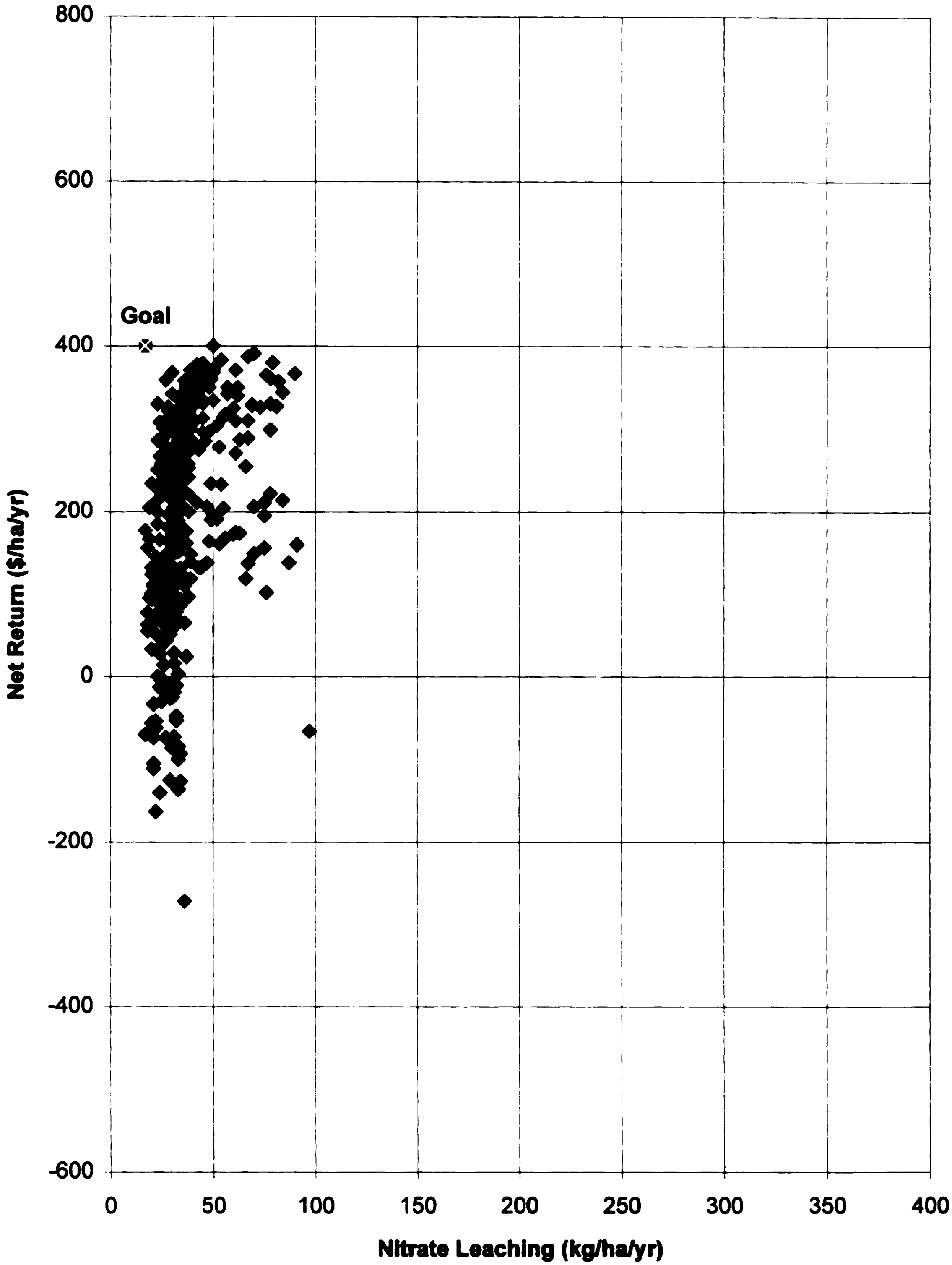

Figure 4-49: Irrigation Uniformity 84 to 88 Percent, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

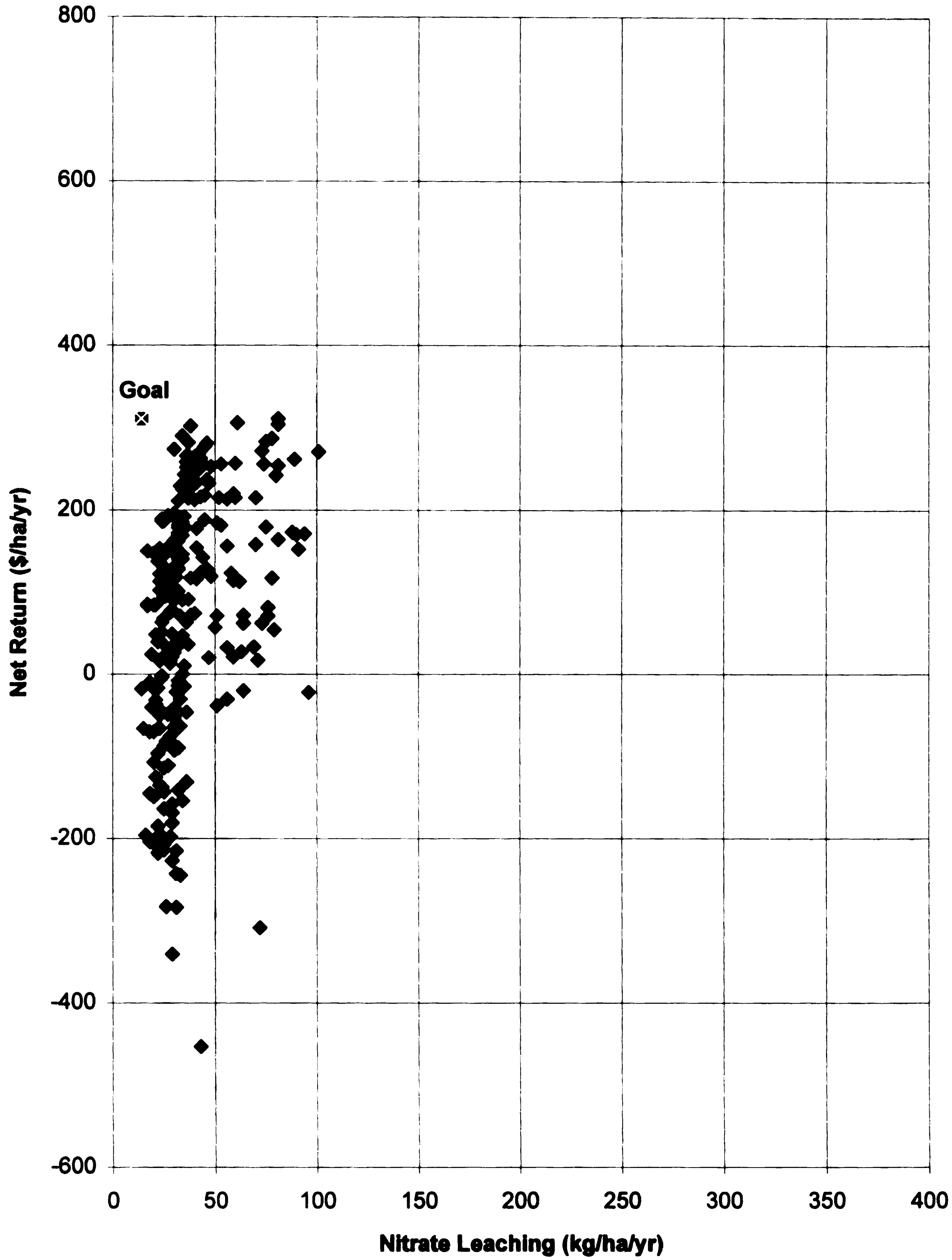

Figure 4-50: Irrigation Uniformity 88 to 92 Percent, Normal Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

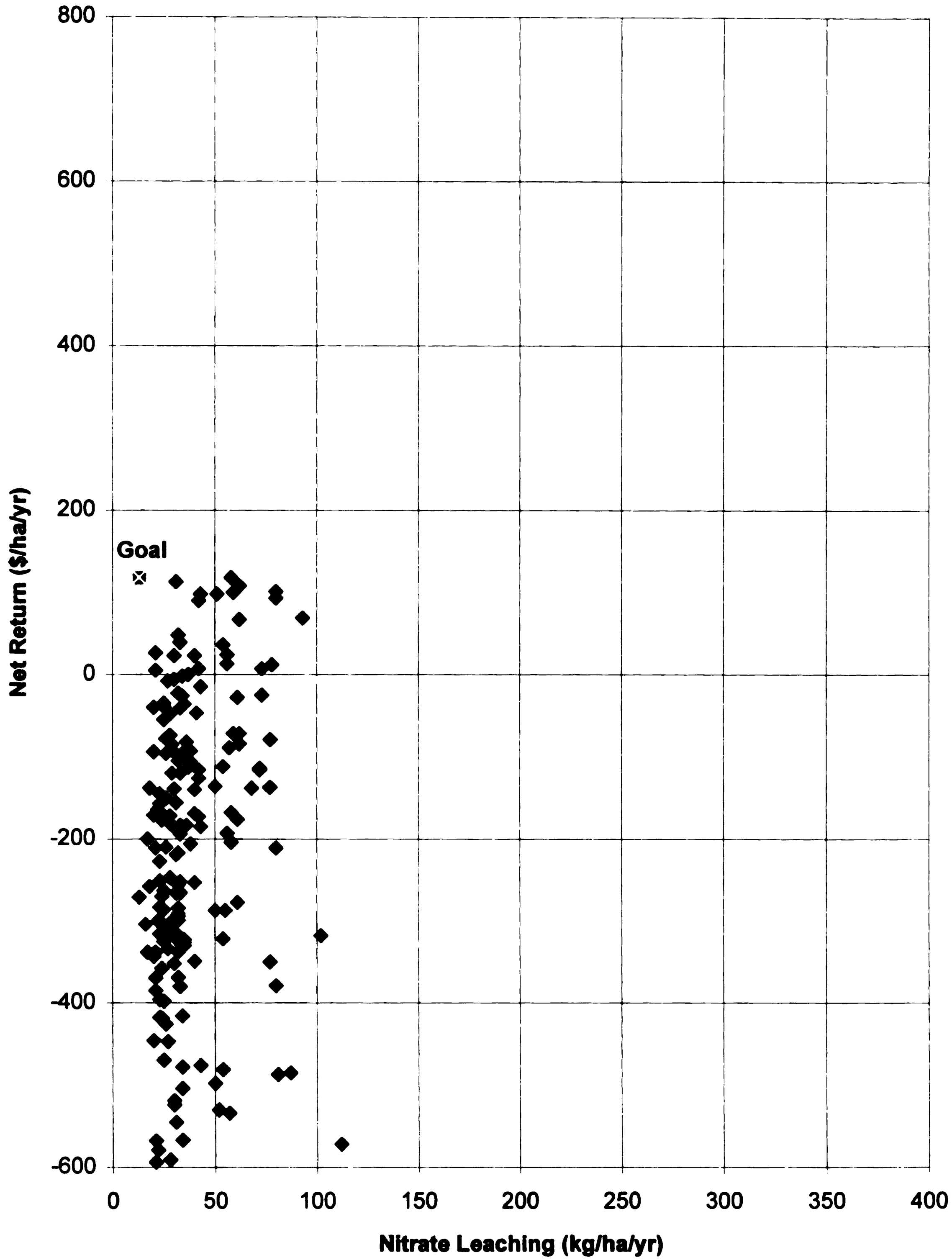

Figure 4-51: Irrigation Uniformity 92 to 96 Percent, Normal Summer and normal Winter, Elston Sandy Loam, Long Season Cultivar.

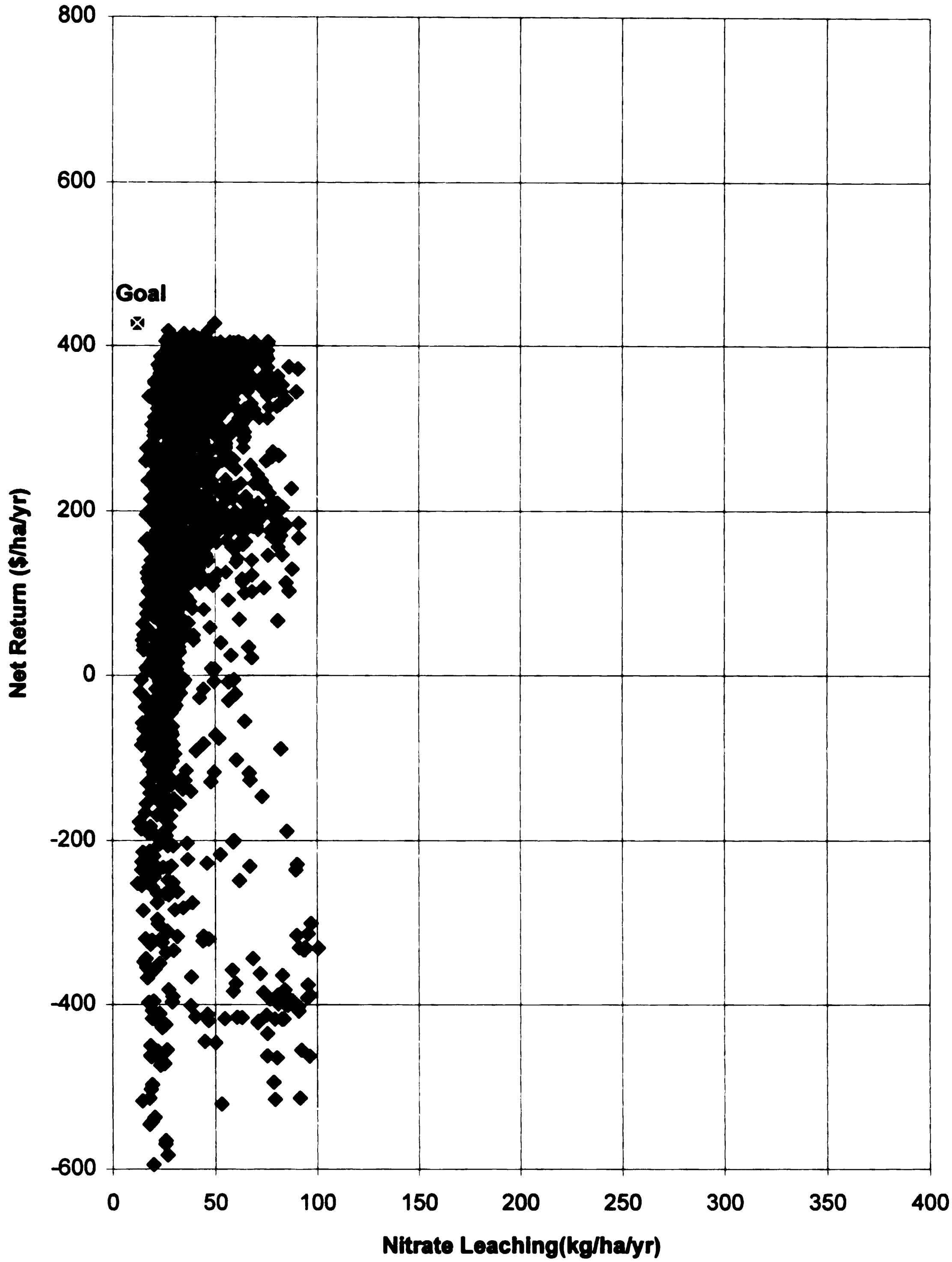

Figure 4-52: Irrigation Uniformity 68 to 96 Percent, Moderate Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

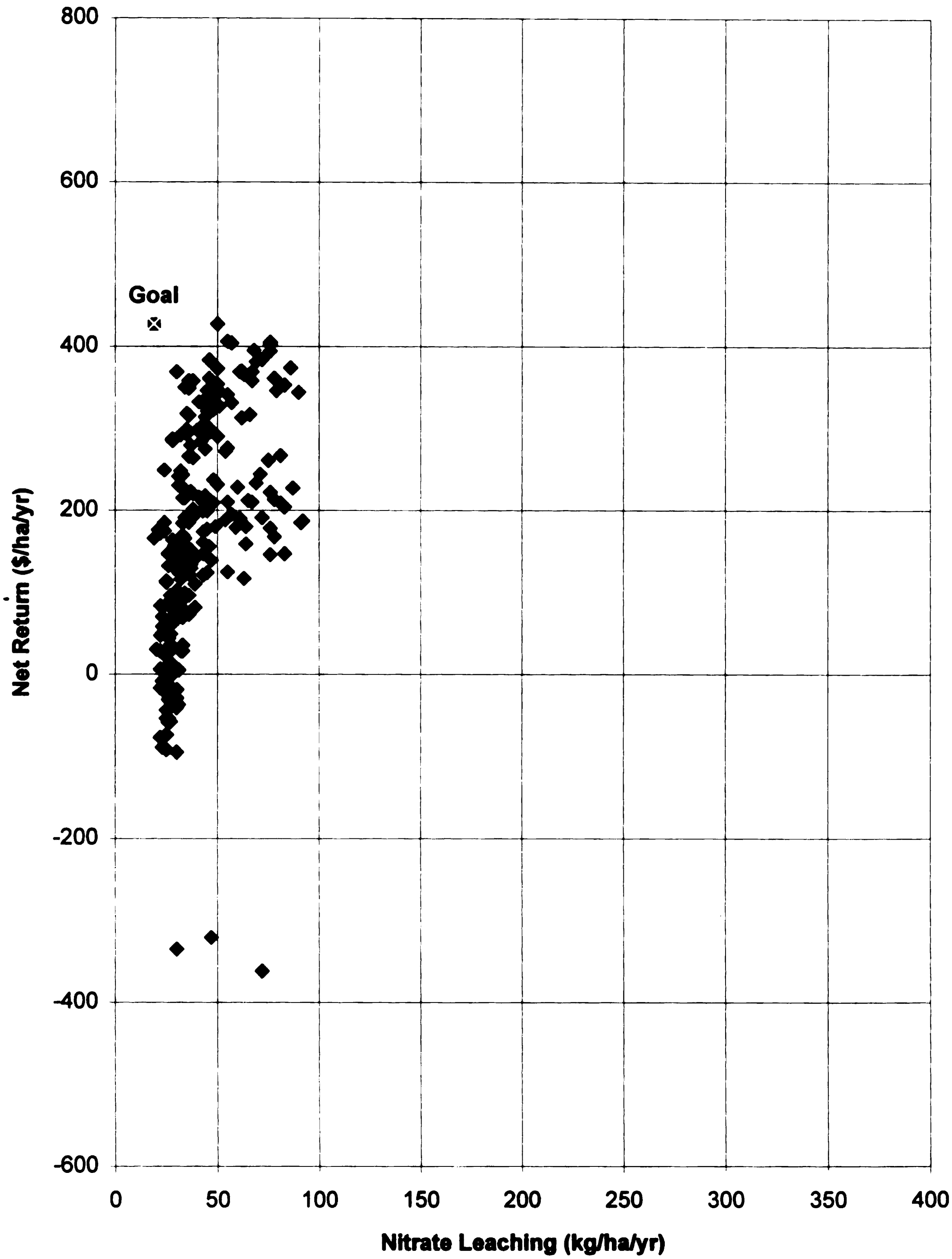

Figure 4-53: Irrigation Uniformity 68 to 72 Percent, Moderate Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

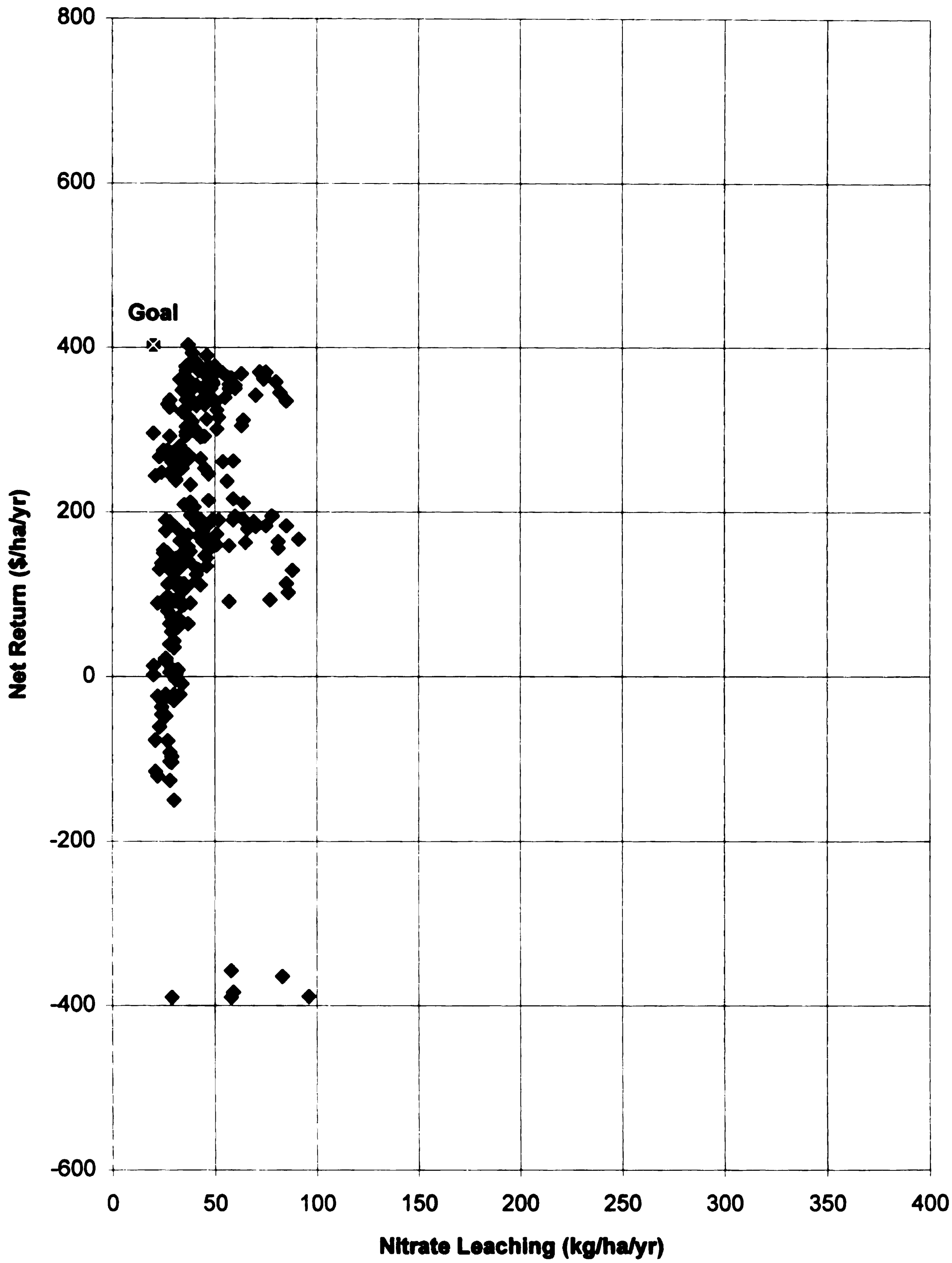

Figure 4-54: Irrigation Uniformity 72 to 76 Percent, Moderate Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

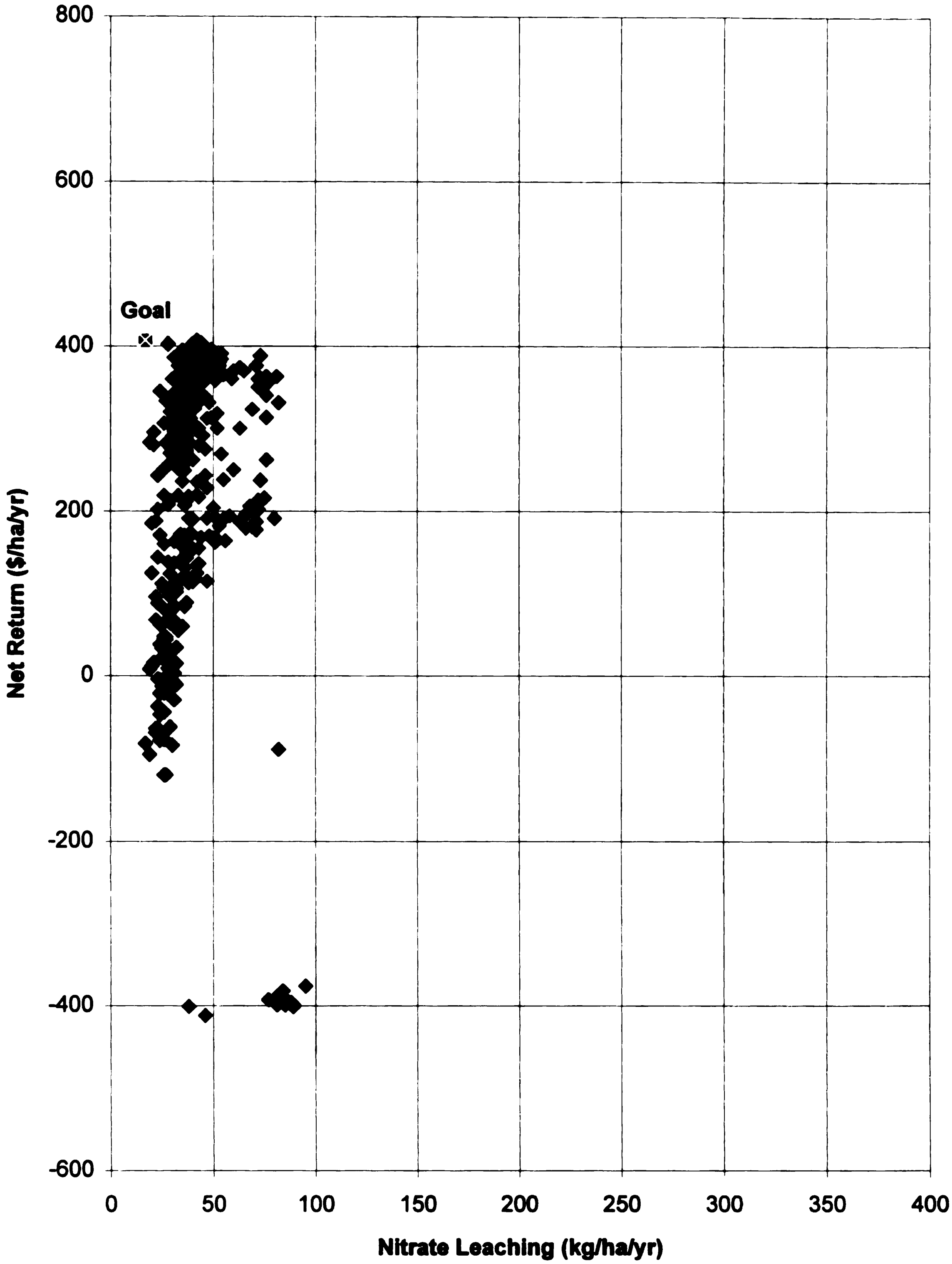

Figure 4-55: Irrigation Uniformity 76 to 80 Percent, Moderate Summer andNormal Winter, Elston Sandy Loam, Long Season Cultivar.

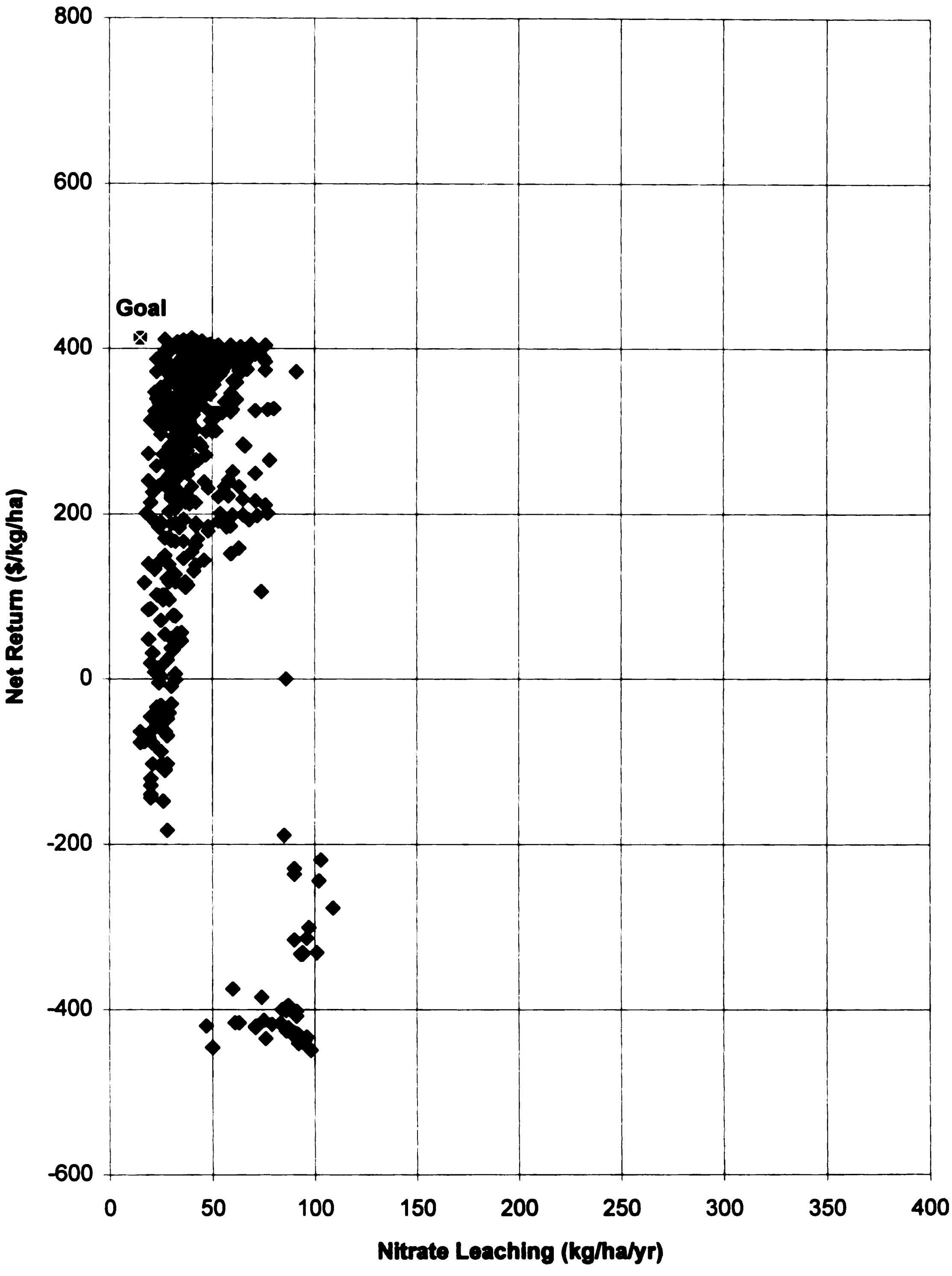

Figure 4-56: Irrigation Uniformity 80 to 84 Percent, Moderate Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

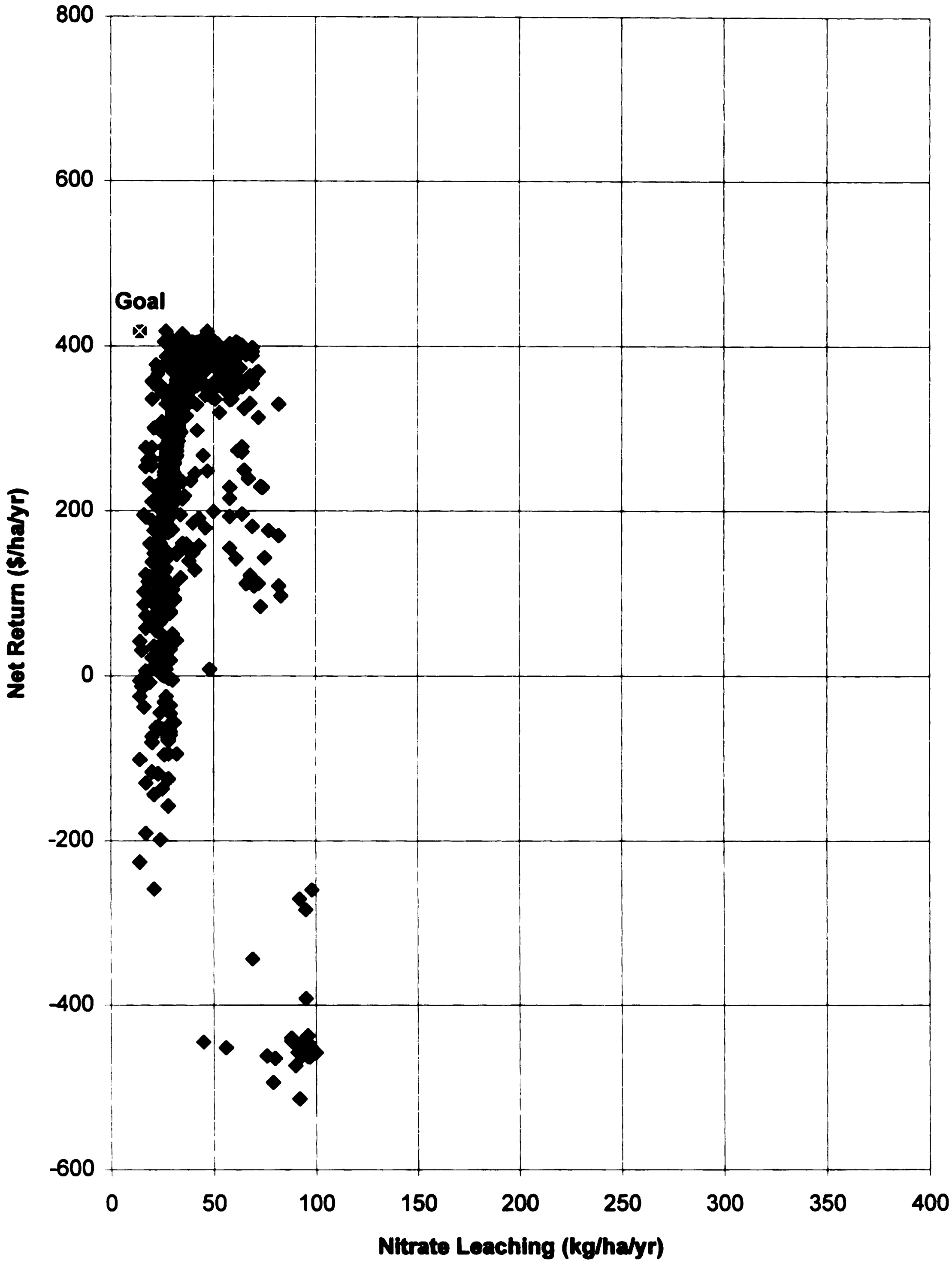

Figure 4-57: Irrigation Uniformity 84 to 88 Percent, Moderate Summer and Normal Winter, Elston Sandy Loam.

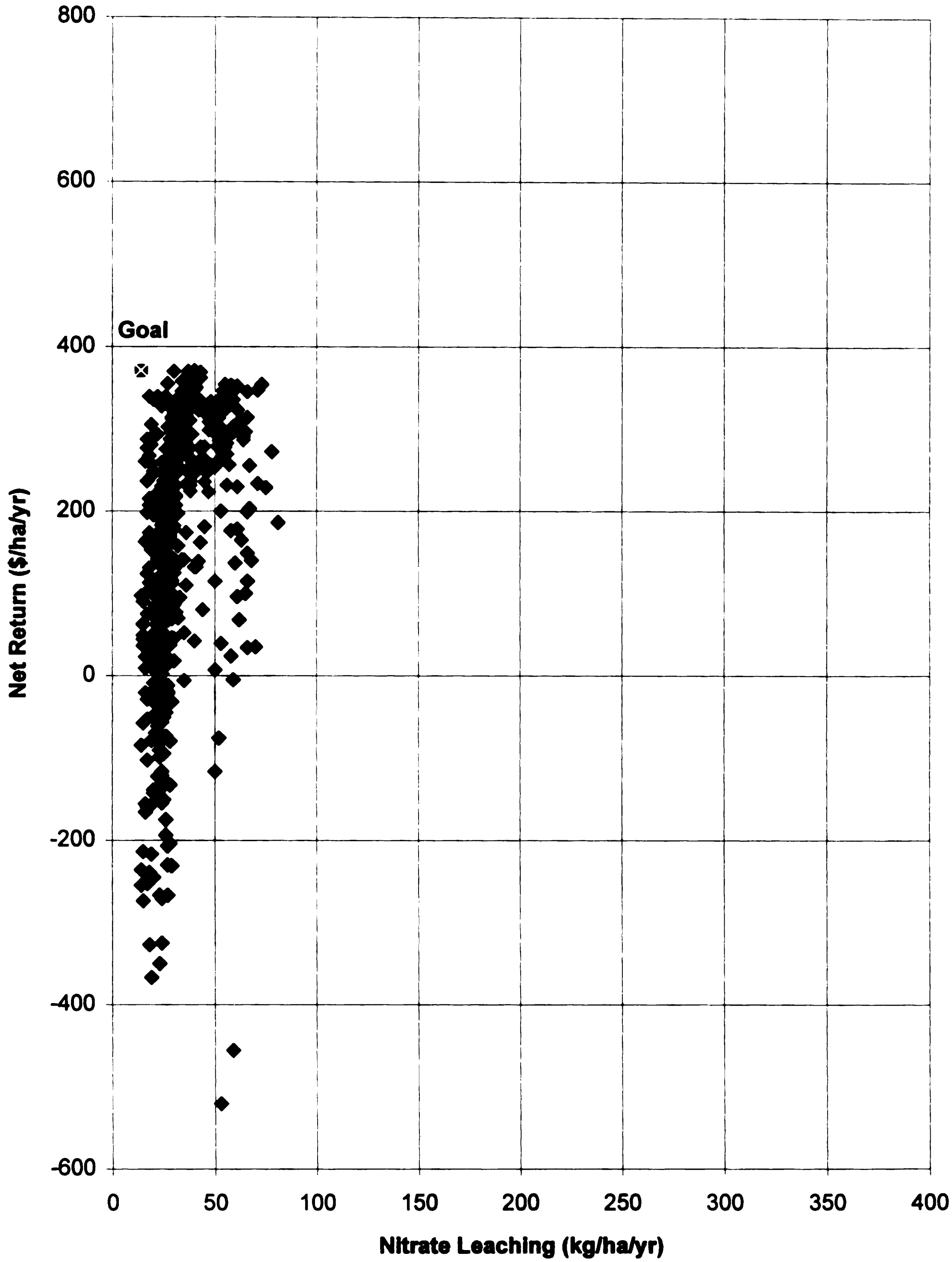

Figure 4-58: Irrigation Uniformity 88 to 92 Percent, Moderate Summer and Normal Winter, Eslton Sandy Loam, Long Season Cultivar.

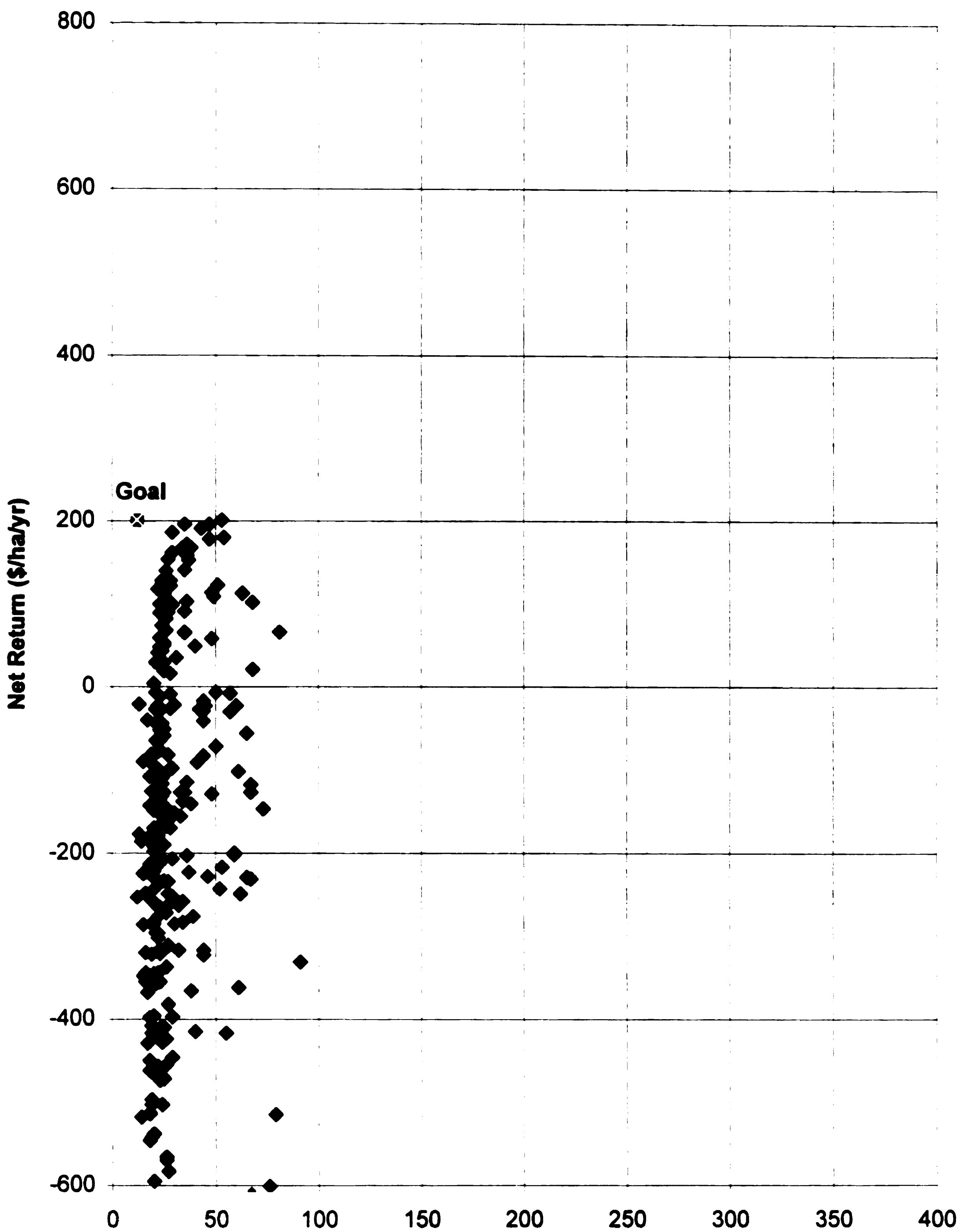

Figure 4-59: Irrigation Uniformity 92 to 96, Moderate Summer and Normal Winter, Elston Sandy Loam, Long Season Cultivar.

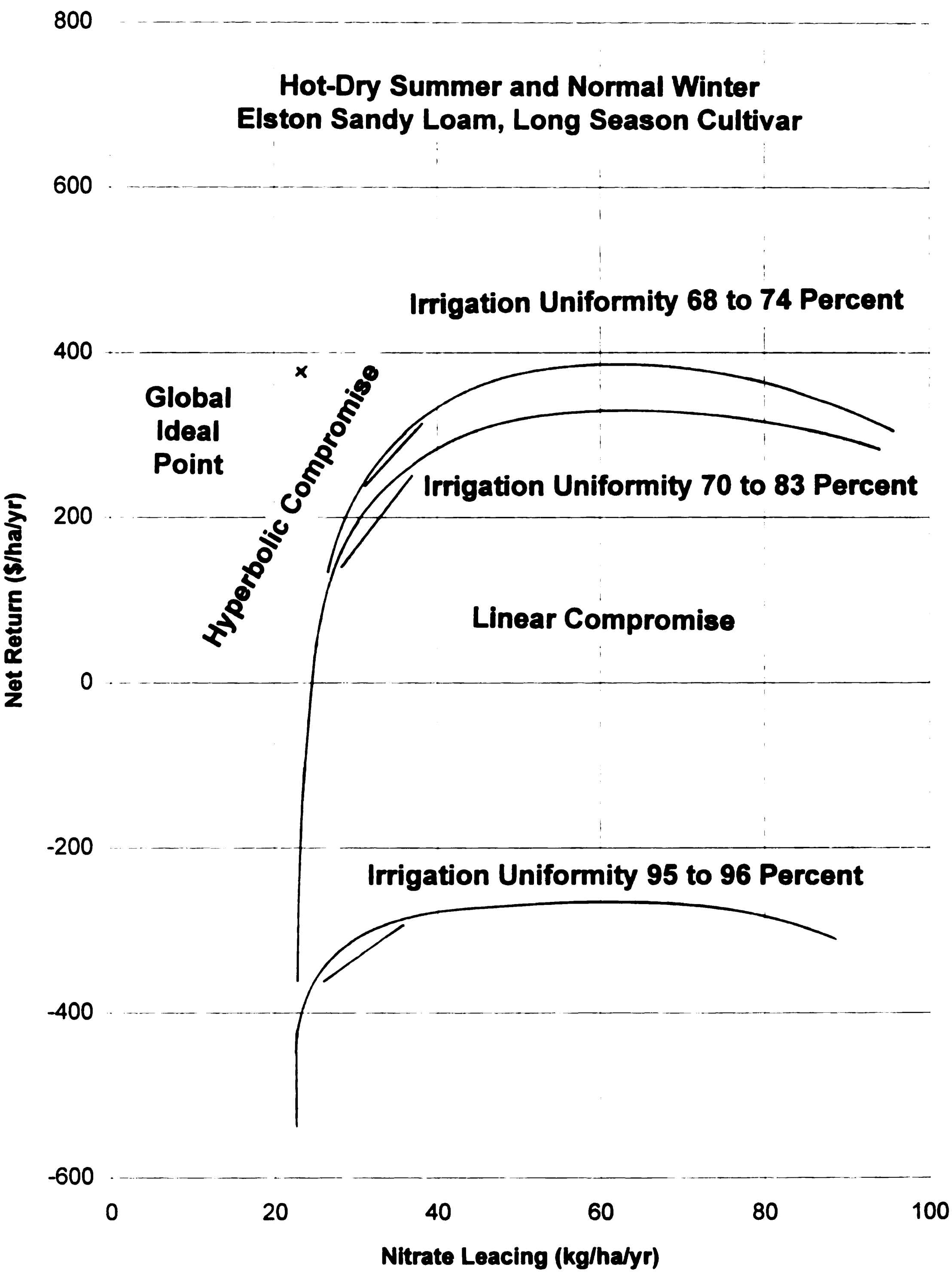

Figure 4-60: Pareto-optimal envelope and position of specific center pivot specifications.

CHAPTER FIVE
DISCUSSSION

"The purpose of computing is insight, not numbers."

R.W. Hamming in Numerical Methods for Scientists and Engineers

The over-arching objective of this research was to define an appropriate quantitative solution procedure for the management of resources and technology according to conflicting and environmentally-conditioned goals regarding a particular biological production system. The grand objective has been met through the accomplishment of the set of five particulars postulated in Chapter One.

Objective One

The first objective of this research, to combine the "best" available simulation models of the various aspects of irrigated maize production into a comprehensive enterprise model that can predict the impact of management alternatives on environmental and economic performance measures, was resolved by: (1) combining AMaize, the animal waste management version of CeresMaize crop-growth model, and the Van Ee field dry-down model, and (2) embedding the combined model within a hierarchical ecological network (a processing network). The combined processing network functioned as a comprehensive enterprise model, giving results that were intuitively correct, with few surprises. The originality in this work is that numerical estimates accompany all results. The inclusion of animal waste and field dry-down in the processing network of the irrigated maize enterprise greatly extends the work by Martin (1992) in that (1) a comprehensive schedule of farming activities and (2) a specification of irrigation technology was produced from the optimization of economic net return and nitrate leaching criteria.

Objective Two

The second objective was to develop procedures for identifying the "best" enterprise organization and time schedule of resources consistent with a given set of yield, economic, and environmental impact targets. To improve convergence to the "best" solution, adaptive goal-seeking capabilities and high-density sampling were appended to multiple-variable sequential-random-search. Whereas traditional sequential-random-search typically makes ten trial solution vectors per variable in a reduction sequence, I have defined "high-density" as making more than twenty such trial solution vectors per search variable.

With this technique, I was able to find the "best" schedule of resources as defined in the multicriteria objective function that was adapted to the local environmental and operating context in parallel with the resource optimization. In order to predict runtime and conserve file space, the *first* result with the *least* deviation from the multiple goals was chosen as the "elite" solution for each succeeding generation of searches within a particular simulation optimization. In case of a tie, the first elite was defined as the "best." It was conceptually possible for an equivalent elite to be discovered during a computer run following the discovery of the first elite; the data files were not stored for succeeding equivalent elites. Multiple equivalent elites, therefore, were not considered within a single simulation; multiple simulations , however, were performed for each set of initial conditions. The "best of the best" for any simulation set was obtained, as well as, the output files for all the best results in the simulation set. Optimizations using different random number sequences approached the performance criteria, but could and did have different resource schedules.

Objective Three

The third objective was to identify from the model the extent to which irrigation could be used to reduce the negative impact of nitrate leaching at an acceptable economic cost. Irrigation played a role in achieving acceptable economic net returns and lessening nitrate leaching for years in which the weather required at least 200 mm of irrigation. The threshold of 200 mm applies to southern Michigan; it is a function of weather, soil, and cultivar.

Irrigation demand depended on length of growing season, temperature, and effective rainfall. Long season cultivars generated great irrigation demand simply as a result of longevity. In moderate temperature-moderate rainfall years, the crop demanded just over 200 mm for the growing season. Any weather year hotter, or dryer would exceed the 200 mm threshold. Only cold-wet, moderate temperature-wet, and cold-moderate rainfall weather years were below the threshold. Significant irrigation was required in six of the nine stereotypical weather years.

A normal temperature-normal rainfall weather year is specific to the climate at a particular location. The normal-normal year was found to be slightly hotter and drier than the moderate-moderate weather year for the Kellogg Biological Station. The normal-normal weather year was derived from the entire set of ninety-nine weather years. Assuming no intermediate- and long-range weather forecasts, the normal-normal weather year was taken to be the best unbiased estimator of forecasted weather, as proposed by Andresen and Stefanski (1991).

For the combination of weather and soils used in this research, irrigation appears to be justified for economic and environmental reasons in sixty-eight percent of the weather years. This corroborates the study by Strommen et al. (1969) who found that drought occurred generally one-third of the time in Michigan. The study by Baten, Eichmeier, and Kidder (1959) found that rainfall was insufficient for four-fifths of the growing seasons in Michigan. High rainfall and/or cold temperatures diminished the ability of irrigation to mitigate nitrate leaching for the remaining thirty-two percent of the years because little, or no irrigation was scheduled.

The technical ability to provide resources at the optimal rate of assimilation by the crop was limited. In terms of mass and energy, the majority of the resources used by the crop were unscheduled (stochastic) from the natural environment. In this context, countermeasures were required to balance the natural availability of stochastic resources with the desired rate of assimilation by the crop. Irrigation was indicated for hot-dry weather and sandy soils. Rather than causing conflict, irrigation achieved balanced production by facilitating efficient management of resources. The conflict arose from pressure to achieve multiple goals simultaneously and from the manageability of resources.

Irrigation mitigated nitrate leaching by guaranteeing the achievement of crop growth. Irrigation compensated for water shortages up to the availability of other resources. Less rain and more evapotranspiration created a greater role for irrigation in this regard. For example, if the cropping plan had been based on a normal-normal year, normal irrigation amounts would have been 250 mm for the growing season on the Elston soil. The nitrogen requirement would have been on the order of 150 kg/ha. If a prolonged drought ensued, the crop would lack another 250 mm. The drought would produce disastrous yields, down from 11,000 kg/ha to 5000 kg/ha. Nitrate leaching would build from 30 kg/ha to 100 kg/ha. If on the other-hand, the weather year became cold and wet, little or no irrigation would occur. An irrigation of 250 mm was beyond that needed to achieve the best growth for the cold-wet year. Because irrigation could be reduced, leaching was limited to 50 kg/ha/yr. Therefore, where irrigation is needed for supporting crop growth, it can also serve to improve the efficient use of other resources.

Objective Four

The fourth objective was to articulate trade-offs between economic return and environmental damage. The multiplicity of acceptable solutions resulted from the convex solution space and a simple multicriteria objective function. The optimization of the objective function could not distinguish among several solutions near the goal vertex for a convex solution space. Solutions at the boundary of the solution space exhibited a trade-off among irrigation schedules, fertilizer schedules, and other field operations. The trade-offs among points nearest to the goal were usually marginal; the solutions differed, none-the-less.

The only remaining source for the differences in solutions from separate optimizations lay in the sequence of random numbers used in the optimization. Differences in random values used to generate trial design vectors appeared to interact with the weather file. In the course of developing the optimization procedure, I found that the random number generators *had to be reseeded* to avoid a false sense of convergence with optimizations of this size. The random number generator was reseeded for search generation during the optimization. It should be noted that some random number generators *are not truly random* for long numerical sequences.

The effect of the random number sequence sometimes resulted in a subtle shift in planting and irrigation dates. Shifting the planting and irrigation dates altered subsequent fertilization and irrigation amounts subtly, but in concert. The result was a multiplicity of acceptable solutions in the neighborhood of the goal. That multiple acceptable answers exist is beneficial to management in that it provides options. Given no additional performance criteria, any acceptable answer will work. In actuality, management may have preferences that cannot be known *a priori*. In the day to day management of a farming enterprise, activities peripheral to the enterprise bring surprises. Between the time when data are collected for the optimization and when the results of the optimization are completed, preferences may develop that were unforeseen.

Considering the whole of the Pareto optimal frontier, an increase in productivity defined purely as crop yield or economic net return came at the expense of the environment. The trade-off between increased production and nitrate leaching became more pronounced as resources shifted. See Figure 4-60.

The highest net returns occurred in the cold-wet year ($650) for which irrigation was minimal (100mm) and leaching was substantial (50kg). The lowest net returns occurred in the hot-dry year ($550) for which irrigation was greatest (450mm) leaching was lowest for crop production (10kg). See Figure 4-30.

Indeed, a trade-off between nitrate leaching and net return was found to exist for the 40 cases studied (10 weather scenarios, two soil types, and two annual weather regimes). For any case, the Pareto optimal frontier appeared to be contained within a hyperbola (signifying a nonlinear trade-off for relatively large ranges) which pointed towards the ideal goal point. The feasible set, however, did not extend to the hyperbolic boundary along the portion nearest the goal; but rather, the feasible points were held back along an apparent straight line (indicating a linear trade-off for a small range nearest the goal) which truncated the nose of the hyperbola. The trade-off was least for the hot-dry year and became progressively greater toward the cold-wet year, indicating a benefit from irrigation. Figures 4-31 to 4-34 show that this pattern was repeated over several optimizations. Figures 4-6 to 4-29 show that each combination of weather, soil, and cultivar have a characteristic shape for selected irrigation technology. Figures 4-35 to 4-60 show that the shapes maintain as technology and environment were changed. The graphs of different irrigation technologies resided at distinguishable locations along the Pareto envelope. This is summarized in Figure 4-60.

The (1) the envelope, or boundaries, of the feasible space for the system and the (2) necessary system accomplishment (system performance) provided the basis for achieving a reasonable compromise. As for the boundaries of the feasible space, the phase diagrams for the various weather stereotypes describe what is possible over a range of weather. For the range of possible conditions, the "best" that can be achieved is bounded by the envelope of feasible solutions, a performance envelope. The hot-dry and cold-wet weather years describe extreme conditions. The phase diagrams of the hot-dry and cold-wet years describe performance envelopes for the irrigated maize production system.

The minimum necessary accomplishment must exist within the system feasible space, otherwise acceptable system performance is not possible. Reference thresholds need to be established. For example, the nitrogen cycle is one of the many biochemical cycles which occur in any ecosystem. Wild or managed, some nitrates leach to groundwater in non-agricultural ecosystems.

The question of an acceptable level of nitrates in groundwater for any location was arbitrated by the allowable level of nitrates among all linked locations in the ensemble system. The simulations of all the cases demonstrated that a level for nitrate leaching in the neighborhood of 40 kg per/ha/yr allowed profits to approach the maximum regardless of the weather and cultivar. The model thus seems to explain farmers' observed propensity to fertilize heavily; the dominant strategy for profitability considering the range of possible weather regimes is to apply excess nitrogen.

Different soils indicated different resource schedules; however, irrigation, if warranted, diminished the differences. High frequency irrigation (less than six mm/day) does not leach nitrate. Topping-up to field capacity before a rain could trigger the movement of nitrate. Through parameter estimation and based on the weather forecast, the reserve soil capacity for rain was calculated in the model.

Objective Five

The fifth objective was to quantify the economic and environmental impacts of using animal waste as the major nitrogen and phosphorous source for irrigated maize production. Based on average values from several sources, I formulated a "generic" recipe for cattle manure. The yield and leaching were similar for applied manure and ammonium nitrate. If the manure were not incorporated, volatilization of ammonia accounted for a significant loss of nitrogen. Compensating for the volatilization loss by increasing the manure application caused additional phosphorus to be applied, upsetting the phosphorus balance with the grain yield. Either manure or chemical fertilizer applied well-in-advance of planting, created a situation with excessive nitrate leaching. Nitrate carried over from the previous cropping season posed a similar risk. The model showed, however, that in actual practice much of the carry-over nitrate would have already leached below the rootzone.

In essence, early season soil fertility along with preplant manure applications and preplant chemical fertilizer must be considered in ensemble to manage nitrate leaching. From the soil chemistry in the model, nitrate is nitrate, the source had no particular significance. Parenthetically, snow effects are included in AMaize, although soil freezing and thawing are not. CeresMaize does not include snow or soil freezing effects. The annual accumulation of nitrate leaching calculated in CeresMaize agrees with lysimeter studies (Martin, 1992) although the timing of leaching events differs through the winter months.

Side-dressing of nitrogen in make-up amounts rarely contributed to leaching. Nitrate leaching was least with long season cultivars. Long season cultivars consumed more nutrient and water resources which would be desirable when disposing of animal waste. Net return, however, was greatest with a cultivar adapted to the specific growing season. A best-management schedule within operational constraints was possible with manure slurry used as a nutrient source. Two special considerations for using manure are the minimizing of volatilization and runoff.

PROOF OF THE HYPOTHESIS

The proof of the hypothesis is based on a comprehensive model of a temperate-climate-irrigated-maize-production-enterprise system that is controllable and measurable. The results of the multicriteria optimization demonstrate that irrigation can be managed to lessen the impact of nitrate leaching to the environment as well as contribute to a positive economic net return. Irrigation was observed to lessen the impact of nitrate leaching about sixty-eight percent of the time; for the remaining thirty-two percent of the time, rainfall and/or cold weather obviated irrigation and thus reduced its controlling influence on leaching.

In the wet years, irrigation helped little to boost yields. In dry years, irrigation guaranteed a good crop yield. The basic cost of a complete center-pivot irrigation system with water well and pump is about 200 $/ha/yr (80 $/ac/yr). The cost of pumping could be as much as 100 $/ha/yr (40 $/ac/yr). Whether the cost of irrigation (300 $/ha/yr) can be justified depends on the market for corn. A grain price of 0.10 $/kg (about 2.50 $/bu) was used in this research. For farmers growing corn in southern Michigan, the decision to install irrigation appears to be based on the cropping plan for the entire farm, rather than cash-corn production alone. This study proceeded from the assumption that irrigation was justified *a priori*.

The context in which management operates ultimately determines if irrigation will be effective in a dual role. The context depends greatly on the natural resources of weather and soils. The sandy-loam soils used in this research have low water holding capacities, are free draining, and thus are prone to leaching. The management of sandy-loams under multiple criteria appears to be difficult, if not impossible, without employing an irrigation scheduling methodology which takes the multiple criteria into account.

In the cold-wet weather regime, irrigation has little or no practical role to play in management of net return and nitrate leaching. When exposed to the hot-dry regime, irrigation made crop production viable, and, by guaranteeing that a crop was produced, prevented off-season leaching which would have occurred from crop failure. The ability of irrigation technology to ensure that goals were achieved for high net return and low nitrate leaching varied with the operating context.

The challenge for management is to determine the future operating context with lead time sufficient to enhance the effectiveness of irrigation. What is true for irrigation technology is also true for the other technologies on which management depends. Crop nutrition, crop protection, crop genetics, and crop harvesting technologies likewise benefit from the ability to predict the operating context. Agricultural technologies are co-dependent on forecasts of the state of the natural environment. As demands on an agricultural biosystem (such as irrigated maize production in temperate climates) become more stringent, the performance of multiple technologies become "inter-dependent" as the management tries to extract the "best possible" performance from the operating context.

The results of the optimizations of the comprehensive model have revealed all this, thus proving the hypothesis. Incidental findings to the foregoing observations are given in Appendix E. A listing of topics for future research is given in Appendix F.

REVELATIONS FROM THE SECOND SERIES OF OPTIMIZATIONS

The stereotypical weather years were developed to consider the "usual" management of operations, not "exceptional" management of risk. The stereotypes were obtained by sorting ninety-nine weather years generated for the locale on the basis of two measures only: monthly temperature and rainfall. The number of rain events and intensity of rain events yielded the cumulative rainfall. The most common event frequency was used to select stereotypical months when a cluster of months was in the neighborhood of the value needed to fit the stereotype. This selection process tended to exclude months with extreme rain events, "cloud-bursts," for example.

The selection process had two impacts on the optimization. With fewer extreme events, storm runoff was reduced and infiltration was increased; that is, more of the rainfall was useful for plant growth. With fewer extreme events, rainfall was more uniformly distributed over the month; the rainfall distribution had a "quasi-scheduled" quality which meant that infiltrated rain was more beneficially timed for plant growth and the potential for leaching was lessened. The cold-wet year that resulted from the selection process happened to be a good year for crop production given the range of possible cold-wet years.

The amount of rain available for crop production varied with factors such as cultivar selection. The amount of rain available to the crop was approximately half of the annual rainfall. A cold-wet growing season could produce a good yield with a very good net return. In simple terms, irrigation compensates for the rainfall deficit in all drier years.

There were two consequences for crop production in drier years when using irrigation to bridge the moisture gap. First, in order to achieve a similar net return, yields needed to be higher to cover the costs of irrigating. Second, if it was not raining, the sun must have been shining. Dry years tended to be hotter with more solar radiation. Dry years, therefore, had the potential for higher yields if irrigation was provided. Because dry years tended to be hotter and plants could yield more, the irrigation demand was more than the simple rain deficit between cold-wet and hot-dry years. The demand for irrigation water in hot-dry years exceeded the typical design capacity for water wells in the area. Table 5.1 summarizes the results of the range of stereotypical summer with normal winters.

In round numbers, the table depicts the results obtained from the second series of optimizations. In the second series, leaching increased in a way that was not anticipated for the hot-dry growing season. The irrigation schedule called for the maximum possible water application for many days throughout the growing season. The maximum irrigation was limited by the well capacity. The crop could not then assimilate as much nitrate which left a larger nitrate residual at the end of the season. With a hot-dry winter, leaching would be minimal. With a normal winter, however, the nitrate residual was flushed from the soil profile, to contaminate the groundwater.

Table 5.1. Results from stereotypical summers with normal winters.

Weather Stereotype	Cold-Wet	Normal	Moderate	Hot-Dry
Annual Rainfall	1458	1007	755	530
Growing Season Rainfall	750	500	350	250
Rain Deficit	0	250	400	500
Minimum Irrigation	0	250	400	500
Maximum Irrigation	150	400	600	*600*

All units are in millimeters

*Maximum irrigation limited by well capacity.

The decision as to what and how much to plant depends on confidence in the commodity market over the year following planting. Selection of which cultivar to plant is affected by the expected weather over the growing and harvest seasons. If seed corn could be purchased just prior to planting, a six-month long-range forecast would be sufficient to support cultivar selection. In order to assure the availability of a specific cultivar and to take advantage of early order discounts, the decision to purchase may be pushed forward another six-months; this implies that cultivar selection needs a weather forecast a year in advance of harvest. A "perfect" weather forecast would enable the farm manager to tune the farming operation to conditions that depart from "normal" and this was found to be worth about $20/ha/yr.

CHAPTER SIX

SUMMARY AND CONCLUSIONS

Multivariable sequential random search incorporating a simple evolution strategy worked reliably with the irrigated maize production biosystem. The efficient population and dispersion of trial solutions for each search generation appears to be problem dependent. Adaptive goal-seeking was successfully appended to the multicriteria objective function. Adaptive goal seeking was performed in parallel with resource scheduling. The optimization method permits the pursuit of secondary goals after primary goals are achieved. Two types of implicit constraints were handled. The type of implicit constraint related to cumulative environmental measures had to be handled in the traditional way and this resulted in tedious nested optimizations. The subset of implicit constraints characterized by the influence of weather on the scheduling of agricultural operations was resolved by functional adjustments to elements of the trial solution vector.

The particular processing network derived from generalized hierarchical ecological network theory accommodated Amaize and Van Ee Dry-down models, although neither was designed to be compatible with this in procedure.

Different soils called for different resource schedules; however, irrigation, if warranted, diminished the differences. High frequency irrigation (less than six mm/day) did not leach nitrate. Topping-up to field capacity before a rain caused the movement of nitrate. Through parameter estimation, the reserve soil capacity for rain was calculated in the model, based on the weather forecast.

There was little *financial* penalty for applying excess nitrogen. The model quantified serious leaching following heavy fertilization and large infrequent water events. Side-dressing of nitrogen in make-up amounts rarely contributed to leaching. Nitrate leaching was least with long season cultivars. Long season cultivars consumed more nutrient and water resources which would be desirable when disposing of animal waste. Net return, however, was greatest with a cultivar adapted to the specific growing season.

Optimization of the technology and management parameters in the irrigated maize production model teaches how to schedule nitrogen to reduce winter leaching. Scheduled irrigation can reduce the amount of nitrate leached; scheduling of all resources in ensemble reduces nitrate leaching more. Resource scheduling needs to be comprehensive (all resources considered simultaneously) especially as an enterprise is managed to satisfy conflicting criteria at the Pareto frontier.

APPENDICES

APPENDIX A

AN OVERVIEW OF MULTIVARIABLE NONLINEAR OPTIMIZATION METHODS

Broyden-Fletcher-Goldfarb-Shanno

The Broydon-Fletcher-Goldfarb-Shanno Method is a variant of the conjugate-gradient Davidon-Fletcher-Powell Method described in sequel. This approach differs only in the handling of mathematical details. A brief description and FORTRAN source code are given in Press et al. (1986, pp. 307-311). QuickBASIC 4.5 source code is also given in Sprott (1991, pp. 237-240).

Complex by Box

The Box Complex Method is an iterative pattern search method which tends to find the global optimum because the initial point pattern (the complex) is randomly dispersed *throughout* the search space (Box 1965, pp. 42-52). Complex is an improvement on the pattern search Simplex Method by Spendley, Hext, and Himsworth. The geometric structure of vertices (the complex) can adapt in shape and can conform to boundaries with more agility than the structure in Simplex (Box, Davies, and Swann 1969, pp. 52-54) In addition to *explicit constraints* on the allowable values for independent variable, Complex accommodates *implicit constraints* derived from functions of the independent variables. Several forms of acceleration to the optimum and convergence criteria have been developed for Complex. No derivatives are required. Several runs with different initial seed values may be needed for multimodal response surfaces. Complex may stall on structures like volcano cones and have to be restarted. Old FORTRAN source code developed by Richardson for constrained problems is listed in Kuester and Mize (1973, pp. 368-375). A description and old BASIC source code is given in Bunday (1984, pp. 98-107). A version of Complex rewritten in QuickBASIC 4.5 and modified from M-OptSim by Manetsch is listed in the Ph.D. Thesis by Richard Alderfer (1990).

Complex-Powell Optimization by Buchner

The Complex-Powell Optimization Algorithm was developed by Buchner to take advantage of the initial global search ability of Complex and then switch to Powell's Method to take advantage of its convergence properties. The hybrid algorithm was tested on a large model for parameter estimation and optimal policy estimation. The method proved to be faster than either method alone for large simulations. The complete development and old FORTRAN code is given in Buchner (1975, pp. 1-183).

Constrained Fletcher-Powell (CONMIN Algorithm)

The Constrained Fletcher-Powell Method incorporates constraints into a modified objective function. The modified objective function is then solved by the Fletcher-Powell Method described in sequel (Haarhoff and Buys, 1970, pp. 178-184). Old FORTRAN source code developed by Haarhoff, Buys, and Molendorff to solve the constrained problem is listed in Kuester and Mize (1973, pp. 464-495).

Constrained Rosenbrock (Hill Algorithm)

The Constrained Rosenbrock Method is adapted from the unconstrained "automatic" Rosenbrock Method to accommodate nonlinear inequality constraints (Rosenbrock and Storey 1966). The starting point for the procedure must be away from the boundaries surrounding the search space. Old FORTRAN source code developed by Yancey and Spear to solve the constrained problem is listed in Kuester and Mize, (1973, pp. 386-398).

Davidon-Fletcher-Powell

The Davidon-Fletcher-Powell Method, or simply the Fletcher-Powell Method initially uses derivatives to calculate the *steepest descent* towards a minimum beginning from a starting point (Davidon, 1959). The method uses the ideas of the Newton-Raphson Method and conjugate direction (Bunday 1984, p. 63). A one-dimensional search is conducted for the minimum along the original gradient. This cycle is repeated until the minimum is located (Fletcher and Powell 1963, pp. 163-168). The gradient with the steepest descent is only a local property; therefore, many iterations are needed for a nonlinear response surface. Despite the intuitive appeal of this method, it is slow to converge. Derivatives of the objective function with respect to the independent variables are needed. Unimodal functionality is assumed; therefore, several searches with dispersed starting points are recommended to verify finding the global optimum. Old FORTRAN source code developed by I.B.M. for the 360 System to solve the unconstrained problem is listed in Kuester and Mize (1973, pp. 355-366). Old BASIC source code is listed in Bunday (1984, pp. 47-55).

Fiacco and McCormick (SUMT Algorithm)

The Fiacco-McMormick Method uses the original objective function to form an unconstrained objective function which is minimized by any appropriate unconstrained, multivariable method (Fiacco and McCormick 1968). A modified objective function is formulated from the original objective function and penalty functions. An “error” parameter is embedded in the modified objective function; this parameter is minimize through the sequences of the optimization and the solution is achieved. First and second derivatives are required. Old FORTRAN source code developed by Mylander, Holmes, and McCormick to solve the constrained problem is listed in Kuester and Mize, (1973, pp. 386-398). This version of the SUMT algorithm uses one dimensional search by Golden Section (modified by Fibonacci), modified Newton-Raphson, Steepest Descent, and Fletcher-Powell methods. Several options are included for convergence criteria. A description and old BASIC source code is given in Bunday (1984, pp. 113-122).

Fletcher-Reeves

The Fletcher-Reeves Method uses derivatives to calculate the steepest descent towards a minimum , or conversely, the steepest ascent towards a maximum from an initial starting point (Fletcher and Reeves 1964, pp. 149-154). Derivatives of the objective function with respect to the independent variables are needed. Unimodal functionality is assumed; therefore, several searches with dispersed starting points are recommended to verify finding the global optimum. Old FORTRAN source code developed by I.B.M. for the 360 System to solve the unconstrained problem is listed in Kuester and Mize, (1973, pp. 344-354). Old BASIC code and a derivation is given in Bunday (1984, pp. 67-74). The "Polak-Ribiere Variant" of the Fletcher-Reeves Method is described and FORTRAN source code given in Press et al. (1986 pp. 301-307). The Fletcher-Reeves-Polak-Ribiere source code in QuickBASIC 4.5 is also given in Sprott (1986, pp. 234-237).

Hooke and Jeeves

The Hooke-Jeeves Method is a pattern search method which works from an initial base point and a conducts parameterized local search about the base point (Hooke and Jeeves 1961, pp. 212-229). No derivatives are needed. Unimodal functionality is assumed; therefore, several searches with dispersed starting points are recommended to verify finding the global optimum. Old FORTRAN source code developed by Johnson to solve the unconstrained problem is listed in Kuester and Mize, (1973, pp. 309-319). Old BASIC source code is listed in Bunday (1984, pp. 32-37). A modified version of Hooke and Jeeves with constraints is described and old BASIC source code is also given in Bunday (1984, pp.93-98).

Grid Search

The Grid Search Method is a standard tabulation method that assumes the minimum lies within the upper and lower bounds of the independent variables. Points in a multidimensional search space are generated at equidistant intervals along each dimension. Each point is evaluated sequentially and the "optimum" value is accepted as the global optimum. Efficiency of solution depends on the number of extraneous points evaluated as with the univariant Total Search Method of Box, Davies and Swann (1969, pp. 16-17).

Nedler and Mead

The Nedler-Mead Method is an extension of the pattern search Simplex Method by Spendley, Hext, and Himsworth. A regular geometric structure, called a Simplex, forms the basis for a pattern search of the response surface (Nedler and Mead 1964, pp. 308-313). This Simplex approach is self-adaptive to the "local landscape" and uses reflected, expanded, and contracted points to locate the minimum. Unimodality (singular optimum) is assumed; therefore, the algorithm should be run several times from dispersed starting points to better guarantee that the optimum found is indeed the global optimum. No derivatives are required. Old FORTRAN source code developed by Bates unconstrained problems is listed in Kuester and Mize (1973, pp. 298-308). Old BASIC source code is listed in Bunday (1984, pp. 37-46). FORTRAN source code is given in Press et al. (1986, pp. 289-293). QuickBASIC 4.5 source code is also given in Sprott (1986, pp. 225-228).

Powell

The Powell Method begins with a starting point and proceeds in search directions parallel to the original axes of the response surface. A sequence of single variable searches is conducted Powell 1964, pp. 155-162). No derivatives are required. Unimodal functionality is assumed; therefore, several searches with dispersed starting points are recommended to verify finding the global optimum. Old FORTRAN source code developed by Powell to solve the unconstrained problem is listed in Kuester and Mize, (1973, pp. 331-343). FORTRAN source code is given in Press et al. (1986, pp. 294-301). QuickBASIC 4.5 source code is given in Sprott (1986, pp. 228-234).

Random Search

The Random Search Method can be regarded as a tabulation method with a "random grid" in the search space (Brooks 1958, pp. 244-251; Spang 1962, pp. 343-365). A number of random points is selected for each independent variable, generally 10 points are used. Random search does not "hang-up" for any type of response surface, ridged, rutted, cratered, unimodal, or not. There is no guarantee that the optimum selected is the best possible if the surface is not unimodal. Like Complex, Random Search tends to find the global optimum of a unimodal response surface. The method is slow to converge to high precision. No derivatives are required. Explicit and implicit constraints are easy to include in the search. Very tight implicit constraints slow the selection of suitable points to be included in the search. A description and old BASIC source code is given in Shoup and Mistree (1987, pp. 65-71).

Rosen (PROJG Algorithm)

The Rosen Method is based on gradient projection (Rosen 1960, pp. 181-217). Derivatives of the objective function with respect to the independent variables are needed. An initial starting point and step size are selected. The search proceeds along the gradient to an optimum. The step size will increase on the search path as long as linear constraints are not violated. At each gradient projection optimum, a new gradient direction is evaluated and the process continues. Old FORTRAN source code developed by Nichols to solve the linearly-constrained problem is listed in Kuester and Mize (1973, pp. 399-411).

Rosenbrock

The Rosenbrock Method begins at a starting point and proceeds by parameteratized steps along a traverse. Evaluations are performed about each point on the traverse. The algorithm rotates the traverse and accelerates towards the optimum (Rosenbrock 1960, pp. 175-184). No derivatives are required. Unimodal functionality is assumed; therefore, several searches with dispersed starting points are recommended to verify finding the global optimum. Old FORTRAN source code developed by Johnson to solve the unconstrained problem is listed in Kuester and Mize (1973, pp. 320-330).

Simplex by Spendley, Hext, and Himsworth

The Simplex Method by Spendley, Hext, and Himsworth is an iterative pattern search method (Spendley, Hext, and Himsworth (1961, pp.441-461). The term "simplex" refers to the geometric structure, which is composed of n+1 mutually equidistant points set in the search space where n is the number of independent variables in the problem. These points form the vertices of a regular simplex. The objective function is evaluated at each vertex.

The least desirable value in the simplex is identified. A line is projected from the least desirable point through the centroid of the simplex. This projected line is taken to be the best search direction in the neighborhood of the simplex. A new point is located on the projection line which is equidistant from the remaining points in the simplex. The least desirable point in the original simplex is then discarded and the objective function is evaluated at the new point.

Eventually the simplex structure centers itself on the optimum. Convergence is tested by a termination parameter which is the number of iterations for which the objective function remains unchanged. After the set iteration number is exceeded, the distance between the points in the simplex is reduced by half and the search process is repeated. Convergence is achieved by exceeding the threshold of a second convergence parameter which is based on the size of the simplex, or change in the measures of the objective function Box, Davies, and Swann (1969, pp. 20-21)

The strong advantage of the Simplex Method is that it works well with objective functions which are "corrupted by random errors" (non-smooth response surfaces). No derivatives are required. Limitations of the Simplex Method arise from the equal distance between vertices. Acceleration along the favorable search direction is not possible. Simplex conforms poorly to ridges and valleys. Simplex has no reliable method to accommodate constraints (Buchner 1975).

The simple computer demands and adaptability of the Simplex Method spurred several modifications to address its handicaps. Campey and Nickols modified the Simplex Method so that size of the structure could adapt (contract and expand) to the geometry of the response surface. The simplex would contract to follow narrow valleys and expand over gently rolling plains (Campey and Nickols 1961). Nedler and Meade further improved the adaptability of the simplex by adding a "reflection coefficient" which would locate new points to the simplex at something other than the fixed distance (Box, Davies, and Swann 1969 pp. 22-24; Shoup and Mistree 1987, pp. 125-133). Box developed Complex to overcome the limitations of Simplex by the choosing of randomly dispersed points from across the expanse of the search space for the initial vertices in the geometric structure, (Box 1965).

No samples of program code where found for the original Simplex Method by Spenley, Hext, and Himsworth, or of the adaptation by Campey and Nickols.

None-the-less, simplex is the benchmark method of pattern search approaches.

Univariant Search

Univariant Search Methods (Univariate in the U.K.) is the simplest class of optimization techniques consisting of a one dimensional search along a reference axis (Buchner 1975, p. 24). Univariant searches fall into two classes: "methods which specify an interval in which the minimum lies", and "methods which specify the position of the minimum by a point approximating to it," (Box, Davies, and Swann 1969, p. 10). The concepts of univariant searches have been incorporated into several of the multivariable methods, sometimes directly encoded.

INTERVAL SEARCH APPROACHES

The "Total Search Method" uses an intuitive approach to narrow the search for an assumed unimodal optimum (a singular global optimum). The total search interval is first subdivided into uniform segments. The objective function is then evaluated at the nodes and possibly at the end points of entire search interval. The optimum value of the initial function evaluations is found and the search is narrowed to the segments to the left and right of the initial optimum. The cycle is repeated until the subsequent search interval is less than a preselected threshold value and convergence is assumed. The Total Search Method is slow. Old BASIC code is listed is listed in Shoup and Mistree (1987, pp. 29-33).

The "Interval Halving Method", or "Three-Point Interval Search" is a subclass of the Total Search Method which reduces the number of extraneous searches for each iteration. Only three uniformly spaced nodes are evaluated in each iteration. The range of the search is reduced by half with each iteration, (Shoup and Mistree 1987, pp. 33-34). By using three points, it is the most efficient of "equally spaced" search methods and is among the easiest to program.

The "Dichotomous Search" is another subclass of the Total Search Method which uses only two evaluation points at each iteration and proceeds as the Interval Halving Method (Shoup and Mistree 1987, pp. 34-36).

The "Golden Section Search", or "Golden-Mean Search" uses one point evaluation on each iteration. The point is strategically positioned 0.618033989 the distance from one end of the search interval. Golden Search does not give as great an interval reduction per iteration as Fibonacci Search, but has the advantage that the number of iterations does not need to be specified *a priori*, (Box, Davies, and Swann 1969, pp. 12-13). The derivation and old BASIC source code are given in Shoup and Mistree (1987, pp. 36-41) and Bunday (1984, pp.18-24). FORTRAN code is given in Press et al. (1986, p. 262). QuickBASIC 4.5 code is given in Sprott (1986, pp. 217-218).

The "Fibonacci Search Method" makes use of a particular sequence of positive integers called the "Fibonacci numbers" (Kiefer 1957, pp. 105-136). Fibonacci Search achieves an interval reduction of 17 percent over Golden Section with each iteration. Although more efficient, it is not necessarily the most accurate, (Box, Davies, and Swann 1969, p .p12-13). A comparison of Fibonacci Search to other univariant methods and old BASIC source code is given in Shoup and Mistree (1987, pp. 42-48) and Bunday (1984, pp. 12-18). The Fibonacci Method does incorporate constraints. Old FORTRAN code by Voorhees is listed in Kuester and Mize (1973, pp. 286-295).

CURVE FITTING APPROACHES

The "Quadratic Interpolation Method," "Powell's Algorithm," or "Powell's Method in one dimension" is based on fitting a quadratic function to the function evaluation at three points. Two problems arise with the method. If the step-size is too large, the search may be slow. If the step-size is too large, the initial turning point may be a maximum instead of a minimum (Box, Davies, and Swann 1969, p. 15). Old BASIC source code is given in Bunday (1984, pp.20-23).

The "Cubic Interpolation Method", or "Davidon's Method" uses the function evaluation and the gradients at two points, which improves the accuracy over Powell's Method (Davidon 1959). Old BASIC source code and an explanation is given in Bunday (1984, pp. 24-28).

The "Davies, Swann, and Campey Algorithm" is a minimization procedure with uses variable step-sizes. The step-size for function evaluations increases if the function is decreasing. The process continues until the function increases. At this point, a quadratic is fitted to the evaluated points and an interpolation is performed (Box, Davies, and Swann 1969, pp. 14-15)

The "Coggin's Method" incorporates two of the preceding methods to gain efficiency and accuracy over Fiboacci Search (Box, Davies, and Swann 1969 pp. 13-15). The two step process makes use of the convergence efficiency of

Powell's Method while avoiding its step-size drawbacks. Old FORTRAN source code to find the unconstrained minimum by Voorhees is given in Kuester and Mize (1973, pp. 276-285).

COMMENT ON SOURCE CODE

Test everything. Hold onto the good. Avoid every kind of evil.

1 Thess. 5:21-22

Verification of source code for optimization methods is obviously important. Algorithms may need to be modified to adapt to particular applications. As a practical measure, this researcher has found it is useful to retain code within the new application for a problem to which the answer is known. Three problems commonly used in the literature are: the cylindrical tank problem, the post office problem, and the traveling salesman problem.

APPENDIX B

DEFINITIONS OF ADAPTIVE SYSTEMS AND ADAPTIVE CONTROL

Definition 1: An adaptive system is a system which is provided with a means of continuously monitoring its own performance in relation to a given figure of merit or optimal condition and a means of modifying its own parameters by a closed-loop action so as to approach this optimum, (Eveleigh, 1967).

Definition 2: An adaptive control system is defined as a feedback control system intelligent enough to adjust its characteristics in a changing environment so as to operate in an optimum manner according to some specified criterion, (Margolis, M. and C.T. Leondes 1959).

Definition 3: Adaptive control belongs to the third of three stages in the evolution of control processes:

1. If the system to be controlled is fully specified and the controller has complete information concerning the behavior of the inputs, the control process is "deterministic."
2. When unknown factors appear in the system to be controlled, or arise from the operating environment, and appear mathematically as random

process is “deterministic.”

2. When unknown factors appear in the system to be controlled, or arise from the operating environment, and appear mathematically as random variables, the control process is "stochastic". Randomness may occur in inputs and parameter values.
3. When control of the system requires a multistage decision process in the absence of complete information about the system and its environment for any time period, the control process is “adaptive.”

Many control problems of the third stage are found in biology, engineering, and economics, (Bellman, R. and R. Kalaba, 1959).

Definition 4: A system is adaptive if, with respect to a family of time functions to which the system is subjected and with respect to an acceptable set of performance criteria, the system performs acceptably well with every source in the time functions. This definition can be written in mathematical terms, (Zadeh, 1963).

Definition 5: An adaptive system is a system designed from an adaptive viewpoint. “Adaptivity” is in the eye of the designer, (Truxal, 1963).

APPENDIX C

PROPERTIES OF AN ADAPTIVE SYSTEM

The adaptive control of a system considers four properties of the system: observability, controllability, stability, and optimality (Narendra and Annaswamy, 1989).

The property of "observability" refers to the ability to measure all components of all state variables that describe the system (Distefano, Stuberud, and Williams, 1995). Observability is considered imperfect in the adaptive control problem. Continued observation over time is used to gather updated partial observations to reestablish control (Narendra and Annaswamy, 1989).

The property of "controllability" answers the question: If a corrective action can be formulated, can it be implemented (Distefano, Stuberud, and Williams, 1995)? Adaptive control theory can accommodate partially-controllable system behavior.

The property of "stability" implies that a system essentially conforms to Newton's Laws. A stable system remains at rest until stimulated. A stable system returns to a "rest state" following the removal of all stimuli (ibid.). Rest state in this context does not mean zero, but refers to some bounded behavior. Bounded input yielding bounded output (BIBO) is the essential stability criterion for non-linear systems (Narendra and Annaswamy, 1989). A numerical model of a stable plant, which mimics the essentially features of the plant is, by extension, bounded input bounded output (BIBO) stable.

Knowledge of system stability is valuable in evaluating whether the adaptive control of a system is "robust" (ibid.). In this context, robustness implies that "the adaptive system performs in essentially the same manner" when exogenous and endogenous disturbances are present.

The property of "optimality" assumes that criteria for preferred system behavior can be specified. Evaluation of a system's performance over time provides information for the evaluation of corrective measures which are administered to the system to achieve "optimality" (Distefano, Stuberud, and Williams, 1995). For adaptive systems, optimality raises the notion of confidence limits on the evaluation of the optimum control strategy evaluated while the system is operating.

APPENDIX D

REQUIREMENTS FOR USABLE CROP MODELS IN AGRONOMIC SYSTEMS

The requirements for crop simulation models in agronomic systems which are orientated towards problem solving are outlined by Whisler et al. (1986) as follows:

1. Commonly available data should be required.
    a. Climate: daily temperature, precipitation, wind humidity, pan evaporation, radiation.
    b. Soil: texture, depth, water availability.
    c. Crop: type, cultivars, planting date, growth stages.
    d. Management: fertilizer application, tillage, irrigation.
2. The input of management factors should be emphasized and easily accomplished.
3. The model must maintain a balance of all parts such as water

balance, salt balance, carbon balance, nitrogen balance, etc.

4. Plasticity of plants (genetic difference and adaptability).

5. Computer requirements should be reasonable. The model should preferably be capable of running on microcomputers or minicomputers. The FORTRAN, or BASIC [additionally C] computer codes should be available as part of each model. Estimates of computer time should be made.

6. General variables should be required. Models should have the minimum of site-specific factors. The model should be capable of giving reasonable answers at a different location from where it was developed using local data.

7. The model should be stable and not include hunting routines that could hang up the computer. If hunting routines are used they should be automatically terminated after several cycles.

8. The model must have been tested under field conditions on a data set other than that on which it was calibrated.

9. Main assumptions and simplifications should be clearly indicated. The principle assumptions should be clearly outlined so the user is well aware of the range of applicability of the model.

10. The potential and actual data output that comes from the model should be given.

APPENDIX E

THE INDONESIAN POST-PRODUCTION RICE PROCESSING MODEL

The following rice post-production network is the result of an unpublished study by Handaka under the direction of E.C.Alocilja in 1989. The model follows the processing of rice from maturity to milling through alternate post-production technologies. The processes represented in the network are:

(A) Rice Harvesting

(B) Traditional Threshing by Hand

(C) Traditional Sun Drying

(D) Mechanical Threshing

(E) Mechanical Drying

(F) Rice Milling

Figure D.1 depicts the network for the Indonesian post-harvest processing model.

This small network is particularly interesting as a computational example because of the cross-linkages from traditional to mechanically assisted processes. This network is essentially the "fractal" model for larger complex process networks.

For process networks with a large number of processors and linkages, alpha-numeric labeling indicative of the processors names facilitates verification of the correctness of computer program code. For this small network example, numeric labeling of the processors provides a logical method of subscripting the solution procedure. Component stimulus variables (primary product) are designated by the process number followed by zero. Response variables are depicted by the process number plus a number greater than zero. Each elemental process has one primary output (rice retained in the system), one secondary output (grain losses), and one or two resource inputs (rice from predecessor processes).

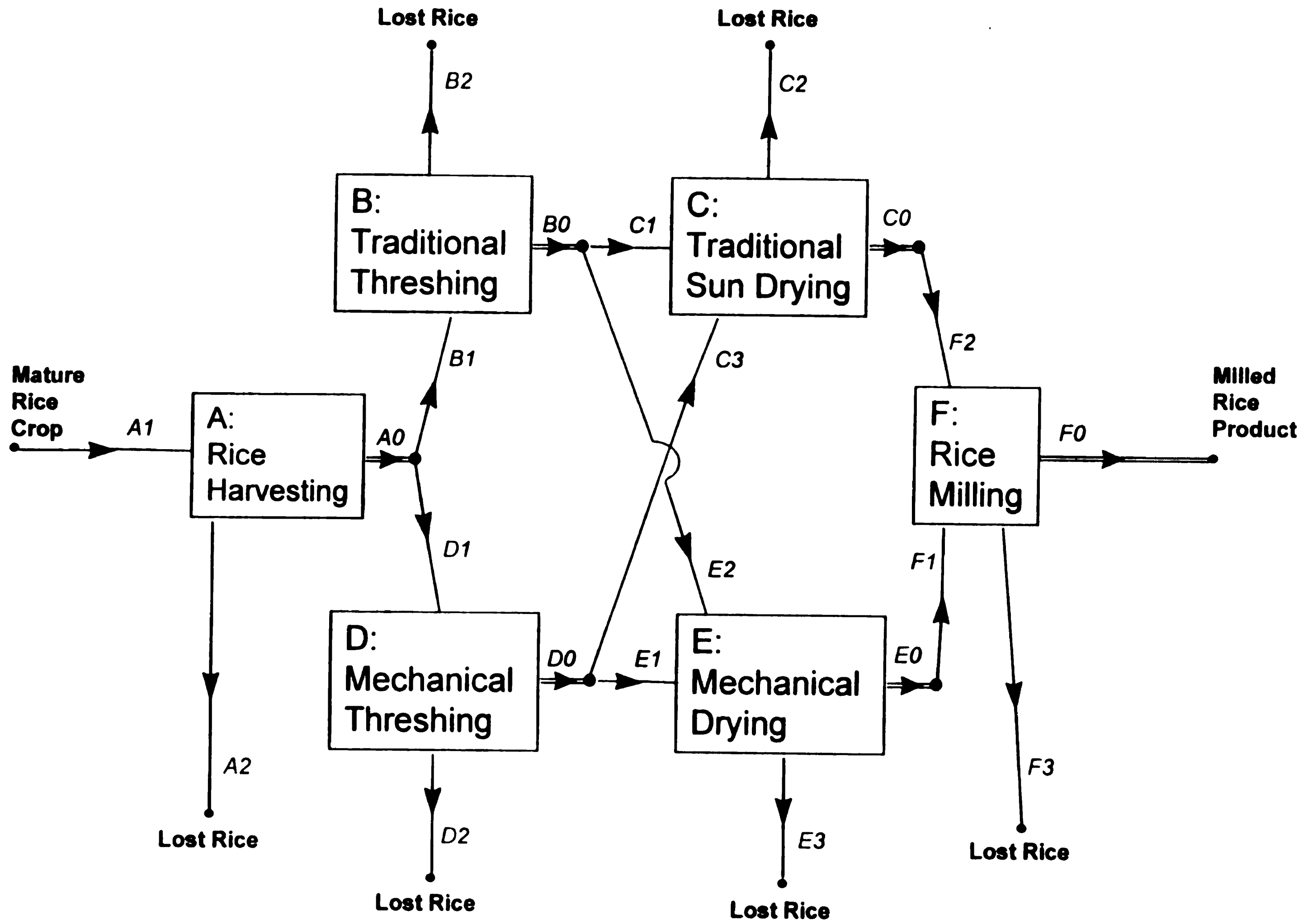

Figure D.1: Indonesian Post-Harvest Processing Model (after Handaka, 1989).

Step1: Component system-independent process model

Transformation process general equations:

Material flux: $$y_i = k_i y_0 \tag{1}$$

where:

y_i = response variable, material input

k_i = technical coefficient of transformation

y_0 = stimulus variable, primary output

Cost function: $$x_0 = -\sum_{i=1}^{n} k_i x_i - f_i(y_0) \tag{2}$$

where:

x_0 = total cost per unit of primary output

x_i = cost per unit of response input

$f_i(y_0)$ = cost of transformation

Material flux and cost equations for each component process in the system:

A. Harvesting:

$$\begin{bmatrix} y_{A1} \\ y_{A2} \end{bmatrix} = \begin{bmatrix} k_{A1} \\ k_{A2} \end{bmatrix} y_{A0} \qquad x_{A0} = -\begin{bmatrix} k_{A1} & k_{A2} \end{bmatrix} \begin{bmatrix} x_{A1} \\ x_{A2} \end{bmatrix} - f_A(y_{A0}) \tag{3}$$

B. Traditional Threshing:

$$\begin{bmatrix} y_{B1} \\ y_{B2} \end{bmatrix} = \begin{bmatrix} k_{B1} \\ k_{B2} \end{bmatrix} y_{B0} \qquad x_{B0} = -\begin{bmatrix} k_{B1} & k_{B2} \end{bmatrix} \begin{bmatrix} x_{B1} \\ x_{B2} \end{bmatrix} - f_B(y_{B0}) \tag{4}$$

(4)

C. Traditional Sun Drying:

$$\begin{bmatrix} y_{C1} \\ y_{C2} \\ y_{C3} \end{bmatrix} = \begin{bmatrix} k_{C1} \\ k_{C2} \\ k_{C3} \end{bmatrix} y_{C0} \qquad x_{C0} = -\begin{bmatrix} k_{C1} & k_{C2} & k_{C3} \end{bmatrix} \begin{bmatrix} x_{C1} \\ x_{C2} \\ x_{C3} \end{bmatrix} - f_C(y_{C0}) \tag{5}$$

D. Mechanical Threshing:

$$\begin{bmatrix} y_{D1} \\ y_{D2} \end{bmatrix} = \begin{bmatrix} k_{D1} \\ k_{D2} \end{bmatrix} y_{D0} \qquad x_{D0} = -\begin{bmatrix} k_{D1} & k_{D2} \end{bmatrix} \begin{bmatrix} x_{D1} \\ x_{D2} \end{bmatrix} - f_D(y_{D0}) \tag{6}$$

E. Mechanical Drying:

$$\begin{bmatrix} y_{E1} \\ y_{E2} \\ y_{E3} \end{bmatrix} = \begin{bmatrix} k_{E1} \\ k_{E2} \\ k_{E3} \end{bmatrix} y_{E0} \qquad x_{E0} = -\begin{bmatrix} k_{E1} & k_{E2} & k_{E3} \end{bmatrix} \begin{bmatrix} x_{E1} \\ x_{E2} \\ x_{E3} \end{bmatrix} - f_E(y_{E0}) \tag{7}$$

F. Milling:

$$\begin{bmatrix} y_{F1} \\ y_{F2} \\ y_{F3} \end{bmatrix} = \begin{bmatrix} k_{F1} \\ k_{F2} \\ k_{F3} \end{bmatrix} y_{F0} \qquad x_{F0} = -\begin{bmatrix} k_{F1} & k_{F2} & k_{F3} \end{bmatrix} \begin{bmatrix} x_{F1} \\ x_{F2} \\ x_{F3} \end{bmatrix} - f_F(y_{F0}) \tag{8}$$

Step 2: Continuity (cut-set) equations

General Equation: $$Y_b = -AY_c \tag{9}$$

$$y_b + y_c = 0 \qquad \text{at all nodes}$$

Specific continuity equations:

$$y_{A0} = y_{B1} + y_{D1} \tag{10}$$

$$y_{B0} = y_{C1} + y_{E1}$$

$$y_{C0} = y_{F2}$$

$$y_{D0} = y_{C1} + y_{E1}$$

$$y_{E0} = y_{F2}$$

Continuity equations in matrix form:

$$\begin{bmatrix} y_{A0} \\ y_{B0} \\ y_{C0} \\ y_{D0} \\ y_{E0} \\ y_{F0} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} y_{B1} \\ y_{C1} \\ y_{C3} \\ y_{D1} \\ y_{E1} \\ y_{E2} \\ y_{F1} \\ y_{F2} \end{bmatrix} \tag{11}$$

Step 3, Compatibility (circuit) equations:

General equation: $$X_c = -A^T X_b \tag{12}$$

Specific compatibility equations:

$$x_{B1} = -x_{A0} \tag{13}$$

$$x_{C1} = -x_{B0}$$

$$x_{C3} = -x_{D0}$$

$$x_{D1} = -x_{A0}$$

$$x_{E1} = -x_{D0}$$

$$x_{E2} = -x_{B0}$$

$$x_{F1} = -x_{E0}$$

$$x_{F1} = -x_{C0}$$

Compatibility equations in matrix form:

$$\begin{bmatrix} x_{B1} \\ x_{C1} \\ x_{C3} \\ x_{D1} \\ x_{E1} \\ x_{E2} \\ x_{F1} \\ x_{F2} \end{bmatrix} = -\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_{A0} \\ x_{B0} \\ x_{C0} \\ x_{D0} \\ x_{E0} \end{bmatrix} \tag{14}$$

Step 4, System terminal representation:

General equations:

$$y_r = K y_s \qquad x_s = -K^T x_r - Df(y_s) \tag{15}$$

Example of reduction process to terminal representation with the lead process taken as A. Harvesting:

$$\begin{bmatrix} y_{A1} \\ y_{B1} \end{bmatrix} = \begin{bmatrix} k_{A1} \\ k_{B1} \end{bmatrix} \left[[y_{A0}] \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \left[\begin{matrix} [y_{B1}] = [k_{B1}] \left[[y_{B0}] = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} [y_{C1}] = [k_{C1}]\left[[y_{C0}] = k_{F2} y_{F2}\right] \\ [y_{E2}] = [k_{E2}]\left[[y_{E0}] = k_{F1} y_{F1}\right] \end{bmatrix} \right] \\ [y_{D1}] = [k_{D1}] \left[[y_{D0}] = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} [y_{C3}] = [k_{C3}]\left[[y_{C0}] = k_{F2} y_{F2}\right] \\ [y_{E1}] = [k_{E1}]\left[[y_{E0}] = k_{F1} y_{F1}\right] \end{bmatrix} \right] \end{matrix} \right] \right] y_{F0} \tag{16}$$

Equations for each response variable:

$$y_{A1} = (k_{A1}k_{B1}k_{C1}k_{F2} + k_{A1}k_{B1}k_{E2}k_{F1} + k_{A1}k_{D1}k_{E1}k_{F1} + k_{A1}k_{D1}k_{C3}k_{F2})y_{F0} \tag{17}$$

$$y_{A2} = (k_{A2}k_{B1}k_{C1}k_{F2} + k_{A2}k_{B1}k_{E2}k_{F1} + k_{A2}k_{D1}k_{E1}k_{F1} + k_{A2}k_{D1}k_{C3}k_{F2})y_{F0}$$

$$y_{B1} = \textit{absorbed}$$

$$y_{B2} = (k_{B2}k_{C1}k_{F2} + k_{B2}k_{E2}k_{F1})y_{F0}$$

$$y_{C1} = \textit{absorbed}$$

$$y_{C2} = (k_{C2}k_{F2})y_{F0}$$

$$y_{C3} = \textit{absorbed}$$

$$y_{D1} = \textit{absorbed}$$

$$y_{D2} = (k_{D2}k_{E1}k_{F1} + k_{D2}k_{C3}k_{F2})y_{F0}$$

$$y_{E1} = \textit{absorbed}$$

$$y_{E2} = \textit{absorbed}$$

$$y_{E3} = (k_{E3}k_{F1})y_{F0}$$

$$y_{F1} = absorbed$$

$$y_{F2} = absorbed$$

$$y_{F3} = k_{F3}y_{F0}$$

Matrix form for reduced system:

$$\begin{bmatrix} y_{A1} \\ y_{A2} \\ y_{B2} \\ y_{C2} \\ y_{D2} \\ y_{E3} \\ y_{F3} \end{bmatrix} = \begin{bmatrix} k_{A1}k_{B1}k_{C1}k_{F2} + k_{A1}k_{B1}k_{E2}k_{F1} + k_{A1}k_{D1}k_{E1}k_{F1} + k_{A1}k_{D1}k_{C3}k_{F2} \\ k_{A2}k_{B1}k_{C1}k_{F2} + k_{A2}k_{B1}k_{E2}k_{F1} + k_{A2}k_{D1}k_{E1}k_{F1} + k_{A2}k_{D1}k_{C3}k_{F2} \\ k_{B2}k_{C1}k_{F2} + k_{B2}k_{E2}k_{F1} \\ k_{C2}k_{F2} \\ k_{D2}k_{E1}k_{F1} + k_{D2}k_{C3}k_{F2} \\ k_{E3}k_{F1} \\ k_{F3} \end{bmatrix} y_{F0} \tag{18}$$

General structural for cost equation:

$$k^*_{A1} = k_{A1}k_{B1}k_{C1}k_{F2} + k_{A1}k_{B1}k_{E2}k_{F1} + k_{A1}k_{D1}k_{E1}k_{F1} + k_{A1}k_{D1}k_{C3}k_{F2} \tag{19}$$

$$k^*_{A2} = k_{A2}k_{B1}k_{C1}k_{F2} + k_{A2}k_{B1}k_{E2}k_{F1} + k_{A2}k_{D1}k_{E1}k_{F1} + k_{A2}k_{D1}k_{C3}k_{F2}$$

$$k^*_{B2} = k_{B2}k_{C1}k_{F2} + k_{B2}k_{E2}k_{F1} \qquad k^*_{C2} = k_{C2}k_{F2}$$

$$k^*_{D2} = k_{D2}k_{E1}k_{F1} + k_{D2}k_{C3}k_{F2} \qquad k^*_{E3} = k_{E3}k_{F1} \qquad k^*_{F3} = k_{F3}$$

$$D^*_{A} = k_{B1}k_{C1}k_{F2} + k_{B1}k_{E2}k_{F1} + k_{D1}k_{E1}k_{F1} + k_{D1}k_{C3}k_{F2}$$

$$D^*_{B} = k_{C1}k_{F2} + k_{E2}k_{F1} \qquad D^*_{C} = k_{F2}$$

$$D^*_{D} = k_{C3}k_{F2} + k_{E1}k_{F1} \qquad D^*_{E} = k_{F1} \qquad D^*_{F} = 1$$

Cost equation for each response variable:

$$x_{F0} = -\begin{bmatrix} k^*{}_{A1} & k^*{}_{A2} & k^*{}_{B2} & k^*{}_{C2} & k^*{}_{D2} & k^*{}_{E3} & k^*{}_{F3} \end{bmatrix} \begin{bmatrix} x_{A1} \\ x_{A2} \\ x_{B2} \\ x_{C2} \\ x_{D2} \\ x_{E3} \\ x_{F3} \end{bmatrix} \tag{20}$$

$$-\begin{bmatrix} D^*{}_{A} & D^*{}_{B} & D^*{}_{C} & D^*{}_{D} & D^*{}_{E} & D^*{}_{F} \end{bmatrix} \begin{bmatrix} f_A(y_{A0}) \\ f_B(y_{B0}) \\ f_C(y_{C0}) \\ f_D(y_{D0}) \\ f_E(y_{E0}) \\ f_F(y_{F0}) \end{bmatrix}$$

$$x_{F0} = -\left[K^*\right]\left[X\right] - \left[D^*\right]\begin{bmatrix} f_A(y_{A0}) \\ f_B(y_{B0}) \\ f_C(y_{C0}) \\ f_D(y_{D0}) \\ f_E(y_{E0}) \\ f_F(y_{F0}) \end{bmatrix} \tag{21}$$

Example of the reduction process applied to the cost equation with the lead process taken as A. Harvesting:

$$x_{F0} = -\left[K^*\right]\left[X\right] - \left[D^*\right]\left[f(D^* y_{F0})\right] \tag{22}$$

$$x_{F0} = -\begin{bmatrix} k^*_{A1} & k^*_{A2} & k^*_{B2} & k^*_{C2} & k^*_{D2} & k^*_{E3} & k^*_{F3} \end{bmatrix} \begin{bmatrix} x_{A1} \\ x_{A2} \\ x_{B2} \\ x_{C2} \\ x_{D2} \\ x_{E3} \\ x_{F3} \end{bmatrix} - \begin{bmatrix} D^*_A & D^*_B & D^*_C & D^*_D & D^*_E & D^*_F \end{bmatrix} \begin{bmatrix} f_A(D^*_A y_{F0}) \\ f_B(D^*_B y_{F0}) \\ f_C(D^*_C y_{F0}) \\ f_D(D^*_D y_{F0}) \\ f_E(D^*_E y_{F0}) \\ f_F(D^*_F y_{F0}) \end{bmatrix} \quad (23)$$

APPENDIX F

INCIDENTAL FINDINGS

he incidental findings from the research are sorted by objective:

Objective One

1. For operations other than irrigation (e.g. fertilization, tillage, crop protection, harvesting, or plant breeding) the approach used here can be used to describe and manage any technology.
2. The variability of soil within the irrigated area can be treated in a manner similar to the way multiple technologies are treated. The potential benefit of precision farming can, therefore, be calculated. Conversely combining soil samples for a field degrades information that could be used.
3. The choice of the CeresMaize crop-growth model makes possible the application of this particular enterprise model to other locations. The method for developing weather scenarios is also generally applicable for other locations and crops. The approach taken to assessing the variability of irrigation distribution applies to other irrigation methods. This enterprise model for sandy-loams in southern Michigan is generally

applicable to irrigated sandy-loams in Nebraska, Florida, Morocco, or Egypt.

- A programming coding structure was required to facilitate debugging of the processing network program code. Coincidentally, this coding structure resulted in a programming heuristic which can be coupled with a graphical user interface. Such a linkage would greatly facilitate the writing of executable program code for large models.

Objective Two

- What is true for irrigated-maize, can be extended for any biosystem driven to achieve “best-performance”.
- Further, what is true for a biosystem, is true for any nonlinear-system employing multiple-technologies.
- The optimization of the irrigated maize enterprise model demonstrates one approach to scheduling multiple technologies employed in one enterprise.
- By extension, the hierarchical ecological network approach will apply to the management of multiple enterprises sharing, or competing for the same resources.
- The better the long-range weather forecast, the more that can be done to better take advantage of “good” weather, conversely, the more that can be done to alleviate the effects of “bad” weather. A good long-range weather forecast enables the manager to synchronize all farming activities with the trends in the weather.

- The modeling and optimization procedure used in this study is generally applicable to multiple resource/multiple criteria problems and is limited only by the capacity of the computing facilities.
- This procedure lends itself to parallel distributed computing using local area networks of personal computers which expands the number of potential users.
- A normal temperature-normal rainfall year (normal-normal year) was the only weather forecast used in this model. Long range weather forecasts are available for a year in advance. These forecasts are not precise, merely forecasts of deviations from normal. The simple classification used in this research is compatible with the terminology used in the long range forecasts.

Objective Three

- The individual criteria within a multicriteria objective function are coupled in ways unique to the model configuration and operating context. The phase diagrams of the criteria have a characteristic "fingerprint" for the configuration and context.
- All nonlinear, nonderivative optimization methods have difficulty locating the global optimum on a relatively flat response surface. The greater the number of independent search variables and the greater the number of criteria in the objective function, the more likely the response surface has flat spots and that the optimum lies on a flat spot. The result is a multiplicity of acceptable solutions.

Objective Four

- Technologies embedded within the same well-managed enterprise (such as fertilization and irrigation schedules) are not really independent when the enterprise is expected to perform at, or near the Pareto frontier.
- Relating to irrigation efficiency, optimality seems more strongly tied to the variance of technology behavior than to its mean, or most likely behavior.
- In regards to variance and the detection of change, change occurs, or is noticed, first at the edges.
- The analytical approach used in this research yields observations of the technology coefficients due to environmental changes, cultivar genetics, and management.

Objective Five

- Nutrient losses due to runoff will be greater for soils with greater slopes and less sand content than the soils used in this study. Conversely, the potential for direct nitrate leaching should be less.

APPENDIX G

TOPICS FOR FUTURE RESEARCH

Recent and ongoing projects provide a number of opportunities for research in biosystem optimization and technology management. For example, marketing can be treated as one technology in a farming enterprise; for this study, the market price was held constant. A forecaster of market conditions can be incorporated into the optimization structure in the same manner a weather; therefore, marketing can be similarly "scheduled." No market forecaster or marketing tools (hedges, options, etc.) were included in the model for this research. For a commodity such as cash grain corn, a market forecast influences the production technology in the intermediate term and area to plant in the short term. Once the production technology and acreage to plant are decided, how to manage maize production is relatively independent of market price. None-the-less, it would be useful to add a market forecaster and a portfolio of marketing tools and observe the behavior on optimization throughout the growing season. The coupling of economic and environmental forecasters is expected to be of more value for crops and livestock were a market forecast would exert more influence on production management.

Some other possibilities for research are:

1. Other farm production enterprises
2. Food processing - essence extraction (sage, onion, etc.)
3. Waste handling - solids separation, handling systems design
4. Animal housing - building ventilation design
5. Urban runoff water quality - storm-water BOD control
6. Machinery systems
7. Building project construction scheduling and costing
8. Economic/Environmental Sustainability
9. Environmental remediation (revisions to CALTOX)
10. Measures defining what is a "neighborhood"
11. Analysis of data streams for selecting the best method of analysis
12. Handling linguistic data concurrently with numerical data
13. Risk management
14. Long-term firm stability and evolution

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