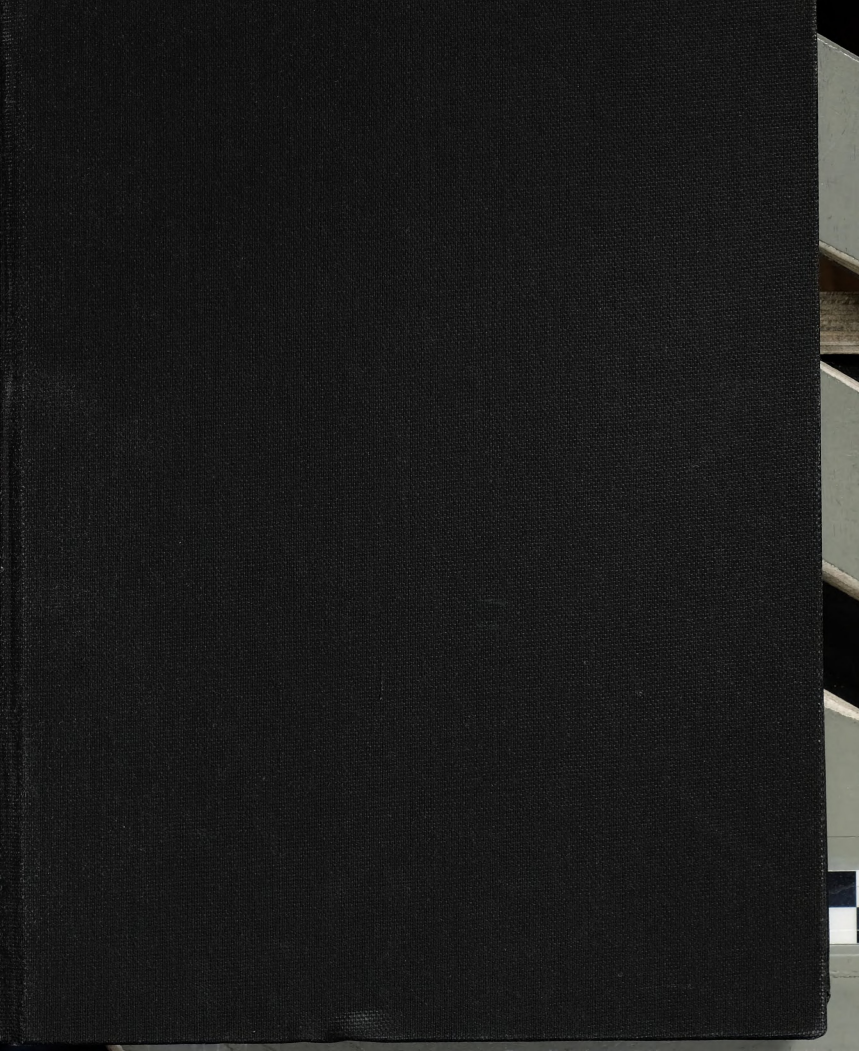
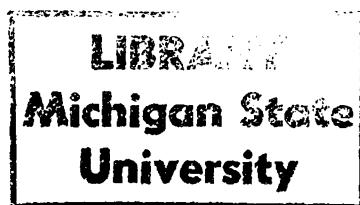






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A COMPUTER-BASED SIMULATION MODEL FOR
AGRO-ECOLOGICAL ZONE YIELD ASSESSMENT

presented by

Nilson Amaral

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of the requirements for

Ph.D. degree in Research Development/
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A COMPUTER-BASED SIMULATION MODEL FOR
AGRO-ECOLOGICAL ZONE YIELD ASSESSMENT

By

Nilson Amaral

A DISSERTATION

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

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ABSTRACT

A COMPUTER-BASED SIMULATION MODEL FOR AGRO-ECOLOGICAL ZONE YIELD ASSESSMENT

By

Nilson Amaral

Computers and information systems are fundamental tools for decision makers and planners. A computer-based simulation model was developed in this study with the objective of providing a practical and useful tool for decision makers and planners to estimate crop yields in relatively large and homogeneous regions, the so-called agro-ecological zones. The simulation model was developed in two modes: First, the deterministic approach was used to analyze yield trends in an a posteriori type of analysis. Second, a stochastic approach, with random environmental inputs, was used to provide decision makers with the yield-distribution parameters necessary to make inferences about yield values, as well as crop-yield prediction.

The technique used in the simulation model does not rely solely on yield time series but on the process of biomass production, where water deficit is a primary constraint. The Monte Carlo approach was employed to generate random

Nilson Amaral

variates based on the distribution parameters of the population data for the exogenous environmental inputs. A variance-partitioning technique, which considers random variation in the input parameter, was used with the Monte Carlo approach.

The simulation results, using three regions in Jamaica and three agro-ecological zones in the Dominican Republic as data sources, showed the validity of the model when results were compared with observed-yield data for those locations, as well as with FAO yield guidelines. Results are presented in the form of tables, scattergrams, and histograms to serve as an aid to decision making and planning.

Limitations do exist in the simulation model and are presented in the last chapter. Data completeness and precision pose some limitations to the final analysis, which indicates a need to improve data collection.

Despite its limitations, the model shows the feasibility of the systems approach to crop-yield estimation and opens new insights into the process of yield prediction for use in decision making and planning, and as a linkage to other models such as economic-optimization models.



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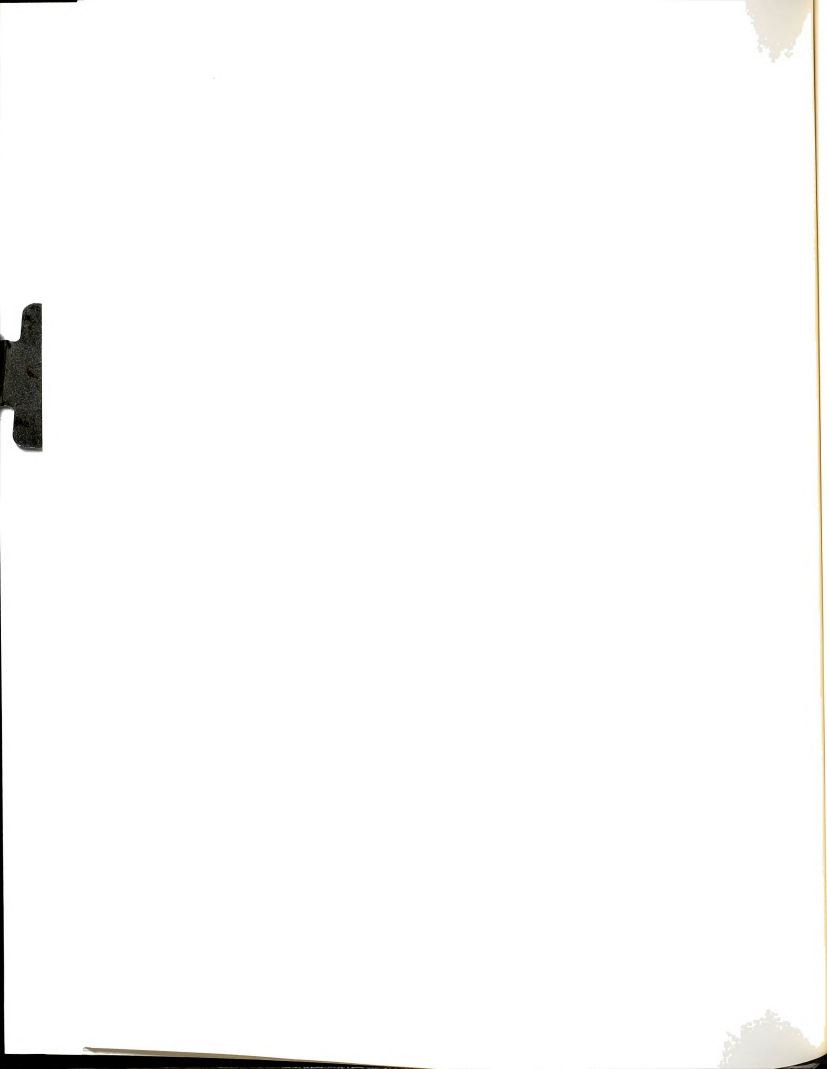
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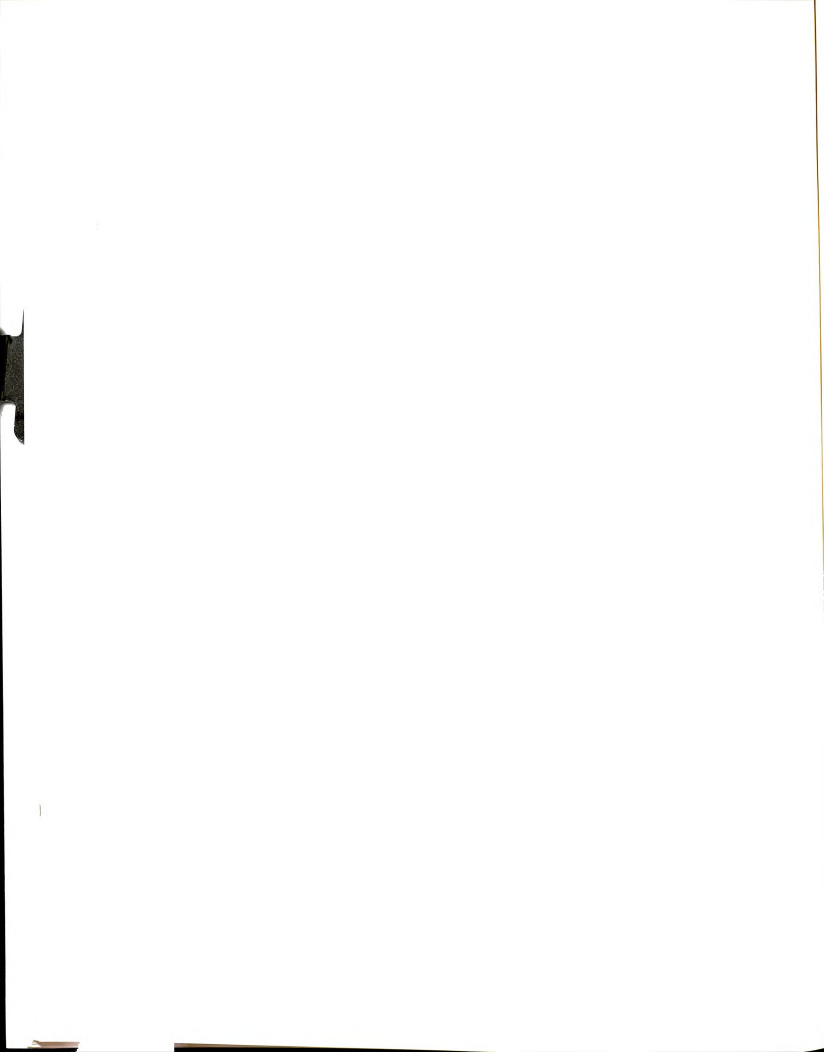


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CHAPTER I

INTRODUCTION

For most developing countries, agricultural productivity has an important influence on economic development, trade, and foreign exchange earnings. Developing nations are seeking areas best suited for crop production to satisfy internal demand, to keep food prices at affordable levels for the large percentage of the population with low income, and to generate foreign exchange to pay for the importation of technology, goods, and services.

Past and predicted crop yields play an important role in the decision-making process in many areas of a country's economy. Information on harvest size is needed for a variety of purposes. Governments require information for administrative and planning purposes, possibly for measures to regulate quantities imported and/or exported, to control prices, and so on. Private firms are interested in appropriate data for their marketing and storage arrangements. Farmers may use harvest data as the basis for their seasonal purchases to obtain particularly favorable prices.



Researchers are interested in optimizing the regional distribution of agricultural production patterns. Heady (1964) used crop yields as a significant variable for a linear optimization model for crop allocation. Vilas (1975), who focused his Ph.D. research on the spatial equilibrium analysis of the rice economy in Brazil, used crop yield as one of the most important variables in the inter-regional analysis. Heiss (1981) discussed the economic benefits of improved crop information on wheat and all cereals for European countries. He developed a model for estimating the economic benefits of crop-yield assessment for the European Community (EC) as well the benefits for producers, consumers, and governmental agencies.

Objectives of the Study

Answers are needed to questions asked by scientists, decision makers, and planners regarding effects of agro-climatic conditions and management practices on the agricultural productivity of cash crops and basic food staples.

Answers are needed to such questions as:

1. How are yield values for the different farming systems estimated? By farming system is meant "the complex arrangement of soils, water sources, crops, livestock, labor, and other resources and characteristics within an environmental setting that the farm family manages in

accordance with its preferences, capabilities and available technologies" (Shaner, 1982).

2. What are the tradeoffs between irrigation investment, the cost of farm management practices, and the increase in productivity through other factors?

3. How can a developing nation, in need of foreign exchange, improve land-use planning for agricultural production?

Those questions demand the application of a new method using computational procedures, preferably a computer-based model, for evaluating responses of a broad range of agricultural crops to agro-climatic (rainfall, temperature, soil, slope, etc.) and farming-system parameters (fertilizer usage, management practices, and so on).

The objective of the present research is to address these questions in a microcomputer-based simulation model that will aid the decision-making process in a "user friendly" manner by predicting crop yields for a homogeneous region or agro-ecological zone. These yield predictions are most representative of relatively large-scale farming systems in mono cultivation.

A computer-based simulation model was developed for use in a deterministic as well as in a stochastic or probabilistic mode for farming-system yield assessment that can be run in an interactive manner on a microcomputer.



The deterministic mode may help decision makers compare the simulation results with the observed yield on a year-by-year basis--a posteriori analysis--and evaluate the current production systems and/or practices and their associated yield response.

The stochastic mode may help decision makers deal with the decision process under conditions of uncertainty. The estimated probability-density statistics such as moments (mean, variance, and skewness) and quantiles, computed from the model's results, provide decision makers with a wealth of information for assessing any uncertainty present in the system.

The simulation model can simulate yield for the most important crops responsible for generating foreign exchange for developing nations, as well as crops responsible for ensuring internal food security. It is also this researcher's objective to use in the simulation model a methodology that does not rely solely on time series of past yield data because data availability and reliability due to, among other things, government intervention are significant constraints in most developing nations.

It is hoped that the simulation model can eventually be linked to an economic-optimization model that can be used to optimize land use and help in determining the "best" land-allocation scheme. The YIELD model developed herein is a

component of the Comprehensive Resource Inventory and Evaluation System--Resource Information System (CRIES-RIS) (Schultink, 1981, 1983, 1984).

The CRIES resource inventory and analysis approach to integrated rural development planning and agricultural sector analysis has two major components: the CRIES-GIS (Geographic Information System) and the CRIES-AIS (Agro-economic Information System). The YIELD simulator is a component of the CRIES-AIS information system (Schultink, 1986).

Policy variables are not explicitly included in the model at this stage, but model results can be analyzed and changes made in the input parameters and variables to reflect various policy scenarios. Alternative policies and climatic, physical, and farming-system characteristics can easily be examined in an interactive manner using a micro-computer. The model is designed for use by those with little or no computer experience. A series of menus and system prompts provides the user interaction.

The simulation model developed herein can aid in evaluating national and international strategies for agricultural-production planning and take advantage of prevailing agro-climatic conditions. The model could form the basis for evaluating irrigation and pest-management decisions during the growth season, evaluating investment



decisions, forecasting yields, or predicting the effects of soil erosion and water deficit during the growing season.

The model can determine the yield value on a seasonal and spatial basis by Agro-Ecological Zone (AEZ) (the so-called Resource Planning Unit or RPU [Schultink, 1983]) for major agricultural crops, including those termed cash crops, such as bananas, sugar cane, soybean, tobacco, and wheat, and food staples such as potato, rice, corn, tomato, bean, and cabbage.

Findings of the study as intended neither as precise descriptions of the real world nor as final predictions. Instead, the model was designed to provide insight into decision-making criteria associated with local, soil, environmental, and management practices and their associated variables used in estimating crop yields. The user should realize that the model provides yield predictions for high-yielding varieties, adapted to the agro-ecological conditions represented. As such, variety-specific yields may change by location and are affected by general crop adaptability, incidence of disease, pests, and other factors.

Literature Review

The role of crop-weather models has become increasingly important in assessing potential crop production based on climate, monitoring crop prospects from current weather data, evaluating the effect of natural or man-induced

climatic variability on crop yields, and interpreting the effect of weather on yields.

Much of the early modeling research on agricultural production systems used statistical analysis as a modeling technique (Smith, 1914; Buck, 1961; Gibson, 1979). Regression models (Botkin, 1969; Thompson, 1975; Vilas, 1979; Bortoluzi, 1978; Heady, 1964) that are based on past crop-yield values are often expressed in a functional format, which contains linear, logarithmic, quadratic, or a combination of these terms involving price, fertilizer usage, and so on, and data such as rainfall, temperature, and time.

The regression approach is one of the most common techniques used in yield estimation. It has some serious limitations due to a vast number of variables and the complexity of the processes involved in plant growth. Before any attempt is made to model a process, basic research is needed to understand fully the theory involved.

Regression modeling was used by Sakamoto (1981) in his paper entitled "Climatic-Crop Regression Yield Model: An Appraisal." He made it clear that despite its limitations, regression analysis is a useful tool. He also indicated that much of the utility of regression analysis is associated with its simplicity of application and the availability of data.

In his paper "Methods of Crop Production Forecasting in the EEC; Present and Expected Trends in Crop Production," Thiede (1981) briefly discussed the methods of estimating harvests that are currently in use. According to Thiede, the methods used to estimate harvests in the EC vary widely from one member state to another, partly for historical reasons and partly because of the differing fundamental attitudes of farmers toward statistics. Thiede also pointed out that, concerning the methods used, a distinction must be made between pure estimates, objective measurements, and calculations based on agricultural meteorological data.

In the late 1960s, researchers turned their attention to understanding better the physical and chemical processes involved in crop growth (DeWit, 1965; Ducan, 1967; Lake, 1967). Those theoretical developments gave rise to relationships that were tested in laboratories, "but they lacked the dynamic properties of the plant systems" (Curry, 1975).

Computer modeling and simulation began to have a place in agricultural production systems in the last decade or so. Several simulation models for single crops were developed for corn (Curry, 1971), soybean (Curry, 1975), and alfalfa (Holt, 1978), based on temporal modeling, without any attempt to have a temporal-spatial resolution for crop yields in aiding the decision-making process. Curry (1971) pointed out that serious limitations still may exist:

The ultimate computer model for the soybean plant would be flexible enough to simulate growth and development at any location for which climate and cultural information is available. The expected results would be reasonable yield estimates and understanding of the physiological processes underlying these yields. Simulations of this type are not limited by mathematical or computer capabilities, but rather by lack of understanding of the interaction of the plant with its environment.

One major use of crop-yield simulation is to improve assessment of technology-transfer options based on regional characteristics. By using the yield simulator, the agricultural researcher can simulate environmental situations and obtain critical information on future research priorities, such as crop adaptation, the potential of introducing new cultivars, and so on. This is only possible if the model is designed to accommodate changes in the simulation process. To permit this, the yield-simulation model must be capable of evaluating the yield response for several sites with different soils and climate characteristics, thereby providing a rapid and effective means of assessing and transferring crop-production technology to developed nations as well as developing countries around the world.

The dynamics of the input variables, together with non-availability of time series data and the spatial-dimension requirements that affect crop yields, requires a more elaborate procedure that goes beyond regression models.

Economic-development studies and policy analysis in agriculture production and land-use planning make the usual

regression technique for estimating crop yield less than appropriate. This requires further research involving dynamic simulation models that provide a more realistic crop-yield assessment.

Essentially, such models exist for most of the world's major economic crops, as Hayes (1982) indicated. Most of these models take into consideration temporal and/or deterministic modeling but do not attempt to assess yield on a spatial or farming-systems basis.

Several attempts have been made to show spatial patterns of photosynthesis or yield modeling at a regional level for a specific crop (Monteith, 1972, Baier, 1976). Hayes (1982) constructed a numerical crop-yield model for 11 crops. The Hayes model is a deterministic model that computes yields for crops that are grown mainly by developed nations (spring wheat, winter wheat, spring barley, winter barley, and so on). The Hayes model, besides focusing mainly on cash crops for developed nations, has requirements for its operation that are out of reach for most developing nations (large mainframe computer, numerical calculus libraries, expertise in computer programming, and so on).

The spatial dimension of the models described above does not consider the yield evaluation for a micro-region such as an agro-ecological zone, a production potential area, or farming systems. However, those characteristics

are critically needed for yield assessment for developing nations, considering the size of the farm holdings and the wide variations in and nonuniformity of the farming systems.

Technique Used

The deterministic model was developed in two major modules. The first module is the data entry/data edit management phase, which allows the user to enter and make changes in the local and climate data set. This module is totally menu driven and has user-friendly design characteristics. The second module is the simulation model itself; interaction with the user occurs on a conversational basis. The user responds to the model prompts and changes parameters according to specific requests. The C programming language is used for the first module (Richie & Kerningham, 1978), whereas the second module is programmed using Fortran 77 (Microsoft, 1984).

The yield-simulation model is designed to run on an IBM-PC XT or compatible microcomputer, with a hard disk (one needs 1.2 MB disk space), math co-processor 8087 to speed up simulation runs, and a printer to obtain a hard copy of yield-simulation results. The option of on-screen reporting is also available.

To achieve the proposed objectives, the model is structured into four components, which permit execution on a

microcomputer with at least 256KB RAM (Random Access Memory).

The YIELD simulator consists of five phases:

- Phase 1: Calculation of the maximum potential yield
- Phase 2: Calculation of the maximum evapotranspiration
- Phase 3: Calculation of the actual evapotranspiration
- Phase 4: Calculation of the estimated yield
- Phase 5: Estimated yield adjustment

The deterministic simulation model has data requirements and default values for the inputs to make it possible to run the model for regions where data are not available or where the expected data precision is low. A discrete time-simulation approach (Forrester, 1961; Manetsch & Park, 1984) is used in all four phases. The numerical integration and differentiation technique (Hamming, 1962; Conte, 1980) is used to implement the equations.

A computation sequence for continuous-flow simulation models is used in the following format (Manetsch & Park, 1984; Chappelle, 1985):

A. Initialization Phase

1. Assign values to model parameters
2. Initialize state or level variables

$$S_1(0), S_2(0), \dots, S_n(0)$$

3. Initialize time $T = 0$
4. Specify characteristics such as length, number, output, etc.

B. Execution Phase

1. Compute rate variables for time T:

$$R_j(t) = g_j(S_1(T), S_2(T), \dots, S_n(T))$$

$$j = 1, 2, \dots, m$$

2. Print rate variables

3. Update time : $T = T + DT$

4. Compute state variables for time $T + DT$

$$S_i(T + DT) = S_i(T) + f_i(R_1(T), R_2(T), \dots, R_m(T))$$

$$i = 1, 2, \dots, n$$

5. Print state variables

6. Return to (1) if simulation run is not completed

7. Terminate simulation run

The model structure is based on the equations developed by Doorenbos and Kassam (1979) and Slabbers et al. (1979), which focus on the relationships between crop yield and water availability. To accommodate the simulation structure outlined above and to account for soil- and management-practice parameters, modifications and additions were made in the equations and procedures provided, and the results were transferred into a simulation model and converted into the C programming language.

The deterministic model relies on environmental variables value distributed annually (daily values or monthly means) for selected target years.

The stochastic or probabilistic model relies on the shape of the distribution and moments (mean, variance, skewness) of the agro-ecological data and parameters associated with management practices. Those variables are then generated internally by the simulator for each day of the growing period and for each simulation run. An input data preprocessing scheme, which uses statistical analysis to determine the shape of the distribution and moments of the agro-ecological variables, is required. A stochastic model component was developed as a separate and independent module that contains all the functions and equations used in the deterministic model.

Organization of the Dissertation

Chapter I was an introductory chapter. Chapter II is mainly concerned with the definition of the regionalization process as a precondition for model execution. Agro-Ecological Zone (AEZ) determination procedures are presented, and model assumptions are stated.

The analytical framework for the deterministic yield simulator, by phases, is shown in Chapter III. Model assumptions, mathematical equations, and the data requirements are also presented.

Chapter IV contains the analytical framework for the stochastic or probabilistic yield simulator. The use of statistical procedures, the random variable generator and

procedures, data requirements, and mathematical equations are presented.

In Chapter V the simulation results of both approaches are presented and discussed. Results are shown in the form of tables and graphs.

Chapter VI contains an analysis of the results in terms of policy decision tools for decision making and development planning. Implications, a summary of findings, conclusions, and suggestions for further research are also discussed.

CHAPTER II

AGRO-ECOLOGICAL ZONE DETERMINATION

A regionalization and an aggregation process must be carried out in the study area to identify agro-ecological zones (AEZs) with common physical characteristics, such as soil, soil textural class, prevailing slope, and climate.

Two concepts in AEZ definitions were given by Schultink (1984), which characterize an AEZ. They are:

- Resource Planning Unit (RPU), a geographically delineated unit of land that is relatively uniform with respect to land forms, soil types and patterns, climate, and natural vegetation.

- Production Potential Area (PPA), an aggregate area of individual soil types and associated climates within an RPU, which is sufficiently homogeneous with respect to plant adaptability, management requirements, and potential productivity to be reliably depicted by unique estimates of those parameters to serve as an analytical reference for national or regional analysis and planning.

Data-Acquisition Process

To accomplish the task of determining AEZs, a data-acquisition process must be activated to collect the required information from and for the study area. The type of data required for AEZ determination will depend on the study objectives, resources and technology available, and so on. Data can be acquired through three main types of data-collection procedures (Chappelle, 1985; Schultink, 1984):

- Primary data, which are data acquired to meet specific information requirements of the project, such as special aerial surveys for topographic mapping, soil analysis, and so on.
- Secondary data, which are existing data with characteristics and format suitable to meet specific information requirements with minor modifications, such as area calculation from vegetation maps, climatic data from meteorological stations, and so on. Secondary sources are the most common and the least expensive sources of data and are frequently used in AEZ-determination processes.
- Derived data, which are existing data with characteristics and format suitable to meet certain information requirements with major modifications, such as reinterpretation of existing soil maps to assess crop-specific production potential using vegetation indicator species and special vegetation surveys and indicator species. In

general, the process involves secondary data collection followed by data transformation or derivation.

- Based on the user and project objectives identified, data aggregation and regionalization is used to define and spatially delineate homogeneous areas with respect to major soil, topographic, and climatic characteristics. The process makes it possible to differentiate relatively large areas for which a specific crop-yield response can be predicted on the basis of homogeneous criteria.

The cost of a project is largely determined by its data-collection procedures. Sometimes a tradeoff between cost of data acquisition and resulting precision must be made to accomplish the project objectives with minimum cost and/or within the project budget.

The system or project design team must be mindful of potential constraints on data availability, such as administrative obstacles, confidentiality obstacles, time and continuity constraints, cost constraints, and data-precision problems. The accuracy of the digital representation of spatial data is governed by both user requirements and the inherent characteristics of the source document and the instruments used to create it.

Computational Tools for AEZ Determination

In general, a large amount of data must be collected and manipulated to determine the AEZs. Existing maps and data, survey observations, and applied remote sensing are some of the methods used in the data-acquisition process. The objective of this section is to describe a "state of the art" technique, which uses computers as tools for AEZ determination.

Computers play a fundamental role in natural-resources assessment today. Several software programs are being developed with the objectives of processing data acquired from remote sensing and other data-acquisition methods. Those programs or systems are usually called Geographic Information Systems (GIS) and have the capability of processing large amounts of data in a spatial context. Examples of such systems are the CRIES-GIS (Schultink et al., 1981) and Canada Geographic Information System (CGIS) (Marble & Peuquet, 1982).

A GIS represents a system, commonly computer-based, for handling spatial data. A critical and unique property of spatial data is that each entry must be defined in terms of its location in a two- or three-dimensional space. The GIS is the main tool for handling spatial data. The major objective of a GIS is to support the spatial decision-making process in resource use and management. The most important

functions of a GIS are as follows (Marble & Peuquet, 1982; Schultink et al., 1981):

Data input: Normally consists of a combination of manual and automatic digitizing operations, together with associated data cleaning and edit activities. By digitizing is meant a process of data capture for spatial data-handling purposes; the main source of data frequently is maps. Manual digitizing has some advantages in terms of correct data assessment, but it is slow and labor-intensive, and errors may be generated by the digitizer operator. Automatic digitizing is now being carried out by a number of methods (Marble & Peuquet, 1982). The most common method is the use of a large drum scanner, such as those employed in graphic arts. Speed and reliability are the main advantages of drum scanners.

Data storage and retrieval: Initial creation of the spatial data base, together with subsequent update operations and query handling. A data base is defined as a collection of interrelated data stored together with controlled redundancy to serve one or more applications in an optimal fashion. The data are stored so that they are independent of programs that use the data (Date, 1977; Martin, 1977). Usually, construction of the data base that contains the spatial indexed information is based on the relational data base theory (Codd, 1970). It is important

to keep in mind that the spatial-dimension characteristics of the GIS require a data-base structure different from the usually known data bases for business applications, such as Data Base Management System (DBMS) and Management Information System (MIS) (Date, 1977).

Data manipulation: Creation of composite variables through processing activities directed toward both spatial and nonspatial attributes of system entities. Any GIS must be capable of performing a series of manipulations on the spatial data held in its files. Each system contains a specific set of these procedures, determined by the requirements of the users of the system.

Analysis: The combination of the various resources' attributes and their associated measurement scales in a set of mathematical operations designed to derive indices relating to optimum-use aspects, given a complex set of physical and socioeconomic criteria, e.g., suitability and effect assessment, economic feasibility analysis, and optimum allocation decisions, given distance parameters and infrastructure.

Report generation and information display: Creation of both tabular (statistical results, tables, and so on) and cartographic reports, maps, and pictures reflecting selectivity retrieval and manipulation of entities within the data base. Those functions or computer-aided procedures are



designed to delineate AEZs, representing areas with physical characteristics considered relatively homogeneous at a pre-defined level of detail.

CRIES-GIS: An Overview

The Comprehensive Resource Inventory and Evaluation System (CRIES) Resource Information System (RIS) has two major components: the Geographic Information System (GIS) and the Agro-economic Information System (AIS) (Figure 1). The YIELD simulator and the AEZs are combined for the AEZ-yield estimation.

The CRIES-GIS provides the capability to store, edit, and process digital map data and creates the master data base (disk files) for subsequent analysis. The CRIES-GIS (Schultink, 1981) has in its analysis module an important phase, called raster OVERLAY. In this process one raster file is superimposed upon another file web, and the (weighted) concurrence of these two data sets and derived indices are determined. The system can overlay up to ten files in one operation.

The OVERLAY analysis of multiple attributes is shown in Figure 2. Its output is a single layer of information with attribute values resulting from a linear combination of the attribute values from the other information layers. The MATCH phase creates new attribute values for user-specified co-occurrences of existing attributes values. The OVERLAY

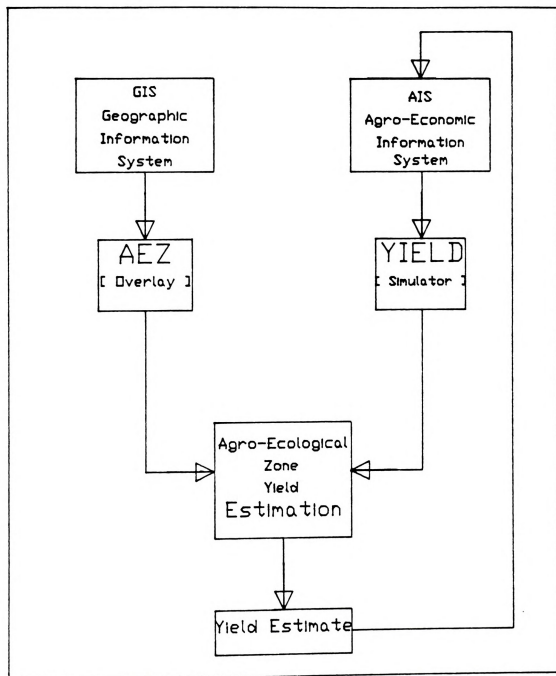


Figure 1. Agro-ecological zone YIELD assessment as a component of CRIES-RIS.

and MATCH phases ultimately provide the spatially defined regions called AEZs.

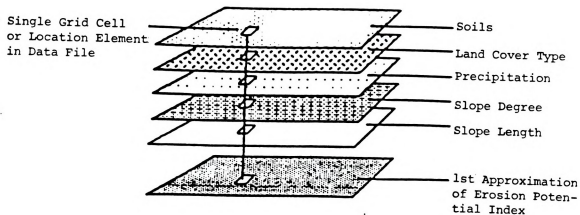


Figure 2. Geographic Information System--OVERLAY analysis.

Some data-manipulation functions included in the CRIES-GIS are (Schultink et al., 1986):

Data Manipulation--Input

Digitizing
Editing
Polygon conversion
Cutter (outline boundaries)

Data Manipulation--Statistics

Histograms
Tally (windowing)
Cross-tabulation

Data Manipulation--Analysis

Erosion (soil erosion)
Grouping
Invert
Match
Normalize
Overlay
Search
Surface (three-dimensional analysis)

Data Manipulation--Display

Character maps
Value maps
Locate

Data Manipulation--Printer Maps

Choroline (map print capabilities)

Data Manipulation--Utilities

Reformat
Mosaic
Aggregate
Disaggregate

The GIS can be used to cross-reference the AEZs with major land use to identify additional areas suitable for agricultural expansion.

Examples of output (Schultink, 1986) from the CRIES-GIS are a scaled character map of elevation for Choluteca Department, Southern Honduras (Figure 3); a cross-tabulation output portion of a Two-Way Cross-Tabulation Between Rain-fall and Elevation, Choluteca Department, Southern Honduras

[illegible][illegible]

HONDURAS DATA BASE - REGIONAL LEVEL
ATTRIBUTE: ELEVATION. ATTRIBUTE VALUES: CONTOUR INTERVALS, VARIABLE
MAP SCALE SELECTED 1 : 500,000

Figure 3. Geographic Information System--character map of elevation.

(Figure 4); and a Choroline, dot-matrix printer map output of land cover/use map derived from Landsat Satellite Data, Choluteca Department, Southern Honduras (Figure 5).

Hardware required to run the CRIES-GIS is:

- IBM PC--XT or compatible microcomputer with 512KB of RAM
- hard disk
- MS-DOS operating system
- Calcomp map digitizer
- dot matrix printer
- Techmar color board
- monochrome and color-enhanced display
- color jet printer
- optional point or mouse system

CRIES-AIS: An Overview

The CRIES-AIS is designed to evaluate and derive benefits from physical and socioeconomic variables such as yields, input cost, and producer prices; to assess the comparative advantage of land-use types in meeting food and export crop demands, and to conduct related economic analyses regarding agricultural policy alternatives. The AEZs are the spatial units of analysis for the AIS system.

The AIS has several components that perform different functions. Usually, the output or results accomplished by one component are inputs to another component. The following are the main components of the AIS system:

- Water balance
- Yield simulator
- Farm budget
- Input/output model
- Optimization model (linear programming)
- Statistical analysis

Prepared by: CRIES-GIS / Michigan State University
Thursday April 10, 1986 Time 09:22

Crosstabulation Table

```

+-----+
|Frequency|
+-----+
Frequency in hectares

Format:  Col Pct
         Row Pct
         Tot Pct
+-----+

```

Attribute		Description: ELEVATION AND PRECIPITATION				
CHOLRAIN.ras						
Attribute						
CHOLELEV.ras						
		Row	Atr Val	Atr Val	Atr Val	Atr Val
		Totals	1	2	3	4
Column Totals		444469	89725	83275	184900	86569
		100.00	100.00	100.00	100.00	100.00
		100.00	20.19	18.74	41.61	19.48
		100.00	20.19	18.74	41.61	19.48
Atr Val		209056	1944	9969	125856	71287
1		47.04	2.17	11.98	68.07	82.35
		100.00	0.93	4.77	60.21	34.10
		47.04	0.44	2.25	28.32	16.04
Atr Val		53113	10106	12494	24069	6444
2		11.95	11.27	15.01	13.02	7.45
		100.00	19.03	23.53	45.32	12.14
		11.95	2.28	2.82	5.42	1.45
Atr Val		82425	25669	23531	26556	6669
3		18.55	28.61	28.26	14.37	7.71
		100.00	31.15	28.55	32.22	8.10
		18.55	5.78	5.30	5.98	1.51
Atr Val		98481	51512	36381	8419	2169
4		22.16	57.42	43.69	4.56	2.51
		100.00	52.31	36.95	8.55	2.21
		22.16	11.59	8.19	1.90	0.49
Atr Val		1394	494	900	0	0
5		0.32	0.56	1.09	0.00	0.00
		100.00	35.44	64.57	0.00	0.00
		0.32	0.12	0.21	0.00	0.00

Figure 4. Geographic Information System--two-way cross-tabulation.



Figure 5. Geographic Information System--choropleth printer map.

The AIS data base is responsible for data manipulations, data storage of agricultural and socioeconomic data, crop requirements, and so on.

The main objective of this study is to develop a yield-simulation model, as a component of the AIS system, that will evaluate crop yield as a function of climatic and local information, management practices, and soil information for AEZs.

CHAPTER III

DETERMINISTIC YIELD SIMULATOR (DYS)

The deterministic or nonprobabilistic yield simulator is designed to generate the maximum potential yield, irrigated yield, and rain-fed yield for different crops. The term "deterministic" is used here to indicate that the model's inputs and parameters have zero variance. This means that they are known with certainty and that their precision is not questionable. Chapter IV considers the case where the variance is not zero for some inputs and model parameters.

The DYS was developed largely based on equations and procedures from the publication Yield Response to Water by Doorenbos and Kassam (1979). Its main objective is to estimate maximum potential yield, irrigated yield, and rain-fed yield for the crops under study, based on the climatic conditions, soil and slope characteristics, and management practices of a single location or agro-ecological zone (AEZ) under investigation. This yield assessment provides additional guidelines for decision makers in land-use planning. Its secondary objective is to serve as an analytical tool

for decision makers and planners to evaluate agricultural production systems in terms of yields, agricultural land use, and natural-resource management in a posteriori analysis.

The nomenclature and different system-input classes that are part of the simulation model are described in Figure 6.

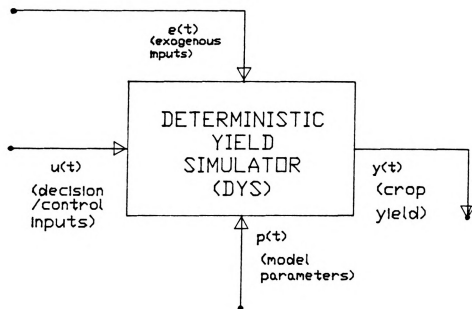


Figure 6. General input/output diagram for the deterministic YIELD simulator with nomenclature.

Exogenous environmental inputs are represented by the vector $e(t)$, decision or control inputs are represented by

$u(t)$, the model's parameters are represented by $p(t)$, and the model response is denoted by $y(t)$.

The model represents a procedure for estimating crop yield based mainly on water availability, the dominant constraint in tropical environments. Water represents the major variable in crop production, and optimum use of available water must be made for efficient irrigated crop production to produce high yields. It is generally believed that water, as an input to crop-production systems, represents 75 to 85 percent of the variation in crop yield. Doorenbos and Kassam (1979) pointed out that:

the upper limit of crop production is set by the climatic conditions and the genetic potential of the crop. The extent to which this limit can be reached will always depend on how finely the engineering aspects of water supply are in tune with the biological needs for water in crop production. Therefore, efficient use of water in crop production can only be attained when the planning, design and operation of the water supply and distribution system is geared toward meeting in quantity and time, including the periods of water shortages, the crop water needs required for optimum growth and high yields.

The production relationships between crops, climate, water, and soil are complex, and many biological, physiological, physical, and chemical processes are involved. Much research information is available on these processes in relation to water. For practical applications, such knowledge must be reduced to a manageable number of major components to allow a meaningful analysis of crop response to water.

Modifications and additions were necessary to transform the theoretical framework as presented by Doorenbos and Kassam into a computer-simulation model that can be useful in assessing potential, irrigated, and rain-fed yields for 30 different crops in a way that is easy and accessible for decision makers in developed countries as well as developing countries to use in planning and policy-analysis processes. The simulation model was designed to minimize requirements in terms of computational tools as well as computational expertise.

Model Assumptions

The 1979 FAO publication by Doorenbos and Kassam entitled Yield Response to Water, from which this yield simulator was derived, assumes that the relationships between crop, climate, water, and soil are very complex and that they are also affected by other factors, such as crop variety, fertilizer, salinity, pests and disease, and agronomic practices.

The relationships presented in this model pertain to high-producing varieties, well-adapted to the growing environment, growing in large fields where optimum agronomic and irrigation practices, including adequate input supply except for water under rain-fed conditions, are present. The predictive accuracy of the model may be increased by adjusting

the model parameters for site-specific conditions and validation through adaptive research.

Local conditions other than climate, such as soil depth and texture, availability of fertilizer, salinity, soil slope, rooting depth, and management practices, will be used to adjust the potential yield values based on AEZ and cropping-system conditions. It is assumed that no post-harvesting losses occur. However, these management-practice parameters can easily be included in the model for site-specific applications upon availability of data.

Crop requirements and crop coefficients are included in the model in the form of tables and model parameters that were derived from experimental crop research.

Socioeconomic factors, such as farmers' preference in relation to market demand, storage facilities, and availability of farm machinery and labor, that are known to affect farmer's management decisions such as selecting the crops to be grown and length of growing season, are not considered in the DYS. Pests and diseases, which are also known to influence yield output, are not considered due to lack of knowledge about explicitly mathematical relationships and probability functions. Numerical relationships and functional forms are requirements for inclusion in the numerical simulation model.

Surface runoff or internal drainage is assumed to be adequate to prevent yield reduction under average climatic conditions. Water logging or excessive water is known to cause crop damage and to reduce yields. The model does not consider damage due to excess water.

Yield adjustment due to soil fertility and fertilizer limitations may be used in the model. If restrictions apply, the user is given the option to adjust productivity accordingly. Crop-rotation considerations and cropping schemes are user-selected.

Micro relief-induced climatic effects on precipitation, wind, and solar radiation and resulting changes in evapotranspiration are not assumed in this model.

Model Structure

In this section an overview of the DYS, its structure with modifications and additions, and the computational procedure are provided (Figure 7).

Five consecutive phases are needed to estimate the yield value for a crop (Y_e). They are:

Phase 1: Determine the maximum yield (Y_m) of the adapted crop variety, dictated by climate, assuming that other growth factors (e.g. farm management, fertilizer, pests and diseases, and so on) are not limiting.

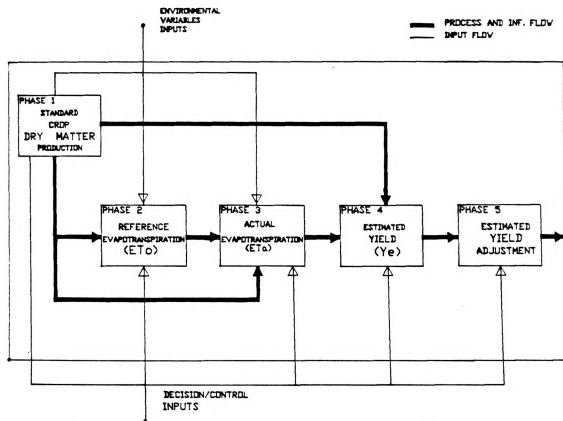


Figure 7. Deterministic YIELD simulator--general diagram.

In the first phase, six steps must be performed in order to determine (Y_m). They are as follows:

- Step 1: Computes gross dry matter production of a standard crop (Y_o).
- Step 2: Applies correction for crop species and temperatures.
- Step 3: Applies correction for crop development over time and leaf area (c_L).
- Step 4: Applies correction for net dry matter production (c_N).
- Step 5: Applies correction for harvested part (c_H).
- Step 6: Computes the maximum potential yield (Y_m).

Phase 2: Calculate maximum evapotranspiration (ET_m) when crop requirements are fully met by available water supply. In this phase, three steps are needed to compute (ET_m).

Step 1: Computes reference evapotranspiration (ET_o) based on the meteorological and crop data available.

Step 2: Computes growing period and length of crop-development stages and selects the crop coefficient k_c .

Step 3: Computes maximum evapotranspiration (ET_m).

Phase 3: Determine actual crop evapotranspiration (ET_a) based on factors concerned with available crop water supply.

Step 1: Determines total available soil water.

Step 2: Computes soil water depletion.

Step 3: Computes actual evapotranspiration (ET_a).

Phase 4: Select the yield response factor (k_y) to evaluate relative yield decrease as related to relative evapotranspiration deficit and obtain actual yield (Y_e).

Phase 5: Estimate crop-yield adjustment. In this phase, the resulting estimated yield from Phase 4 is adjusted for fertilizer availability, soil salinity, and moisture content.

Mathematical Formulation

Phase 1: Calculate Gross Dry Matter Production of a Standard Crop (Y_o).

To compute the gross dry matter production of a standard crop (Y_o) for a given location or AEZ, the DeWit (1965) method is used. This method is based on the level of incoming active shortwave radiation for standard conditions, modified after Doorenbos and Kassam (1979). Equation 1.1 provides the rate of change in gross dry matter production of a standard crop as a function of time.

$$\frac{dY_o(t)}{dt} = F(t) * y_o(t) + [1.0 - F(t)] * y_c(t) \quad (1.1)$$

where:

- $Y_o(t)$ = total gross dry matter production for a standard crop [kg/ha]
- $F(t)$ = fraction of daytime the sky is clouded [fraction]
- $y_o(t)$ = gross dry matter production rate of a standard crop for a given location on a completely overcast day [kg/ha/day]
- $y_c(t)$ = gross dry matter production rate of a standard crop for a given location on a clear (cloudless) day [kg/ha/day]
- t = time index [days]

Doorenbos and Kassam (1979) provided tables to determine the values of maximum active income shortwave radiation (R_{se} in cal/cm²/day) and gross dry matter production on

overcast (y_o) and clear days (y_c) (in kg/ha/ day) for a standard crop for time (t) and latitude in degrees. Numerical techniques for function interpolation such as Tablex and Spline are presented (Appendix A) and are used to obtain intermediate or interpolated results.

The total gross dry matter production for a standard crop (in Kg/ha), from time $t = t_o$ to t_1 is presented in Equation 1.2:

(1.2)

$$Y_o(t_1 - t_o) = \int_{t=t_o}^{t=t_1} \{F(t) * y_o(t) + [1.0 - F(t)] * y_c(t)\} dt$$

Numerical-integration techniques are applied to the above equation to obtain an expression that can easily be used in a simulation model (Forrester, 1961; Manetsch & Park, 1984).

Euler's approximation formula (Hamming, 1962; Conte, 1980) is used to find an approximate numerical solution to Equation 1.2. Euler's method was derived from the Taylor expansion series by setting the parameter $k = 1$. (Appendix B shows that procedure in more detail.) Its general form is given by:

$$\text{if } \frac{dy(t)}{dt} = f(x,y) \quad \text{then, } y(t) = \int_{t=t_o}^{t=t_1} f(x,y) dt$$

$$\text{and } y(n+h) = y(n) + h * f(X_n, Y_n)$$

where:

h = fixed step size

$y = f(x,y)$ is the functional relationship

Applying the above numerical approximation to Equation 1.2 and assuming $t_0 = 0$ and $t_1 = t$, results in Equation 1.3, which gives the cumulative total dry matter production for a standard crop from time $t = 0$ to time $t = t + dt$.

(1.3)

$$Y_o(t + dt) = Y_o(t) + dt * \{F(t) * y_o(t) + [1.0 - F(t)] * y_c(t)\}$$

Equation 1.3 is corrected and adjusted to reflect different crop groups, according to De Wit's (1965) concept, resulting in Equation 1.4:

(1.4)

$$Y_o(t + dt) = Y_o(t) + dt * \{F(t) * [0.8 + 0.01 * y_m(t)] * y_o(t) + [1.0 - F(t)] * [0.5 + 0.025 * y_m(t)] * y_c(t)\}$$

for $y_m(t) \geq 20.0 \text{ kg/ha/hour}$; and

$$Y_o(t + dt) = Y_o(t) + dt * \{F(t) * [0.5 + 0.025 * y_m(t)] * y_o(t) + [1.0 - F(t)] * [0.5 * y_m(t)] * y_c(t)\}$$

for $y_m(t) < 20.0 \text{ kg/ha/hour}$

where the $y_m(t)$ term is the production rate for crop groups and mean temperature, in kg/ha/day . The gross dry matter production is crop-species and temperature dependent. The production rate, $y_m(t)$, can be larger or smaller than 20.0



kg/ha/hour as assumed for the standard crop. Doorenbos and Kassam (1979) gave the production rates, $ym(t)$, in kg/ha/hour for crop groups and mean temperatures.

Additional corrections are applied to the gross dry matter production computed above; they are:

- Crop Development over Time and Leaf Area (cL). The model assumes, for the standard crop, an active leaf area index of five times the ground surface. When leaf area is smaller, a correction must be applied; when greater than five, the effect is small and is not considered in the model. Correction gives the correction values for different leaf area indices, as supplied by Doorenbos and Kassam (1979).

- Net Dry Matter Production (cN). Energy is required by the plant to maintain dry matter production for the within-plant growth processes (also called respiration). Only the remaining energy fraction can be used to produce new growth, which is, according to Doorenbos and Kassam, about 0.6 for cool temperatures (mean < 20 degrees Celsius) and 0.5 for warm temperatures (> 20 degrees Celsius).

- Correction for Harvested Part (cH). In most cases, only a part of the total dry matter such as grain, sugar, or oil produced is harvested. Doorenbos and Kassam provided the ratio between net total dry matter production and the

harvested yield for high-producing varieties under irrigation.

Using these correction factors, Equation 1.5 gives the potential yield of a high-producing, climatically adapted variety grown under constraint-free conditions (Doorenbos & Kassam, 1979):

(1.5)

$$Y_m(t + dt) = Y_m(t) + cL * cN * cH * dt * \{F(t) * [0.8 + 0.01 * y_m(t)] * y_o(t) + [1.0 - F(t)] * [0.5 + 0.025 * y_m(t)] * y_c(t)\}$$

for $y_m(t) \geq 20.0\text{kg/ha/hour}$, and

$$Y_m(t + dt) = Y_m(t) + cL * cN * cH * dt * \{F(t) * [0.5 + 0.025 * y_m(t)] * y_o(t) + [1.0 - F(t)] * [0.5 * y_m(t)] * y_c(t)\}$$

for $y_m(t) < 20.0\text{kg/ha/hour}$

A general system diagram, showing phase 1 of the deterministic YIELD simulation model, is supplied in Figure 8.

Phase 2: Maximum evapotranspiration (ET_m).

Climate is an important factor in determining the crop water requirements needed for unrestricted growth and optimum yield. Crop water requirements are normally expressed by the rate of evapotranspiration (ET), in mm/day. The level of ET is related to the evaporative demand of the air, which can be expressed as the reference evapotranspiration

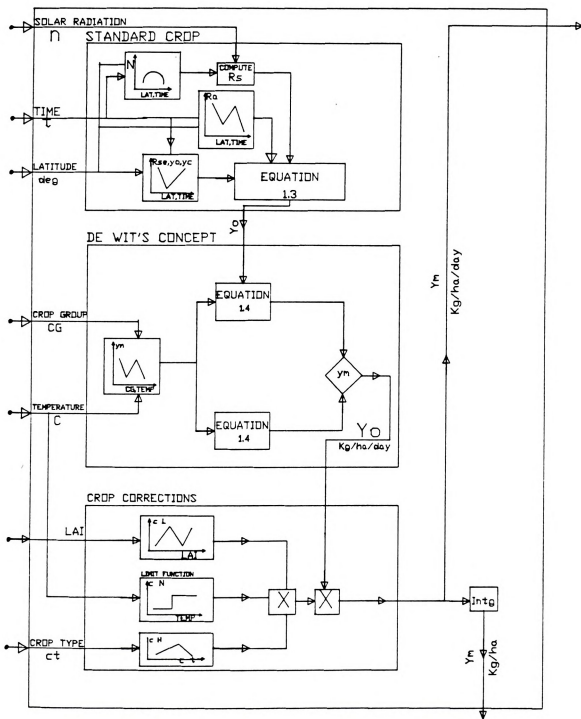


Figure 8. Deterministic YIELD simulation model--Phase 1: general system diagram.



(ET_o), which, when computed, predicts the effect of climate on the level of crop evapotranspiration. ET_o represents the rate of evapotranspiration of an extended surface of an 8 by 15 cm tall green grass cover, actively growing, completely shading the ground and without water deficit (Doorenbos & Kassam, 1979).

Several methods can be used to calculate ET_o: the Penman, Radiation, and Pan Evaporative methods shown in Doorenbos and Kassam; the Thornthwaite method (Thornthwaite, 1948); the Hargreaves method (Hargreaves, 1977); and the Priestley and Taylor method (Priestley & Taylor, 1972). Selection of Penman's method (Penman, 1948) for use in the model was based on worldwide validations of the method for the computation of reference evapotranspiration (ET_o) (Hayes, 1982; Doorenbos & Pruitt, 1977; Todhunter, 1981; Burt et al., 1980, 1981).

The basis for computation of evapotranspiration for this model was Penman's (1948) equation. The equation was successively modified to include the effects of a variety of factors, such as crop type, crop growth stage, and site factors (Doorenbos & Pruitt, 1977). These adjustments include the influence of extreme climatic environments, crop coefficients adjusting ET for specific growth stages, and soil moisture budget considerations.

Empirically determined crop coefficients (k_c) can be used to relate E_{To} to maximum crop evapotranspiration (E_{Tm}) when water supply fully meets the water requirements of the crop. The value of k_c varies with crop, crop development stage, and to some extent windspeed and humidity. Values of k_c for different crops were given in Doorenbos and Kassam (1979).

The methodology has the advantage of applicability and the fact that the mathematical relationships are well defined for many crops applications.

For a given climate, crop, and crop development stage, the maximum evapotranspiration (E_{Tm}) is provided by Equation 1.6:

$$E_{Tm}(t) = k_c(t) * E_{To}(t) \quad (1.6)$$

where:

$$\begin{aligned} E_{Tm}(t) &= \text{maximum evapotranspiration} && [\text{mm/day}] \\ k_c(t) &= \text{crop coefficient} && [\text{fraction}] \\ E_{To}(t) &= \text{reference evapotranspiration} && [\text{mm/day}] \end{aligned}$$

The reference evapotranspiration (E_{To}) is computed by means of the Penman method (Penman, 1948), modified by Doorenbos and Pruitt (1977), which provides Equation 1.7:

$$\begin{aligned} E_{To}(t) = c(t) * \{ & W(t) * R_n(t) + [1.0 - W(t)] * f[U(t)] \\ & * [e_a(t) - e_d(t)] \} \end{aligned} \quad (1.7)$$

where:

$$f(U(t)) = 0.27 * [1 + U(t) / 100.0]$$

$$Rn(t) = 0.75 * Rs(t) - Rnl(t)$$

$$Rs(t) = 0.25 + 0.50 * [n(t) / N(t)] * Ra(t)$$

$$Rnl(t) = f[T(t)] * f[ed(t)] * f[n(t) / N(t)]$$

$$f(T) = 1.99E-09 * Tk^4(t)$$

$$ed(t) = ea(t) * RH(t) / 100.0$$

$$f(ed) = 0.34 + 0.044 * [ed(t)]^{1/2}$$

$$f(n/N) = 0.1 + 0.9 * n(t) / N(t)$$

and

ea(t) = saturation vapor pressure [mbar]

ed(t) = actual vapor pressure [mbar]

U(t) = wind velocity measured at 2m height [km/day]

n(t) = actual sunshine duration [hour/day]

N(t) = maximum possible sunshine duration [hour/day]

Ra(t) = extra-terrestrial radiation at time t [mm/day]

RH(t) = relative humidity at time t [percent]

Rnl(t) = net longwave radiation [mm/day]

W(t) = temperature and altitude dependent weighting factor [fraction]

c(t) = adjustment factor [fraction]

T(t) = temperature in degree Celsius [C]

Tk(t) = temperature in degree Kelvins [K]

Doorenbos and Kassam (1979) provided tables to determine the values of those parameters. In summary, they permit determination of:

1. Saturation Vapour Pressure (e_a) in mbar as a Function of Mean Air Temperature (T) in Degrees Celsius.
 2. Extra-terrestrial Radiation (R_a) Expressed in Equivalent Evaporation in mm/day.
 3. Mean Daily Duration of Maximum Possible Sunshine Hours (N) for Different Months and Latitudes.
 4. Values of Weighting Factors (W) for the Effect of Radiation on E_t at Different Temperatures and Altitudes.
 5. Adjustment Factor (c) in Presented Penman Equation.
- All of these tables are included in the simulation model, and an interpolation process is used to determine intermediate values.

A general system diagram of the second phase of the YIELD simulation model is provided in Figure 9.

Phase 3: Actual Evapotranspiration E_t

Crop water demand in the root zone is met by available soil moisture. The actual rate of water uptake by the crop from soil moisture in relation to its maximum evapotranspiration (E_{Tm}) is determined by whether the available water in the soil is adequate or not. If not enough water is available, water-induced crop stress will occur.

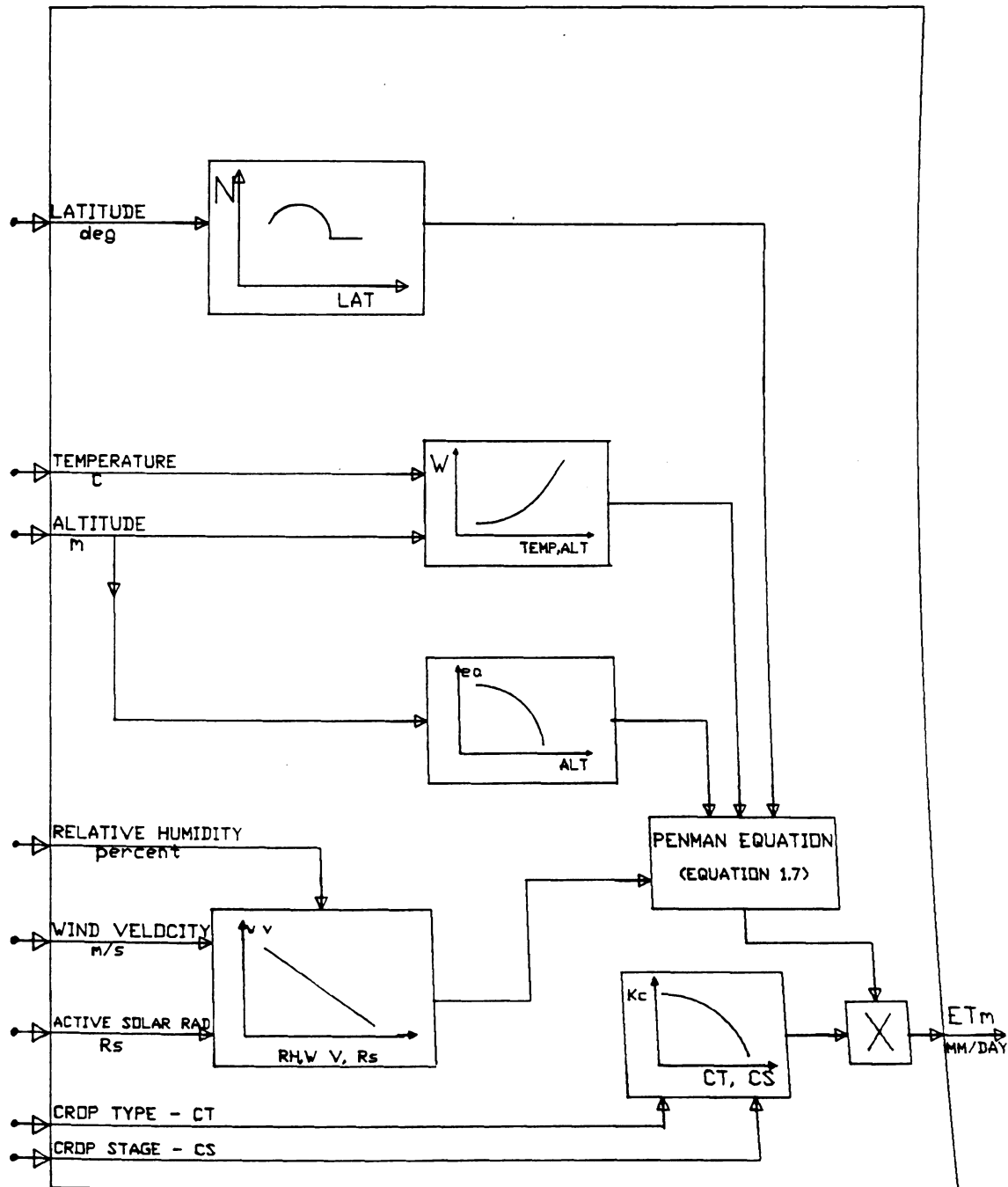


Figure 9. Deterministic YIELD simulation model--Phase 2: system diagram.

To compute the actual evapotranspiration (ETa), the level of available soil water must be considered. First, the available soil water index (ASI) is computed. This index indicates when available soil water is adequate to meet full crop requirements (ETa = ETm). A combination of ASI value, maximum evapotranspiration (ETm), and the remaining available soil water [(1-p)*Sa(t)*D(t)] provides an estimate of the actual evapotranspiration (ETa) (Doorenbos & Kassam, 1979).

The available soil water index (ASI) may be calculated using Equation 1.8:

$$\text{ASI}(t) = \frac{\text{In}(t) + \text{Pe}(t) + \text{Wb}(t) - [(1 - p) * \text{Sa} * \text{D}(t)]}{30 * \text{ETm}(t)} \quad (1.8)$$

where:

In(t)	=	net monthly irrigation application	[mm]
Pe(t)	=	monthly effective rainfall	[mm]
Wb(t)	=	available soil water moisture	[mm]
p	=	depletion factor	[fraction]
Sa(t)	=	total soil water holding capacity	[mm/m]
D(t)	=	root depth	[m]

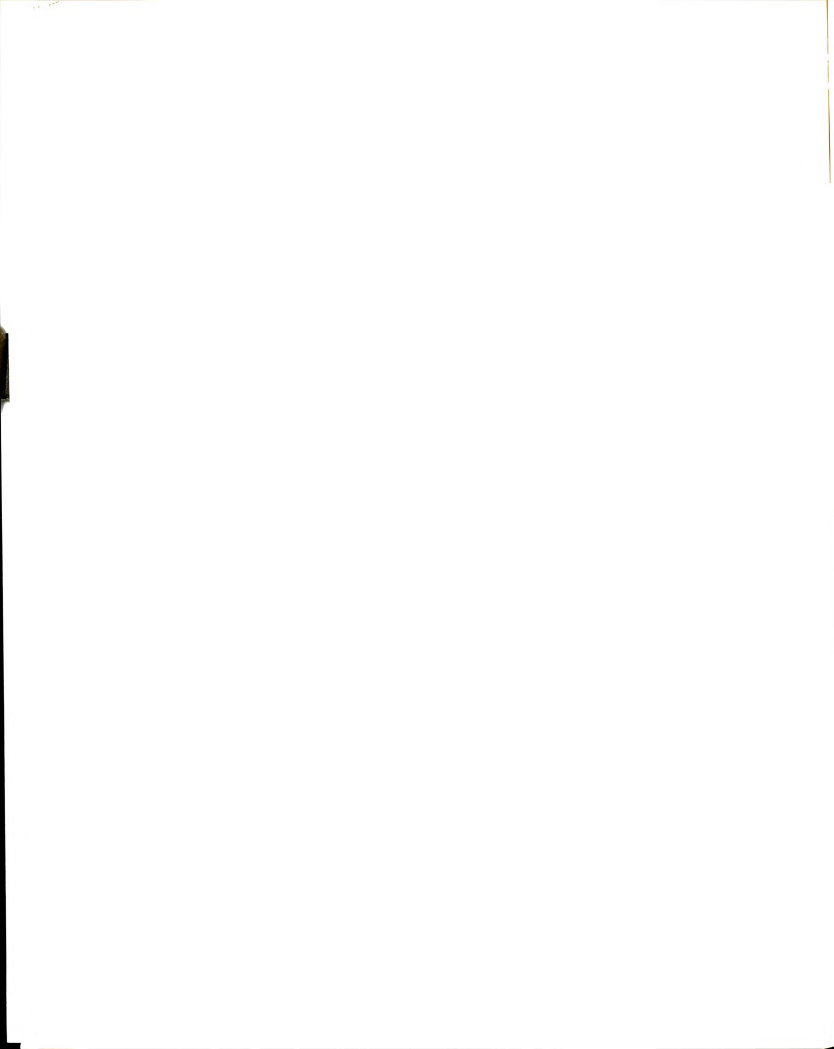
when $\text{ASI}(t) \geq 1.0$, then $\text{ETa} = \text{ETm}$

$\text{ASI}(t) < 1.0$, then Eta is computed according to Doorenbos and Kassam (1979)

The growth and development of crops depend on water availability. Sources of water include moisture stored in the soil, rainfall, irrigation, and surface runoff. Precipitation and irrigation recharge soil moisture in successive soil layers from the surface downward. Precipitation and irrigation in excess of that required to bring the crop root zone up to water-holding capacity is removed by runoff, which is a function of soil texture, slope, and infiltration rate. For a short dry period, crop growth may not be affected, even in the critical growth period, if there is sufficient soil moisture to support the crop's demand for water.

Soil moisture is difficult to measure in the field. Several methods have been proposed to estimate soil moisture content. Thornthwaite's (1948) model is based on simple water-balance equations for gains and losses within a single soil layer. A more complex, two-layer soil-moisture budget model was developed by Palmer (1965).

The soil-moisture model used in this study is a modified version of Thornthwaite's model, which includes an evaporation-reduction factor to account for farm management practices such as mulching and tillage, and a water-depletion factor, which is crop specific. Adams (1976) stated that, based on his research findings, it may be inferred that management systems that combine trash mulch



tillage and narrow-row spacing should add to the beneficial effects of both plant canopy soil shading and mulch. In addition, he stated that the use of mulch at a rate of 4,000 kg/ha with no soil shading reduces evaporation by as much as 58 percent as compared to potential evaporation measured from a bare plate with no canopy, for first-stage drying.

Much more research is needed to determine the effect of an evaporation-reduction factor and to make it practical for direct implementation into a numerical simulation model. One additional side effect of some evapotranspiration-reducing management practices is the increased occurrence of pests and diseases, which in some countries and/or regions may cause a significant reduction in yield.

The computation of soil moisture is given at time t by Equation 1.9:

$$Wb(t) = Wb(t-1) + [Pe(t) + Ir(t)] * Roff - p * Wb(t-1) - ETa * (100.0 - Mu) / 100.0 \quad (1.9)$$

where:

$Wb(t)$	=	soil moisture at time t	[mm]
$Wb(t-1)$	=	soil moisture at time $t-1$	[mm]
$Pe(t)$	=	precipitation at time t	[mm]
$Ir(t)$	=	irrigation at time t	[mm]
$Roff$	=	runoff coefficient	[fraction]
p	=	water depletion factor	[fraction]

$Eta(t)$ = actual evapotranspiration at time t [mm]

Mu = evapotranspiration reduction factor [percent]

The runoff coefficient ($Roff$) is a function of soil slope and soil textural class. According to Beasley et al. (1984), adjustment in infiltration rate due to soil slope and soil textural class may be accomplished using Table 1.

Table 1: Percentage of water that percolates into the soil as a function of percentage slope and soil textural classes

Slope Class	Soil Texture		
	Coarse Loamy	Fine Silty, Fine Loamy & Fine	Very Fine
0 - 4%	90%	80%	70%
4 - 8%	70%	60%	50%
8 - 12%	62%	52%	42%
12 - 15%	55%	45%	35%
15 - 20%	50%	40%	30%
20 - 30%	40%	30%	20%
30 - 50%	38%	25%	18%
> 50%	37%	27%	17%

Source: Beasley et al., 1984.

The water-balanced equation, adjusted for soil texture and topology, is used to keep track of the moisture content of the soil from time t to time $t + dt$.

A system diagram of phase 3 of the deterministic YIELD simulation model is provided in Figure 10.



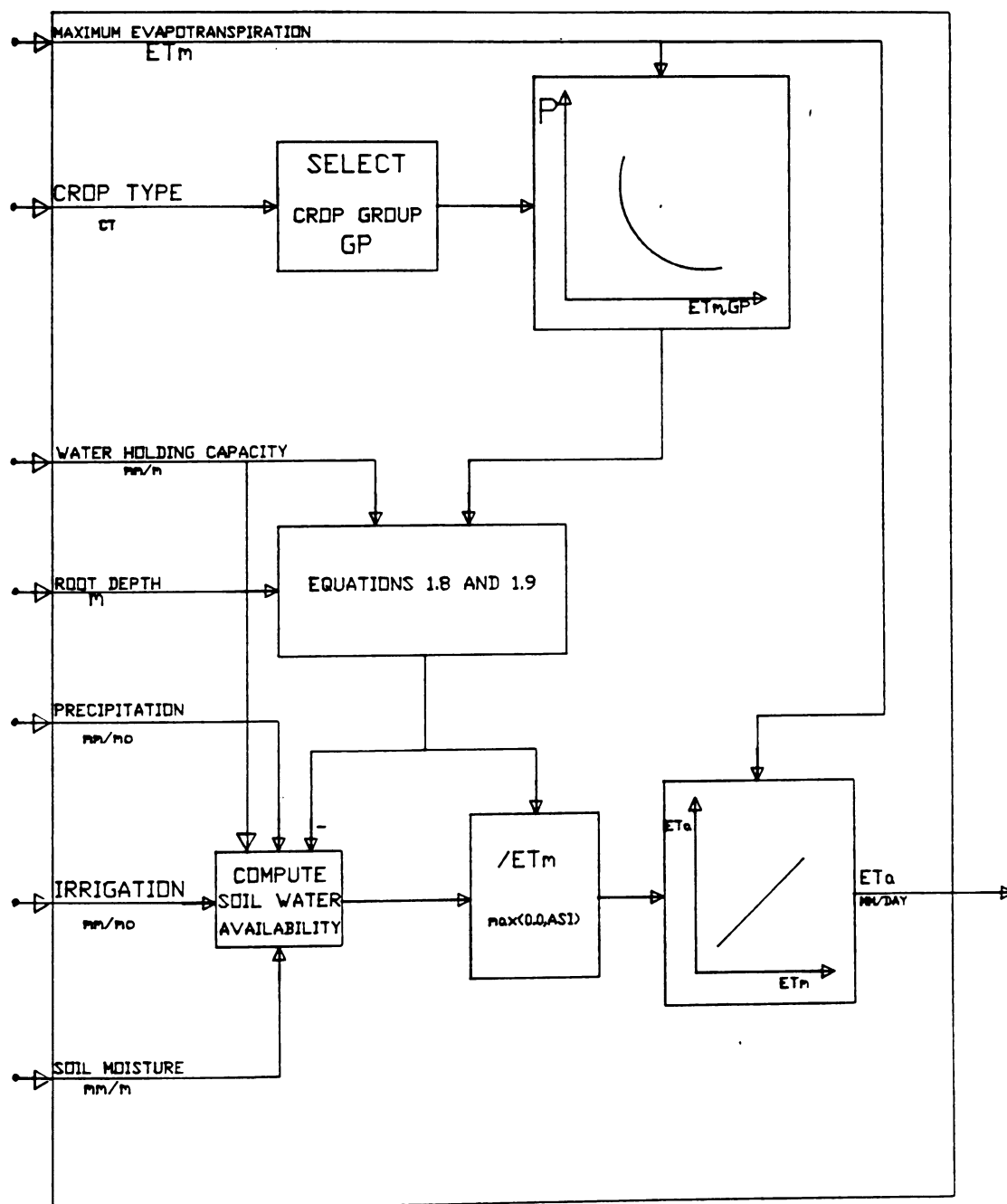


Figure 10. Deterministic YIELD simulation model--Phase 3: system diagram.



Phase 4: Estimated Yield (Ye)

Soil water stress influences crop evapotranspiration and yield. An index of water stress is the ratio of actual to maximum evapotranspiration, ET_a/ET_m . Similarly, an index of crop yield is the ratio of estimated to maximum possible yield, Y_e/Y_m . The way the first ratio affects the second (called yield response factor [k_y]) varies with crop species and crop-development stages or time. Under sufficient water supply, $ET_a = ET_m$.

The rate of change of the estimated harvested yield, at time t , is given by Equation 1.10, modified after Doorenbos and Kassam (1979):

$$\frac{d[Y_e(t)]}{dt} = Y_m(t) * [1.0 - k_y(t) * [1.0 - ET_a(t)/ET_m(t)]] \quad (1.10)$$

or

$$Y_e(t) = \int_{t=t_0}^{t=t_1} \{Y_m(t) * [1 - k_y(t) * [1 - ET_a(t) / ET_m(t)]]\} dt$$

Using Euler's numerical approximation formula and assuming $t_0 = 0$, results in Equation 1.11:

$$Y_e(t + dt) = Y_e(t) + dt * \{Y_m(t) * [1.0 - k_y(t) * [1.0 - ET_a(t) / ET_m(t)]]\} \quad (1.11)$$

where:

$Y_e(t)$	=	estimated harvested yield	[kg/ha/day]
$Y_m(t)$	=	potential yield	[kg/ha/day]
$ET_a(t)$	=	actual evapotranspiration	[mm/day]
$ET_m(t)$	=	maximum evapotranspiration	[mm/day]
$k_y(t)$	=	yield response factor	[fraction]
t	=	time	[days]

The deterministic YIELD simulation model system diagram, Phase 4, is provided in Figure 11.

Phase-5: Estimated Yield Adjustment

The $Y_e(t)$ computed from Equation 1.11, above, may be adjusted further if fertilizer (NPK) applications are less than optimum, or for the sensitivity of the crop to saline soil conditions. A simplified assumption is made that requirements are met if composite ratio equals 100 percent. In fact, the amounts of N, P, and K requirements are crop specific, and each crop has a different response curve for nutrient applications. Using Evans (1980) and Hayes (1982), the NPK response curve (Figure 12) was derived to compute the yield decrease factor due to fertilizer availability. This represents the generalized yield adjustment due to general fertilizer availability for all crops considered in the model.

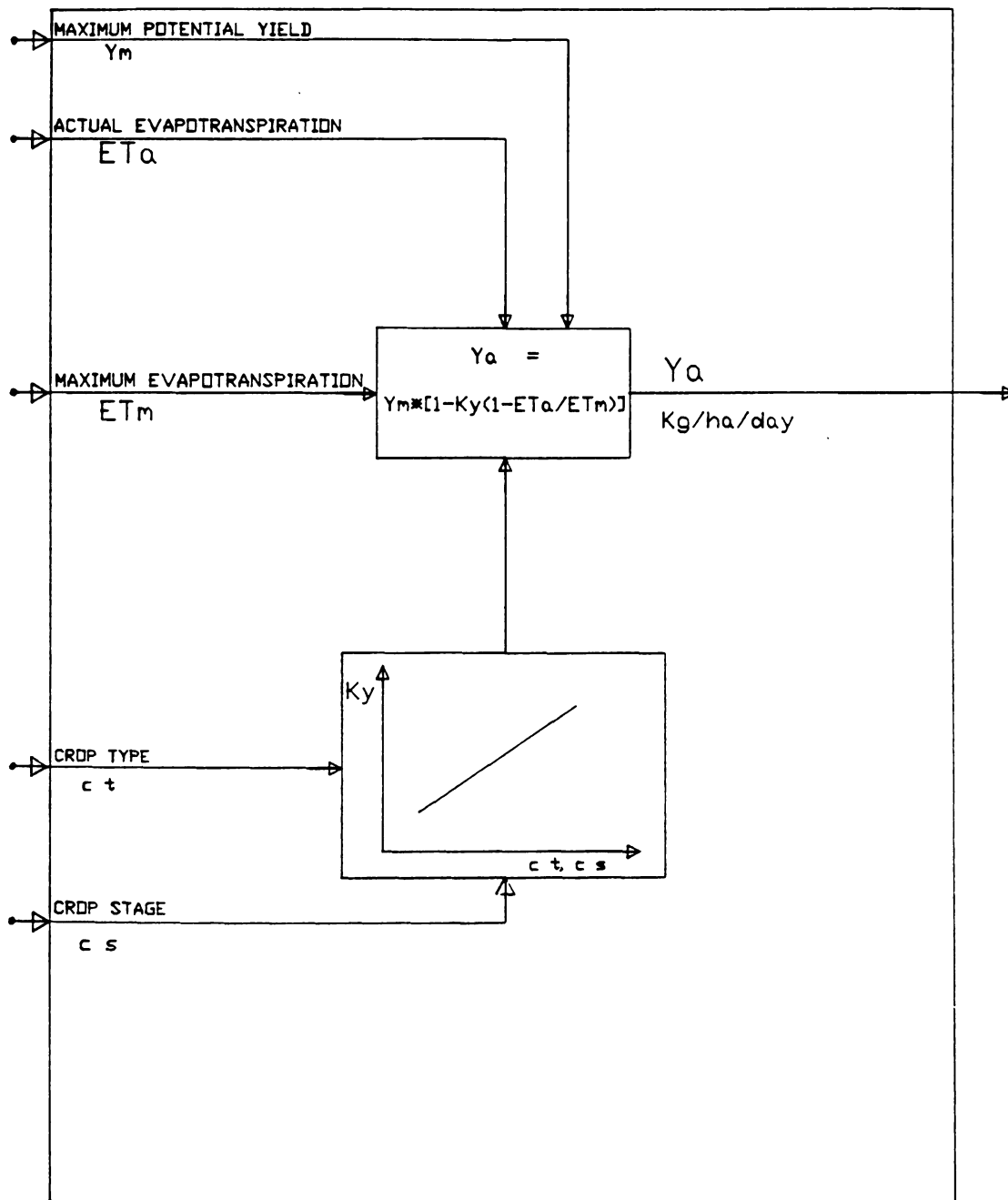


Figure 11. Deterministic YIELD simulator--Phase 4: system diagram.



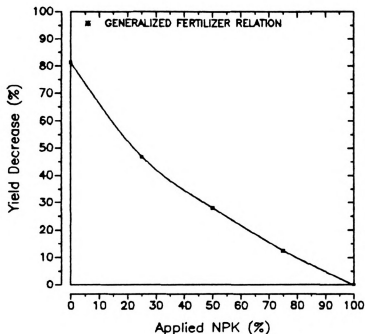


Figure 12. Yield adjustment based on generalized fertilizer availability for all crops. (From Evans, 1980 and Hayes, 1982.)

Future model refinements will require more elaborate research for specific crops' responses to different levels and types of fertilizer, including natural soil fertility. The decision to use a generalized fertilizer curve for all crops reflects the incomplete and inconclusive research of effects of fertilizer availability and toxicity on varying crops under a wide range of agro-ecological conditions (see also Hayes et al., 1982).

Doorenbos and Kassam (1979) provided the optimum fertilizer requirements (nitrogen-phosphorus-potassium combined)

for all crops included in this simulation model. The user should determine the actual deviation from the optimal fertilizer requirements for each crop, considering soil fertility and fertilizer applications.

The effect of salinity levels on yields was compiled from Doorenbos and Kassam (1979) for all crops included in the simulation model. The results are summarized in Table 2 and incorporated into the model for interpolation.

A final conversion of predicted yield is provided to the user. The option is provided to calculate estimated yield as total harvestable biomass or dry matter. This reflects the need to calculate the total harvest production or the final yield amount as dry matter production.

The current model adjustment is made by calculating total biomass from dry matter, based on ratios derived from Doorenbos and Kassam (1979). If needed, crop-variety-specific adjustments may be made via model modifications, and these may be adjusted to the specific site.

In summary, the result is Equation 1.12, after incorporating all the adjustments:

(1.12)

$$\begin{aligned}
 Y_e(t + dt) = & Y_e(t) + dt * \{ Y_m(t) * [1.0 - k_y(t) \\
 & * [1.0 - E_{Ta}(t) / E_{Tm}(t)] \\
 & * (1.0 - y_{df}) * (1.0 - y_{ds} / 100.0) \\
 & / cf \}
 \end{aligned}$$

Table 2. Crops, salinity levels in mmhos/cm, and percentage yield decrease values

Crop Type	Percentage Yield Decrease.....				
	0.0	10.0	25.0	50.0	100.0
Banana					
Tropical	1.0	1.5	2.3	3.6	6.5
Subtropical	1.0	1.5	2.3	3.6	6.5
Bean					
Green	1.0	1.5	2.3	3.6	6.5
Dry	1.0	1.5	2.3	3.6	6.5
Cabbage	1.8	2.8	4.4	7.0	12.0
Cotton	7.7	9.6	13.0	17.0	27.0
Grape	1.5	2.5	4.1	6.7	12.0
Groundnut	3.2	3.5	4.1	4.9	6.5
Maize					
Sweet	1.7	2.5	3.8	5.9	10.0
Grain	1.7	2.5	3.8	5.9	10.0
Onion					
Dry	1.2	1.8	2.8	4.7	7.5
Green	1.2	1.8	2.8	4.7	7.5
Pea, Fresh	1.0	1.5	2.3	3.6	6.5
Pepper, Fresh	1.5	2.2	3.3	5.1	8.5
Potato	1.7	2.5	3.8	5.9	10.0
Rice	3.0	3.8	5.1	7.2	11.5
Safflower	5.3	6.2	7.6	9.9	14.5
Sorghum	4.0	5.1	7.2	11.0	18.0
Soybean	5.0	5.5	6.2	7.5	10.0
Sugarbeet	7.0	8.7	11.0	15.5	24.0
Sugarcane	1.7	3.3	6.0	10.4	18.6
Sunflower	0.0	4.5	9.5	10.0	13.0
Tobacco	0.0	0.0	0.0	0.0	0.0
Tomato	2.5	3.5	5.0	7.6	12.5
Watermelon	2.5	3.3	4.4	6.3	10.0
Wheat	6.0	7.4	9.5	10.0	13.0
Alfalfa	2.0	3.4	5.4	8.8	15.5
Citrus	1.7	2.3	3.3	4.8	8.0
Olive	4.5	7.0	8.0	9.0	10.0

Source: Compiled from Doorenbos and Kassam (1979).

where:

ydf	=	yield decrease factor from fertilizer usage	[fraction]
yds	=	yield decrease factor from salinity soil levels	[percent]
cf	=	correction factor for humidity inclusion	[fraction]

Data Requirements

To run the deterministic YIELD simulator successfully, the user must assemble a data base. As indicated before, the model predicts yields for homogeneous agro-ecological conditions based on agro-climatic criteria. The delineation of AEZs involves data aggregation and area delineation. Data aggregation is employed to assemble the data set for the local area or AEZ being considered. Primary weather station and secondary weather station are the main source of climatic data. Those weather stations should be located inside the AEZ (optimal situation). Data collected outside the AEZ boundaries may be interpolated in a trend surface algorithm to obtain the best possible approximation for the AEZ considered.

In the case of wind velocity and solar radiation, extra precautions must be taken in the data-collecting procedure to account for shadow effects from elevation and for air current resulting from systematic air flow.

The data base must contain several data sets that provide the information necessary to run the model. They include:

A. LOCAL data set is needed to identify the location, region, or AEZ for which the simulation will take place.

The local data set contains the following information:

1. Average altitude [m]
2. Average latitude [degrees]
3. Hemisphere (north or south)
4. Slope class specification (Table 1)
5. Soil type and texture and associated moisture-holding capacity (Table 1)
6. Soil moisture at sowing date [mm/m]
7. Soil salinity level [mmhos/cm]
8. AEZ parameters identification
 - code
 - name

B. FARM MANAGEMENT PRACTICES data set is required to identify farming-system techniques. The growth period is divided into five stages called crop stages. The duration of the initial stage (first stage) is defined as the time period, in days, from germination to 10 percent of ground cover. The duration of the crop-development stage (second stage) is defined as the time period, in days, from 10 percent to 80 percent ground cover. The duration of the mid-season stage (third stage) is defined as the time period, in days, from 80 percent ground cover to the start



of ripening. The duration of the late season (fourth stage) is defined as the time period, in days, from ripening to harvest. The duration of the harvest stage (fifth stage) is defined as the time period, in days, of the harvest.

1. Crop sowing date and harvesting date
 - day
 - month
 - year
2. Crop first stage duration [days]
3. Crop second stage duration [days]
4. Crop third stage duration [days]
5. Crop fourth stage duration [days]
6. Crop fifth stage duration [days]
7. Fertilizer availability [percent]
8. Evaporation reduction factor [percent]
9. Irrigation parameters
 - by crop development stages

C. CROP INFORMATION data set must contain the following information:

1. Crop type
2. Rooting depth for the first stage [m]
3. Rooting depth for the second stage [m]
4. Rooting depth for the third stage [m]
5. Rooting depth for the fourth stage [m]
6. Rooting depth for the fifth stage [m]
7. Crop production rate group
8. Crop water depletion group

D. ENVIRONMENTAL-CLIMATE data set. Values are taken as average for the AEZ considered.

1. Temperature in daily or monthly mean [C]
2. Precipitation in daily or monthly mean [mm]
3. Relative humidity in daily or monthly mean [percent]
4. Solar radiation in daily or monthly mean [hours/day]
5. Wind velocity and wind velocity day/night ratio [m/s]

CHAPTER IV

STOCHASTIC YIELD SIMULATOR (SYS)

The stochastic or probabilistic yield simulator is designed to estimate maximum potential yield, irrigated yield, and rain-fed yield with its statistically derived distribution densities (mean, variance, skewness, and so on) for different crops. The word "stochastic" is used here to indicate that the model's inputs and/or parameters (at least one) have nonzero variance. This means that the model's inputs and/or parameters (at least one) are not known with certainty, but statistics and distribution densities can be estimated from their sample data set.

The major objective of the SYS is to provide decision makers and planners with information on potential, irrigated, and rain-fed yields in the form of descriptive statistics such as mean, variance, skewness, and quantiles, and associated histograms. This information will provide insight into stochastic behavior of the yield model and may serve as an important tool in agricultural and land-use planning, as well as natural resource management.

Several sources of uncertainty and error are present in models. Modeling error may be present because of uncertainty regarding a particular phenomenon or the difficulty of expressing or modeling real-world behavior in mathematical expressions. Errors may be introduced into the simulation model by its parameter-estimation procedures and the data-collection technique used. Exogenous environmental-variable inputs such as precipitation, temperature, and relative humidity are probabilistic in nature. Besides, data-collection methods may introduce variation and error into the input data set that will be used by the simulation model.

Stochastic models are useful under conditions in which nonreliable estimates are available for the model's parameters and a large amount of money and time is needed to improve parameter estimates (Manetsch, 1986).

The stochastic yield simulator has an analytical structure similar to that of the deterministic yield simulator (DYS) discussed in Chapter III. In the DYS, all the inputs and model parameters were assumed to be known with certainty, whereas in the SYS some degree of uncertainty is included in the modeling process. From this point of view, the SYS can enhance the contribution of the DYS model in the decision-making and planning process by accounting for some inherent real-world randomness.

The use of a simulation model for planning and policy making in developing nations has frequently been described in the literature (Manetsch et al., 1970; Manetsch, 1971, 1984, 1985; Rossmiller et al., 1978). The experience of those models is sometimes characterized by the expression "structure rich/data poor" (Manetsch, 1986), which means that the structure of the problem under investigation is available but time and money are required to provide good estimates for many of the parameters included.

Stochastic Approach

There are two sources of uncertainty in the SYS model, random exogenous model inputs and uncertainty in the values of the parameters. Appropriate terminology for this mode condition is introduced in Figure 13.

Following Manetsch (1986), the nomenclature used is:

- $u(t)$ = defined as control and/or input vector of variables to the simulation model
- $e(t)$ = defined as vector of exogenous environmental variables, whose values are given by probability density functions $f_1(e_1(t)), f_2(e_2(t)), \dots, f_n(e_n(t))$
- $p(t)$ = defined as vector of model parameters whose values are given by probability density functions $g_1(p_1(t)), g_2(p_2(t)), \dots, g_m(p_m(t))$

$y(t)$ = defined as the simulation output vector, which is also given in terms of its distribution functions $h_1(y_1(t)), h_2(y_2(t)), \dots, h_k(y_k(t))$, and statistics (mean, variance, skewness, etc.)

The sources of randomness for the simulation model are $e(t)$ and $p(t)$. The term "control vector" is used here to indicate variables that are totally under the decision maker's control.

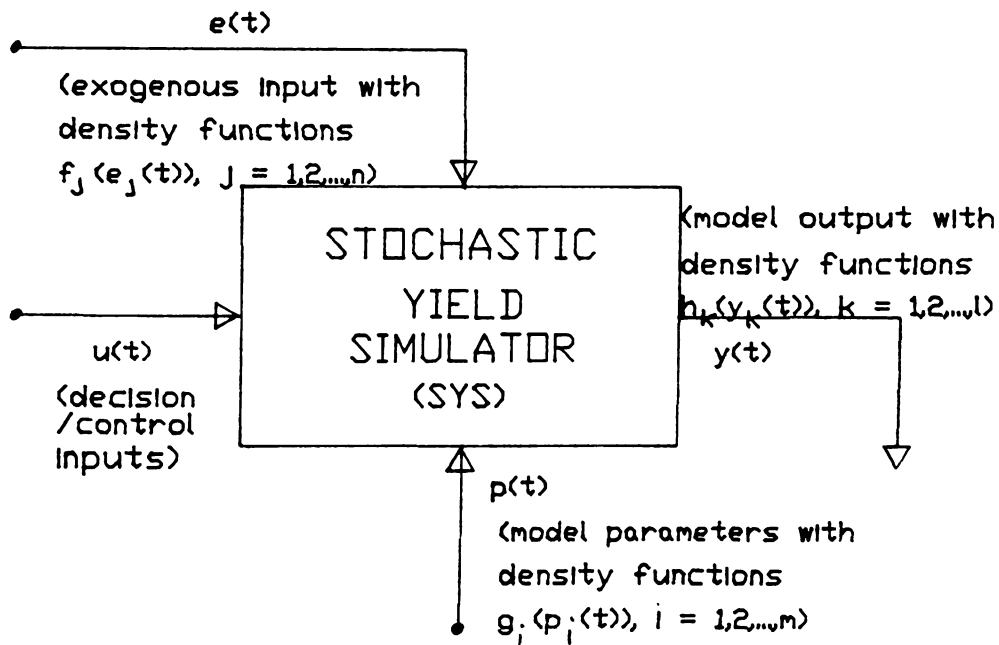


Figure 13. General input/output diagram for the stochastic YIELD simulator with nomenclature.

From the environmental data base, which contains information for the environmental variables used in the model, such as precipitation, temperature, solar radiation, relative humidity, and wind velocity, distribution shape and statistics are determined.

To find the "correct" stochastic distribution for use in the model, a frequency histogram is prepared. Such a frequency distribution (Figure 14) will help to determine the shape of the distribution density function that provides a "best" fit with our data set or sample data set.

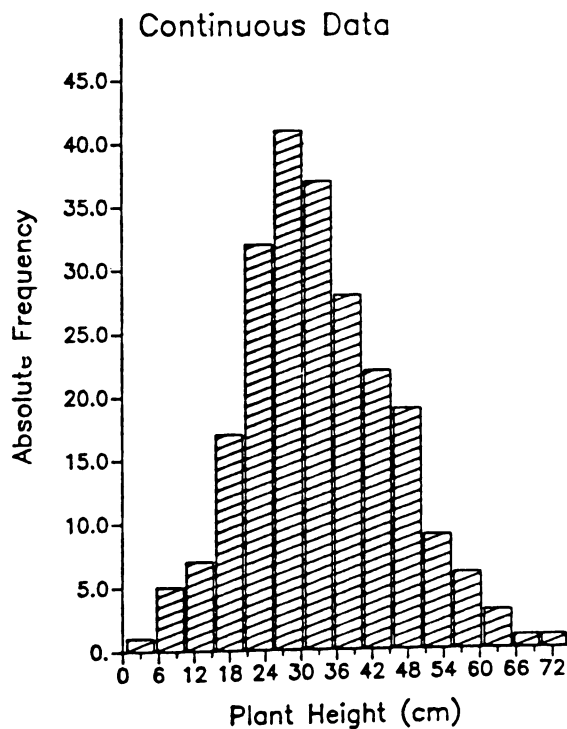


Figure 14: Stochastic YIELD simulator--an example of histogram plot.

Expert assistance in providing information for estimating probability density functions for the most important parameters plays an important role in estimating the distribution of a density function. Appropriate experts can and do provide information from which approximate density functions can be derived.

A manual method may be used to construct the frequency histogram, but several software packages such as Plotit (1985), SAS (1985), SPSS (1984), MSTAT (1984) do exist that can be and are used to provide the statistics needed to run the simulation model.

In determining the moments of the distribution function, such statistics as mean, variance, and skewness are of concern. The skew factor, or skewness, is a descriptive statistic that provides information on the tendency of the deviations to be larger in one direction than in another. The skew factor is computed by:

$$\text{skewness} = m_3 / m_2^{(3/2)}$$

where:

$$m_j = \frac{\sum_{i=1}^N (x_i - \bar{x})^j}{N}$$

m_j = moment of order j ($j = 1, 2, 3$)

x_i = random variate value ($i = 1, 2, \dots, N$)

$\bar{x}$ = mean value

N = sample size

For negative values of skewness, the distribution tail is to the left; for positive values the tail is to the right. Values of the skew factor > 0.5 or < -0.5 correspond to distributions with significant positive skewing (Figure 15). The distribution statistics computed are used in the simulation model to generate random variates that are approximated random variables drawn from distribution of the variable's population.

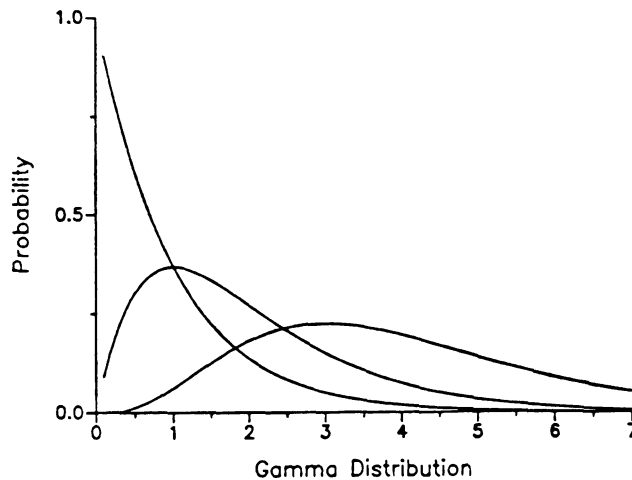


Figure 15: Stochastic YIELD simulator--probability density function skewing factor variation.

The most common distributions used in the simulation process for environmental variables are normal, gamma, triangular, and uniform distribution. The choice of the distribution function will depend on the "goodness of fit" test with the available data and/or the shape of histogram plot, and the variable characteristics being modeled.

One especially important family of theoretical distributions is the normal or Gaussian distribution. A normal distribution is a smooth, symmetric function often referred to as "bell-shaped." Its skewness is zero. A normal distribution can be completely specified by only two parameters: mean and standard deviation. Approximately 68 percent of the values in a normal distribution are within one standard deviation of the population mean; approximately 95 percent of the values are within two standard deviations of the mean; and about 99.7 percent are within three standard deviations.

The gamma distribution (Figure 15) is one of the most useful continuous distributions available to the simulation analyst. If the variables from some random phenomenon cannot assume negative values and generally follow a unimodal distribution, then the chances are excellent that a member of the gamma family can adequately simulate the phenomenon. The gamma distribution is defined by two parameters, a and k , where a is the shape parameter and k is the scale

parameter. As the two parameters vary, the gamma density can assume a wide variety of shapes, making it one of the most versatile of distributions for simulation purposes (Shannon, 1975).

The triangular distribution (Figure 16) is useful when data are very limited. The parameters used for determining the triangular probability density function are as follows (Manetsch, 1985, 1986):

- a lower limit (A_i) for the parameter value i
- an upper limit (C_i) for the parameter value i
- a most likely value (B_i) for the parameter value i

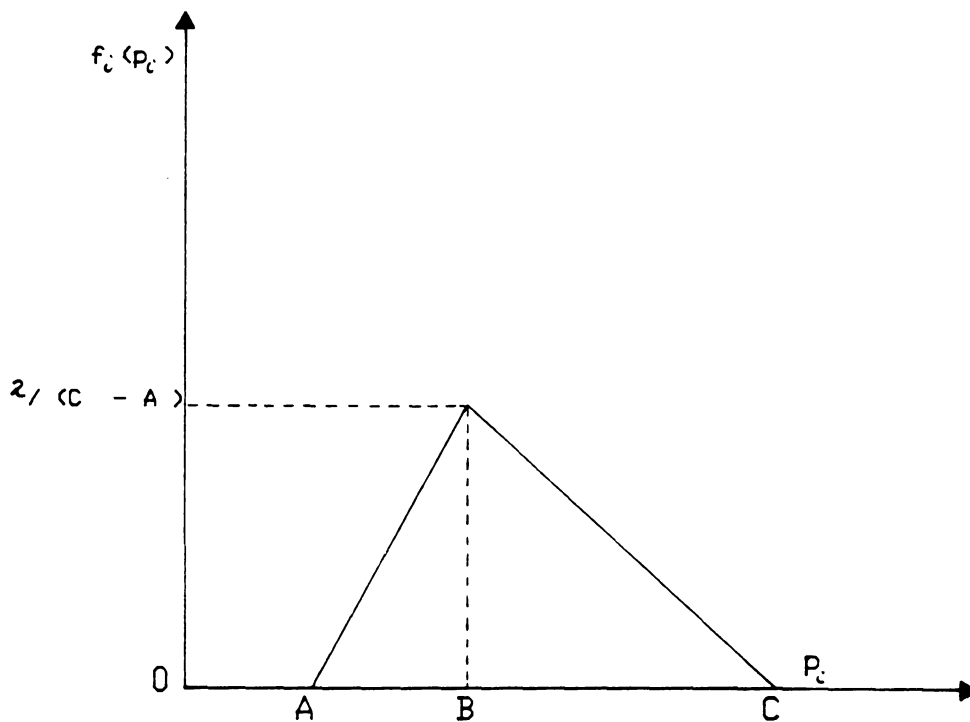


Figure 16: Stochastic YIELD simulator--triangular probability density function.

From this information a probability density function for a triangular distribution can be used over the interval (A_i, C_i) with mode B_i in the simulation model.

The uniform distribution is a continuous probability density function, which is constant over the interval from, say, A to B, and zero otherwise. The uniform distribution is useful for simulating random phenomena with little or no strong variations.

Random-Variates Generation

Once the distribution that fits best in the sample data set is known through its moments or statistics, one is in a position to generate the random variates with the same statistics. The inverse transformation method (Naylor, 1968; Shannon, 1975; Manetsch, 1984) is used to generate random variates from a particular statistical population whose density function is given by $f(x)$. (A more detailed description is provided in Appendix C.)

The following formulas will be used in the inverse transformation process to generate variates from gamma distribution $f(x)$ with a given mean and variance (Naylor, 1968):

$$f(x) = \frac{a^k * x^{k-1} * e^{-ax}}{(k-1)!} \quad a, k, x > 0$$

$$a = \frac{\text{mean}(x)}{\text{variance}(x)}$$

$$k = \frac{[\text{mean}(x)]^2}{\text{variance}(x)}$$

One of the problems that limited the use of gamma distribution in the past was the lack of a good generator if k is not an integer. Phillips (1971) developed a two-parameter gamma generator to overcome this problem. Shannon (1975) provided the Fortran code for the Phillips two-parameter gamma generator. Naylor (1948) used a simple alternative method to generate gamma random variates when the gamma distribution parameter k is not an integer.

An Erlang gamma distribution (k is an integer) may be generated by simply reproducing a process on which the Erlang distribution is based. This can be accomplished by taking the sum of exponential variates, $x_1, x_2, \dots, x_n$, with identical expected value $1/a$.

Several probability distributions are related to gamma variables. Two of the more important ones are the chi-square and beta distributions (Naylor, 1968).

A view of the gamma-variates-generation process to be used in the simulation model is provided in Figure 17.

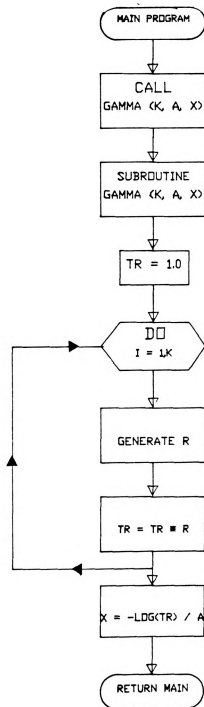


Figure 17. Stochastic YIELD simulator--gamma-variates-generation process.

Variance Partitioning and Common Scenario Analysis

This section, compiled from Manetsch (1986), deals with different combinations of sources of uncertainty in simulation runs. As previously indicated, two sources of uncertainty exist for any model, the exogenous inputs and uncertainty in the values to be assigned to model parameters.

From the results of the simulation runs, that is from the histogram plot generated from the potential, irrigated, and rain-fed yield values, the decision maker can determine how much of the random variation observed in the final results is due to poor data and how much is due to input-parameters estimates. Random variation can be reduced by further data collection, and associated time and cost can be optimized based on that information.

To obtain that information, the simulation model must be run with and without randomness in the model parameters. When the simulation is run with model parameters set at most likely values (parameters value assumed to be known with certainty), the procedure is called "variance partitioning." Variance partitioning is a valuable procedure in helping decision makers evaluate the importance of poor model data and the need for further data collection.

It may be necessary and/or desirable to carry out this variance partitioning for individual parameters or subsets

of parameters to provide better-defined data-collection priorities.

A different but very useful simulation technique for facilitating decision making under uncertainty is the "common scenario analysis." Manetsch (1986) provided examples of this technique. Common scenario analysis is very useful when different policy-input alternatives have to be compared. Alternative policies are analyzed with the same sequence of random numbers, which then specify a common scenario for random exogenous inputs and parameter variations. In this manner, alternative policies are compared in such a way that the only difference in the comparison is the differing policy specifications.

The stochastic yield simulator developed in this study deals with variance partitioning for selected environmental variables. The model's parameters such as crop coefficient (k_c), yield response factor to evapotranspiration deficit (k_y), and so on, were given by Doorenbos and Kassam (1979) as fixed values. The environmental variables used in the model are the main source of randomness in the stochastic yield simulator.

Stochastic Yield Simulator (SYS) Structure

In this section, the simulation model structure for the SYS is presented. The basic structure for the SYS is the

same as that used in the deterministic yield simulator (DYS), discussed in Chapter III.

The Monte-Carlo method is the basis for the SYS simulator. In the Monte-Carlo technique, artificial experiences or data are generated by the use of a random-number generator, resulting in the cumulative probability distribution of interest. The random-number generator may be a table of random digits, a computer subroutine or function, or any source of uniformly distributed random digits. The probability distribution to be sampled may be based on empirical data derived from past records, may result from a recent experiment, or may be a known theoretical distribution such as gamma distribution. The random-number generator, as seen in the last section, is used to produce a randomized stream of variates that will duplicate the expected experience, based on the probability distribution being sampled.

Some changes in the deterministic yield simulator had to be made to accommodate the stochastic characteristics of the input variables and parameters.

A general flowchart for the simulation run with exogenous input and randomness in the environmental inputs and/or parameters is provided in Figure 18.

The stochastic yield simulator (SYS) structure follows, with some modifications and additions, the equations and procedures in Yield Response to Water Model (Doorenbos &

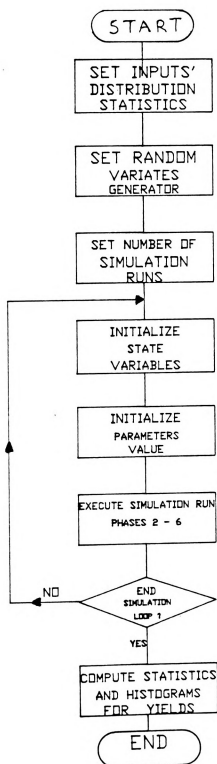


Figure 18. Stochastic YIELD simulator--general flowchart of the simulation process.

Kassam, 1979), used in the deterministic yield simulator (DYS).

Mainly seven consecutive phases are needed to estimate the probability density function statistics for the crop yields. They are:

Phase 1: Determination of the probability density function and its statistics for the parameters and environmental inputs. Three steps are to be followed in this phase (see Figure 19):

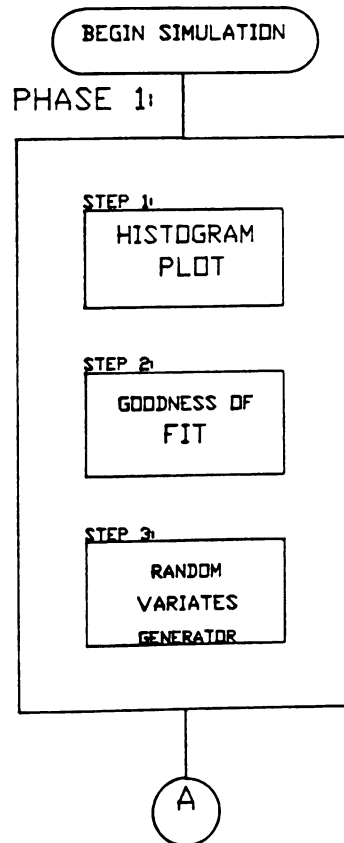


Figure 19. Stochastic YIELD simulator--Phase 1 flowchart.

- Step 1: Identify the probability density function using the histogram plot.
- Step 2: Conduct a "goodness of fit" test to fit a distribution density function and compute the distribution statistics such as mean, variance, skewness, and so on.
- Step 3: Implement the random variates generator, using the inverse transformation method.

Phase 2: Determination of the maximum yield (Y_m) of the adapted crop variety, dictated by climate, assuming that other growth factors (e.g. farm management, fertilizer, pests and diseases, and so on) are not limiting. In the second phase, six steps are needed to determine (Y_m) (see Figure 20):

- Step 1: Computation of the gross dry matter production of a standard crop (Y_o).
- Step 2: Application of the correction factor for crop species and temperatures.
- Step 3: Application of the correction factor for crop development over time and leaf area (c_L).
- Step 4: Application of the correction factor for net dry matter production (c_N).
- Step 5: Application of the correction factor for harvested part (c_H).
- Step 6: Computation of the maximum potential yield (Y_m).

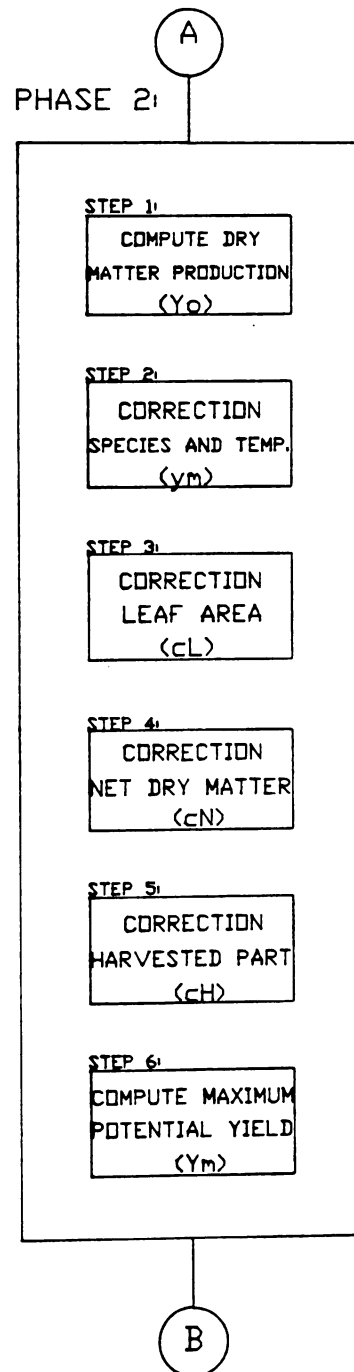


Figure 20. Stochastic YIELD simulator--Phase 2 flowchart.

Phase 3: Calculation of the maximum evapotranspiration (ET_m) when crop requirements are fully met by available water supply. In this phase, three steps are needed to compute ET_m (see Figure 21):

- Step 1: Computation of the reference evapotranspiration (ET_o) based on the meteorological and crop data available.
- Step 2: Computation of the growing period and length of crop-development stages and selection of the crop coefficient k_c .
- Step 3: Computation of maximum evapotranspiration (ET_m).

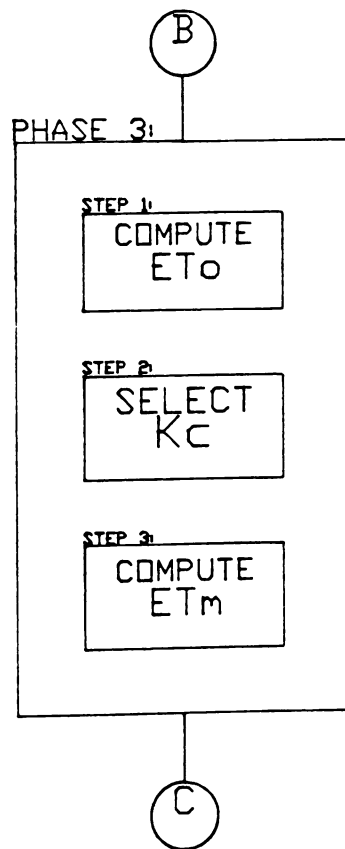


Figure 21. Stochastic YIELD simulator--Phase 3 flowchart.

Phase 4: Determination of the actual crop evapotranspiration (ETA) based on factors concerned with the available water supply to the crop (see Figure 22). This includes:

- Step 1: Determination of the total available soil water.
- Step 2: Computation of the soil water depletion.
- Step 3: Computation of the actual evapotranspiration (ETA).

Phase 5: Selection of the yield response factor (k_y) to evaluate relative yield decrease as related to relative evapotranspiration deficit, and calculation of the actual yield (Y_e) (see Figure 22).

Phase 6: Estimation of crop-yield adjustment. In this phase, the resulting estimated yield from Phase 5 is adjusted for fertilizer usage, soil salinity, and moisture content (Figure 23). Three steps are needed in this phase:

- Step 1: Adjustment of the estimated yield for fertilizer availability.
- Step 2: Adjustment of the estimated yield for salinity levels.
- Step 3: Adjustment of the estimated yield for moisture content.

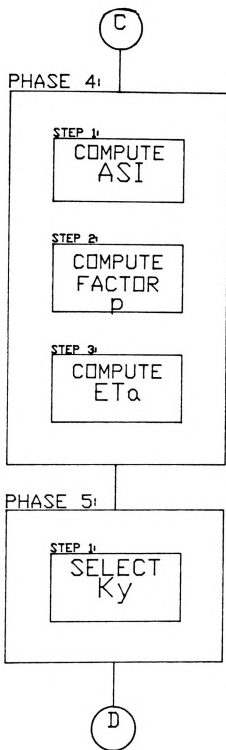


Figure 22. Stochastic YIELD simulator--Phases 4 and 5 flowchart.

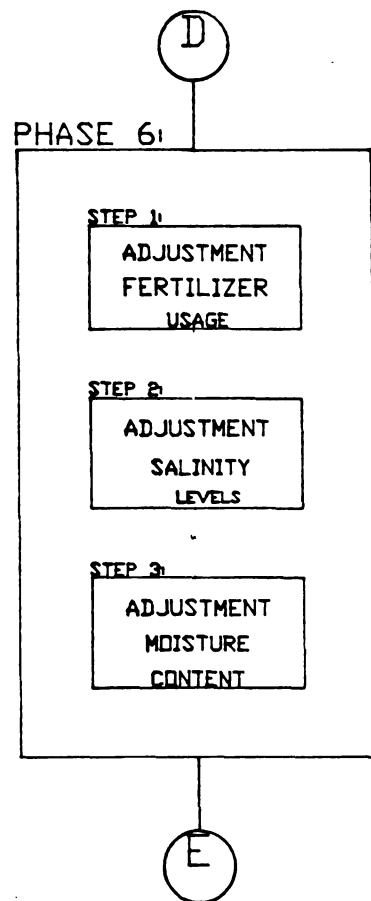


Figure 23. Stochastic YIELD simulator--Phase 6 flowchart.

Phase 7: Determination of the probability density functions and computation of the final yield statistics.

The following three steps are needed (see Figure 24):

- Step 1: Identify the probability density function using the histogram frequency plot.
- Step 2: Conduct "goodness of fit" test for selection of the probability density function.
- Step 3: Compute the distribution density function statistics for potential, irrigated, and rain-fed yields.

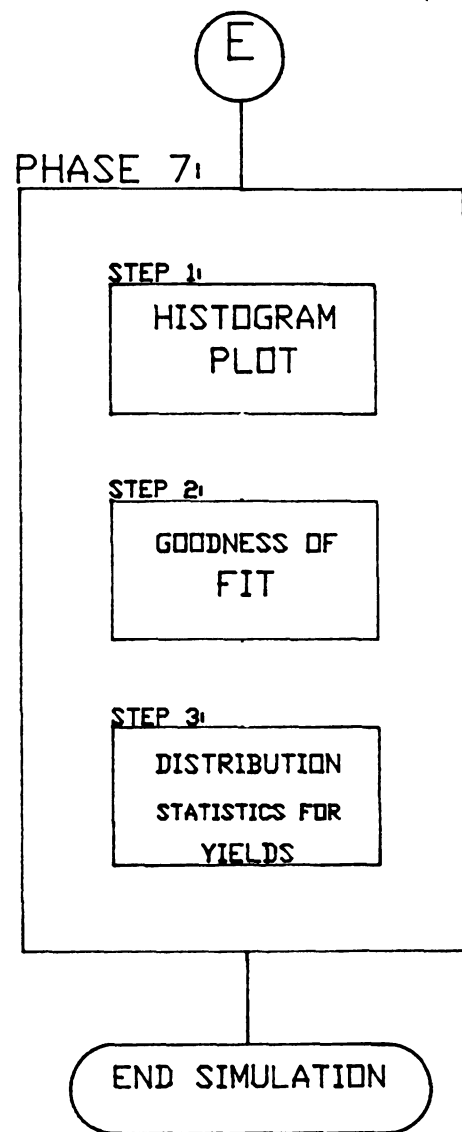


Figure 24. Stochastic YIELD simulator--Phase 7 flowchart.

Mathematical Formulation

The mathematical formulation of the stochastic yield simulator follows the procedures used in the deterministic yield simulator. Repetition of the phases, equations, and procedures involved in the deterministic yield simulator is necessary for completeness, consistency, and clear identification of the random factors included in the model and its relationships with the other components.

Phase 1. Determination of the probability density function and its statistics for the parameters and environmental inputs. The mathematical and statistical procedures were discussed in the section on random-variates generation.

Phase 2: Determination of the maximum yield (Y_m) of the adapted variety, dictated by climate, assuming that other growth factors (e.g. farm management, fertilizer, pests and diseases, and so on) are not limiting.

Refer to Equation 1.1, Chapter III, for the relationship of dry-matter production for a standard crop.

$F(t)$, fraction of daytime the sky is clouded, is determined from the following formulas (Equation 1.7, Chapter III):

$$F(t) = [R_{se}(t) - 0.5 * R_s(t)] / [0.8 * R_{se}(t)]$$

$$R_s(t) = 0.25 + 0.50 * [n(t) / N(t)] * R_a(t)$$

Randomness is entered, in Phase 2, through the environmental variable $n(t)$, number of sunshine hours a day. The value of $n(t)$ variable is generated for every time (t) from the probability density function statistics derived from the sample data set "number of sunshine hours a day." The parameters $y_0(t)$, $y_c(t)$ (Equation 1.1, Chapter III), $R_{se}(t)$, $R_a(t)$, and $N(t)$ are entered into the model by means of table look-up function (tablex, spline) and are assumed to have zero variance; that is, they are values known with certainty.

The variable $y_m(t)$ (Equation 1.4, Chapter III) depends on the environmental variable temperature, which is a random variable generated by a random variate generator.

In summary, Phase 2 of the stochastic yield simulator has two different random variates: an environmental input, number of sunshine hours a day-- $n(t)$, and dry matter production rate-- $y_m(t)$, which is a function of the environmental input temperature. A third stochastic variable, which is assumed to vary within a predefined range, is crop-growth duration. In some cases, the sowing or planting date is not known with certainty, and it changes from year to year. If this is the case, a random variate can be defined in a planting interval in days and generated in the model by means of the random-variate generator.

Phase 3: Computation of maximum evapotranspiration (ET_m). The stochastic environmental variables of Phase 3 of the simulation model are as follows (refer to Equations 1.6 and 1.7, Chapter III):

Wind velocity $U(t)$, an exogenous environmental variable generated by a theoretical probability density function whose statistics and shape are determined from the wind velocity sample data set.

The number of sunshine hours a day $n(t)$, an exogenous environmental variable generated by a theoretical probability density function whose statistics and shape are determined from the number of sunshine hours a day data set.

Mean daily temperature value $T(t)$, an exogenous environmental variable generated by a theoretical probability density function whose statistics and shape are determined from the temperature data set.

Relative humidity value $RH(t)$, an exogenous environmental variable generated by a theoretical probability density function whose statistics and shape are determined from the relative humidity data set.

All other parameters in this phase are deterministic; that is, their values are assumed to be known with certainty.

Phase 4: Computation of actual evapotranspiration (ET_a). In this phase (refer to Equations 1.8 and 1.9,

Chapter III), precipitation $P_e(t)$ is an exogenous environmental variable that is generated from a theoretical probability density function whose statistics are determined from the precipitation data set. Other parameters considered in this phase are assumed to be nonprobabilistic.

Phase 5: Computation of estimated yield (Y_e). Equations 1.10 and 1.11 (Chapter III) are used in this phase. The model parameter $k_y(t)$ is assumed to be known with certainty, making it a deterministic parameter.

Phase 6: Estimated yield adjustment. The model input factors (refer to Equation 1.12, Chapter III) y_{df} and y_{ds} and the model parameter cf are assumed to be known with certainty, and their values are selected by the user.

Phase 7: Yield statistics generation. Using the results of Phase 6 after several simulation runs, the data set is statistically analyzed to determine the probability density function statistics and the histograms for the potential, irrigated, and rain-fed yield. In this phase, statistical-analysis software is used to provide the frequency histogram shape needed to determine the probability density function. The next step is to compute the distribution moments such as mean, variance, skewness, and so on, to aid in the process of planning and decision making in economic analysis, land-use planning, and natural resource management.

Data Requirements

To run the stochastic YIELD simulator successfully, the user must assemble and analyze a data base. The data base must contain several data sets, which will provide the information necessary to estimate the probability density function statistics to run the model. For more detailed information on data requirements, refer to the section on data requirements in Chapter III.

A. A LOCAL data set is required to identify the location, the region, or the AEZ parameters where the simulation will be done. All variables in the local data set are deterministic.

B. A FARM MANAGEMENT PRACTICES data set is required to identify farming-system techniques.

1. Crop planting data interval [days]
- a stochastic input variable
2. Crop first stage duration [days]
- a stochastic input variable
3. Crop second stage duration [days]
- a stochastic input variable
4. Crop third stage duration [days]
- a stochastic input variable
5. Crop fourth stage duration [days]
- a stochastic input variable
6. Crop fifth stage duration [days]
- a stochastic input variable
7. Fertilizer availability [percent]
- a stochastic input variable

8. Evaporation reduction factor [percent]
- a deterministic input variable
9. Irrigation parameters
- by crop development stages, a
deterministic input variable

C. A CROP INFORMATION data set must contain the deterministic exogenous variables described in Chapter III.

D. An ENVIRONMENTAL-CLIMATE data set, which contains the stochastic exogenous environmental variables:

1. Temperature in daily or monthly mean [C]
2. Precipitation in daily or monthly mean [mm]
3. Relative humidity in daily or monthly mean [percent]
4. Solar radiation in daily or monthly mean of sunshine hours [hours/day]
5. Wind velocity and wind velocity day/night ratio [m/s]

CHAPTER V

MODEL VALIDATION AND SIMULATION RUNS

The objective of this chapter is to validate the deterministic YIELD simulator (DYS) and the stochastic YIELD simulator (SYS). According to Shannon (1975), model validation is a process of bringing to an acceptable level the user's confidence that any inference about a system derived from the simulation is correct. It is not possible to show that a model is the exact representation of the system being modeled. In the modeling process, one is, in general, not concerned with the "truth" of the model, but how it provides insights with a certain confidence in the results of the simulation. In general, one can say that it is the operational utility of the model and its structure and not the "truth" of its structure that is usually of concern.

To validate a model, Shannon (1975) indicated that it has to pass three tests, called the "test of validation." First, one must ascertain that the model has face validity; i.e., one must ask if the model results appear to be reasonable. This can be done by comparing the model's results with the system's results--that is, the real-world results.

Often, an expert opinion is needed to help analyze the model's results. The second method of validation is testing the model assumptions. The third test for model validation involves testing input-output transformations.

Kaplan (1964) outlined model validation in terms of norms of validation. He indicated that, to be considered valid, the model must pass the norms of validation tests, which he defined as the correspondence, coherence, and pragmatic norms of validation.

Fisherman and Kiviat (1967) divided the evaluation of simulations into three categories: verification, insuring that the model behaves the way the experimenter intends; validation, testing the agreement between the behavior of the model and that of the system; and problem analysis, drawing statistically significant inferences from the data generated by the computer simulation. Schrank and Holt (1967) proposed that "the criterion of the usefulness of the model be adopted as the key to its validation, thereby shifting the emphasis from a conception of its abstract truth or falsity to the question of whether the errors in the model render it too weak to serve the intended purposes."

The validation process used in this study represents a combination of all the above. The following means of validating the yield model are performed: First, for Jamaica,

20 runs will be conducted on a yearly basis, for sugarcane in the regions of Worthy Park, Caymanas, and Monymusk, using the deterministic approach. These represent traditionally rich sugarcane-producing regions. Observed yields are available for a period of 20 years or 1963-1982, to evaluate the model's performance.

Second, simulations will be conducted for tobacco and sorghum for the same locations. Observed yields are not available on a year-by-year basis, but some statistics, such as average tobacco and sorghum yield, are available for Jamaica. The simulation runs will be made in the "average" mode, with the deterministic model using average values of the environmental variables precipitation, temperature, relative humidity, solar radiation, and wind velocity. The simulation results will be compared to the actual average yield for tobacco and sorghum for the Worthy Park, Caymanas, and Monymusk regions in Jamaica.

Third, 500 simulation runs will be made with the stochastic YIELD simulator for sugarcane, tobacco, and sorghum for the same location in Jamaica. The probability density functions for the environmental variables precipitation, temperature, relative humidity, solar radiation, and wind velocity will be computed and used to generate, in a Monte Carlo simulation approach, the yield values. (The Monte Carlo approach is a technique for generating random variates

as input and/or parameters from a population described by some probability function to be used in the simulation process.) Yields resulting from those simulations will be given in terms of yield probability density function statistics. Comparisons will be made with observed yield data and average yield data for Jamaica's Worthy Park, Caymanas, and Monymusk regions to infer and measure the yield model's performance. Results will be shown in tables, graphs, and histograms and in the form of statistics such as means, standard deviation, and quantiles. Graphics and summary statistics such as histograms are valuable to decision makers and planners in providing a better understanding of the simulation results.

Fourth, 500 simulation runs will be made with the stochastic YIELD model for rice, potato, fresh pea, onion, and cabbage for the Agro-Ecological Zones (AEZs) in the Dominican Republic's Ocoa Watershed, which are called Valdesia, Ocoa, and Azua. The AEZs were determined by the use of the CRIES-GIS Geographic Information System using the OVERLAY and MATCH procedures (Schultink, 1986) and the spatially referenced information on soil, slope, evapotranspiration, temperature, and precipitation. In that simulation process, the probability density function statistics for the environmental variables precipitation, temperature, relative humidity, solar radiation, and wind velocity will be

computed using the Statistical Analysis System (1985) to generate, in a Monte Carlo simulation approach, the values of those environmental variables for each year. Yields resulting from those simulations will be given in terms of yield probability density function statistics. Comparison will be made with observed yield data and average yield data for the Dominican Republic's Valdesia, Ocoa, and Azua AEZs to evaluate the model's performance. Also, the simulation results will be compared with the yield results and guidelines given by Doorenbos and Kassam (1979).

Deterministic YIELD Simulator Run.
Jamaica--Introduction

For Jamaica, the DYS model was used to simulate crop productivity for some of the most important "cash" crops, which are responsible for a large part of Jamaica's foreign exchange earnings, such as sugarcane and tobacco. The model was used to predict yields for sugarcane, tobacco, and sorghum. Sugarcane simulation was done for every year from 1963 to 1982 for three known producing regions: Worthy Park and Caymanas in the parish of St. Catherine and Monymusk in the parish of Clarendon. Twenty years of observed yield data are available for sugarcane, which is considered to be a relatively well organized and primarily state-controlled industry. For tobacco and sorghum, also important crops in

the Jamaican economy, only average, no yield data were available. The model was run for an "average" year.

Deterministic YIELD Simulator Run,
Jamaica--Environmental Inputs

The Jamaican national data base, put together by the Comprehensive Resource Inventory and Evaluation System (CRIES) at Michigan State University, was used to input the environmental data into the simulation model. The required environmental data used to run the simulations are:

1. monthly mean temperature values
2. monthly mean precipitation values
3. monthly mean relative humidity values
4. monthly mean solar radiation values
5. monthly mean wind velocity values and day/night wind ratio

Environmental and local data set, part of the CRIES-Jamaica national data base, were used on a yearly basis for AEZ conditions associated with Worthy Park, Caymanas, and Monymusk for sugarcane, tobacco, and sorghum.

The model was designed to accept as input daily or monthly mean values for the environmental variables described above. It is difficult, if not impossible, to obtain daily measurements for those variables for under-developed or developing nations. However, the daily option is included because it is more realistic to use daily values when available.

Deterministic YIELD Simulator,
Jamaica--Crop Parameters

Parameters for sugarcane, tobacco, and sorghum required to run the model were supplied by the Jamaica Ministry of Agriculture, Rural and Physical Planning Division (RPPD) and complemented, when necessary, by the data set contained in Doorenbos and Kassam (1979). The crop parameters used are:

1. average root size for each phase of the growing period
2. leaf area index (LAI)
3. water depletion factor (p)
4. production rate (ym)
5. crop coefficient (kc)
6. yield response factor (ky)

Crop parameters used in the simulation runs for the Worthy Park, Caymanas, and Monymusk regions of Jamaica are provided in Table 3.

In a year-by-year simulation run of the deterministic YIELD simulator, the user enters values of crop parameters at specific prompts during the simulation process. The values for crop parameters (Table 3) were used for each of the three regions where the simulation took place. Being crop specific, they do not vary with location or time. They do vary, however, from crop to crop.

Deterministic YIELD Simulator, Jamaica--
Farm-Management-Practice Parameters

Several farm-management-practice parameters must be available to the user to run the simulation model. The parameter values used were provided by the Rural Physical

Table 3. Deterministic YIELD simulator: Jamaica--crop parameters--sugarcane, tobacco, and sorghum for Worthy Park, Caymanas, Monymusk

Crop Parameter Type	Sugarcane	Tobacco	Sorghum
Root Size Variation (cm) ^a	20-120	10-150	10-175
Leaf Area Index (LAI)	3	3	2
Water Depletion Factor Variation (p) ^b	.400-.875	.400-.875	.400-.875
Production rate (ym in kg/ha/day) ^c	0-65	0-35	0-65
Crop coefficient (kc) ^d	.40-1.30	.30-1.20	.30-1.15
Yield response factor (ky) ^e	.10-.75	.20-1.00	.20-.55

Source: Doorenbos and Kassam (1979).

Note: The values separated by "-" represent ranges of variation to be used by the numerical interpolation function in the model. Crop stage was defined in the data requirements in Chapter III.

^aAdjusted for local conditions according to RPPD data.

^bET_m--Maximum evapotranspiration dependent factor.

^cTemperature dependent factor.

^dDepend on crop stage, wind velocity, and relative humidity.

^eDepend on crop stage.

Planning Division of the Jamaica Ministry of Agriculture. Additional parameter values were derived from Doorenbos and Kassam (1979).

Farm-management-practice parameters vary from crop to crop, from region to region, and from year to year. The following farm-management-practice parameters are considered in the simulation model:

1. sowing or planting date
2. harvesting date
3. duration of each stage of the growth period
4. irrigation parameter and/or values
5. evaporation reduction factor
6. fertilizer usage

The values of farm-management-practice parameters used in the simulation runs for sugarcane, tobacco, and sorghum for the Worthy Park, Caymanas, and Monymusk regions of Jamaica are listed in Table 4.

Deterministic YIELD Simulator, Jamaica-- Local Parameters

Parameters that identify the location, region, AEZ, or production potential unit are necessary to run the model. Those parameters give very detailed and specific spatial information for the simulation model. They are spatially referenced parameters, which means that for each location a specific set of parameters is used.

Information on the following specific local parameters was collected from the CRIES-Jamaica national data base. Local parameters, by being local specific, do not vary from

Table 4. Deterministic YIELD simulator: Jamaica--farm-management-practice parameters for sugarcane, tobacco, and sorghum, for Worthy Park, Caymanas, and Monymusk

Farm-Management- Practice Parameters	Sugarcane	Tobacco	Sorghum
Sowing or Planting Date MM/DD/YY	02/15/YY	02/15/YY	02/15/YY
Harvesting Date MM-MM/YY+ ^a	01-04/YY+1	05-06/YY	06-07/YY
Duration of Growth Stages in Days ^b			
stage 1	30-80	10-15	15-20
stage 2	80-120	20-30	20-30
stage 3	100-220	30-35	15-20
stage 4	30-80	30-40	35-40
stage 5	30-60	10-20	10-15
Irrigation Parameter or Value ^c	F	F	F
Evaporation Reduction Factor ^d	N	N	N
Fertilizer Usage ^e	80-100	80-100	80-100

Source: Jamaica Ministry of Agriculture, Rural and Physical Planning Division.

^a+1 means following year.

^bCompiled from Doorenbos and Kassam, (1979) and adjusted with RPPD data. The deterministic model uses the average value of the range identified.

^cFull irrigation was used. No data available on irrigation scheme or amount of water used in irrigated crops.

^dNo evaporation reduction factor was used; information not available.

^eFertilizer usage expressed in percent relative to the crop-requirement guidelines as defined by Doorenbos and Kassam's (1979) crop-requirement guidelines.

crop to crop or from time to time. The average local-specific parameters necessary to run the model are as follows:

1. altitude
2. latitude
3. location (northern or southern hemisphere)
4. slope class (Table 1, Chapter III)
5. soil type (Table 1, Chapter III)
6. soil textural class
7. soil moisture availability
8. soil salinity level

The local parameter values for Worthy Park, Caymanas, and Monymusk to be used in simulation runs are provided in Table 5. In spite of a possible variation in time of the local parameters, no time variation was considered from run to run because the local parameters do not change very much in the short or medium time period and because no data are available about changes in those local parameters, such as variations in soil salinity levels, soil-moisture availability at sowing date, and so on, from year to year.

Deterministic YIELD Simulator, Jamaica-- Simulation Results

Twenty simulation runs were conducted for sugarcane from 1963 to 1982 for two areas in the parish of St. Catherine and one area in the Clarendon parish. For tobacco and sorghum, an "average" year was simulated for each of those locations, to permit a comparison with variations in average observed yield for the country.

Table 5. Deterministic YIELD simulator: Jamaica--local parameters for Worthy Park, Caymanas, and Monymusk

Crop Parameter	Worthy Park	Caymanas	Monymusk
Average Altitude in Meters	381.00	27.75	9.15
Average Latitude in Degrees	18.09	17.58	17.48
Location	1	1	1
Average Slope Class ^a	0-4	0-4	0-4
Average Soil Type ^a	fine silty	fine silty	fine silty
Average Soil Textural Class mm/m ^b	115	125	125
Soil Moisture mm/m ^c	90	90	90
Soil Salinity Level ^d	N/A	N/A	N/A

Source: Jamaica Ministry of Agriculture, Rural and Physical Planning Division.

^aTable 1, Chapter III.

^bMoisture holding capacity.

^cInitial soil moisture at sowing date.

^dN/A--Data not available.

Results of the yearly simulation runs for sugarcane for irrigated yield and rain-fed yield are presented for the Worthy Park region in Table 6.

Table 6. Deterministic YIELD simulator: Jamaica--St. Catherine--Worthy Park. Sugarcane--observed irrigated yield and simulated irrigated and rain-fed yield, 1963-1982 (tons/ha)^a

Year	Observed Yield ^b	Simulated Irrigated Yield	Simulated Rain-fed Yield
1963	80.82	86.94	81.90
1964	76.00	85.39	82.67
1965	79.95	94.67	89.71
1966	81.06	97.59	80.89
1967	71.58	79.16	72.12
1968	86.55	102.95	95.17
1969	76.99	82.60	74.05
1970	89.31	94.48	86.30
1971	78.87	86.97	79.63
1972	90.97	93.98	83.93
1973	85.64	89.66	85.49
1974	82.50	82.15	71.78
1975	79.34	90.10	85.19
1976	85.31	91.11	76.30
1977	63.77	95.04	91.93
1978	95.49	93.86	90.75
1979	90.72	89.04	86.25
1980	79.31	100.43	99.00
1981	85.58	92.21	81.98
1982	77.73	91.66	85.46

^aCompiled from simulation results.

^bSource: Jamaica Ministry of Agriculture, Rural and Physical Planning Division.

A time plot of the observed sugarcane yield and simulated irrigated yield for Worthy Park is presented in Figure 25. Yields for sugarcane from 1963 to 1982 are shown, and comparisons can be made between them.

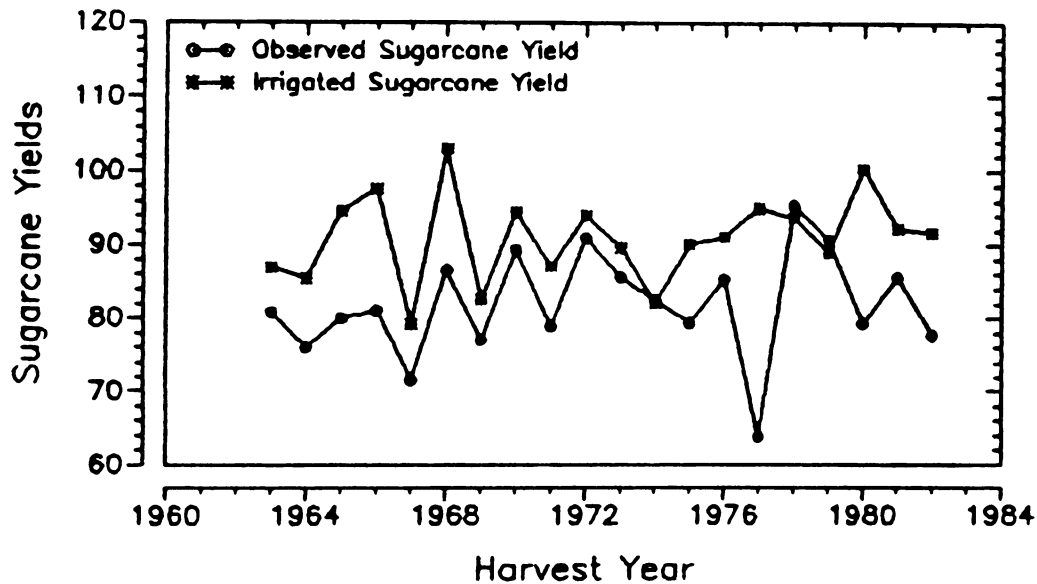


Figure 25. Deterministic YIELD simulator: Jamaica--Worthy Park, observed irrigated yield and simulated irrigated yield for sugarcane for the period 1963-1982 (t/ha).

Simulated results represent the trend in observed yield from 1963 to 1974. In those years (see Figure 25), an almost cyclical yield trend occurred for observed irrigated

yield and predicted irrigated yield. From 1975 to 1982, there was no clear relationship between simulated irrigated yield and observed yield. This may be explained by several reported changes in the government of Jamaica, affecting the sugarcane industry. It has been reported that sugar mills and sugar states were going through a process of nationalization, and that process had a strong influence on sugarcane yield. In addition, strikes took place during that period, affecting the reliability of observed yield data for any meaningful analysis.

The observed yield values are usually below the irrigated simulated values (Figure 25 and Table 6). That may be an indication that, holding other factors constant, improved water-management procedures may improve yields. The relationship between the sugarcane observed yield and simulated rain-fed yield is also presented in Figure 26. In this case, rain-fed production is simulated. It can be observed (Figure 26) that the simulated rain-fed yield is much closer to the observed yield as compared to irrigated yield for the years from 1963 to 1974 (Figure 25). Again, the effects of reported political and socioeconomic conditions related to the sugarcane industry in Jamaica may account for a strong variation in the observed-yield trend from 1975 to 1982. Some simulated rain-fed yields (1964, 1965, 1968, and so on) are larger than the observed yields, suggesting that other

yield-reducing factors not included in the model, such as pest and disease, or a major weather phenomenon such as storms, affected yields. Government policies in terms of agricultural and economic policies and/or external market conditions may affect variations, as well.

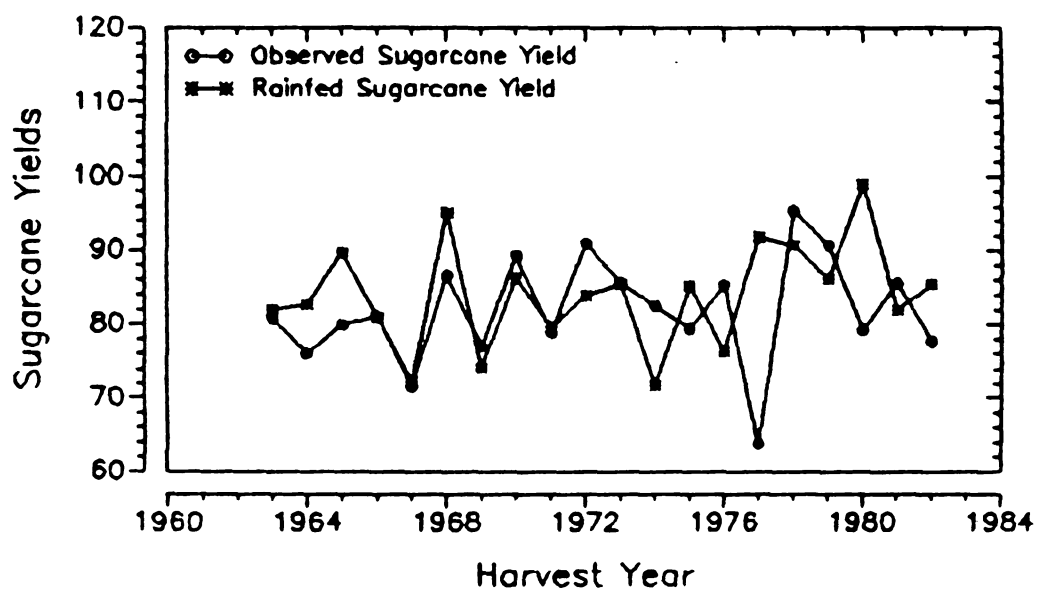


Figure 26. Deterministic YIELD simulator: Jamaica--Worthy Park, sugarcane irrigated observed yield and simulated rain-fed yield from 1963 to 1982 (t/ha).

For the period from 1975 to 1982, random variations are present. It has been reported that political unrest and government policy in the sugarcane industry were major

factors responsible for the random behavior of observed yields for the 1975 to 1982 period.

Correlation coefficients were computed from the results presented in Table 6 for a simple linear regression equation and a logarithmic-inverse regression equation. For observed yield and simulated rain-fed yield, using the total data set (20 years), the coefficients of correlation were very low ($R^2 = .247$ for the linear regression and $.283$ for the logarithmic-inverse regression). Observed yield and simulated irrigated yield correlation coefficients were also very low ($R^2 = .153$ and $.243$ for the linear and logarithmic cases, respectively).

When the outliers were removed from the data set for the regression analysis, the correlation coefficient for the linear case changed to $.436$ and for the logarithmic-inverse case to $.497$. The significance level of the F-test for the linear case was $.0398$; for the logarithmic-inverse case, it was $.0268$. For the simulated irrigated yield the correlation coefficient for the linear form was $.578$ and $.629$ for the logarithmic-inverse form, with the significance levels of the F-test $.0432$ and $.0346$, respectively.

In a multiple regression approach in which the dependent variable is observed yield, and considering fertilizer usage (N, P, K) (presented in Table 16) and simulated rain-fed yield as independent variables, the correlation

coefficient for the linear functional form (taking out the outliers) is .955, with significance of the F-test equal to .1024. For the logarithmic-inverse functional form (taking out the outliers), the correlation coefficient is 0.92, with significance of the F-test equal to .1062.

When the simulated rain-fed yield was replaced by simulated irrigated yield in the multiple regression equation, the correlation coefficient changed to 0.85 for the linear case and to 0.92 for the logarithmic-inverse case, with significance levels of the F-test at .0873 and .0745, respectively.

The degree of association between the observed yield and the simulated rain-fed yield is, of course, increased by entering the fertilizer variable in the regression equation.

A different perspective on the relationship between the simulated sugarcane yield results and the observed sugarcane yield is presented in the form of a scattergram in Figures 27 and 28. The sugarcane observed yield and sugarcane irrigated yield results are clustered above the 45-degree line (Figure 27). The 45-degree line indicates equal values for both variables. The values of simulated irrigated yield are in most cases greater than the values of the observed yield.

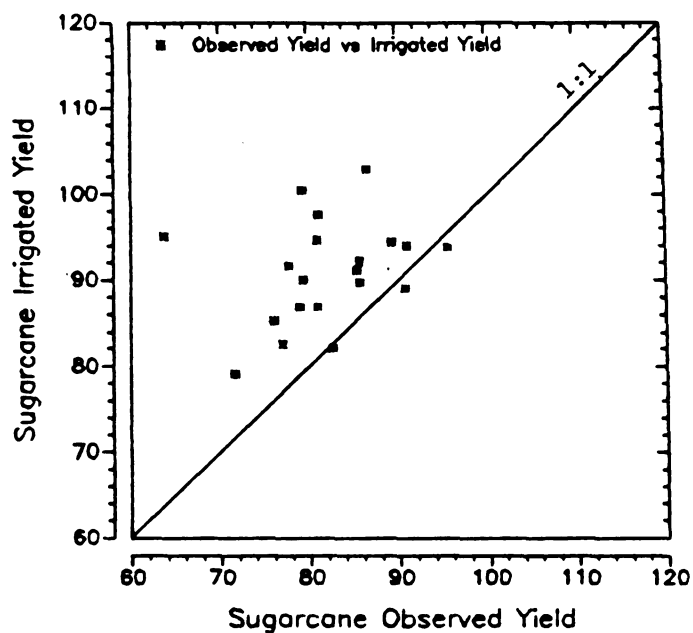


Figure 27. Deterministic YIELD simulator: Jamaica--Worthy Park, sugarcane observed irrigated yield versus simulated irrigated yield (t/ha).

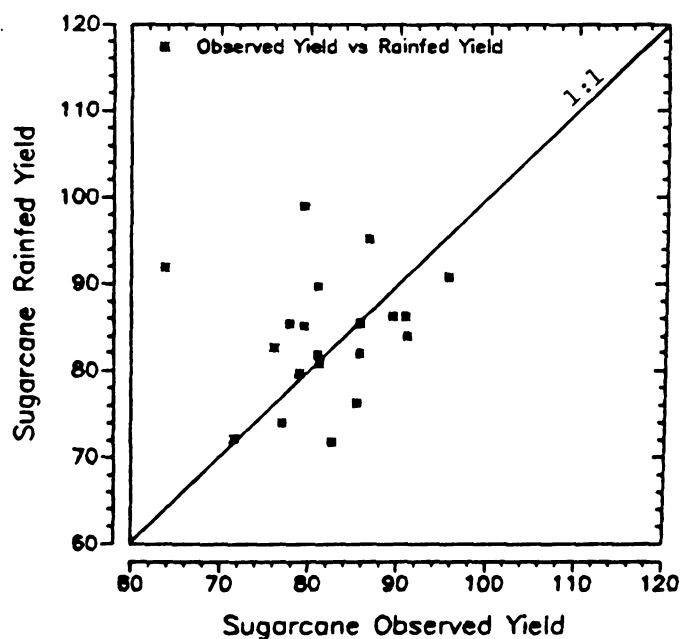


Figure 28. Deterministic YIELD simulator: Jamaica--Worthy Park, sugarcane irrigated observed yield versus simulated rain-fed yield (t/ha).

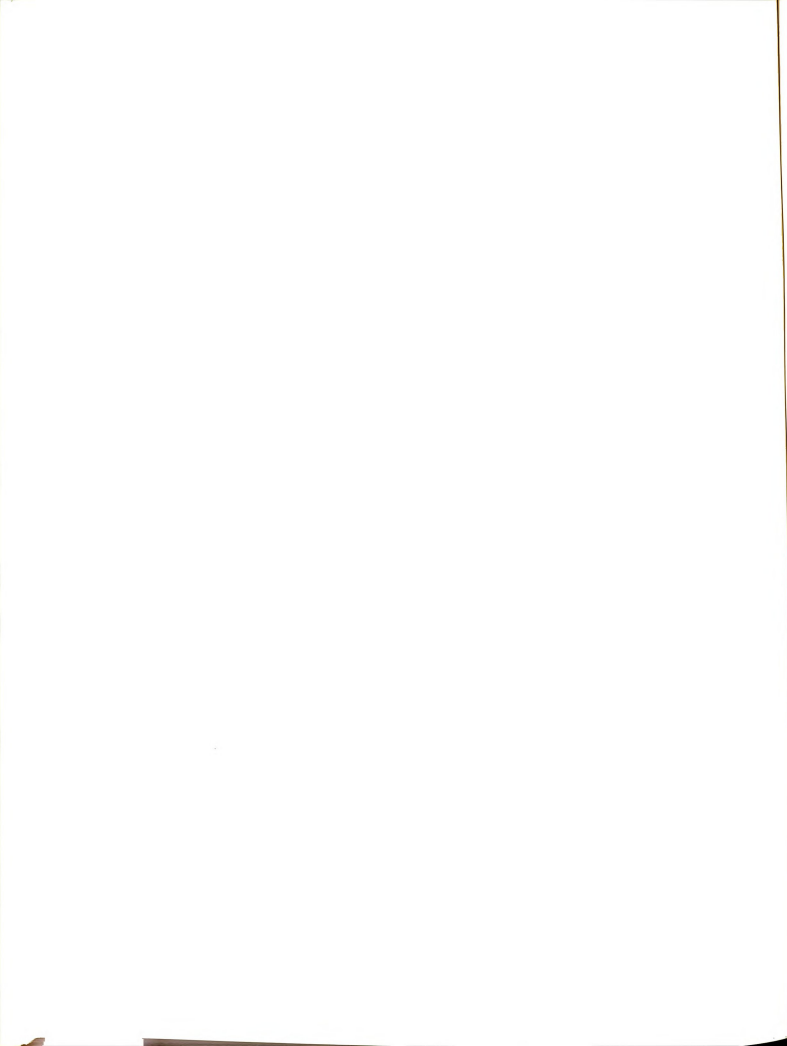
The sugarcane observed yield is also plotted against the rain-fed observed sugarcane yield (Figure 28). Here the points are clustered along the 45-degree line. This is an indication that the results of the rain-fed simulation are closest to the observed sugarcane yield.

In both figures, some outlying values can be seen. They represent the years for high and low values and unusual conditions. If one views the cluster center location as one of the performance measures of the model, it can be inferred that the model results reflect, or are similar to, the results of rain-fed yield.

The simulation results for the Caymanas region in the parish of St. Catherine in Jamaica are presented in Table 7. The results are from the simulated irrigated yield, the simulated rain-fed yield, and the observed irrigated yield for the 1963 to 1982 period.

A plot of the observed sugarcane yield and simulated irrigated yield for Caymanas is shown. Yields for sugarcane from 1963 to 1982 are presented in Figure 29.

The model's performance as a measure of how the simulated irrigated yield tracks the observed yield may be considered very good (values are very close and the trend is replicated) for the period from 1963 to 1976. In those years, as one can observe from the data presented in Figure



29, the repetition of the observed-yield trend is followed by the irrigated-yield values.

Table 7. Deterministic YIELD simulator: Jamaica--
St. Catherine--Caymanas. Sugarcane--observed
irrigated yield and simulated irrigated and rain-
fed yield, 1963-1982 (tons/ha)^a

Year	Observed Yield ^b	Simulated Irrigated Yield	Simulated Rain-fed Yield
1963	95.39	101.91	72.17
1964	91.46	102.03	82.67
1965	93.46	111.35	80.74
1966	91.29	110.56	75.98
1967	94.18	111.55	82.15
1968	76.62	110.06	64.34
1969	77.48	97.59	57.55
1970	84.62	102.60	80.79
1971	79.63	97.81	75.66
1972	97.39	115.87	74.97
1973	84.18	96.55	75.26
1974	82.20	98.77	63.82
1975	92.28	106.51	73.38
1976	78.72	95.29	60.27
1977	63.75	101.99	56.96
1978	68.98	105.07	67.97
1979	67.67	96.72	68.67
1980	63.72	102.90	82.62
1981	61.91	104.51	81.02
1982	65.75	101.02	77.95

^aCompiled from simulation results.

^bSource: Jamaica Ministry of Agriculture, Rural and
Physical Planning Division.

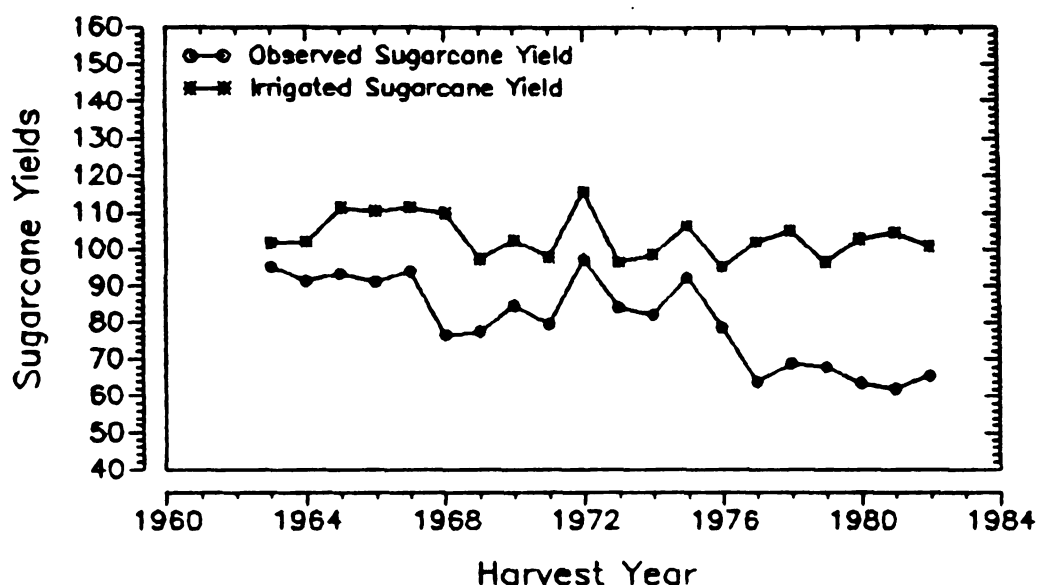


Figure 29. Deterministic YIELD simulator: Jamaica--Caymanas, sugarcane observed irrigated yield and simulated irrigated yield from 1963 to 1982 (t/ha).

For the period from 1977 to 1982, there is no clear relationship between the simulated irrigated yield and the observed yield. As pointed out before, for the Worthy Park region, during that period several changes occurred in the government of Jamaica in relation to the sugarcane industry. Also, sugar mills and sugar farms were going through a nationalization process, and that process had a great influence on sugarcane yield. Strikes, political unrest, crop destruction by the farm's labor force, farm employees'

refusal to harvest the crop, losses in harvesting and transportation, and, in some cases, failure to record proper yield data left the sugarcane industry in chaos.

Also, the observed yield values are below the irrigated simulated values (Figure 29 and Table 7). Again, that may be an indication that, holding everything else constant, a better water-management procedure may improve sugarcane yields.

The relationship between sugarcane observed yield and simulated rain-fed yield is plotted in Figure 30. It can be observed that the simulated rain-fed yield is closest to the observed yield for the years considered. Observed sugarcane yield values are in most cases above those for simulated sugarcane rain-fed yield. This fact may suggest that some irrigation was used, but not effectively, because crop-water stress still occurred.

The results for Caymanas may also indicate that, everything else being equal, better water-management procedures may generate yield increases in sugarcane. Again, the effects of political problems related to the sugarcane industry in Jamaica are shown by a strong random variation in the observed yield trend from 1975 to 1982.

There was no reported major disease outbreak or pest infestation on sugarcane crop fields during the period studied, which leaves the government interventions on the

sugarcane farms and mills and associated factors as major causes of the random behavior of observed yields for the period from 1977 to 1982.

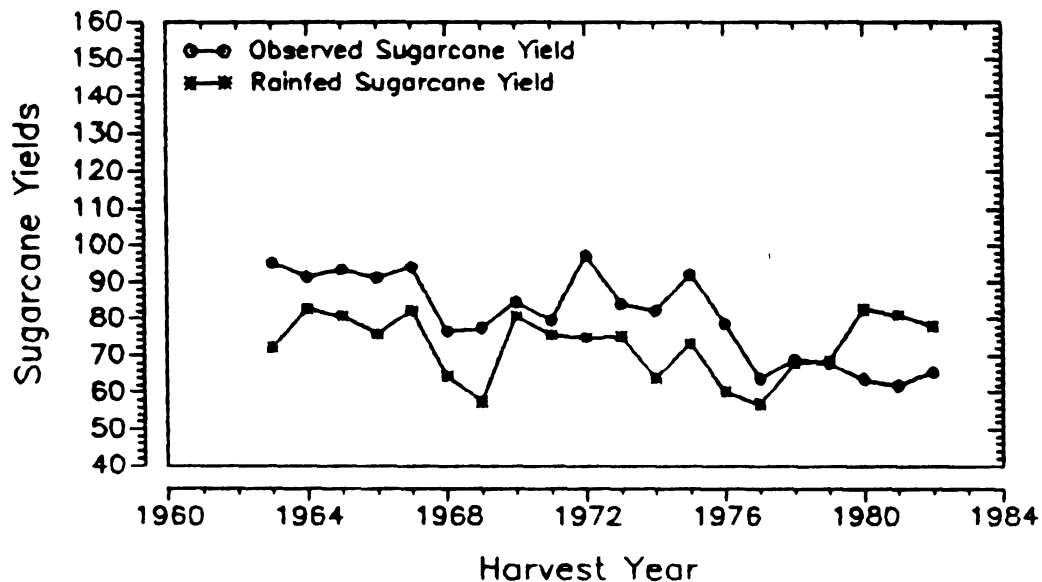


Figure 30. Deterministic YIELD simulator: Jamaica--Caymanas, sugarcane observed irrigated yield and simulated rain-fed yield from 1963 to 1982 (t/ha).

A scattergram of the simulated sugarcane yield results and the observed sugarcane yield is provided in Figures 31 and 32, which provides a different perspective for analysis of the simulated results.

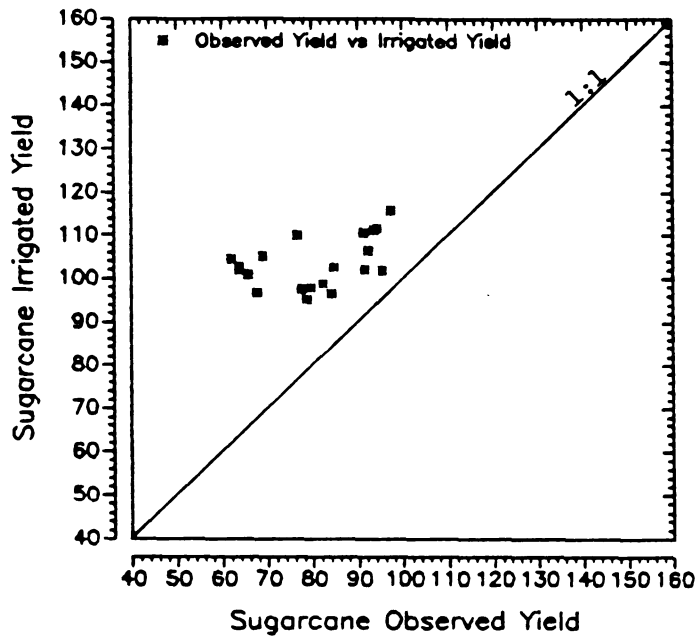


Figure 31. Deterministic YIELD model: Jamaica--
Caymanas, sugarcane observed irrigated yield
versus simulated irrigated yield (t/ha).

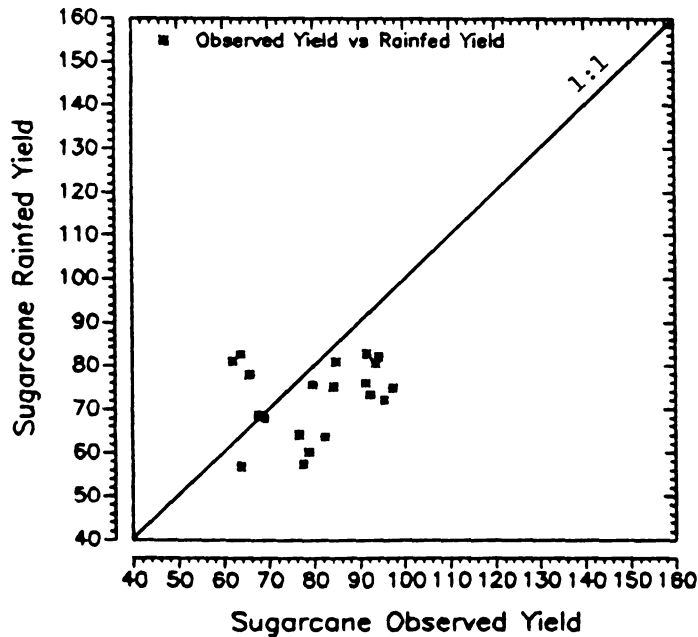


Figure 32. Deterministic YIELD model: Jamaica--
Caymanas, sugarcane observed irrigated yield
versus simulated rain-fed yield (t/ha).

Sugarcane observed yield and sugarcane irrigated yield results are clustered above the 45-degree line (Figure 31). The values for both variables show, as seen before, that the values of simulated irrigated yield are greater for all studied years than the values of the observed yield. Sugarcane observed yields are also plotted against the rain-fed observed sugarcane yields (Figure 32).

Essentially, three clusters can be seen (Figure 31). It can be noted that, for this case, the model predicts yields better for higher values than for lower values (clusters of high values are closest to the 45-degree line). Values are clustered mainly below the 45-degree line, an indication that the yields of the rain-fed simulation are smaller than the observed sugarcane yield. If the location of the cluster center is taken as one of the performance indicators of the model, one can infer that the model reflects more the results of rain-fed yield than those of irrigated yield. The result may also suggest that some irrigation scheme was used.

Simulated irrigated, rain-fed, and observed sugarcane yields for the Monymusk region in Clarendon parish for the period from 1963 to 1982 are presented in Table 8.

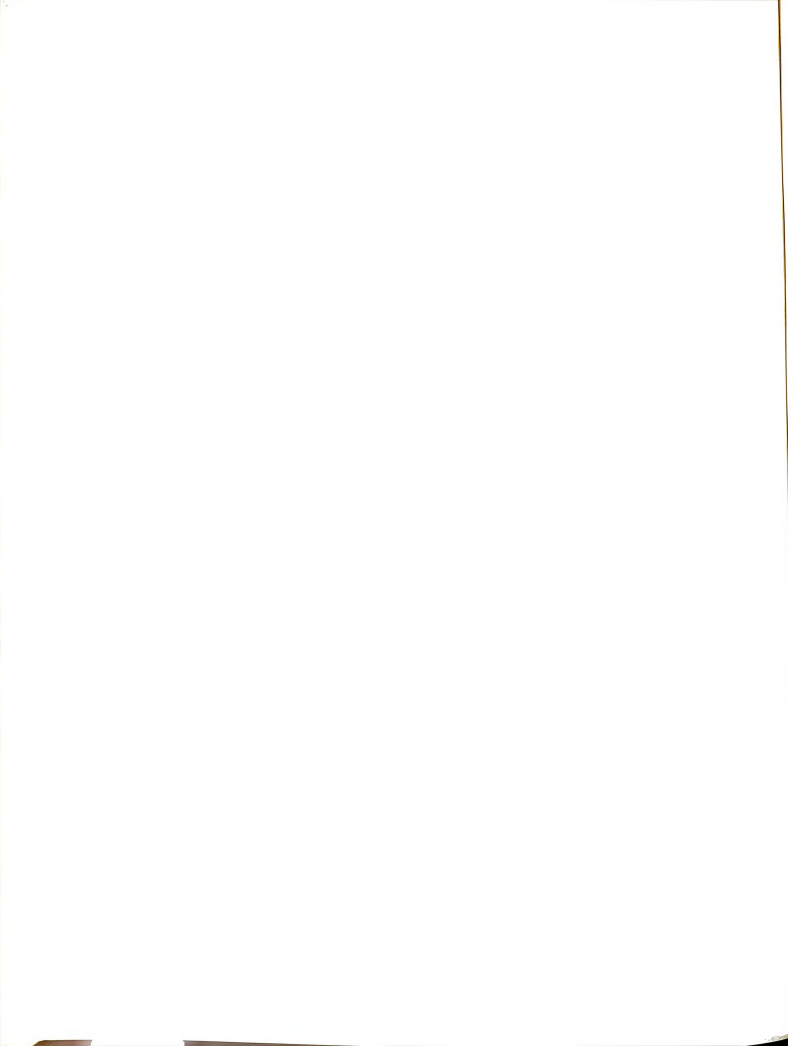


Table 8. Deterministic YIELD simulator: Jamaica--Clarendon
--Monymusk. Sugarcane--observed irrigated yield
and simulated irrigated and rain-fed yield, 1963-
1982 (tons/ha) ^a

Year	Observed Yield ^b	Simulated Irrigated Yield	Simulated Rain-fed Yield
1963	92.35	118.66	87.29
1964	86.94	111.05	87.75
1965	83.76	108.25	80.39
1966	90.97	126.55	92.77
1967	76.68	108.28	81.63
1968	70.62	106.53	58.78
1969	78.03	115.05	77.65
1970	82.97	121.92	102.62
1971	71.21	106.28	83.29
1972	78.57	122.41	105.05
1973	62.15	104.16	81.39
1974	70.47	109.70	81.13
1975	71.18	107.99	77.61
1976	72.37	117.84	68.69
1977	54.43	110.33	68.84
1978	74.00	129.05	99.12
1979	67.23	116.88	85.06
1980	61.50	127.45	103.86
1981	55.55	120.31	93.31
1982	53.92	131.90	116.33

^aCompiled from simulation results.

^bJamaica Ministry of Agriculture, Rural and Physical
Planning Division.

A graphic representation of observed yields and simulated irrigated yields for Monymusk from 1963 to 1982 is shown in Figure 33.

Again, the model simulates fairly well the trend in observed yield from 1963 to 1974. In those years, the data

show a good association of the vacillations in the simulated values when compared to the irrigated yield trend.

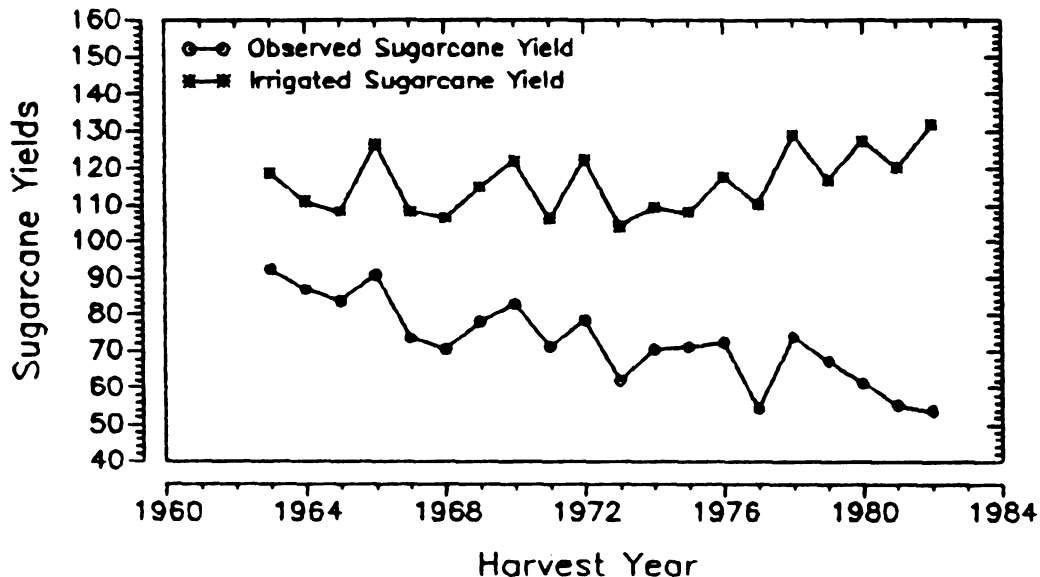


Figure 33. Deterministic YIELD simulator: Jamaica--Monymusk, sugarcane observed irrigated yield and simulated irrigated yield from 1963 to 1982 (t/ha).

From 1975 to 1982, there was no clear relationship between simulated irrigated yield and observed yield. The specific causes for this were explained before.

The fact that the observed yield values are approximately 20 to 40 percent below the simulated irrigated yield values may be an indication that, everything else remaining the same, better water-management procedures are needed to improve sugarcane yields. The relationship between

sugarcane observed yield and simulated rain-fed yield is provided in Figure 34.

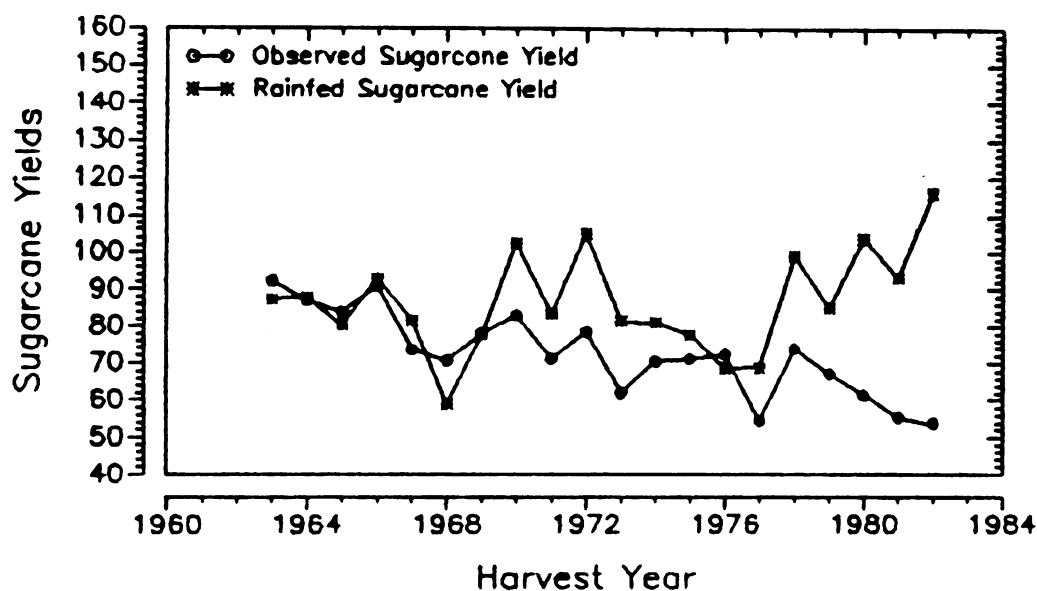


Figure 34. Deterministic YIELD simulator: Jamaica--Monymusk, sugarcane observed irrigated yield and simulated rain-fed yield from 1963 to 1982 (t/ha).

From the results presented, it may be observed that the simulated rain-fed yield is closer to the observed yield, as compared to the simulated irrigated yield, for the years from 1963 to 1977. Observed sugarcane yield values are in most cases below the simulated sugarcane rain-fed yield. This fact may suggest that some other factor influenced the decrease in sugarcane yield, such as pest and disease, storms, and/or labor and market conditions.

The observed sugarcane yield trend for Monymusk is repeated by the simulated rain-fed sugarcane yield for the years 1963 to 1973. Again, effects of a socio-political nature may have caused strong variations in the observed yield trend from 1974 to 1982, especially because there were no reported cases of major disease outbreaks or pests on sugarcane crop fields during the period studied.

Scattergrams of the simulated sugarcane yield results and the observed irrigated sugarcane yield are presented in Figures 35 and 36.

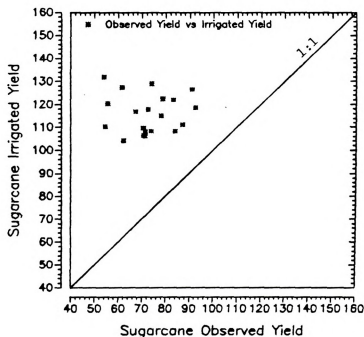
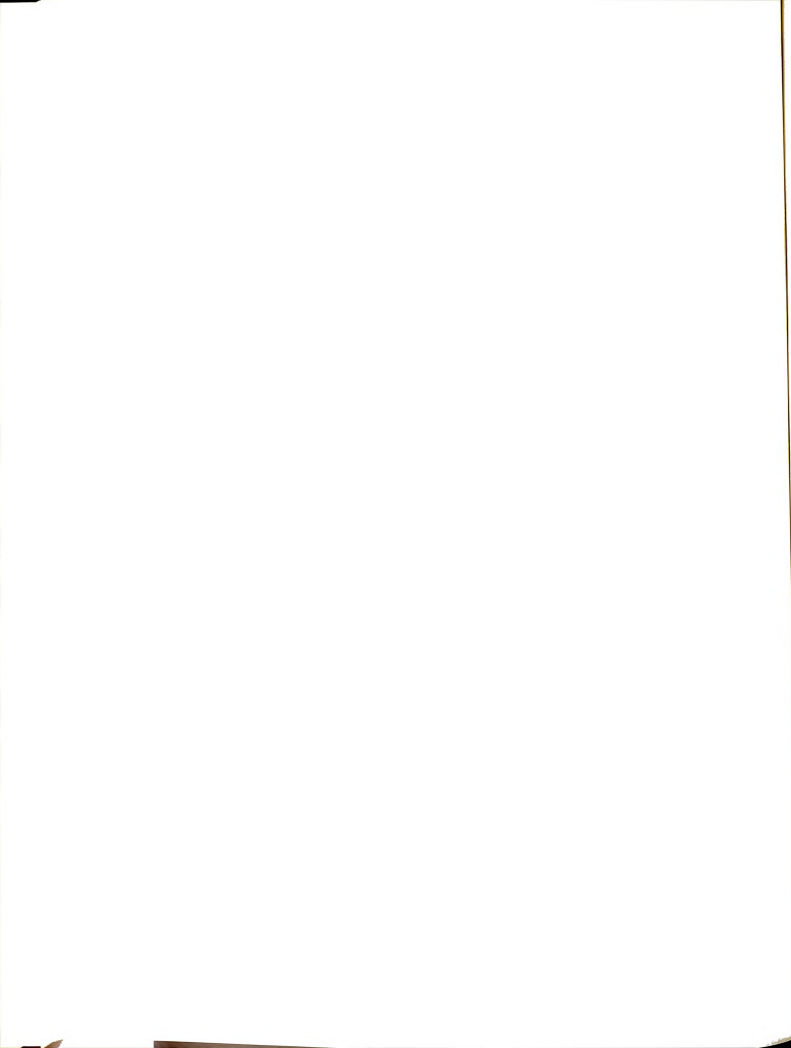


Figure 35. Deterministic YIELD simulator: Jamaica--Monymusk, sugarcane irrigated observed yield versus simulated irrigated yield (t/ha).



Sugarcane observed yield and sugarcane irrigated yield results (Figure 35) are clustered above the 45-degree line. For all years studied, the values of simulated irrigated yields were larger than the values of the observed yields. Also, sugarcane observed yields were plotted against rain-fed observed sugarcane yields (see Figure 36).

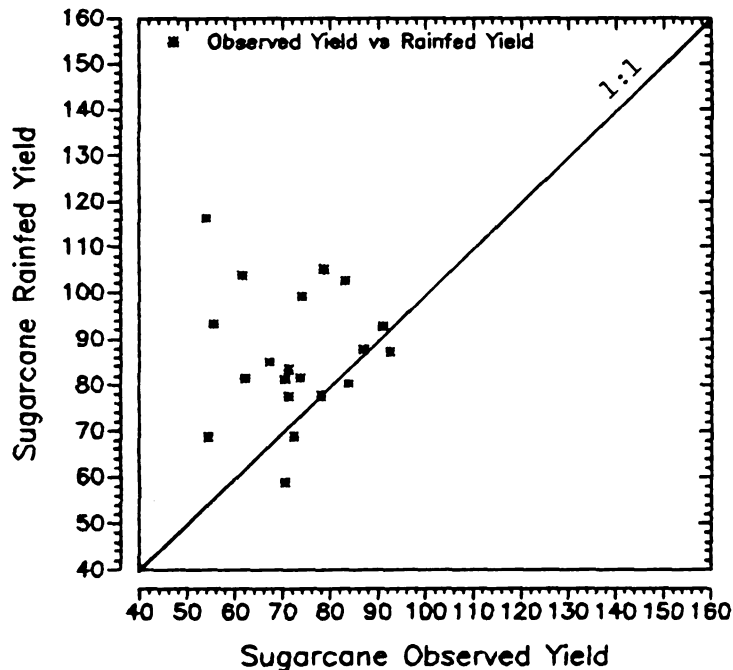


Figure 36. Deterministic YIELD simulator: Jamaica--Monymusk, sugarcane irrigated observed yield versus simulated rain-fed yield (t/ha).

The yield data presented in this case are also clustered slightly above the 45-degree line. This is an indication that the results of the rain-fed simulation are larger than the observed sugarcane yield.

From the location of the cluster center, it can be inferred that the model reflects more closely the results of rain-fed yield than of irrigated yield when compared to observed yield. The results also suggest that irrigation scheme, in addition to other management practices, must have been used to improve yields. One can also conclude from the results that water deficit affected final yield.

The deterministic YIELD simulator model was also used to simulate average yield values of two other crops in Jamaica: tobacco and sorghum. For these crops, only average and no yearly observed yield was available for the study regions. The simulation model was run only once through, to simulate yield for the "average" year; the environmental variables were averaged on a month-by-month basis to generate one year of average values for precipitation, temperature, relative humidity, solar radiation, and wind velocity to simulate the irrigated and rain-fed yields.

The results of the simulation run for the "average" year for tobacco and sorghum for the Worthy Park, Caymanas, and Monymusk regions are presented in Table 9.

The average yields for Jamaica were provided by the Ministry of Agriculture. They are:

1. tobacco: 1.0 to 2.0 tons per hectare
2. sorghum: .297 to 1.028 tons per hectare;
under good management and cultivar, 1.136 tons
per hectare

Table 9. Deterministic YIELD simulator: tobacco and sorghum: Jamaica--Worthy Park, Caymanas, and Monymusk. Simulated "average" yield results over the period from 1963 to 1982 (tons/ha)

Region	Tobacco.....		Sorghum.....	
	Irrigated	Rain-fed	Irrigated	Rain-fed
Worthy Park	3.148	2.462	3.869	3.803
Caymanas	3.033	2.212	3.308	2.866
Monymusk	4.862	3.589	3.627	3.250

Source: Compiled from simulation results.

Doorenbos and Kassam (1979) indicated the following yields of high-producing varieties adapted to the climatic conditions of the available growing season under adequate water supply and high level of agricultural inputs under irrigated farming conditions for sugarcane, tobacco, and sorghum:

1. sugarcane (cane) 100.00 to 150.00 tons/ha
2. tobacco (leaf) 1.50 to 2.50 tons/ha
3. sorghum (grain) 2.00 to 5.00 tons/ha

The deterministic YIELD simulator results for sugarcane are within the yield value ranges given by Doorenbos and Kassam (1979). For sorghum, the simulation results are quite good when compared to Doorenbos and Kassam but very high when compared to Jamaica's average, suggesting that

there is room for improvement in Jamaica's sorghum-production system.

The simulation results in terms of yield average are very high compared to the average Jamaica tobacco yield and also very high when compared to Doorenbos and Kassam's yield values. That fact may be an indication that a refinement of the model's parameters or an adjustment of the yield generated by the model may be necessary for tobacco, considering its unique production system. Tobacco is transplanted to the crop field at a certain stage of the growing season, and the harvesting technique is unique. The leaves are harvested during a long period.

To summarize the discussion of the deterministic YIELD simulator for agro-ecological conditions represented by the Worthy Park, Caymanas, and Monymusk regions in Jamaica, as a tool in formulating policy decisions regarding the production of sugarcane, the results indicated that there is room for improvement in the sugarcane-production system; more effective water-management procedures may improve yields. For sorghum, a complete review of Jamaica's production system may be justified to improve yields. For tobacco, some refinements in the model may be needed to improve simulation results and to obtain a more significant relationship between observed yield and simulated results.

Improvements in the tobacco-production system seem justified.

The data set used in the deterministic YIELD model was used to run the stochastic YIELD model (SYS). With the stochastic YIELD model, some random variations are introduced that are inherent in the exogenous environmental variables. Also, variations will be introduced to some control inputs to the model. It is expected that the SYS will provide insights into the yield variations as some of the exogenous inputs are taken as random variables.

Stochastic YIELD Simulator, Jamaica-- Environmental Inputs

The CRIES-Jamaica national data base was used to estimate the probability density function statistics for the environmental inputs. The Statistical Analysis System (SAS, 1985) software package was used for the statistical analysis and to identify the probability density function and distribution parameters to use in the simulation model.

Probability density function statistics for the environmental variable precipitation for each month of the year were used to run the simulation model. The statistics for Worthy Park, Caymanas, and Monymusk are presented in Tables 10, 11 and 12, respectively.

Monthly mean precipitation was used because of the sensitivity of the model to precipitation values. Also,

seasonal rainfall distribution is important for agricultural production systems and hence for yield production. No correlation between precipitation in different months was assumed; that is, each month was considered independent of the others.

Table 10. Stochastic YIELD simulator: precipitation probability density function statistics for Jamaica--Worthy Park, for the years 1963 to 1982 (mm/month)

Month of the Year	Mean	Standard Deviation	Skewness
January	88.900	91.766	2.521
February	52.211	39.146	1.554
March	44.027	38.751	1.370
April	97.084	68.330	1.304
May	186.831	116.363	0.377
June	124.178	89.878	1.673
July	111.478	28.973	0.610
August	181.751	116.140	2.107
September	199.249	117.639	1.921
October	197.838	110.303	1.534
November	94.262	60.328	0.838
December	52.776	24.289	0.705

Source: Compiled from CRIES-Jamaica National Data Base (CRIES-MSU).

Table 11. Stochastic YIELD simulator: precipitation probability density function statistics for Jamaica--Caymanas, for the years 1963 to 1982 (mm/month)

Month of the Year	Mean	Standard Deviation	Skewness
January	18.473	22.006	2.042
February	16.625	14.255	0.514
March	16.972	13.608	0.631
April	41.679	51.519	2.975
May	107.026	108.403	1.296
June	51.954	61.014	1.663
July	44.681	42.362	0.882
August	87.053	77.524	2.211
September	113.492	135.541	3.463
October	166.254	141.858	1.947
November	76.200	66.545	2.737
December	42.603	40.639	1.280

Source: Compiled from CRIES-Jamaica National Data Base (CRIES-MSU).

Variations in temperature, relative humidity, solar radiation, and wind velocity are not as large as variations in precipitation, and the available data values, mainly solar radiation and wind velocity, allied to precision and the assumption that water availability is the main factor in biomass production, influence the decision to use annual and not monthly distribution as was done with precipitation. Minimum and the maximum annual values for those variables were taken to run the model.

Table 12. Stochastic YIELD simulator: precipitation probability density function statistics for Jamaica--Monymusk, for the years 1963 to 1982 (mm/month)

Month of the Year	Mean	Standard Deviation	Skewness
January	43.053	42.226	2.190
February	18.034	13.861	1.248
March	31.115	30.844	1.340
April	40.259	43.107	2.589
May	115.062	84.825	1.103
June	82.042	72.393	0.577
July	45.212	37.797	0.920
August	91.186	64.241	1.754
September	142.240	153.340	2.907
October	167.386	96.305	1.097
November	81.153	47.279	0.044
December	51.689	41.165	1.387

Source: Compiled from CRIES-Jamaica National Data Base (CRIES-MSU).

A uniform random number generator can be used to generate random variates for all environmental variables. The values derived from the CRIES-Jamaica national data base are presented in Tables 13, 14, and 15.

Table 13. Stochastic YIELD simulator: temperature, relative humidity, solar radiation, and wind velocity probability density function statistics for Jamaica--Worthy Park for the years 1963 to 1982

Environmental Variable	Minimum	Maximum
Temperature ^a	20.44	30.78
Relative Humidity ^b	75.50	91.50
Solar Radiation ^c	4.00	7.60
Wind Velocity ^d	0.00	2.50

Source: Compiled from CRIES-Jamaica National Data Base (CRIES-MSU).

^aTemperature units are in degrees Celsius.

^bRelative humidity units are in percentage.

^cSolar radiation units are in hours/day.

^dWind velocity units are in meters/second, day/night wind ratio assumed to be 1.

Table 14. Stochastic YIELD simulator: temperature, relative humidity, solar radiation, and wind velocity probability density function statistics for Jamaica-Caymanas for the years 1963 to 1982

Environmental Variable	Minimum	Maximum
Temperature ^a	25.06	29.44
Relative Humidity ^b	52.00	87.00
Solar Radiation ^c	1.00	8.00
Wind Velocity ^d	0.00	2.50

Source: Compiled from CRIES-Jamaica National Data Base (CRIES-MSU).

^aTemperature units are in degrees Celsius.

^bRelative humidity units are in percentage.

^cSolar radiation units are in hours/day.

^dWind velocity units are in meters/second, day/night wind ratio assumed to be 1.

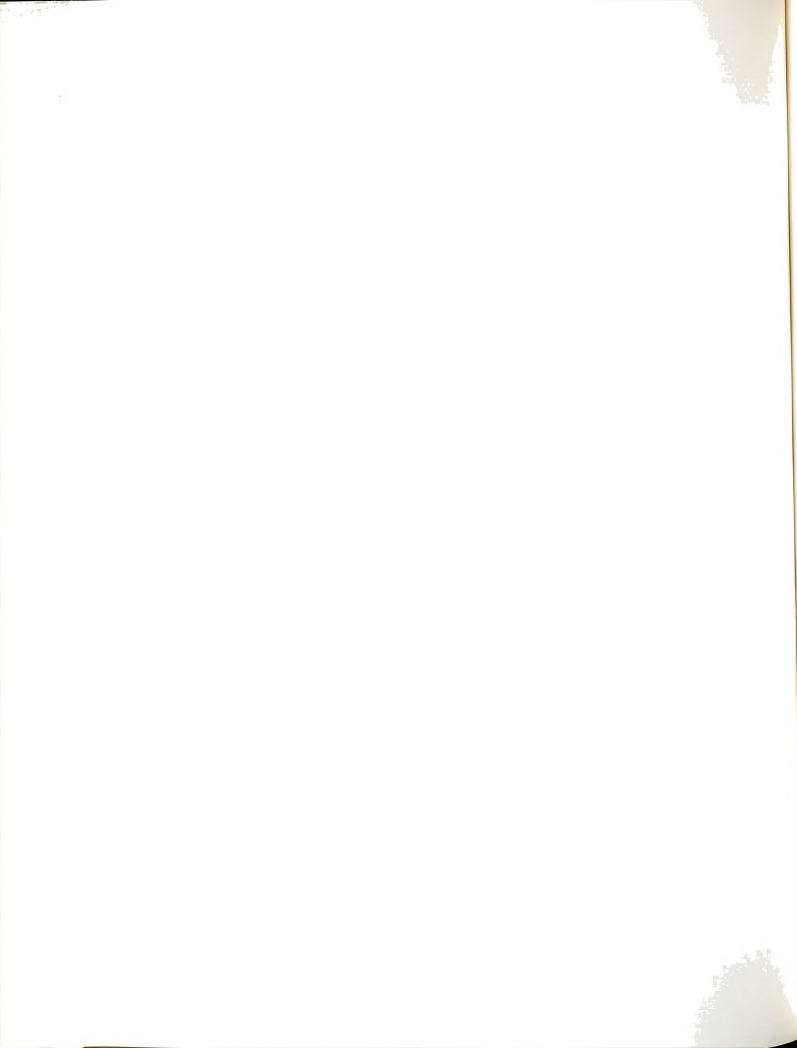


Table 15. Stochastic YIELD simulator: temperature, relative humidity, solar radiation, and wind velocity probability density function statistics for Jamaica--Monymusk for the years 1963 to 1982.

Environmental Variable	Minimum	Maximum
Temperature ^a	23.89	29.33
Relative Humidity ^b	61.00	93.00
Solar Radiation ^c	5.20	9.60
Wind Velocity ^d	0.00	2.50

Source: Compiled from CRIES-Jamaica National Data Base (CRIES-MSU).

^aTemperature units are in degrees Celsius.

^bRelative humidity units are in percentage.

^cSolar radiation units are in hours/day.

^dWind velocity units are in meters/second, day/night wind ratio assumed to be 1.

Other stochastic inputs for sugarcane used to run the simulation model are:

1. Sowing or planting date for sugarcane. This is generated in the model by a uniformly distributed random number in the interval from 01/30/YY to 03/25/YY for Worthy Park, Caymanas, and Monymusk. Those values were derived from the sowing or planting scheme given by the RPPD in

Jamaica as a result of variations in sugarcane planting dates.

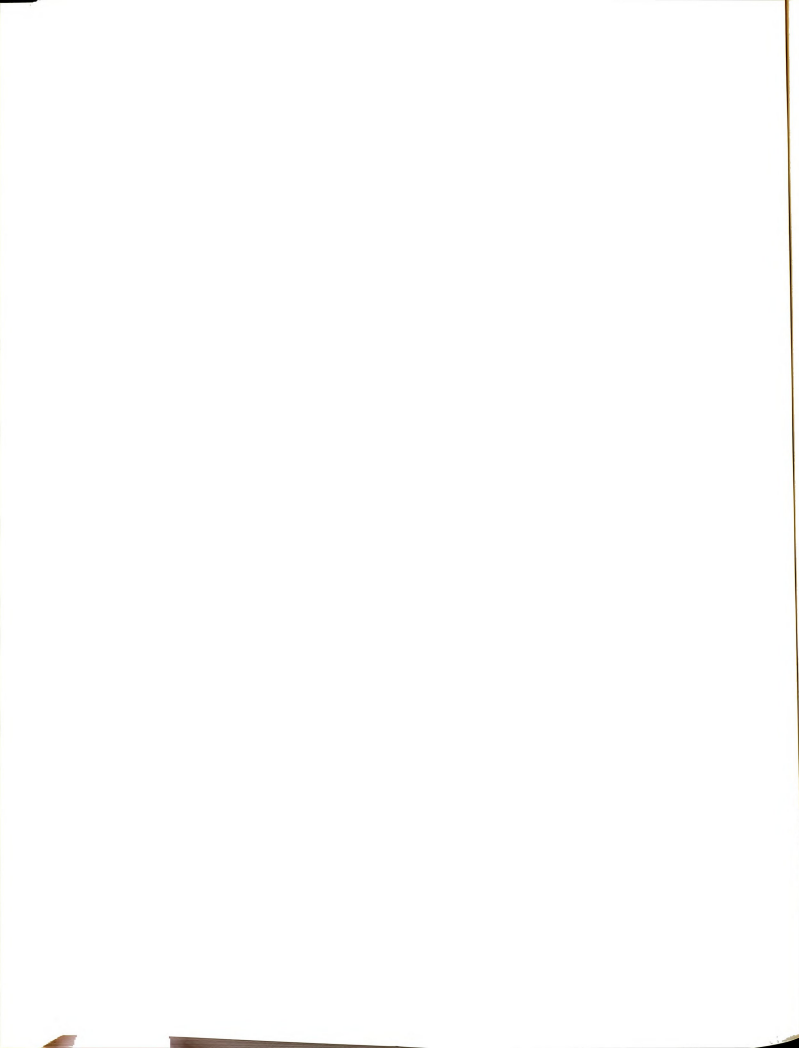
2. Number of days for each growth stage of the growing period for Worthy Park, Caymanas, and Monymusk was generated for the model by a uniformly distributed random-number generator in the interval given by Doorenbos and Kassam (1979).

3. Fertilizer availability, in percentage, was used in the intervals from 36.92 to 100 percent, 40 to 100 percent, and 48.68 to 80.69 percent for Worthy Park, Caymanas, and Monymusk, respectively, derived from fertilizer-availability data (Table 16, 17 and 18) and crop fertilizer requirements as given by Doorenbos and Kassam (1979).

Other stochastic inputs for tobacco and sorghum used to run the simulation model are:

1. The sowing or planting date for tobacco and sorghum, derived from uniformly distributed random numbers in the interval from 01/15/YY to 03/15/YY. Those values were derived from the sowing or planting scheme given by the RPPD in Jamaica as a result of variations in tobacco and sorghum planting dates.

2. The number of days for each growth stage of the growing period. This was generated in the model from a uniformly distributed random-number generator in the interval provided by Doorenbos and Kassam (1979).



3. Fertilizer availability, in percentage. This was assumed to vary in the interval from 50 to 100 percent. No data on fertilizer usage for tobacco and sorghum were available.

Table 16. Stochastic YIELD simulator: fertilizer usage for sugarcane, Jamaica--Worthy Park, for the years 1963 to 1982 (kg/ha)

Year	Fertilizer Usage.....		
	Nitrogen(N)	Potassium(P)	Phosphorus(K)
1963	72.68	24.51	98.98
1964	74.50	26.54	105.96
1965	99.20	28.47	139.54
1966	75.92	27.03	110.05
1967	68.54	24.13	102.65
1968	66.84	22.56	96.06
1969	66.84	22.56	96.06
1970	84.93	23.94	99.73
1971	70.02	17.93	78.20
1972	82.87	27.00	106.67
1973	85.20	275.88	106.77
1974	96.94	41.18	139.44
1975	121.15	40.29	108.54
1976	94.31	24.18	119.17
1977	93.85	30.95	117.57
1978	99.03	31.15	138.88
1979	80.54	a	108.84
1980	89.84	32.29	121.48
1981	92.05	38.03	127.39
1982	95.69	18.43	143.57

Source: Jamaica, Ministry of Agriculture, Rural and Physical Planning Division.

^aMissing data.

Table 17. Stochastic YIELD simulator: fertilizer usage for sugarcane, Jamaica--Caymanas, for the years 1963 to 1976 (kg/ha)

Year	Fertilizer Usage.....		
	Nitrogen(N)	Potassium(P)	Phosphorus(K)
1963	95.11	94.37	128.22
1964	95.29	106.69	134.38
1965	94.71	69.05	163.88
1966	94.58	91.84	164.65
1967	94.61	89.19	162.01
1968	94.12	87.98	167.91
1969	94.12	87.98	168.44
1970	41.69	20.20	24.67
1971	43.15	20.04	22.67
1972	103.35	86.96	13.00
1973	46.28	19.36	18.55
1974	107.53	80.00	138.71
1975	101.20	81.78	129.79
1976	110.42	76.03	137.80

Source: Jamaica, Ministry of Agriculture, Rural and Physical Planning Division.

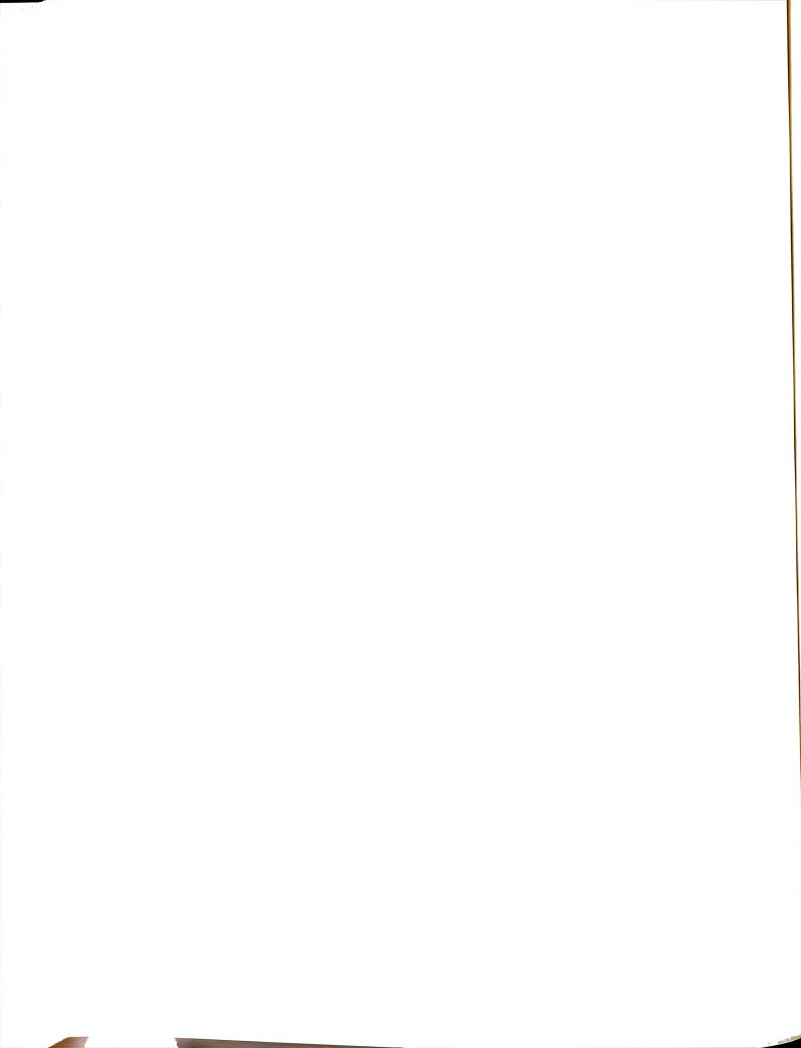


Table 18. Stochastic YIELD simulator: fertilizer usage for sugarcane, Jamaica--Monymusk, for the years 1963 to 1976 (kg/ha)

Year	Fertilizer Usage.....		
	Nitrogen(N)	Potassium(P)	Phosphorus(K)
1963	94.96	31.50	67.37
1964	93.91	38.23	70.69
1965	95.21	39.35	66.93
1966	95.35	42.14	66.57
1967	95.71	43.62	72.45
1968	98.79	51.23	71.75
1969	98.79	51.23	71.75
1970	99.19	53.69	88.17
1971	99.98	54.62	95.96
1972	99.97	54.33	110.77
1973	93.82	a	125.81
1974	94.34	a	45.13
1975	94.69	a	a
1976	94.25	a	a

Source: Jamaica, Ministry of Agriculture, Rural and Physical Planning Division.

^aMissing data.

Stochastic YIELD Simulator, Jamaica-- Simulation Results

Five hundred simulation runs for sugarcane, tobacco, and sorghum were made for Worthy Park, Caymanas, and Monymusk. The resulting yield statistics were computed using the Statistical Analysis System (SAS, 1985) software package for microcomputer.

Descriptive statistics for sugarcane potential yield, sugarcane irrigated yield, and sugarcane rain-fed yield are presented in Table 19.

Table 19. Stochastic YIELD simulator: sugarcane results, Jamaica--Worthy Park, Caymanas, and Monymusk (tons/ha)

Statistics	Worthy Park	Caymanas	Monymusk
Potential Yield			
Mean	102.311	104.035	124.171
Std Dev	8.554	10.886	12.958
Skewness	0.005	0.141	0.068
Quantiles			
100%	127.968	135.145	157.732
75%	107.931	111.700	133.765
50%	102.679	103.671	124.053
25%	96.181	95.978	115.044
0%	78.217	78.534	88.981
Irrigated Yield			
Mean	84.511	86.969	99.724
Std Dev	7.058	9.107	10.451
Skewness	-0.004	0.130	0.063
Quantiles			
100%	106.044	112.709	127.279
75%	89.136	93.505	107.156
50%	84.782	86.760	99.621
25%	79.390	80.274	92.384
0%	64.736	65.197	71.370
Rain-fed Yield			
Mean	75.984	59.519	68.574
Std Dev	6.846	6.099	6.846
Skewness	-0.049	0.116	0.015
Quantiles			
100%	97.210	77.518	87.363
75%	80.576	63.881	73.213
50%	76.206	59.444	68.795
25%	71.342	55.039	63.957
0%	57.001	43.088	49.317

Source: Compiled from stochastic YIELD simulator results.

For each simulation representing a crop year, random variates were generated by random-number generator for that particular simulation. The exogenous environmental inputs were generated and entered into the simulation model as a random number derived from the probability density functions. The planting date and duration of each stage were also random variables entered into the simulation run and were assumed to be uniformly distributed (equal chance of being selected, replacing sample) in a given interval. Fertilizer availability was also assumed to be uniformly distributed in an interval because data availability and precision were very poor.

The model parameters were assumed to be known with certainty, implying the use of the variance partitioning approach discussed in Chapter IV.

The stochastic YIELD simulation results for sugarcane in the Worthy Park, Caymanas, and Monymusk regions are provided in Table 19. Probability density function statistics for potential, irrigated, and rain-fed yield for those regions, such as mean, standard deviation, skewness, and quantile values, were computed and are included in the discussion. Once again, potential, irrigated, and rain-fed results were within the FAO yield results presented in Doorenbos and Kassam (1979).

The standard deviation was somewhat expected. In general, it was 8 to 10 percent of the mean value. Some skewness to the right, a positive but not very significant skew factor, was noted in the results for Caymanas (Figure 38 a, b and c).

No significant skew factor (all skew factors computed were close to zero) was computed for Worthy Park and Monymusk, which indicates a tendency to cluster around the mean value by the simulated yield. Quantiles also are presented in Table 19, which includes the minimum (0 percent) and the maximum (100 percent) values for the simulated yield.

In general, the shape of the distribution function generated from a simulation model resembles the Gaussian or normal distribution (where the skew factor is zero). Considering that, it can be said (SAS, 1985) that in 68 percent of the cases, the yield estimated is within one standard deviation (std) of the population mean; that is:

$$P(\text{mean} + \text{std} \leq \text{yield} \leq \text{mean} + \text{std}) = 0.68$$

and that in 95 percent of the cases, the yield estimated is within two standard deviations of the population mean; that is:

$$P(\text{mean} + 2 * \text{std} \leq \text{yield} \leq \text{mean} + 2 * \text{std}) = 0.95$$

and that in 99.7 percent of the cases, the yield estimated is within three standard deviations of the population mean; that is:

$$P(\text{mean} + 3 \cdot \text{std} \leq \text{yield} \leq \text{mean} + 3 \cdot \text{std}) = 0.99$$

where: $P(a \leq X \leq b) = p$ is the probability (p) of the random variable X being greater than or equal to a and less than or equal to b.

The results for Worthy Park indicated that:

For the irrigated sugarcane yield

$$P(77.453 \leq \text{yield} \leq 91.569) = .68$$

$$P(70.395 \leq \text{yield} \leq 98.627) = .95$$

$$P(63.337 \leq \text{yield} \leq 105.685) = .997$$

For the rain-fed sugarcane yield

$$P(69.138 \leq \text{yield} \leq 82.830) = .68$$

$$P(62.292 \leq \text{yield} \leq 89.676) = .95$$

$$P(55.446 \leq \text{yield} \leq 96.522) = .997$$

In a more general form, the probability of any yield value can be computed from:

$$P(a \leq X \leq b) = \int_a^b f(x) dx$$

where:

$$f(x) = \frac{1}{\sqrt{\text{std} \cdot [2\pi]}} e^{-1/2 \left(\frac{x - \text{mean}}{\text{std}} \right)^2}$$

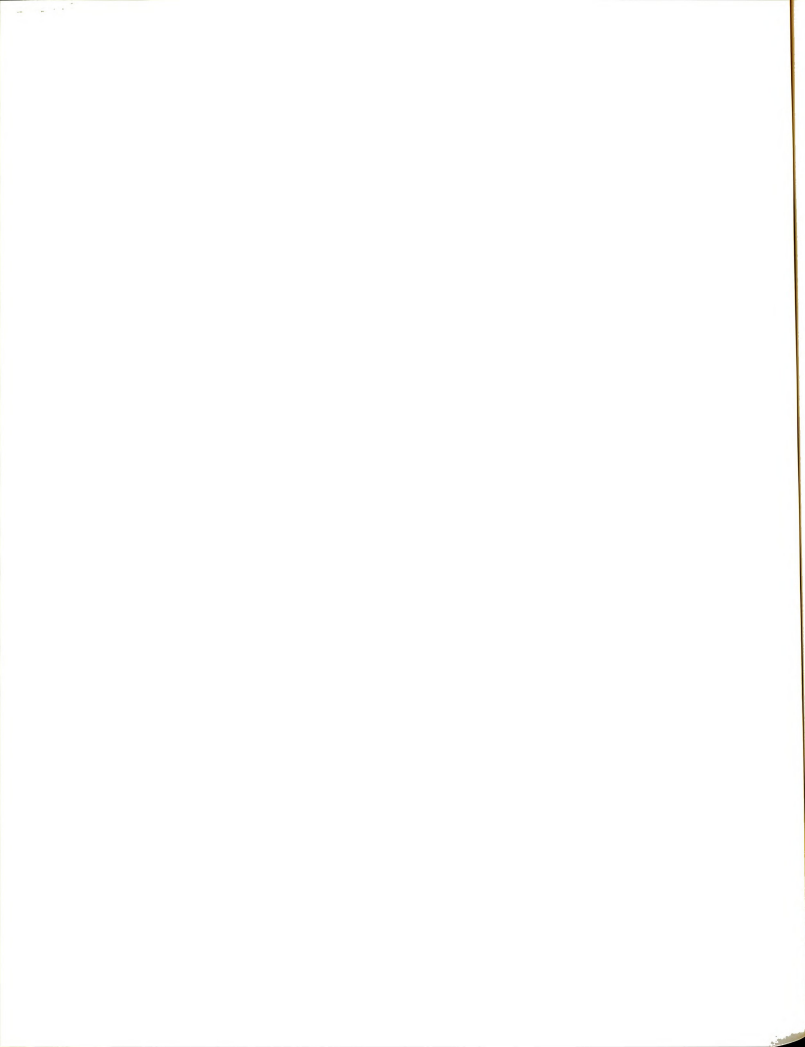
or with the use of normal distribution tables.

Histograms are provided for the three simulation results--that is, potential, irrigated, and rain-fed yield--for sugarcane, for Worthy Park, Caymanas, and Monymusk (Figures 37, 38 and 39, a, b, and c, respectively). The histograms were plotted using the results of the 500 simulation runs of the stochastic YIELD simulator, each with a different scenario of 500 years of crop-growth simulation.

In the histogram plot, the horizontal axis shows, in tons per hectare, the variation in yield results. The vertical axis of the histogram plot represents the number of occurrences for each yield value or group of values of the simulation results and is called absolute frequency.

Clearly, the information displayed in Figure 37 can be generated by a number of alternatives of interest to decision makers and policy planners by making changes in controllable inputs such as planting date, fertilizer availability, evaporation reduction factor, soil salinity levels, and so on.

In addition to giving numerical results such as means, standard deviation, skewness, and quantiles, histograms facilitate assessment of the degree of risk involved or associated with highly unfavorable outcomes. If the skewness is toward the right, the probability of obtaining large yield values is higher than if there is a negative skew factor, with skewness to the left. Also, histograms and/or



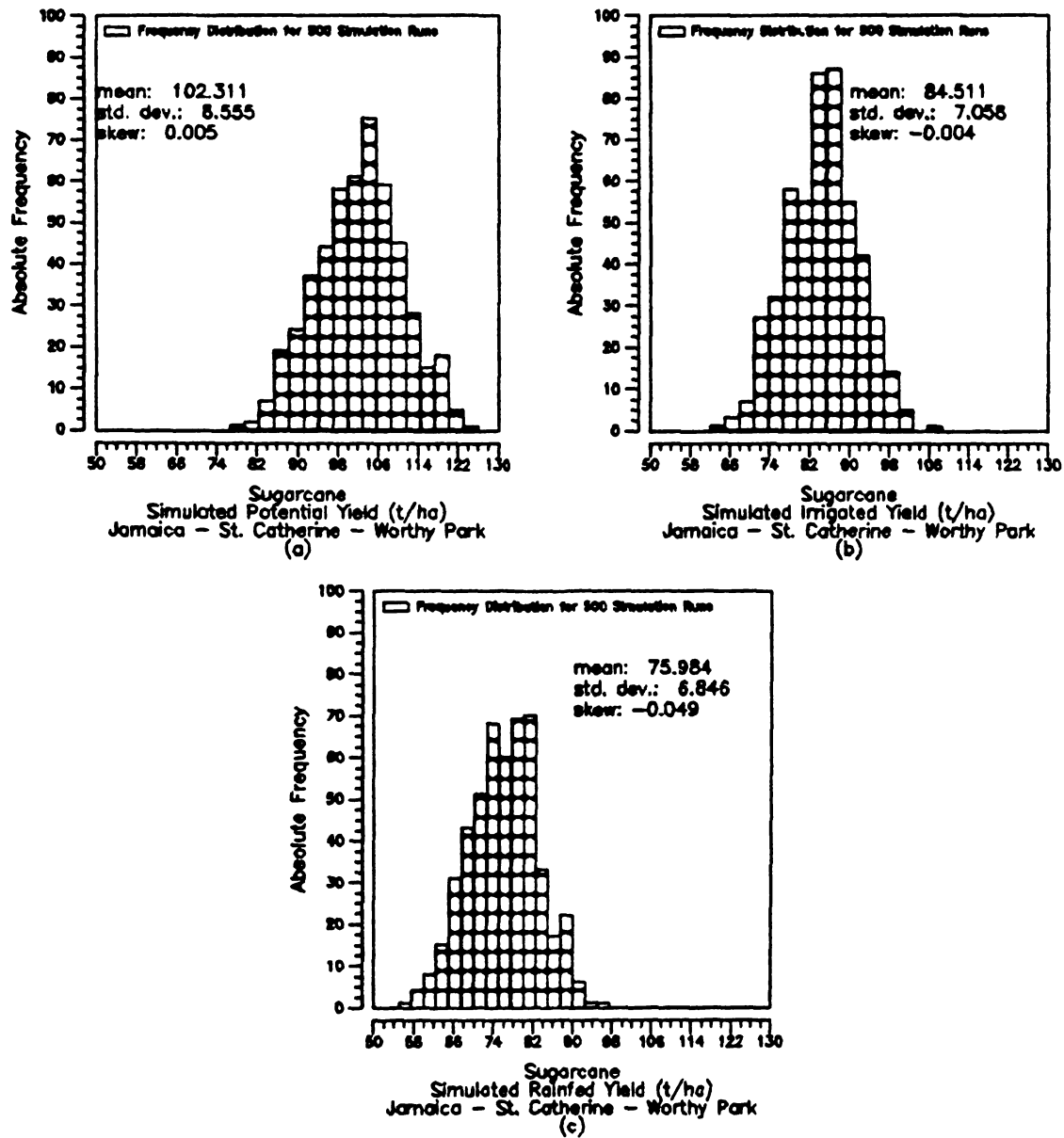


Figure 37. Stochastic YIELD simulator: Jamaica--Worthy Park. Sugarcane absolute frequency histogram for potential, irrigated, and rain-fed yield.

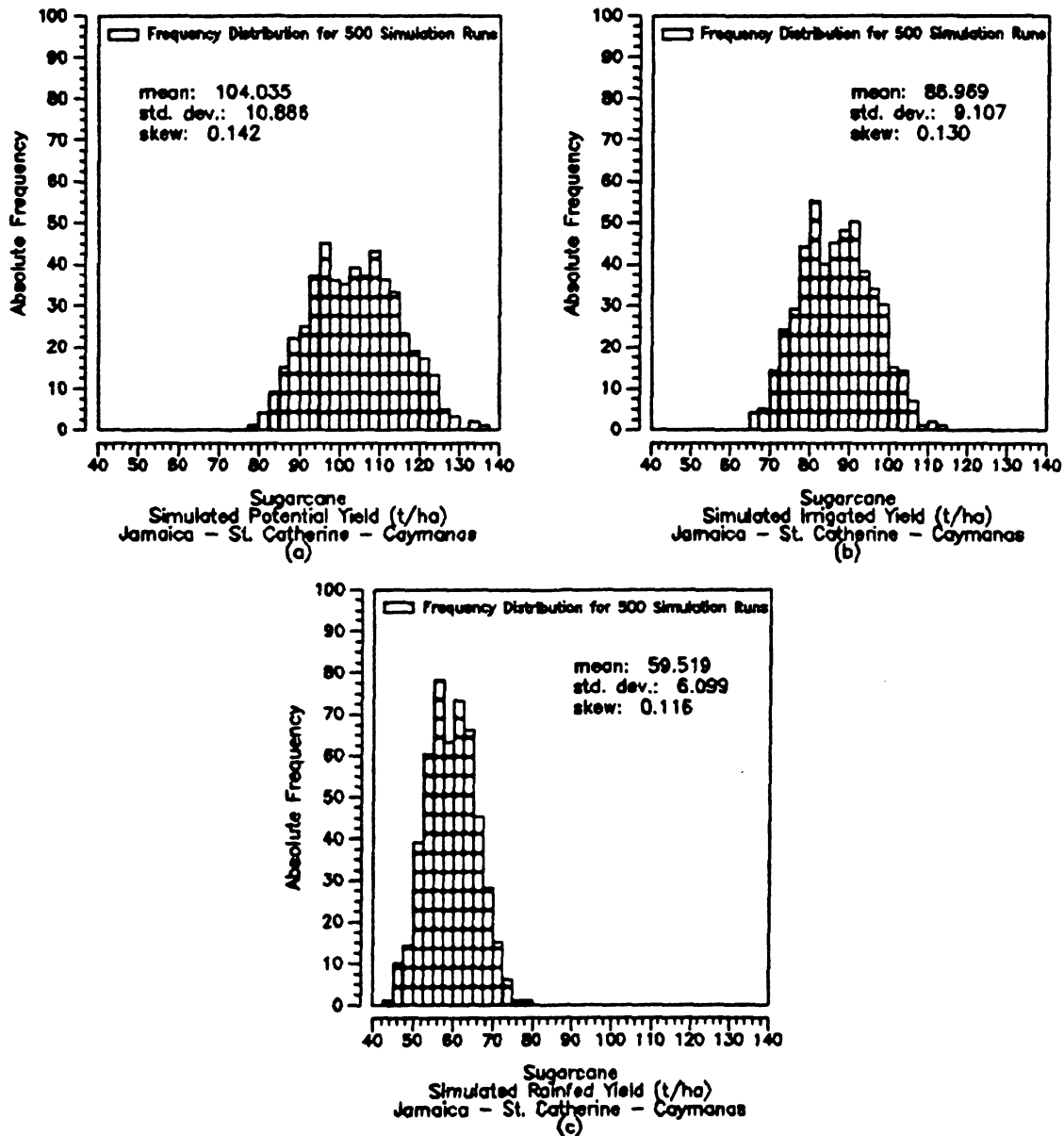
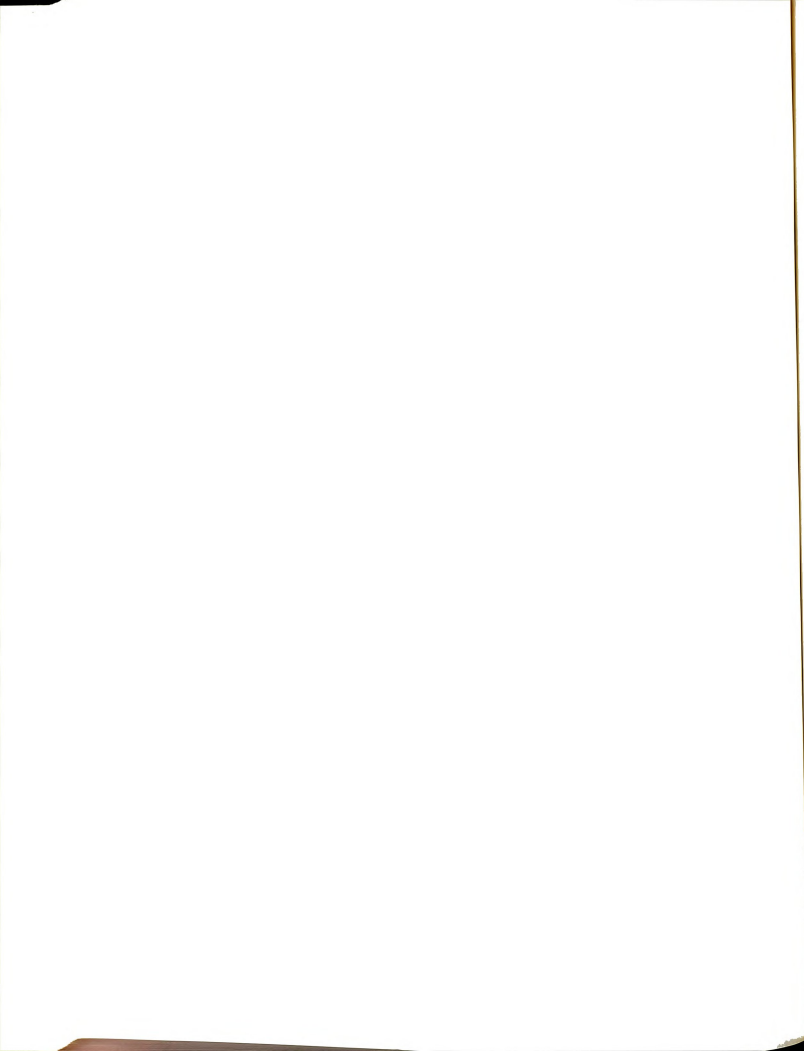


Figure 38. Stochastic YIELD simulator: Jamaica--Caymanas. Sugarcane absolute frequency histogram for potential, irrigated, and rain-fed yield.



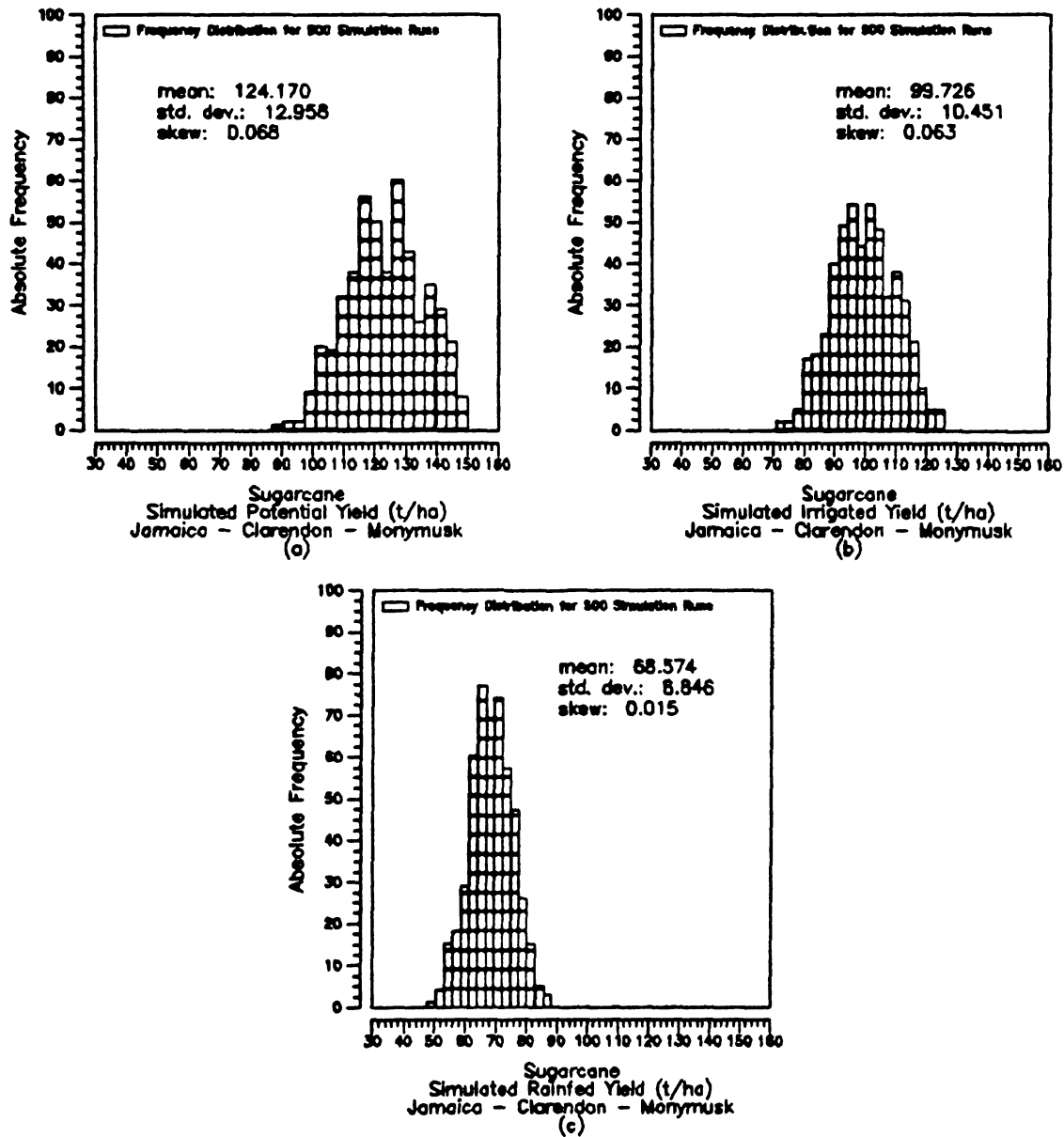


Figure 39. Stochastic YIELD simulator: Jamaica--Monymusk. Sugarcane absolute frequency histogram for potential, irrigated, and rain-fed yield.

graphic representations are more readily understood and evaluated by decision makers than are such abstract concepts as "standard deviation."

Comparisons can be made between the potential, irrigated, and rain-fed yields, and these comparisons can be used as input to a feasibility study on investment in irrigation projects.

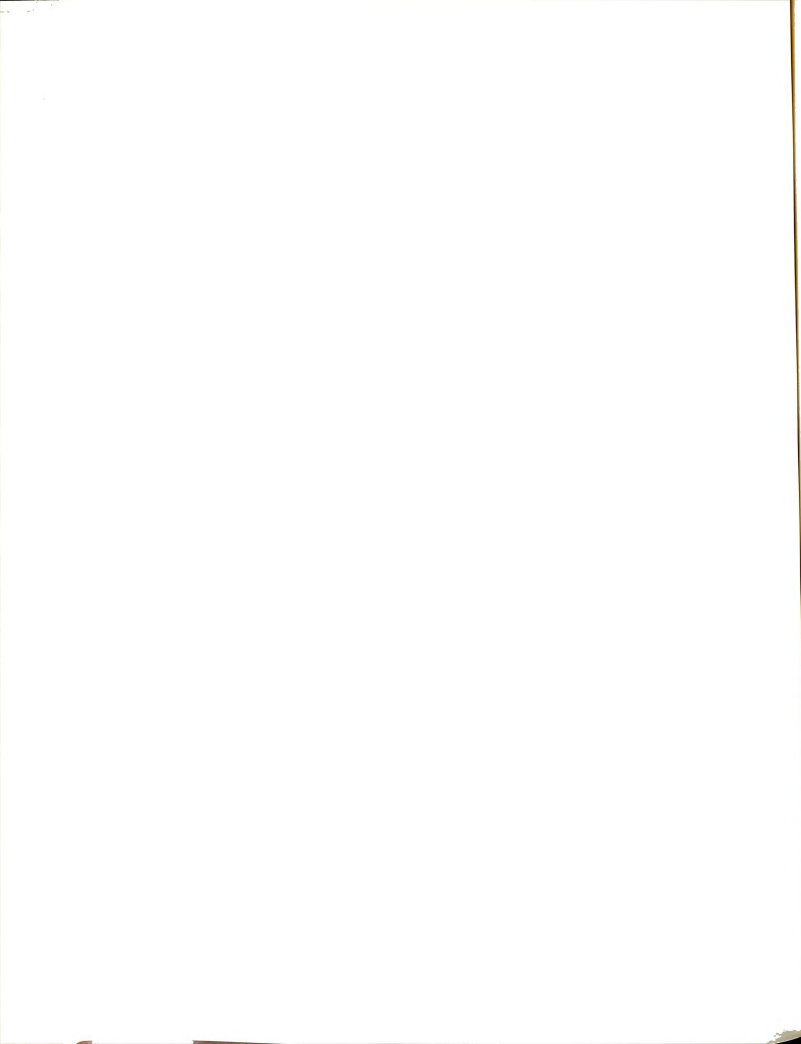
Results of the stochastic simulator for tobacco in the Worthy Park, Caymanas, and Monymusk regions are provided in Table 20. Potential, irrigated, and rain-fed yield statistics such as means, standard deviation, skewness, and quantiles are shown.

Yield for tobacco is quite high as compared to Jamaica's average tobacco yield. As discussed before, some model refinements may be justified, together with some more reliable data-collection techniques, which would lead to more precise data for inputs and also improve model results. Also, the introduction of randomness into the model's parameters might indicate which parameters are sensitive and aid in the data-collection plan. The quantile statistics indicate the minimum value and the maximum simulated value of tobacco yield for potential, irrigated, and rain-fed conditions.

Table 20. Stochastic YIELD simulator: tobacco results, Jamaica--Worthy Park, Caymanas, and Monymusk (tons/ha)

Statistics	Worthy Park	Caymanas	Monymusk
Potential Yield			
Mean	4.178	3.974	4.577
Std Dev	0.370	0.378	0.410
Skewness	0.015	0.069	0.002
Quantiles			
100%	5.133	4.927	5.579
75%	4.443	4.236	4.862
50%	4.189	3.978	4.598
25%	3.913	2.969	4.283
0%	3.245	1.958	3.512
Irrigated Yield			
Mean	3.625	3.325	3.966
Std Dev	0.326	0.317	0.356
Skewness	0.006	0.070	-0.008
Quantiles			
100%	4.448	4.114	4.827
75%	3.868	3.537	4.216
50%	3.622	3.330	3.976
25%	3.395	3.080	3.712
0%	2.803	2.433	3.045
Rain-fed Yield			
Mean	2.483	2.188	2.375
Std Dev	0.279	0.243	0.259
Skewness	0.107	0.112	-0.043
Quantiles			
100%	3.317	2.831	2.956
75%	2.679	2.361	2.580
50%	2.477	2.187	2.371
25%	2.278	2.006	2.173
0%	1.800	1.609	1.690

Source: Compiled from stochastic YIELD simulator results.



The skew factor was not significant for tobacco for any of the regions considered. For Caymanas, the skew factor for tobacco was 0.112, which indicates some but not very significant skewing to the right. The variation in tobacco yield was quite large if one considers the minimum value simulated, which is 1.609 t/ha for Caymanas rain-fed minimum, and the maximum value simulated, which is 5.579 t/ha for Monymusk potential yield.

Histogram plots for tobacco are shown for Worthy Park, Caymanas, and Monymusk in Figures 40, 41, and 42, respectively, which illustrate the potential, irrigated, and rain-fed yield. The horizontal axes plot the simulated yield values in tons per hectare, and the vertical axes show the absolute frequency of each value. Histograms give decision makers and planners a good perspective on yield variations.

The statistical results for sorghum, generated by the stochastic YIELD simulator for Worthy Park, Caymanas, and Monymusk, are presented in Table 21. Mean, standard deviation, skewness, and quantiles are included. Sorghum yield varied from a minimum value under rain-fed conditions in Caymanas, which was 2.346 t/ha, to a maximum value of potential yield for Monymusk, which was 5.321 t/ha. The skewness factor was very small for all regions and under all conditions.

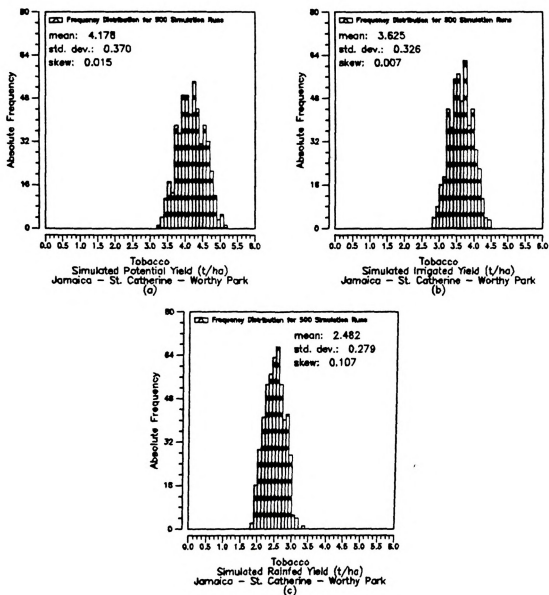


Figure 40. Stochastic YIELD simulator: Jamaica--Worthy Park. Tobacco absolute frequency histogram for potential, irrigated, and rain-fed yield.

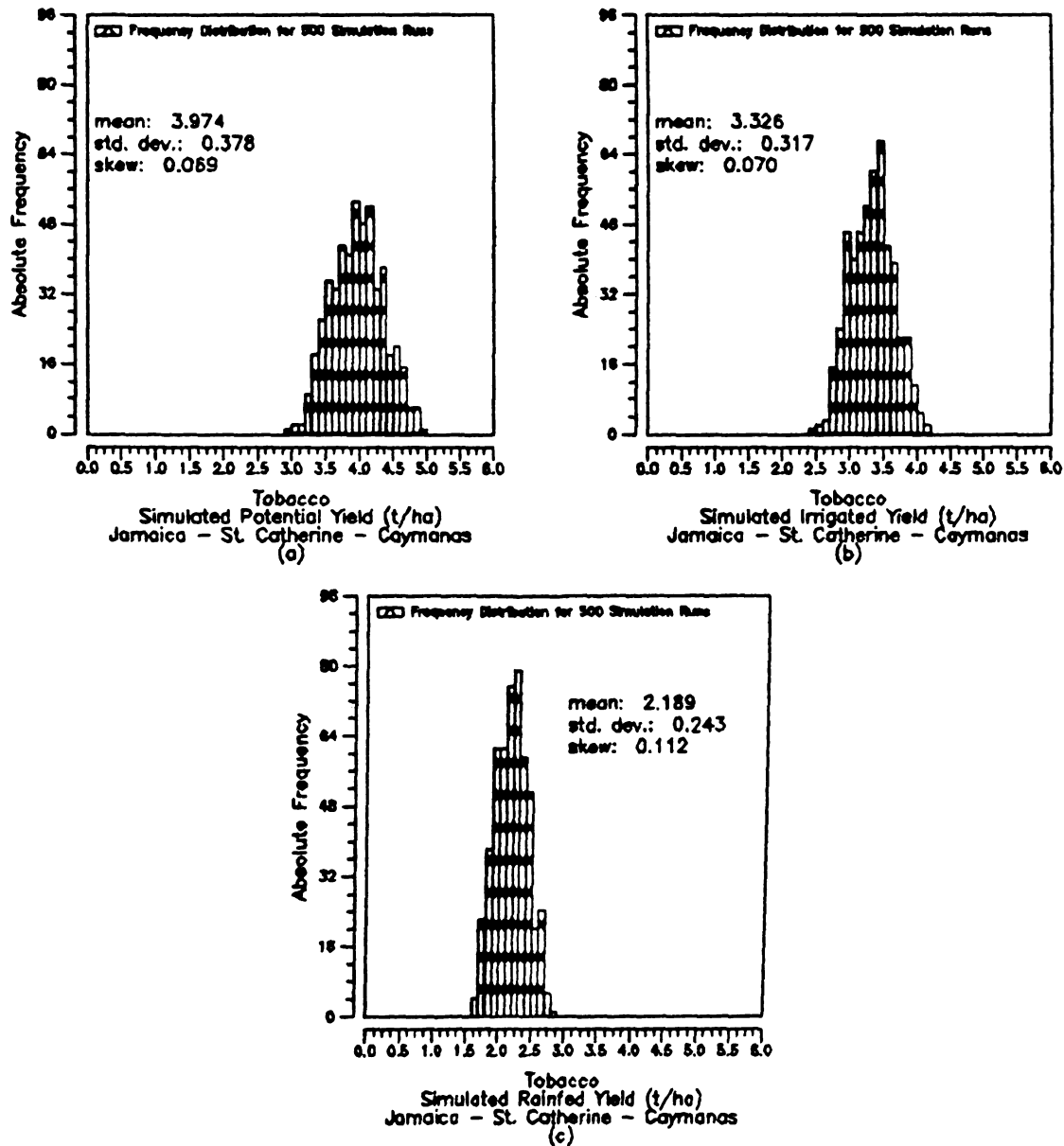
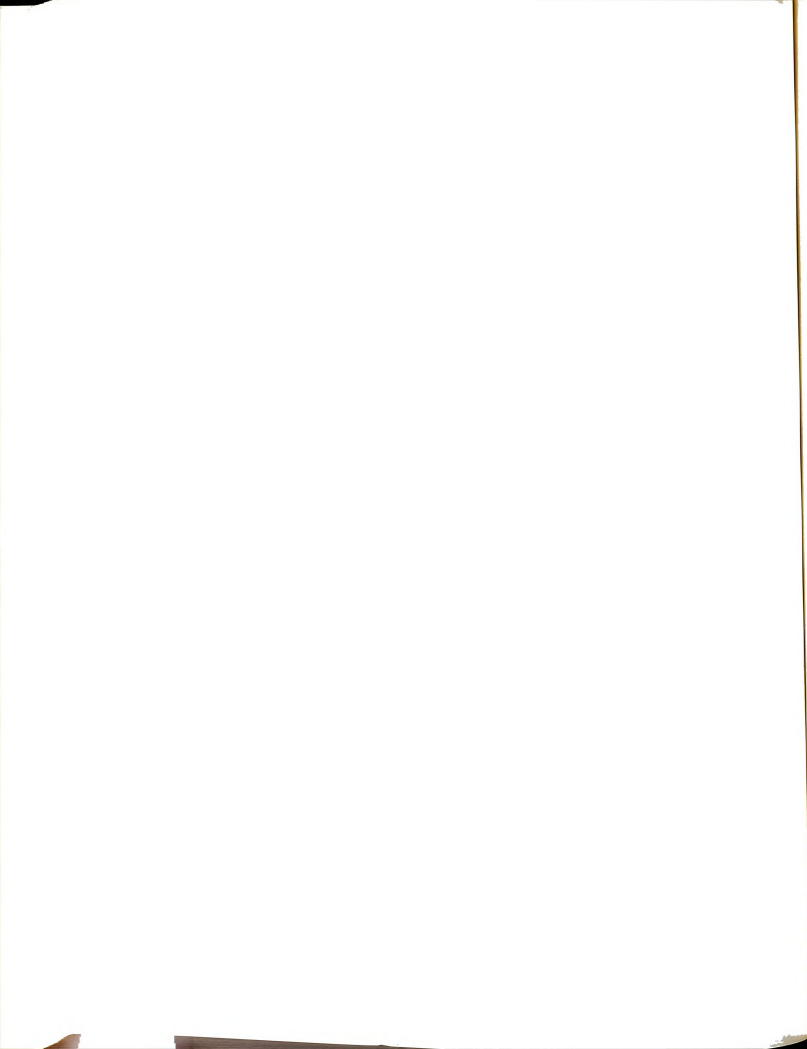


Figure 41. Stochastic YIELD simulator: Jamaica--Caymanas. Tobacco absolute frequency histogram for potential, irrigated, and rain-fed yield.



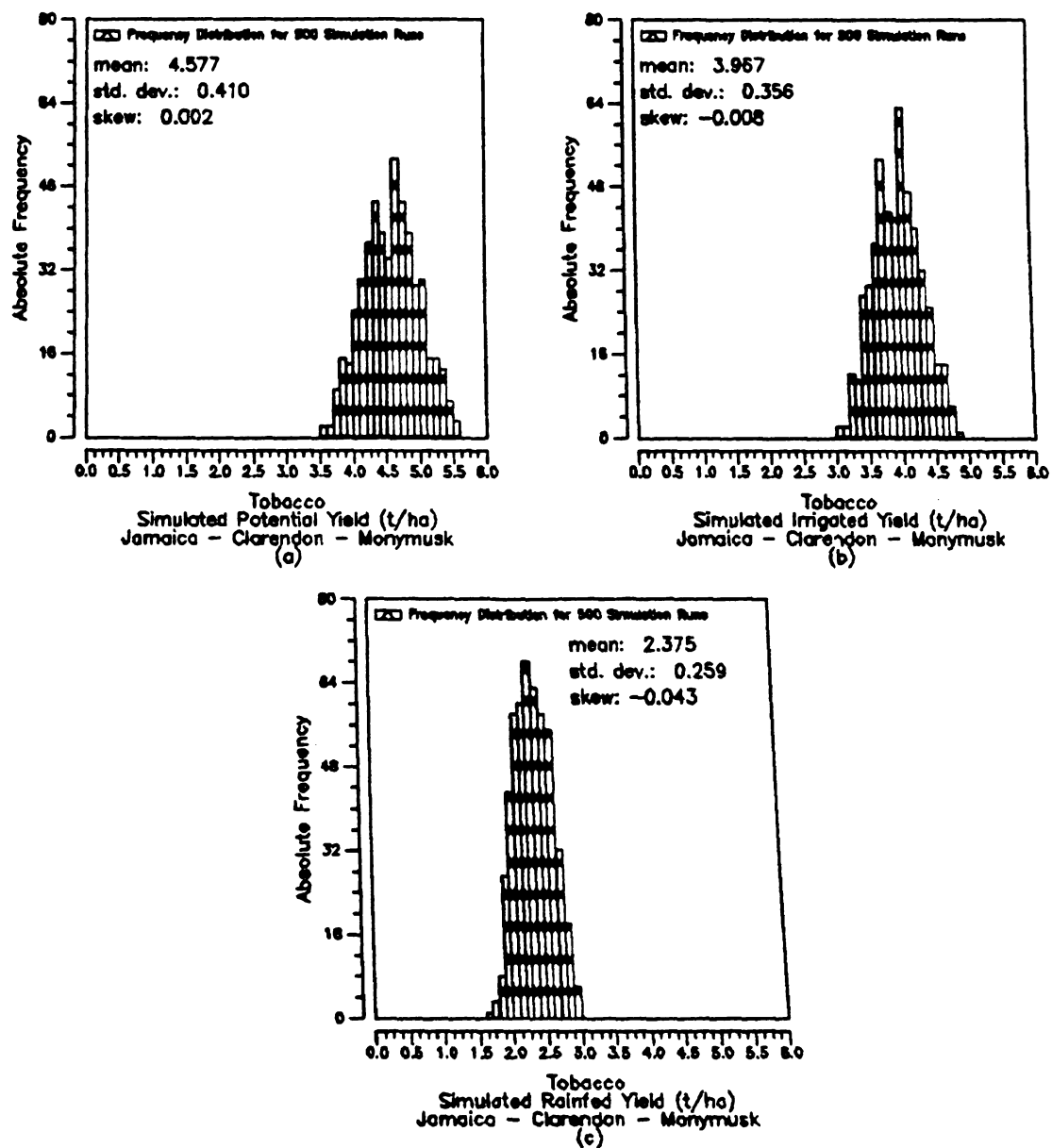


Figure 42. Stochastic YIELD simulator: Jamaica--Monymusk. Tobacco absolute frequency histogram for potential, irrigated, and rain-fed yield.

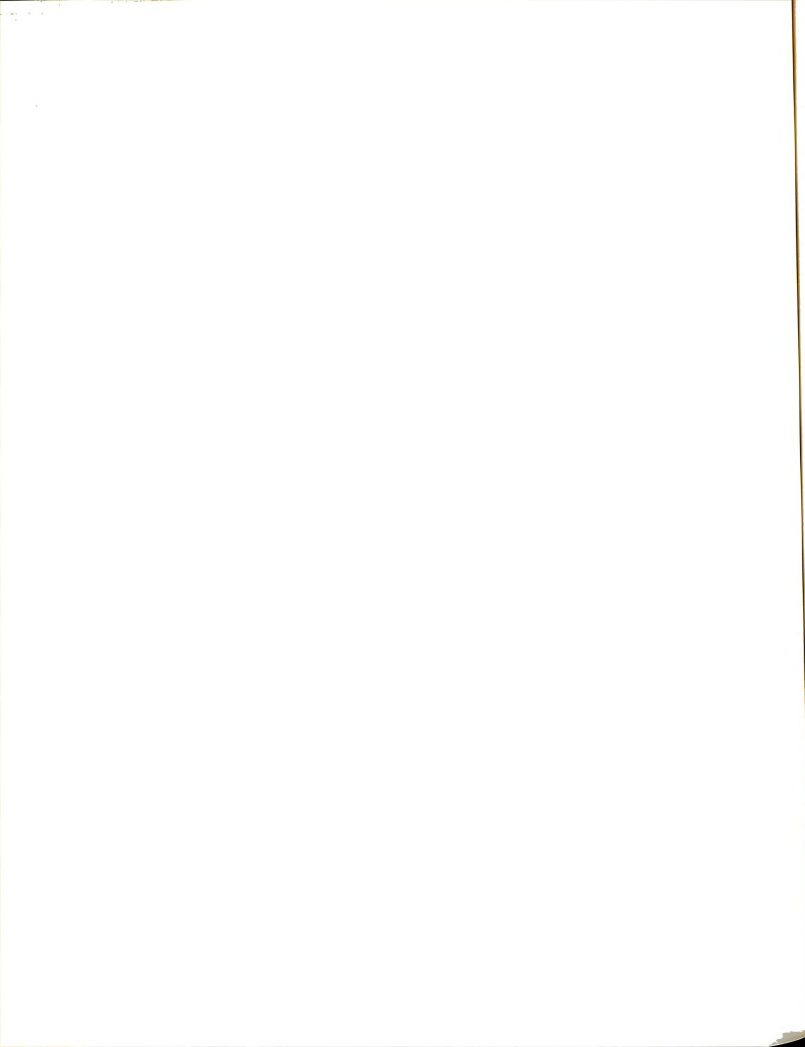


Table 21. Stochastic YIELD simulator: sorghum results, Jamaica--Worthy Park, Caymanas, and Monymusk (tons/ha)

Statistics	Worthy Park	Caymanas	Monymusk
Potential Yield			
Mean	4.632	4.494	5.321
Std Dev	0.430	0.399	0.454
Skewness	0.006	0.028	-0.065
Quantiles			
100%	5.691	5.733	6.520
75%	4.957	4.757	5.626
50%	4.622	4.514	5.327
25%	4.319	4.228	5.009
0%	3.368	3.391	3.861
Irrigated Yield			
Mean	4.016	3.757	4.613
Std Dev	0.375	0.337	0.395
Skewness	-0.011	0.013	-0.051
Quantiles			
100%	4.967	4.805	5.648
75%	4.295	3.973	4.874
50%	4.010	3.773	4.615
25%	3.743	3.545	4.353
0%	2.909	2.762	3.363
Rain-fed Yield			
Mean	3.570	3.200	3.814
Std Dev	0.363	0.287	0.329
Skewness	-0.059	0.034	0.007
Quantiles			
100%	4.470	4.161	4.736
75%	3.827	3.386	4.022
50%	3.575	3.211	3.818
25%	3.324	3.009	3.596
0%	2.533	2.346	2.759

Source: Compiled from stochastic YIELD simulator results.

Some skew factors had negative values. This is an indication that there was a tendency to skew toward the left, which shows a high probability of low yield values. Observed yield values for Jamaica were very low, in terms of average, as compared to the stochastic yield results and the FAO yield values given in Doorenbos and Kassam (1979).

Again, although the results were within the yield range given by Doorenbos and Kassam (1979), a suggestion for further research would be to introduce some variance into the model's parameters. This would permit evaluation of the parameters' sensitivity and also guide future model refinement as well as data-collection procedures.

Histogram plots for sorghum in the Worthy Park region of Jamaica are presented in Figure 43. Three histograms are shown (Figure 43 a, b, and c): potential sorghum yield, irrigated sorghum yield, and rain-fed sorghum yield.

The histograms for stochastic yields resulted from the simulator for the Caymanas region of Jamaica. Potential, irrigated, and rain-fed yield are shown in Figure 44 a, b, and c histograms, respectively.

Histogram plots for the Monymusk region of Jamaica, derived from the stochastic YIELD simulator results (Figure 45 a, b, and c) represent the histogram for potential

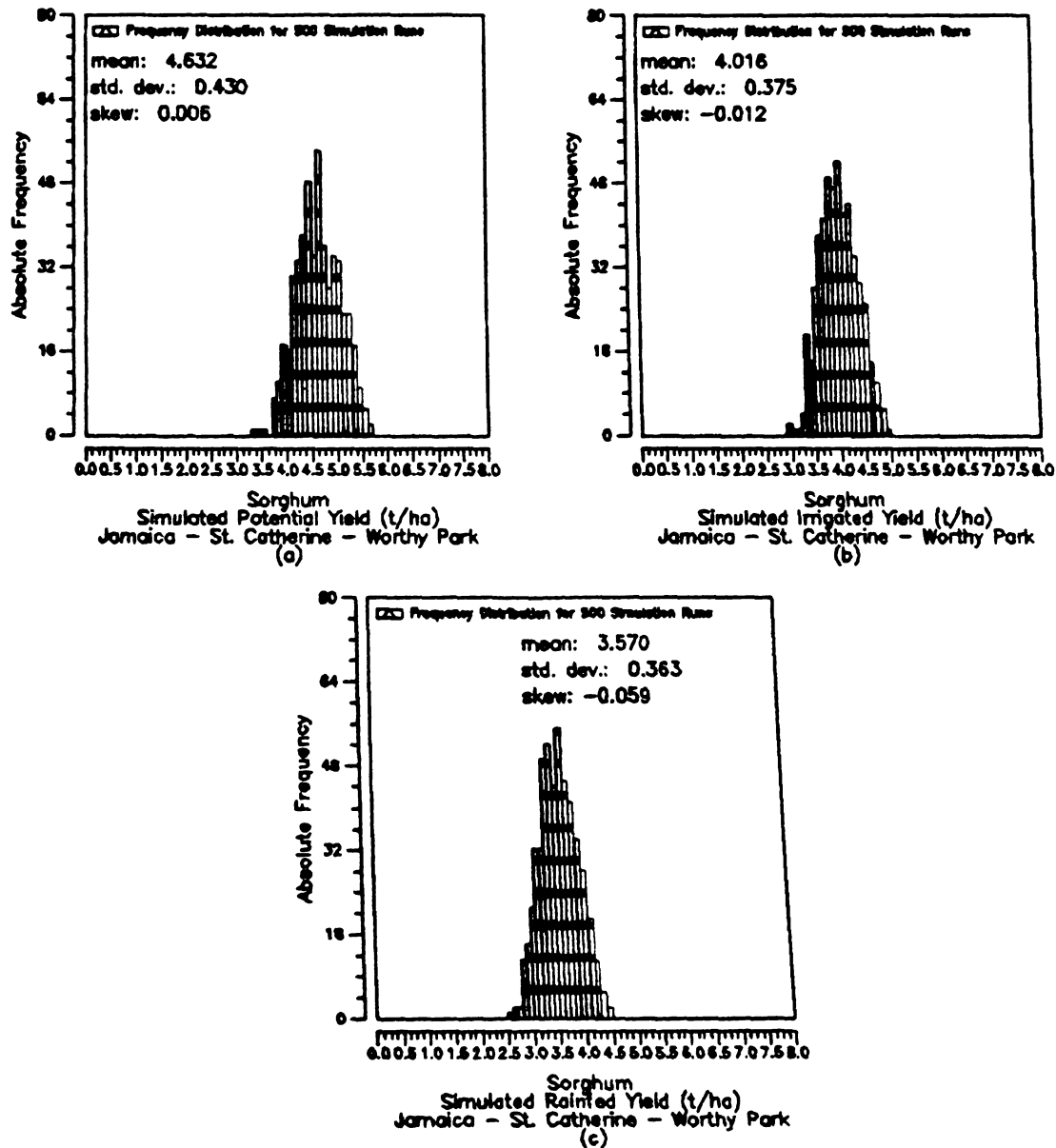


Figure 43. Stochastic YIELD simulator: Jamaica--Worthy Park. Sorghum absolute frequency histogram for potential, irrigated, and rain-fed yield.

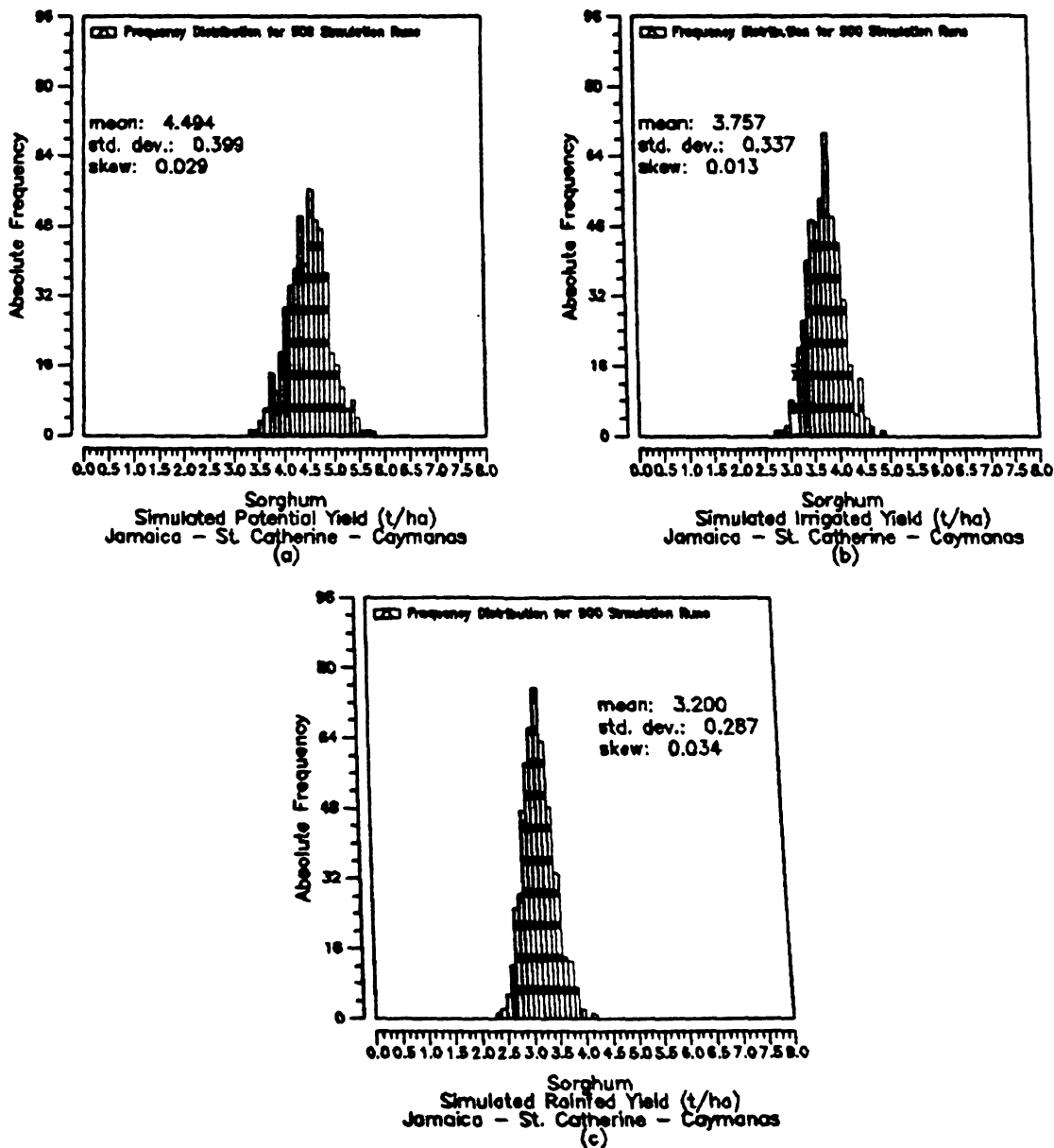
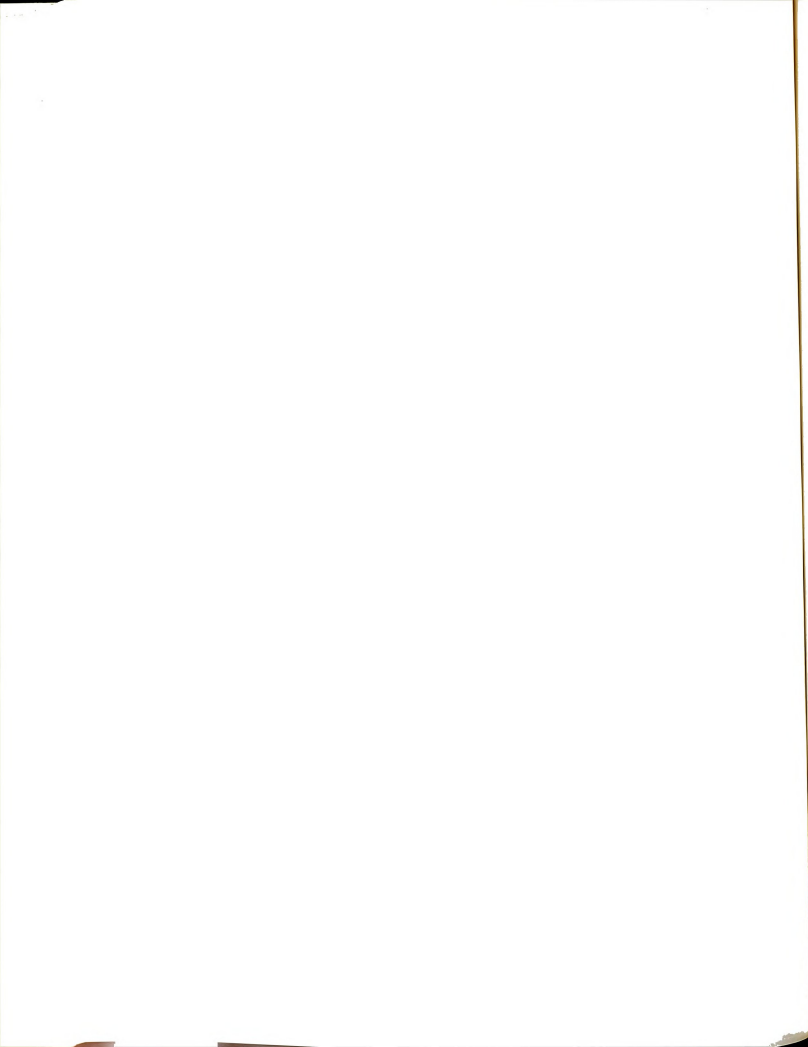


Figure 44. Stochastic YIELD simulator: Jamaica--Caymanas. Sorghum absolute frequency histogram for potential, irrigated, and rain-fed yield.



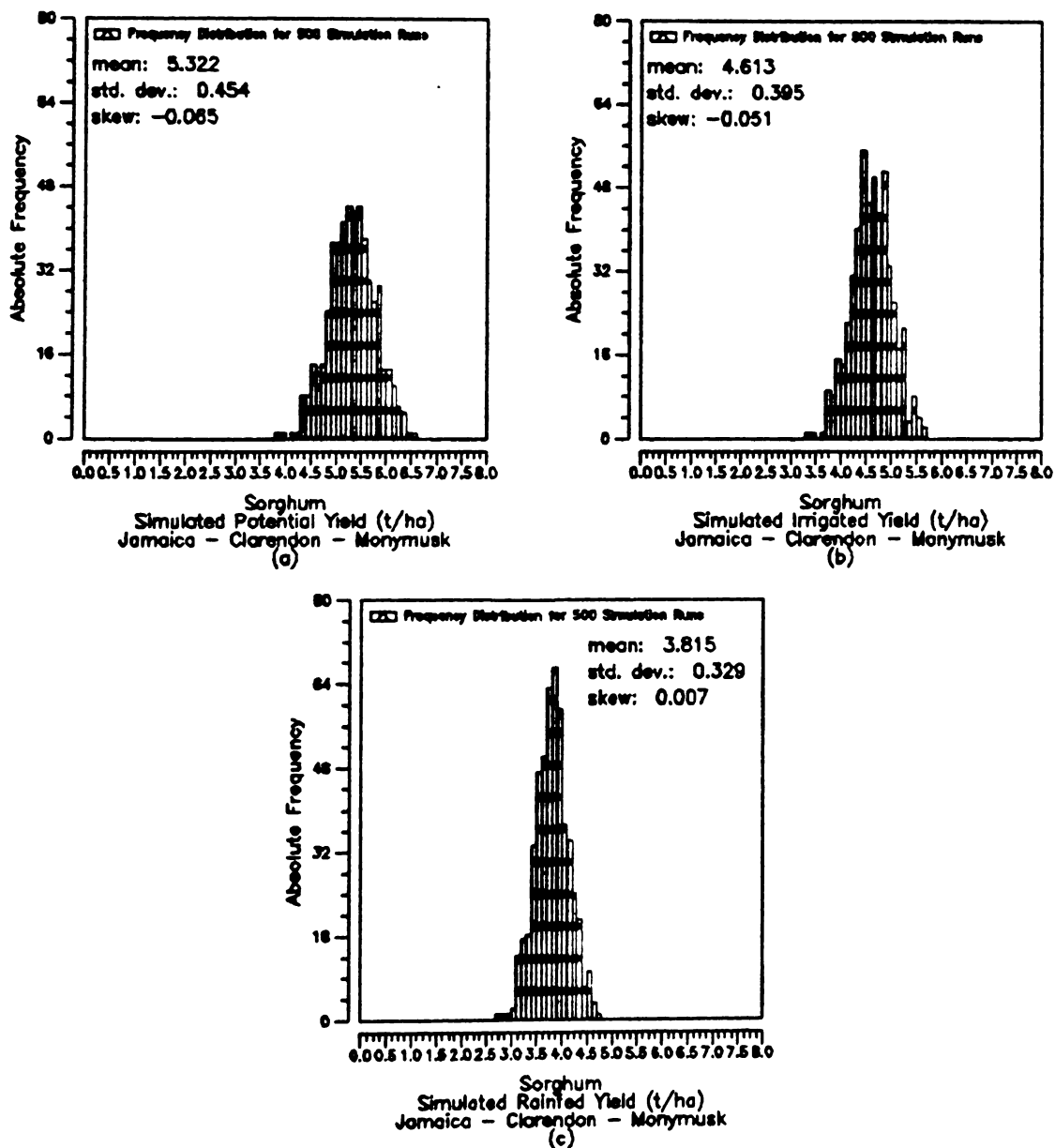
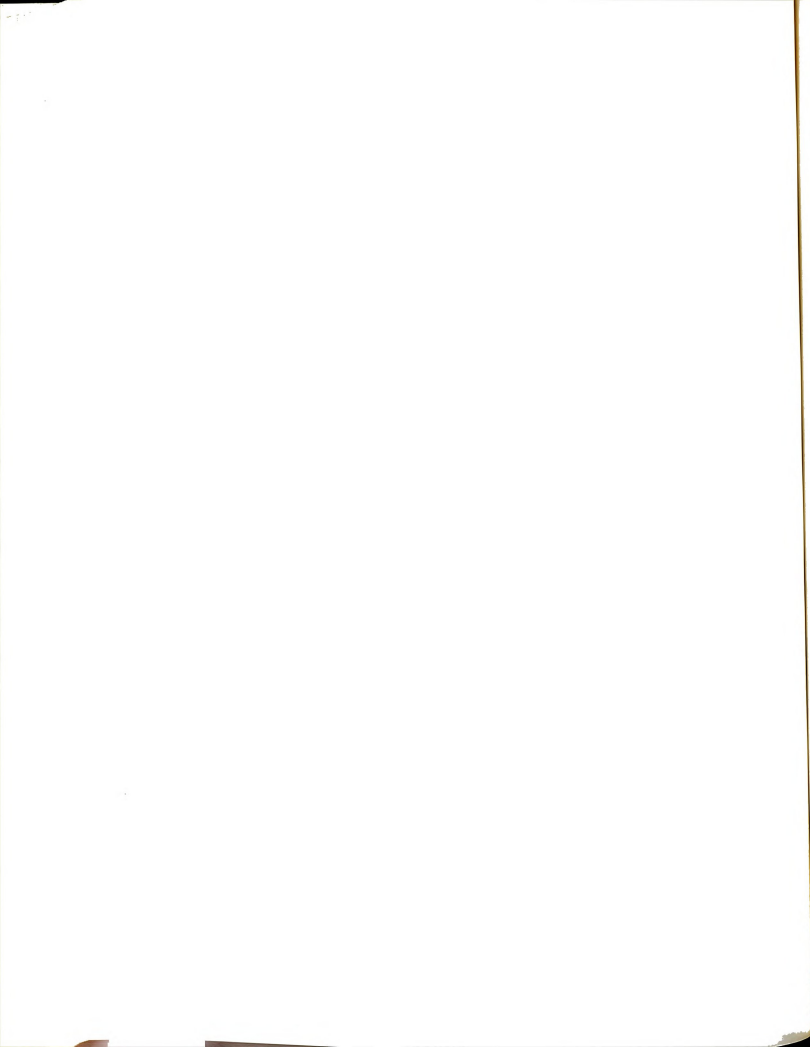


Figure 45. Stochastic YIELD simulator: Jamaica--Monymusk. Sorghum absolute frequency histogram for potential, irrigated, and rain-fed yield.



sorghum yield, for irrigated sorghum yield, and for rain-fed yield.

Stochastic YIELD Simulator, Dominican Republic--
Environmental Inputs

The CRIES-Dominican Republic (DR) national data base was used to estimate the probability density function statistics for the environmental inputs. The Statistical Analysis System (SAS, 1985) software package was used for the computation and statistical analysis to identify the distribution parameters as inputs to the simulation model.

Probability density function statistics for the environmental variable precipitation, for the Valdesia, Ocoa, and Azua Ocoa Watershed AEZs, used to run the simulation model, are provided in Tables 22, 23 and 24, respectively.

Monthly mean precipitation values were used because the model is very sensitive to precipitation values. Also, the seasonal rainfall pattern is important for agricultural production systems, and large variation occurs with important effects on yield response.

Variations in temperature, relative humidity, solar radiation, and wind velocity were not as strong as variations in precipitation (Tables 25, 26, and 27). The availability of data for solar radiation and wind velocity is very poor in comparison to the availability of data for precipitation. The model's sensitivity to solar radiation and wind

velocity inputs is not as significant as for precipitation, and there is no important seasonal variation. These considerations are taken into account, and the interval of variation in those environmental variables is taken on an annual basis and not on a monthly basis, as was done for the precipitation inputs.

Table 22. Stochastic YIELD simulator: precipitation probability density function statistics for the Dominican Republic Ocoa Watershed's AEZ Valdesia, for the years 1970 to 1984 (mm/month)

Month of the Year	Mean	Standard Deviation	Skewness
January	56.138	34.076	0.923
February	60.300	29.619	-0.384
March	58.100	50.932	1.950
April	90.946	71.414	1.442
May	219.708	207.483	2.006
June	233.085	165.796	0.368
July	142.561	83.638	0.733
August	199.531	96.655	0.653
September	186.354	66.737	0.084
October	192.577	76.736	0.581
November	84.169	45.014	1.076
December	68.162	43.388	1.141

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

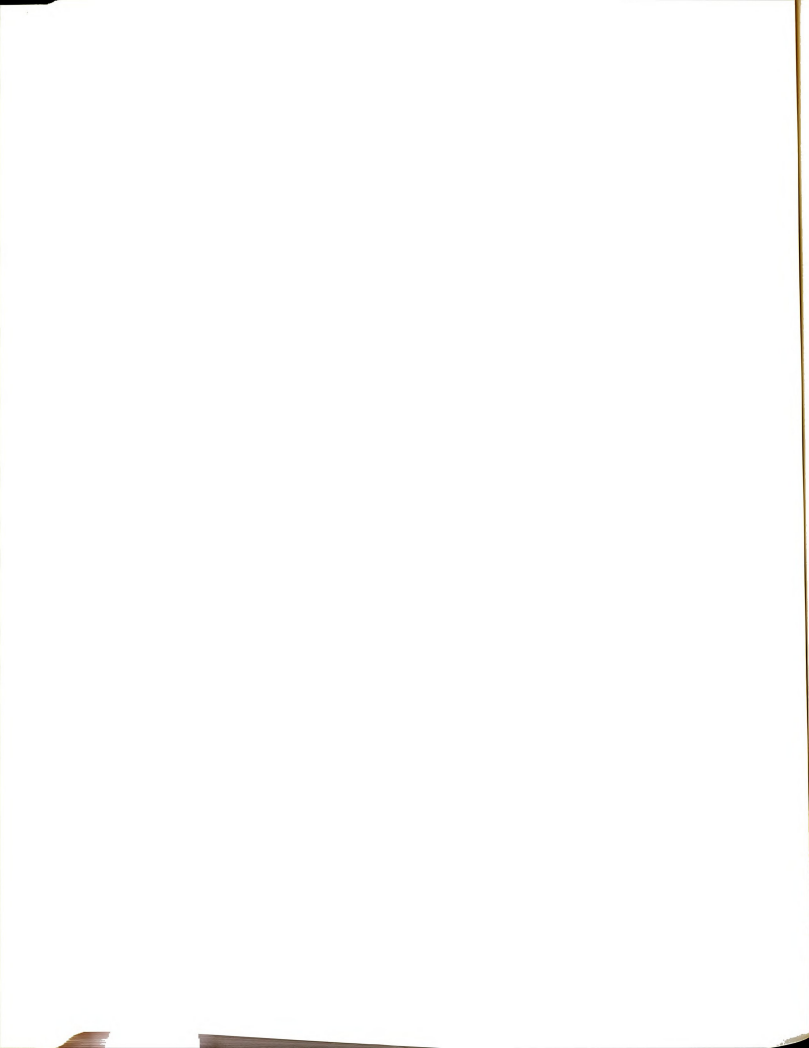


Table 23. Stochastic YIELD simulator: precipitation probability density function statistics for the Dominican Republic Ocoa Watershed's AEZ Ocoa, for the years 1970 to 1982 (mm/month)

Month of the Year	Mean	Standard Deviation	Skewness
January	14.761	19.755	2.786
February	23.523	17.934	0.245
March	23.346	19.935	0.612
April	51.577	61.848	2.455
May	145.754	105.729	1.083
June	80.954	67.267	0.404
July	67.961	60.386	2.442
August	104.131	111.028	1.836
September	140.015	151.684	2.337
October	106.369	62.610	0.457
November	37.780	22.789	0.100
December	25.108	23.586	1.256

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

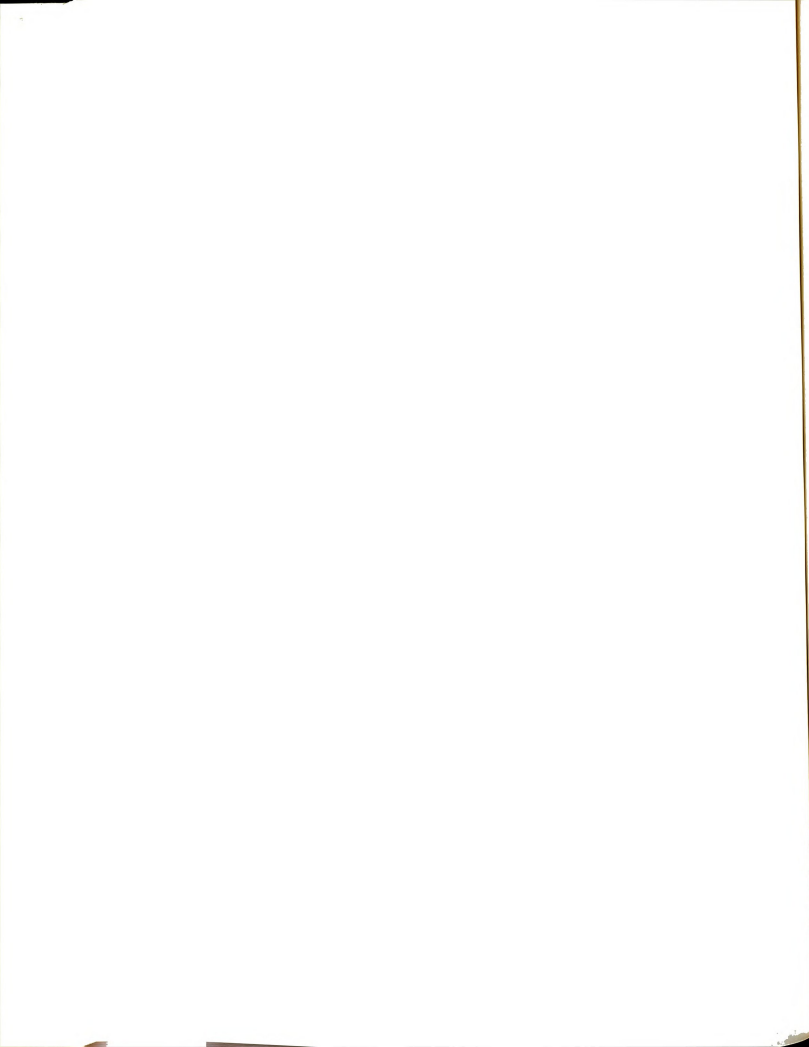


Table 24. Stochastic YIELD simulator: precipitation probability density function statistics for the Dominican Republic Ocoa Watershed's AEZ Azua, for the years 1970 to 1984 (mm/month)

Month of the Year	Mean	Standard Deviation	Skewness
January	11.707	28.495	3.615
February	7.313	10.912	1.613
March	16.320	26.873	2.946
April	14.880	15.229	1.554
May	78.926	76.947	0.867
June	55.193	71.649	1.395
July	28.400	35.197	1.191
August	55.087	37.823	0.111
September	84.507	124.418	3.056
October	88.247	62.215	0.762
November	19.547	26.655	1.754
December	17.647	38.000	3.215

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

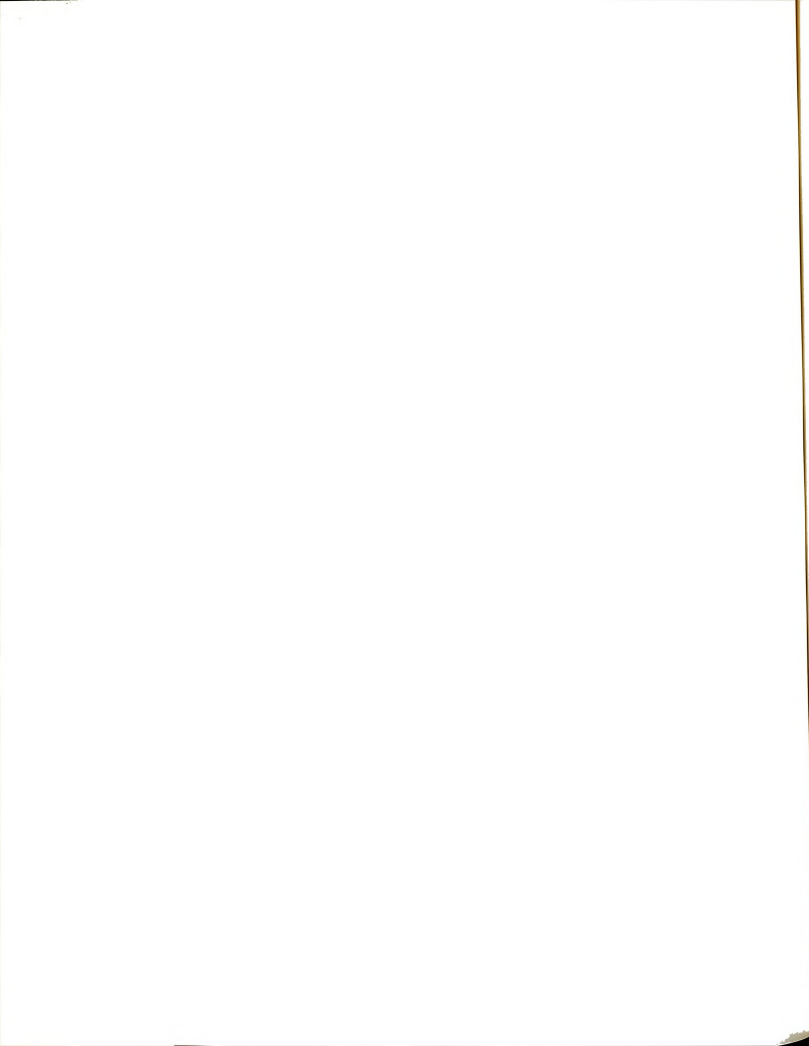


Table 25. Stochastic YIELD simulator: temperature, relative humidity, solar radiation, and wind velocity probability density function statistics for the Dominican Republic's Ocoa Watershed AEZ Valdesia, for the years 1970 to 1984

Environmental Variable	Minimum	Maximum
Temperature ^a	23.90	27.80
Relative Humidity ^b	64.90	84.70
Solar Radiation ^c	7.30	9.60
Wind Velocity ^d	0.70	5.50

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

^aTemperature units are in degrees Celsius.

^bRelative humidity units are in percentage.

^cSolar radiation units are in hours/day.

^dWind velocity units are in meters/second, day/night wind ratio assumed to be 1.

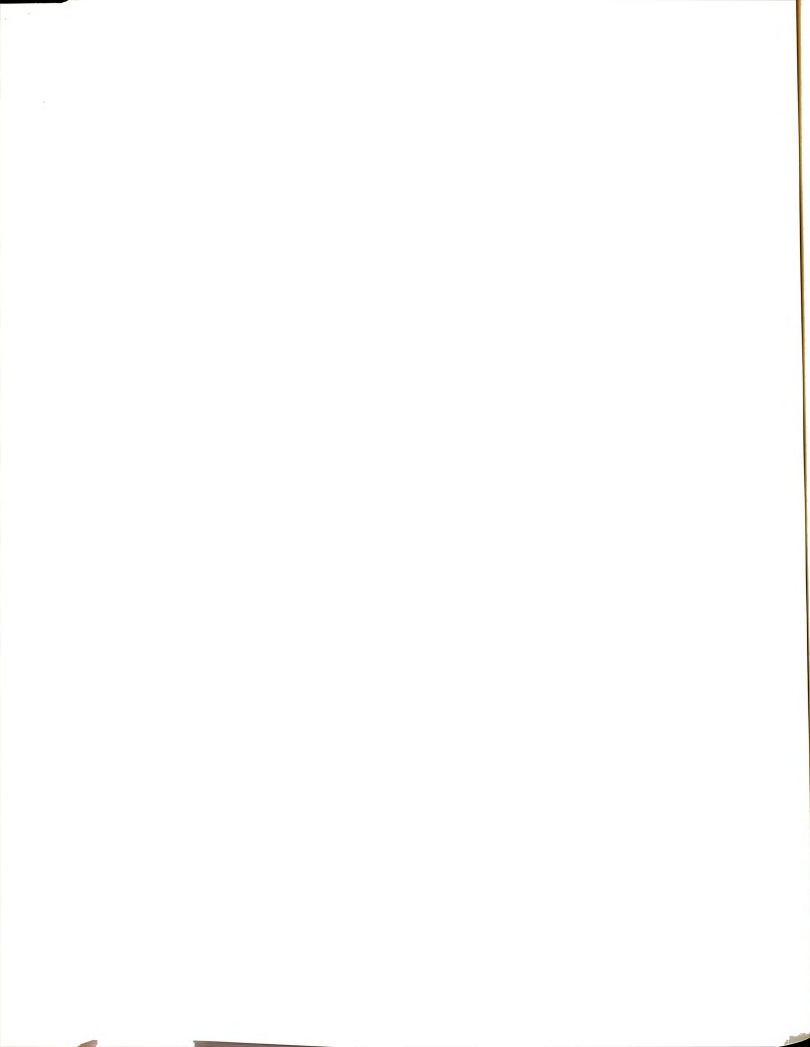


Table 26. Stochastic YIELD simulator: temperature, relative humidity, solar radiation, and wind velocity probability density function statistics for the Dominican Republic's Ocoa Watershed AEZ Ocoa for the years 1970 to 1984

Environmental Variable	Minimum	Maximum
Temperature ^a	21.40	24.80
Relative Humidity ^b	65.00	87.90
Solar Radiation ^c	5.00	9.00
Wind Velocity ^d	0.10	4.50

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

^aTemperature units are in degrees Celsius.

^bRelative humidity units are in percentage.

^cSolar radiation units are in hours/day.

^dWind velocity units are in meters/second, day/night wind ratio assumed to be 1.

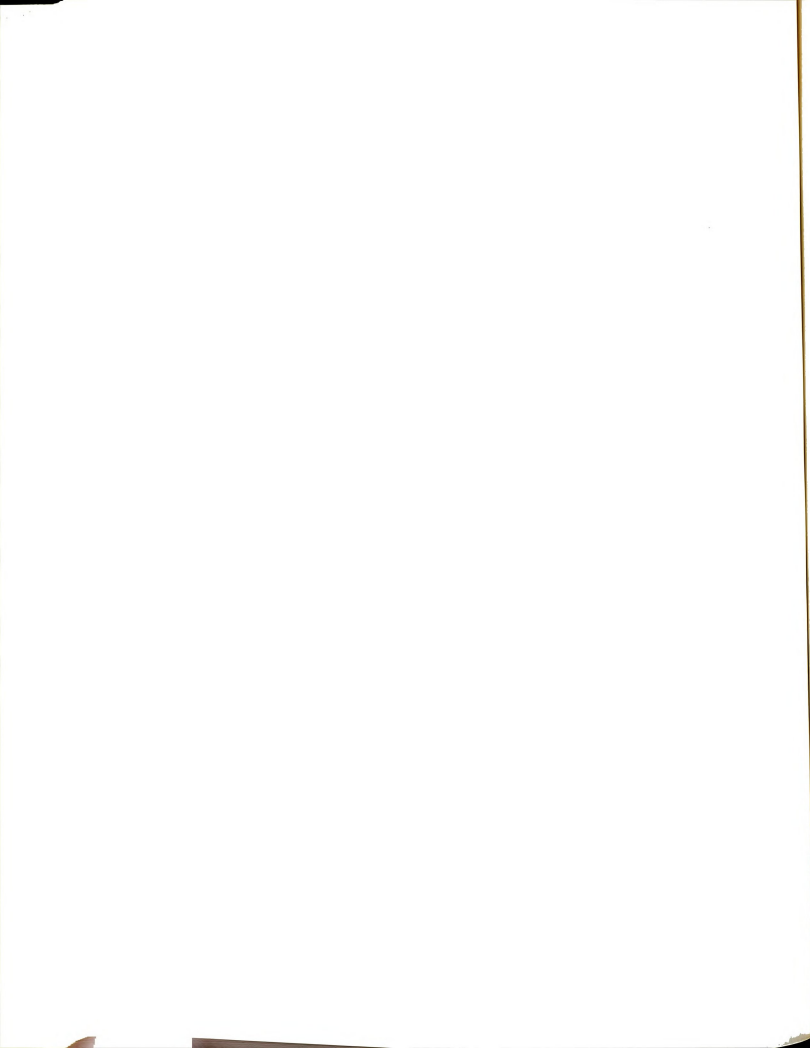


Table 27. Stochastic YIELD simulator: temperature, relative humidity, solar radiation, and wind velocity - probability density function statistics for the Dominican Republic's Ocoa Watershed AEZ Azua for the years 1970 to 1984

Environmental Variable	Minimum	Maximum
Temperature ^a	23.10	27.90
Relative Humidity ^b	64.10	87.50
Solar Radiation ^c	1.80	8.30
Wind Velocity ^d	0.00	3.50

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

^aTemperature units are in degrees Celsius.

^bRelative humidity units are in percentage.

^cSolar radiation units are in hours/day.

^dWind velocity units are in meters/second, day/night wind ratio assumed to be 1.

Crop parameters for the simulation of rice, potato, and fresh pea yields for the Ocoa Watershed's Valdesia, Ocoa, and Azua AEZs are given in Table 28. It was assumed that there were no variations from region to region because those regions are close together, and no detailed information on differences among them is available. Values were derived

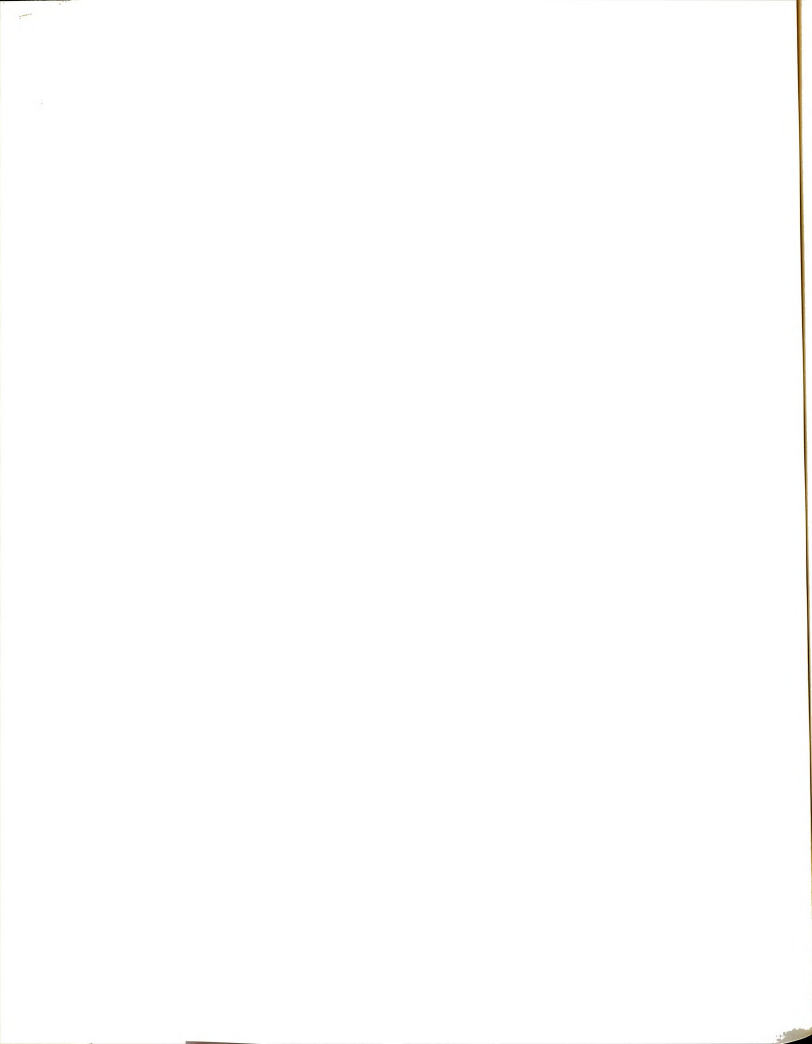


Table 28. Deterministic YIELD simulator: Dominican Republic
 --Ocoa Watershed crop parameters--rice, potato,
 fresh pea for Valdesia, Ocoa, and Azua (Doorenbos
 & Kassam, 1979)

Crop Parameter Type	Rice	Potato	Fresh Pea
Root Size Variation (cm)	0.0 -100.0	0.0 -50.0	0.0 -150.0
Leaf Area Index (LAI)	3	4	3
Water Depletion Factor (p) Variation ^a	.300 -.800	.175 -.500	.225 -.675
Production Rate (ym in kg/ha/ day) ^b	.0-35.0	.0-20.0	.0-20.0
Crop Coefficient (kc) ^c	.95 -1.15	.40 -1.20	.40 -1.20
Yield Response Factor (ky) ^d	.20 -1.15	.20 -1.10	.20 -1.15

Source: Compiled from CRIES-Dominican Republic National
 Data Base (CRIES-MSU).

^aET_m--Maximum evapotranspiration dependent factor.

^bTemperature dependent factor.

^cDepend on crop stage, wind velocity, and relative
 humidity.

^dDepend on crop stage.

from Doorenbos and Kassam (1979) and adjusted for conditions in the Dominican Republic, using information from the CRIES-DR national data base. In the stochastic YIELD simulator, those values are assumed to be known with certainty; that is, they have zero variance.

Crop parameters used in the model for simulation runs for onion and cabbage are presented in Table 29.

Farm-management parameters for rice, potato, and fresh pea used in the stochastic yield simulator are provided in Table 30.

For onion and cabbage, the farm-management-practice parameters used in the stochastic simulation process are given in Table 31.

Parameters that identify the locality, region, or AEZ are presented in Table 32. Values are given for Valdesia, Ocoa, and Azua, the three AEZs in the Ocoa Watershed.

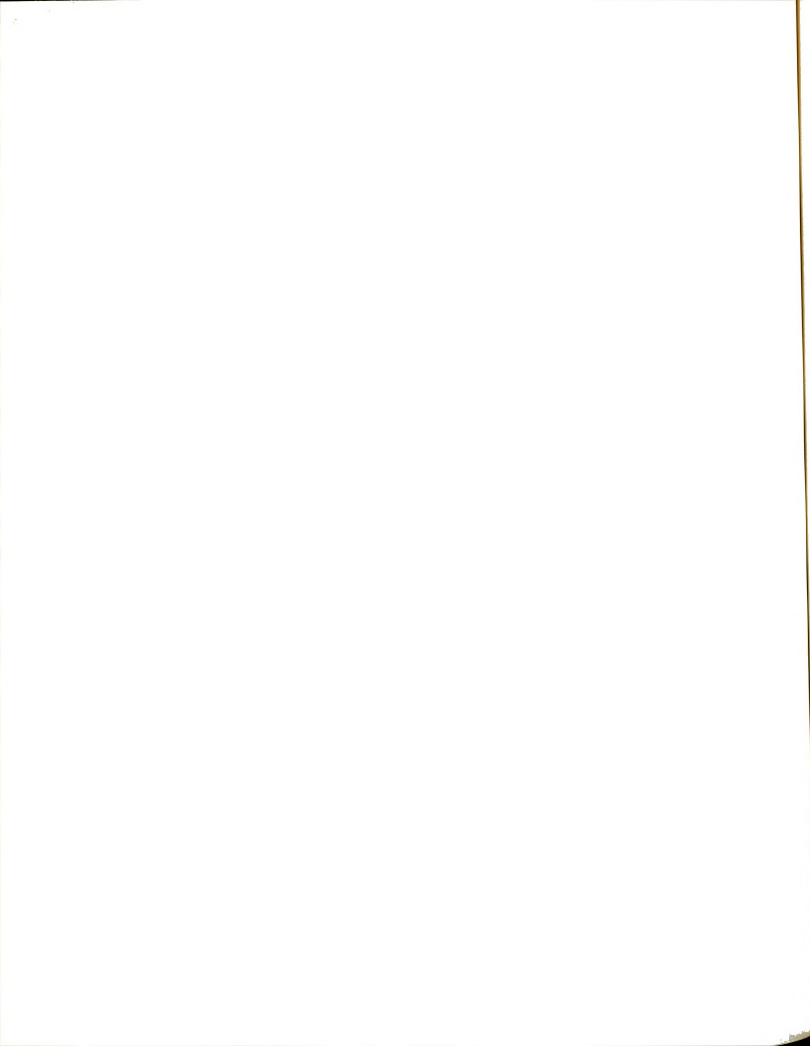


Table 29. Stochastic YIELD simulator: Dominican Republic
 --Ocoa Watershed crop parameters--onion and
 cabbage for Valdesia, Ocoa, and Azua (Doorenbos
 & Kassam, 1979)

Crop Parameter Type	Onion	Cabbage
Root Size Variation (cm)	0-50	0-50
Leaf Area Index (LAI)	3	4
Water Depletion Factor (p) Variation ^a	.175-.500	.225-.675
Production Rate (ym) ^b	0-65	0-20
Crop Coefficient (kc) ^c	.40 -1.10	.40 -1.10
Yield Response Factor (ky) ^d	.30 -1.10	.20 -.95

Source: Compiled from CRIES-Dominican Republic National
 Data Base (CRIES-MSU).

^aET_m-Maximum evapotranspiration dependent factor.

^bTemperature dependent factor.

^cDepend on crop stage, wind velocity, and relative
 humidity.

^dDepend on crop stage.

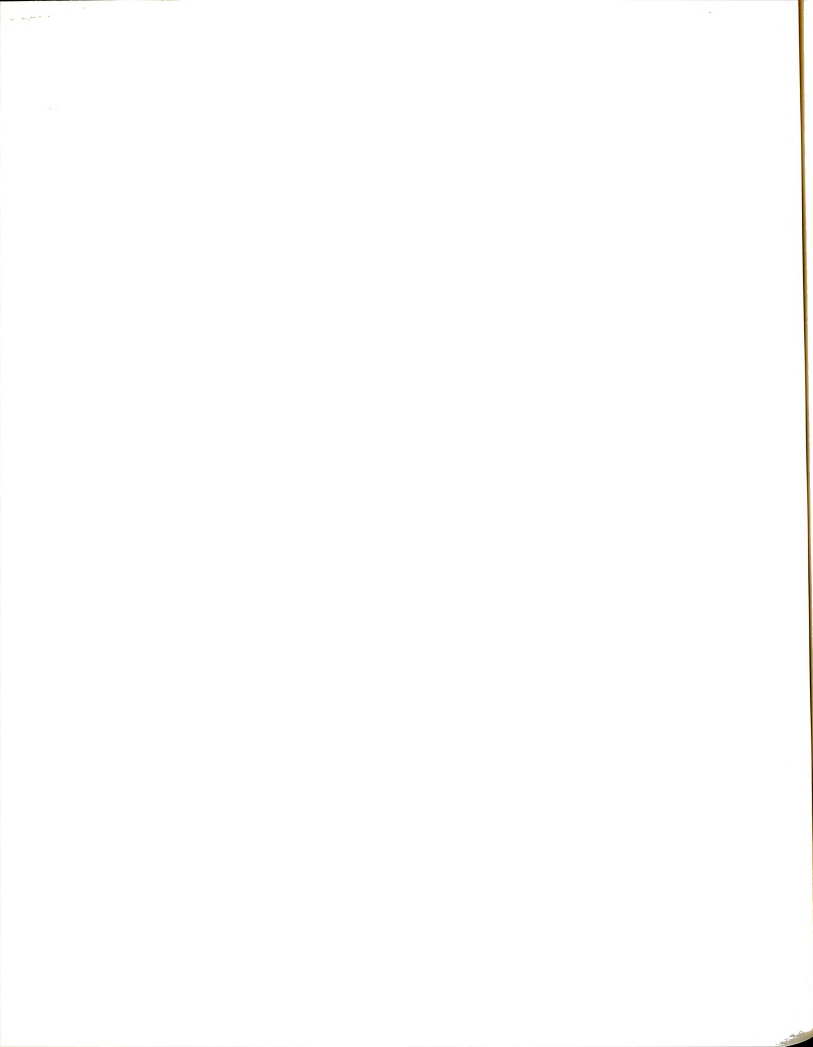


Table 30. Stochastic YIELD simulator: Dominican Republic--Ocoa Watershed farm-management-practice parameters--rice, potato, and fresh pea for Valdesia, Ocoa, and Azua

Farm-Management-Practice Parameters	Rice	Potato	Fresh Pea
Sowing or Planting date MM/DD/YY	08-09/YY	01-02/YY	07-08/YY
Harvesting date MM-MM/YY ^a	12-01/YY+1	05-06/YY	12-01/YY
Duration of growth stages in days			
stage 1	15-20	20-30	10-25
stage 2	15-20	25-40	20-25
stage 3	40-80	25-45	15-20
stage 4	20-35	20-35	15-20
stage 5	5-8	0-8	0-5
Irrigation parameter or value ^c	F	F	F
Evaporation Reduction Factor ^d	N	N	N
Fertilizer Usage ^e	0-10 20-50 80-100	0-10 20-50 80-100	0-10 20-50 80-100

Source: Compiled from CRIES-Dominican Republic National Data Base (CRIES-MSU).

^a+1 means following year.

^bCompiled from Doorenbos and Kassam (1979) and adjusted to DR conditions.

^cUnless rain-fed production, full irrigation was used. No data available on irrigation scheme.

^dNo evaporation reduction factor was used.

^eFertilizer usage (Valdesia, Ocoa, and Valdesia, respectively) in percentage relative to Doorenbos and Kassam's (1979) crop-requirement guidelines.

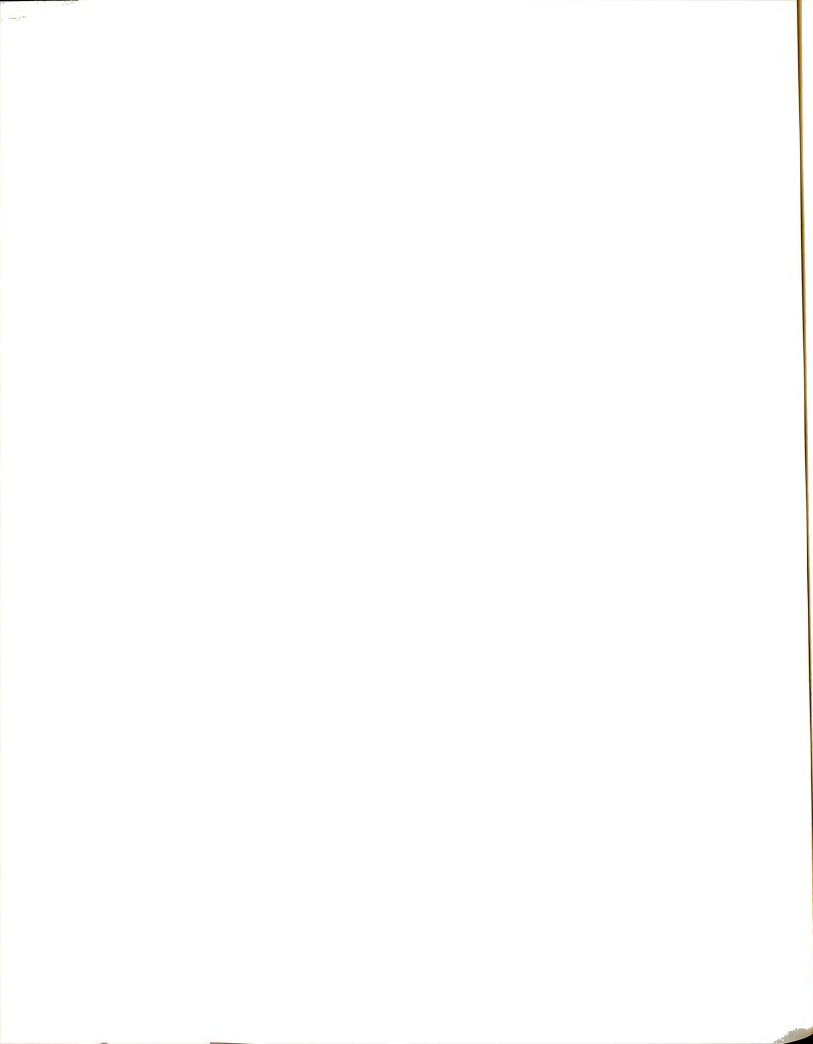


Table 31. Stochastic YIELD simulator: Dominican Republic--
Ocoa Watershed farm-management-practice
parameters--onion and cabbage for Valdesia, Ocoa,
and Azua

Farm-Management- Practice Parameters	Onion	Cabbage
Sowing or Planting date MM/DD/YY	09-10/YY	07-09/YY
Harvesting date MM-MM/YY ^a	12-01/YY+1	10-12/YY
Duration of growth stages in days ^b		
stage 1	15-35	15-35
stage 2	25-35	20-30
stage 3	30-50	25-40
stage 4	10-30	10-30
stage 5	5-8	5-8
Irrigation parameter or value ^c	F	F
Evaporation Reduction Factor ^d	N	N
Fertilizer Usage ^e	0-10 20-50 80-100	0-10 20-50 80-100

Source: Compiled from CRIES-Dominican Republic National
Data Base (CRIES-MSU).

^a+1 means following year.

^bCompiled from Doorenbos and Kassam (1979) and
adjusted to DR data.

^cFull irrigation was used. No data available on
irrigation scheme.

^dNo evaporation reduction factor was used.

^eFertilizer usage (Valdesia, Ocoa, and Valdesia, respec-
tively) in percentage relative to Doorenbos and Kassam's
(1979) crop-requirement guidelines.

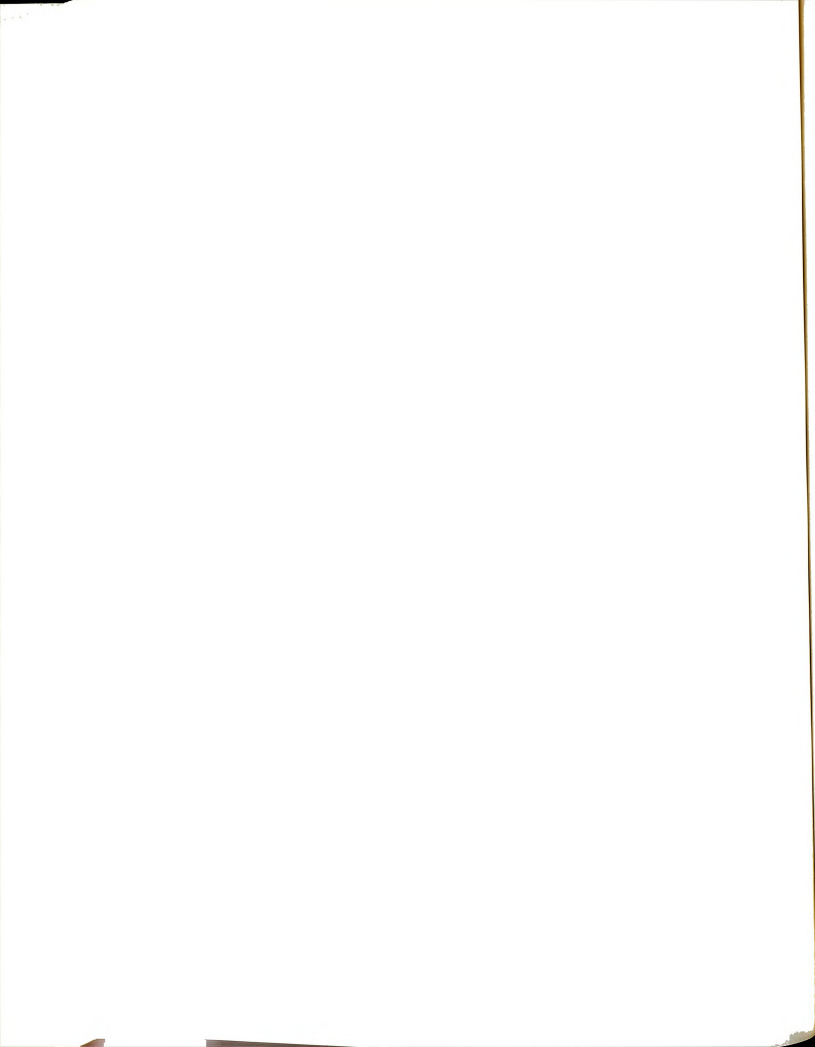


Table 32. Stochastic YIELD simulator: Dominican Republic--
Ocoa Watershed local parameters for Valdesia,
Ocoa, and Azua.

Crop Parameter	Valdesia	Ocoa	Azua
Average altitude in meters	2000.0	1000.0	160.0
Average latitude in degrees	18.0	18.0	18.0
Location	1	1	1
Average slope percent range ^a	20-30	12-15	4-8
Average soil type ^a	fine silty	fine silty	fine silty
Average soil textural class in mm/m	40	78	109
Soil moisture in mm/m ^b	40	78	109
Soil salinity level ^c	N/A	N/A	N/A

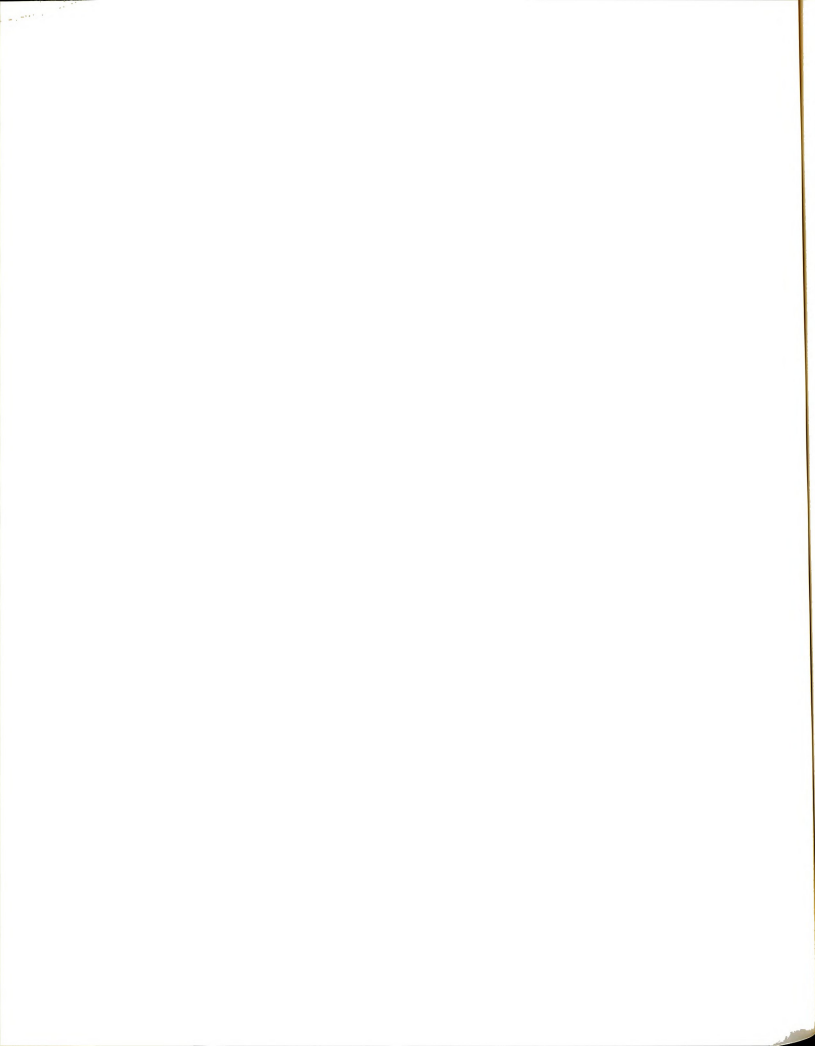
Source: Compiled from CRIES-Dominican Republic National
Data Base (CRIES-MSU).

^aTable 1, Chapter III.

^bMoisture at sowing date.

^cN/A--data not available.

Doorenbos and Kassam (1979) provided the following
yields of high-producing varieties adapted to the climatic
conditions of the available growing season under adequate



water supply and high levels of agricultural inputs under irrigated farming conditions for rice, potato, fresh pea, onion, and cabbage:

- | | | | |
|----|-----------|---------|------------------------|
| 1. | rice | (paddy) | 4.00 to 8.00 tons/ha |
| 2. | potato | (tuber) | 15.00 to 40.00 tons/ha |
| 3. | fresh pea | (pod) | 2.00 to 3.00 tons/ha |
| 4. | onion | (bulb) | 35.00 to 45.00 tons/ha |
| 5. | cabbage | (head) | 40.00 to 60.00 tons/ha |

The average yields for Ocoa Watershed for rice, potato, fresh pea, onion, and cabbage are as follows (compiled from CRIES-Dominican Republic National Data Base; CRIES-MSU):

- | | | | |
|----|-----------|---------|------------------------|
| 1. | rice | (paddy) | 3.79 to 4.94 tons/ha |
| 2. | potato | (tuber) | 7.55 tons/ha |
| 3. | fresh pea | (pod) | 1.89 tons/ha |
| 4. | onion | (bulb) | 31.45 tons/ha |
| 5. | cabbage | (head) | 12.58 to 37.74 tons/ha |

The yield values given by Doorenbos and Kassam (1979) were much higher than the actual yield values known for the Dominican Republic, whose crops are not, of course, grown in optimal conditions as Doorenbos and Kassam assumed for their yield values.

Stochastic YIELD Simulator, Dominican Republic-- Simulation Results

The results of the 500 simulation runs of the stochastic yield simulator for onion are presented in Table 33.

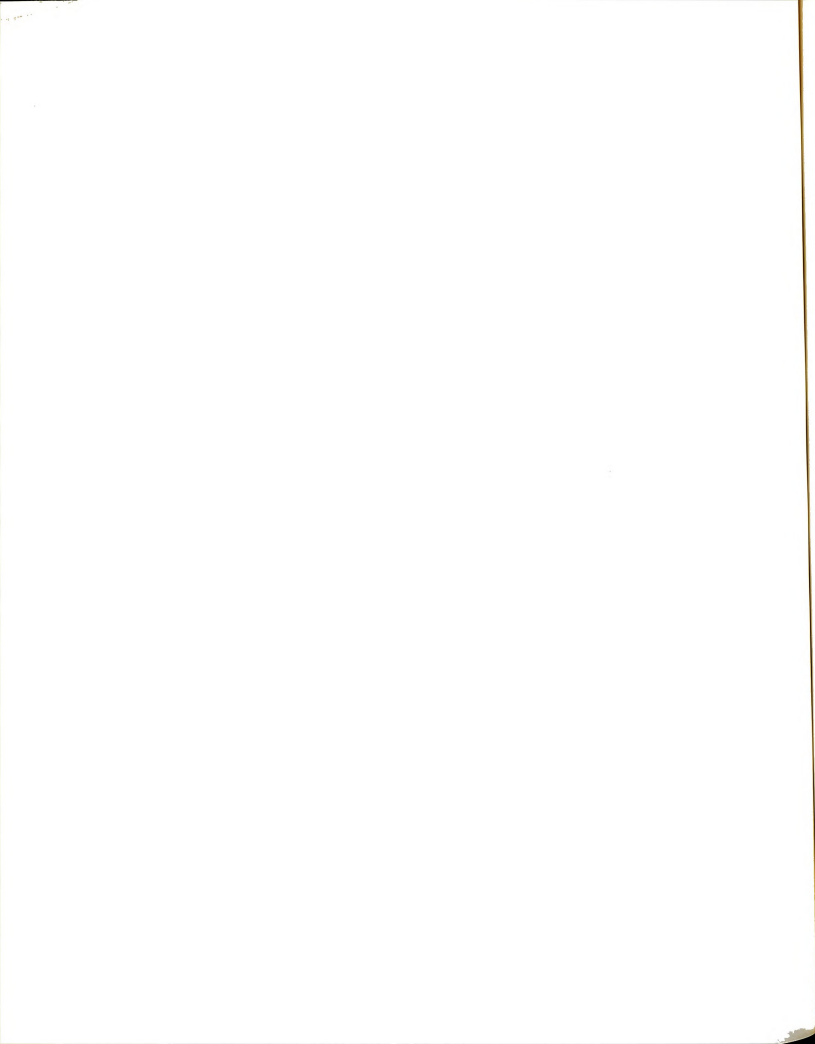
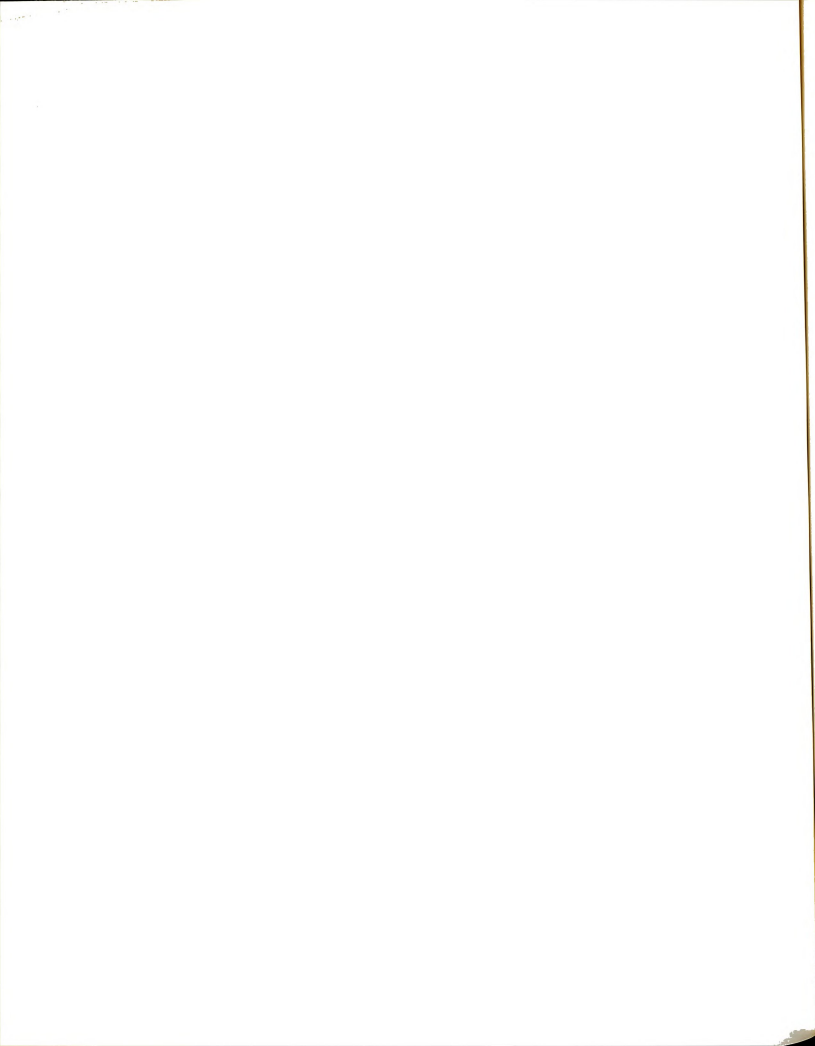


Table 33. Stochastic YIELD simulator: probability density function statistics results for onion for the Dominican Republic--Ocoa Watershed--Valdesia, Ocoa, and Azua AEZs (tons/ha)

Distribution Statistics	Valdesia	Ocoa	Azua
Potential Yield			
Mean	60.347	43.332	56.716
Std Dev	4.651	3.523	4.672
Skewness	0.141	-0.154	0.040
Quantiles			
100%	73.846	51.773	69.707
75%	63.447	45.703	59.831
50%	60.158	43.309	56.721
25%	57.191	41.083	53.467
0%	46.083	34.455	42.999
Irrigated Yield			
Mean	15.468	37.566	53.883
Std Dev	1.197	3.086	4.424
Skewness	0.149	-0.136	0.033
Quantiles			
100%	18.886	45.245	66.170
75%	16.217	39.603	56.783
50%	15.457	37.588	53.826
25%	14.632	35.628	50.796
0%	11.778	30.081	40.872
Rain-fed Yield			
Mean	9.887	24.058	38.571
Std Dev	0.767	1.952	3.299
Skewness	0.161	-0.078	-0.053
Quantiles			
100%	12.127	28.899	47.172
75%	10.414	25.478	40.833
50%	9.834	23.976	38.577
25%	9.322	22.792	36.298
0%	7.568	19.059	28.394

Source: Compiled from the stochastic YIELD simulator results.

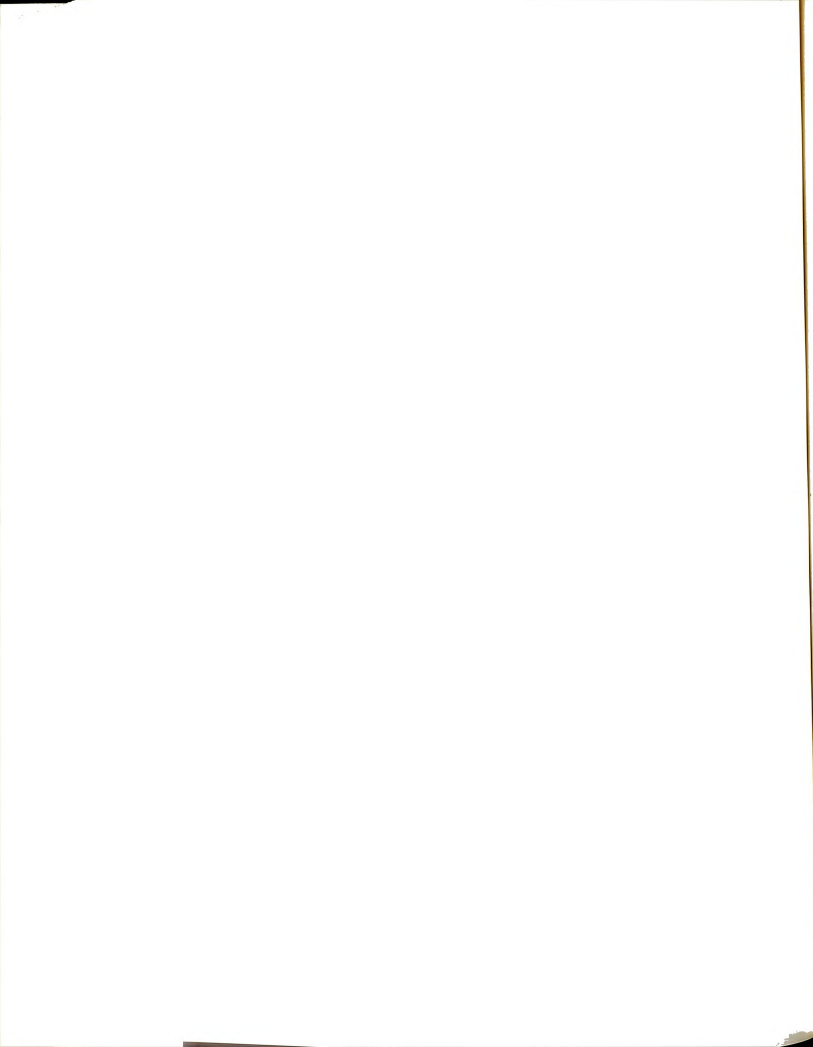


The table shows the statistics computed for the probability density functions derived from the simulated yield values. The data show the potential, irrigated, and rain-fed yields for the AEZs in the Ocoa Watershed. The results are within the FAO and DR observed yield ranges.

Values for Valdesia are very low as a result of median to steep slope conditions, reducing infiltration and recharge of soil moisture. Higher onion yields are shown in the Azua AEZ, which has a gentler slope and better conditions for growing crops. The skew factors are not very significant; some are negative and some are positive as a result of wide variations in the exogenous inputs.

Histogram plots for the simulated yield for the Ocoa AEZ in the Ocoa Watershed are displayed in Figure 46. The plots illustrate the variations in the yield results for onion resulting from variations in the exogenous inputs for the simulation model in potential onion yield, irrigated onion yield, and rain-fed onion yield results (Figure 46 a, b, and c).

Results for rice for the Valdesia, Ocoa, and Azua AEZs in the Ocoa Watershed are presented in Table 34. Once again, the values are close to those presented by Doorenbos and Kassam (1979). As a comparison, the average yield values for the Ocoa Watershed are generally quite low (3.79 to 4.94 tons/ha).



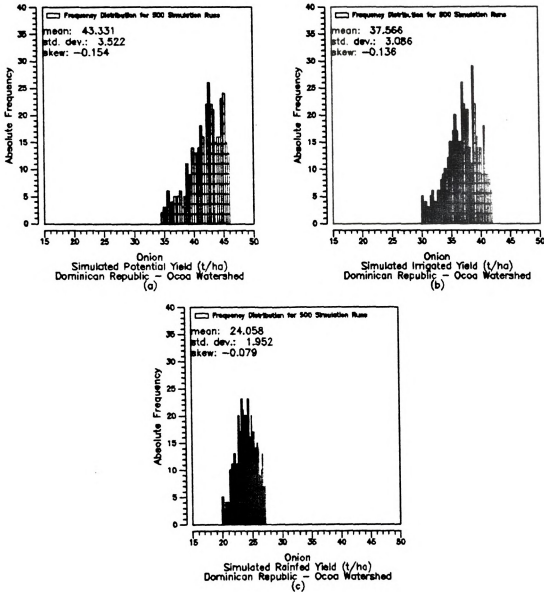


Figure 46. Stochastic YIELD simulator: Dominican Republic, Ocoa Watershed--Ocoa--Onion. Absolute frequency histogram for potential, irrigated, and rain-fed yield.

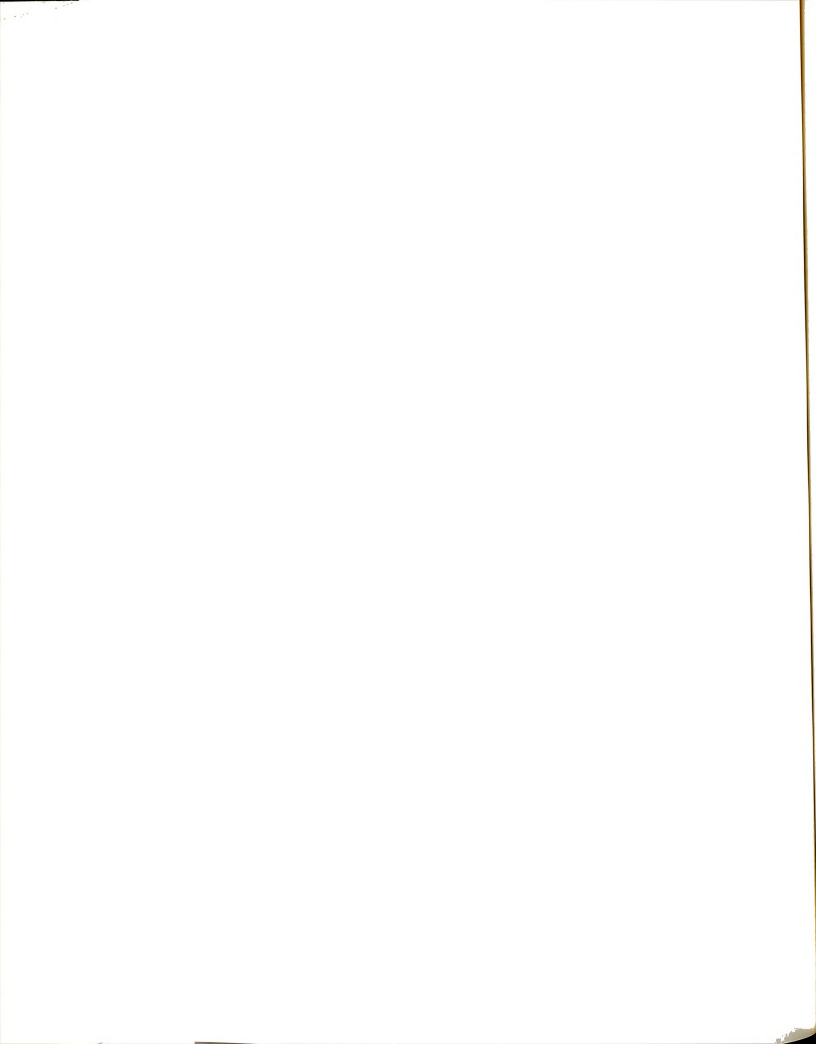
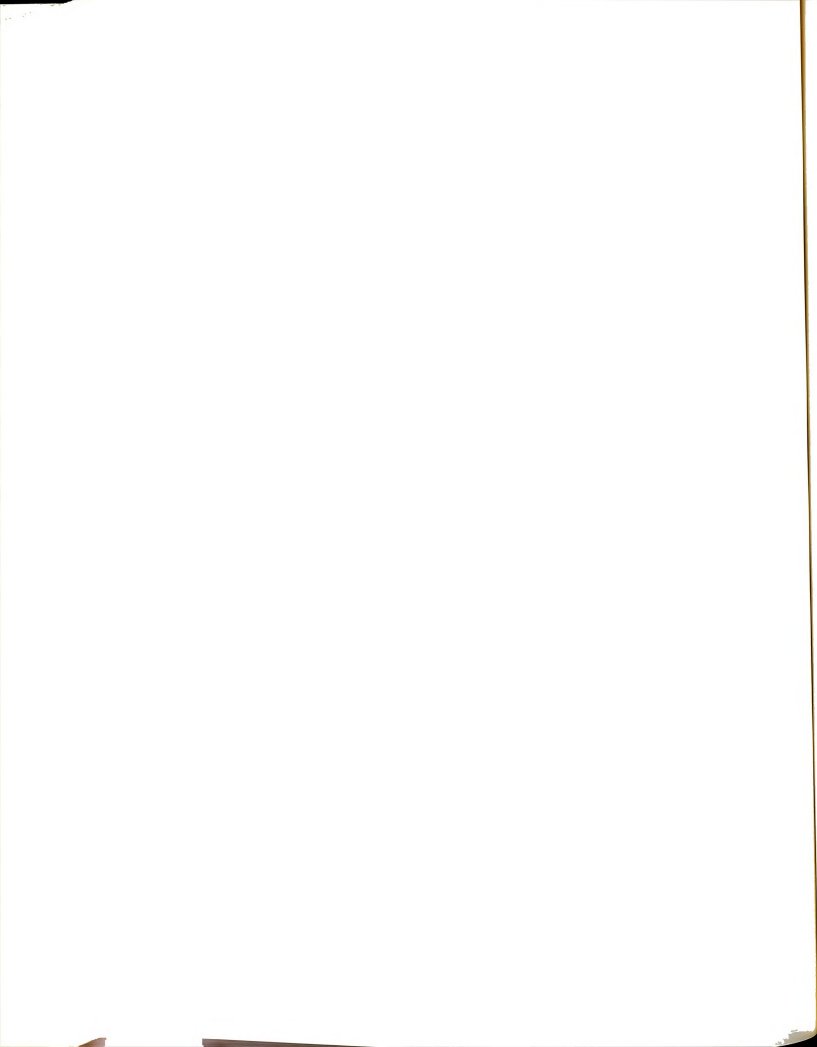


Table 34. Stochastic YIELD simulator: probability density function statistics results for rice for the Dominican Republic--Ocoa Watershed--Valdesia, Ocoa, and Azua AEZs (tons/ha)

Distribution Statistics	Valdesia	Ocoa	Azua
Potential Yield			
Mean	6.307	5.793	5.330
Std Dev	0.557	0.518	0.462
Skewness	-0.040	0.049	-0.011
Quantiles			
100%	7.623	6.965	6.465
75%	6.736	6.171	5.686
50%	6.328	5.804	5.336
25%	5.883	5.388	4.970
0%	4.883	4.553	4.172
Irrigated Yield			
Mean	1.616	3.932	5.063
Std Dev	0.146	0.352	0.439
Skewness	0.016	0.057	-0.013
Quantiles			
100%	2.005	4.742	6.123
75%	1.729	4.195	5.407
50%	1.617	3.930	5.074
25%	1.504	3.659	4.721
0%	1.282	3.060	3.972
Rain-fed Yield			
Mean	1.018	2.672	3.742
Std Dev	0.078	0.215	0.303
Skewness	0.036	0.066	-0.041
Quantiles			
100%	1.245	3.225	4.477
75%	1.075	2.822	3.983
50%	1.021	2.674	3.749
25%	0.959	2.514	3.506
0%	0.830	2.103	2.972

Source: Compiled from the stochastic YIELD simulator results.

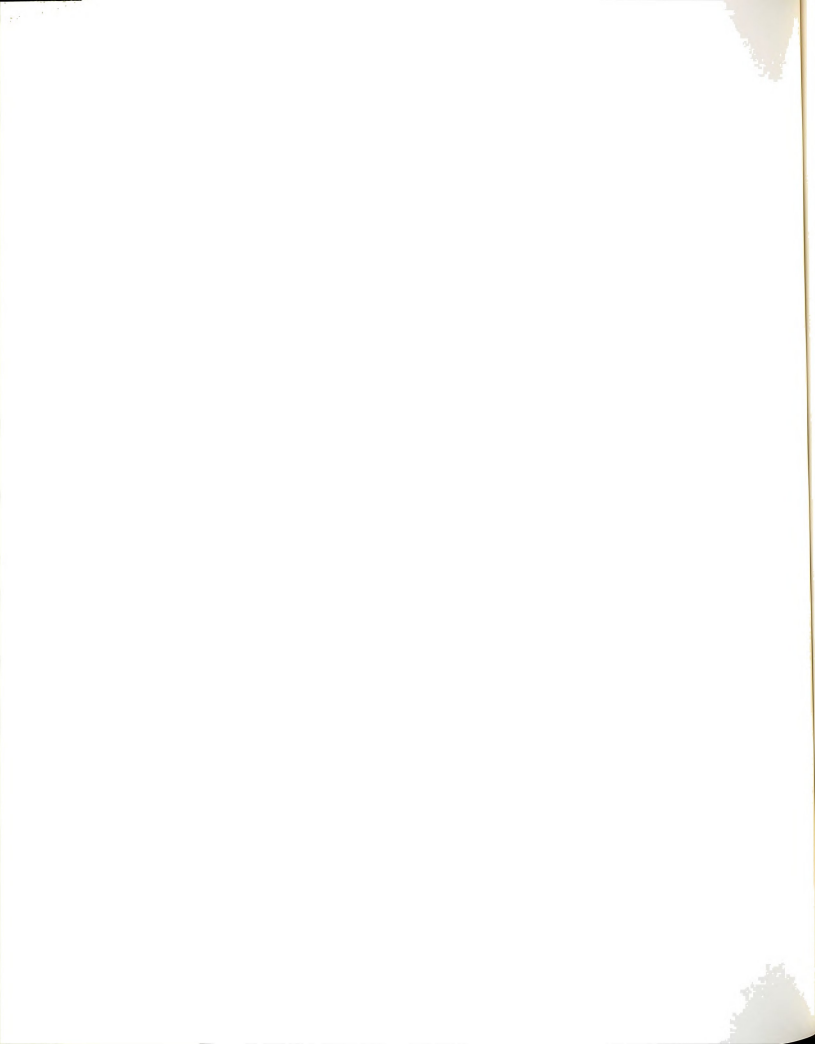


A wide range of simulated yields exists as a result of the large variation among the AEZs. The skew factors are small and therefore not significant, and they assume positive and negative values. The yield variation for rice is from the minimum 0.83 tons/ha to the maximum 7.623 tons/ha. This is largely caused by the steep slope conditions not considered in potential yield.

Histograms for the rice-yield results for the Ocoa AEZ are displayed in Figure 47.

Results for fresh pea for the Ocoa Watershed are shown in terms of probability density function statistics (Table 35). The model fairly represents the average fresh pea yield for the AEZs. Yields are slightly higher if compared to the average observed yield for the Ocoa Watershed. The range for fresh pea for the watershed is from a minimum of 1.492 tons/ha for Valdesia rain-fed yield to a maximum of 5.642 tons/ha for Ocoa potential yield.

The skew factors are not very significant, and they have positive and negative signs. The range of variation is from -0.027 to 0.123. Because of local conditions, among other things, Valdesia has the most losses in yield among the AEZs considered.



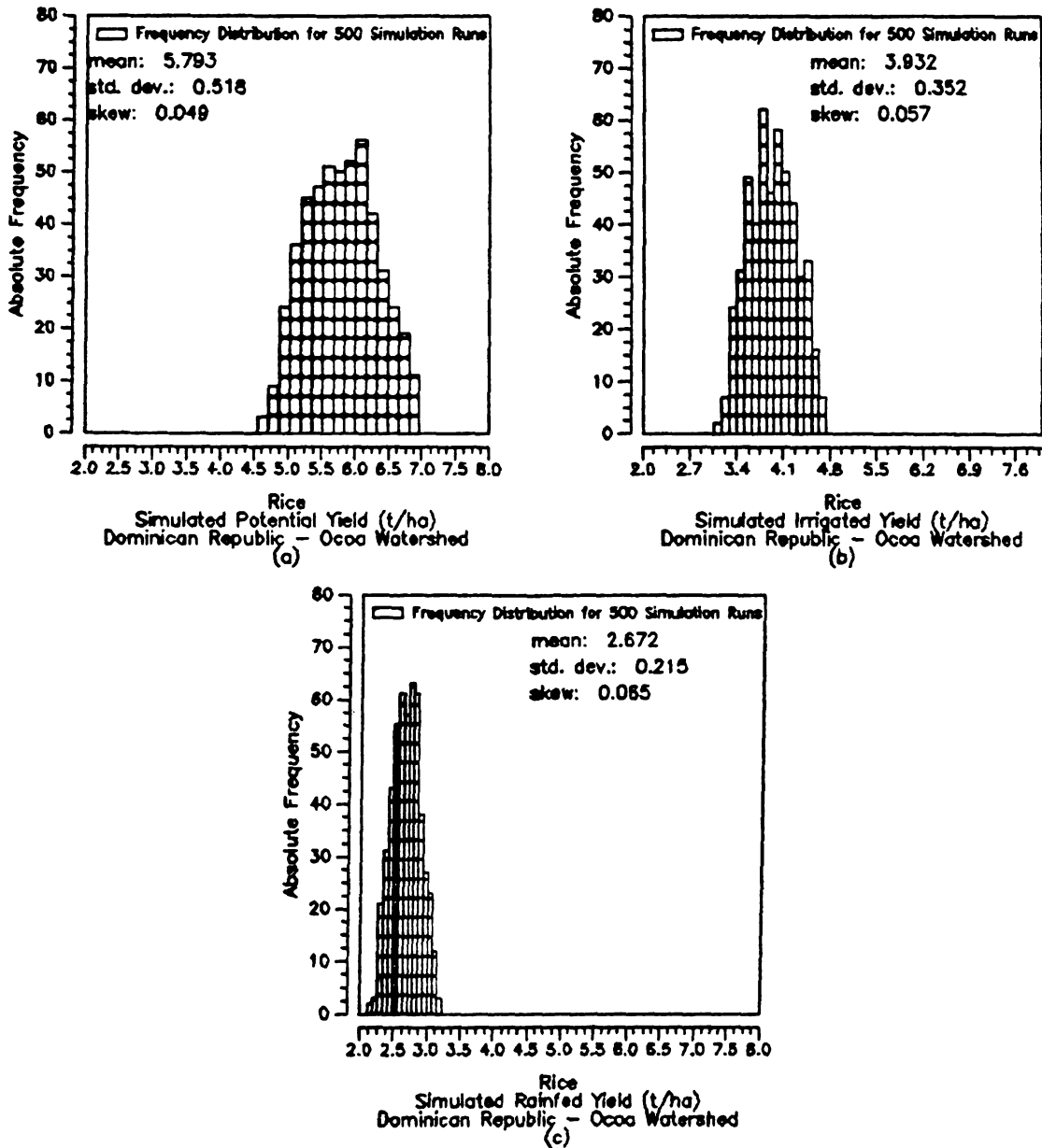
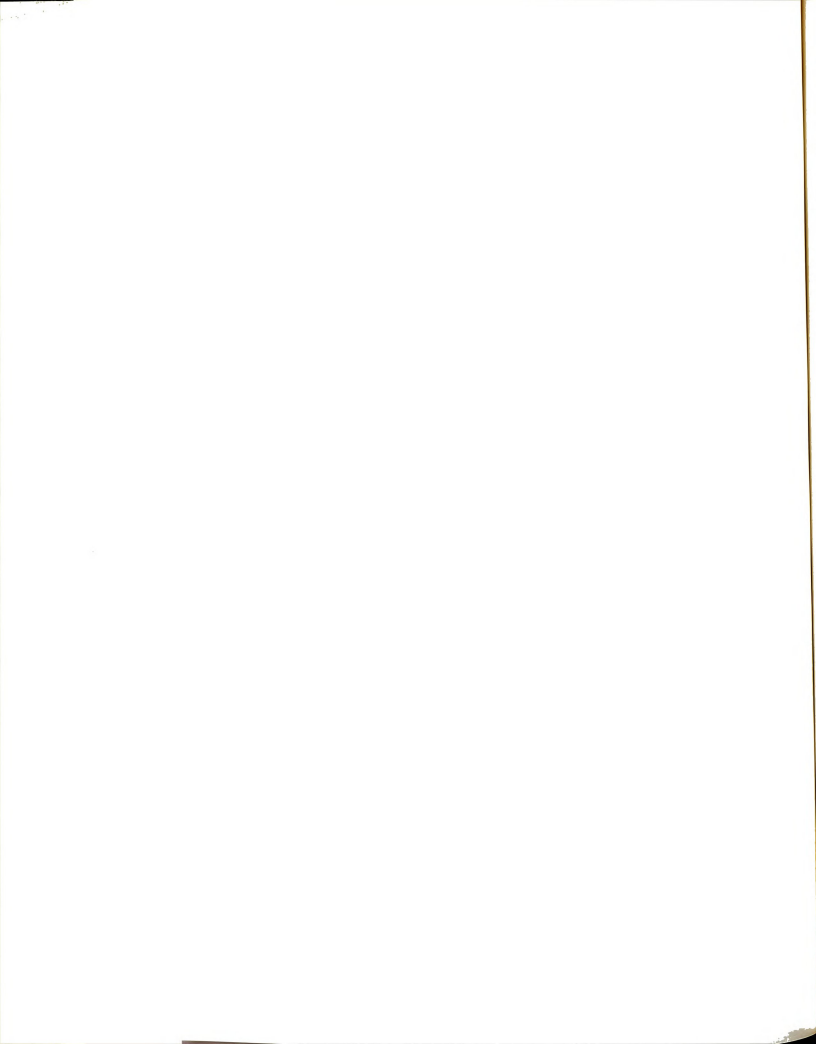


Figure 47. Stochastic YIELD simulator: Dominican Republic--Ocoa Watershed--Ocoa--Rice. Absolute frequency histogram for potential, irrigated, and rain-fed yield.

Table 35. Stochastic YIELD simulator: probability density function statistics results for fresh pea results for Dominican Republic--Ocoa Watershed--Valdesia, Ocoa, and Azua AEZs (tons/ha)

Distribution Statistics	Valdesia	Ocoa	Azua
Potential Yield			
Mean	3.935	4.692	3.757
Std Dev	0.259	0.323	0.230
Skewness	0.073	0.069	-0.024
Quantiles			
100%	4.674	5.462	4.314
75%	4.130	4.951	3.934
50%	3.932	4.674	3.763
25%	3.746	4.449	3.584
0%	3.303	3.867	3.089
Irrigated Yield			
Mean	2.671	3.184	3.570
Std Dev	0.177	0.220	0.219
Skewness	0.077	0.063	-0.027
Quantiles			
100%	3.209	3.721	4.101
75%	2.792	3.367	3.730
50%	2.668	3.167	3.573
25%	2.538	3.017	3.406
0%	2.197	2.620	2.921
Rain-fed Yield			
Mean	1.857	2.372	2.799
Std Dev	0.157	0.203	0.217
Skewness	0.123	-0.017	-0.007
Quantiles			
100%	2.292	2.824	3.345
75%	1.970	2.546	2.963
50%	1.845	2.371	2.795
25%	1.736	2.211	2.631
0%	1.492	1.883	2.185

Source: Compiled from the stochastic YIELD simulator results.



In Figure 48, histograms are presented showing the variations in the simulated yield for the Ocoa AEZ for fresh pea. Histogram (a) displays the potential fresh pea yield, (b) displays the irrigated fresh pea yield, and (c) displays the rain-fed fresh pea yield. These histograms are useful to decision makers and planners in visualizing the variation involved in the simulation runs when the exogenous environmental variables are stochastic.

The tabulated statistics of the simulation for potato are provided in Table 36. Results are within the yield range provided by Doorenbos and Kassam (1979) but are very high compared to the average potato yield for the Ocoa Watershed.

Considering the rain-fed results of the yield model, it may be concluded that they represent fairly well the average potato yield for the AEZs. Irrigated potato yields of the model are, however, considerably higher.

The variations in the simulated yields range from a minimum of 3.214 tons/ha for the Valdesia rain-fed yield to a maximum of 36.543 tons/ha for the Valdesia potential yield.

The skew factors have negative and positive signs, but the values are small for potential and irrigated yield and larger, but not very significant, for rain-fed yield.

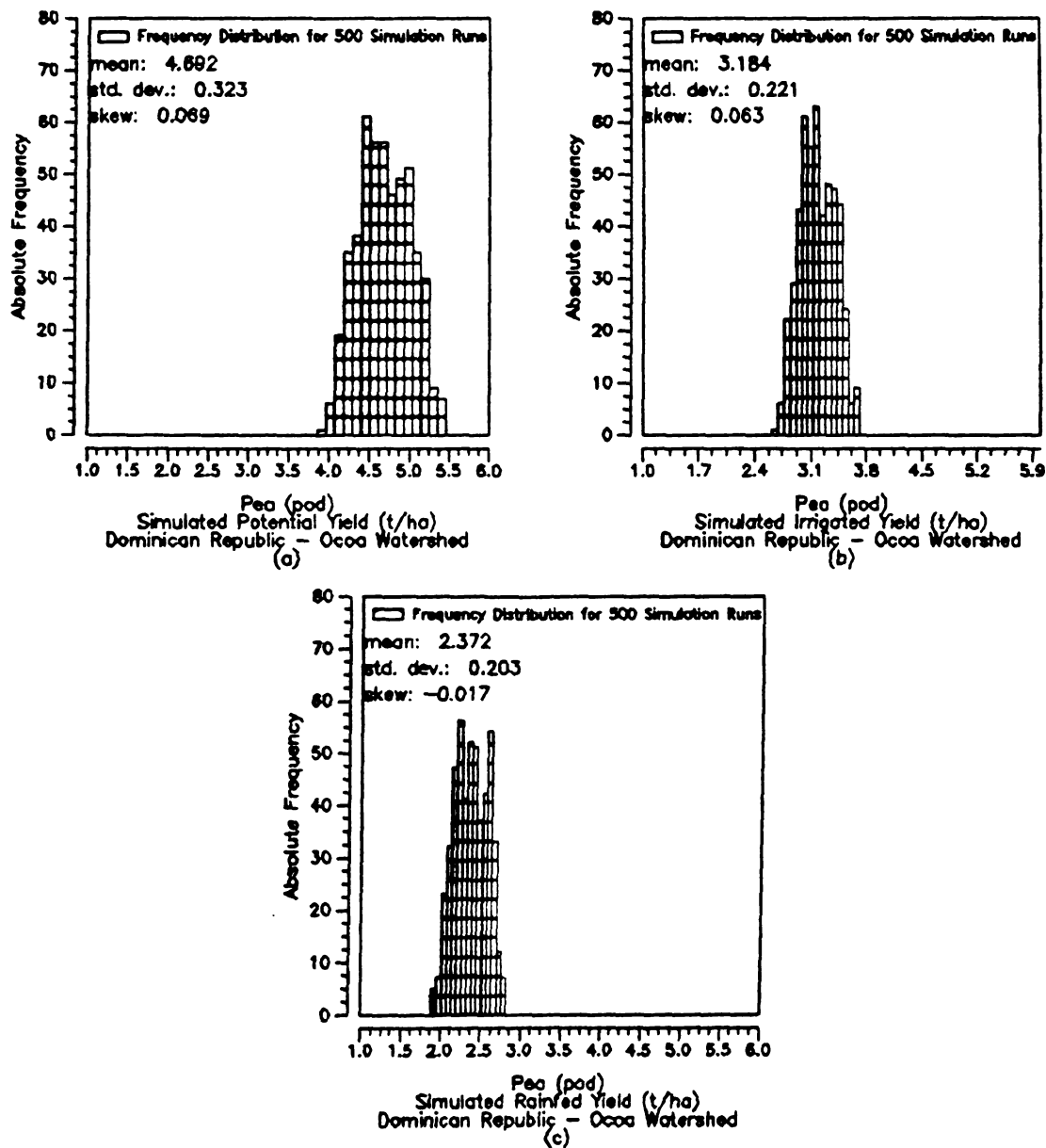


Figure 48. Stochastic YIELD simulator: Dominican Republic--Ocoa Watershed--Ocoa--fresh pea. Absolute frequency histogram for potential, irrigated, and rain-fed yield.

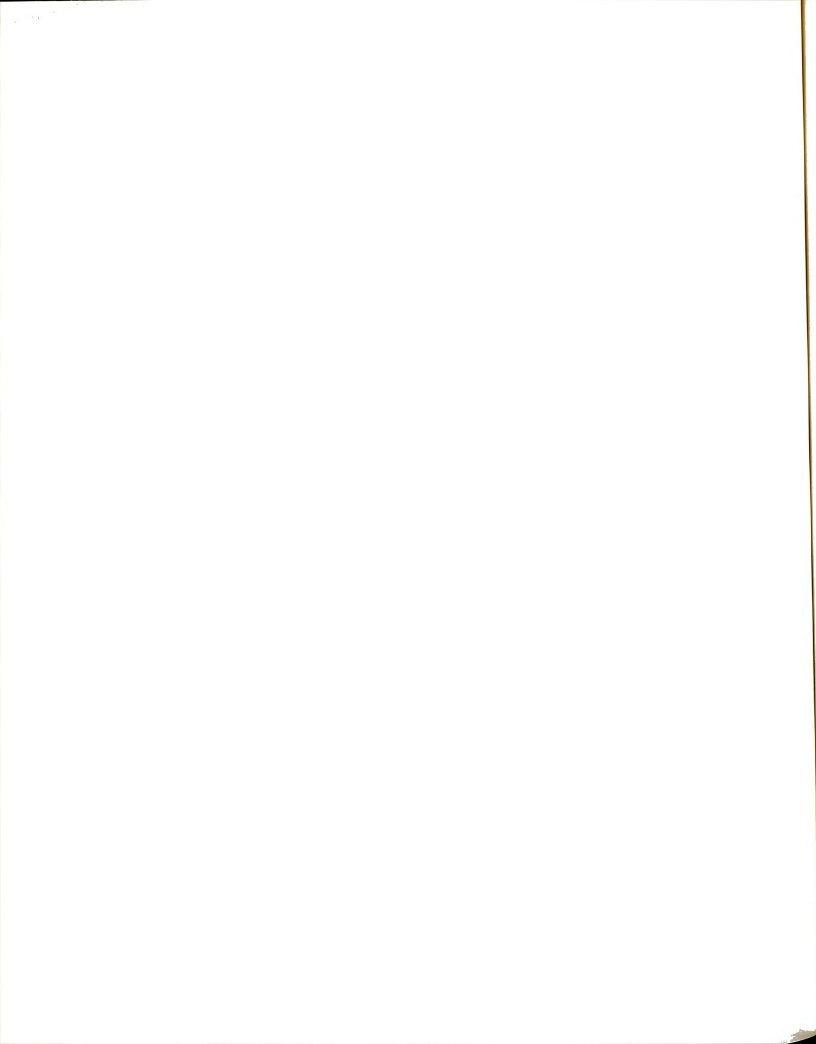
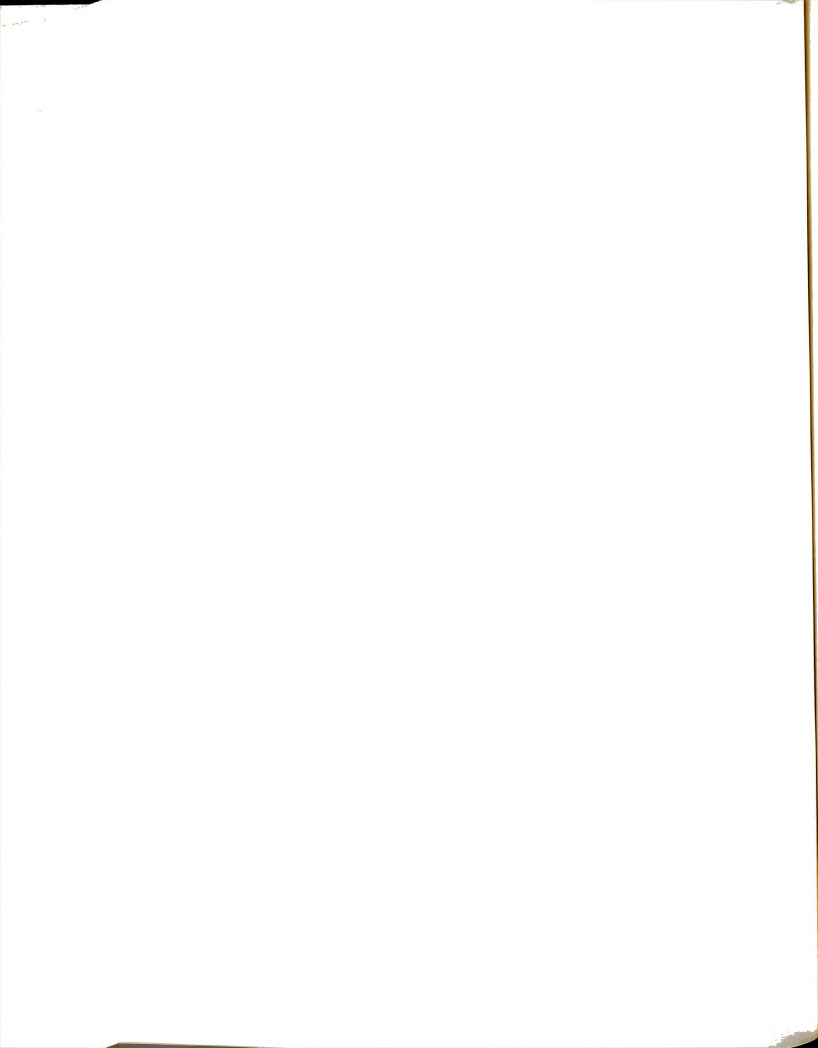


Table 36. Stochastic YIELD simulator: probability density function statistics results for potato for the Dominican Republic--Ocoa Watershed--Valdesia, Ocoa, and Azua AEZs (tons/ha)

Distribution Statistics	Valdesia	Ocoa	Azua
Potential Yield			
Mean	29.915	14.177	25.297
Std Dev	2.269	1.393	2.283
Skewness	-0.029	-0.094	-0.055
Quantiles			
100%	36.543	17.914	30.671
75%	31.439	15.192	26.944
50%	30.021	14.219	25.320
25%	28.387	13.180	23.634
0%	23.598	10.506	19.104
Irrigated Yield			
Mean	7.661	9.621	24.029
Std Dev	0.601	0.948	2.166
Skewness	-0.012	-0.092	-0.051
Quantiles			
100%	9.457	12.118	29.192
75%	8.057	10.315	25.593
50%	7.686	9.629	24.067
25%	7.245	8.956	22.488
0%	6.033	7.081	18.122
Rain-fed Yield			
Mean	4.147	5.286	13.650
Std Dev	0.366	0.594	1.283
Skewness	0.153	0.111	0.092
Quantiles			
100%	5.259	6.907	17.220
75%	4.369	5.693	14.491
50%	4.149	5.267	13.628
25%	3.891	4.871	12.729
0%	3.214	3.785	9.764

Source: Compiled from the stochastic YIELD simulator results.



In Table 37, the stochastic YIELD results for cabbage are given in the form of their probability density function statistics for the AEZs considered in this study. Variation ranges from a minimum value of 5.735 tons/ha for rain-fed yield in Valdesia to a maximum of 49.233 tons/ha for potential yield in Ocoa. The skew factors vary from -0.106 to 0.191, which are not very significant (Figure 49 and Table 37).

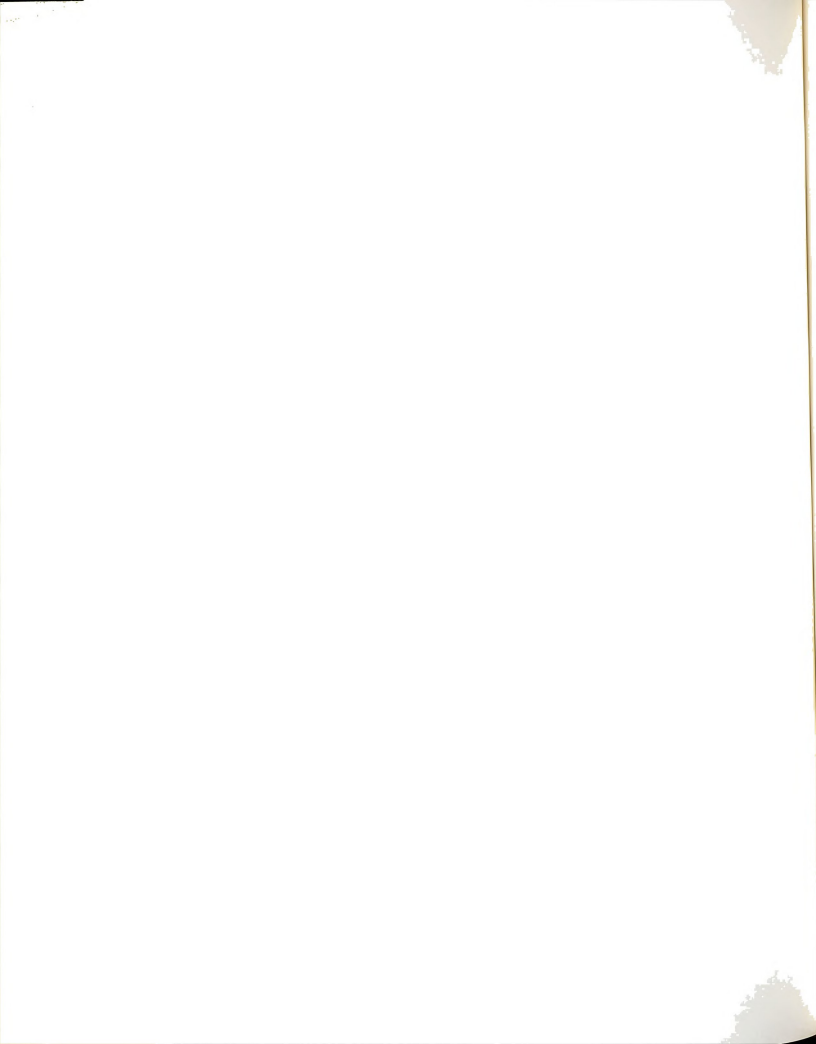
The values that resulted from the stochastic model are within the yield ranges specified by Doorenbos and Kassam (1979). The average yields for the Watershed are fairly well replicated by the model and are represented best by the irrigated production system.

The histograms with the results of the stochastic yield simulator are presented in Figure 49. Some skewness can be noticed in histogram (c) for rain-fed yield simulated results.

Table 37. Stochastic YIELD simulator: probability density function statistics results for cabbage for the Dominican Republic--Ocoa Watershed--Valdesia, Ocoa, and Azua AEZs (tons/ha)

Distribution Statistics	Valdesia	Ocoa	Azua
Potential Yield			
Mean	33.563	39.871	31.526
Std Dev	2.841	3.294	2.596
Skewness	-0.106	0.092	0.186
Quantiles			
100%	41.219	49.233	40.021
75%	35.681	42.254	33.159
50%	33.654	39.687	31.455
25%	31.600	37.601	29.701
0%	26.244	31.321	24.952
Irrigated Yield			
Mean	8.596	27.063	29.956
Std Dev	0.734	2.229	2.461
Skewness	-0.097	0.070	0.191
Quantiles			
100%	10.615	33.700	38.130
75%	9.118	28.745	31.542
50%	8.593	26.988	29.864
25%	8.100	25.504	28.217
0%	6.680	20.888	23.641
Rain-fed Yield			
Mean	7.323	23.053	26.148
Std Dev	0.623	1.868	2.131
Skewness	-0.100	0.069	0.185
Quantiles			
100%	8.991	28.474	33.010
75%	7.747	24.472	27.574
50%	7.333	23.051	26.153
25%	6.897	21.677	24.591
0%	5.735	17.715	20.983

Source: Compiled from the stochastic YIELD simulator results.



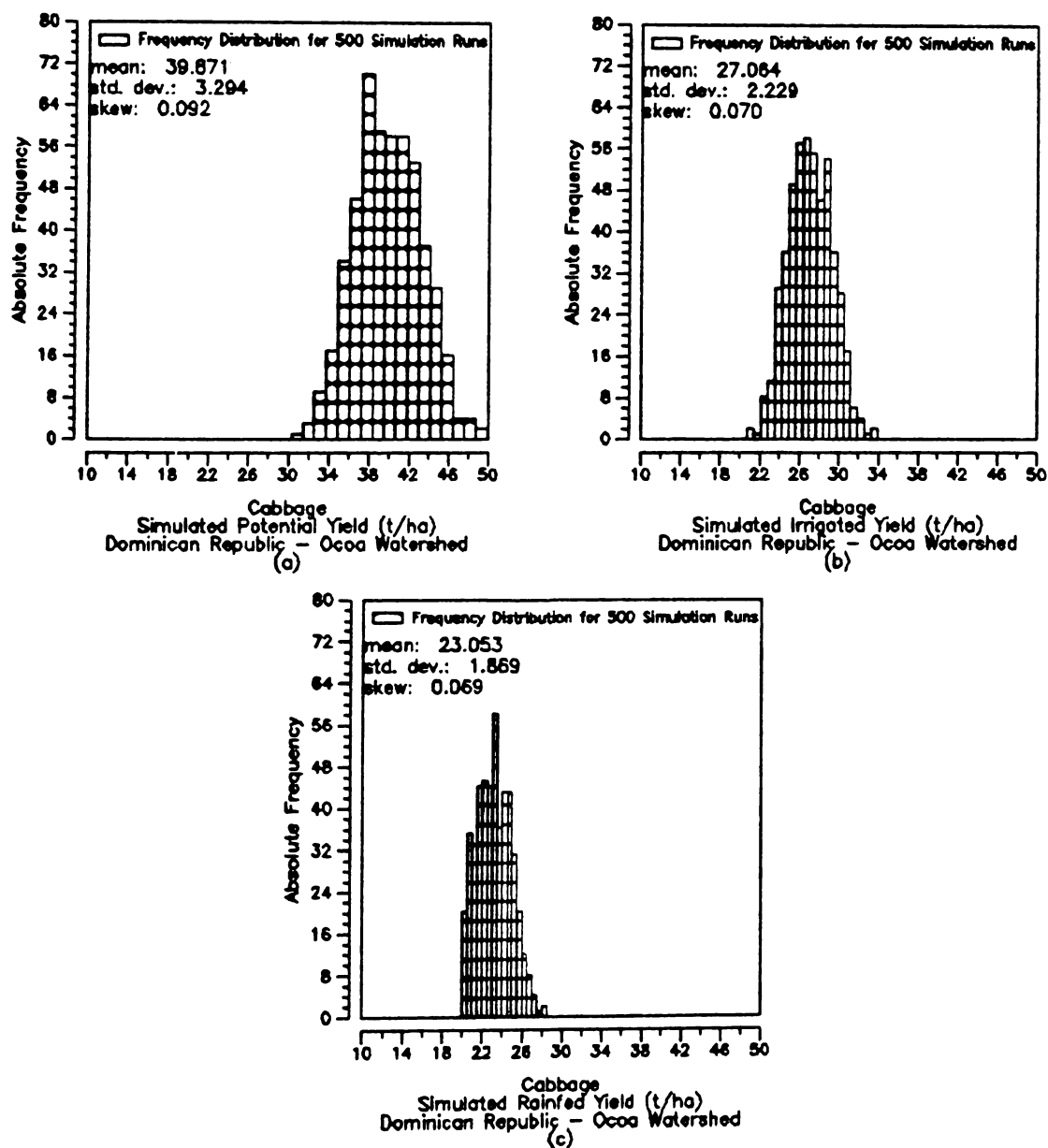


Figure 49. Stochastic YIELD simulator: Dominican Republic--Ocoa Watershed--Ocoa--cabbage. Absolute frequency histogram for potential, irrigated, and rain-fed yield.

CHAPTER VI

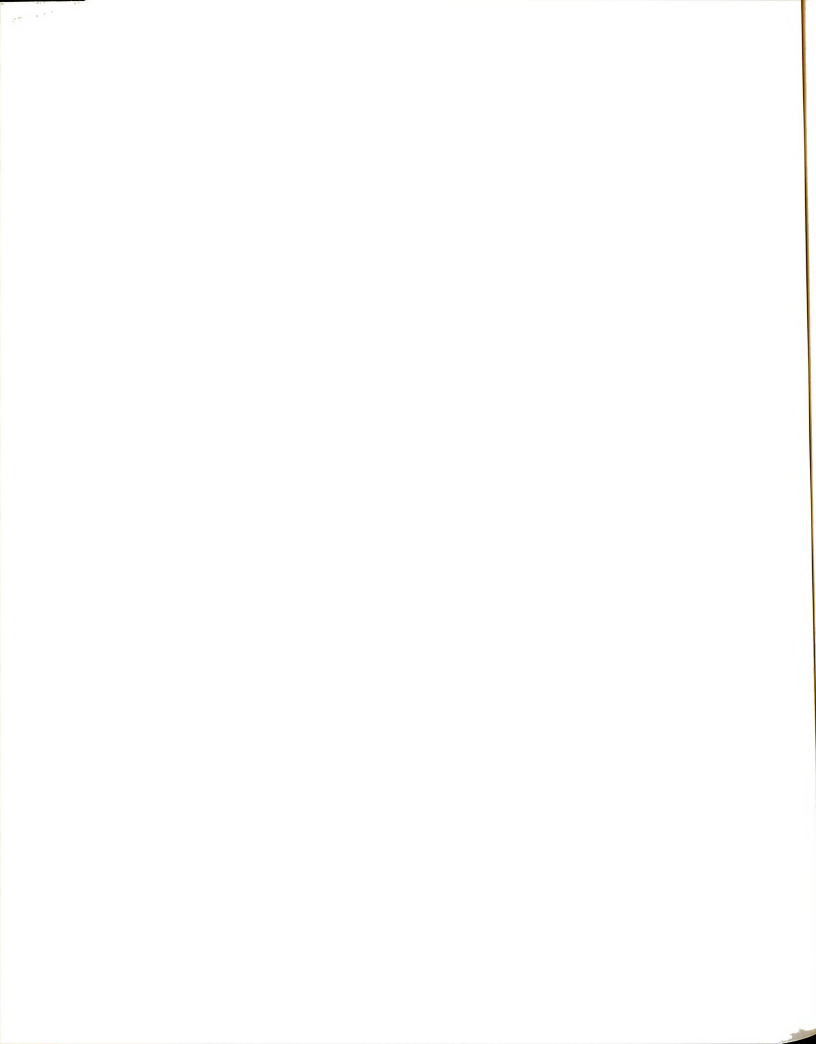
SUMMARY, CONCLUSIONS, AND SUGGESTIONS FOR FURTHER RESEARCH

Summary

Agricultural economists, planners, decision makers, and researchers quite often rely on crop yields for their work and studies. Crop yields are very important for most regional and interregional econometric, economic-optimization projects involving the agricultural sector, which for many countries is the main source of foreign exchange.

Trade and sector analysis relies on past and projected crop-yield values to forecast a nation's balance of trade and to determine export/import goals. Developed and industrialized nations use crop yield to study price tendencies of international commodity markets. Developing nations are interested in producing food and cash crops to satisfy internal demand and to generate foreign exchange to pay for the importation of industrial goods.

In summary, yield estimation is essential for policy analysis and planning in the agricultural sector. Within



this context, governments are seeking ways to estimate yield for various agro-ecological zone conditions and farming systems to provide decision makers and planners with essential information for economic planning. The lack of information on past yield data is a common problem in most developing nations. Time series data of reliable crop yield values by location are practically nonexistent, making any study based on yield time series data difficult or unreliable.

Several studies have been done that relied on time series analysis of yield data to forecast yield (Vilas, 1975; Heady, 1964; Gibson, 1979). Most of the time, in regional or spatial research, yields are derived from the national average because of lack of better data.

Despite the existence of a relatively large number of studies on crop-yield prediction for many different crops, there exists a need for computational models that allow decision makers and planners, with relative ease and with minimum data requirements, to estimate crop yields for different production scenarios. Developing and underdeveloped nations, in particular, are most interested in yield-estimation procedures.

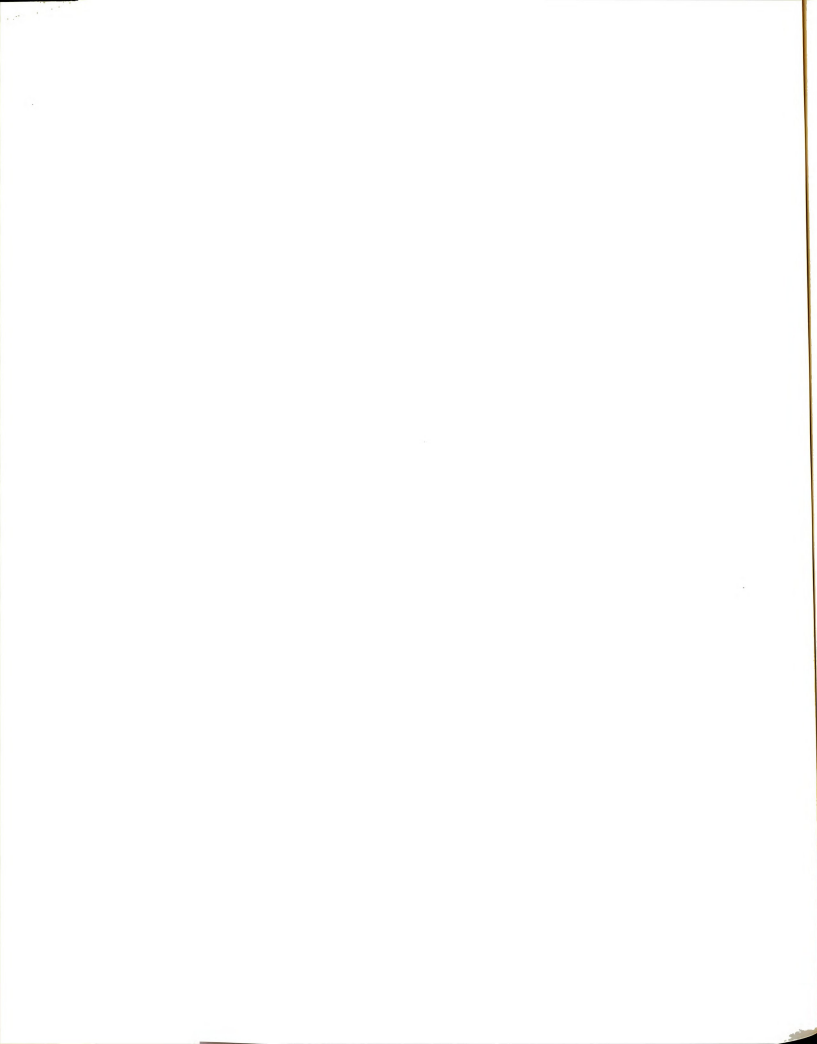
Technological advances in remote sensing, automated cartography, image-processing technology, computer science, and advances in modeling plant growth and biomass production with a larger set of environmental variables make applied

research in yield estimation and forecasting possible. These technologies provide new ways to explore the intricate world of mathematical crop-yield modeling in a time and space domain.

This study was intended to provide decision makers and planners with a reliable state-of-the-art tool for multiple crop yield prediction, using some of the latest developments in crop modeling and plant growth and computer simulation. The use of a geographic information system improves the reliability of estimates over space and time.

One of the prime objectives of this study was to provide potential users with computer software that permits the incorporation of exogenous environmental variables such as precipitation, temperature, wind velocity, solar radiation, relative humidity, and local information to estimate yield for a large variety of crops.

The crop-yield model developed here can, depending on the data available for the homogeneous zones or locations, be refined to represent accurately the local crop-growth conditions. The simulation model can also be used to identify, for the location and/or crop selected, the inputs and/or parameters responsible for strong yield variation and aid in the allocation of scarce resources for data collection. The identification of critical input and/or model parameters maximizes the use of research funds for data

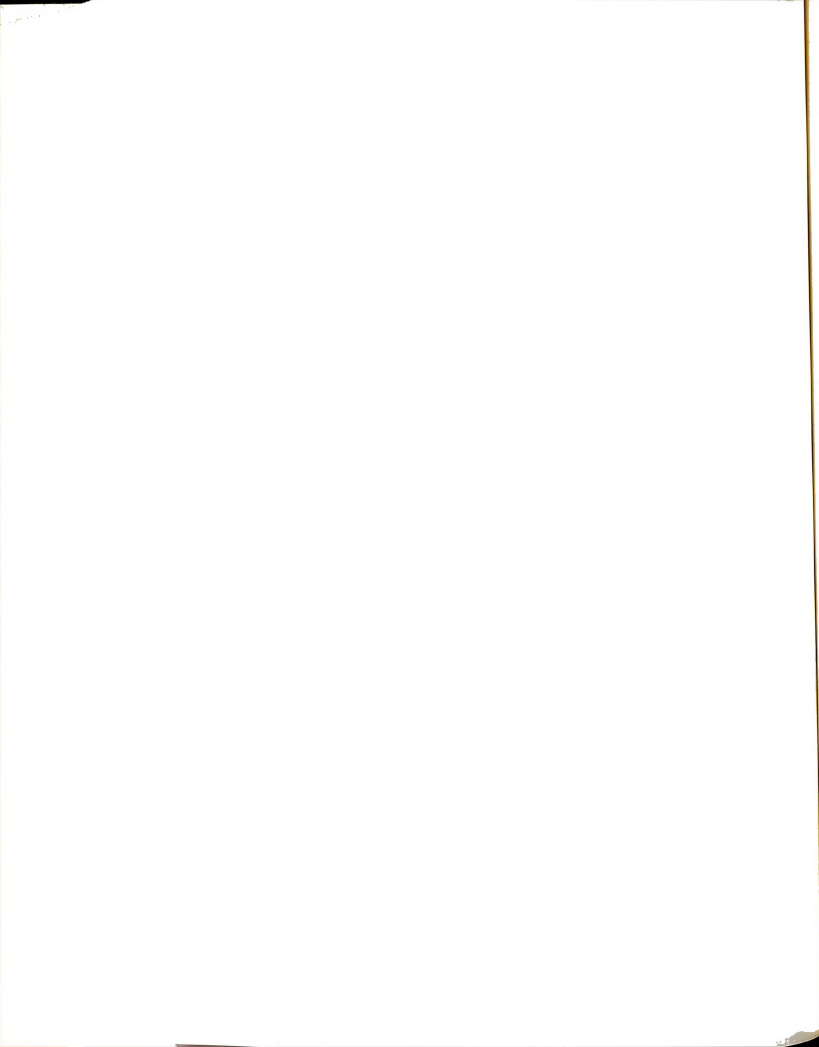


collecting. Through the simulation model developed here, this process can be carried out in a practical and useful manner.

Policy and management decisions affecting the irrigation scheme and water-use efficiency are some of the control variables in the simulation model. By varying the water quantities for irrigation, important insights may be obtained to improve irrigation and water-management efficiency, while optimizing crop yield.

Most developing countries rely on importing inputs such as fertilizer to their production systems. Fertilizer availability may be used as a policy and input variable into the simulation model. The associated yield response effect can then be measured within the context of price/cost scenarios.

Crop allocation and planting decisions are based on numerous factors, such as domestic and international commodity prices, government policies, transportation costs, input availability and cost, and so on. The yield simulator provides a useful and practical tool for yield estimation as a function of exogenous inputs and can aid in the selection of the best planting scheme according to defined goals, public or private. This includes the simulation of different crop yields for different regions and agro-ecological zones, based on a study of a broad range of possibilities of

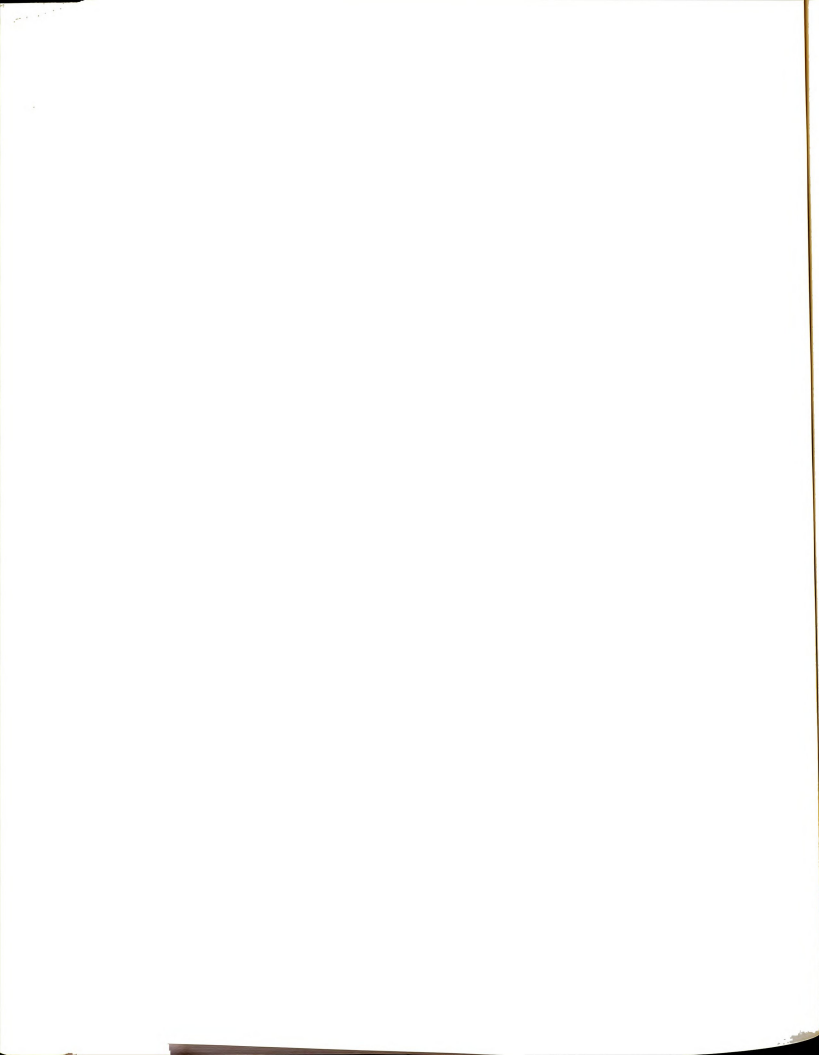


planting schemes to satisfy policy objectives such as price supports, income or labor stabilization, regionalization of production, and so on.

In a policy-analysis framework, the yield simulator can aid in the analysis of intermediate stages of the simulation process to identify the causal relationship of biomass production. This is possible for a specific crop and a specific location under a variety of conditions representing the exogenous environmental variables as well as model parameters.

Economic benefits derived from improved crop information, such as yield and area planted, are fundamental to government policy analysis. In many countries, government agencies play an active role in agricultural markets. Information of this nature can be critical in ensuring an orderly market, reasonable consumer prices, and adequate farm income. Such knowledge permits public authorities or large private enterprises to plan their inventory holdings, sales, and commodity purchases and to deal with supply fluctuations through identification and remedial action in the prevailing market structure.

Crop-production forecasting may be undertaken during the crop-growth period using information on current exogenous environmental variables. Such "real time simulation" may provide critical insights for policy makers and planners



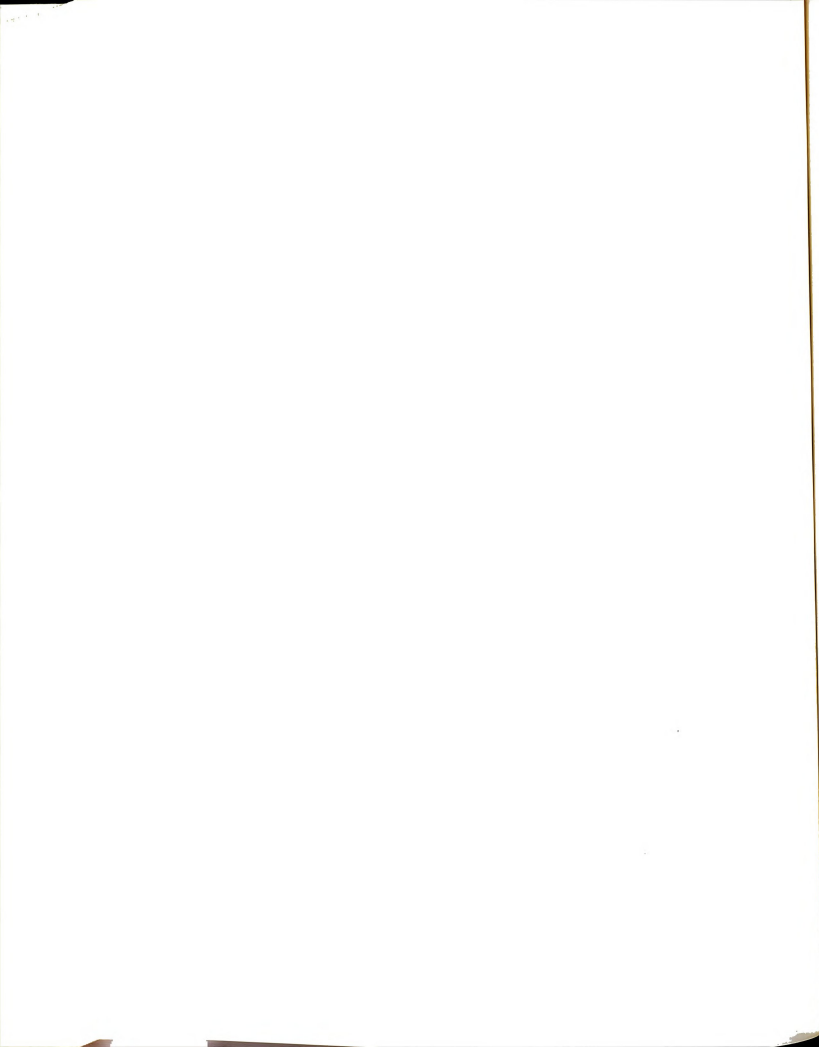
on the expected total production volumes for selected or critical food or cash crops.

Prediction of yield by region can provide government officials with information needed to design plans with the objective of coping with environmental disaster as well as trade between and among regions. In that sense, the yield simulator provides a useful and practical tool for inter-regional and national policy analysis.

Conclusions

The following conclusions represent a brief summary of the material presented in the preceding chapters.

The implementation of the YIELD simulator for Jamaica, where sugarcane is one of the main export products, provided insights into the sugarcane, tobacco, and sorghum production systems. Observed sugarcane yields were available for 20 years for Worthy Park, Caymanas, and Monymusk, the main sugarcane-producing regions in Jamaica. Predicted sugarcane yield estimates were close to the observed yield for 14 of the 20 years. Political changes in the sugarcane industry in the mid- to late 1970s introduced some random variation in observed yields that could not be "tracked" by the model. Yield differences for sugarcane in irrigated production systems for the three regions in Jamaica may be analyzed by comparing the irrigated yield results and observed yield values. Decision makers and planners may use this procedure



for irrigation scheduling, irrigation investment, and project planning. The model results may also be used by decision makers and planners to evaluate crop-production systems in use and to determine the economic feasibility of further improvements.

Tobacco, another major crop in Jamaica's economy, was also included in this study. No observed yield data were available for tobacco, and the yield results were compared to national averages. Simulated tobacco yields were very high when compared to Jamaica's tobacco yield average. As discussed before, lack of observed yield for tobacco in the regions considered is a constraint to further discussion. A comparatively high simulated yield for tobacco and a low observed average suggests that further model refinement or adjustment may be needed for agro-ecological and management factors, as well as improvement in Jamaica's tobacco-production system.

One additional crop, which is being considered as a substitute grain crop in Jamaica, was the focus of the third simulation. Sorghum yields were predicted for the three regions considered in this study. Simulated yield results were quite good when compared to the FAO yield values given by Doorenbos and Kassam (1979), but were quite high when compared to Jamaica's sorghum national average. Again, no data were available for observed sorghum yield, imposing a

strong constraint on more complete analysis. The model results, however, suggest that improvements are needed in the sorghum-production system, such as improved crop management and probably the use of a well-adapted sorghum variety for the regions considered.

The simulation model provided consistent results for all three crops for all three regions in Jamaica, when compared to the scarce yield data available and to the FAO yield values.

The simulation model was also used to simulate yield for five food crops in the Dominican Republic (DR). Crops simulated for the DR are totally different from those used in Jamaica, but weather conditions and data availability were very similar.

Yield predictions were made for three previously determined agro-ecological zones in the Ocoa Watershed: Valdesia, Ocoa, and Azua. The crops simulated were rice, onion, potato, fresh pea, and cabbage. Crop selection was based on the demonstrated interest by the Dominican Republic's Department of Agriculture.

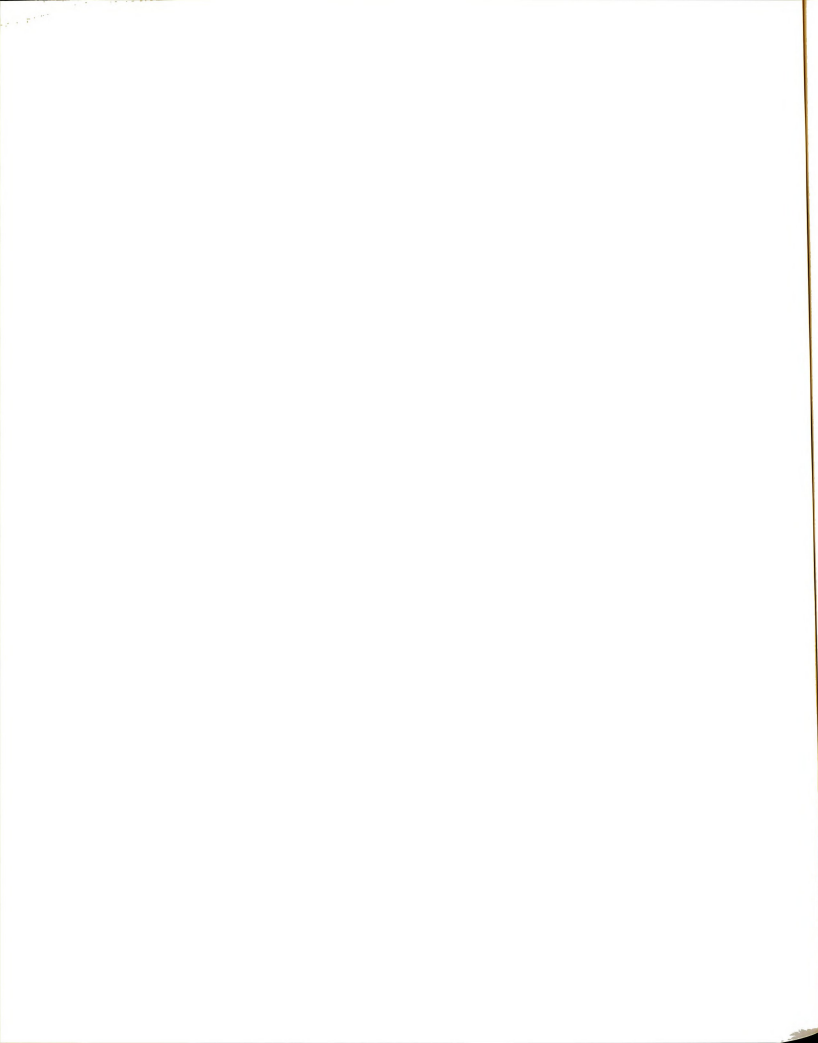
The simulation model was used to generate potential, irrigated, and rain-fed yield estimates for rice, onion, potato, fresh pea, and cabbage for all three agro-ecological zones. Simulated rice yield was unusually high, when compared to the national average. The results were consistent

with FAO guidelines for rice yields, which are very high compared to the DR rice-yield average. Again, this result may suggest that rice-production systems in the DR should be improved to obtain higher yields and that the model input may be modified to include local rice species as well as more specific farming-system parameters representative of the Ocoa Watershed region in the Dominican Republic, such as fertilizer inputs, row spacing, weed control, and pest and disease control.

Simulated results for other crops were also consistent with FAO yield results but also high when compared to Ocoa Watershed yield averages.

In general, the lack of reliable yield data restricted model validation for the countries and regions in this study. The yield simulator, however, performed very well, when compared to FAO yield results and guidelines. It performed well when compared to observed yield data available for those regions.

As proved in this study, the simulation approach can be very useful in presenting decision makers and planners with relevant statistics and histograms that reflect the effect on yield outcome of the uncertainty of agro-ecological conditions inherent in exogenous environmental inputs.



Suggestions for Further Research

As with any research, the present study was subject to a number of limitations. Some of those limitations represent areas in which research would be of considerable value in improving yield estimation. The following suggestions are intended for the benefit of individuals considering the possibility of pursuing further research on crop-yield modeling and plant growth.

Although the primary objective of the present study was to simulate yield production for a wide variety of crops and agro-ecological conditions rather than to simulate plant growth in exact detail, it is desirable to design simulation models that are able to approximate as closely as possible real production systems. As indicated in Chapter V, the results represent a reasonable degree of plausibility, although the comparison of model results with actual observed yield, where available, indicated that the model has some limitations.

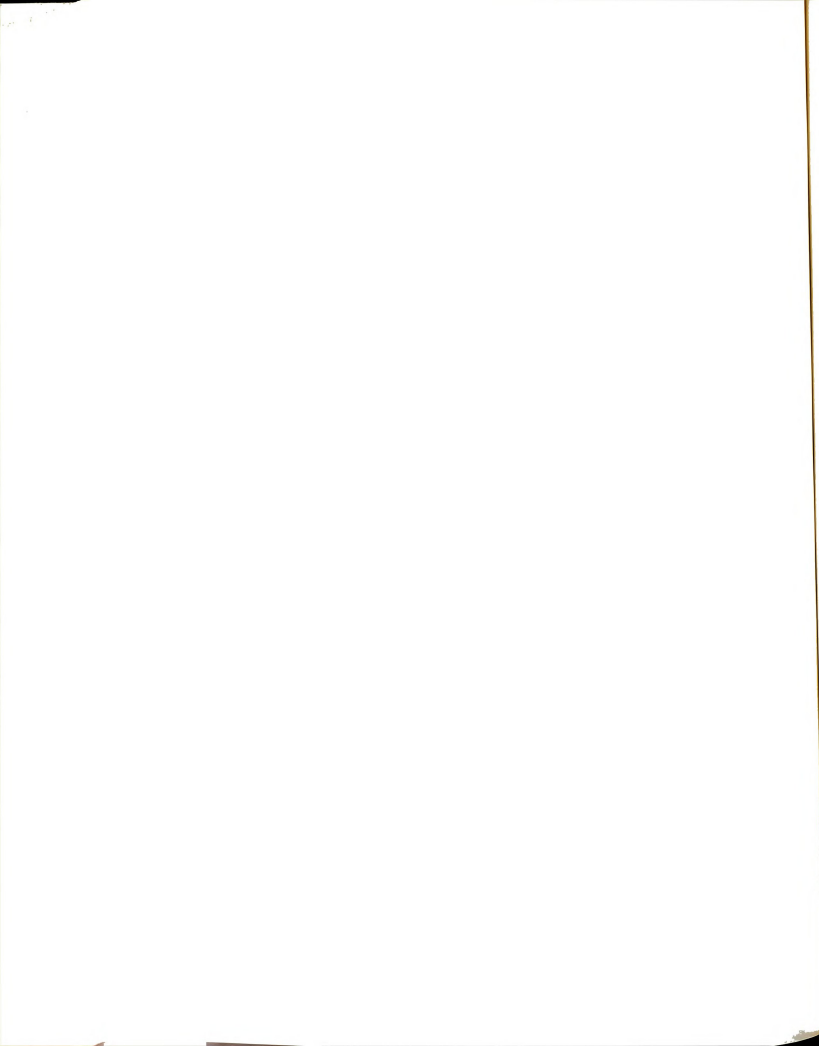
Some of the suggestions for the improvement of model performance are related to site-specific conditions. This means that an effort should be made to provide more precise results through the incorporation of detailed model parameters that can be adjusted for the zone or region for which the simulation will be conducted. This is a basic property of the current model because it is spatial-dependent. Also,

the model results might be improved if crop parameters are adjusted for specific crop species, adapted to agro-ecological conditions.

Yield response to fertilizer is a function of, among other things, the fertilizer-specific response curve, the type of crop, crop species, and soil fertility. It would be desirable to include in the model detailed, crop-specific yield response functions, instead of using the generalized fertilizer function. The inclusion of crop-specific response functions would increase the model's performance for single crops and regional differentiation. For those countries where fertilizer availability is not known, a generalized fertilizer response curve may be used as an approximation.

An important improvement could be made by introducing crop coefficients such as crop response to water deficit (k_y) for specific crop cultivars because the final yield estimate is highly dependent on evapotranspiration rates. Research priorities should be directed to the derivation of crop-specific coefficients for the crops involved in the simulation model.

Harvest coefficients are important in determining what fraction of the total biomass production is harvestable. This coefficient is crop (variety) dependent; therefore, an adjustment of that parameter for different crop varieties



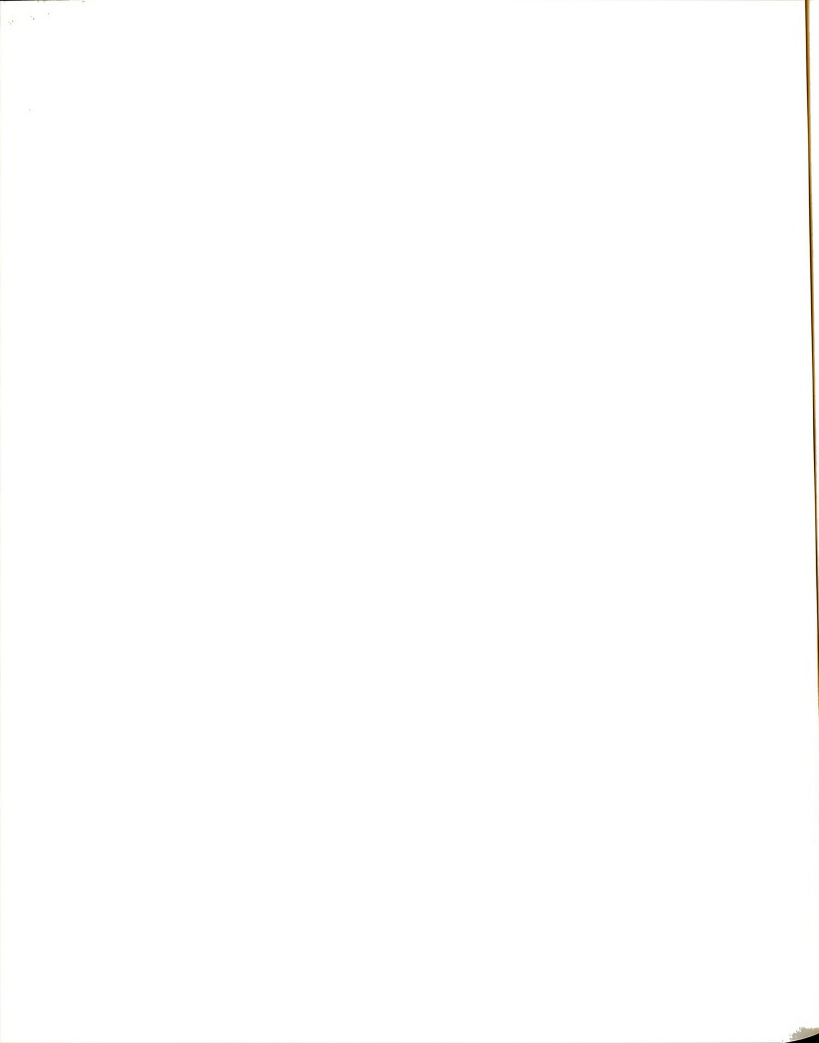
will likely improve the yield estimates. Again, research should be directed toward determining those values for different crop varieties, as well as for different cultivars.

The dry-matter production rate (y_m), which is a temperature- and crop-dependent factor, should also be determined through agricultural research for the different crop varieties. This procedure may generate more realistic yield values for the varieties involved.

The use of evaporation-reduction techniques such as mulching and minimum tillage, and their effect on the soil-water balance, should also be studied in more detail. A better understanding of this relationship may improve yield estimates. Also, such farm-management practices as row spacing in crop planting and intercropping should be explored to establish relationships with yields. It is known that optimum plant spacing will affect soil evaporation, hence final yields.

A module to account for pests and disease in crop fields and their effect on yields would help to improve yield estimates and to improve the control of pests and disease.

The water-balance component of the yield model, which uses one soil type and layer, should be improved to include multiple soil layers, increasing the precision of the water-depletion and uptake mechanism through the root system.



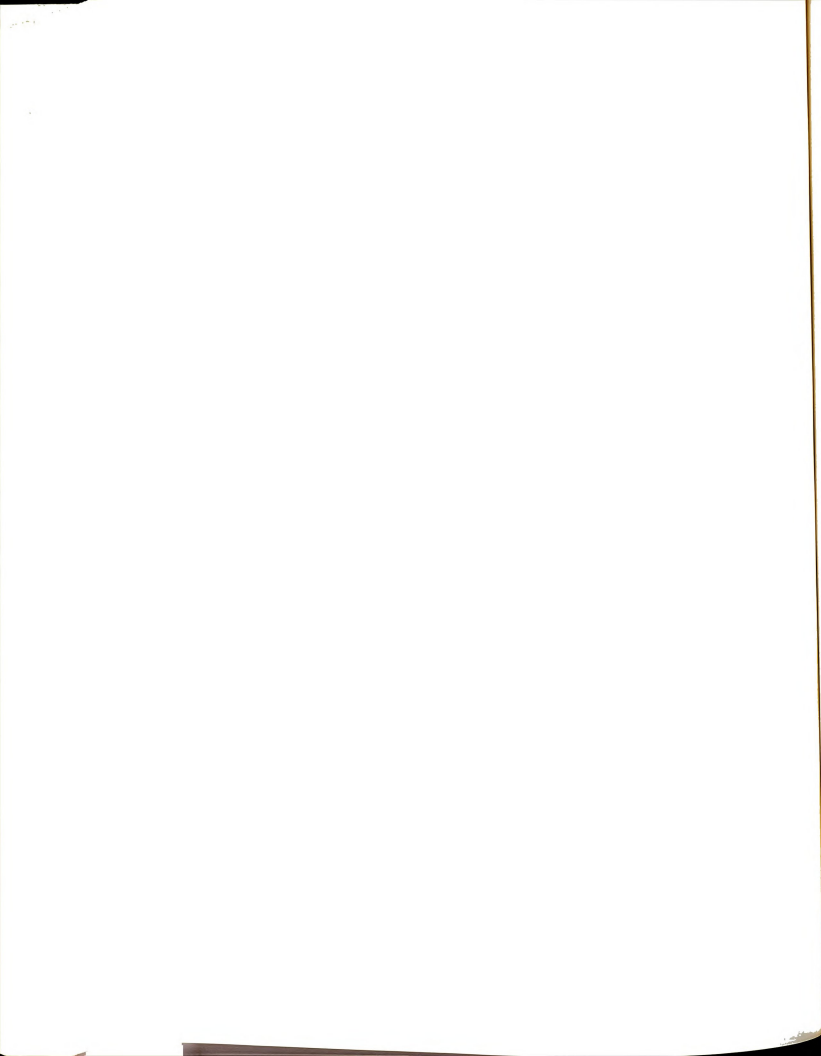
This would result in a better estimation of biomass production.

Excessive availability of water is known to reduce yield in many crops. Waterlogging effects on yield estimate will improve the simulation model results. Additional research is needed to determine the functional form for the effect of waterlogging on yields.

The use of the model as a policy tool could also be increased if the model itself were included in a broader study whose objective is to analyze food production, export policies, land use, and agricultural zoning, as well as in an economic-optimization model. The repercussions of selected policy decisions could be analyzed by running the model under a broader range of assumptions.

Variance-partitioning procedures make it possible to readily assess the effect of parameters such as yield response factor (k_y), dry matter production rate (y_m), and other variables, if taken as uncertainty, on further data-acquisition procedures to reduce variance in uncertain parameter values.

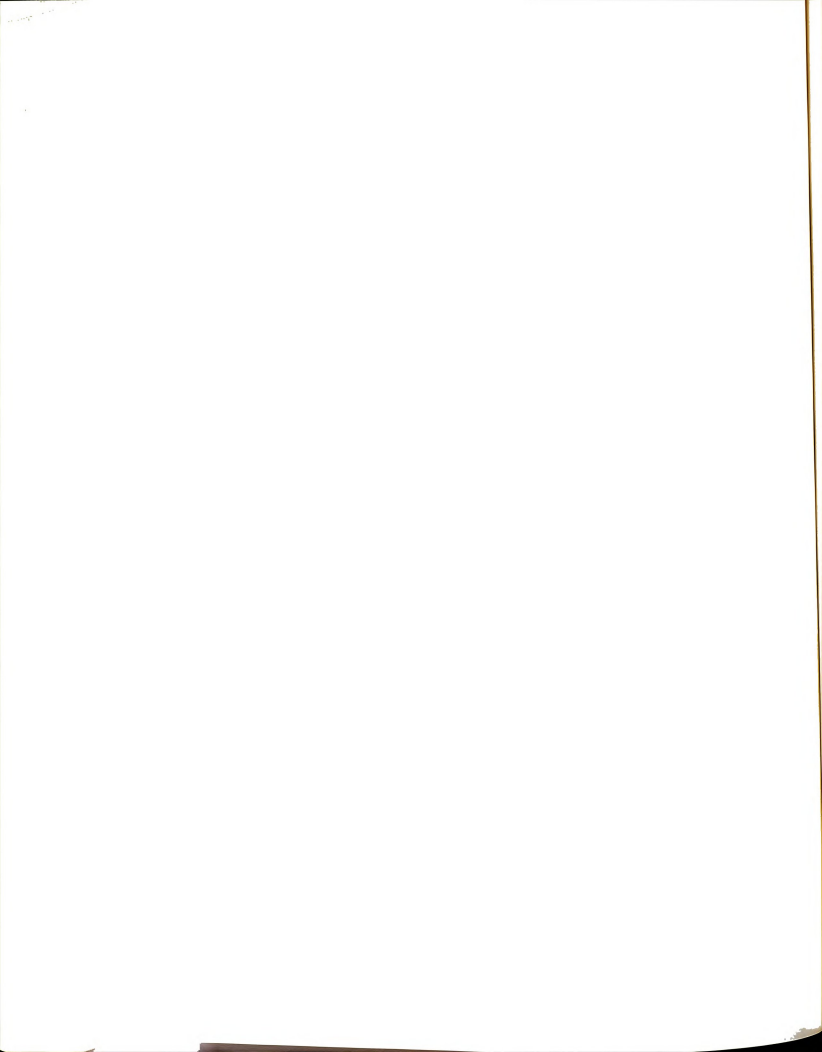
As with most empirical studies, the results of the present investigation were dependent on the quality of data available. Moreover, the estimates reflect the prevailing situation during the period under analysis. Yield estimates would improve if precise data were available for the



exogenous environmental variables such as precipitation, temperature, relative humidity, solar radiation, and wind velocity on a daily basis and not solely in monthly means. Also, the location of the data-collection station for exogenous environmental data should be carefully chosen to obtain the most representative environmental data. This would reduce spatial interpolation errors involved in the simulation process and provide more realistic yield estimates.

The operational YIELD model was developed with CRIES project support funding and is copyrighted by CRIES-Michigan State University. Copies are available through a license agreement with the CRIES Project, 302 Natural Resources, Michigan State University, East Lansing, Michigan 48824.

APPENDICES



APPENDIX A

INTERPOLATING FUNCTIONS

The value of a function $f(x)$ is sometimes known by a set of points $x_1, x_2, \dots, x_n$ in a table format and not by an analytical expression that enables the calculation of the function value at an arbitrary point. For instance, the (x_i) 's might result from some physical measurement or from a long numerical calculation that cannot be cast into a simple functional form.

The task now is to estimate $f(x)$ for arbitrary x by, in some sense, drawing a smooth curve through, and perhaps beyond, the x_i . If the desired x is in between the largest and smallest of the x_i 's that is $x_{\min} \leq x \leq x_{\max}$, the problem is called interpolation; if x is outside that range, it is called extrapolation.

A plausible functional form must be used to model the function given by the table generated by the empirical experiment to be useful in a simulation model.

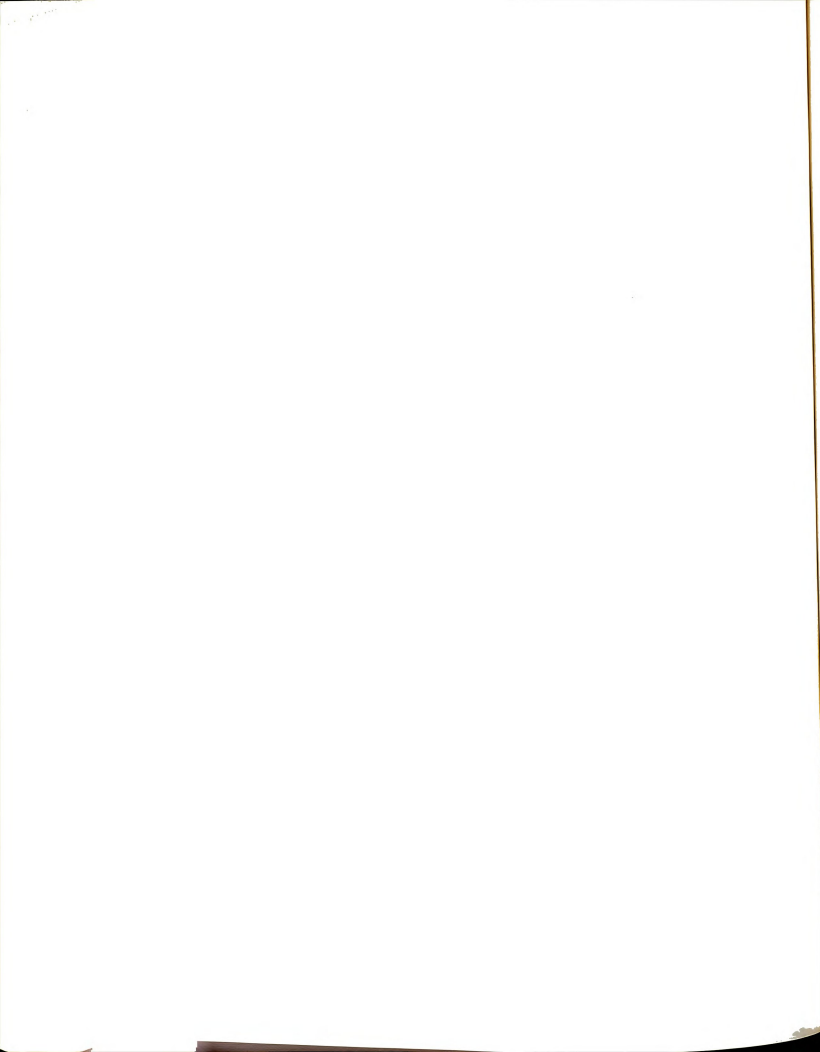
Extensive mathematical literature is devoted to theorems about what sorts of functions can be well approximated by which interpolating functions (Ralston, 1978; Conte, 1980; Press, 1986), but for practical applications in

a simulation model, one wants to look at some special features of the interpolating procedure, such as the shape of the data given in a table format, if there will be extrapolated values.

An important feature that is considered to be the main reason for the choice of an interpolating function is processing time--that is, how long it takes to interpolate one value. In most simulation programs, thousands of interpolations are done, and the interpolation routines are the ones that take a long time to accomplish. Another important feature that should be considered is the error involved in the interpolation procedure.

A trade off between size of the error produced by the interpolation procedure and the time it takes to get the interpolated value is often studied, as well as the importance or sensitivity of the variable to be interpolated in the process of simulation in terms of affecting the model response. Also, the availability of data and the precision of the values in the functional table play a role in deciding the functional form to be used in the interpolating function.

Press (1986) presented several sophisticated polynomial interpolating-function algorithms from which the cubic spline interpolation was derived and used in this research. The cubic spline use a cubic polynomial function whose



coefficients are computed based on the tabulated functional values. The cubic spline is a smooth curve that will go through the points and behave well between observations.

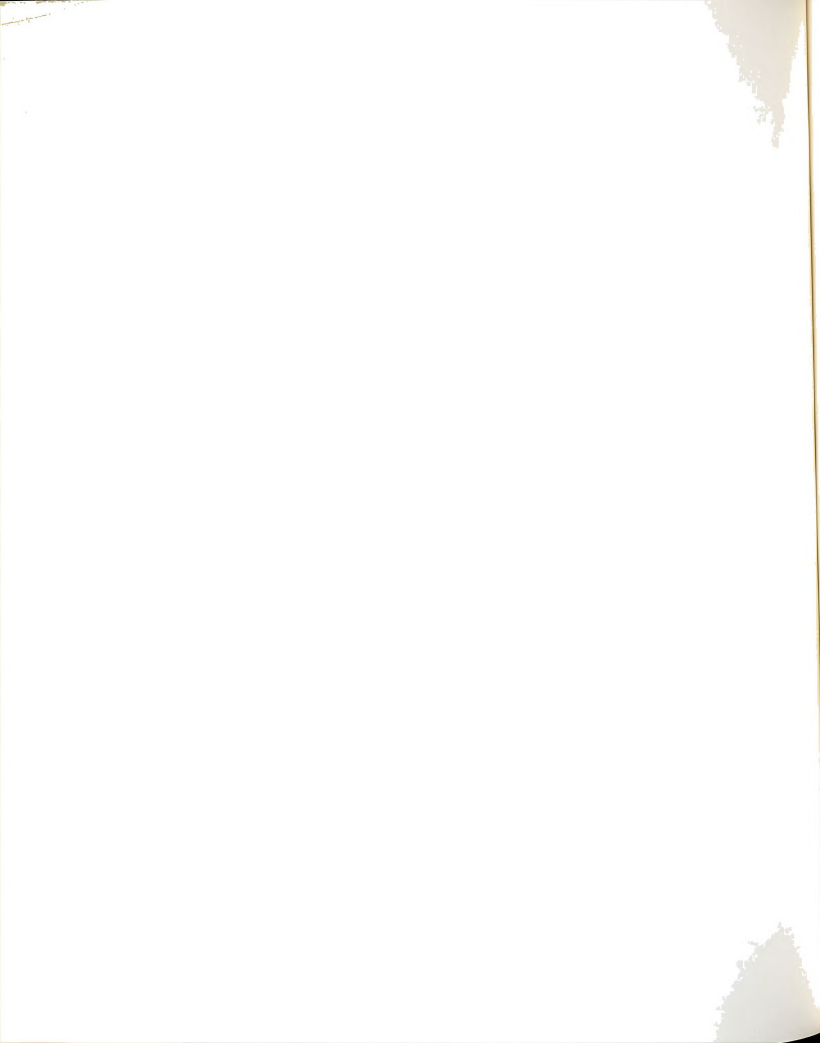
Cubic spline approximation uses a piecewise third-degree polynomial for each set of two adjacent points. The data to be fitted must exhibit a functional relationship; that is, there can be only one $f(x)$ value for each x value, and the x values must be in ascending order.

The computer routine for cubic spline for polynomial interpolation used in this study was derived from Press (1986). A C language code was made and implemented in the simulation model.

```

/*
**      x    = array of x values
**      y    = array of y values of function values
**      n    = number of data points
**      ypl  = first derivative of interpolating point at
**            point l
**      ypn  = second derivative of interpolating point at
**            point n
**      y2   = array of points returned
**
*/
#define MAXDIM 100
spline(x, y, n, ypl, ypn, y2) /* generate vector y2 */
float x[], y[], ypl, ypn, y2[];
int n;
{
    float u[MAXDIM], sig, p, qn, un;
    int i;
    if(ypl > .99e+30)
    {
        y2[0] = 0.0;
        u[0] = 0.0;
    }
    else

```

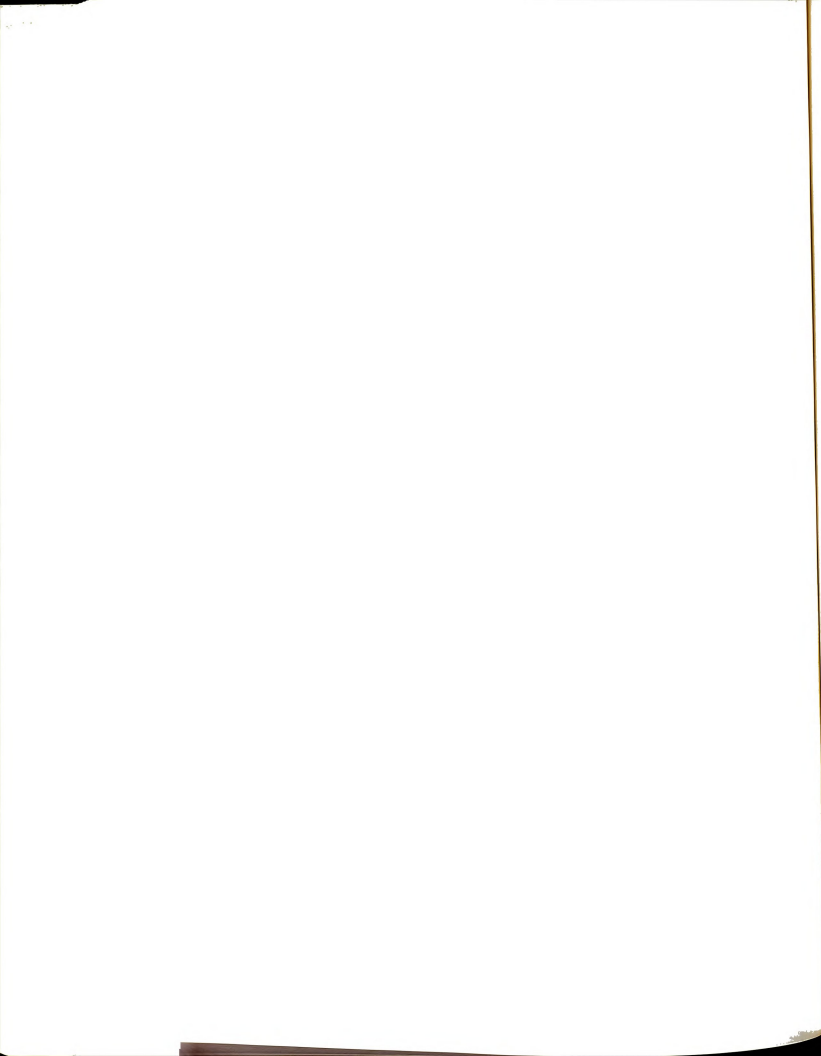


```

{
    y2[0] = -0.5;
    u[0] = (3.0 / (x[1] - x[0])) * ((y[1] - y[0])
        / (x[1] - x[0]) - ypl);
}
for(i = 1; i <= n-2; i++)
{
    sig = (x[i] - x[i-1]) / (x[i+1] - x[i-1]);
    p = sig * y2[i-1] + 2.0;
    y2[i] = (sig - 1.0) / p;
    u[i] = (6.0 * ((y[i+1] - y[i]) / (x[i+1] - x[i])
        - (y[i] - y[i-1]) / (x[i] - x[i-1]))
        / (x[i+1] - x[i-1]) - sig * u[i-1]) / p;
}
if(ypn > .99e+30)
{
    qn = 0.0;
    un = 0.0;
}
else
{
    qn = -0.5;
    un = (3.0 / (x[n-1] - x[n-2])) *
        (ypn - (y[n-1] - y[n-2]) / (x[n-1] - x[n-2]));
}
y2[n-1] = (un - qn * u[n-2]) / (qn * y2[n-2] + 1.0);
for(i = n-2; i >= 0; i--)
{
    y2[i] = y2[i] * y2[i+1] + u[i];
}
}
/*
**      x      = array of x values
**      y      = array of y values of function values
**      n      = number of data points
**      y2     = array of interpolated coefficients
**      yp     = interpolated results
**      xp     = point to be interpolated
**
*/

splint(x, y, y2, n, xp, yp)      /* generated point yp */
float x[], y[], y2[], xp, *yp;
int n;
{
    int klo, khi, k;
    float h, a, b;
    klo = 0;
    khi = n-1;

```

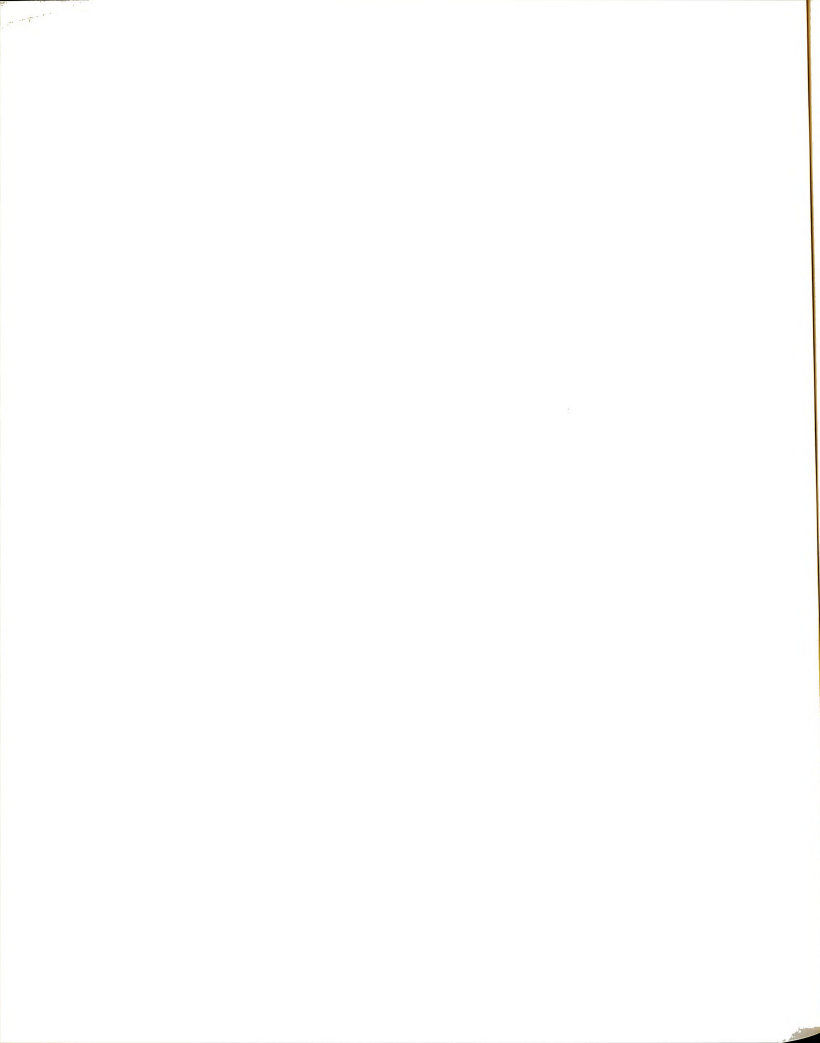
```

while((khi - klo) > 1)
{
    k = (khi+klo) / 2;
    if(x[k] > xp)
    {
        khi = k;
    }
    else
    {
        klo = k;
    }
}
h = x[khi] - x[klo];
if(h == 0.0)
{
    printf("bad x[] input. x[]'s must be distinct");
    exit();
}
a = (x[khi] - xp) / h;
b = (xp - x[klo]) / h;
*yp = a * y[klo] + b * y[khi] + ((a * a * a - a) *
y2[klo] +
    (b * b * b - b) * y2[khi]) * (h * h) / 6.0;
}

```

Also used in the simulation model are the table look-up functions called `Tablie` and `Tablex` Manetsch (1984). `Tablie` for table interpolation and `tablex` for table extrapolation gave more speed to the simulation model (about five to eight times faster), with some increase in the interpolation error, but not to a point where the simulated results were compromised.

Other types of errors, such as data input errors, parameter-estimation error, and so on, overshadow in most cases the error incurred by the choice of not using a more sophisticated polynomial interpolation algorithm, such as the time-consuming cubic spline interpolation function.



The tablex table look-up function was derived from the following relationship (Figure 50), where x_p is the value to be interpolated.

$$\frac{y_p - y_{i-1}}{y_i - y_{i-1}} = \frac{x_p - x_{i-1}}{x_i - x_{i-1}}$$

The interpolated value is given by the formula:

$$y_p = \frac{(y_i - y_{i-1}) * (x_p - x_{i-1})}{(x_i - x_{i-1})} + y_{i-1}$$

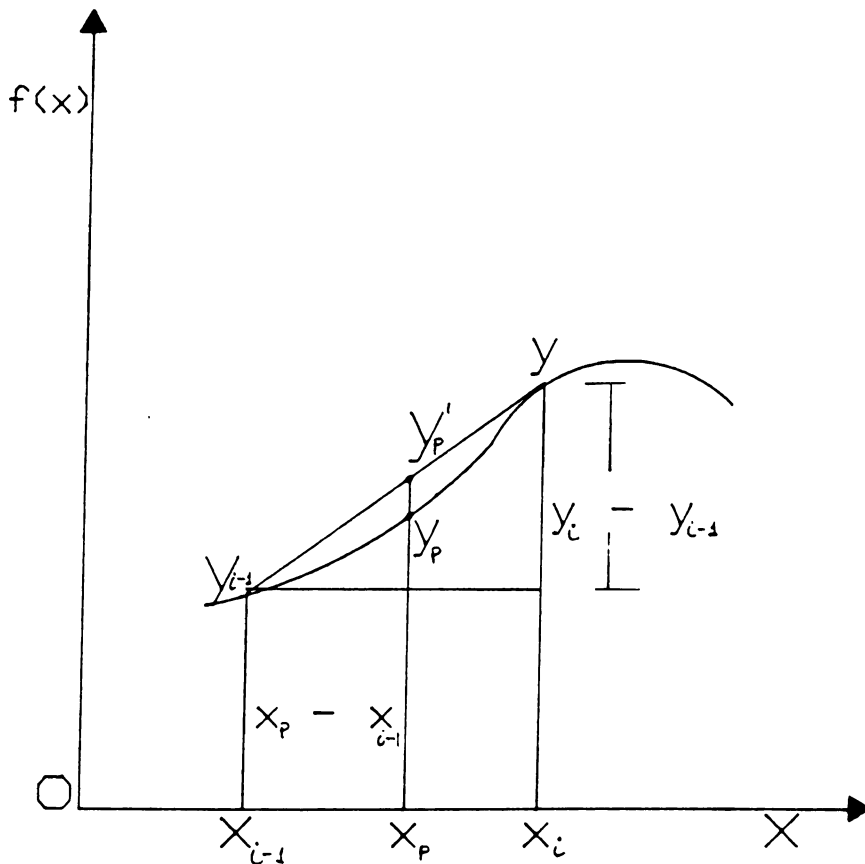
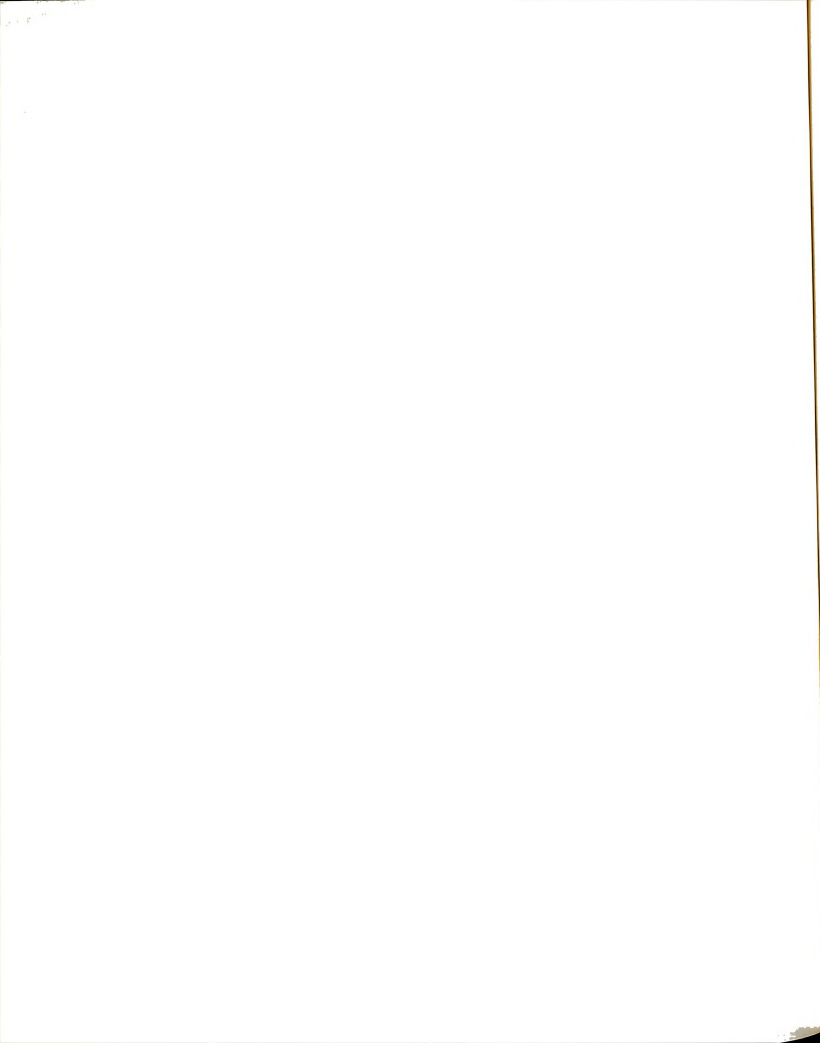


Figure 50. Tablex: Algorithm for functional interpolation.



The C language code for the tabex table look-up function is given as follows:

```

/*
**
**
**
**
**          TABLEX
**
**      This function does table look-up function through
**      interpolation.  Extrapolation is also possible for values
**      of independent variables outside of the given vectors.
**
**      Input:  y      = vector of dependent variables
**              x      = vector of independent variables
**              n      = vector dimension
**              xp     = independent variable to be interpolated
**
**      Output: yp     = valor interpolated (or extrapolated)
**
**
**
**
*/

tabex(x, y, n, xp, yp)
float x[], y[], xp, *yp;
{
    int i;
    for(i = 1; i < n; i++)
    {
        if(xp <= x[i])
        {
            *yp = (xp - x[i-1]) * (y[i] - y[i-1]) /
                  (x[i] - x[i-1]) + y[i-1];
            return;
        }
    }
    i = n - 1;
    *yp = (xp - x[i-1]) * (y[i] - y[i-1]) /
          (x[i] - x[i-1]) + y[i-1];
    return;
}

```


APPENDIX B
NUMERICAL INTEGRATION AND DIFFERENTIATION

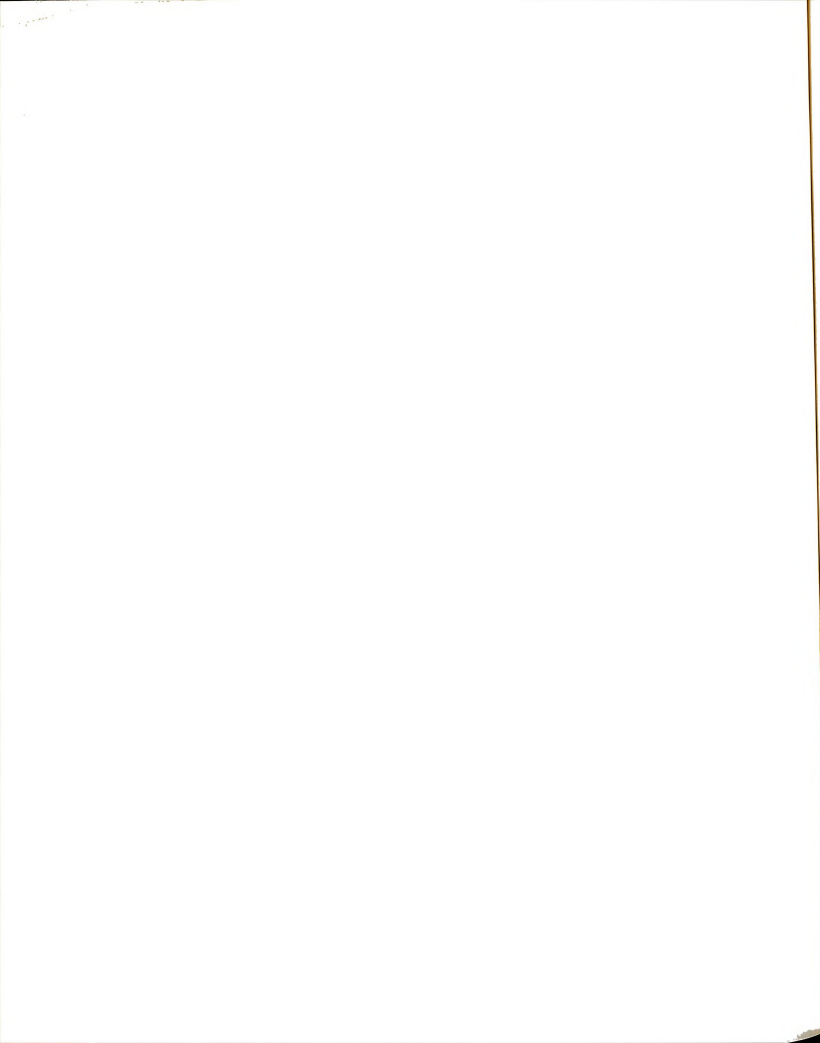
In Appendix A, some techniques for approximating a given function, in a tabular format, by a polynomial by interpolation were presented. Here, a major use of such approximating polynomials is considered: a complicated or a merely tabulated function by an approximating polynomial, so that the fundamental operations of calculus can be performed more easily, or can be performed at all.

Techniques of numerical differentiation and integration are the main focus of almost all numerical calculus books (Hamming, 1962; Conte, 1980; Press, 1986. A common technique used in most simulation models to numerically approximate a differential and integral equation is called numerical integration by Taylor series. The Taylor series about the point $x = x_0$ has the following form:

$$y(x) = y_0 + (x - x_0) * y'(x_0) + \frac{(x - x_0)^2}{2!} * y''(x_0) + \dots$$

where:

$y' = f(x,y)$, and initial condition $y(x_0) = y_0$



The function $f(x,y)$ may be linear or nonlinear and is assumed to be differentiable with respect to both x and y .

To find an approximate solution to the differential equation

$$y' = f(x,y)$$

$$y(a) = y_0$$

over the interval $[a, b]$, the following steps must be followed:

1. Choose a step $h = (b - a)/N$
2. Set $x_n = a + n * h$, for $n = 0, 1, 2, \dots, N$
3. Generate approximations y_n to $y(x_n)$ from the recursion $y_{n+1} = y_n + h * T_k(x_n, y_n)$, for $n = 0, 1, \dots, N-1$

where $T_k(x_n, y_n)$ is the k th term of the Taylor series.

On setting $k = 1$ in the above algorithm, the Euler method and its local error is obtained by the formulas

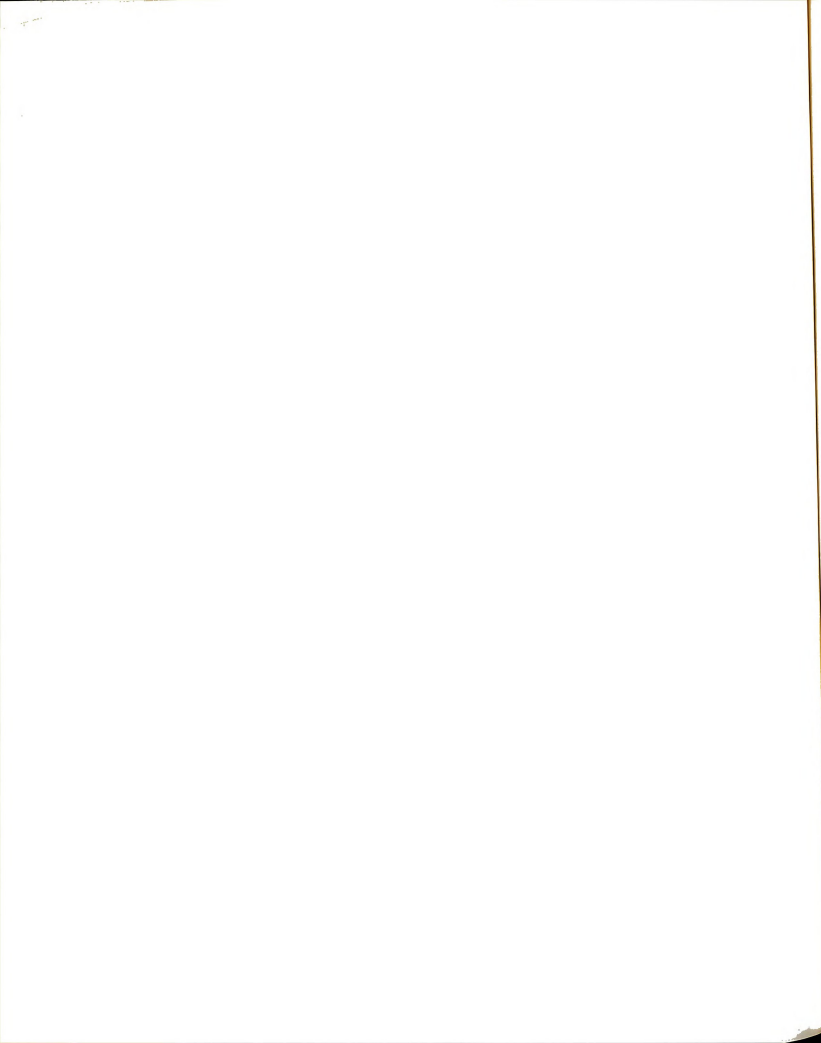
$$y_{n+1} = y_n + h * f(x_n, y_n), \text{ and the local error term}$$

$$E = \frac{h^2}{2} * y''(\theta)$$

The Euler method is the simplest and most commonly used method in simulation work. Several other techniques can be used with the Euler method to improve the interpolated value at a desired precision level. For instance, the predictor-corrector method is commonly used in simulation (Manetsch,

1984) and can greatly improve the results, when needed, of a numerical integration and differentiation numerical approximation.

Again, trade off between precision and time is a problem to be approached by the systems analyst and the model user. The predictor-corrector method is time consuming, and a number of interactions must be computed to achieve the desired approximation level.



APPENDIX C
THE INVERSE TRANSFORMATION METHOD

If one wants to generate random variate x_i 's from a particular population whose density function is given by $f(x)$, the cumulative distribution function $F(x)$ must be obtained (Figure 51).

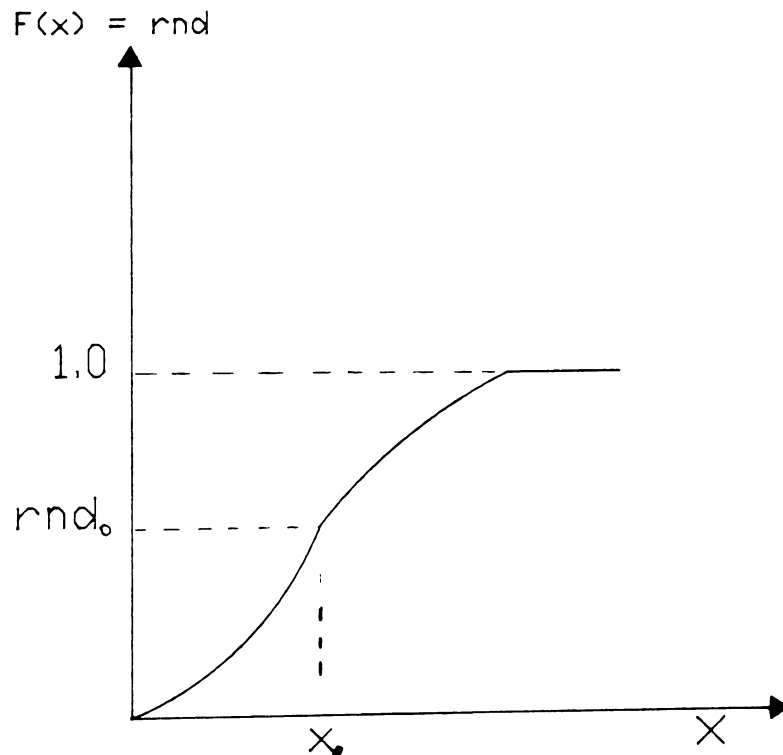
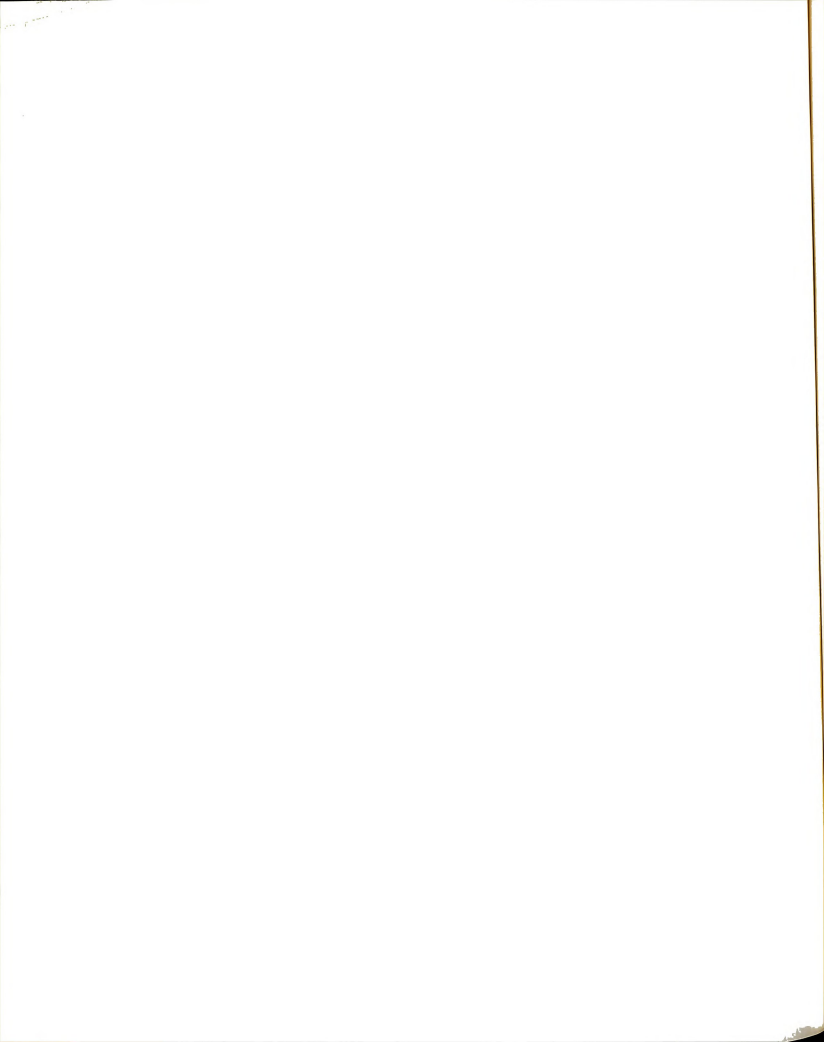


Figure 51. Cumulative distribution function.



Because $F(x)$ is defined over the range 0 to 1, uniformly distributed random numbers (rnd) can be generated and $F(x) = \text{rnd}$. It is clear that x is uniquely determined by $\text{rnd} = F(x)$. It follows, therefore, that for any particular value of rnd , say, rnd_0 , that is generated, it is possible to find the value of x , in this case x_0 , corresponding to rnd_0 by the inverse function of F if it is known. That is,

$$x_0 = F^{-1}(\text{rnd}_0),$$

where $F^{-1}(\text{rnd})$ is the inverse transformation or mapping of rnd on the unit interval into the domain of x .

This method can be summarized mathematically by saying that if one generated uniform random numbers corresponding to a given $F(x)$,

$$\text{rnd} = F(x) = \int_{-\infty}^x f(t) dt$$

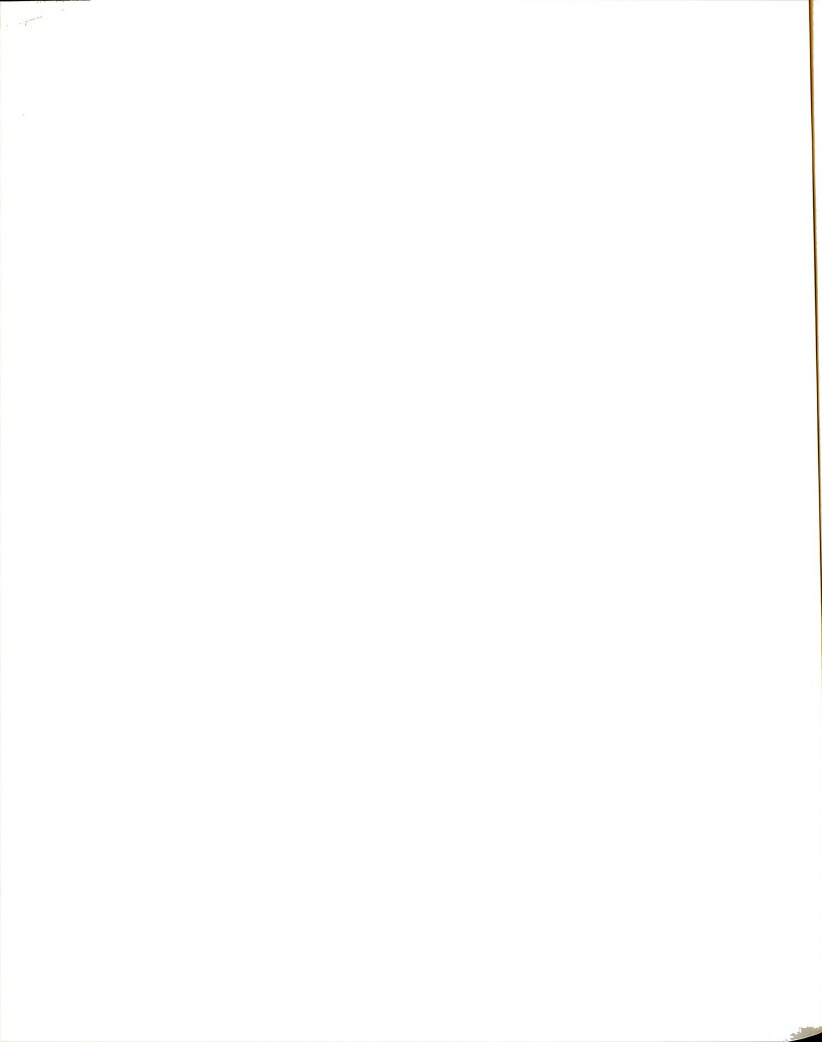
then,

$$P(X \leq x) = F(x) = P[r \leq F(x)] = P[F^{-1}(\text{rnd}) \leq x],$$

and consequently $F^{-1}(\text{rnd})$ is a variate that has $f(x)$ as its probability density function.

The inversion method was applied for the uniform, gamma, normal, and triangular distributions and was used in the simulation model.

The C language code that enables the generation of those random variates is given below:



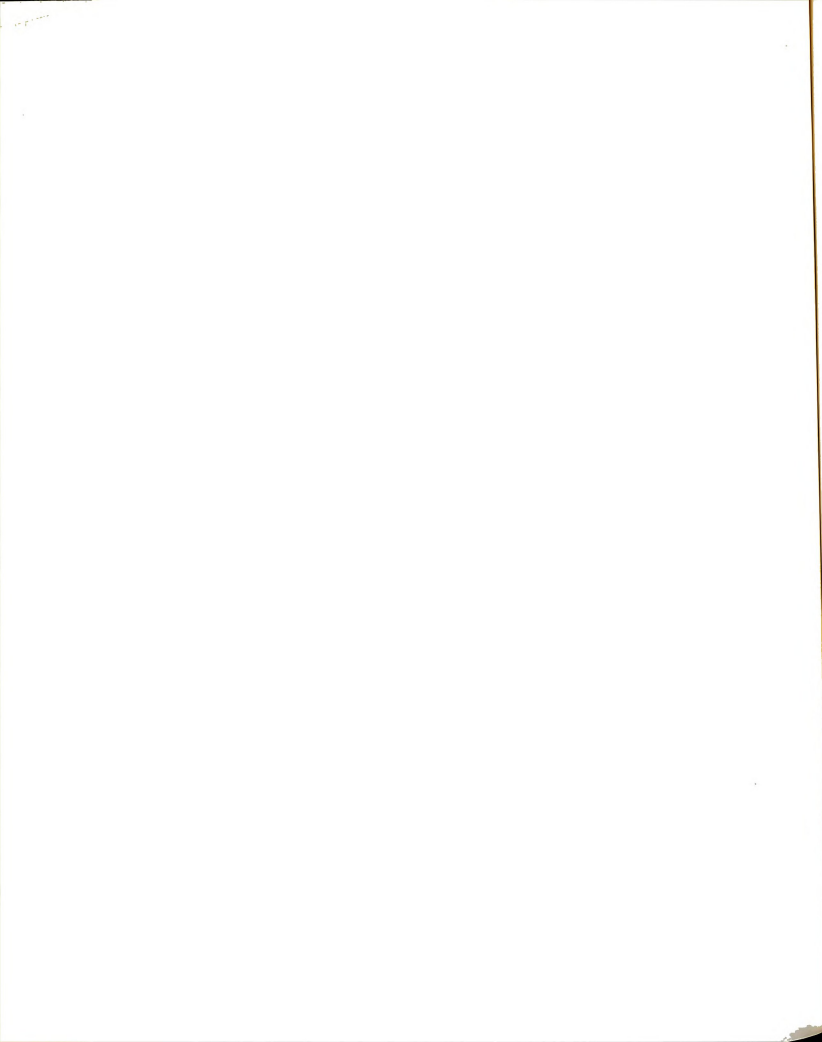
```

/*
**
**                                uniform variates
**
**  Input:  a  =  lower limit of the interval  $a < x < b$ 
**           b  =  upper limit of the interval  $a < x < b$ 
**           seed= seed for the random number generator
**
**  Output: x  =  uniform random variate
**
**  Functions called from here:  none
**
**  Main function must have:  #include <math.h>
**                           #include <limits.h>
**
**
*/

uniform(a, b, seed, x)
float a, b, *x;
short seed[];
{
    double rn, erand48();
    rn  =  erand48(seed);
    *x  =  (float)(a + (b - a) * rn);
}

/*
**
**                                gamma variates
**
**           a  =  k parameter of the gamma distribution  $a > 0$ 
**
**           b  =  alpha parameter of the gamma distribution
**
**           b > 0
**
**  Input: mi  =  mean value
**           var =  variance value
**           seed= seed for the random number generator
**
**           mean      =  a / b
**           variance  =  a / b**2
**
**  Output: x  =  gamma random variable
**
**  Functions called from here:  none
**

```



```

** Main function must have: #include <math.h>
**                          #include <limits.h>
**
**
*/

gamma(mi, var, seed, x)
float mi, var, *x;
short seed[];
{
    float a, b;
    int i;
    double rn, erand48(), lg, log(), tr;
    a = mi * mi / var + 0.5;
    if(a < 1.0)a = 1.0;
    b = mi / var;
    tr = 1.0;
    for(i = 0; i < (int)a; i++)
    {
        rn = erand48(seed);
        tr = tr * rn;
    }
    lg = -log(tr);
    *x = lg / b;
}

/*
**
** normal variate
**
** Input:  mi      = mean value
**         sigma   = standard deviation
**         seed    = seed for the random number generator
**
** Output: x      = normal random variable
**
** Functions called from here: none
**
** Main function must have: #include <math.h>
**                          #include <limits.h>
**
**
*/

normal(mi, sigma, seed, x)
float mi, sigma, *x;
short seed[3];
{
    int i;
    double rn, erand48(), sum;

```



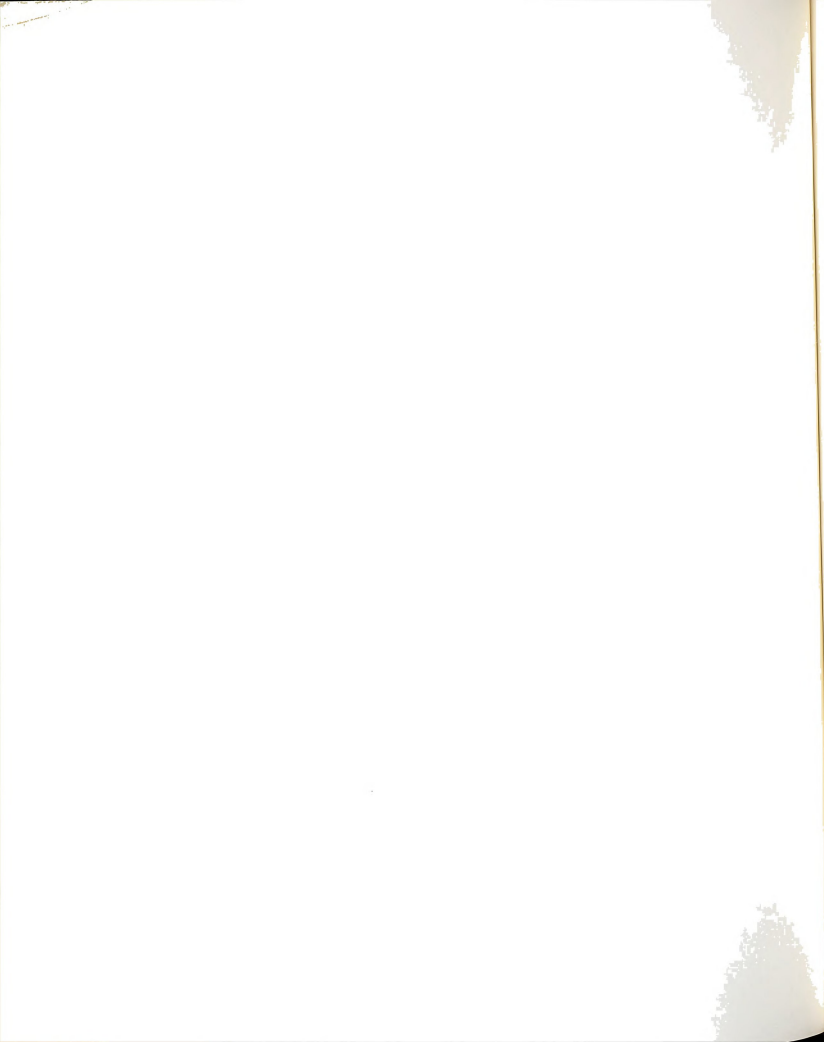
```

sum = 0.0;
for(i = 0; i < 12; i++)
{
    rn = erand48(seed);
    sum = sum + rn;
}
*x = sigma * (sum - 6.0) + mi;
}

/*
**
**
**                               triangular distribution
**
** Input:  a = minimum value
**          b = maximum value
**          c = mode
**          seed= seed for the random number generator
**
** Output: x = triangular random number
**
** Functions called from here: none
**
** Main function must have: #include <math.h>
**                          #include <limits.h>
**                          #include <dos.h>
**                          #include <stdio.h>
**
**
*/
triang(a, b, c, seed, x)
float a, b, c, *x;
short seed[];
{
    double sqrt(), erand48(), rn;
    rn = erand48(seed);
    if(rn < (double)((c - a) / (b - a)))
    {
        *x = a + sqrt(rn * (c - a) * (b - a));
    }
    else
    {
        *x = b - sqrt((1 - rn) * (b - c) * (b - a));
    }
}

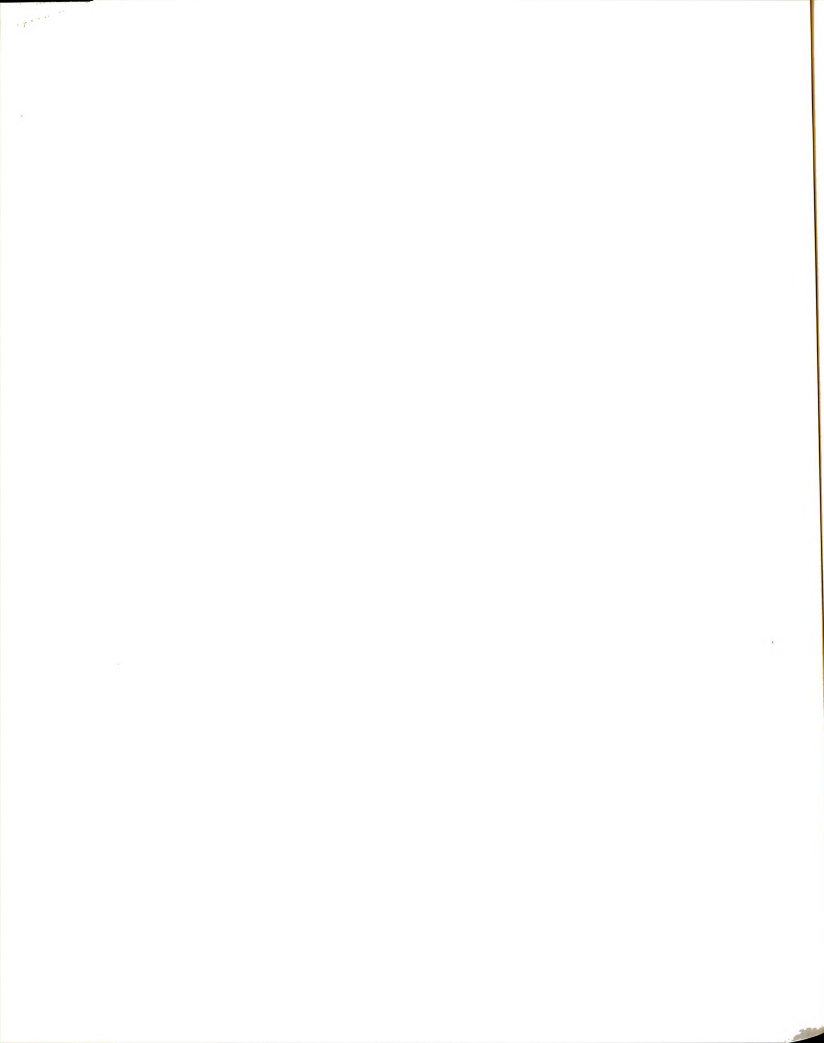
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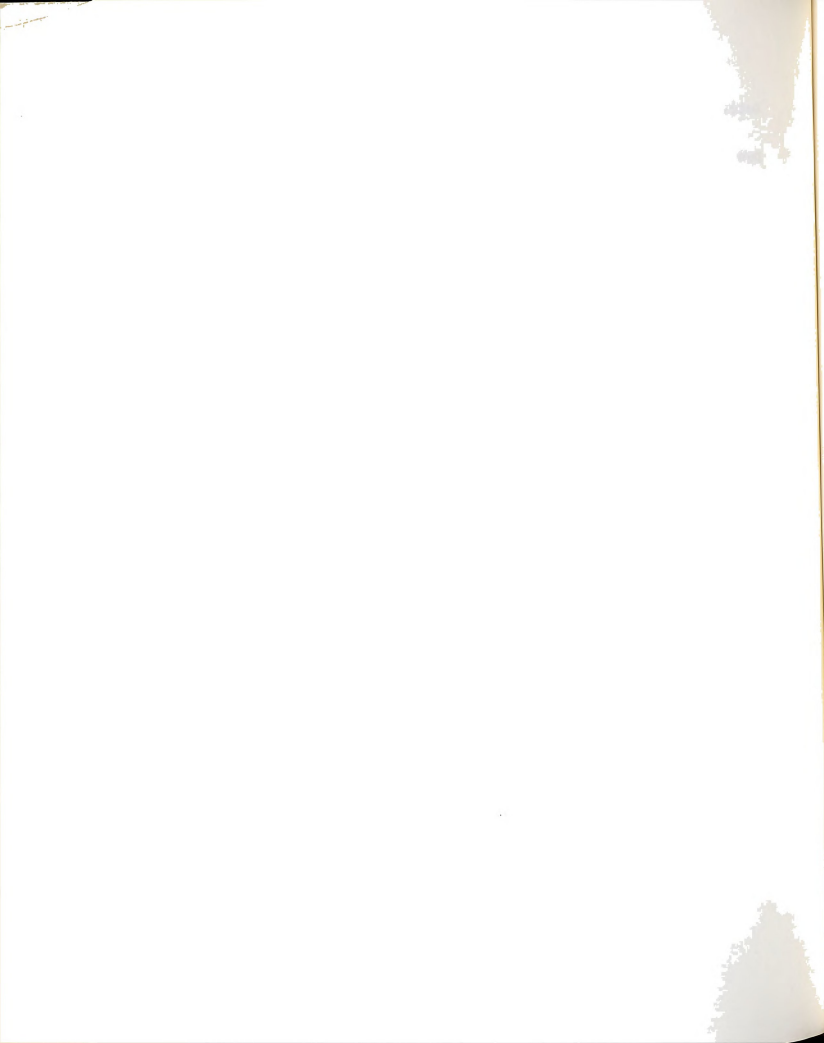
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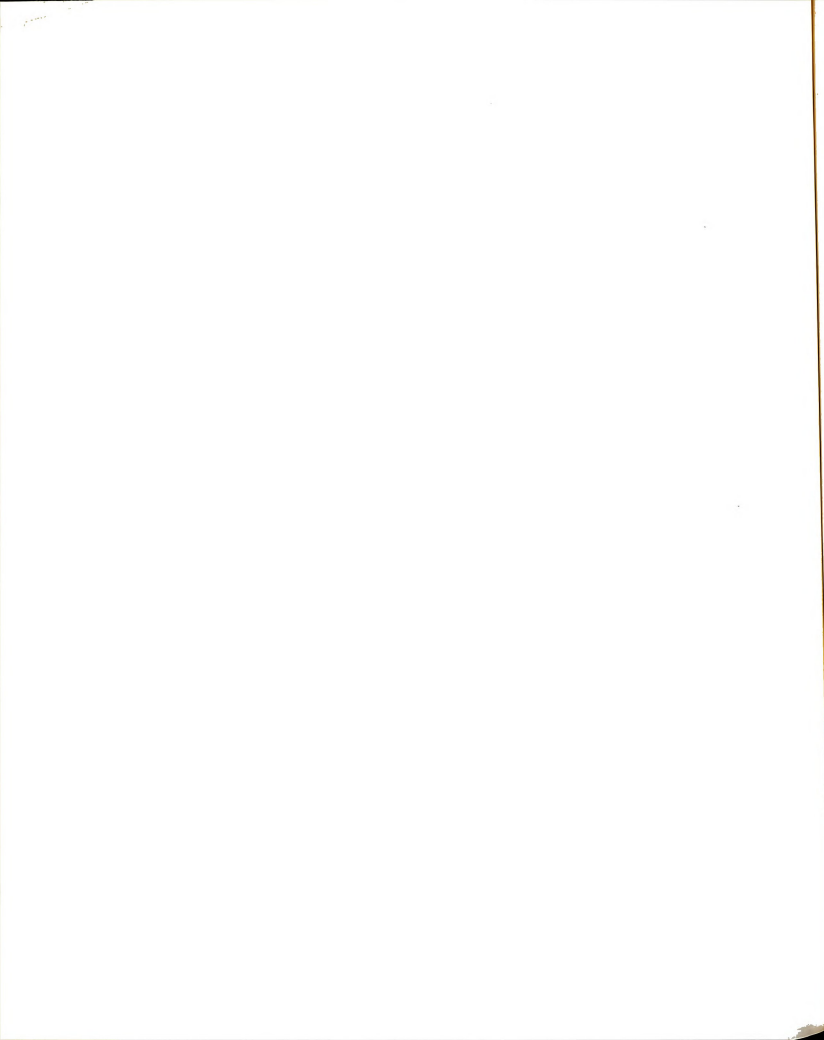


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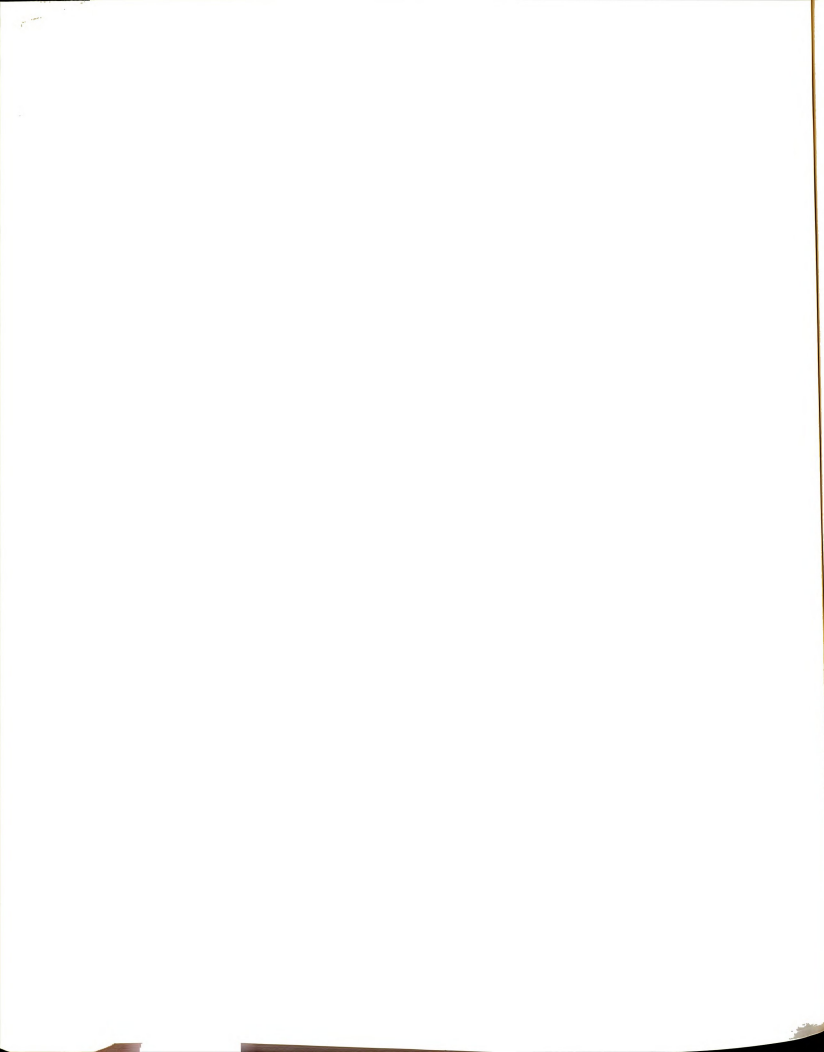
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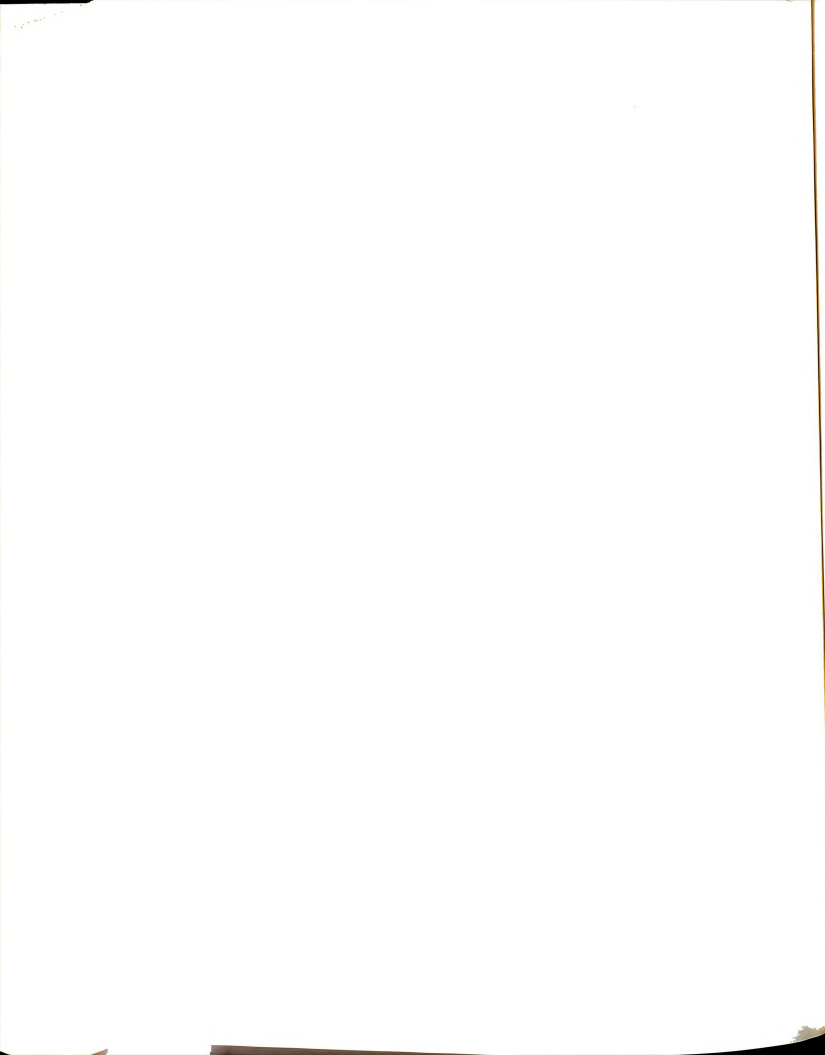
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