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Existing forest site maps have been described as "invaluable tools" in forest management. Their economic value potentially materializes as the summed advantage from better decisions in all phases of forestry.

Via Bayesian decision analysis, this study establishes optimal use and economic value of site information for one facet of management only: The choice of an optimal planting density in Douglas-fir reforestation. Two case studies were undertaken in extremely different environments of Southwestern and Northwestern Oregon.

The prior analysis is based on a review of existing reforestation records and a simulation model. Optimal prior acts differ substantially from present policies. Their implementation may reduce expected costs by approximately $50 per acre.

Based on ecological variables observed on 350 survival plots, prediction aids for first-year survival and site class, the main sources of uncertainty, are established. Plant water relations, and particularly the available water capacity of soils, emerge as prime determinants of survival and productivity.

During preposterior analysis, Bayes' strategy translates ecological knowledge directly into optimal managerial choices for specific site units. Site information is evaluated economically, based on prospective reduction of reforestation costs. Expected values of site information are relatively low and almost identical in both ownerships. In the Northwestern Oregon study, it is a rather uniform environment for reforestation which limits the value of information. In the very diverse environment of the Southwestern Oregon ownership, lower marginal costs for plantation establishment, and smaller opportunity losses set these limits. A larger potential value of site information is likely for activities with high marginal costs in Southwestern Oregon.

Bayesian decision analysis emphasizes the duality of ecology and economics in forest management. Combined with a system of collecting and analyzing operational records, it resembles a traditional forestry approach to uncertainty: Biolley's control method. As an extended, economically, statistically and computationally refined equivalent of the control method, Bayesian decision analysis deserves a place in the theory of forestry and in practical management of our forests.

The Valuation and Use of Site Information for Douglas-fir Reforestation in Western Oregon: A Decision Analysis

by

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DEDICATED TO

Mary Schöne, Jens Schöne, and the forests of the Northwest, with thanks and admiration.

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I. INTRODUCTION

The Conceptual Problem

When one of the first scientific books on forestry was published in 1765, its author, Carl Christoph Oettelt (1730-1800), titled it: "Praktischer Beweis, dass die Mathesis bey dem Forstwesen unentbehrliche Dienste thue" (Practical evidence, that mathematics provides an indispensable service in forestry). In it he uses what may have been one of the first mathematical models in forestry; he approximates tree volume by the formula for the cone. Only one year later the first book on forest economics appears, Wilhelm Gottfried von Moser's "Principles of Forest Economics."

Since then, foresters have lived with mathematical and economic models. They use such approximation whenever they consult a yield table; even more significantly, it is a mathematical model, Christian Hundeshagen's "Normal Forest," that expresses in clear and simple form the very essence of forestry, namely the idea of sustained yield. However, theoretical and economic models have on occasion also created havoc in our forests. When German forests were rebuilt from ruins after centuries of abuse and exploitation, there was no lack of economic knowledge; the first scientifically trained foresters of that period, such as Beckmann (1739-1811), Stahl (1718-1790) and Trunk (1745-1802) were essentially economists. König (1813) and Faustmann (1849) had already derived their famous formula. Yet, in spite of this amazing degree of sophistication, foresters had to look on as forests, created and tended according to these principles, never reached their proposed rotation age because of disease, windthrow, snowbreak, soil degradation or insect plagues; or, spread from these calamities, produced inferior, low-quality products.

Recently, the use of management science models has proliferated in forest management with the advent of operations research and the electronic computer. Acronyms, programs, and models abound; originators become fascinated with their creations, and practical users are carried away by the apparent power of their new tools. The answers to vexing management problems emerge authoritatively from the line printer.

How good are these solutions? Will forest history repeat itself? How, in the first place, could such a simple, generally accepted, and theoretically correct concept as the maximization of the soil expectation value lead, at times, to rather poor results?

In statistical terminology, the problem appears to be one of "lack of fit" in two respects. First, while any mathematical or economic model must necessarily simplify, it must also capture those problem characteristics that are "essential." Omitting key features leads to incorrect solutions at best and to failure at worst.

For one, forest managers face a virtual maze of risk, uncertainty and lack of knowledge. Yet, traditional economic and many more recent, sophisticated operations research models assume perfect knowledge and certainty. In view of a production process that spans decades and perhaps centuries, in view of our limited knowledge about forest ecosystems, and, finally, in view of the probability of uncontrollable man-made or natural disturbances, how useful are solutions to deterministic formulations of the true stochastic problem?

Omission of crucial constraints may be a second reason for "lack of fit" and undesirable consequences. Foresters manage an amazingly complex and sometimes unstable ecosystem. It is essentially given and can be manipulated only within certain limits, the natural constraints. Only within this ecological "space" is there room for management science solutions. Thus, for better fit, formulations and solutions should vary by ecosystem, or, in practical terms, by site.

Ever since Wilhelm Pfeil (1783-1863) rejected the broad, uniformly applied general management prescriptions of his time in favor of site-specific management, forest site has meant more than a rough description of an ecosystem by the sum total of significant edaphic and atmospheric variables. It became a key to management opportunities and limitations for a specific parcel of land, a key to the variability of an entire forest and, therefore, a key to the fascinating duality of ecology and economics in forest management.

The overall forest production process, then, is far less random than we might assume initially. Its variability decreases, as only specific sites are considered. By the same reasoning, its predictability improves. The total value of site exploration potentially materializes in the form of better decisions in each phase of the management regime, from regeneration to harvest, and in the organization of the forest enterprise as a whole.

Faustmann's followers in the early 19th century, under the influence of neo-classical economic theory, failed to consider risk and uncertainty. At the very beginning of scientific forestry, they simply lacked ecological knowledge. Today, nearly 200 years later, our decision tools possess amazing power. We have accumulated more knowledge about the forest ecosystem, and we had the chance to learn from practical success and failure.

Perhaps unfortunately, we have also turned into specialists as forest biologists, economists, or management foresters. We have started to talk different tongues, and think along differing paths. Communication has become a problem. The temptation lies in following established, routine procedures on the one hand, and in sophisticated but one-sided, perhaps impractical, solutions on the other. Practical, feasible, integrated economic and ecological approaches are the challenge.

The Practical Problem

The need for such an integrated, practical approach appears particularly urgent for some reforestation problems in Western Oregon. Each year, Oregon's public and private forest owners invest approximately 36 million dollars to regenerate an estimated 180,000 acres of recently cutover land. Some incur additional and, proportionally, even higher expenses when they rehabilitate segments of those 550,000 acres in the Coast Range alone which were classified as "non- or severely understocked" (Oregon State Department of Forestry, 1977).

Reforestation success varies considerably, both within and between major vegetational zones in Western Oregon. A preliminary survey of plantation records for state-owned forest lands in Northwestern Oregon indicated that first-year survival varied between 20% and 100% for individual plantations. Most areas were interplanted two to three times; some units received none, others as many as seven replants in ten years. It is not only financially but environmentally significant that herbicide use increased with the number of retreatments. Not all plantations present problems, however, and districts currently face a backlog of stands in need of precommercial thinning.

In Southwestern Oregon, characterized by generally harsher growing conditions and a larger climatic and geological variability, forest managers confront an even greater challenge than their colleagues in the humid and more uniform Northwestern area. What is the correct planting density for clearcuts that precludes regeneration lag on the one hand, and overstocking in the other extreme?

In both areas, the problem is compounded by uncertainty about potential site productivity, which tends to accentuate the financial effects of regeneration lag. In conversion projects, it determines the rate of return. Clearly, methods to predict both seedling mortality and site index for specific areas would aid in rational management.

Such predictions, based on biological models, are only a first step in an integrated solution. They must be translated into operational strategies, economically sound managerial practice for a given site. Given ecological forecasts for a specific area, what constitutes an optimal policy? How much expense is justified in the development and acquisition of the forecast information? How much, and what site information should be collected? Finally, where, geographically, are the priorities for site mapping?

Decision Analysis Prospect

Any solution technique for the previously stated conceptual problem, and any specific solution to our practical reforestation problem, should provide for the risks and uncertainties of the production process. Optimal policies must be site specific. Finally, we wish not only to apply, but to value various intensities and kinds of information.

Decision analysis, not really a rigid mathematical model, but rather a logical, consistent procedure for selecting among risky choices, uniquely fits our purpose. We will see in the following chapters that it bridges a crucial gap by translating scientific findings into prescriptions for managerial actions. Moreover, it formalizes and incorporates previously existing concepts into a broad, generally applicable approach to forest management problems.

Finally, it is perhaps worth noting that one of the most important components of decision analysis, namely Bayes' theorem, dates back more than 200 years, to 1763. Its emergence thus neatly coincides with the appearance of those books mentioned at the beginning of this somewhat philosophical but, I believe, necessary perspective of a topic with rather technical and practical objectives.

II. OBJECTIVES

Existing forest site maps have frequently been described as "invaluable tools" in forest management. It is my objective to determine optimal use and economic value of forest site information for the artificial regeneration of Douglas-fir (Pseudotsuga menziesii (Mirb.) Franco), as a function of mapping intensity for two environmentally extreme regions in western Oregon.

This objective requires establishment of ecological models which relate Douglas-fir productivity and seedling survival to easily observed environmental variables.

It further requires an economic model which indicates optimal use of site information, and which yields its value as the difference between expected revenues with and without this information.

III. THE GENERAL MODEL OF DISCRETE DECISION ANALYSIS WITH LINEAR UTILITY FOR MONEY

Expository, Simplistic Formulation of the Reforestation Problem

Prior Analysis

A large public forest ownership has established a target stocking rate of 450 trees per acre for Douglas-fir plantations. Stocking surveys indicate, however, that many young stands fail to meet this goal. The management planning specialist must determine whether to continue a present policy of planting 500 seedlings to the acre, or to raise planting density to 700 trees per acre.

The consequence of any policy will be a function of both the "acts," namely, the rate chosen, and the "state of nature," that is, the actual but *a priori* unknown seedling survival. Total costs are at a minimum when the lower planting density coincides with high survival. In all other instances, additional expenses arise. After computing these, the analyst summarizes the problem conveniently in the form of a "payoff matrix," in our case, actually a table for additional costs (Table 1). A cost-minimizing objective function appears appropriate.

Bent on avoiding the worst, one decision maker chooses the density, which surely will minimize the maximum possible cost; he applies what is known as the "minimax criterion," and plants 700 trees to the acre. In a more optimistic frame of mind, he might instead use the "minimin criterion," and focus on minimizing the lowest possible total cost. Now he would settle on a density of 500. Being slightly more realistic, the analyst progresses to simply averaging consequences for each action alternative, thus weighing each outcome equally and implying that both states of nature occur with equal frequency. He has now arrived at the "principle of insufficient reason," or the "Laplace criterion," with an optimal planting

TABLE 1. The Simplistic Formulation.

Prior Analysis

(Table entries represent additional costs in $ per acre)

States of Nature	Acts: Plant 500/acre	Plant 700/acre	Prior Probability
Survival high	0	160	0.75
Survival low	200	70	0.25
Expected value	50	137.5	

Optimal prior act	Plant 500
Expected cost with prior information only:	$ 50.00
Expected cost with perfect information:	$ 17.50
Expected value of perfect information:	$ 32.50

rate of 500. Conceptually, he has calculated an "expected value" by assigning weights and probabilities, in our case, equal probabilities, to the states of nature and their consequences.

Are the states of nature really equally likely? Is there sufficient reason to refute this "diffuse" prior probability distribution? Clearly, since the analysis aims at optimizing the process for the future, no "objective" probabilities can be established; they may not even be available for the past, since incomplete records were kept, and since clearcut location was anything but random. Using any and all information available, the planning specialist examines past and, unfortunately, scanty stocking surveys, compares notes with colleagues, calls on his experience and intuition, and, finally, assigns "conviction weights" in the form of subjective, judgmental probabilities to the states of nature.

He has now defined the components necessary for a preliminary or "a priori" solution: Acts, states of nature, payoffs and prior probabilities. After computing expected values for each act, he identifies the optimal prior act by its minimum expected value and has now completed the "prior analysis" (Table 1).

With perfect knowledge of future survival he could adjust planting densities to survival and reduce overall total costs; uncertainty, in other words, is a costly input. How much could we afford to pay a "clairvoyant" for a perfect survival prediction? We calculate the expected value with perfect information by selecting the optimal act for each possible state of nature, and by weighting the associated cost by the respective prior probability. Comparing this value with the expected value of the prior, optimal decision, we obtain the expected value of perfect information; in essence, a "research ceiling," since, realistically, any possible information will be less than perfect.

Preposterior Analysis

A consultant approaches the decision maker and, in addition to his fee schedule, supplies him with his "track record" for past performance in survival prediction. Should the expert be hired? From the data provided, the analyst estimates--again subjectively--the only additional input needed, namely the "likelihoods." He then applies Bayes' theorem to revise the prior distribution for each possible prediction (Table 2).

Using this set of "posterior" distributions, he computes expected values for each act and each prediction (Table 3). The so-called "Bayes' strategy" assigns an optimal act to each possible forecast signal. We now weight each optimum by the associated, marginal probability of the forecast, and arrive at the expected value of Bayes' strategy; that is, we compute the expected value with imperfect information.

By contrasting this value with the cost of the optimum prior act, we can decide if the information offered by the consultant will be worth his fees, even before receiving the experts actual forecast we have computed, *ex ante*, its expected value to us. Thus, we have carried out the so-called "preposterior analysis."

Mathematical Formulation

Basic symbols are:

a_j = the j^{th} act, $j = 1,2,\ldots,n$

Θ_i = the i^{th} state of nature, $i = 1,2,\ldots,m$

$P(\Theta_i)$ = the prior probability of Θ_i

x_{ij} = the consequence associated with act j when the true state of nature is i

$EV(\cdot)$ = the expected value of $(\cdot)$

Z_k = the k^{th} forecast signal, $k = 1,2,\ldots,s$

TABLE 2. Revision of Prior Probabilities by Bayes' Theorem.

$$\text{Bayes' theorem:} \quad P(S_i/Z\ ) = \frac{P(Z_k/S_i) \cdot P(S_i)}{\sum\limits_i P(Z_k/S_i) \cdot P(S_i)} = \frac{P(Z_k S_i)}{P(Z_k)}$$

States of Nature	Prior Probabilities $P(S_i)$	Likelihoods $[P(Z_k/S_i)]$		Joint Probabilities $[P(Z_k S_i)]$	
		Z_{high}	Z_{low}	Z_{high}	Z_{low}
Survival high (1)	0.75	0.9	0.1	0.675	0.075
Survival low (2)	0.25	0.2	0.8	0.050	0.200
Marginal probabilities for the predictions $P(Z_k)$				0.725	0.275

Symbols:

S_i = actual survival class i; i = 1,2

Z_k = predicted survival class k; k = 1,2

Posterior Probabilities $[P(S_i/Z_k)]$

	Z_{high}	Z_{low}
Survival high (1)	0.93	0.272
Survival low (2)	0.07	0.728

TABLE 3. Preposterior Analysis.

States of Nature	Act: Plant 500	Act: Plant 700	Posterior Probabilities Z_{high}	Posterior Probabilities Z_{low}
Survival high	0	160	0.93	0.272
Survival low	200	70	0.07	0.728

Expected Cost Matrix

	Z_{high}	Z_{low}
Plant 500	14.0*	145.6
Plant 700	153.7	94.5*
Marginal Probability for prediction:	0.725	0.275
Bayes' Strategy:	Plant 500	Plant 700

"*" indicates optimal value for each prediction

Expected cost with information: $36.14

Expected cost of prior optimal act: 50.00

Expected value of sample information: 13.86

$P(Z_k/\Theta_i)$ = the conditional probability or "likelihood" of obtaining forecast signal k when the true state is i

$P(\Theta_i/Z_k)$ = the conditional, posterior probability that the state of nature i will occur after the forecast k is received

C = the cost of the forecast device which generates the set $\{Z_k\}$ of possible signals

$P(Z_k)$ = the marginal probability of obtaining signal k

A single asterisk will be used to denote optimality with respect to prior probabilities, e.g., a_j^* , and a double asterisk with respect to posterior probabilities, e.g., a_j^{**}. A perfect forecast and its associated optimal act will be labeled by a prime, e.g., Z_k' or a_j' . The objective of profit maximization is assumed in the following; the extension to a cost minimization goal is straightforward. Underlined quantities represent vectors or matrices.

Prior Analysis

The expected value of the j^{th} act, without forecast information, is:

$$EV(a_j) = \sum_{i=1}^{m} x_{ij} P(\Theta_i)$$

The analyst chooses the optimal prior act such that

$$EV^* = EV(a_j^*) = \max_j[EV(a_j)] = \max_j \left[\sum_{i=1}^{m} x_{ij} \cdot P(\Theta_i)\right]$$

$\underline{EV}$ is 1 x n

Suppose a perfect forecast device is available. There will be one, and only one, signal for each state of nature, and

$$P(Z_k) = P(\Theta_i) \qquad \text{if } k = i$$

$$P(Z_k) = 0 \qquad \text{if } k \neq i$$

and

$$m = s$$

With the perfect forecast, the decision maker would select for each possible signal an alternative, a_j', such that

$$x_{ij}' = \max_j[x_{ij}] \qquad \text{for } i = 1,2,\ldots m$$

The expected value of this strategy, <u>a priori</u>, is:

$$EV' = \sum_{i=1}^{m} x_{ij}' \cdot P(\Theta_i) = \sum_{i=1}^{m} (\max_j[x_{ij}]) \cdot P(\Theta_i)$$

We obtain an expected value of perfect information, EVPI:

$$EVPI = EV' - EV^*$$

<u>Revision of Prior Probabilities</u>

Now suppose an imperfect predictive device is available. For each possible prediction, there will be a different, revised distribution over the states of nature.

By Bayes' theorem:

$$P(\Theta_i/Z_k) = \frac{P(Z_k/\Theta_i) \cdot P(\Theta_i)}{\sum_{i=1}^{m} P(Z_k/\Theta_i) \cdot P(\Theta_i)} = \frac{P(Z_k,\Theta_i)}{P(Z_k)}$$

since

$$P(Z_k/\Theta_i) \cdot P(\Theta_i) = P(Z_k,\Theta_i)$$

and since

$$\sum_{i=1}^{m} P(Z_k/\Theta_i) \cdot P(\Theta_i) = P(Z_k)$$

The matrix of posterior probabilities is of dimension m x s, as is the matrix of likelihoods. The marginal probabilities $P(Z_k)$ form a vector with dimension 1 x s.

<u>Preposterior Analysis</u>

For each $\{Z_k, a_j\}$

$$EV(a_j) = \sum_{i=1}^{m} x_{ij} \cdot P(\Theta_i/Z_k)$$

The matrix of expected values has dimension n x s

Denoting $\left(a_j^{**}/Z_k\right)$ as a_{jk}^{**}

$$EV(a_{jk}^{**}) = \max_j[EV(a_j)]$$

Bayes' strategy for the ordered set $\{Z_k\}$ is $\underline{a}^{**}$ of dimension 1 x s. The probability for each a_{jk}^{**} to be taken equals $P(Z_k)$. The expected value of Bayes' strategy is:

$$EV^{**} = \underline{a}^{**} \cdot \underline{P}^T(Z_k)$$

where T indicates the transposed vector

The expected value of sample information, EVSI, is

$$EVSI = EV^{**} - EV^{*}$$

The expected net gain from sampling, ENGS, is

$$ENGS = EVSI - C$$

Decision rule:

Purchase information, if ENGS > 0

IV. REVIEW OF THE LITERATURE

Prospect

From the pèle-mêle of ideas from the fields of forest management, operations research, statistics and, last but not least, soil science, I attempt in the following to highlight only a few, essential concepts, hopefully without ever obstructing the view of the role of these concepts in the following decision analysis.

In keeping with the spirit of my research topic, I admit to purpose, bias, belief and personal utility in the selection and treatment of review topics. There have been previous studies of decision analysis in forestry, hence I propose to treat subjects lightly or not at all, which have already received forestry attention (e.g., Thompson, 1966).

Instead, I will focus on items which, in my mind, should transgress the interdisciplinary boundaries and diffuse into practical forest management.

First, I attempt to sketch an outline of decision theory onto a background of conventional treatments of risk and uncertainty, and show its potential.

Traditional Treatment of Risk and Uncertainty in Forest Management

One reaction to risk is to simply ignore it. In management planning, Hartig (1795) provides a classic and flagrant example. His harvest schedules span an entire rotation; revisions are explicitly "verboten." Other classics acted less "Prussian." Pfeil and Cotta acknowledge the uncertainties of the future, and concede little trust in yield forecasts (Baader, 1942:244-245). More recent plans usually employ 10-year planning horizons, with provisions for even earlier reviews.

In addition to frequent replanning, current management plans cope with uncertainty by reserving options. They "hedge" by striving for high inventory levels and, to some extent, by favoring well-dispersed age-acre arrays (Bell and Fight, 1977). Plans may even be conditional on uncertain events: contingency plans.

While a perceived low overall risk once helped justify the classic, low "forestry interest rate" of 3% (Speidel, 1967:105), several more recent studies have indicated the need for surprisingly high risk allowances. Speidel (1967:67) provides numerical estimates, and Germann(1975) has summarized relevant results. The magnitude of the problem usually escapes detection in view of "the vast expanse of our forests"; moreover, losses "fail to sum up visibly in our records" (Mülder, 1951).

Managers may react by practicing risk reduction, risk dispersion, or various forms of risk sharing (Speidel, 1967). In addition to obvious examples, such as seedling protection, species mix or fire insurance, some are less distinct. Since risks are sometimes age-class specific, a long rotation may be seen as a means of risk dispersion (Speidel, 1967; Bell and Fight, 1977), and because some risks are also site-specific, site mapping serves the purpose of risk reduction. Quantitative measures of risk for various sites are scarce (German, 1975), but numerous qualitative associations have been established (Youngberg, 1955; Lemmon, 1958; Lloyd et al., 1956; Buongiorno, 1972; Depta, 1975; Thomas and Burroughs, 1975; Mason and Tigner, 1972; Ruth, 1957; McNutt, 1976).

By now it should be apparent that practical forestry has recognized and responded, for the most part, to risk and uncertainty; it should also be obvious that this occurred without the aid of traditional forest economics theory (Thompson, 1966). What constitutes an optimal mix of tree species in light of different productivities and risk susceptibilities? Under which circumstances should we protect or shade seedlings? Does it pay to reduce overall risk of an ownership by lengthening the rotation? What should this rotation be?

The latter problem is such a "cause célèbre" in forestry that some reflections from the perspective of risk and uncertainty appear justified. Gregory (1972) establishes soil expectation value as a valid criterion for determining rotation length, and in no uncertain terms, condemns the forest rent approach: "The idea is, admittedly, appealing in its simplicity. Unfortunately, it is bad economics, bad business, and bad forestry" (p. 294). Yet, when Gregory (1972) acknowledges uncertainty, and introduces it in a sensitivity analysis, optimal rotations vary by decades as a function of cost, yield and price assumptions. No theoretical solution is offered. But, it is exactly for reasons of risk, uncertainty and non-acceptance of the single profit maximizing criterion that most European foresters reject the Faustmann model (Speidel, 1967:19). In practice, they prefer the forest rent approach, not for theoretical reasons, but simply because resulting rotations and inventory levels appear more in line with realistic requirements and experience. In short, "the exact solution to the approximate problem is not as good as the approximate solution to the exact problem" (Carter, 1972). I believe that decision analysis will eventually provide an answer to this vexing theoretical problem.

There is at least one formal body of knowledge in forestry that specifically acknowledges uncertainty, and deals with it systematically. I am speaking of the control method. The "méthode du contrôl" (Biolley, 1920) rejects the deterministic, deductive approach to harvest scheduling and growing stock regulation. Instead, optimal growing conditions for a forest are established inductively, by trial and error, that is by a continuous process of monitoring. The conventional control method has serious statistical shortcomings (Prodan, 1965), but, freed from the narrow mensurational and silvicultural context, the underlying concept is literally "operations research"; it forms the core of modern management planning procedures (Henne, 1973), and, as we shall see, systematic application of decision analysis in practical forest management is merely an extension of, a refinement to, or a complement to this old idea.

Thus, foresters have recognized risk and uncertainty and have adapted, but from a practical point of view only. There is room and need for correct theoretical treatment. A promising approach is outlined next.

Decision Analysis: Concepts, Implications, Applications

Bayesian decision theory, once merely a controversial subject in theoretical statistics (Hartley, 1963; Bross, 1969), has become a popular topic in disciplines that ranges from psychology, sociology, economics and law, over the management sciences and business, into areas such as medicine, meteorology, agriculture, horticulture, entomology, pathology and forestry. As a consequence, the respective literature has assumed intimidating proportions. Complete coverage may be found in excellent books such as Winkler (1972), Halter and Dean (1971), Anderson et al.

(1977), or in classic references, such as Hadley (1967), Raiffa (1968), Schlaifer (1969), Chernoff and Moses (1959), as well as in numerous reviews (Dillon, 1971; Hampton et al., 1973; Tversky and Kahneman, 1974; Slovic et al., 1977; Swindel, 1972; Hirshleifer and Riley, 1979; Anderson and Hardaker, 1972; Hogarth, 1975).

In the following, I will merely explore facets of the entire framework, which appear crucial for forestry applications: The concept of subjective probability, the derivation of likelihoods, the potentials of Bayes' theorem, and the controversy surrounding it. Utility theory, the complement to subjective probability, is admittedly underexposed.

I will briefly focus on the relationship decision analyst-decision maker, which, in forestry, assumes special connotations. Finally, extensions of the general model, and interrelationships with other operations research models are at least pointed out to provide perspective and overlap.

Let us progress to judgmental probabilities, the crux and hub of decision theory.

Subjective Probability

Since the use of personal probabilities is a crucial and useful, but apparently still controversial (Swindel, 1972), facet in forestry decision analysis, and since "the notion of subjective probability runs against the grain of those raised on objective frequencies" (Dillon, 1971), the concept is reviewed in some detail below.

A priori, probabilities have no meaning whatsoever. They can be developed as an abstract system based on certain axioms. The entire probability model consists of relations among numbers which happen to be called probabilities, and the rules for calculating with these numbers (Winkler, 1972).

This system, however, has several real world interpretations. Classical or logical probabilities have been defined, originally by Laplace or Cardano (Hampton et al., 1973; Raiffa, 1968), as the ratio of the number of favorable outcomes to the total number of possible, equally likely outcomes. They can be found by logically considering the possible events in the usual urn-experiments, coin-flipping, or in games of chance. For most practical decisions, we cannot deduce such simple, a priori probabilities.

The so-called "objective" probabilities have been defined by Venn (Hampton et al., 1973) and Poisson (Raiffa, 1968) for "the long run," as infinite limits of relative frequencies. They are "posterior" probabilities, found only after an infinite number of trials under constant conditions. However, some situations are clearly non-repetitive, hence the empirical definition is totally inapplicable. In other cases, we may possess long-run frequencies. Strictly speaking, however, "objective" probabilities must remain a myth by their very definition.

We are left with the personal interpretation of probability, where "subjective probability does not describe the real world, but instead expresses our uncertainty about the world" (Tani, 1978). In brief, subjective probabilities represent conviction weights, degrees of belief, our quantified judgment about the state of the world. Our judgment obeys the rules and axioms of mathematical probability.

This meaning or use of probability, while perhaps less intuitive to most people, is by no means less respectable, and perhaps as old as other interpretations. It was recognized by Daniel Bernoulli (1713), and later expanded by Ramsey (1926) and by von Neumann and Morgenstern (Raiffa, 1968). A first, apparently successful application of the subjective judgmental concept in fire weather forecasting for forestry is reported by Schroeder (1954). It can be shown that, given a person obeys certain simple and non-controversial "axioms of coherence," or "axioms of consistent behavior," the existence of subjective probabilities that follow the rules of mathematical probability is implied (Winkler, 1972). Since objective probabilities, strictly speaking, do not exist in realistic decision problems, the subjective interpretation is far more useful.

This is not meant to imply that subjective probabilities may not be based on long-run frequencies, so-called actuarial probabilities. On the contrary, this is a highly desirable and advantageous approach (Beach, 1975). The decision to modify these historic frequencies, or to accept them as representative and applicable to future decisions, however, is strictly subjective. "Unqualified use of what are thought to be objective probabilities must be described as the inefficient and ignorant use of subjective probabilities chosen in a lazy mechanical fashion" (Dillon, 1971).

Experts in some fields, such as meteorology, find no problems in quantifying their judgment and achieve considerable reliability, accuracy and skill (Winkler et al., 1978; Murphy and Winkler, 1977; Murphy and Winkler, 1974; Schroeder, 1952). Some "substantive" experts (Hogarth, 1957), however, may not be good "normative" experts, that is, they may face problems in quantifying judgment in probabilistic form. Hence, intricate elicitation procedures have been devised (Anderson, 1974) and used practically (McNutt, 1976).

Different methods may produce varying distributions (Winkler, 1967). It appears that the elicitation technique should be adapted both to the decision problem and the statistical sophistication of the decision maker. Francisco and Anderson (1972), working with natural resource managers, used a simple and efficient visual impact method. It appears very applicable to forest management situations, where other methods, in my estimation, tend to tax the patience of the person interviewed.

Sometimes there may not exist sufficient data to construct preliminary, actuarial distributions. In this situation, the "sparse data method" (Anderson, 1974; Anderson et al., 1977), a non-parametric, statistical procedure to establish cumulative frequency distributions from few observations, proves extremely useful.

Since subjective probabilities simply express beliefs, "goodness" cannot be judged by agreement with later real world events. For instance, a judgmental probability of a "90% chance of precipitation" may have been a "good" assessment, in spite of the fact that sunny weather prevailed. Goodness, then, means really authenticity (Tani, 1978).

Unfortunately, even an authentic assessment may reflect bias. We now cross into the fascinating area of behavioral decision theory. Generally, humans are "poor intuitive statisticians" (Hogarth, 1975), and act like a "selective, stepwise information processing system with limited capacity" which is "ill-equipped for assessing subjective probability distributions," and "frequently just ignores uncertainty" (Hogarth, 1975).

Any reader upset about this mediocre rating should test his intuitive statistical abilities by reading Kahneman and Tversky (1973). The authors demonstrate how our minds use several simple heuristics, "rules of thumb," namely representativeness, availability, "anchoring" and adjustment, to form subjective beliefs. Under some circumstances, these heuristics lead to significant bias, even in the minds of the experts.

In addition to these cognitive biases, motivational biases exist. Rubenstein and Schröder (1977) demonstrate how project responsibility, participation in project idea generation, and organizational position affect assessed success-probabilities in research projects.

Since decision analysis admits subjective estimates, entire models can be built, based solely on the quantified judgment of experts. In situations where little recorded evidence exists, this approach is entirely justified initially. In forestry, McNutt (1976) and Payandeh (1977), as well as Teeguarden (1969) have chosen such an approach.

But how good are the experts? Answers vary. Experts perform admirably in some fields, such as meterology (Murphy and Winkler,1974); they have failed embarrassingly in other instances, such as for the stock market (Beach, 1975). Bankers and stock market experts performed so poorly in predicting closing prices for selected stocks that they would have done better with a Laplace strategy, that is, using a uniform distribution (Slovic et al., 1977). Worse, a tendency for overconfidence showed among experts in military intelligence (Brown et al., 1974), judges, jurors, doctors, nuclear power safety personnel, and economists (Slovic et al., 1977; Howell, 1972). In view of behavioral decision theory findings, it would appear that expertise and familiarity are not synonyms. One does not become an expert by prolonged exposure to a certain sector, but rather by systematic analysis and control.

Whose judgment should the subjective probabilities represent? Very often, groups decide, hence the problem of combining differing distributions arises. McNutt (1976) intuitively chose one of the various methods described by Winkler and Cummings (1977), namely, the simple average. Other purely mathematical possibilities, such as the natural conjugate method, or behavioral approaches, like the Delphi-technique, appear attractive but cumbersome.

In view of all these vagueries, should we assess and apply subjective probabilities in forest management decisions? Certainly "garbage in-garbage out" applies, "with the particular danger that undue respect may be given to garbage produced by high-powered and expensive grinding" (Slovic et al., 1977). First, there simply are no strictly objective probabilities. Most foresters dealt with confidence intervals in mensuration. Objectively, we may calculate means, variances and corresponding confidence intervals. However, we may not conclude that the true mean lies within given numerical confidence limits with a certain probability (Swindel, 1972; Brunck, 1975:229). In the long run, in repeated sampling, the computed confidence limits will include the true mean with the chosen probability. This only correct interpretation is unsatisfactory from a decision standpoint; very often we cannot afford waiting for the "long run." In forest science, objectivity is a credo; clinging to objective probability in management leads to inaction, inconsistent decision and hampers progress. Initially, we simply may have to rely on meager evidence and vague distributions. But, in my judgment, decision analysis in forest management planning will not be a "one-shot" affair. As we become aware of crucial weaknesses in our chain of knowledge, we can close these gaps by monitoring operations, by systematically collecting, interpreting and incorporating new information. In short, we apply, at least in concept, the "méthode du contrôl."

Assessment of Likelihoods

Likelihoods, that is the conditional probabilities of observing a forecast signal when we know the true state of nature, form the means to incorporate new information into the Bayesian framework. They are the only additional input required. Like all probabilities in decision analysis, they are subjective. Once we have specified the likelihoods, we can determine the so-called predictive distribution (Winkler, 1972), that is, the probabilities of receiving various forecasts.

Basically, assessment techniques for the likelihoods need not vary from those for the prior distributions. However, since an entire conditional distribution is associated with each predictor, the amount of judgment tends to "explode." Numerous applications, therefore, employ historical performance records, and adjust the likelihoods judgmentally from actuarial frequencies (Conklin et al, 1977; Bullock and Logan, 1970; Byerlee and Anderson, 1969). Hence, an initial, rough shape for the likelihood distribution is obtained by listing, ex post, the incidences of the various signals for the states of nature in a contingency table.

In medical diagnosis, these tables carry the name "public models" or "symptom-disease matrices" (Beach, 1975). I can see no reason why similar tables should not aid in the diagnosis of tree disease or nutrient deficiencies, stand volume predictions from cruises, yield tables, or aerial photographs. They appear to offer an appealingly simple option to accumulate knowledge about predictive association.

Sometimes, statistical models, such as the binomial, the normal, hypergeometric or Poisson distribution, can facilitate derivation of likelihoods (Winkler, 1972). Anderson et al. (1972), Swindel (1972), and Sorensen (1969) provide hypothetical examples, but realistic applications appeared missing in the literature. We derive likelihoods in this case, apparently very objectively, from statistical tables; however, this approach is by no means more "objective" than judgmental assessment; it is merely more convenient. Subjectivity enters when we judge the applicability of the particular statistical model. Faced with the difficulties of eliciting numerous likelihood distributions, there is a strong temptation to stretch reality and accept a statistical model.

The appeal of relying on statistical models is particularly great for continuous distributions, where the natural conjugate method allows incorporation of sample evidence with intriguing ease and elegance. Winkler (1972) and Brunk (1975) outline the underlying theory and illustrate applications. For the beta-distributions, where sample evidence is obtained by binomial sampling, there must exist countless possible applications in forestry. None were found in the literature.

Similarly, posterior distributions emerge directly from the normal regression model by means of prediction intervals for the random response variable (Carlson, 1970; Carlson, 1969; Eidman et al., 1967; White and Eidman, 1971; Halter and Dean, 1971). To avoid misunderstanding, the difference between the previously mentioned confidence intervals and prediction intervals should be stressed: For the former, no probability statement is applicable, once numerical intervals are specified. In the latter case, we don't deal with a fixed parameter, but with a random variable. We may make a probability statement about the value to be taken by this random variable (Neter and Wasserman, 1974). In this context, few authors seem to have dealt with such problems as varying confidence limits for different values of the independent variables, or the problem of prediction bias (Neter and Wasserman, 1974).

Use of Bayes' Theorem and the "Bayesian Controversy"

Bayes' theorem forms part of the abstract model of probability and, hence, applies to both objective and subjective probabilities. Its use is non-controversial. I will review some economic applications later. Here, I merely cite some examples for inferential uses in a range of situations, where new evidence must be weighed.

Finkelstein and Fairley (1970) illustrate the potential of Bayes' theorem in the judicial system. In the Bayesian context, the phrase "guilty beyond a reasonable doubt" may turn into a quantitative statement. These authors and Beach (1975) cite two salient applications in paternity cases.

When do grasshopper sightings signal an outbreak (Dillon and Officer, 1971)? A submarine has been sighted leaving the Mediterranean--was it a nuclear version? Again, analysts used Bayes' theorem, an example for its apparently widespread application in military intelligence (Brown et al., 1974; Beach, 1975). Medical diagnosis and pest control provides numerous illustrations (Betaque and Gorry, 1971). Halter and Dean (1971) assess the theorem's role in the scientific process.

Bayes' theorem may be applied repeatedly (Winkler, 1972). After each iteration, the newly computed posterior distribution serves as a prior in the next stage. However, information sources should be conditionally independent and signals must not be redundant. Sequential decision making assesses the need for further information stepwise before any terminal action (Winkler, 1972).

Why bother with Bayes' theorem, when posterior probabilities may be assessed directly--for example, from a contingency table, where the incidence of each state of nature is recorded for the forecast? Webster (1977), Dean (1966), Depta (1975) and White and Eidman (1971) used this approach. First, likelihoods provide in some instances the "hard evidence," that is, the sample result. Through Bayes' theorem, it may be combined with varying distributions, thus allowing for differences in prior judgment. More important, humans, as "poor intuitive statisticians," process information often incorrectly, and apparently, for the most part, conservatively (Beach, 1975; Winkler, 1972; Francisco and Anderson, 1972). They produce posterior probabilities nearer the prior probabilities than those specified by Bayes' theorem (Slovic et al., 1977). This again raises the question of the adequacy of any prior distributions: Riddled with normative, perhaps even motivational bias, they may also result from faulty previous information processing. Hartley (1963) uses this argument in "Dr. Bayes' consulting room."

"Cascaded inference" alludes to the opposite phenomenon: Because the unreliability of bits of information in a multi-step aggregation process have been ignored, a subjects posterior probabilities are more extreme than those prescribed by the model (Slovic et al., 1977).

To combat these human flaws, probabilistic information processing systems (PIP) rely on computers rather than on human perception to aggregate judgment in medical diagnosis and military intelligence. Not surprisingly, machines have, on occasion, outclassed the experts.

The "Bayesian controversy" (Bross, 1969; Hartley, 1963; Raiffa, 1968; Swindel, 1972) centers not on Bayes' theorem, but rather on its use in the "Bayesian school" of statistics. "Classical" statistics bases inference solely on objective sample information. Subjective considerations enter at best informally in the choice of a particular model or, perhaps, in independence assumptions. The Bayesian, on the other hand, formally incorporates any previous knowledge as a prior, subjective distribution. He then revises this prior judgment after seeing the sample evidence (Winkler, 1972). Both approaches yield identical numerical results, for example confidence intervals, whenever "objective" distributions are available before sampling. The same is true for the mostly hypothetical case, where the Bayesian relies merely on an uninformative, diffuse prior (Winkler, 1972). The interpretations vary strikingly, however: Bayes' disciples consider the parameter of interest as a random variable, express their convictions via personal probability statements and "credible intervals" (Brunck, 1975). Classical statistics specifies probabilities only _a priori_, before taking the sample; _a posteriori_, probability statements about the fixed population parameter have no meaning.

The role of classical statistics ends with a "statistical significance statement." Dillon and Officer (1971) speak of the "hoax of statistical significance" in applied research, and argue "that particular significance levels did not come to us as a statistical post-script to the decision rules which Moses received from on high." Borch (1968) criticizes the argument that "we must force ourselves to forget what we believe, in order to be completely rational or scientific. Such an argument has no content. Worse still, it implies that by acting otherwise, one loses scientific objectivity, an identification that is not easy to give up" (p. 278).

Some provocative extensions to forest management: In timber inventory, need we really "start from scratch," when we really possess a good prior knowledge from aerial photographs or yield tables? Is a back-breaking, systematic, intensive stocking survey always necessary, when a much smaller, objective sample, combined with, perhaps, even a "windshield survey" might suffice? As long as we report prior knowledge and sample result separately, anyone may specify his own prior impressions, and arrive at his own posterior distribution. Some extensions of statistical decision theory, such as the revision of continuous distributions in the context of the beta- or normal model, the concept of linear or quadratic loss functions, Bayesian point estimation and hypothesis testing (Winkler, 1972) offer the prospect of literally countless, non-trivial applications in forest management.

Chappelle (1976) concludes that "statistical decision theory continues to be largely abstract, and textbook examples of its principles are extremely simple, hence providing little guidance to its application to forestry decisions." Dillon and Officer (1971) ask from a related field: "Why then do classical procedures persist? Probably the main reason is that agricultural researchers and field workers, in the main, are neither well-trained nor adept in statistics. They have to rely on biometrical advisers who are usually overly imbued with classical statistics and have little appreciation of economic considerations." In forestry, Swindel's view (1973) appears symptomatic.

So far, we essentially reviewed the concepts which allow a decision maker to express and revise his opinions as best as he can. Decision analysis also incorporates personal preferences. This subject, utility, is introduced next.

Utility

Utility expresses the subjective value attached to different levels of wealth (Halter and Dean, 1971). Intriguingly, the existence of such a personal utility function is implied by the same basic axioms of consistent behavior that lead to the subjective probability notion (Anderson et al., 1977). The concept was established by Daniel Bernoulli 200 years ago, and formally introduced by von Neumann and Morgenstern in the 1940's. The so-called Bernoulli principle says that, faced with a risky prospect, a person should act to maximize expected utility. This general principle includes as a special case the maximization of an expected monetary value.

Several authors exposed foresters to the utility concept (Davis, 1968; Thompson, 1965; Dane, 1965; Newton and Leuscher, 1975). I encountered but one somewhat realistic application (Timinger, 1974).

Utility functions may be elicited, like subjective probabilities, by well-established techniques, such as the ELCE-method (based on considering an equally likely risky prospect and finding its certainty equivalent), or the ELRO-method (based on preferences between acts with equally likely but risky outcomes)(Anderson et al., 1977). Their shape reveals risk neutrality, or linear preference, when the second derivative (y") of the utility function equals zero. Often, decision makers display risk-aversion (y" < 0), sometimes risk preference (y" > 0).

Since utility is measured on an arbitrary, cardinal scale, utilities among individuals cannot be compared. However, the "Pratt coefficient" (Pratt, 1964), defined as the negative ratio of the second and first derivative of the utility of wealth function, permits interpersonal comparisons of risk attitude.

Are foresters risk averse? No specific investigation was found, but if farmers' attitudes are any indication, most are risk-avoiding. Risk neutrals and risk seekers have been identified repeatedly among farmers (Young, 1979; Dillon, 1971; Whittacker and Winter, 1980; Conklin et al., 1977; Brink and McCarl, 1978). Persons may simultaneously exhibit risk aversion by possessing insurance, and risk preference, by buying a lottery ticket. Thus, utility functions may reflect varying attitude towards risk (Halter and Dean, 1971) over their entire range.

Instead of formally eliciting utility functions, an analyst may merely list the attribute values of various outcomes lexicographically (Anderson et al., 1977; Halter and Dean, 1971). "E,V-analysis" provides a well-known example, where both the expectation and the variance of an act serve as criteria. The decision maker may reveal his preferences among outcomes, for instance, by maximizing profit, subject to a safety constraint. He will avoid alternatives for which "disastrous" consequences occur with high probability (White and Eidman, 1971; Eidman et al., 1967).

What are possible implications of utility in forest management? For one, utilities cover non-monetary outcomes, too. Moreover, in multiple-use forestry, multi-attribute utility shows promise (Timinger, 1974).

In repeated decisions, "things average out." Linear utility functions or, in other words, the expected value criterion applies, provided the decision maker can afford to participate in the particular "gamble" repeatedly. With high stakes, a small ownership may not survive for a repeat trial. For forestry extension this means that optimal procedures, developed characteristically in cooperation with larger ownerships, are possibly non-optimal for small woodland owners. General fertilizer recommendations, for instance, may not be risk-efficient for small owners. On the other hand, decision makers in large public and private forests should often take more risks to benefit the entire organization. Organizational and individual goals typically diverge: There is ample evidence that line managers tend to act overly risk averse (Trueman, 1974:131), in order to "cover their rears."

Attitude towards risk is of interest from a policy standpoint. Would a subsidy for fire insurance affect production decisions? Is research on high performance, high-risk technology beneficial for the majority of forest owners (Anderson, 1974)? For non-normative, positive purposes, Lin et al. (1974) found utility superior to mere profit maximization for predicting farmers' actual behavior.

Utilities for large groups of certain forest owners cannot practically be derived, nor can they be combined to form a group utility function (Borch, 1968; ch. 15). However, as long as we know general attitudes toward risk in a group, the concept of first- and second-degree stochastic dominance (Anderson, 1974; Anderson et al., 1977) may be used to narrow the set of permissible actions, by eliminating "dominated" options.

Decision Analyst and Decision Maker

While this topic has received treatment in the general literature, it has escaped notice in forestry so far. Yet, the relationship may assume special significance in our field.

Business applications usually cast the analyst in the role of a normative, but not substantive, expert. He is a staff specialist at headquarters, often an outsider, sometimes even a professional decision analyst working for one of several firms in this field (Brown et al., 1974). The agricultural literature treats the topic usually in the context of extension (Halter and Dean, 1971; Young, 1979), hence familiarity of the analyst with the problem seems implied.

In forestry, too, substantive expertise will undoubtedly aid in decision analysis. However, the outside consultant, even the extension or service forester, might find routine applications of decision analysis tedious: Utilities and probabilities must be elicited, specific costs and revenues derived. Lengthy interviews may fail to properly identify and structure the problem. In my opinion, decision analysis will achieve its full potential as a tool in the arsenal of the inside management specialist or management planner. Simpler versions, such as decision trees, may aid line personnel in less complicated or less consequential choices. Both can rely on familiarity with organizational structures, they know how to locate and use records, and they employ their own judgment as well as that of colleagues to derive probabilities.

Without much difficulty, they can capture organizational policy in appropriate utility functions and monitor model performance in reoccurring processes. In this context, decision analysis in forest management can avoid the pitfalls described by Grayson (1973) and Brown (1970). It will fit neatly into the well-established relation between management planner and forest manager (Speidel, 1967; Mantel, 1959) and enhance communication at this level.

The Field of General Applications

"Do managers find decision theory useful?" (Brown, 1970). Or has the technique shared the fate of operations research which, in the words of Grayson (1973), may have "grown so remote from and unmindful of the conditions of live management, that it has abdicated its usability?"

The literature contains many purely hypothetical examples in auditing (Sorenson, 1969), nuclear engineering (Budnick et al., 1977), farm management (Holt and Anderson, 1978), pricing (Green, 1963), and marketing (Roberts, 1963). Ulysses' mythical problem between Scylla and Charybdis characterizes the underlying problem structure.

In realistic settings, the technique helps turkey producers and cattle feedlot operators to cope with uncertain yields and prices (Eidman et al., 1970; Ladd and Williams, 1977; Bullock and Logan, 1970). Widely varying range conditions stimulate applications of decision analysis to the stocking rate problem in lifestock grazing (Dean, 1966; Dean et al., 1966). A further concentration appears in the field of crop disease control, where uncertainty centers around potential losses (Carlson, 1969; 1970). Carrol and Dean (1980) report an innovative application in a plant location decision.

As a first impression, however, the immense body of theoretical knowledge appears to have spawned soberingly few reported realistic applications. But, decision theory is alive in management: Numerous organizations, among them major corporations, routinely use it (Brown et al., 1974). Furthermore, decision analysis is such a versatile, flexible tool that, at times, considerable effort is required to discern the basic model in a variety of intriguing, alternate forms. Dean (1966) suggests that "the rigid textbook format of payoff matrices can be more of a handicap than an asset." Below, I attempt to classify and describe these variants of the general model.

Decision trees are particularly useful in structuring and solving less complex, often sequential decision problems. They suffer from the "curse of dimensionality" and tend to degenerate rapidly into the proverbial "bushy mess." On the other hand, they explicitly capture some of the uncertainties which frequently "hide" in payoff table entries. Described in detail by Magee (1966) and almost any operations research textbook, decision trees have been applied to oil drilling decisions (Grayson, 1960), medical malpractice (Forst, 1974), countless business problems (Moore and Thomas, 1973; Brown et al., 1974), raisin production (Lave, 1963), farm management (Holt and Anderson, 1978), hurricane seeding (Howard et al., 1972) and horticulture (Rae, 1973). Up to now, models treated acts, states of nature and payoffs in discrete form. All may be continuous, however. In the most simple case, decision involves a dichotomous choice of actions, and consequences form a continuous, linear function of the uncertain, continuous state of the world. For instance, does it pay to spray against fungal crop diseases? Consequences will depend on the potential crop loss (Webster, 1977; Gilmour and Fawcett, 1973). For a certain precipitation forecast, should raisins in California's raisin drying industry be protected or not? (Kolb and Rapp, 1962). Which of two advertising strategies should a car manufacturer select? (Roberts, 1963). In each instance, a simple comparison between the "breakeven value," calculated from the parameters of the linear payoff function, and the expected value of the uncertain state indicates the correct choice. Winkler (1972) provides the details. For certain distributions, such as the normal or beta density function, we may even evaluate sample information via tabulated "linear loss integrals."

Sometimes, the set of possible actions is numerically identical to the set of states. Some inventory problems can serve as an example: Ideally, for each period, inventory should equal demand. For this "decision theoretic equivalent to classical point estimation" (Winkler, 1972), it is the cost of over- or underestimating which leads to optimal point estimates. Again, fairly simple expressions permit us to determine an optimal policy and the value of information. This structure is known as the "infinite action problem."

The entire payoff table may be expressed in a continuous equivalent as a production function or response surface. Here, payoffs, that is the dependent variable, vary as a function of more or less continuous acts, as a function of uncontrollable but known factors, and in response to uncontrollable random inputs. For instance, net returns from fertilization change with application rate, soil characteristics and weather conditions. This particular decision problem has received considerable attention in the agricultural economics literature. Not surprisingly, some interest has focused on the value of information in the form of rainfall predictors, soil tests, or soil surveys (Harlicek and Seagraves, 1962; Colwell, 1968; Byerlee and Anderson, 1969; Doll, 1972; Anderson and Dillon, 1968; Ryan and Perrin, 1974; Perrin, 1976; Bie and Ulph, 1972).

For these continuous payoff functions, interesting interactions exist between the mathematical form of the utility function, and the probability distribution of returns. Essentially, the utility of any prospect can be calculated from the derivatives of the utility function and the moments about the mean of the distribution. Halter and Dean (1971) provide mathematical detail; Byerlee and Anderson (1969) illustrate the procedure.

Besides assuming various forms, decision analysis may be combined with linear programming (Dean et al., 1966; Gebremeskel and Shumway, 1979), or simulation (Conklin et al., 1977). Components of the technique reappear in the theory of games (Walker et al., 1960), or in stochastic, dynamic programs (Yager et al., 1980). The latter technique appears particularly promising for sequential decisions that exceed the limitations of the decision-tree approach.

Information theory contributes a further intriguing and rather unexplored extension (Leuthold, 1971) with the concept of entropy. Essentially, entropy measures the amount of information contained in a message, decision analysis valuates it. A specific value for a "bit" of information can be derived.

In turn, other mathematical programming techniques such as discrete stochastic programming (Rae, 1971), quadratic risk programming and its linear alternative, MOTAD (Hazell, 1971; Anderson et al., 1977), may substitute for traditional decision analysis.

In summary, decision analysis has been applied in many and diverse fields, in research as well as in routine management. It assumes a multitude of forms in that spectrum of management science which deals with uncertainty. Forestry applications will be reviewed next.

Forestry Applications

When Thompson (1966) reviewed the forestry literature on decision analysis, he found some awareness of the uncertainty problem (Flora, 1964; Davis, 1965), a fictitious example in forest engineering by Dane (1965), and a theoretical paper by Marty (1961). While the latter author felt noticeably uncomfortable with the concept of subjective probability, he deserves credit for introducing stochastic dominance, for elaborating on the problem of state variable definition, and, finally, for recognizing "hidden uncertainties" in the payoffs. Thompson (1966) aids the diffusion process of decision theory into the forestry literature; an application to the problem of optimal extent of land ownership for an industrial forestry firm remains, to some degree, hypothetical. A later extension (Thompson and Haynes, 1971) solves a realistic version of the same problem.

Apparently, one of the first practically successful applications of subjective probabilities in forest management took the form of judgmental quantification of uncertainty in fire weather forecasts (Schroeder, 1954). Later, Davis (1968) illustrates the technique in a hypothetical fire-fighting situation, besides enriching the forestry literature with a hilarious, fictitious decision problem.

We owe Dane (1965) the first example for an "infinite-action" problem, an inventory situation, where the mill owner must optimize the size of his "cold deck" in the face of uncertain mill requirements. Later, Hamilton (1979) exposes the same structure in mensuration, where costs may be associated both with under- or overestimating inventories. Bell and Fight (1977) show, how social loss functions combine with either conservative or speculative assumptions in timber harvest scheduling.

Newton and Leuschner's (1975) pest management example points out important fringe benefits of decision analysis. A similar problem is addressed by Talerico et al. (1978) in gypsy moth control.

Foresters did not hesitate to incorporate decision theory concepts into related uncertainty models. The transition probabilities used by Hool (1966) and Lembersky (1972; 1976) in their Markovian decision processes are essentially judgmental or actuarial. Whole simulations have been built around these quantified judgments (Payandeh, 1977), in spite of the fact that subjective interpretations of probability appear not to have received the blessing of forestry statisticians (Swindel, 1972).

Utility, while introduced nominally, appears neglected and unappreciated in forest management. Timinger (1974) provides a glimpse of its potential when he evaluates a spectrum of harvest methods for small timber in terms of multi-attribute utilities. Teeguarden (1973) implies the need for such utilities in several dimensions when he states that "we tend to simplify . . . by assuming proximate criteria for performance, such as least cost, greatest net benefit, or some other simple monetary or physical objective. Yet rarely do these criteria reflect fully the multi-objectives of forestry organizations." Similar concerns are voiced by Speidel (1970).

While decision analysis in stochastic, dynamic programming form proved useful in agriculture (Yager et al., 1980), I have not found forestry applications. However, an interesting version emerged recently (Dixon et al., 1980): In this control theory approach, actions are not only taken to bridge the gap between a current and a desired final state, but also to gain more information about the underlying process. Describing the same technique, Taylor and Chavas (1980) raise the question, which appears particularly relevant to applied decision analysis: They question the application of response functions that were "estimated with data from carefully controlled experimental plots" to actual operations, and propose a system where "every input decision may have two roles. First, it is used to control the mean and higher moments of profits. Second, it will influence the generation of new observations, which will allow the farmer to learn about his particular production technology, and thus make better decisions in the future." This "active, adaptive control formulation" can be described as "learning by doing" (Ying, 1967).

Again, it should be apparent that operations research, in a sense, has rediscovered, formalized and abstracted the central concept of the classic "method of control" in forest management.

Some applications of decision theory to realistic operational forestry problems deserve special mention. Curiously, some authors appear to have been oblivious to the fact that they actually used decision analysis concepts. Teeguarden (1969) elicits and pools expert judgment to establish subjective probabilities of reforestation success. Depta (1975) forecasts Douglas-fir survival in Western Oregon, and applies the normality assumption about residuals in normal regression to tabulate the probabilities of various stocking and financial outcomes of reforestation policies. He uses actual, operational reforestation records and costs. The need for site-specific prescriptions is basically recognized and, finally, forecasts are probabilistic.

German (1975) tackles the difficult problem of specifying risk and calculating realistic payoffs that are site-specific. McNutt's (1976) study demonstrates versatility in decision analysis when he includes probabilistic information about erosion into a timber harvest and roading analysis for an unstable watershed. He uses site variables and simulated hydrological conditions to estimate erosion event probabilities via Bayes' theorem. Both priors and likelihoods are elicited from a panel of substantive experts.

Most operations-oriented forestry applications have realized and incorporated the site concept into decision analysis. The exception is Payandeh (1977) who incorporates experts' subjective probabilities into a simulation, which "optimizes" regeneration for several species, but without apparent regard for site.

Do forest managers find decision analysis useful? So far, we have reviewed applications emerging mostly from the "ivory towers." There are indications that foresters can and do successfully apply the technique. Sadler (1970) solves a timber-fisheries multiple use decision problem under uncertainty. Knapp and Turpin (1980) tackle the sensitive issue of need and usefulness of herbicides in vegetation management. Their decision trees vary by broadly defined sites, the appropriate costs, revenues and probabilities are backed by district records. Finally, they add an original idea to the decision analysis framework: If an originally feasible and optimal act is eliminated by a change in policy, in our case a ban on herbicides, the impact of such a strategy may be assessed as the difference in optimal expected returns. The advantages of decision analysis appear particularly distinct in this example: Discussions center on probabilities, costs, revenues. The ultimate conclusion emerges merely as a logical consequence.

In summary, decision analysis has materialized in the forestry literature in many hypothetical, but also in realistic applications. Like in the general field, its shape ranges from the conventional payoff table format to continuous loss functions in the infinite action problem, from simple decision trees to sophisticated simulations. Finally, some concepts have transgressed into linear programming, control theory and Markovian processes. Some examples appear to indicate that decision analysis, perhaps more than other management science models, remains within the capabilities of the manager. Its results need not emerge from the proverbial black box, nor even from the line printer.

Here the excursion into the concepts and applications of decision analysis ends. Review of one central ecological concept that is essential for this dissertation will conclude the chapter.

Available Soil Water as a Key to Seedling Survival and Site Productivity

A survey of climatograms for western Oregon (Loy et al., 1976) makes clear that precipitation by far exceeds total evapotranspiration during the fall, winter and parts of the spring season. During this time high amounts of rainfall recharge soils with moisture. Very little rain falls during the growing season. Interception may reduce its effectiveness further and, apart from dew, fog contributions, and occasional influences of stagnant water, plants depend essentially on a rather fixed supply of water stored in the solum. The literature contains abundant direct and indirect evidence of the critical importance of this moisture "reservoir" for yield (Steinbrenner, 1963, 1979; Gessel and Lloyd, 1950; Urie, 1959) and seedling survival (Thomas and Burroughs, 1975; Youngberg, 1955, 1959; Lowry, 1955; Edgren, 1972; Owen, 1953; Oregon State University, 1978; Wert et al., 1977; Hobbs et al., 1980). How then do we capture this "supply side" of plant water relations in site mapping?

The available-water capacity, AWC, indicates the amount of water retained in a given volume of soil between an upper and lower bound of availability, that is, between the so-called "field capacity" (FC), and the "permanent wilting point" (PWP). After heavy rainfalls, some water percolates through the solum under the influence of gravity and escapes from the rooting zone. Part of the water, which is retained in the soil pores by the forces of adsorption, adhesion and cohesion, is held with such force that plant roots absorb it with difficulty or not at all. The AWC, expressed usually as mm rainfall, volume percent, inches per foot of soil depth or, metrically, as mm per dm depth, remains to satisfy plant needs.

The appealingly simple, old and established concept, a paradigm of soil science, AWC has subsequently fallen into some disrepute due to questions of measurement and meaning. Correctly, field capacity should be measured as the water content of undisturbed, thoroughly wetted soil after all drainage ceases. Measurement of the PWP uses the so-called sunflower technique (Peters, 1965). Routine laboratory approximation most commonly defines AWC as the amount of water retained in a soil sample between suctions of 1/3 and 15 atmospheres.

There is evidence that this procedure underestimates available water in coarse textured soils, and leads to overestimates in clayey samples (Salter and Williams, 1965). Numerous other pressure values have been suggested (Reeve et al., 1973; Gradwell, 1971; Pidgeon, 1972; Salter and Haworth, 1961) and results have been compared (Broadfoot and Burke, 1958). It appears that there does not exist a single, correct set of pressures.

Measurements on disturbed samples and undisturbed cores produce contrasting results. This is particularly the case for field capacity which tends to depend on structure. The wilting point relates mainly to texture; most authors consider measurements on disturbed samples as permissible (Salter and Williams, 1965). Routine laboratory analysis may under- or overestimate AWC; results vary with bulk density (Hill and Sumner, 1967), organic matter (Miller, 1969; Salter and Hayworth, 1961), stone content (Petersen et al., 1968; Reinhart, 1961) and temperature (Daubenmire, 1957).

Apart from measurement problems, does AWC adequately express soil water supply? There is no doubt that an entire tension curve, that is the function which relates soil water content and corresponding tension, is much more instructive. Infiltration and redistribution characteristics as well as the hydraulic conductivity at various moisture contents should be considered. Moreover, supply characteristics depend not only on the soil, but also on plant and atmospheric conditions (Slatyer, 1967).

Essentially, water moves to and through the plant in a dynamic process; it involves numerous pressure differentials and resistances located in various stages of the soil-plant-atmosphere continuum. In contrast to the simplistic "flower vase concept" implied by the indiscriminate use of AWC, it is entirely possible for plants to develop high moisture stress in moist soils. On the other hand, when atmospheric demand is low, they may take up water held with tensions beyond the PWP. Slatyer (1967), Hillel (1971), Kozlowski (1968) and Pierre et al. (1966) discuss these and related topics.

Considerable evidence links AWC to soil texture, a parameter which is usually and quite reliably assessed in the field (Salter and Williams, 1967). A thorough review of reported values revealed an amazingly constant relationship between AWC and texture, despite varying methods, definitions and locations (Gradwell, 1971, 1974, 1976; Miller, 1969; Salter andWilliams, 1965a, 1965b; Scrivner et al., 1972; Gaiser, 1952; Salter et al., 1966; Renger, 1971; Longwell et al., 1963; Fransmeier et al., 1960; Broadfoot and Burke, 1958; Rivers and Shipp, 1972; Shrivastava and Ulrich, 1977; Eder, 1980). Roughly speaking, AWC rises from very low values (e.g., 2mm/dm) in sands to a maximum in silt loams (e.g., 25 mm/dm) and decreases with finer texture to intermediate values in clays and sandy clays (e.g., 12 mm/dm).

Unfortunately, individual values tend to vary considerably about the means (Salter and Williams, 1965). Field assessment of AWC will only be feasible if we can explain this variation in terms of observable soil parameters.

Numerous authors report that AWC is a highly variable soil parameter, with much of total variability sometimes occurring over distances of only a few feet (Cassel and Bauer, 1974; Bethlamy, 1963); Alban, 1974; Hammond et al., 1958; Mader, 1963; Hallin, 1968; Aljibury and Evans, 1961). The latter authors calculated, for example, that in order to estimate the mean AWC of an 18-acre tract, previously mapped as a single soil series, over 30 samples were needed to achieve an accuracy of ± 10% with 95% confidence.

Variability in forest soils may be even greater; in addition, we may not be able to take undisturbed samples in these stony soils. Furthermore, AWC is usually measured as a difference between two random variables, FC and PWP, and this difference in turn is multiplied by a third random variable, bulk density. Hence, besides physical reasons, there are statistical reasons for an extremely high variance. If we succeed in specifying AWC in terms of field texture and observable profile characteristics locally, a field estimate, based on this general function, may provide better estimates than few and expensive laboratory tests.

Overall, while the use of AWC to characterize soil water supply constitutes a rather gross simplification, the concept has been used successfully in forest regeneration (Wert et al., 1977; Thomas and Burroughs, 1975) and has proved useful in site productivity prediction (Weissen and André, 1970). Current site productivity predictors in the Pacific Northwest (Steinbrenner, 1979; Urie, 1959) stop barely short of actually employing AWC. However, by including soil depth, rock content, depth of the A-horizon and clay content as independent variables, its use is implied.

Western Oregon's unique climate serves as an added incentive to introduce the AWC concept judiciously as a simple but practical index for soil water supply into site mapping for survival and productivity.

V. METHODS

Selection of Case Study Areas and Scope

The objective of this study called not only for a demonstration of the valuation technique in general, but also for specific value estimates for the defined reforestation purpose. It is obvious that, for a given amount of site information, there exists not only one constant economic value, particularly under the widely varying environments and forest practices in Western Oregon.

Deductively, the following model was hypothesized as a first approach:

$$EVSI = f(MI, MD, ED, EQ, Ec)$$

where

EVSI = Expected value of site information
MI = Level of management intensity
MD = Management diversity
ED = Environmental diversity
EQ = Overall environmental quality
Ec = Economic factors

An exploratory survey of environmental conditions in Western Oregon, based on available climatological, vegetational and geological data (Franklin and Dyrness, 1973), and a preliminary evaluation of reforestation success, indicated that extremes appeared to be located in the Northwestern and Southwestern parts of the state. Since time and financial constraints dictated a small sample, I decided to focus on just one ownership in each area. In other words, it was decided to undertake two case studies to establish a range for the value of site information.

Based on target stocking goals, reforestation policies and projected stand management regimes, the management intensity in the South Umpqua Resource Area of the Roseburg Bureau of Land Management (BLM), appeared somewhat lower than the intensive management regime in the Tillamook State Forest. Rather severe environmental conditions, a highly variable geology, and a corresponding wide range in individual sites in Roseburg, contrasted, as desired, with a more humid, uniform general setting in Tillamook.

Regeneration Procedures Analysis

After selection of case study areas, this next step preceded the actual model building process and served a triple purpose. First, while any forest management planning should include careful study of the past, this step gains in importance when we employ management science models. We must understand the system clearly, its overt or hidden constraints and interrelationships, its operating characteristics and past performance. There is little use for "the correct solution to the approximate problem," yet the temptation is great to conform to a basic structure which underlies all operations research models, at the expense of reality. The goal then is to make past operations and achievements transparent, perhaps confront the manager with the results of this analysis and, in an iterative process, clarify the problem, both in the manager's and the analyst's mind. The second purpose, hence, is to use this operations analysis as a means for communication with the decision maker. Lastly, we need cost figures, technological coefficients, which emerge with little additional effort from the analysis, provided the ownership possesses an effective record-keeping system.

Both cooperators had established records about original plantations and herbicide use, interplants and stocking surveys. Where these records were kept by year and not by plantation name or number, a rather heroic effort proved necessary to trace the fate of one plantation through hundreds of documents. Some errors undoubtedly occurred, particularly in Tillamook where plantation identification in the past has not always been unequivocal.

The Tillamook State Forest had established operational, fixed survival check plots during the years preceding 1975. Consisting of 50 staked trees in one or two rows, these plots covered a "representative" part of the unit, and were checked for three years following to planting. During 1967 to 1975, 209 survival plots were established which proved of great value in the analysis. For Roseburg, no such plots were available, unfortunately. A study of all applicable ownership guidelines completed this part of the study.

The Set of Actions

Reforestation guidelines for both ownerships provide target stocking levels for established stands. Since natural "fill-in" is rare, and not a policy consideration, one would not choose to plant fewer trees than these targets, initially. They serve as lower limits for feasible planting densities. Upper boundaries were dictated by considerations of seedling availability and by the occurrence of suitable planting spots. Since, for the latter reason, crews cannot plant exactly in prescribed patterns, planting densities which increased in discrete increments of 100 were selected. Seven intervals were chosen in both case studies to cover the range from approximately 500 to 1100 trees per acre. Interviews with the "decision maker," that is the reforestation specialists and the timber management staff, indicated also that reforestation ranks so high among management activities that budgetary constraints could be omitted. Hence, stand level optimization appeared justified.

In Tillamook, animal damage may hamper reforestation efforts. Plastic netting or budcaps protected seedlings on all but a few units included in this study; hence, a comparable level of protection is implicitly assumed in the chosen acts.

Both ownerships have used 2/0 stock overwhelmingly, hence, strictly speaking, actions imply this stock type, or stock selection by criteria comparable to those used in the past. An analysis in Tillamook indicated no difference between seedling and transplant performance, and Edgren (1977) arrived at a similar conclusion experimentally. Judicious extrapolation appears possible. All units included in the field study described later had been burnt, more or less successfully. Again, since vegetation cover varied between 0 percent and 100 percent, expansion of model results seems possible.

Specifically, the action, plant "n" trees per acre ($500 \leqslant n \leqslant 1100$) in Tillamook means: Slash-burn and plant "n" 2/0, bare-rooted seedlings per acre, and protect them by means of budcapping or netting where needed. In Roseburg, the action does not include any animal protection, excludes artificial shading, but includes occasional planting spot improvement by ravel removal or "micro-site planting."

The States of Nature

Plantations experience the bulk of total mortality during the first season; however, they are subject to less severe, random mortality in subsequent years, too. Consequences, that is, ultimate net revenues, vary not only with initial and sequential mortality, but also with site-class, that is, productivity. Plantation failures and production losses due to understocking and lengthening of the time span until maturity, hurt financially, particularly on sites with high mean annual increment. To account for the main source of uncertainty and to achieve independence from the actions, we define the state space by the joint occurrence of site class, a sufficiently definite measure of productivity, and percent first-year survival in judgmentally chosen intervals of 10 percent.

In Tillamook, site classes as defined by King (1966), ranged from one to four. In Roseburg, managers mainly use McArdles (1949) tables; site classes vary between two and five. Overall, then, there are 40 states of nature, each defined as the joint occurrence of one site class and one first-year survival class. This produces a 40x7 payoff matrix, giving 280 possible combinations; the consequences of one act and one state of nature each.

Some reflection at this point will indicate that our chosen acts and states do not define the consequences yet. The next section will deal with this aspect.

The Payoff Matrix Entries

First, which criterion should we maximize, minimize or optimize? In the financial dimension--applying some concepts reviewed in the literature--should we incorporate the decision-makers' attitude toward risk, or can we assume a linear utility function for money? Halter and Dean (1971) indicate that in repetitive situations decision makers should act risk-neutral, particularly if the range of possible outcomes cannot jeopardize the owner's existence in any one period. Both case studies involve large public ownerships which regenerate ca. 1000 acres annually, hence linear utility for money is clearly indicated.

Should we consider additional, non-monetary consequences? For example, adoption of a particular policy will influence such important aspects of the overall operations as the number and the timing of interplants, the chance of total failures, the use of herbicides, the time any one plantation remains in the rehabilitation system, the number of precommercial thinnings in the future, as well as the overall effect on administrative effort, use of labor, public relations or the professional reputation of the responsible decision makers. One reason given by BLM cooperators for an observed trend towards higher planting densities was the hope to reduce controversial, troublesome herbicide applications. Moreover, based on the ownership's policy, units that fail to meet minimum stocking requirements within specified times may be withdrawn from the land base which is used to calculate the allowable cut. No doubt, additional consideration beyond economic aspects enter reforestation decisions.

In this approach, I chose to focus on monetary consequences with linear utility only, and selected a cost minimization criterion, where total costs include both direct managerial costs as well as opportunity losses. The latter may arise if plantations grow up understocked, or if final harvest is delayed due to initial regeneration failures. However, since managers showed a great interest in non-monetary consequences, I will also supply the decision maker with additional information about such consequences of a chosen planting policy.

The action and state space defined so far, that is, planting densities, site and initial survival, clearly will not uniquely determine the physical or financial fate of any plantation yet. Rather, outcomes are a function of further random variables, namely subsequent, yearly, marginal mortality on one hand, and the owner's reaction to it on the other.

Both agencies have issued reforestation- and precommercial thinning guidelines that prescribe stocking survey timing and procedures, and which specify desired target stocking levels. Plantations that fail to achieve these targets will only be interplanted if they also fall short of acceptable minimum stocking. These guidelines incorporate tradition, experience, perhaps economic analysis and intuition; they are not necessarily economically or managerially optimal. To limit the scope of this study, I decided to accept these standards and policies. Hence, results of this analysis will be conditional on the reforestation policy of both owners. This should not be troublesome, since results of any decision analysis will not and cannot be absolute, as described in the review of the literature.

Once we know and accept the owner's reforestation policies, and once we can specify probabilities for subsequent yearly mortality, we can simulate performance of any one plantation in physical and monetary terms. In mathematical terminology: For any initial survival on a site with given productivity, the fixed reforestation policy is a function which transforms subsequent random mortality into new random variables, namely total cost and associated operating characteristics. Outcomes for several simulations will vary randomly, but we can obtain their distribution and associated descriptive statistics in repeated simulation runs.

To recapitulate: Payoff matrix entries are representative costs which result from the intersection of an action with a given state of nature. In our case, a chosen planting density and a given first-year survival site class combination account for the greatest part of total variability. Any additional uncertainty of costs is due to random subsequent mortality and the owner's deterministic response to it. We can simulate the fate of a sufficient number of plantations and determine each matrix entry as an average value. We will focus on the simulation next.

An Overview of the Reforestation Simulator

Here, we merely "lift the lid" of the proverbial "black box" to provide continuity, confidence and basic familiarity (Figure 1).

Each plantation is treated as an "entity," moving from its establishment in the spring of year one to the end of the rehabilitation phase, in this study, the fall of year ten. Once surviving trees have reached this age, further fill-planting becomes a fruitless effort, and the young stand is assumed to develop deterministically as a function of stocking achieved at age ten, and the owner's anticipated management regime until harvest.

During the simulated reforestation phase the plantation experiences "events," that is, occurrences beyond which we cannot describe the course of further development with certainty, but merely stochastically in the form of a probability distribution. There are only two events, namely stocking surveys and planting operations.

Reforestation guidelines for both ownerships require stocking surveys one, three and five seasons after the last planting action. Thus, a plantation established at a fixed density (our act) and experiencing a given first-year survival rate (our state) faces its first event, a stocking exam, in the fall of year one. If it passes, that is, meets minimum standards, the next event, a survey again, is scheduled for the fall of year three. In the case that the unit fails its first survey, it will be interplanted in the spring of year two. At this point, a second first-year survey is scheduled for the fall of the same year. Each plantation in the total sample--in our case a size of 75 was chosen--moves from event to event, until it either passes a successful fifth-year survey, is considered established and filed away, or until the simulation ends in the fall of year ten.

The simulation language, GASP IV (Pritsker et al., 1974) advances time and maintains the order of events, besides performing other

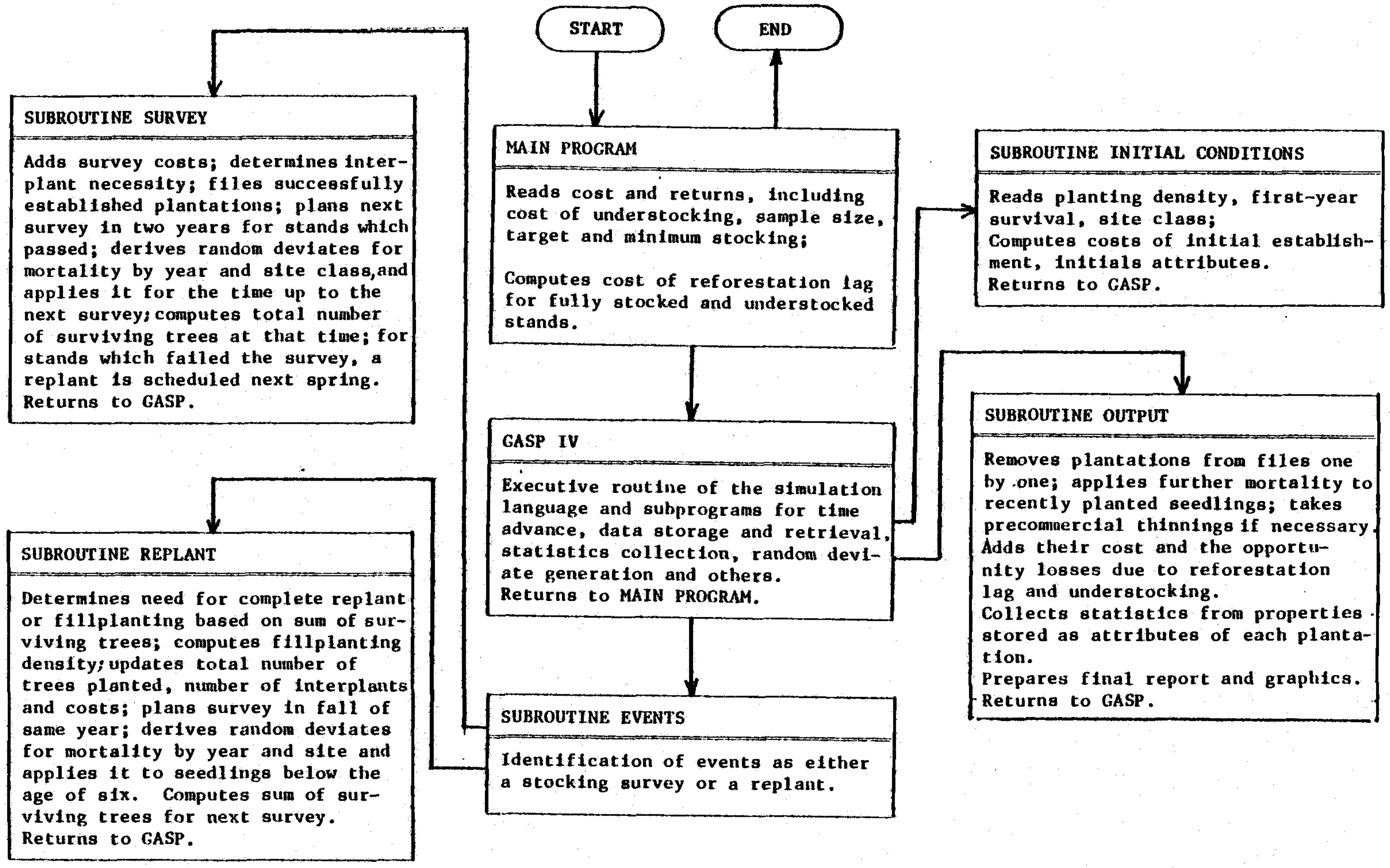
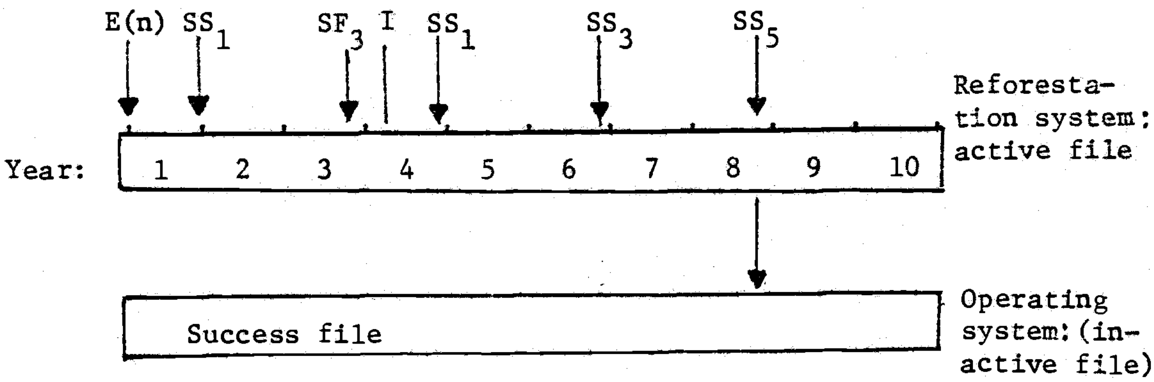


FIGURE 1. Descriptive Flowchart of the Reforestation Simulator

routine chores, such as collecting statistics. Here, we need not be concerned with details and we will also postpone for the moment the question of how mortality and costs are derived.

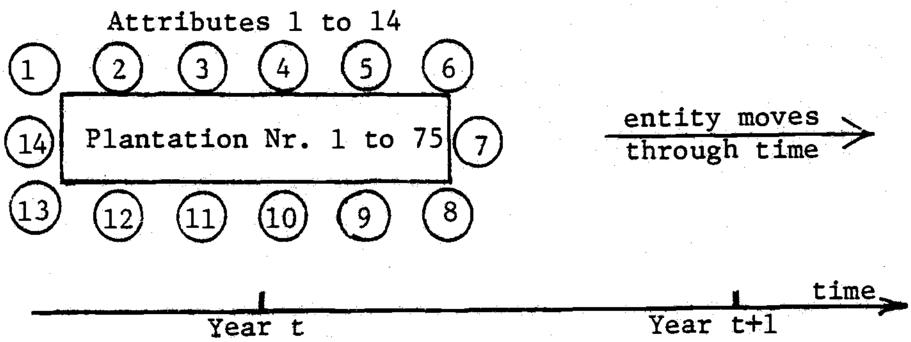
During both events, subsequent mortality up to the time of the following event is scheduled. For instance, after a successful survey, random mortality, as specified in the form of probability distributions, will occur in the next and over next year. It will be detected and acted upon in the subsequent stocking examination, two seasons later. After an interplanting, only one season's mortality will occur, since, according to the owner's policy, the unit is due to be inspected in the fall of the same year. The following diagram may further clarify matters by illustrating the assumed fate of one plantation:



Symbols are:

E(n)	=	Establishment with n number of trees per acre
SS_1	=	Successful first-year survey
SF_3	=	Failed third-year survey
SS_3	=	Successful third-year survey
SS_5	=	Successful fifth year survey
I	=	Interplanting

Each plantation-entity carries "permanently attached labels," so-called attributes, as it advances through the reforestation phase. We may visualize this as follows:



Each label is reserved to record one aspect of interest during the simulation. For instance, ten attributes are reserved to record number of trees planted in years one to ten. It is these numbers to which mortality percentages are applied; that is, the number of trees entered here tends to shrink as trees die. Seedling mortality is assumed to cease five years after planting.

At survey time, the sum of surviving seedlings, recorded and maintained in a further attribute, is checked against standards, and the area may then be interplanted when needed. Further attributes carry a tally of the total number of trees planted, or function as accounts by registering and appropriately discounting each cost item as it occurs.

After all plantations in the sample have progressed to time ten, or have been removed from the active file as successes, the simulation stops. However, it applies further mortality to plantations which have recently been interplanted. For instance, one season after an interplanting in the spring of year ten, the simulation ends; no further surveys are scheduled. Yet, some mortality will still occur up to the fall of year 14. Finally, one by one, units are removed from files. For overdense stands the accounting system "rings up" the cost for a precommercial thinning at age 15. Whenever applicable, the costs of understocking or reforestation delay are added. Delay is computed as the difference between "ideal" age at time 15, and actual weighted average age.

The program collects data for all plantations, calculates statistics and prepares a final report. It then begins processing a new "batch" of plantations for a new first-year survival-site class-planting density combination. Overall in this study there will be (7x40) 280 runs of 75 samples, one for each payoff matrix element. Potentially, there could be 50 states and ten acts. To facilitate interpretations of this considerable bulk of results, a matrix generator stores the final results for each run in an array element. There are eight arrays for financial and other consequences, each with a dimension of 50x10. Thus, up to ten acts may be considered, and site classes may cover the full range from one to five.

The first array is the needed payoff matrix, that is, a matrix, the elements of which contain the mean total cost for each simulation run. The corresponding variances of the means are stored in the second table. Further matrices exhibit the final, surviving trees per acre, the total number of trees planted, the soil expectation value, and direct management costs, which encompass all costs up to and including any precommercial thinnings, but exclude the opportunity losses due to reforestation lag and understocking. Two further tables present the number of precommercial thinnings, and the percentage of units successfully reforested within the ten-year reforestation phase. The decision maker should primarily focus on the payoff table, the first array; he might consult other arrays for operational characteristics.

Once he has chosen a particular planting density, he may wish to inspect this policy further by calling for a visual display of all financial and physical outcomes in the form of frequency histograms, and for a listing of relative and cumulative probability distributions.

He may further vary target and minimum stocking levels, rotations, change the interest rate or the length of the rehabilitation phase and, thus, test the sensitivity of results. Finally, a planner may apply the program to investigate optimal policies for artificially shaded trees, or for vexar tubing. He merely enters the corresponding costs, which are now assumed zero, but must supply revised survival distributions. The rehabilitation policy itself, that is the timing of stocking surveys or the density up to which units are interplanted, is contained in the code. Since reforestation policies vary with ownership, the computer programs for the simulation are not identical for the two case studies.

We complete this section by dealing with mortality. Reforestation records indicated that seedling mortality essentially ceased after year five. Marginal survival distributions for each year of this period were specified in continuous form by the parameters of a distribution from the beta family. Here it suffices to say that the simulation mechanism randomly selects individual survival fractions for a given age in such a way that, over the total sample of one run, the distribution of these marginal survival percentages closely corresponds to the desired and specified probability distribution for the respective age. These distributions emerge as a result of the operations analysis, hence their derivation will be described there. However, the general methods of distribution fitting, and some statistical test employed in the process, will be outlined next. (Appendix D).

Fitting Probability Distributions to Empirical Observations

Frequently, the need arose to test whether observations from two samples represented the same, or two different parent populations, where no prior knowledge about the shape of these parent distributions could reasonably be assumed. In this situation, the "runs-test" (Brunk, 1975) was applied. In attempts to smooth the shape of irregular, inconsistent frequency histograms, the "sparse data method" described by Anderson et al. (1977) proved extremely helpful, and much less cumbersome than a semi-graphical technique proposed by Schlaifer (1969). Beta distributions were fitted to the cumulative distributions by the method described by Derman et al. (1973).

Fit was mostly apparent merely by visual inspection of plots. In doubtful cases a formal χ^2-test for goodness of fit to the hypothetical beta distribution was applied (Brunk, 1975).

Usually, shape parameters for the fitted beta distributions were real, while conventional tabulations of the fractiles of this distribution assume integer parameters only. The fractiles could have been read simply from graphs of the cumulative distribution function. However, a considerably more convenient and accurate method was available (Lindstrom, 1980) as a computer program.

Cost and Returns: Budgeting the Consequences

The simulation process models the physical fate of the sample plantations, but it also budgets the representative costs or payoffs for each action-state combination. Only those costs and returns are included in this process, which are actually and differentially affected by the alternate choices; in other words, we prepare a partial budget. By considering delayed harvest returns and reduced returns due to understocking as opportunity costs, we may express consequences as costs only, and set a minimization objective.

A recent decision analysis (Turpin and Knapp, 1980) in a large, public ownership in Western Oregon contained current, up-to-date cost and return figures in great detail. Managers in both ownerships were confronted with these figures, and adjusted them for the purpose of their own organizations.

Two cost items, namely the cost of understocking, and the cost of delayed present and future harvests due to an initial regeneration lag proved more troublesome. The following procedure was selected:

Turpin and Knapp (1980) provide a yield table for managed, fully stocked and understocked Douglas-fir stands of site-index 170. Based on an analysis of sales values for several Western Oregon forests, they also estimate stumpage prices for commercial thinnings as a function of age or average diameter. The Oregon State Department of Forestry supplied a net stumpage value equation for clearcuts at final harvest age. Based on these yield table data for site-index 170, and the corresponding revenues, total discounted revenue figures for a rotation of 75 years were computed for all available stocking levels, using a three percent interest rate. Present values for the various stocking levels on site-index 170 were plotted as a function of the number of trees at age ten. This curve subsequently served as a guide curve for the entire set of curves for the five site classes. The "endpoints" of these other functions, for full stocking at 450 trees per acre at age 15, were estimated by means of DFIT (Bruce et al., 1977). Fixed percentage value reductions,obtained from the guide curve, were then applied to adjust present values for full stocking to different stocking densities at age 15. Thus, the shape of all curves follows that of the guide curve, and together they form an anamorphic series. Figure 2 displays results. The cost of understocking was simply read from these curves as the difference in present net values resulting from target stocking and actual stocking.

Reforestation lags delay harvests during the first and all following rotations. For the purpose of this analysis, full stocking, timely harvest,and a uniform total reforestation and precommercial thinning cost of $600 per acre was assumed for all future rotations.

The cost of delay of the first harvest is:

$$D_1 = (R_t - U) - [(1+i)^{-j}(R_t - U)]$$

$$= (R_t - U)[1-(1+i)^{-j}]$$

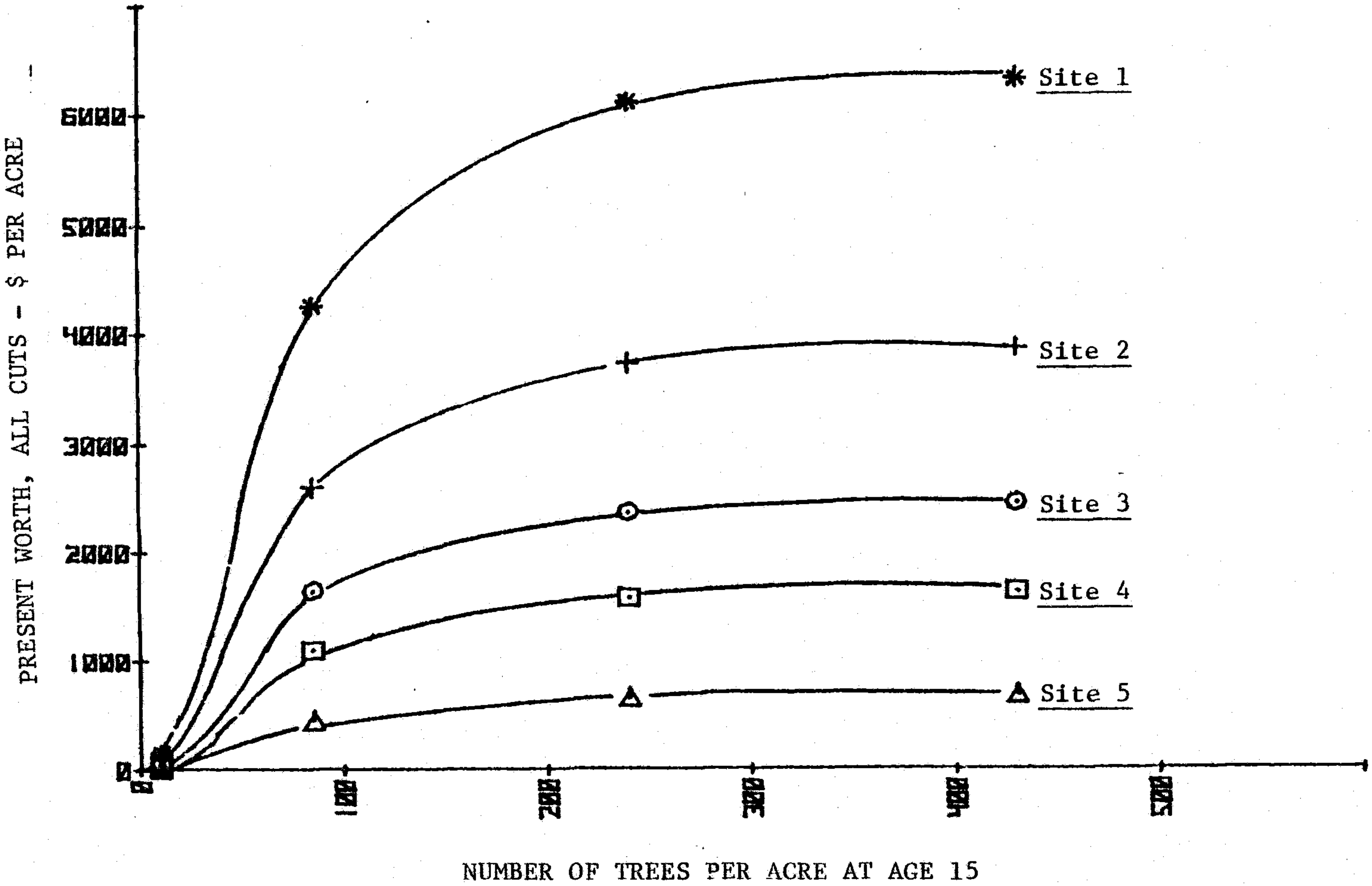


Figure 2. Discounted revenues from one rotation at three percent interest--exclusive of any reforestation and precommercial thinning costs--as a function of stand density at age 15

$$D = D_1 + D_2$$

$$= [R_t - U] \cdot [1 - \frac{1}{(1+i)^j}] + [R_t - 600)] \frac{[(1+i)^j - 1]}{[(1+i)^r - 1](1+i)^j}$$

All seven figures are presented in the form of sample output (Table 6 in Chapter VI). Without doubt, both uncertainty and ignorance surround these costs of understocking.

This concludes the overview of the plantation simulator. For a complete prior analysis, we need one more input, namely the prior distribution.

The Joint Prior Distribution

We defined the state space of the decision analysis as the joint occurrence of a given site class and a specified first-year survival percentage interval. Hence, the prior distribution over these states must reflect not the marginal but the joint distribution of two random variables. Moreover, since first-year survival and site class are influenced to some extent by the same variables, they are statistically dependent.

We compute,

$$P(S_i, t_j) = P(S_i/t_j) \cdot P(t_j) \tag{1}$$

or, equivalently

$$P(S_i, t_j) = P(t_j/S_i) \cdot P(S_i) \tag{2}$$

where:

$P(S_i)$ = the marginal probability of observing survival class i, $i = 1,2, \ldots ,10$

$P(t_j)$ = the marginal probability of observing site class j, $j = 1,2,\ldots, 5$

$P(S_i/t_j)$ = the conditional probability of observing survival class i, given site class j

$P(t_j/S_i)$ = the conditional probability of observing site class j, given survival class i

$P(S_i,t_j)$ = the joint probability of observing both site class j and survival class i

Up to now, we have only seen how the joint prior distribution is derived computationally. The necessary marginal and conditional probability distributions themselves emerged as a result of the operations analysis. I chose to develop them in that context, particularly since their derivation varies by ownership.

Revision of Joint Probabilities for Two Dependent Variables

Special problems arise with the application of Bayes' theorem when the state space consists of two jointly distributed random variables, particularly if they are dependent. For two dependent events, knowing one implies at least some added information about the other. Hence, knowledge about either state variable leads in our problem to a revision of the prior probabilities. Several versions will be applied in this study; the underlying theory follows:

a.) Suppose we find a perfect predictor, $Z_k (k=1,2, \dots ,5)$, for site class, but possess no further survival information. What is the value of perfect site information by itself?

By Bayes' law:

$$P(S_i,t_j/Z_k) = \frac{P(Z_k/S_i,t_j) \cdot P(S_i,t_j)}{\sum_{j=1}^{5} \sum_{i=1}^{10} P(Z_k/S_i,t_j) \cdot P(S_i,t_j)}$$

For perfect site information:

$$P(Z_k/S_i,t_j) = 1 \qquad k = j$$

$$P(Z_k/S_i,t_j) = 0 \qquad k \neq j$$

Hence

$$P(S_i,t_j/Z_k) = \frac{P(S_i,t_j)}{\sum_{\substack{i=1 \\ k=j}}^{10} P(S_i,t_j)} \qquad \text{for } k = 1,2,\dots,5$$

By (4) above

$$\sum_{i=1}^{10} P(S_i,t_j) = P(t_j)$$

Hence

$$P(S_i,t_j/Z_k) = \frac{P(S_i,t_j)}{P(t_j)} = P(S_i/t_j)$$

The posterior distribution for a perfect site predictor equals the conditional distribution of survival for the given site class. We calculate the value of perfect site information alone by carrying out preposterior analysis as stated in the general model.

b.) Suppose we possess a site map with less than perfect accuracy for site class prediction, which yields the forecasts Z_k ($k = 1,2, \ldots ,5$), for site class. What is the value of this map for reforestation purposes?

We are willing to believe that the likelihood of Z_k, given a certain actually observed site class, does not vary with the actually observed survival on that site. In other words, we assume conditional independence:

$$P(S_i,t_j/Z_k) = \frac{P(Z_k/S_i,t_j) \cdot P(S_i,t_j)}{P(Z_k)} \quad \text{by Bayes' Law}$$

$$P(S_i,t_j/Z_k) = \frac{P(Z_k/t_j) \cdot P(S_i,t_j)}{P(Z_k)}$$

since, by conditional independence,

$$P(Z_k/S_i,t_j) = P(Z_k/t_j)$$

Under the assumed conditional independence, the joint posterior distribution of site class and survival for an imperfect site class predictor is equal to the product of joint prior probabilities and the likelihoods for the site forecast, divided by the marginal probability of the site forecast.

c.) Usually, productivity indices for a species are grouped into three to five broad site classes. Correctly assessing these classes appears feasible. Survival, on the other hand, varies as a function of literally hundreds of factors and their interactions. Flawless survival forecasts will remain a myth. What is the combined value of correct site, but imperfect survival forecasts?

From version a.) above, for a perfect site class signal, Z_k,

$$P(S_i,t_j/Z_k) = P(S_i/t_j)$$

Applying Bayes' theorem a second time for the survival forecast, Y_ℓ,

$$P(S_i,t_j/Z_k,Y_\ell) = \frac{P(Y_\ell/S_i,t_j,Z_k) \cdot P(S_i,t_j/Z_k)}{P(Y_\ell)}$$

$$= \frac{P(Y_\ell/S_i,t_j,Z_k) \cdot P(S_i/t_j)}{P(Y_\ell)}$$

Since site class prediction is perfect:

$$P(Y_\ell/S_i,t_j,Z_k) \geqslant 0 \qquad \text{if } j = k$$

$$P(Y_\ell/S_i,t_j,Z_k) = 0 \qquad \text{if } j \neq k$$

$$P(Y_\ell/S_i,t_j,Z_h) = P(Y_\ell/S_i,t_j)$$

$$P(S_i,t_j/Z_k,Y_\ell) = \frac{P(Y_\ell/S_i,t_j,Z_k)\cdot P(S_i/t_j)}{P(Y_\ell)} \qquad \text{for } j = 1,2,\ldots,5.$$

For perfect site class identification, we cannot assume conditional independence of survival information. Likelihoods for survival prediction will vary by site class; however, much fewer likelihoods must be assessed than in the previous case, i.e., 10 instead of 50.

Since posterior probabilities, by necessity, can only be non-zero if site-class and site-class predictor coincide, posterior analysis may be carried out independently, one site class at a time. For each site class, decision analysis will yield a Bayes' strategy for each possible survival forecast. By contrasting the overall expected value of this strategy with the expected value under perfect site information only, we arrive at the marginal value of survival prediction for this site class.

When we weight the expected value of Bayes' strategy for each site class by the respective marginal probabilities of these classes, we compute an overall expected value with site and survival forecasts. We obtain the value of all information by comparing the result with the expectation of the prior optimal act.

Now we have specified acts, states of nature and associated prior probabilities, and we are familiar with the plantation simulator, which provides us with economic and non-monetary consequences of each act. These are the prerequisites for the prior analysis.

For the subsequent preposterior analysis we have demonstrated the technique for revision of probabilities, after receiving various kinds and intensities of information. The method of generating these forecast signals is outlined next, when we focus on the ecological models for this study.

Development of a Survival Predictor

Field Procedures

In the winter and spring 1978/1979 sample survival plots, each consisting of 15 Douglas-fir seedlings marked by wire-flags, were established on routinely and operationally planted clearcuts in both study areas. There were 133 of these roughly circular plots with somewhat varying radii in Tillamook, and 214 in Roseburg. Table 4 shows sample allocation in detail.

The selected clearcuts represented all slash-burnt units of the years 1977/78 and 78/79. Plot allocation to individual areas reflects the size of the units. The allotted number of plots were located randomly, without any stratification, on each timber sale map. A transparent millimeter grid, placed over the unit boundaries, provided a coordinate system; random numbers from a table served as coordinates in this system. Whenever the respective point fell within the unit boundaries, plot location was fixed with the prick of a needle.

When clearcuts that were planted 1977/78, and interplanted a year later, lacked sufficient original seedlings within an acceptable distance from the plot center, first-year, interplanted trees were selected instead. Only very few, quite obviously damaged or very poorly planted seedlings were excluded. All but very few seedlings were 2/0-stock. Contract planting prevailed in Roseburg; Tillamook had used both contract and prison inmate labor. No obvious difference was apparent.

TABLE 4. Allocation of Sample Survival Plots.

Treatment	Tillamook	Roseburg
Clearcuts planted 1978/79	12	22
First-year plots without artificial shade	70	107
First-year plots with artificial shade	--	14
Total number of first-year plots from first planting	70	121
Clearcuts planted originally 1977/78 without shade	8	12
First-year plots in interplants without shade	22	24
First-year plots in interplants with shade	--	6
Second-year plots without shade	41	36
Clearcuts planted originally 1977/78 and shaded	--	2
Second-year plots with shade	--	13
Total number of first-year unshaded plots	92	145
Total number of second-year unshaded plots	41	36
Total number of first-year shaded plots	--	20
Total number of second-year shaded plots	--	13
Total number of plots	133	214

Close to the plot center, a one-meter long, steel soil probe was driven into the soil as far as possible with a long-handled hammer of high-impact plastic. It is fair to say that without this equipment (Erdbohrstock nach Dr. Pürkhauer) site mapping of such a large number of plots on frequently very stony soils would have been impractical. From the "feel" of the ingoing probe and from the examination of its content coarse fragment content, depth, organic matter content and, most important, field texture were estimated. When the soil was conspicuously loose or dense, this was noted.

A rough estimate of vegetation density as percent ground cover, measurement of slope in percent, and aspect from geographic North completed site data collection. Stock condition was recorded as good, mediocre or poor. Samples of the top 20 cm of most profiles were taken for subsequent analysis. After one growing season, that is, in the winter and spring 1979/80 plots were rechecked and survival noted. Field soil analysis was repeated.

As long as seedlings exposed any live green needles, they were considered alive. Occasionally, particularly in Tillamook, missing trees occurred. They include oversights of mortality and, most likely, animal impact. I chose to simply disregard these missing trees, perhaps introducing slight bias in the analysis. However, survival percentages on each plot were weighted by tree count in the regression model.

In Tillamook, field procedures included a revisit to some of the original operationally established survival plots after a period from 10 to 13 years. While highly instructive, this effort was scaled down quickly, when relocation of these plots proved difficult. The same site data were collected for these plots as for the 1979 study plots.

Soil Analysis and Estimation of Available-water Capacity

Out of a large collection of soil physical data provided by the Oregon State University Soils Department, I selected analyses of 190 forested soils from Western Oregon, and used them to investigate the influence of texture on the available-water capacity (AWC). Only 31 of my own surface soil samples were routinely analyzed for texture, organic matter and AWC on a weight basis. Inspection of the large data collection indicated that no serious error would be introduced if a bulk density of one gram per cm^3 was assumed for all soils of the Roseburg study. For the low-density Tillamook soils a correction was needed. I used the OSU data collection to establish a regression for bulk density of Tillamook soils, in which texture and soil organic matter entered as independent variables.

A second model, based on 31 analyses of soils from the survival plots, relates AWC to observable soil parameters, such as texture, density and organic matter. Estimates were tested against sets of independent data from the OSU collection and the Roseburg Soils Inventory (Wert et al., 1977).

Regression Model for First-Year Survival in Tillamook

Table 5 represents a listing and definitions of potential independent variables, which, together with the customary transformations, and indicator variables were considered in a stepwise, weighted regression procedure described by Neter and Wasserman (1974:382).

Operations analysis had indicated a strong effect of summer rainfall on survival. However, only much less meaningful annual isohyetal and isothermal data were found on maps (State Water Resources Board, 1960; Soil Conservation Service, 1964). Hence, substitute variables, such as distance inland and altitude, were chosen reluctantly.

East and west aspects receive identical amounts of radiation (Sullivan, 1976); however, its physiological effect may vary considerably, since plants recover some turgor during the night. Moreover, in the Tillamook area, dewfall occurs frequently during the vegetation period, and may remain on leaves until late morning. Therefore, aspect classes, as defined in Table 5, appeared more meaningful than the conventional 90° sections starting from true North.

In spite of a generally humid environment, some interior valleys of the Coast Range are likely to experience a "Föhn"-effect (Blüthgen, 1964). These low areas are sheltered from prevailing winds by higher mountain ridges, and receive considerably less rainfall, and more clear-sky radiation. They have lower relative humidity and higher summer temperatures (Geiger, 1965:408). An isohyetal map of the Tillamook forest reveals one large such area in the valley of the Wilson River. There must be others which do not show up at the scale of these maps. Again, with detailed climatological data missing, an interaction of altitude and distance inland had to serve as a proxy variable.

So far, we have only considered independent variables. Missing trees created problems with the dependent variable. When stakes could not be relocated in the survival plots, a correction was applied in the weighting procedure. When seedlings were missing at the wire flags, I chose to compute survival percentage based on the number of relocated plants only.

Following a procedure suggested by Neter and Wasserman (1974) the dependent variable, that is, percent first-year survival of each plot, was transformed by the logistic function. This "logit" transformation linearizes typical binary response functions. In this study, it also eliminated the problem of heteroscedasticity of the error variances.

TABLE 5. Potential Independent Variables in Regression Model for First-year Survival in Tillamook

Variable	Symbol	Definition and Derivation
Rock content	ROCK	Coarse fragment > 2mm in percent by volume, estimated as the mean of two samples taken with the soil probe
Available-water capacity	WATER	Estimated, based on silt content, organic matter and packing density of the soil. Expressed in volume percent or as mm per dm of depth
Soil depth	DEPTH	Depth of profile in cm read from the steel probe, from at least two samples, after solid resistance is encountered
Effective soil depth	EFFDEPTH	DEPTH, multiplied by a factor of [(100 - ROCK) : 100] to indicate soil volume available for storage of water
Available water in the solum	EFFAWC	Product of EFFDEPTH and WATER x 10^{-1} in mm or as liters per m^2 soil surface
Indicator variables for aspect	INDN INDE INDS INDW	Set to 1 if plot is located on a slope > 30%, and if aspect from true North is: > 337.5, ≤ 45; > 45, ≤ 157.5; > 157.5, ≤ 270; > 270, ≤ 337.5, respectively
Distance inland	RANGE	Distance east of the range line between Range 9 and 10, which transects Tillamook, determined by simple section count on the map
Altitude	ALTIT	Altitude in feet as read from contour lines of map
Available water in the rooting zone	ROOTAWC	The smaller of either DEPTH or 40 cm multiplied by ROCK x 10^{-2} x WATER
Slope	SLOPE	Slope of plot as measured with clinometer in percent

(continued)

TABLE (continued)

Variable	Symbol	Definition and Derivation
Precipitation	RAIN	Annual precipitation as read from an isohyetal map in inches (State Water Resources Board, 1960)
Silt content	SILT	Indicator variable which was set to 1 if silt content was estimated to be below 30% by weight
Transformation	SRTRAN	$\sqrt{\text{RANGE}}$
Interaction	ALTSRTR	ALTIT x $\sqrt{\text{RANGE}}$
Interaction	WATERN	WATER x (INDN + INDW + INDE)

Regression Model for First-Year Survival in Roseburg

Some additional variables were defined for Roseburg, such as an indicator variable for soils with high clay content. These soils assumed a brick-like, hard consistency when summer-dry. Since vegetation cover could be presumed to affect soil moisture, an estmate of the area fraction covered was included.

An isohyetal map (Soil Conservation Service, 1964) provided normal annual rainfall data, which again must serve as an extremely poor proxy variable for precipitation during the growing season. Otherwise, regression procedures equal those in Tillamook.

Productivity Prediction Models

In the absence of a suitable stand of trees, managers of the Tillamook State Forest may determine site class by two methods: They can consult a recent soil survey (1:31680, Westerberg et al., 1978) which assigns both a mapping unit name and an average site index to each parcel of the forest. There are two sources of error: Mapping units may not coincide with actual soil conditions on the ground, and even if they do, actual productivity may vary randomly or even systematically about the predicted average for the soil unit. To eliminate these mapping inaccuracies, soil specialists can predict site-class from observable site parameters, using one of several regression models presented by Steinbrenner (1979). The latter approach does not require identification of the soil series. Besides the usual random errors, estimates may contain prediction bias (Neter and Wasserman, 1974), particularly since none of the original observations lay in the Tillamook Forest (Steinbrenner, 1979).

I assessed the accuracy of the model (Steinbrenner, 1979)

"Douglas-fir: Western Oregon Residual Soils with Precipitation over 60 inches" based on two sets of observations: First, the ownership supplied me with a standard description of 28 modal soils, for which site index measurements had been taken during the conception of the soil survey. For these plots, I calculated site index based on a detailed profile description and location on a map, and compared it with measured values. The second test set was a randomly selected sample of stands 40 years or older from a listing of the adjacent Forest Grove district. The Tillamook forest, due to its fire history, generally lacks older stands, and site index determinations in young stands are easily subject to error (Kramer, 1962). In each stand, 5-acre tracts were randomly located on contrasting soil series identified in the soil map. In each parcel, 17 overall, we selected two plots, sampled the soil with the steel probe, and measured site index as outlined by King (1966). By comparing the point estimate based on the "soil-site" equation with the measured index we could, again, assess its predictive power. A second comparison between site index measurement and map estimate allowed an assessment of map accuracy. Since managers would rarely be interested in point accuracy, we averaged plot measurements for each 5-acre tract in this comparison.

One additional test set was available in Tillamook. Since all site information was available for each survival plot, and since regression predictions proved reliable, I could assess differences between site map estimate and site index derived from the site data via regression model.

Foresters of the South Umpqua Resource Area cannot accurately predict site index without a suitable stand of trees, in spite of the fact that agency guidelines condition treatment prescriptions by site class. The district's soil inventory (1:62500, Wert et al.,

1977) "does not identify soil series or slope at any one particular spot on the landscape." Fortunately, it contains sample site index measurements for most mapping units.

Initially, I tested the predictive power of one of Steinbrenner's models (1979) against these data, in spite of obvious extrapolations. When results proved unsatisfactory, I established a regression model based on detailed descriptions of modal soils, and corresponding site index measurements. The data base may have been confounded in many ways, hence results are preliminary and tentative at best. They are contained in Appendix A.

VI. RESULTS AND DISCUSSION: THE TILLAMOOK CASE STUDY

The Natural and Organizational Environment for Reforestation

Geology, soils, topography, climate and vegetation of the Northwestern Coast Range have been described in great detail (Lowry, 1955; Bailey and Hines, 1971; Hines, 1973; Knox et al., 1965; Franklin and Dyrness, 1973). Environmental conditions appear nearly ideal for regeneration, if one excludes brush competition: With 90-150 inches of annual rainfall (State Water Resources Board, 1960) the area qualifies as one of the most humid in the United States (Loy et al., 1976). During the dry growing season, low clouds and fogs frequently drift into the mountains during late afternoon and fail to recede until late morning. After clear nights, dew will cover vegetation sometimes until noon. Cool average annual temperatures of 9 to 12°C prevail; even average temperatures of the hottest month range only from 14-18°C. Temperature rises inland, and decreases only slightly with altitude. Forest lands have been soil-mapped extensively (Westerberg et al., 1978). Derived from basalt, tertiary sandy or silty sediment and volcanic breccias, these soils possess an amazingly high organic matter content. As a consequence, and perhaps because of additions of volcanic ash, the presence of allophane, and a climate that favors high biological activity, bulk densities reach extraordinarily low values. Originally described as "sols brun acides," the soils have been reclassified as "Haplumbrepts" in the 7th Approximation (Soil Survey Staff, 1960).

Rock contents tend to increase with slope; simultaneously, soil depth often decreases. In most cases, depth did not exceed the range of the "Pürckhauer." that is, one meter, in the study plots. Figure 3

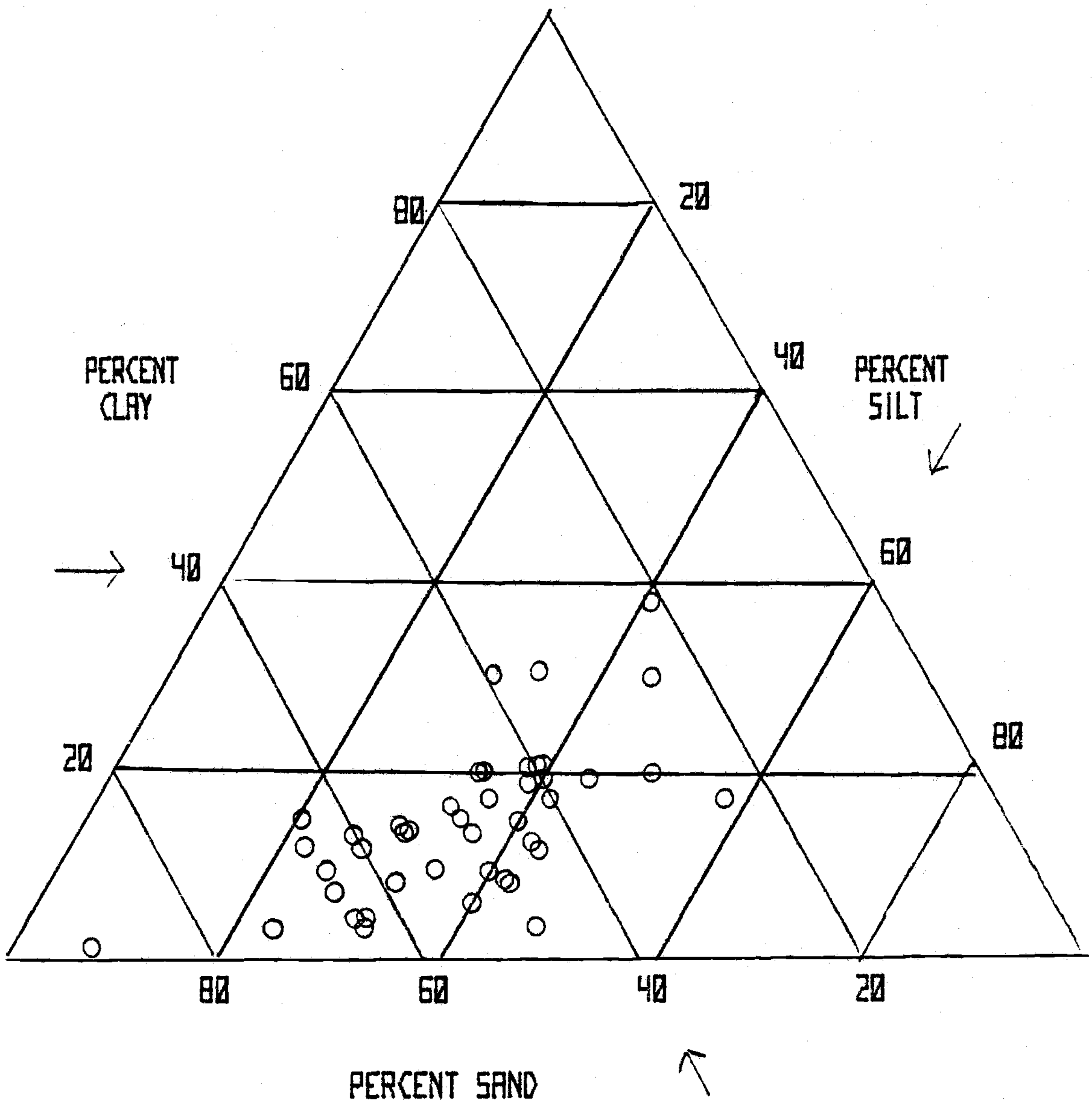


Figure 3. Sample soil textures for Tillamook.

depicts texture distribution on these plots. Damages by animals, from elk (*Cervus canadensis*), deer (*Odocoileus hemionus*) and mountain beaver ("boomer") (*Aplodontia rufa*) definitely qualify as environmental factors. I observed both intense browsing, as well as an amazing tenacity of horribly mutilated seedlings to "hang on." No doubt, animal damage contributes by itself, and in interactions to, mortality (Black et al., 1979). Other studies indicate that its impact on survival is perhaps overestimated by reforestation personnel, a prime example for the cognitive and motivational biases described in the literature review (Crouch and Paulson, 1968; Crouch, 1980; Black et al., 1969; Hines, 1973).

Westerberg et al. (1978) found an average site index (50 years) of 2.27. According to his soil map, site classes 1, 2, 3, and 4 assume proportions of 9.45 percent, 55.37 percent, 33.45 percent and 1.73 percent, respectively. Organizationally, guidelines specify stocking targets for the most intensive regime of 450 trees per acre during the reforestation phase. If density estimates during first-, third- or fifth-year surveys fall below 300 trees to the acre, areas are interplanted.

A "dual stocking standard" takes the distribution of survival into account. This study circumvents the problem of "clumpiness." It assumes uniform mortality distribution over an area which has been ascribed to a single "site unit" in a more or less intensive site mapping and stratification procedure. Thus, the analysis presumes that gross differences in mortality on a single clearcut result from significant, *a priori* recognizable site differences. Treatment should vary for "significantly large" strata, as defined by the ownership, a result, which Ruth (1957) obtained *ex post*. A comparison of operational stocking survey maps, depicting mortality by area, with site data collected in the field tended to substantiate this hypothesis.

Some Operating Characteristics for Reforestation

Are there reforestation problems in Tillamook? Figure 4 indicates that inter- or replants occur frequently; approximately 82 percent of all plantations in a sample of 125 had been totally or partially interplanted at least once by 1980. Some added planting may still be necessary in some cases.

An associated problem appears in Figure 5. Why the high incidence of herbicide use? The Tillamook environment and its vegetation definitely favors fierce plant competition to seedlings. Figure 6 suggests a contributing, added possibility: There is an intuitively reasonable tendency for an increase in herbicide applications with rising number of interplants. Once a first reforestation effort fails, conditions tend to deteriorate. Hence, having a strategy that reduces troublesome interplantings might also lead to a decrease in herbicide use as a financially, environmentally or politically desirable consequence. Overall, a "problem" does exist in Tillamook.

A detailed analysis, based on 209 syrvival plot records for the years 1967 to 1975 follows.

Average survival drops from approximately 78 percent in the first year to 65 percent and 58 percent in the second and third year, respectively. As a consequence of random mortality over the years, the distributions of total survival approach normality after three years (Figures 7-9).

In decision analysis, we should use any and all available information. Before we accept these historical frequencies as a basis for judgmental probabilities, let us substantiate them.

What influence has rainfall during the vegetation period? If rainfall had varied substantially from the long-run average during the period 1967 to 1975, then our actuarial distribution should be adjusted judgmentally. Much of the year-to-year variability of average first-year survival in Tillamook is explained by varying amounts

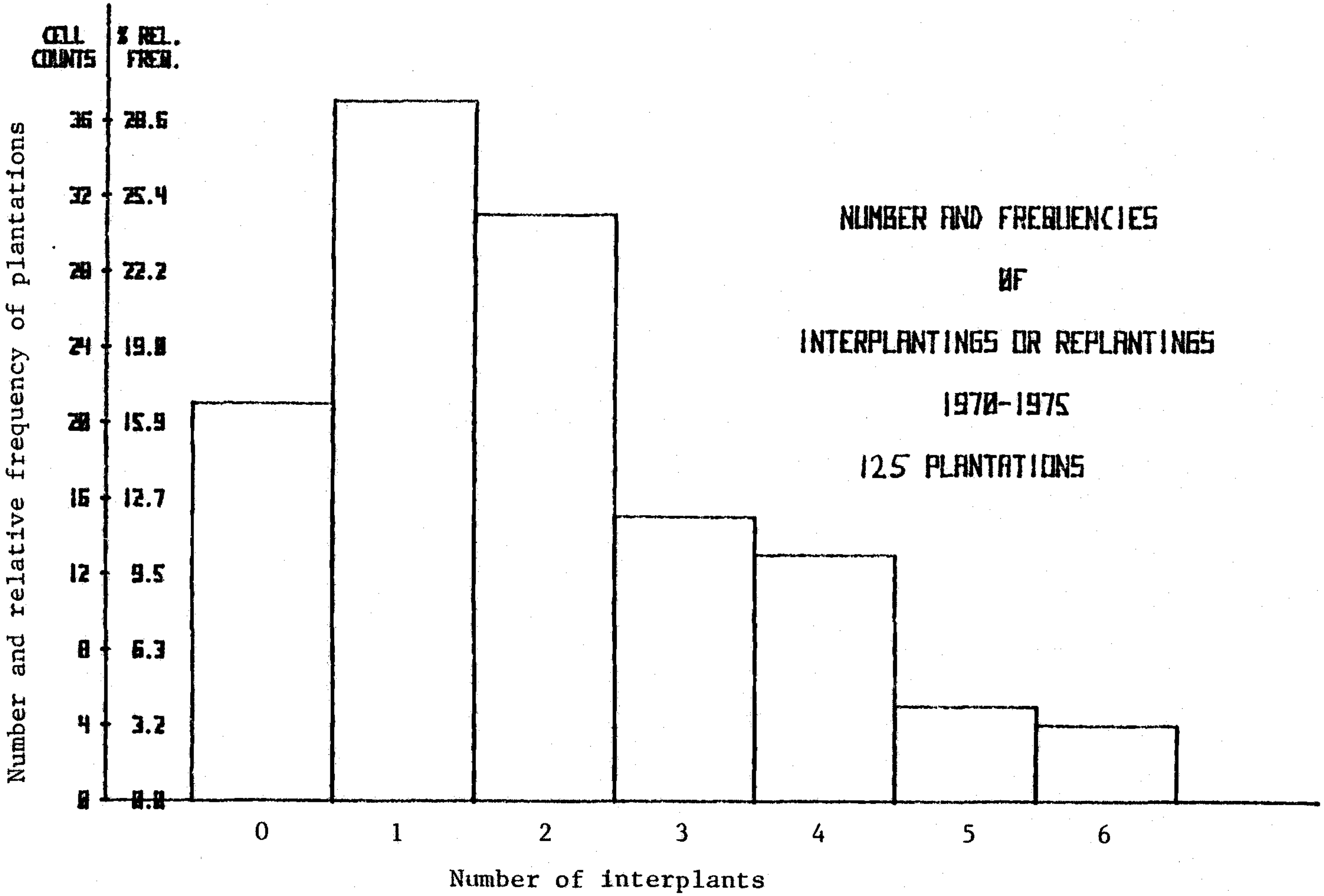


FIGURE 4. Histogram of fill planting frequencies in Tillamook for plantations 1970 to 1975.

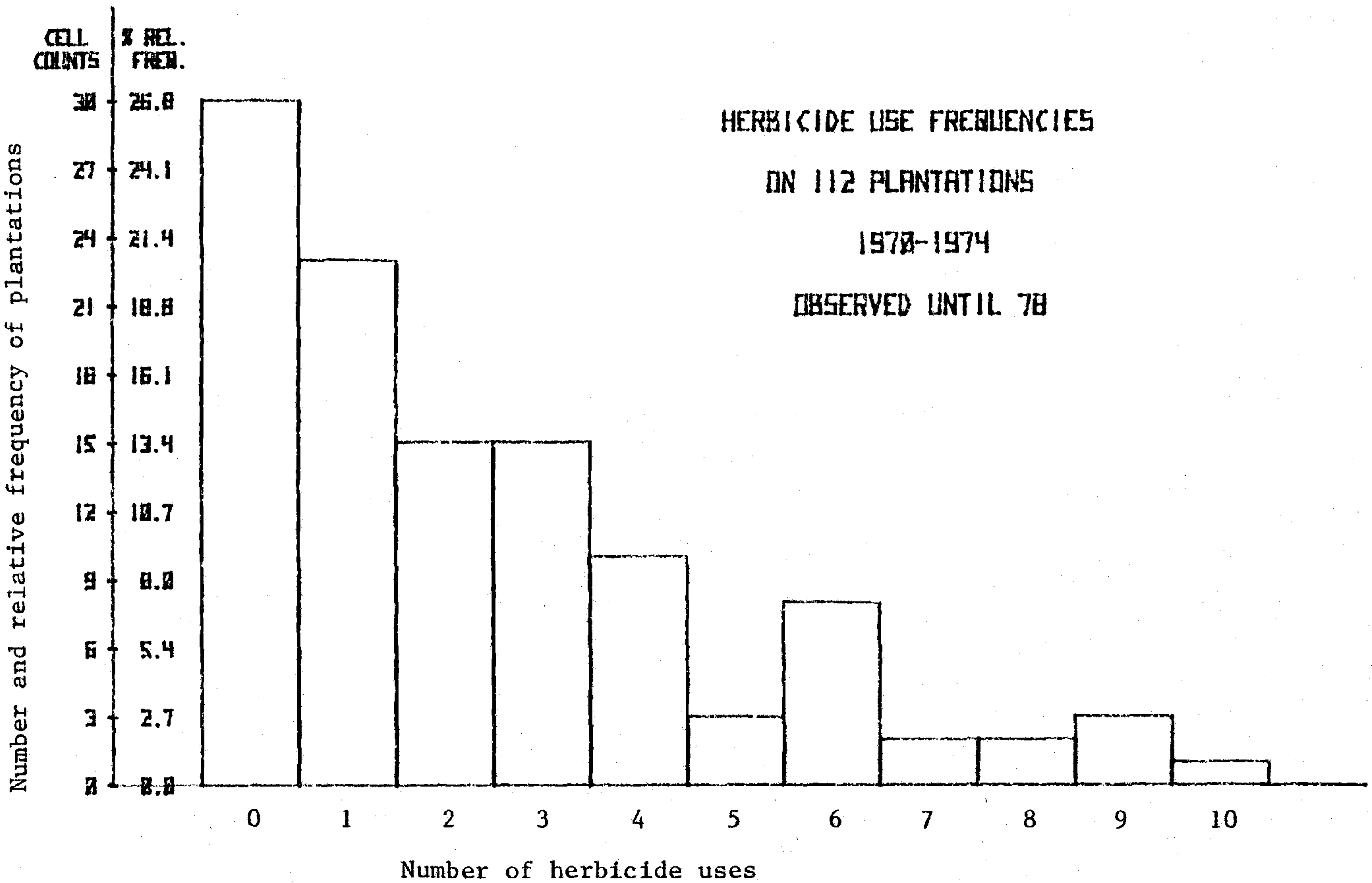


FIGURE 5. Histogram of herbicide use frequencies for plantations in Tillamook established 1970 to 1974 and observed until 1978.

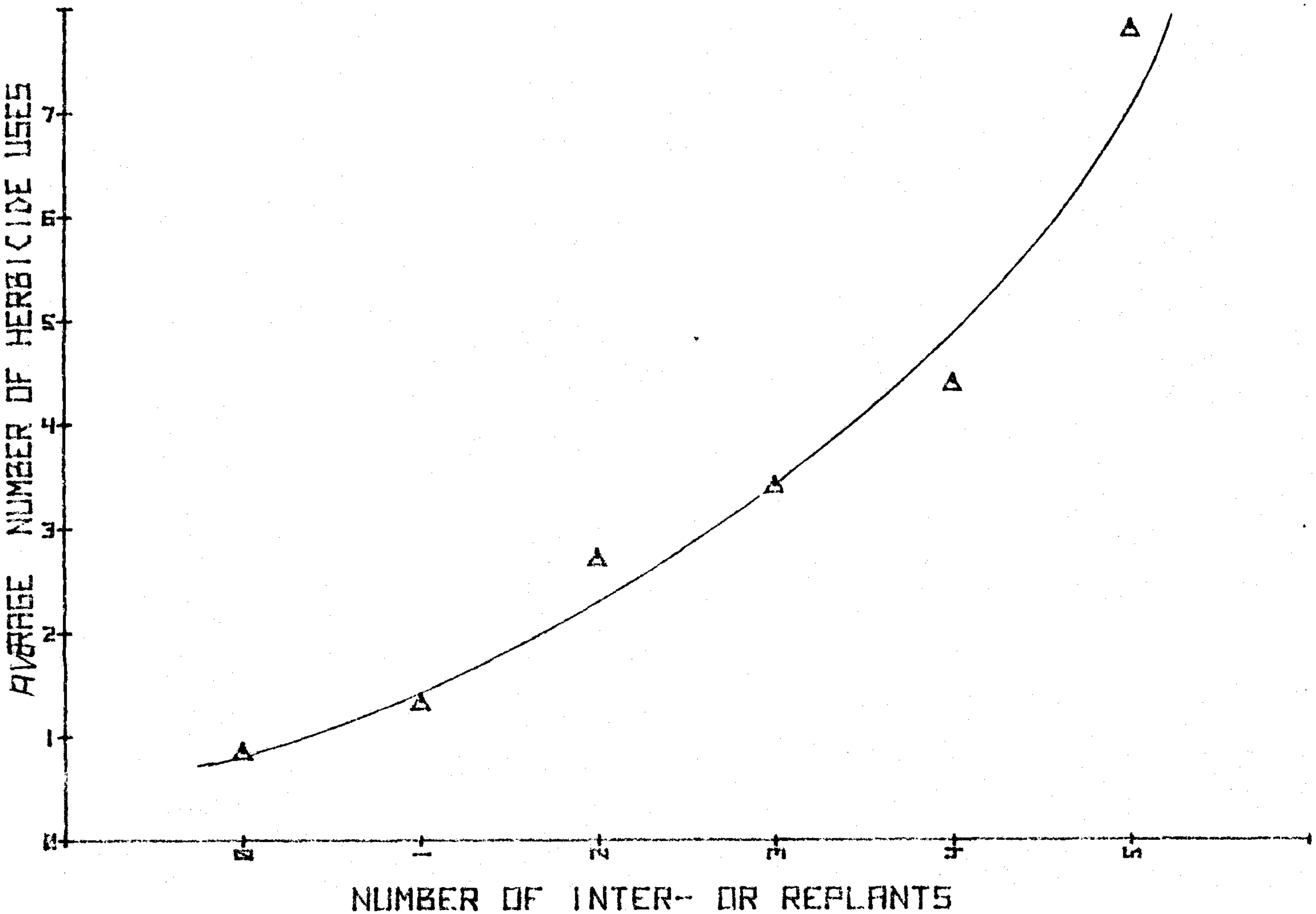


FIGURE 6. Average number of herbicide applications in Tillamook as a function of the number of interplants.

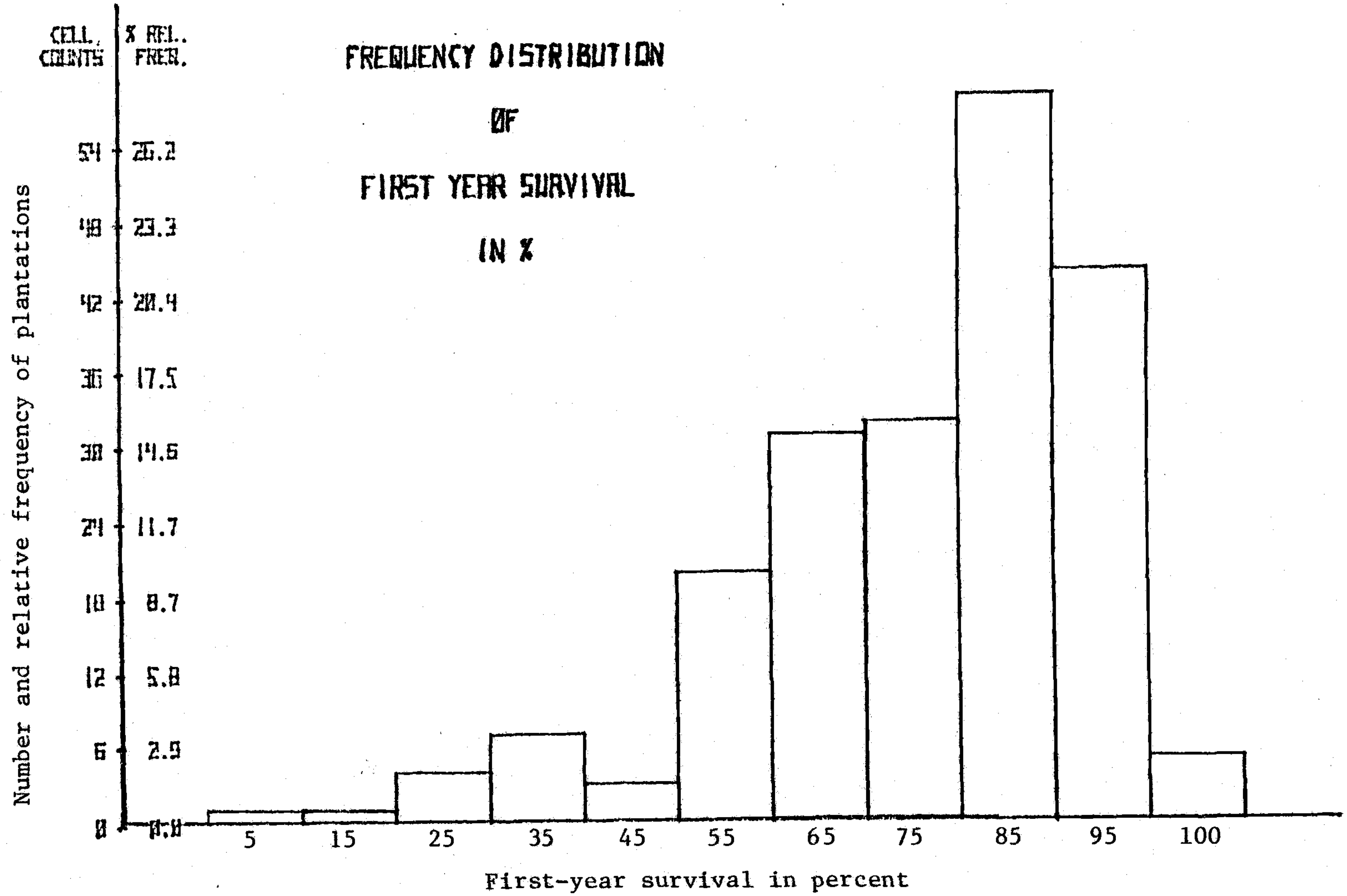


FIGURE 7. Histogram of first-year survival percentage in Tillamook.

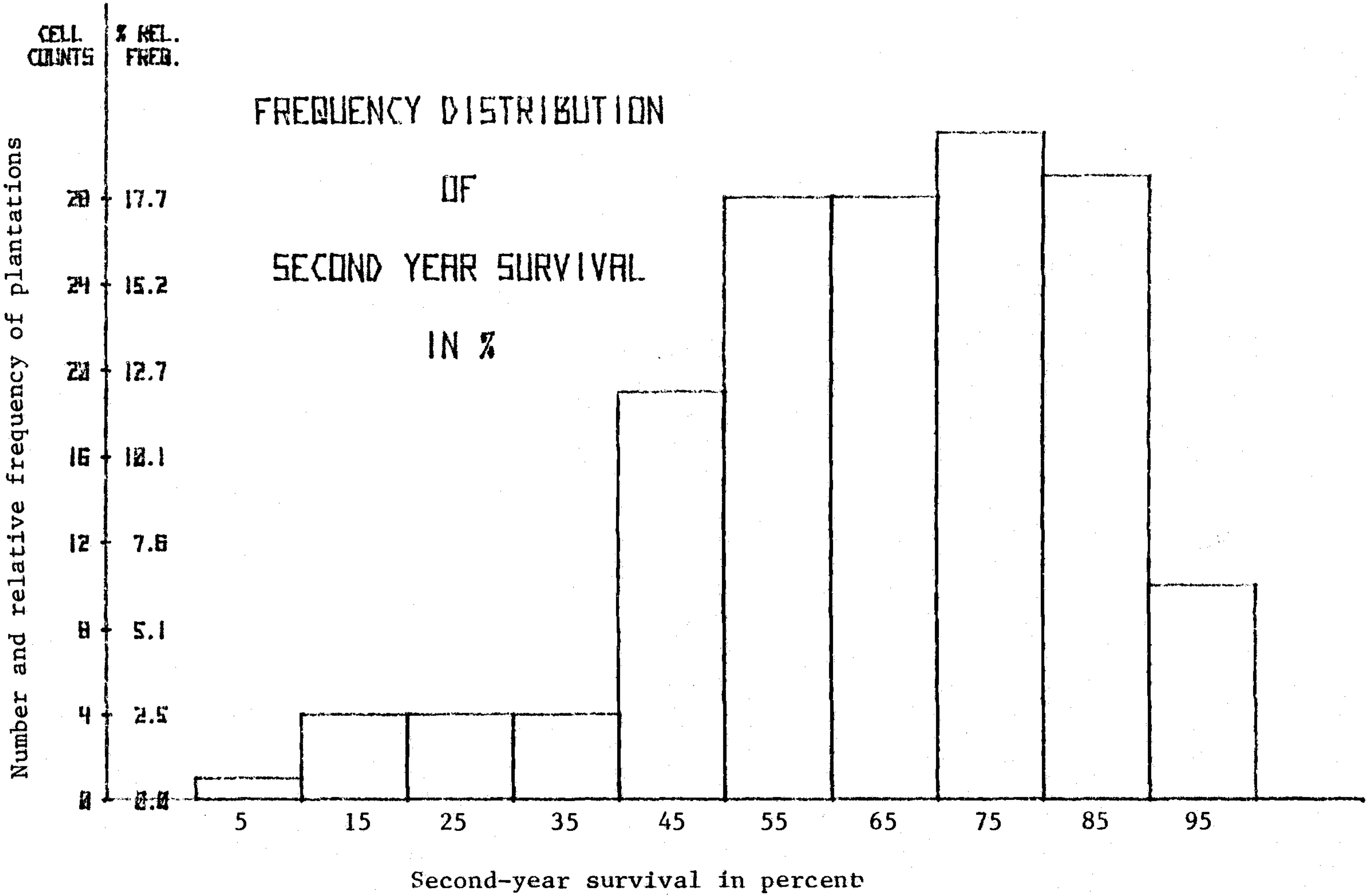


FIGURE 8. Histogram of survival percentage after the second year in Tillamook.

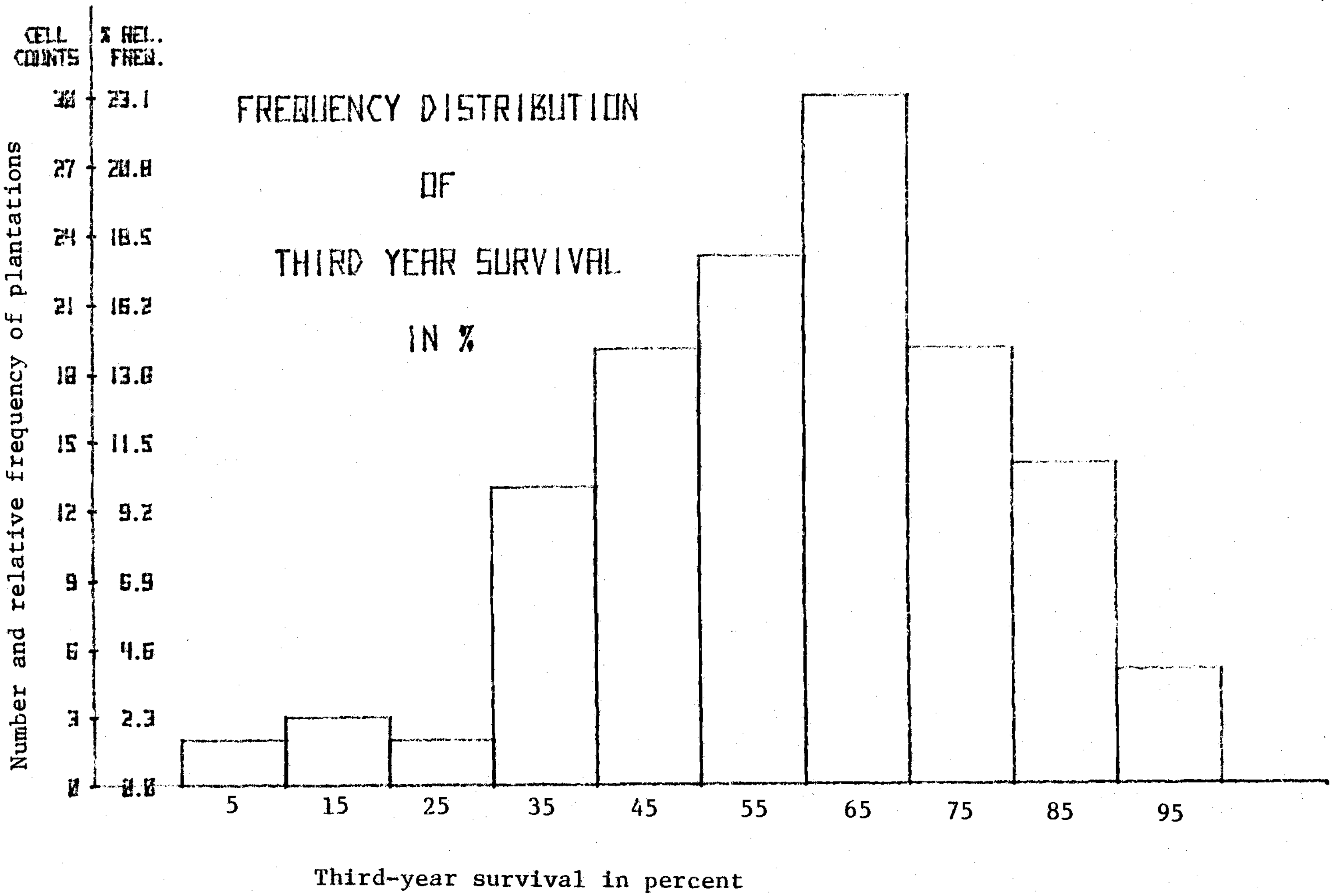


FIGURE 9. Histogram of survival percentages after the third year.

of precipitation during the critical May to August drought period, as apparent in Figure 10.

Further examination of entire first-year survival distributions by year reveals the existence of typical "wet-, medium- and dry-year distributions." Characteristically, it is the incidence of high survival (> 80%) which suffers in dry years. First-year survival percentages from the ownerships survival plots were pooled into three groups, which had received high, average, or low amounts of rainfall during the growing season. Pairwise runs-tests of the resulting cumulative distributions did indeed confirm differences at the five-percent level of significance. Distribution functions are displayed in Figure 11.

Do results of the 1978/79 survival plots conform? In 1979, the area received 2.76 inches precipitation from May to August, slightly above average. A comparison of the corresponding cumulative distributions reveals a high degree of conformity (Figure 12).

There appears no chance to predict summer rainfall during the preceding winter and spring planting season. Hence, we must accept this source of variability as a random, non-predictable and non-controllable input. Since the average May to August rainfall during the period 1968 to 1975 did not deviate appreciably from the long-term average for Tillamook (United States Department of Commerce, 1967 to 1980) no adjustment of the actuarial distribution of first-year survival appeared necessary. Overall, considerable confidence in our actuarial distribution seems justified. The decision maker, confronted with these results, felt comfortable with them, and did not wish to judgmentally adjust the prior probabilities for first-year survival.

After the preceding analysis, survival distributions can be expected to vary with productivity, too. Cumulative distribution functions for sites two and four, based on first-year survival of operational survival plots and corresponding site class, as read from the

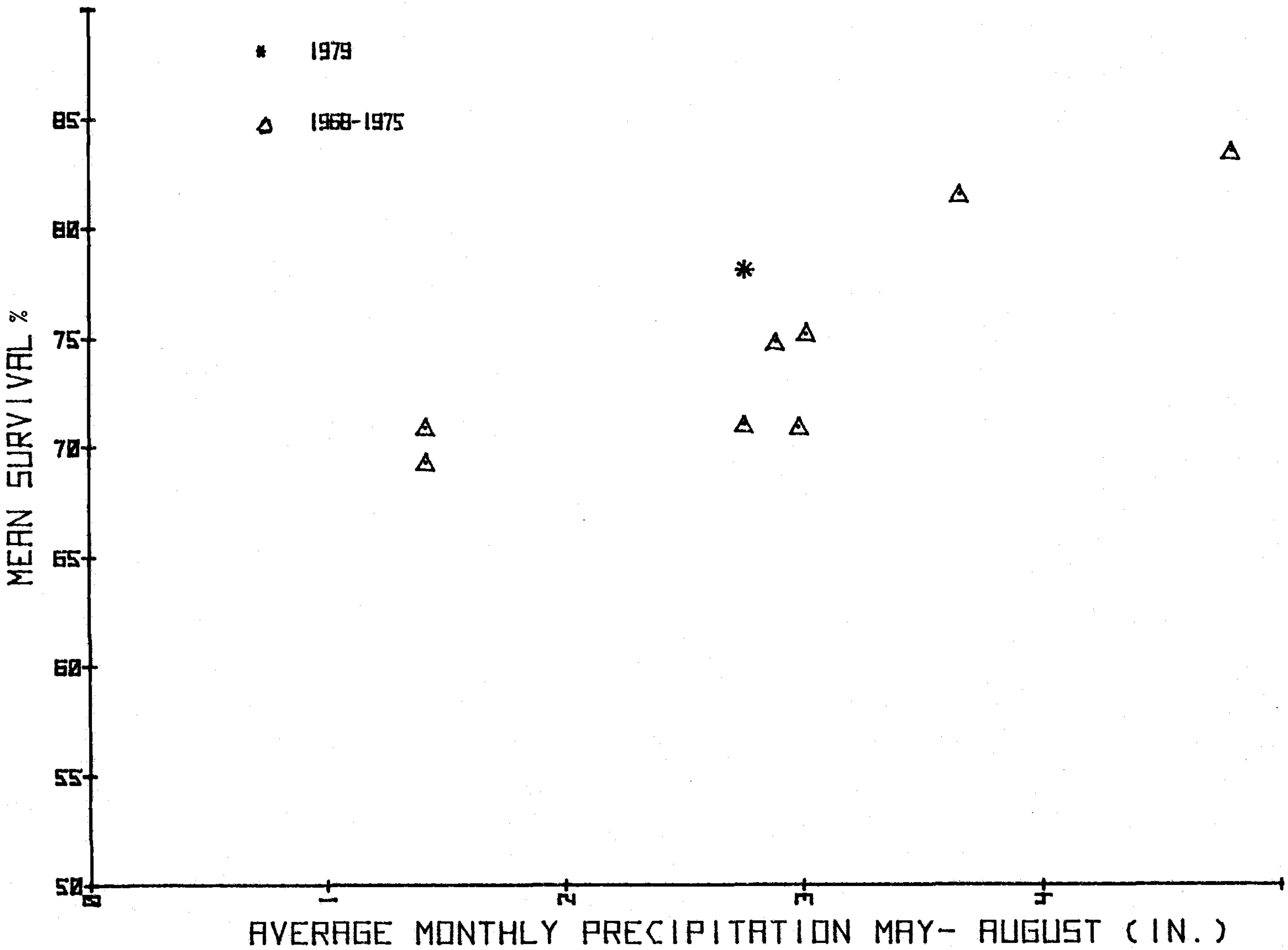


FIGURE 10. Average first-year survival in Tillamook as a function of average monthly precipitation from May to August.

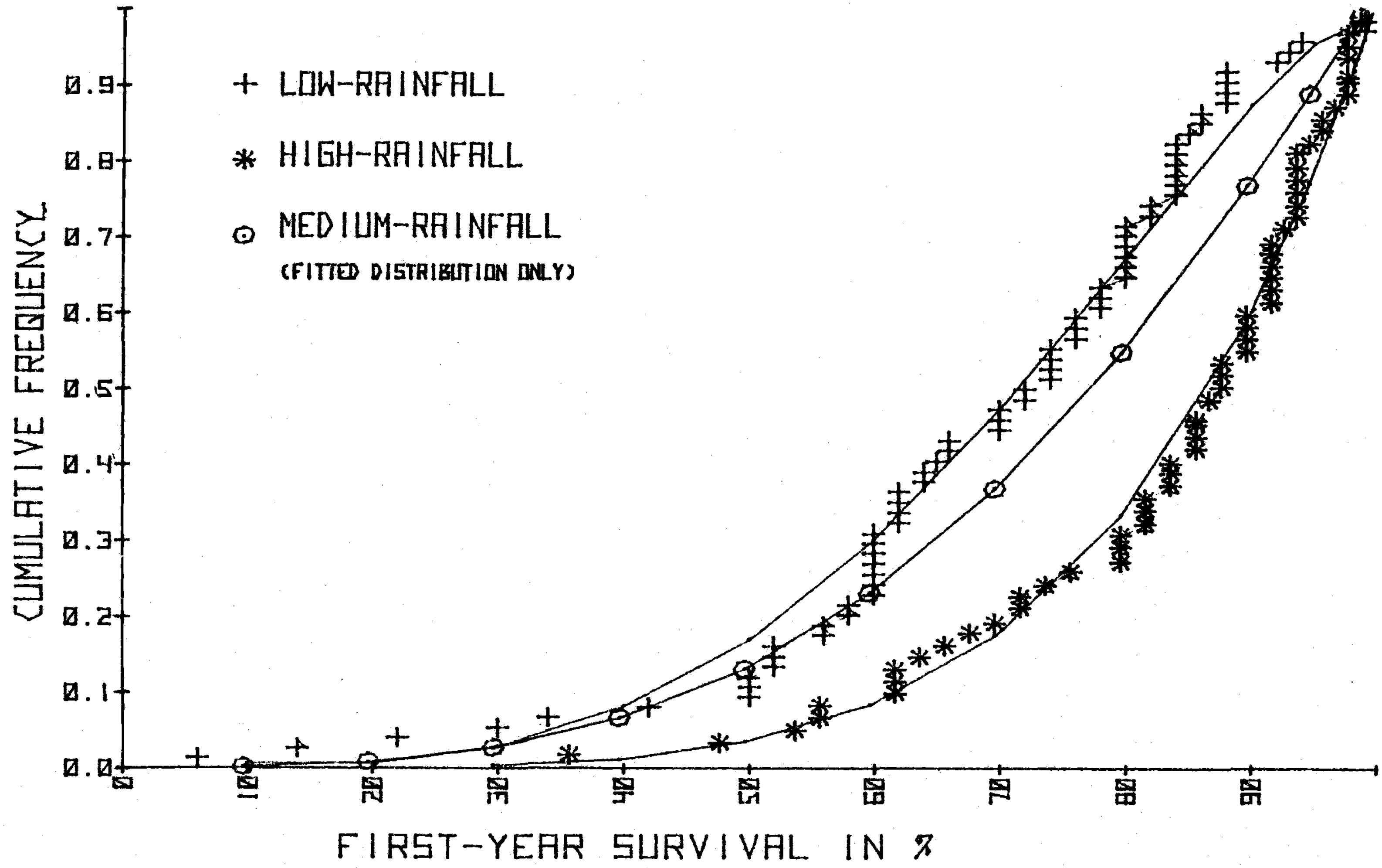


FIGURE 11. Cumulative distributions of first-year survival in Tillamook as a function of three levels of rainfall during the May to August period. (Symbols represent actual observations; solid lines correspond to fitted beta-distributions.)

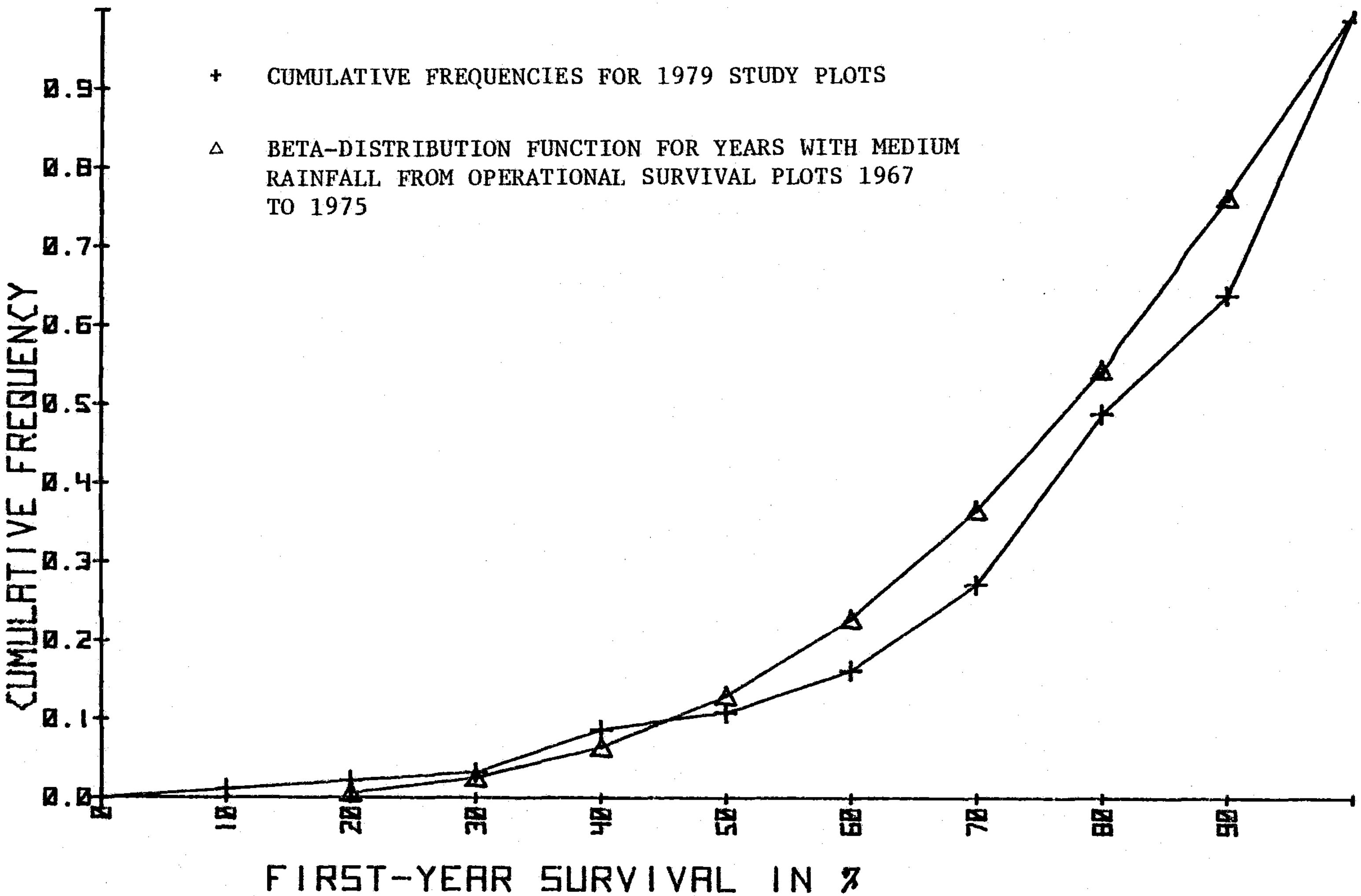


FIGURE 12. Cumulative distributions of first-year survival for Tillamook study plots (1979), and for operational plots in years with average rainfall.

soil map (Westerberg et al., 1978), are displayed in Figure 13. Pairwise runs-tests confirmed differences between all four of these distributions at the 95 percent level.

Clearly, the distributions reflect some judgment; they may contain inaccuracies of the soil map. However, they also reflect a large sample of operational records and may represent the best information currently available. Moreover, they are substantiated by a comparison with site-dependent survival on the study plots. For site class 3, for instance, Figure 14 reveals reassuring correspondence.

Mortality carries over into the second year, that is, plantations with low survival in the first-year experience relatively high mortality in the second year, too. Figure 15 depicts this relationship. Subsequent mortality in the third year was independent, however. By means of a regression with indicator variables for site class, this function was specified as follows:

$$p = \frac{e^{-0.2017 + 0.025X}}{1 + e^{-0.2017 + 0.025X}}$$

where

p = marginal second-year survival fraction

X = first-year survival in percent

The logit transformation (Neter and Wasserman, 1974) achieved both normality of the residuals about the regression (tested in a Chi goodness of fit test) and equality of variances over the range of the independent variable, as shown by Bartlett's test (Neter and Wassermann, 1974). These checks were important for the subsequent simulation process.

All of the indicator variables for site class proved nonsignificant. Hence, while marginal second-year survival may and does vary by site class, this follows as a consequence from differences

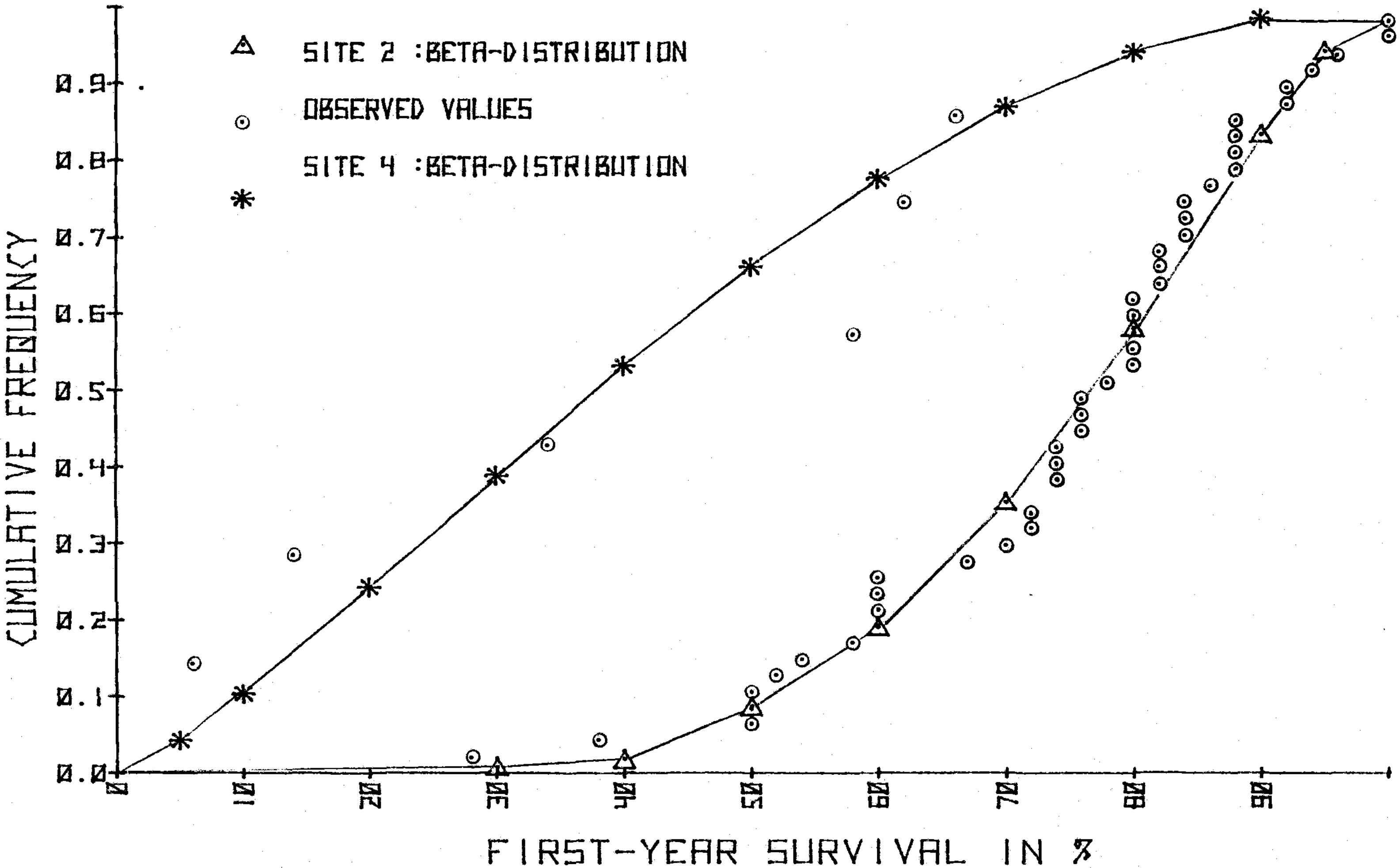


FIGURE 13. Cumulative distribution functions of first-year survival in Tillamook--site classes two and four.

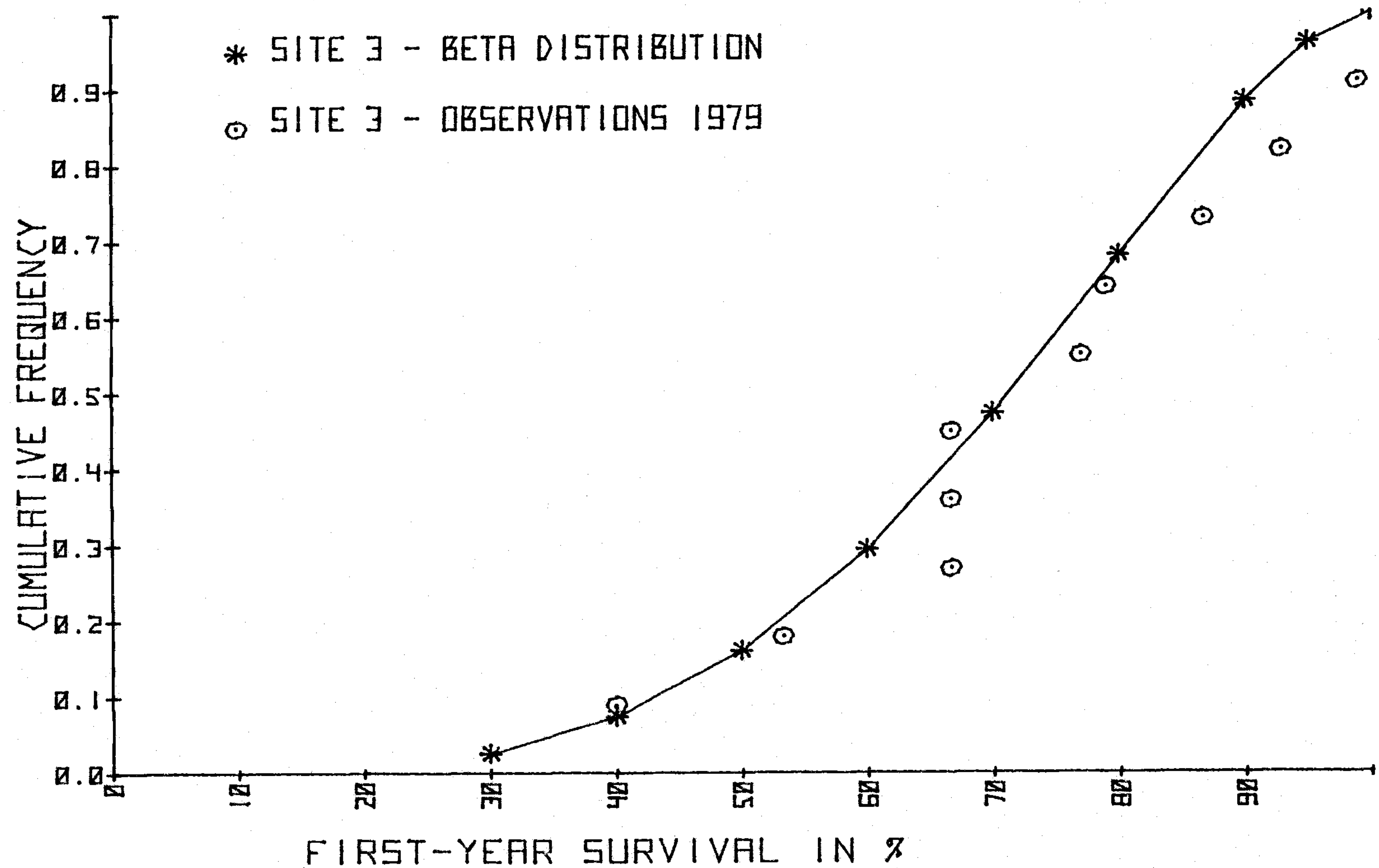


FIGURE 14. Cumulative distribution functions of first-year survival in Tillamook in 1979 and during 1967 to 1975 site class three.

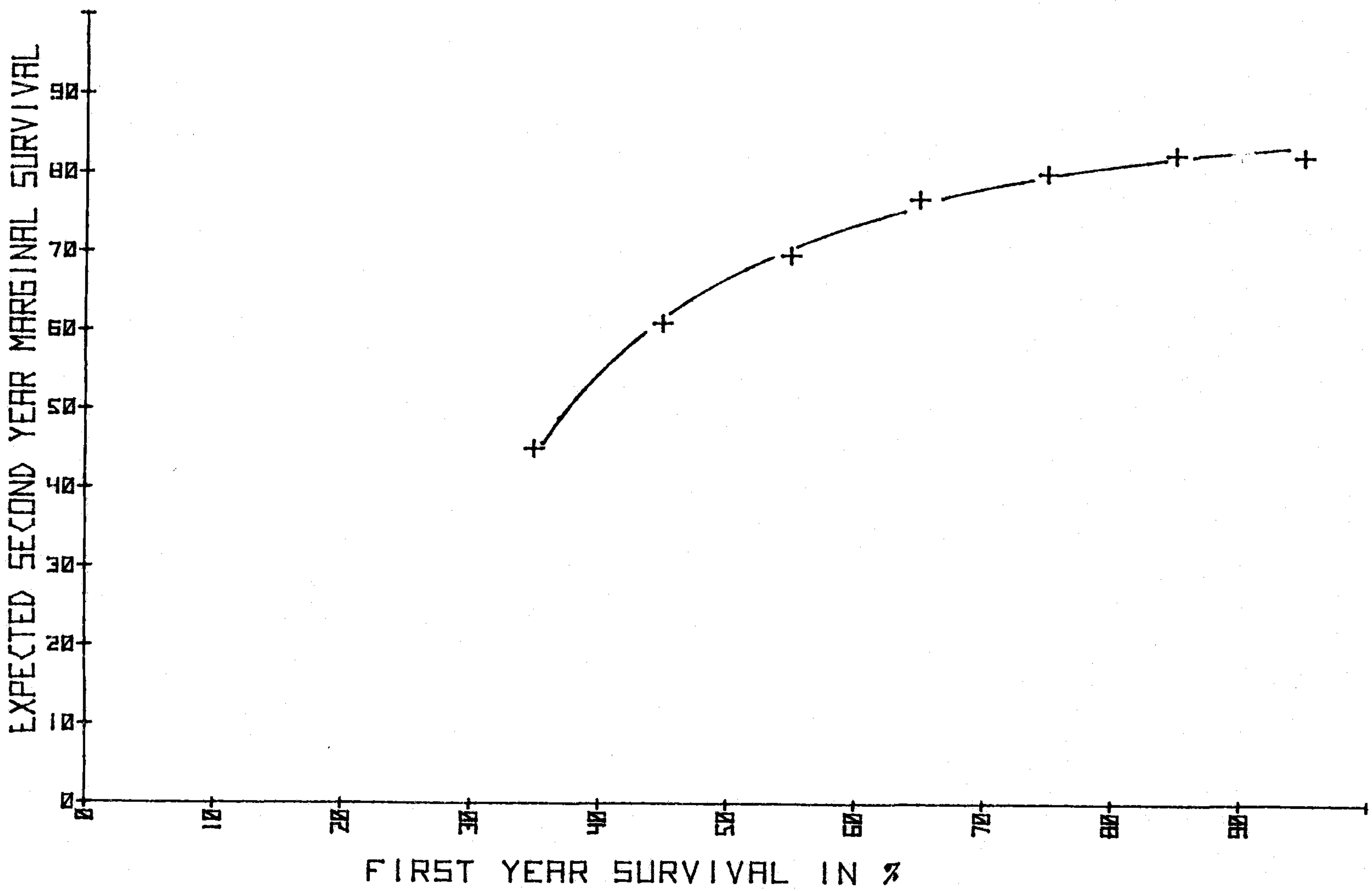


FIGURE 15. Mean second-year marginal survival as a function of first-year survival in Tillamook.

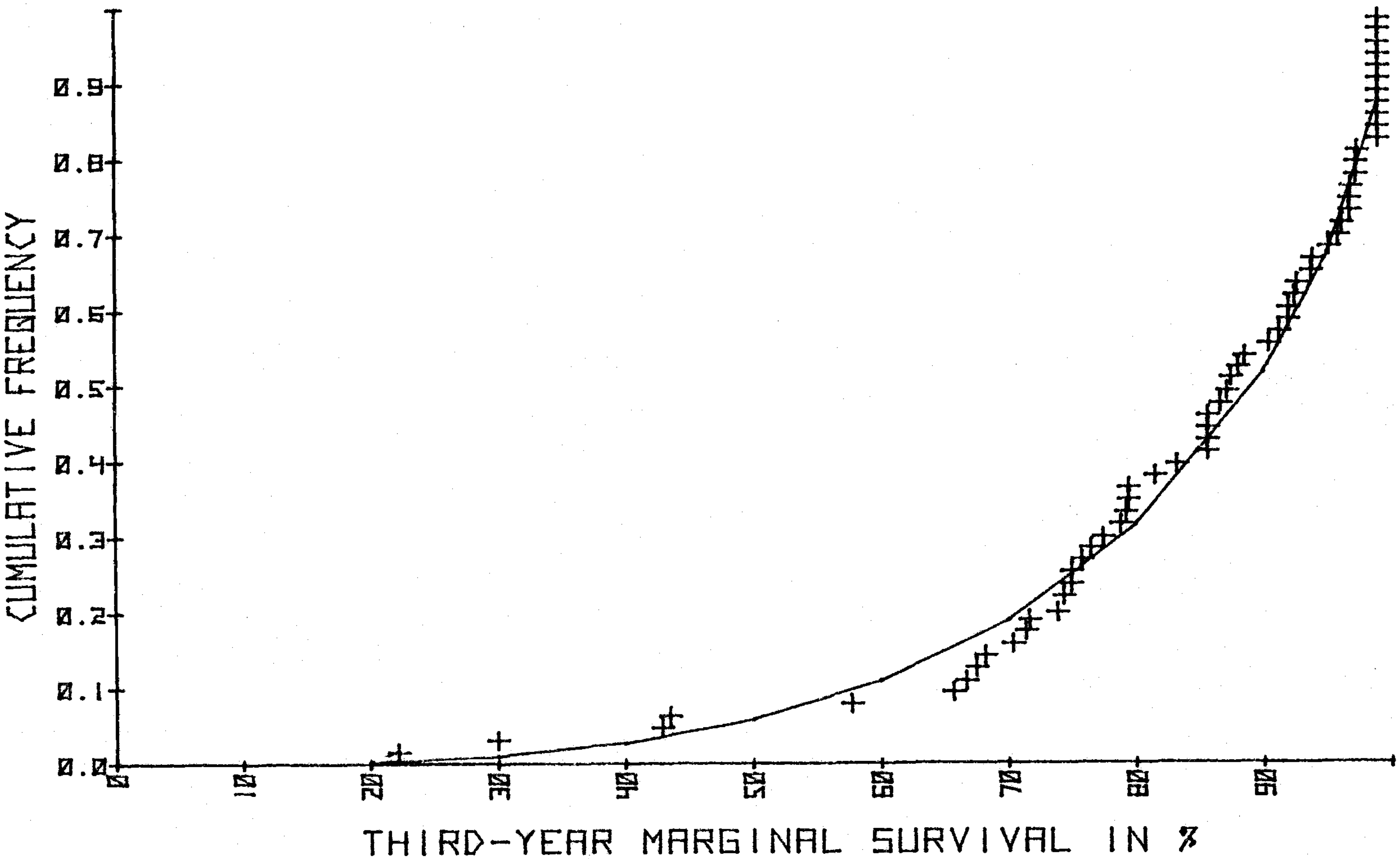


FIGURE 16. Cumulative distribution of third-year marginal survival in Tillamook.

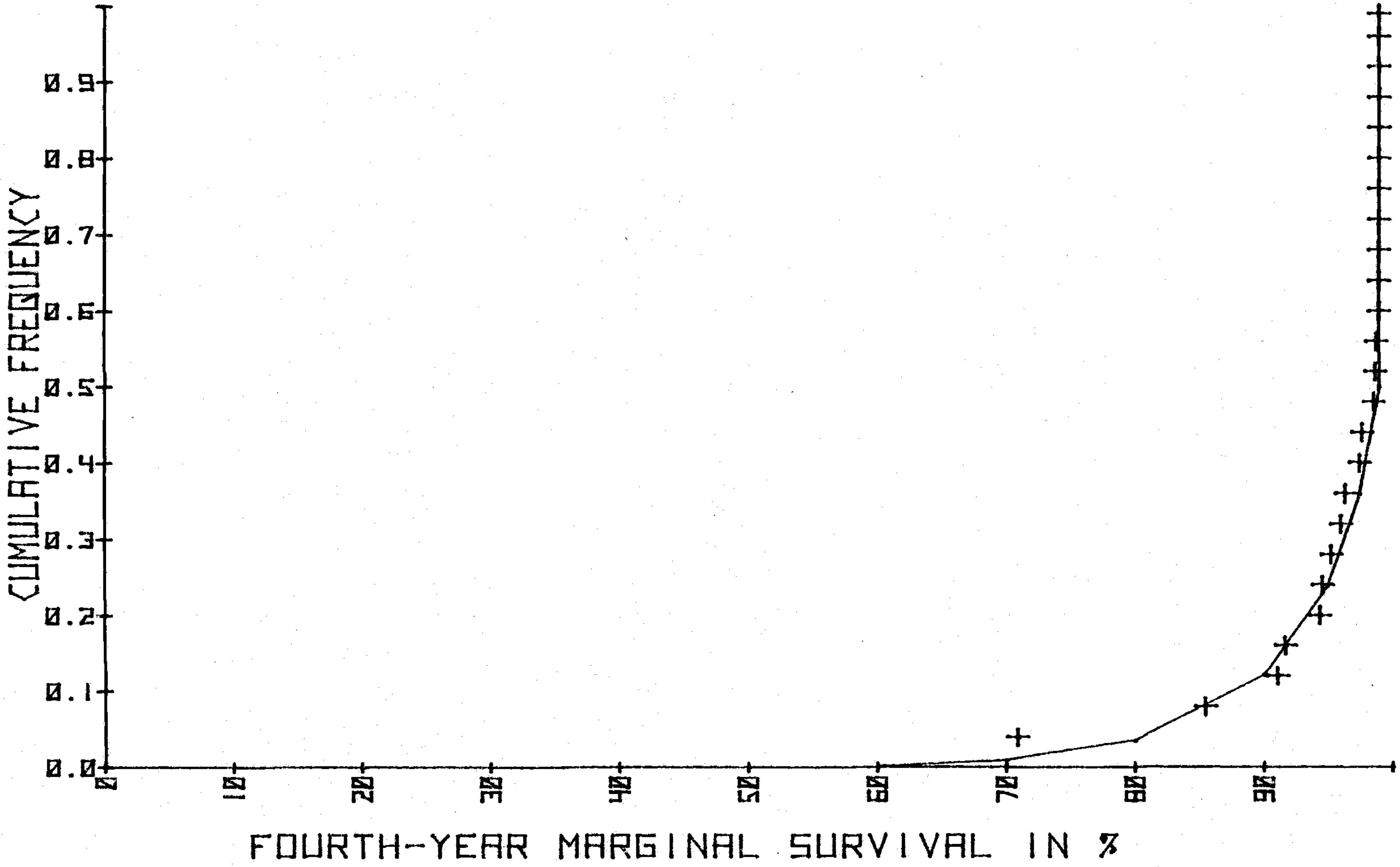


FIGURE 17. Cumulative distribution of fourth-year marginal survival in Tillamook.

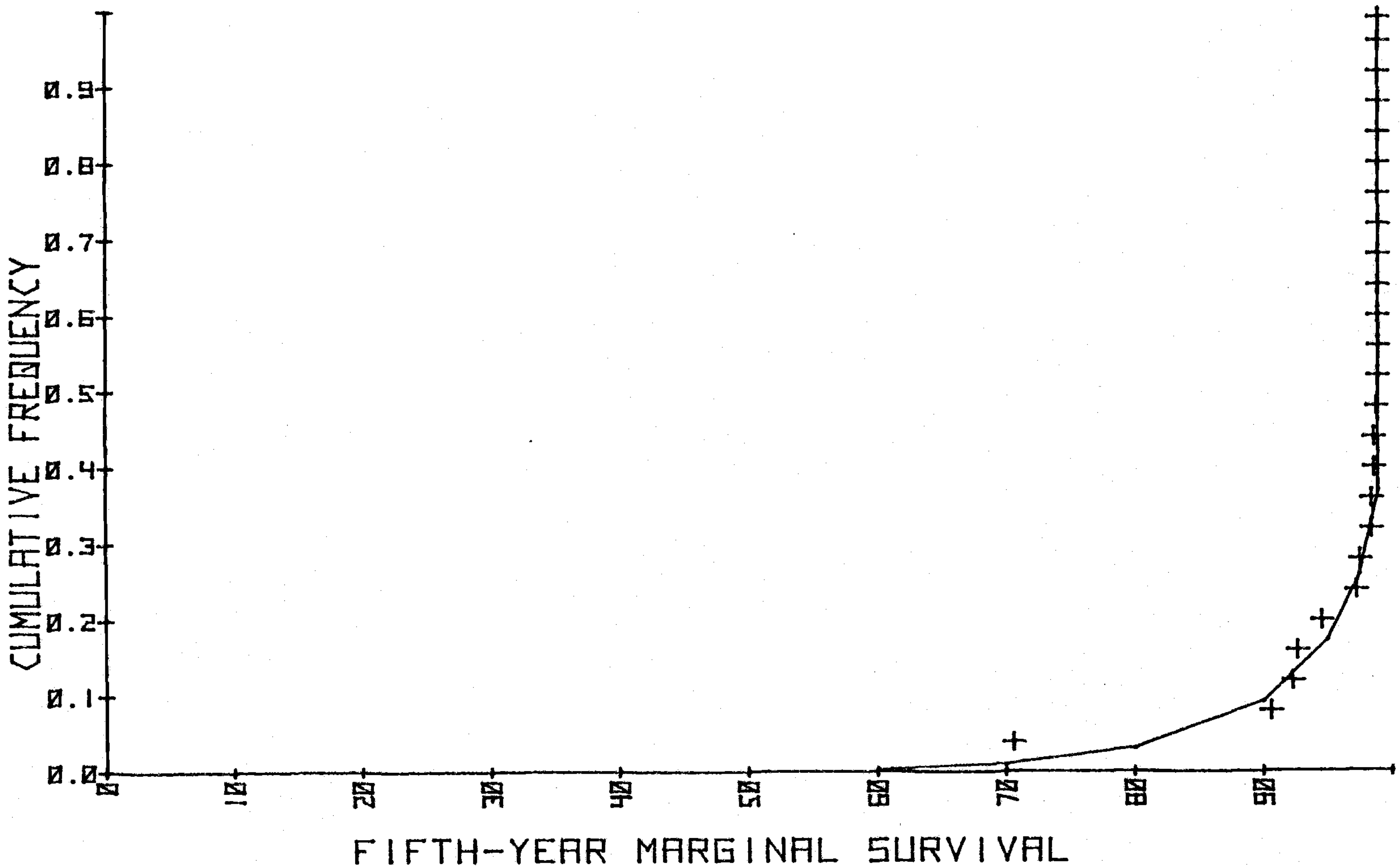


FIGURE 18. Cumulative distribution of fifth-year marginal survival in Tillamook.

in first-year survival. Mortality recedes rapidly after year two, as revealed in the marginal survival distributions for years three to five (Figures 16-18). Data for years four and five were obtained from 25 installations of CADS (Black et al., 1979) in the Tillamook forest.

What have we achieved? The environmental part of the analysis points to factors which may influence survival and productivity. The analysis of available records outlined the problem, revealed its urgency and dimension. Analysis of survival plot records established interrelationships of survival distributions with general environment, weather and site productivity. Moreover, it provided us with the inputs for the subsequent solution process in the form of marginal and conditional distributions. We are ready for the first step in the Bayesian decision model, namely the prior analysis.

Prior Analysis

The Optimal Prior Act

Table 6 shows input variables for the simulation runs. The fixed reforestation policy is shown in Table 7. Opportunity losses due to understocking, regeneration delays or both are computed internally, and displayed in Table 8. Table 9 exhibits program output in the form of a conventional decision matrix. Its first row lists the planting densities considered. Discrete states of nature, that is, the joint site and survival classes, appear in two columns at the left margin. Corresponding joint prior probabilities are found in the right margin. Total average costs per acre for each state-action combination make up the body of the table. We recall that each entry represents the mean of 75 simulation runs. Weighted averages, that is, expected costs for each planting density under the assumed prior distribution of states, appear in the last row. Each figure represents a weighted average of 3000 simulation runs; 99999.00-entries represent blanks.

TABLE 6. Independent variables for the Tillamook simulation.

Interest rate:	3%
Variable costs per seedling in $:	
Seedlings	0.18
Cost of original planting	0.17
Interplanting of less than 200 trees per acre	0.30
Interplanting of 200 to 350 trees per acre	0.25
Interplanting of over 350 trees per acre	0.19
Bud capping and netting	0.13
Fixed cost per acre in $:	
Burning	96.00
Trapping	10.00
Precommercial thinning of stands with:	
500 to 600 trees per acre	70.00
601 to 800 trees per acre	90.00
801 to 1000 trees per acre	110.00
Over 1000 trees per acre	130.00
Stocking survey	1.00
Administrative costs	2.00
Herbicide application	60.00
Target stocking, trees per acre	450
Minimum stocking, trees per acre	300

TABLE 7. Reforestation policies of the Tillamook District for its intensive management regime.

Original planting density:	450 trees per acre independent of site class
Replanting density:	Original density, whenever less than 100 trees are found during survey. Otherwise, fill planting up to 450 trees per acre
Stocking surveys:	1, 3, and 5 years after each planting or replanting
Replanting when stocking is:	300 or less trees per acre
Precommercial thinning taken at:	550 trees per acre and above
Stocking reduced to:	450 trees per acre

TABLE 8. Cost of reforestation lag and understocking for Tillamook, based on actual stocking at age 15 and a target stocking of 450 trees per acre

COST OF DELAYED HARVEST, STOCKING: 450

	YEAR 1	YEAR 2	YEAR 3	YEAR 4	YEAR 5	YEAR 6	YEAR 7	YEAR 8	YEAR 9	YEAR 10
SITE 1:	204.60	403.25	596.11	783.35	965.14	1141.63	1312.98	1479.35	1640.86	1797.68
SITE 2:	124.22	244.82	361.91	475.59	585.96	693.11	797.14	898.14	996.20	1091.41
SITE 3:	77.89	153.51	226.93	298.20	367.41	434.59	499.83	563.16	624.64	684.34
SITE 4:	51.41	101.31	149.77	196.81	242.48	286.83	329.88	371.67	412.25	451.65
SITE 5:	20.30	40.02	59.15	77.73	95.77	113.29	130.29	146.80	162.83	178.39

COST OF DELAYED HARVEST, STOCKING: 350

SITE 1	202.95	399.98	591.28	777.00	957.32	1132.38	1302.35	1467.36	1627.57	1782.11
SITE 2	123.21	242.82	358.96	471.71	581.17	687.45	790.64	890.81	988.07	1082.50
SITE 3	77.25	152.25	225.06	295.75	364.38	431.02	495.71	558.52	619.50	678.71
SITE 4	50.98	100.47	148.52	195.17	240.46	284.44	327.13	368.58	408.82	447.89
SITE 5	20.12	39.66	58.63	77.04	94.92	112.28	129.14	145.50	161.38	176.81

COST OF DELAYED HARVEST, STOCKING: 250

SITE 1	198.89	391.99	579.47	761.48	938.20	1109.76	1276.33	1438.05	1595.06	1747.49
SITE 2	120.73	237.94	351.74	462.23	569.50	673.64	774.75	872.91	968.22	1060.75
SITE 3	75.68	149.15	220.48	289.74	356.98	422.26	485.64	547.17	606.91	664.91
SITE 4	49.93	98.40	145.46	191.15	235.50	278.57	320.38	360.98	400.39	438.65
SITE 5	19.68	38.79	57.35	75.36	92.85	109.82	126.31	142.31	157.85	172.94

COST OF DELAYED HARVEST, STOCKING: 150

SITE 1	184.34	363.31	537.07	705.77	869.56	1028.57	1182.95	1332.84	1478.36	1619.64
SITE 2	111.84	220.41	325.83	428.17	527.54	624.01	717.67	808.60	896.88	982.59
SITE 3	70.04	138.05	204.07	268.17	330.41	390.83	449.49	506.44	561.74	615.42
SITE 4	46.16	90.97	134.49	176.72	217.73	257.54	296.20	333.73	370.16	405.54
SITE 5	18.10	35.68	52.75	69.31	85.40	101.02	116.18	130.90	145.19	159.07

COST OF DELAYED HARVEST, STOCKING: 50

SITE 1	75.65	149.10	220.41	289.64	356.85	422.11	485.47	546.98	606.70	664.68
SITE 2	45.40	89.49	132.28	173.83	214.18	253.34	291.37	328.28	364.13	398.92
SITE 3	27.97	55.13	81.50	107.10	131.96	156.09	179.52	202.27	224.35	243.79
SITE 4	18.01	35.49	52.47	68.95	84.95	100.49	115.57	130.21	144.43	158.23
SITE 5	6.31	12.43	18.37	24.14	29.74	35.18	40.46	45.59	50.57	55.40

COST OF UNDERSTOCKING:

	-000	-100	-200	-300	-400
SITE 1:	0.00	56.90	196.10	695.70	4427.40
SITE 2:	0.00	34.80	119.80	425.20	2706.00
SITE 3:	0.00	22.00	75.90	269.30	1713.70
SITE 4:	0.00	14.70	50.80	180.20	1146.60
SITE 5:	0.00	6.17	21.30	75.50	480.60

TABLE 9. Decision matrix for prior analysis in Tillamook. (Matrix entries are expected, total, discounted costs in $ per acre.)

PRIOR ANALYSIS
$$$$$$$$$$$$$$

NUMBER OF TREES PLANTED

Site Class	Survival	450	550	650	750	850	950	1050	0	0	0	PRIOR PROBability
1	95	704.81	618.62	614.17	624.82	664.95	703.34	767.39	99999.00	99999.00	99999.00	.017620
1	85	817.26	760.89	695.00	688.87	676.53	735.87	752.61	99999.00	99999.00	99999.00	.030220
1	75	947.65	859.04	802.09	787.46	776.34	776.34	799.47	99999.00	99999.00	99999.00	.023840
1	65	1002.17	1019.91	951.21	925.44	919.15	899.49	887.22	99999.00	99999.00	99999.00	.013783
1	55	1081.49	1140.33	1142.69	1088.24	1086.98	1036.98	1031.28	99999.00	99999.00	99999.00	.006223
1	45	1166.73	1072.02	1039.34	1278.07	1242.68	1247.15	1244.36	99999.00	99999.00	99999.00	.002243
1	35	1191.88	1146.74	1095.88	1085.17	1113.25	1443.71	1492.21	99999.00	99999.00	99999.00	.000530
1	25	1246.66	1200.87	1157.30	1185.42	1173.34	1213.56	1241.91	99999.00	99999.00	99999.00	0.000000
1	15	1261.62	1215.35	1219.25	1227.45	1255.71	1250.20	1283.28	99999.00	99999.00	99999.00	0.000000
1	5	1313.76	1274.45	1293.31	1299.35	1322.08	1327.39	1372.05	99999.00	99999.00	99999.00	0.000000
2	95	616.35	581.79	590.30	610.42	657.23	697.03	760.16	99999.00	99999.00	99999.00	.092551
2	85	714.46	689.01	644.11	658.39	659.21	718.80	745.04	99999.00	99999.00	99999.00	.140150
2	75	840.90	754.48	732.06	738.34	736.36	749.26	776.00	99999.00	99999.00	99999.00	.124561
2	65	893.28	905.17	867.33	849.35	854.97	948.38	845.67	99999.00	99999.00	99999.00	.091045
2	55	944.18	989.11	979.68	974.54	966.91	953.56	970.95	99999.00	99999.00	99999.00	.057136
2	45	1006.55	990.58	948.40	1106.61	1137.93	1104.92	1147.87	99999.00	99999.00	99999.00	.030459
2	35	1054.05	1031.98	1011.01	1032.30	1070.20	1274.22	1290.88	99999.00	99999.00	99999.00	.013119
2	25	1105.93	1079.27	1075.56	1076.37	1121.03	1149.20	1193.09	99999.00	99999.00	99999.00	.004098
2	15	1135.68	1084.87	1119.89	1138.76	1168.30	1196.69	1230.65	99999.00	99999.00	99999.00	.000720
2	5	1155.98	1149.92	1189.64	1185.58	1226.31	1269.50	1303.75	99999.00	99999.00	99999.00	0.000000
3	95	578.72	563.94	591.27	611.62	656.69	706.64	762.57	99999.00	99999.00	99999.00	.038430
3	85	672.94	638.65	620.54	639.60	658.27	717.70	753.22	99999.00	99999.00	99999.00	.067823
3	75	765.44	701.44	694.59	712.02	728.58	740.73	775.00	99999.00	99999.00	99999.00	.069860
3	65	869.79	840.60	831.67	810.79	828.09	830.73	831.07	99999.00	99999.00	99999.00	.059685
3	55	929.29	916.05	923.49	933.83	918.39	902.10	927.90	99999.00	99999.00	99999.00	.044609
3	45	1008.14	960.03	980.03	1071.07	1055.32	1054.39	1080.06	99999.00	99999.00	99999.00	.029152
3	35	1029.45	1031.66	1004.69	1040.71	1090.09	1191.66	1219.59	99999.00	99999.00	99999.00	.016089
3	25	1078.20	1042.29	1056.69	1106.99	1127.99	1170.93	1213.12	99999.00	99999.00	99999.00	.006884
3	15	1109.36	1108.19	1122.62	1135.25	1183.83	1229.54	1250.68	99999.00	99999.00	99999.00	.001833
3	5	1158.49	1163.39	1164.88	1180.90	1262.66	1284.77	1299.08	99999.00	99999.00	99999.00	.000134
4	95	636.38	578.91	603.45	604.54	653.06	706.20	759.06	99999.00	99999.00	99999.00	.000270
4	85	726.46	669.54	649.34	660.33	666.12	707.25	751.72	99999.00	99999.00	99999.00	.000770
4	75	872.01	758.22	725.07	731.10	734.98	731.98	770.72	99999.00	99999.00	99999.00	.001228
4	65	1033.06	938.22	886.63	803.88	807.91	930.73	835.24	99999.00	99999.00	99999.00	.001631
4	55	1131.47	1070.94	991.55	999.66	962.36	963.38	935.30	99999.00	99999.00	99999.00	.001977
4	45	1234.73	1145.41	1142.42	1117.36	1109.18	1113.95	1109.14	99999.00	99999.00	99999.00	.002256
4	35	1333.31	1260.70	1229.94	1139.79	1266.62	1285.46	1245.20	99999.00	99999.00	99999.00	.002451
4	25	1387.37	1336.02	1356.63	1344.72	1312.75	1308.20	1363.69	99999.00	99999.00	99999.00	.002530
4	15	1456.32	1419.45	1405.52	1407.04	1400.51	1417.93	1444.76	99999.00	99999.00	99999.00	.002422
4	5	1524.18	1475.59	1467.59	1479.13	1516.33	1495.13	1486.06	99999.00	99999.00	99999.00	.001799
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000

EXPECTED VALUES OF ACTS:

822.38	790.14	770.94	784.07	795.11	819.60	846.70	99999.00	99999.00	99999.00

(99999.00 entries represent blanks)

As a result of the prior analysis, foresters of the district should deviate from the present practice of planting 450 trees to the acre and, instead, raise planting densities to 650.

What are the consequences? The recommended policy will reduce total costs--including opportunity losses--by approximately $50 per acre per year on the average. Expressed differently: Discounted net revenues should increase, on the average, by approximately $50,000 per year, given that an annual area of about 1000 acres will be regenerated as in the past. This figure includes opportunity costs, which, admittedly, depend on future and uncertain revenues and costs. We must remember, however, that the discounting process tends to diminish the impact of these uncertainties.

Figure 19 displays total costs as well as discounted cash expenditures during the reforestation phase for the two site class extremes. As expected, regeneration is much more expensive on low sites. Opportunity losses weigh heavily at low stocking levels on good sites. Further consequences for managerially inclined readers are contained in Appendix B.

With regard to decision analysis it appears important to note that this result is a mere logical consequence of consistently using existing information in Bayesian analysis.

Could we further increase revenues by obtaining more information about the uncertain states of nature? This question is tackled next.

The Value of Perfect Information

Let us recall that we have established the role of this fictitious value as a "research ceiling," that is, an index for the potential, maximum value of additional information about the uncertain states of nature.

Computer output is reproduced in Table 10. For convenience and greater clarity we first convert the payoff table (Table 9) into an opportunity loss or "regret" table, by subtracting the

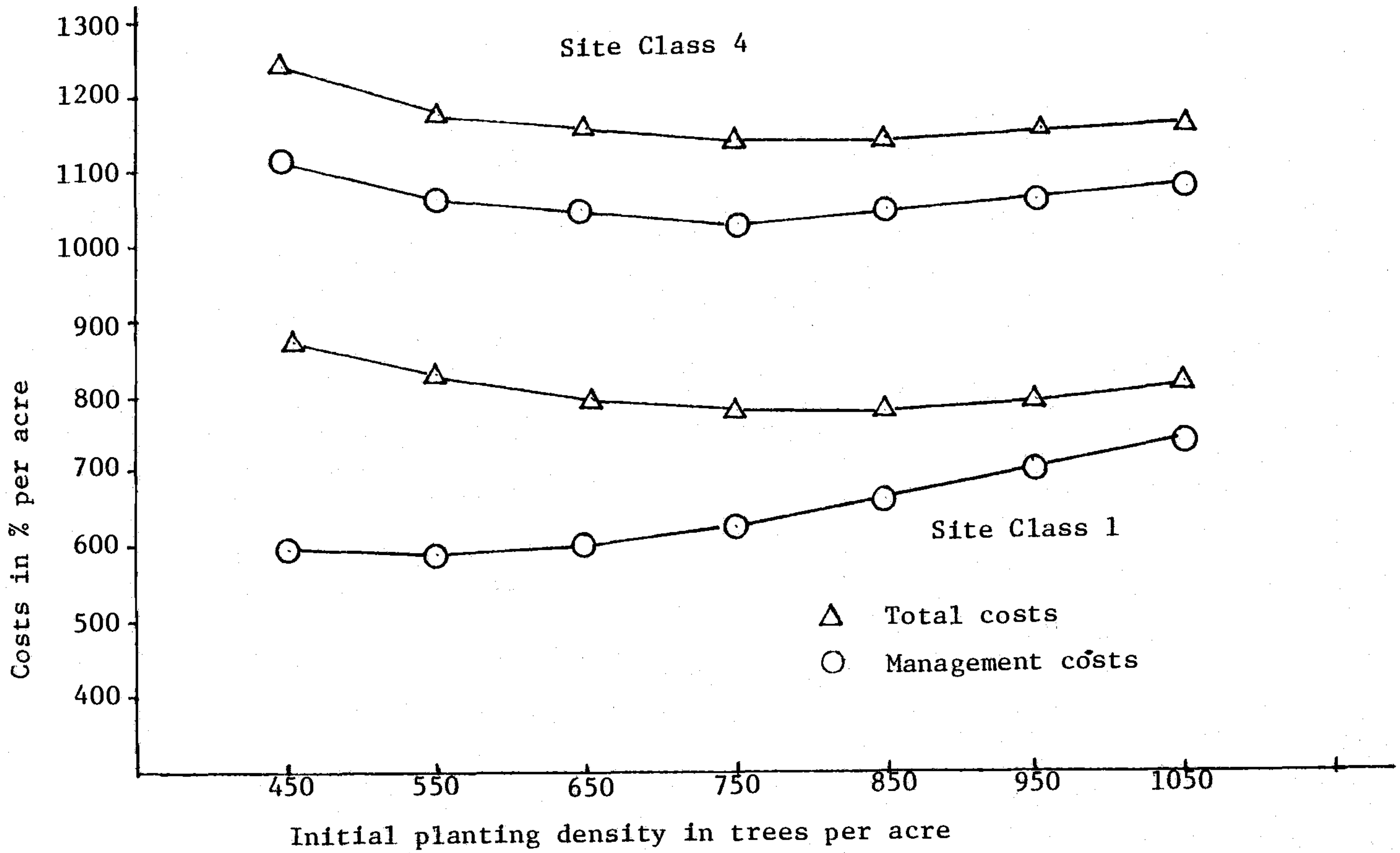


FIGURE 19. Expected total costs and direct management costs during reforestation in Tillamook as a function of initial planting density for site classes one and four.

TABLE 10. Prior Analysis for the Tillamook Case Study. (Matrix entries represent total expected discounted costs in $ per acre.)

REGRET TABLE

Site Class	Survival	NUMBER OF TREES PLANTED 450	550	650	750	850	950	1050	PRIOR PROBability
1	95	90.64	4.45	0.00	10.65	50.78	89.17	153.22	.017620
1	85	140.73	84.36	18.47	12.34	0.00	59.34	76.08	.030220
1	75	171.31	82.70	25.75	11.12	0.00	0.00	23.13	.023840
1	65	114.95	132.69	63.99	38.22	31.93	12.27	0.00	.013783
1	55	50.21	109.05	111.41	56.96	55.70	5.70	0.00	.006228
1	45	128.39	33.68	0.00	239.73	204.34	208.81	206.02	.002243
1	35	106.71	61.57	10.71	0.00	28.08	358.54	407.04	.000530
1	25	89.36	43.57	0.00	28.12	16.04	56.26	84.61	0.000000
1	15	46.27	0.00	3.90	12.10	40.36	34.85	67.93	0.000000
1	5	39.31	0.00	19.36	25.40	47.63	52.94	97.60	0.000000
2	95	34.56	0.00	8.51	28.63	75.49	115.24	178.37	.092551
2	85	70.35	44.90	0.00	14.28	15.10	74.69	100.93	.140150
2	75	108.84	22.42	0.00	6.28	4.30	17.20	43.94	.124561
2	65	47.61	59.50	22.16	3.68	9.30	2.71	0.00	.091045
2	55	0.00	44.93	35.50	30.36	22.73	9.38	26.77	.057136
2	45	58.15	42.18	0.00	158.21	189.53	156.52	199.47	.030459
2	35	43.04	20.97	0.00	21.29	59.19	263.21	279.87	.013119
2	25	30.37	3.71	0.00	.81	45.47	73.64	117.53	.004098
2	15	50.81	0.00	35.02	53.89	83.43	111.82	145.78	.000720
2	5	6.06	0.00	39.72	35.66	76.89	119.68	153.83	0.000000
3	95	14.78	0.00	27.33	47.68	92.75	142.70	198.63	.038430
3	85	52.40	18.11	0.00	19.06	37.73	97.16	132.68	.067823
3	75	70.85	6.85	0.00	17.43	33.99	46.19	80.41	.069860
3	65	59.00	29.81	20.88	0.00	17.30	19.94	20.28	.059685
3	55	27.19	13.95	21.39	31.78	16.79	0.00	25.80	.044609
3	45	48.11	0.00	20.00	111.04	95.29	94.36	120.03	.029152
3	35	24.76	26.97	0.00	36.02	85.40	186.97	214.90	.016089
3	25	35.91	0.00	14.40	64.70	85.70	128.64	170.83	.006884
3	15	1.67	0.00	14.43	27.06	73.64	120.35	142.49	.001833
3	5	0.00	4.90	6.39	22.41	104.17	126.28	140.59	.000134
4	95	57.47	0.00	24.54	25.63	74.15	127.29	180.15	.000270
4	85	77.12	20.20	0.00	11.49	16.78	57.91	102.38	.000770
4	75	146.94	33.15	0.00	6.03	9.91	6.91	45.65	.001228
4	65	229.18	134.34	82.75	0.00	4.03	26.85	31.36	.001631
4	55	195.67	135.14	55.75	63.86	26.56	27.58	0.00	.001977
4	45	125.59	36.27	33.28	8.22	.04	4.81	0.00	.002256
4	35	144.02	70.91	40.15	0.00	76.83	95.67	55.41	.002451
4	25	79.17	27.82	48.43	36.52	4.55	0.00	55.49	.002530
4	15	55.81	18.94	5.01	6.53	0.00	17.42	44.25	.002422
4	5	56.59	8.00	0.00	11.54	48.74	27.34	18.47	.001799
EXPECTED REGRETS		63.57	31.33	12.13	25.26	36.30	60.78	87.89	

optimal value in each row from all its other entires. Now, the optimal choice for a given state will be indicated by a "zero" entry in the regret table. With perfect foresight there would not be any regret, we would always pick the optimal choice. Hence, the expected regret of the prior optimal act, in our case the 650-tree option, points out the expected value of perfect information.

In Tillamook, "clairvoyance" would frequently not alter the optimal choice of the prior analysis. "Zero"-entries in the regret table occur quite often in the column which represents the optimal prior choice, and particularly in rows, which correspond to states with a high associated prior probability. For the "standard," 30-acre clearcut, perfect information would be worth about $360, on the average, and, depending on the perfect forecasts obtained, a manager would vary planting densities over the entire range of choices.

We cannot hope for perfect survival predictions. Correct productivity estimates appear possible, since site classes cover quite a range of site indices. How much could we afford for flawless site class predictions?

Table 11 summarizes computations. Site classes 2 and 3 dominate the Tillamook forest by a wide margin, and, again, for both site classes, we would not deviate from the optimal prior act. Hence, the value of perfect site class prediction for the purpose of adjusting planting densities during reforestation is, on the average, minimal only. In other words: If we determine site class for every plantation we will, on the average, identify site classes 2 and 3 in 88.82 percent of all trials, since they assume this fraction of the forest. In these instances we would plant 650 trees to the acre, that is, we would opt for the same action which was indicated in the prior analysis. Hence, our site mapping effort would have been in vain.

TABLE 11. Expected Costs, Optimal Choices(*), and the Value of Perfect Site Class Information in Tillamook

Site Class	Marginal Probability	Planting Density per Acre						
		450	550	650	750	850	950	1050
		Expected Cost per Acre						
1	0.0945	883.99	831.49	784.75	778.87	777.92*	799.86	821.04
2	0.5537	807.21	780.48	755.58*	769.64	780.36	805.79	833.47
3	0.3345	808.03	774.21	772.47*	790.75	805.99	830.50	859.35
4	0.0173	1243.46	1176.50	1155.23	1140.07*	1145.54	1153.12	1160.55

The expected value of perfect site class information is
0.0945 x (784.25 - 777.92) + 0.0173 x (1155.23 - 1140.07) = 0.86.

In 9.45 percent of the trials, we are likely to identify site class one. Now, a planting density of 850 trees would save us, on this site, $106.07 per acre, against the present policy of only planting 450 seedlings. Compared with the optimal prior act, we stand to gain $6.33. Correspondingly, on site class four lands, we should raise stocking densities from the present 450 to 750 trees to gain $103.39, and $15.16 per acre against the prior optimal act. We can expect site four land in 1.73 percent of all trials. The expected value of complete site class information is merely the weighted average of those savings.

We find the expected value of perfect survival information as the difference between the worth of "clairvoyance" and correct site class identification. With $11.27 per acre (12.13-0.86), we could spend $338 on the average-size clearcut to obtain this information.

At this stage, we shall leave the decision analysis model and deal with the second subject of this dissertation, namely the ecological models for seedling survival and site productivity.

The Ecological Models

In the previous section, it was established that further information on the state variables might be worthwhile. Here it is my goal to find prediction models for both variables; but, first, we need to characterize soil water supply, which is likely to influence both survival and productivity.

Soil Parameters

Soil test results of 14 surface soil samples from Tillamook survival plots (Table 12) reveal extraordinarily high organic matter contents. One conspicuous exception is the "East Beaver

TABLE 12. Laboratory Analysis of Tillamook Surface Soils (water content measurements are means of duplicate determinations)

Location (Section, Township, Range)	Particle Sizes: Sand	Particle Sizes: Silt	Particle Sizes: Clay	Textural Class	Organic Matter	Water Content: 1/3 at	Water Content: 15 at	Water Capacity
	% Oven-dry Weight				% by weight	% by weight		% by weight
East Beaver (S2,3S,9W)	91.2	8.3	0.5	sand	0.27	20.6	17.6	3.0
Ginger Creek (S36,1S,9W)	44.9	42.7	12.4	loam	13.07	41.6	23.9	17.7
Gods Valley (S3,3N,9W)	65.8	27.5	11.7	sandy loam	8.62	47.9	33.2	14.7
Roy Creek (S28,3N,9W)	48.3	47.7	4.0	sandy loam	29.33	56.7	38.4	18.3
Juno Hill (S18,1S,9W)	64.4	30.7	4.9	sandy loam	17.60	49.3	28.6	20.7
Juno Hill (S18,1S,9W)	49.2	41.3	9.5	loam	1.44	48.0	33.4	14.6
Juno Hill (S18,1S,9W)	53.2	40.7	6.1	sandy loam	1.17	51.0	29.2	21.8
Beaver Salvage (S20, 3S,9W)	65.8	29.2	5.0	sandy loam	30.98	51.9	34.5	17.4
East Beaver (S1,3S,9W)	72.8	23.3	3.9	sandy loam	6.13	32.5	22.6	9.9
Detrek Ranch (S15,3S, 8W)	48.2	42.5	9.3	loam	10.93	44.3	23.3	21.0
Detrek Ranch (S15,3S, 8W)	58.9	31.7	9.4	sandy loam	13.87	50.3	29.1	21.2
Foland Creek (S32,3S, 9W)	65.6	31.5	2.9	sandy loam	20.64	57.9	41.4	16.5
Detrek Ranch (S15,3S, 8W)	40.3	40.9	18.8	loam	14.83	54.0	33.8	20.2
Mesabi Road (S21,2S,7W)	81.5	17.6	0.9	loamy sand	18.13	36.5	21.2	15.3
MEAN					13.35	45.89	29.3	16.59

(S2,35,9W)" location, where seedlings grew on severely disturbed soil.

Water contents at both field capacity and wilting point surpass any values I found in the literature, with the exception of Gradwell's results from New Zealand (1974).

How can we assess soil water supply in routine site mapping? In the Tillamook forest, as elsewhere (Lund, 1949; Bartelli and Peters, 1959; Petersen et al., 1968; Abrol et al., 1969), it is mostly silt content which influences the upper and lower levels of available water and the AWC. If this is true, then the variability of AWC within textural classes is not surprising. Silt content of a sandy loam, for instance, may vary between 0 and 50%. Textural classes simply were not defined in terms that are very meaningful in plant water relations (Black, 1968).

It is also known that organic matter has little influence in raising the AWC of soils, unless they are coarse-textured (Petersen et al., 1968; Jamison and Kroth, 1958; Lund, 1959; Bartelli and Petersen, 1959; Jamison, 1955). Results from Tillamook agree with this observation.

The following regression model was fitted to the 14 observations from Tillamook and tested against an independent data set from the Soils Department collection (Figure 20).

$$AWC_w = 0.4726 \times SILT + 0.2122 \times IND \times ORG$$

where

AWC_w = Available-water capacity per unit weight

SILT = Silt content in grams per 100 grams oven-dry soil

IND = Indicator variable which is 1 for a silt content below 30% and 0 otherwise

ORG = Organic matter content is n percent by weight

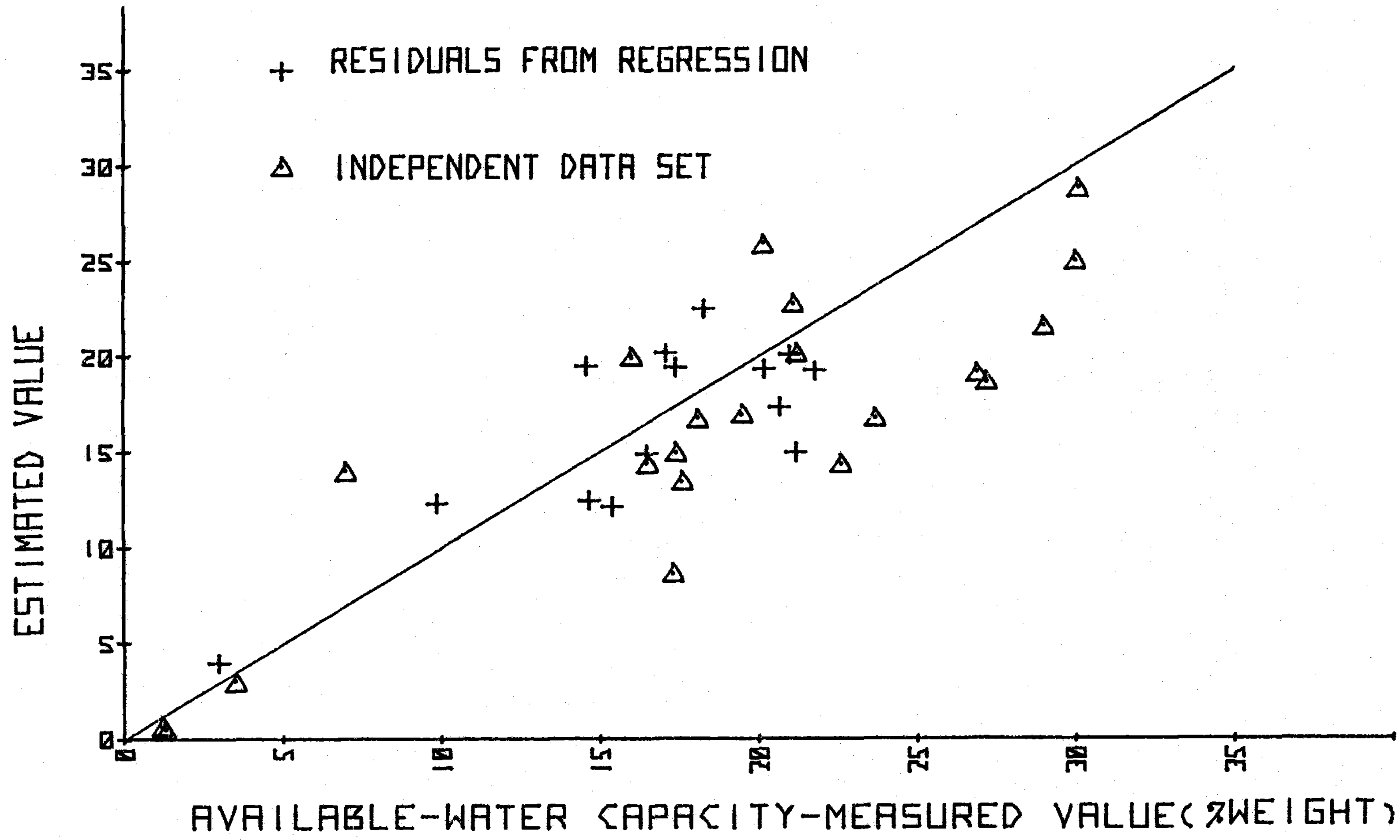


FIGURE 20. Comparison of estimated AWC with measured values on a weight basis.

Coefficients of the model are significant at the 95%-level, and the relation explains 62% of the total variation (R = 0.79). The relation should not be extrapolated beyond a silt content of 50%. In judging fit of the model (Figure 20), we should remember that AWC measurements tend to vary considerably, even among samples taken in close proximity. The reader is referred again to the chapter on AWC in the literature review.

So far, we have estimated AWC on a weight basis only. Since Tillamook area soils are known to possess extraordinarily low bulk densities (Knox et al., 1965), we must convert estimates to a volume basis, otherwise they would not be ecologically meaningful.

Sample measurements of 24 forest soils from the OSU Soils Department collection revealed that bulk densities in forest soils of the Northwestern Oregon area tend to decrease with silt content and increasing humus content. The latter relation is linearized by logarithmic transformation.

The following regression explained 64 percent of the total variation (R = 0.8); all coefficients are significant at the 95-percent level.

$$BD = 1.3172 - 0.3415\ LOGORG - 0.0062\ SILT$$

where

BD = Bulk density in grams per cc

LOGORG = The decadic logarithm of organic matter content in percent by weight

SILT = Silt content in percent by weight.

We are now able to transform AWC_w (AWC by weight) to a volume basis by simply multiplying each estimate, which depends on silt content and organic matter only, with the corresponding bulk density, which is also a function of these variables. For a low

(3%), medium (10%), and high (20%) content of organic matter, Figure 21 depicts AWC by volume (AWC_v) as a function of silt content.

Coarse soils tend to possess high bulk densities; here organic matter contributes appreciably to available water capacity, either directly, or by its effect on soil structure. As a net effect, AWC_v increases with humus content. Beyond a silt content of twenty to thirty percent, the role of organic matter in AWC tends to be detrimental: It does not contribute appreciably to the storage of available moisture, but decreases bulk density. As a consequence, medium and fine-textured soils with high humus content in the solum will tend to be droughty. The same will apply to soils which have low densities for other reasons, for instance, soil disturbances.

As a consequence, it appears that, contrary to the common belief about the dangers of soil compaction in the Pacific Northwest, some compaction actually aids seedling water relations in the Tillamook forest. During field work, it was noted, incidentally, that seedlings appeared to survive well on logging trails.

In summary, there are three factors which strongly influence AWC_v of soils in the Tillamook forest: Values rise with silt content, fall as density declines, and, for coarse soils only, increase with organic matter content. We can, after calibration with a set of standards, estimate silt content by finger touch within ± 5 percent and, in coarse soils, assess humus content by color and feel (Arbeitskreis Standortkartierung, 1978). How can we capture density? Following an approach by Renger (1971), Shrivastava and Ulrich (1977) and Eder (1980), we define three classes of "packing densities." For Tillamook conditions, I arbitrarily defined "medium density" as the density assumed in the regression model by an undisturbed soil with an organic matter content of 10 percent by weight. A "dense" soil shall have values at least 0.15 grams per cm^3 above, and a "loose" soil at least 0.15 grams per cm^3 below these values. Deviations from "medium" density may occur naturally, as a consequence of very low (< 4%) or high

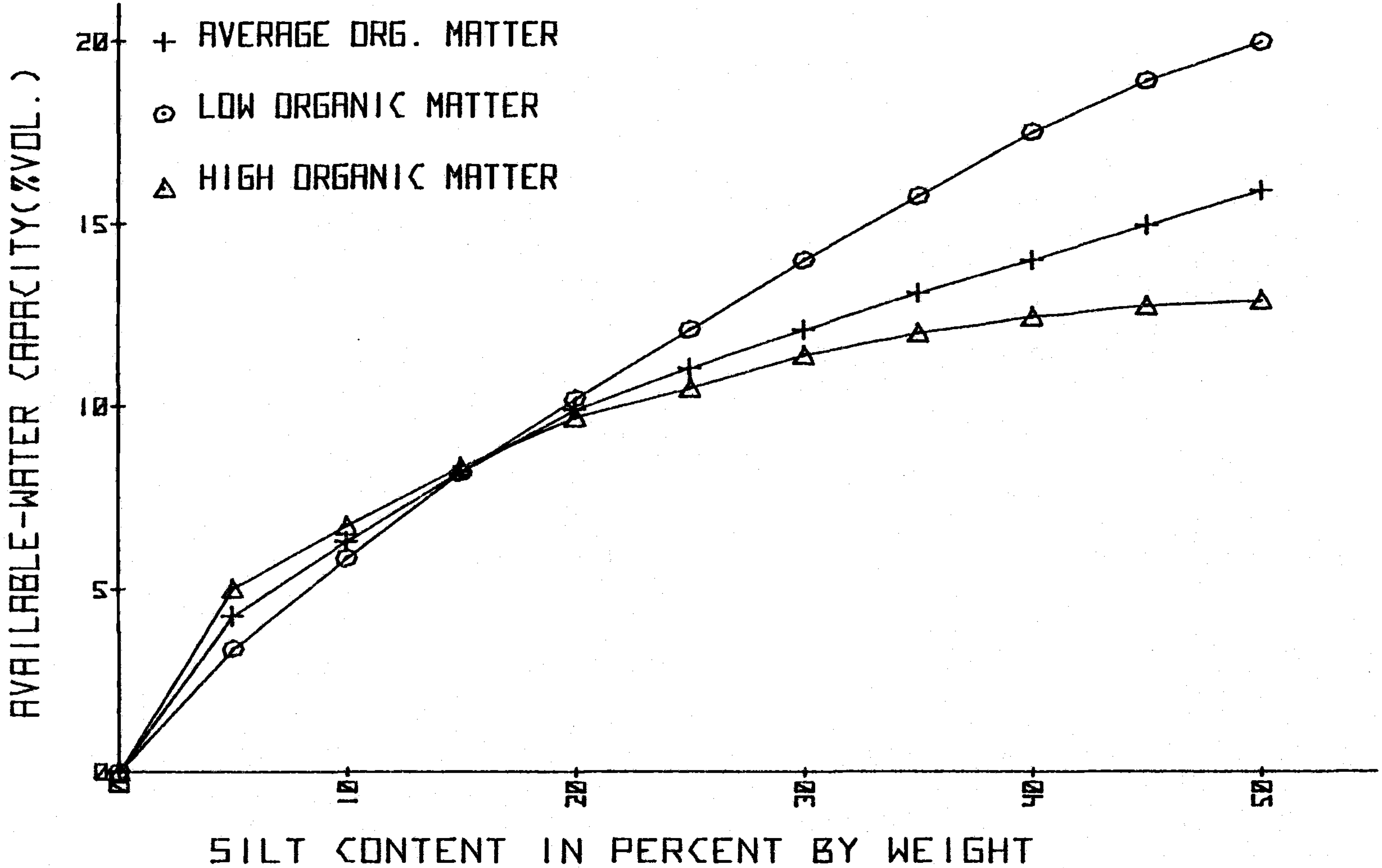


FIGURE 21. Available-water capacity by volume of Tillamook soils as a function of silt content by weight at three levels of organic matter content.

(> 25%) contents of organic matter, but may also result from natural or man-made disturbances.

Density classes can be assessed in the field by the method described by Benecke (1978), or simply by the force needed to drive or push the soil probe into the ground. Based on these classes and the regression models for AWC developed previously, the following estimates will be used to index soil-water supply in the Tillamook forest (Table 13).

They are preliminary only, based on a very small sample, comparisons with known measurements, and a study of the literature, and they reflect subjective judgment.

TABLE 13. Field Estimates for the Available-water Capacity of Tillamook Forest Soils

Silt Content	Estimated Field Values Density:		
	Low	Normal	High
Percent	Vol. %	Vol. %	Vol. %
< 10	4	5	6
11 - 20	7	9	11
21 - 30	8	11	14
31 - 50	10	14	18

A Prediction Model for First-Year Survival

Table 14 provides simple correlation coefficients between the logit transformation of first-year survival and independent variables considered in the regression procedure (Table 5). All carry the sign we would expect, with the exception of RANGE and ALTIT, the effect of which was, a priori, not clear.

TABLE 14. Simple Correlation Coefficients (R) between the Logit Transformation of First-Year Survival and Site Variables in Tillamook

Variable	R	Range
SILT	+ 0.27	10 - 50%
ROCK	- 0.14	0 - 95%
ALTIT	- 0.21	200 - 2060 ft.
RANGE	+ 0.05	1 - 12
SLOPE	- 0.01	0 - 100%
EFFDEPTH	+ 0.17	15 - 95 cm
EFFAWC	+ 0.47	8 - 130 liter
ROOTAWC	+ 0.49	3 - 70 liter
WATER	+ 0.56	3 - 18 mm/dm
INDN	+ 0.17	0 - 1
INDS	- 0.06	0 - 1
INDW	+ 0.03	0 - 1
INDE	+ 0.03	0 - 1

Table 15 provides details of the multiple regression model finally accepted. The reader is cautioned against overt or "hidden" extrapolations (Neter and Wasserman, 1974:248). The models explain only 54 percent of total variability. When plantations are stratified into areas of similar soil or aspect, predictions approach observations rather closely (Figure 22).

Figure 23 shows the effect of "distance inland" and "altitude," the proxy variables for lacking climatological data. The model indicates low survival expectations at low elevations inland, and at high elevations near the coast. The "Föhn"-effects described by Geiger (1965), and high wind speeds at high elevations near the coast, respectively, offer *ad hoc* explanations.

So far, we have merely fitted a regression model. We have not developed an objective prediction model for first-year survival in Tillamook. Observations include 1979 plantations only, and these represent not a random, but merely an accessibility sample. Probability statements about prediction intervals from this model would represent a misuse of statistics.

We are left again with a subjective, informal assessment of model performance, and eventually, derivation of subjective likelihoods for the Bayesian analysis. Figure 24 illustrates a basic and important feature of the model, a typical survival function (Neter and Wasserman, 1974) for a binary, qualitative response variable with repeat observations at each level of the independent variables. Let us interpret this response function:

At the lower end of the range of independent variables--perhaps on a very shallow, sandy and stony soil on a South slope of an interior valley--essentially no seedling will survive. An improvement of conditions, perhaps a "wet" year, or better planting stock, will not help until a "threshold" in "site" is reached. At this point, slight changes in plantation environment or different reforestation methods will produce major changes in survival,

TABLE 15. Multiple regression model for first-year survival in Tillamook. (The response variable, LOGITD, is the logit transformation of survival expressed as a fraction.)

```
LOGITD  =
 -2.29655      (CONSTANT)
 -.618983E-02 ALTIT
 -.995632     RANGE
  .231909     WATER
  .113468E-01 EFFAWC
  .837224     INDN
  .426551E-01 WATERN
 3.03453      SRTRAN
  .220822E-02 ALTSRTR
```

VARIABLE	S.E. OF REGR. COEF	T
CONSTANT	1.3051	-1.760
ALTIT	.12014E-02	-5.152
RANGE	.30696	-3.243
WATER	.56881E-01	4.077
EFFAWC	.61533E-02	1.844
INDN	.48232	1.736
WATERN	.22295E-01	1.913
SRTRAN	1.2304	2.466
ALTSRTR	.43794E-03	5.042

ANALYSIS OF VARIANCE TABLE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
TOTAL	91	3337.68	36.6778
REGRESSION	8	1817.88	227.235
RESIDUAL	83	1519.80	18.3108

R SQUARED = .5447

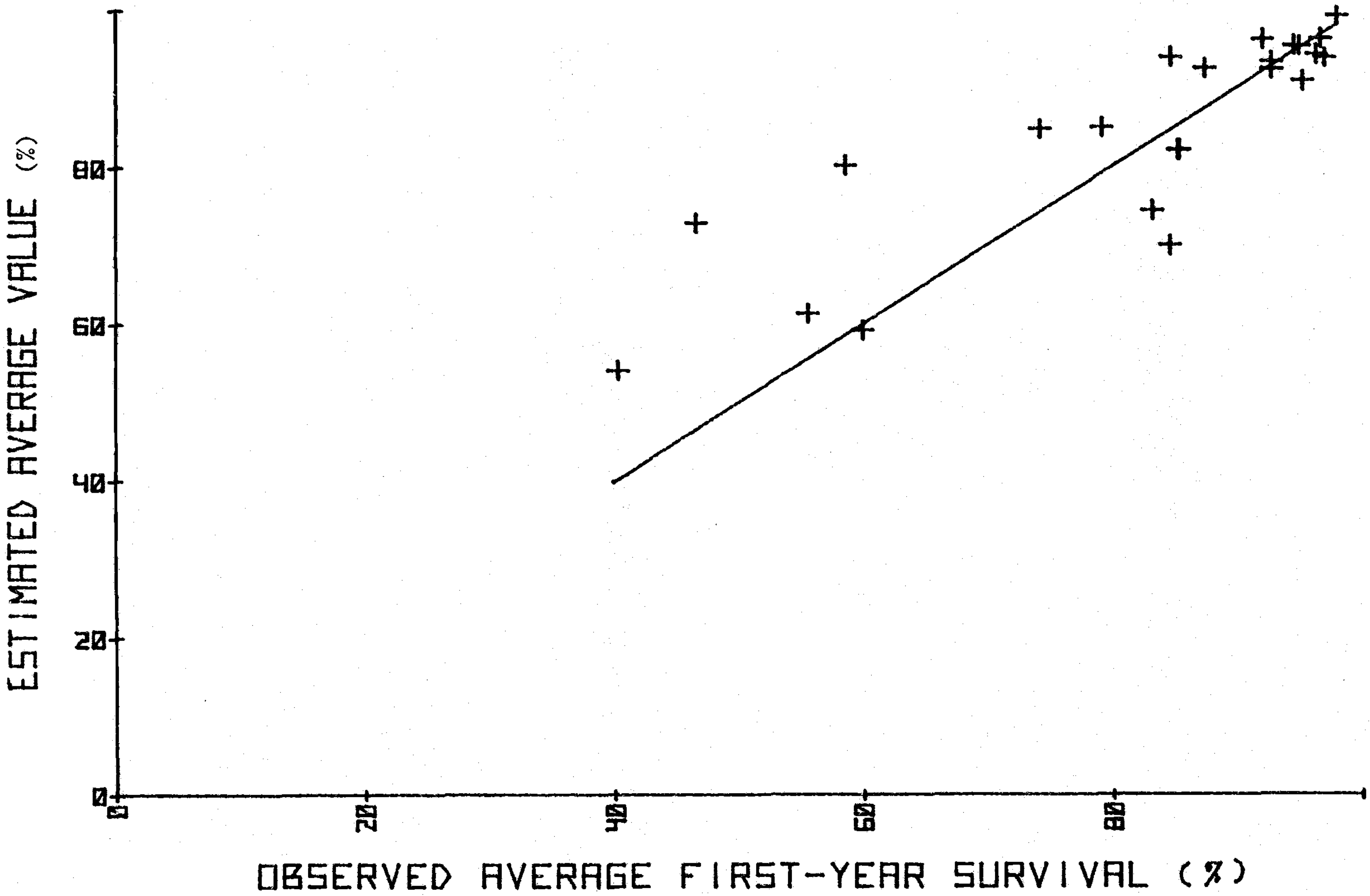


FIGURE 22. Observed and estimated average survival for uniform strata within clearcuts in Tillamook .

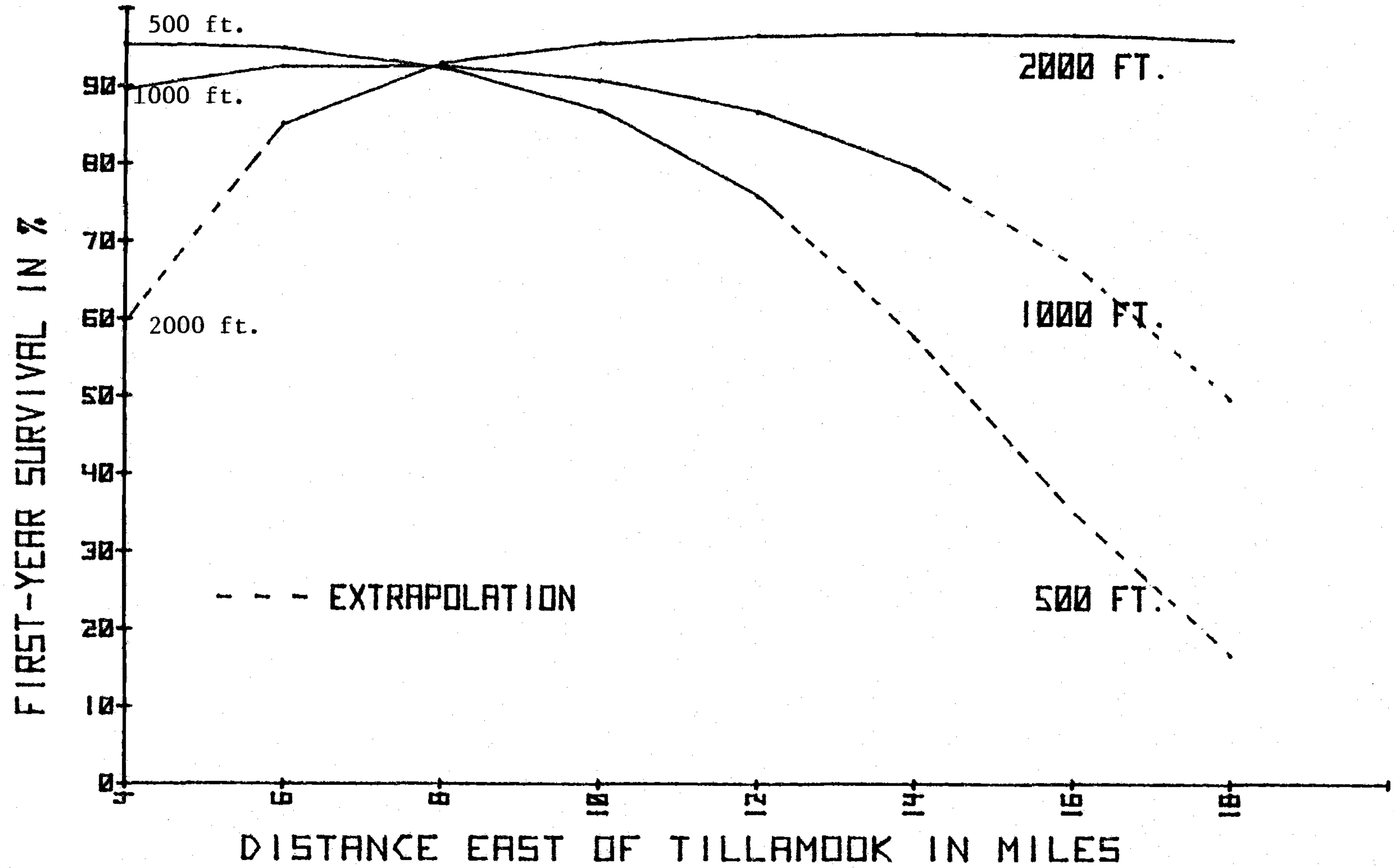


FIGURE 23. Estimated first-year survival in Tillamook as a function of location inland and altitude.

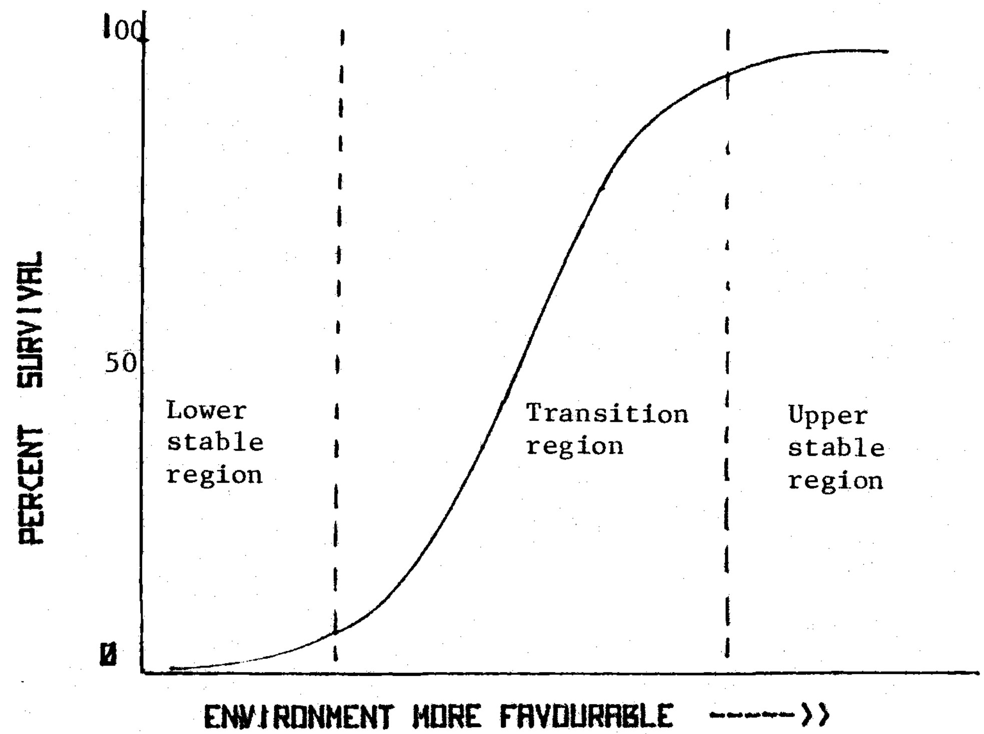


FIGURE 24. A typical survival function for a binary response variable with repeat observations at each level of the independent variables.

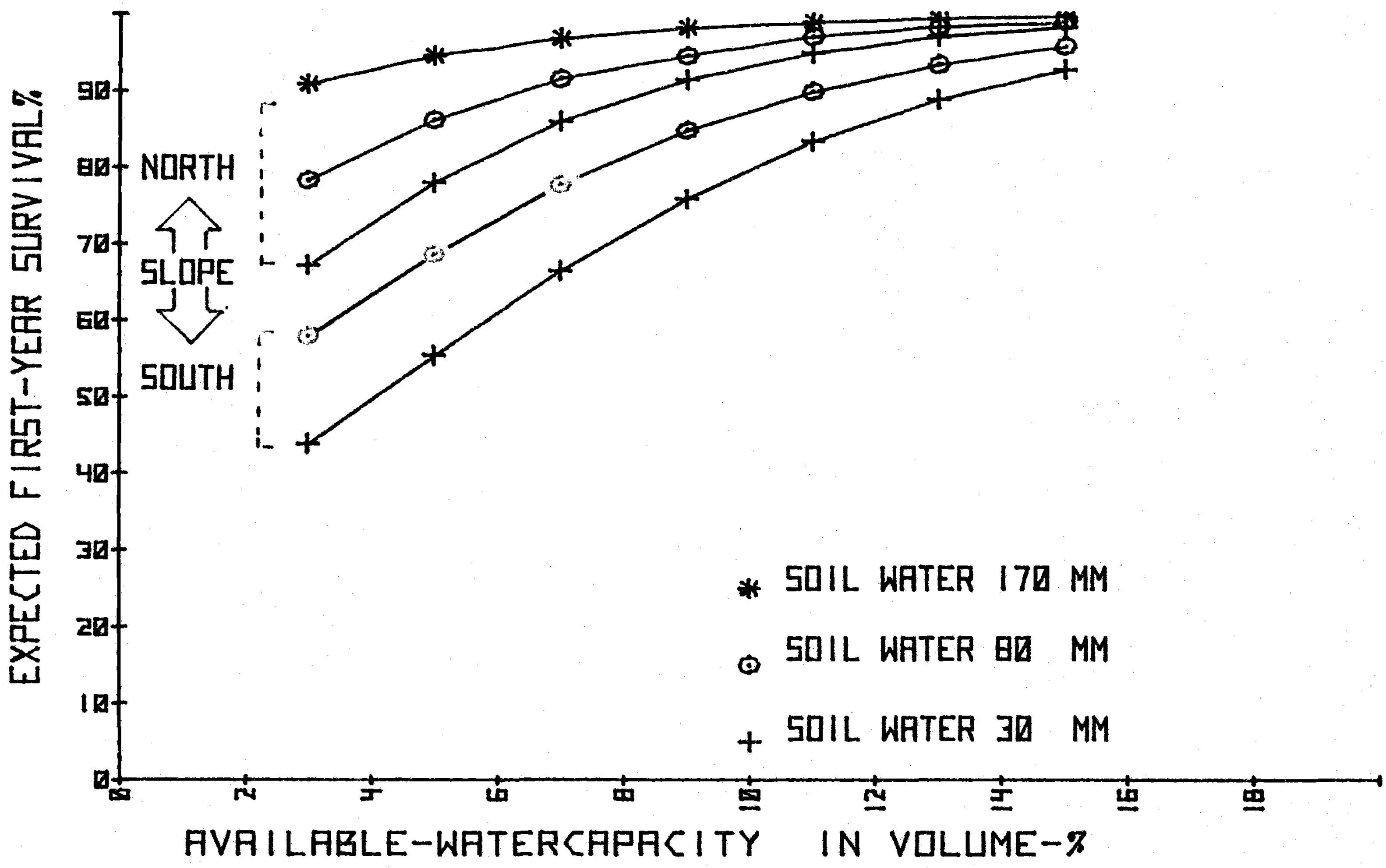


FIGURE 25. Expected survival in Tillamook as a function of available-water capacity, available-water in the profile, on two aspects (elevation 2000 ft., 9 miles inland).

TABLE 16. Definitions of Four Survival Predictions for Tillamook.

Prediction Class	First condition: Regression Estimate Percent survival	Additional conditions which the site must meet: Distance East Miles	Altitude Feet	Soil Water mm in the profile	Aspect Class
Y_1 (Excellent)	⩾ 90%	⩾ 8	⩾ 2000	⩾ 100	East, West
			⩾ 1600	⩾ 100	North
		< 8, ⩾ 4	⩽ 1200	⩾ 100	North
			⩽ 1200	⩾ 170	East, West
		< 4	⩽ 500	⩾ 100	North
			⩽ 500	⩾ 170	East, West, South, level
Y_2 (Good)	⩾ 90%	All sites other than those listed above			
Y_3 (Medium)	⩾ 75% < 90%	No additional conditions			
Y_4 (Poor)	< 75%	No additional conditions			

until an upper "stable" region is attained. Here, perhaps on a deep residual silt loam at low altitudes near the ocean, the environment is favorable to the extent that even a "bad" year, or frost-damaged stock or poor planting will do little harm.

I believe that the shape of this response function is responsible for contradictory results in research, conflicting experiences in operations, and frustration among reforestation foresters.

Figure 25 represents a proposed response function from the upper stable zone and the transition region for one selected site of the Tillamook forest. In practical terms, the hypothesis can be summed as follows: In the upper plateau region of the response surface, reforestation success comes consistently and almost effortless; in the lower, stable zone, conventional "good" reforestation practices will not help. Radical and usually expensive measures, such as shading and irrigation, are needed. It is in the transition zone that good practices achieve their full importance, but success is not always within the manager's power. Risk is high, and variability large.

For our purpose of forecasting first-year survival, we can hope for reliable predictions only in the upper and lower plateau regions of the response surface. In the transition zone we will have to accept low precision of forecasts. For instance: The regression model will predict over 90 percent survival for a North-slope site 9 miles east of Tillamook at 2000 feet, when AWC is either 30 or 170 mm (Figure 25). We can trust in this prediction for the soil with high water storage in the profile. On the other hand, an unusually dry summer or poor planting might drastically lower survival on the shallow "30-liter" soil.

As a consequence, I chose to limit myself to just four survival prediction signals, which are defined in Table 16. The predictions "medium survival" and "poor survival" depend on the regression estimate only, and apply, whenever predictions by regression fall into the intervals defined in Table 15.

Whenever the regression model predicts survival of 90 percent and above, additional criteria, listed in Table 16, serve to differentiate between the forecasts "excellent" and "good" survival. The former category includes only the very best sites, where survival can be expected to be consistently high, and relatively independent of annually changing random inputs. These sites correspond to points of the upper plateau region of the survival function, with a large "safety margin" towards the transition zone. For sites corresponding to the "good" category, on the other hand, this margin is small. Predicted high survival may not always materialze, due to random and adverse conditions in any one year. These sites are not "buffered."

For these clearcuts that had been planted initially in 1977/1978, site information was available for 41 plots (Table 4). After stratifying these eight areas into 17 uniform strata or "site units," the "Y-predictor" was tested informally, based on whether these areas had needed an interplanting in 1979 or not (Table 17). Very few plantations, for which "excellent" or "good" survival would have been predicted, had actually been interplanted. On the other hand, all areas with "poor" or "medium" survival predictions had received interplants one year after establishment. We will assess the likelihoods more formally later, and next turn to productivity forecasting.

Prediction of Site Class and Likelihood Probabilities for Forecasts

Figure 26 illustrates the relationship of actual site index measurement and regression estimate (Steinbrenner, 1979) for the set of test plots on model soils provided by the ownership. Means of measurements and estimates did not differ significantly. Ninety-three percent of all predictions differed by less than 18 feet from corresponding determinations in the field, and 40 percent differed by less than 5 feet, disregarding two noteworthy cases: The overestimate of 37 feet occurred for a clayey soil, and an underestimate of 19 feet for a soil with imperfect drainage.

TABLE 17. A Test of Survival Predictions in Tillamook with 17 Plantations from Year 1978.

Survival Prediction: Y_1 (excellent)	Y_2 (good)	Y_3 (medium)	Y_4 (poor)	
4	5	-	-	Area had not been interplanted 1979
-	2	3	3	Area has been interplanted 1979

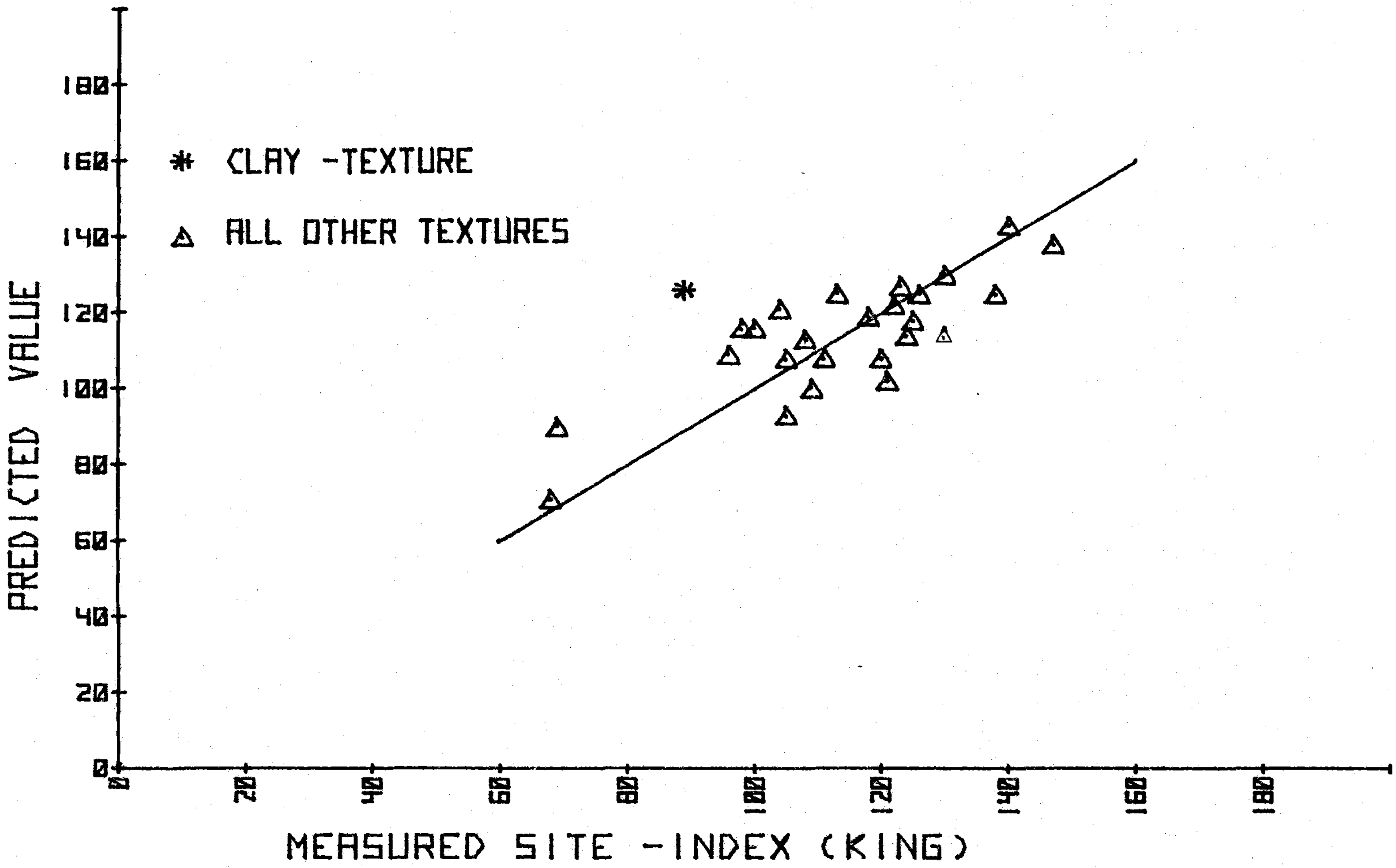


FIGURE 26. Comparison of measured site index on modal soils with regression estimate based on site data.

For the Forest Grove check plots, Table 18 provides mean regression estimates based on two soil samples for a five-acre tract and the corresponding site index mesaurements in the field. Again, both sets do not differ significantly over all samples. Site classes cover a wide range of site indices (King, 1966). For an average 30-acre clearcut, 5 to 10 samples with the soil probe should ascertain site class average, based on Steinbrenner's model (1979). In other words, we can reasonably assume that collection of site information "on the spot," in the field, will provide perfect information on site class as a state of nature.

Is the field trip necessary? Why not simply read site class from the ownership's soil map? Managers have trusted this map to the extent of not taking height measurements in forest inventories. Were they justified?

For the Forest Grove check plots and for some clearcuts in Tillamook--the soil map does not cover the entire district--I could compare map prediction and a site class that was either actually measured or estimated from site data.

Results of this admittedly small sample and the subjectively assessed likelihoods are displayed in Table 19. The soil map appears reasonably accurate.

Assessment of Likelihoods for Survival Predictions

As a final input to the Bayesian process, we need the likelihoods, that is, the probabilities of obtaining a certain survival signal, given that we know actual survival, and site class. We assume a flawless site class estimate from regression (Steinbrenner, 1980).

For each site class and for each actual, observed survival, we must assess the distribution of the "Y-predictors" from "excellent" to "poor." It is essential to notice that at this point economic and ecological models merge; the likelihoods represent the vehicle by which new, in our case biological, information enters decision analysis.

TABLE 18. Forest Grove Plots: Regression Estimates and Average, Measured Site Index for 5-acre Tracts

Estimated (ft)	Measured (ft)	Difference (ft)
109.0	85.7	23.3
125.0	116.0	9.0
126.0	104.5	21.5
121.0	105.0	16.0
127.0	124.5	2.5
120.0	130.0	-10.0
132.0	131.5	0.5
112.0	125.5	-13.5
111.0	125.0	-14.0
119.0	123.0	- 4.0
114.0	100.0	14.0
104.0	120.5	-16.5
112.0	109.5	2.5
105.5	121.5	-16.0
108.0	118.0	-10.0
116.36	116.0	0.36

TABLE 19. Likelihoods for Prediction of Site-Class by Soil Map.

Actual Observations

Forest Grove Check Plots

Predicted Site Class: by Site Map

Actual Class:	1	2	3	4
1	-	-	-	-
2	-	7=0.77	2=0.23	-
3	-	1=0.2	4=0.8	-
4	-	1	-	-

Tillamook Survival Plots

Predicted Site Class: by Site Map

Point Estimate by Equation	1	2	3	4
1	-	-	-	-
2	-	6=0.86	1=0.14	-
3	-	2=0.4	3=0.6	-
4	-	-	-	-

Subjective Assessment of Probabilities

Class Predicted by Site Map:

Actual Class:	1	2	3	4
1	0.900	0.100	-	-
2	0.020	0.800	0.175	0.005
3	0.005	0.175	0.800	0.020
4	-	0.050	0.100	0.850

TABLE 20. Derivation of Likelihoods for Survival Forecasts for Site Class One in Tillamook.

Raw Data

None*

*Site I is scarce in the Tillamook, and no survival plot on Site 1 land was contained in the sample.

Assessed Likelihoods

$S_i \backslash Y_L$	Y_1	Y_2	Y_3	Y_4
95	0.90	0.10		
85	0.10	0.90		
75	0.02	0.98		
65		1.00		
55		1.00		
45		1.00		
35		1.00		
25				
15				
5				

TABLE 21. Derivation of Likelihoods for Survival Forecasts for Site Class Two in Tillamook

Raw Data

S_i \ Y_L	Y_1	Y_2	Y_3	Y_4	Sample Size
95	8(0.5)	6(0.375)	2(0.125)	--	16
85	1(0.125)	4(0.5)	1(0.125)	2(0.25)	8
75	--	1(0.50)	1(0.50)	--	2
65	--	--	1(1.0)	--	1
55	--	--	--	--	--
45	--	--	--	1(1.0)	1
35	--	--	--	--	--
25	--	--	--	--	--
15	--	--	--	--	--
5	--	--	--	--	--

Assessed Likelihoods

S_i \ Y_L	Y_1	Y_2	Y_3	Y_4
95	0.5	0.45	0.05	--
85	0.125	0.500	0.225	0.05
75	0.05	0.400	0.50	0.05
65	0.01	0.090	0.30	0.60
55	--	0.05	0.20	0.75
45	--	0.01	0.14	0.85
35	--	--	0.05	0.95
25	--	--	0.01	0.99
15	--	--	--	1.0
5	--	--	--	1.0

Note: Numbers in parentheses represent relative frequencies in the sample.

TABLE 22. Derivation of Likelihoods for Survival Forecasts for Site Class Three in Tillamook.

Raw Data

S_i \ Y_L	Y_1	Y_2	Y_3	Y_4	Sample Size
95		7(1.0)			7
85		3(0.75)	1(0.25)		4
75		1(0.5)	1(0.5)		2
65		1(0.25)	1(0.25)	2(0.5)	4
55			1(1.0)	1(1.0)	1
45					1
35					0
25					0
15					0
5					0

Assessed Likelihoods

S_i \ Y_L	Y_1	Y_2	Y_3	Y_4
95		0.90	0.10	-
85		0.75	0.20	0.05
75		0.40	0.50	0.10
65		0.10	0.20	0.70
55		0.05	0.10	0.85
45		0.01	0.05	0.94
35			0.01	0.99
25				1.00
15				1.00
5				1.00

Note: Numbers in parenthesis represent relative frequencies in the sample.

TABLE 23. Derivation of Likelihoods for Survival Forecasts for Site Class Four in Tillamook.

Raw Data

S_i \ Y_L	Y_1	Y_2	Y_3	Y_4	Sample Size
95					
85					
75			1		1
65				1	1
55					
45					
35				1	1
25					
15					
5					

Assessed Likelihoods

S_i \ Y_L	Y_1	Y_2	Y_3	Y_4
95		1.0	-	-
85		0.5	0.5	-
75		0.20	0.60	0.20
65		0.10	0.40	0.50
55		0.05	0.25	0.70
45		0.01	0.05	0.94
35			0.01	0.99
25				1.00
15				1.00
5				1.00

Unfortunately, there is simply no "track record" for the survival prediction model. I relied on two sets of observations to obtain at least a crude, actuarial basis for subsequent subjective assessment of likelihoods. For each of the operationally established 50-tree survival plots, for which site data were available, I calculated, ex post, the applicable survival forecast (Figure 27). In addition, I compared average survival on each stratum of the 1979 sample of survival plots with the corresponding prediction (Figure 22). Neither set was particularly desirable. The old survival plots may represent outdated reforestation procedures and, particularly, a low level of animal protection. Correspondingly, overestimates dominate (Figure 27). The 1979 sample does not represent an independent data set.

Raw data and assessed distributions are displayed in Tables 20 to 23. Probabilities must sum to one over all predictions; when assessing them, the following question applies: "Given that actual survival on site "t_j" is "S_i", what is the probability of obtaining the prediction "Y_ℓ"? For those joint prior probabilities that are zero, no likelihoods need be assessed, since posterior probabilities will equal zero anyhow.

Preposterior Analysis

Productivity Prediction by Soil Map: Bayes' Strategy and Expected Value of Information

Should Tillamook foresters, before planning for a reforestation project, check their soil map for site class? How should they respond to the forecasts? Table 24 displays expected costs for each planting density under the posterior distributions, and their minima, our optima. Bayes' strategy associates one optimal planting density with each message (Table 25). Its expected value is only $0.33 per

TABLE 24. Contingency Table of Expected Costs for Each Planting Density and for Each Site Class Prediction

Planting Density	Prediction			
	Site 1	Site 2	Site 3	Site 4
450	874.03	809.46	809.87	1073.02
550	824.76	781.37	777.77	1019.84
650	780.83	758.72*	769.81*	1003.55
750	778.05*	772.85	786.81	1000.98*
850	778.70	783.86	800.81	1009.75
950	801.08	809.09	825.49	1024.04
1050	823.13	836.75	853.93	1039.70

Note: An asterisk represents optimality for each forecast.

TABLE 25. Bayes' Strategy for Soil Map Prediction of Site Class

Soil map prediction: Site Class	Optimal act: Plant
1	750 trees per acre
2	650 trees per acre
3	650 trees per acre
4	750 trees per acre

Expected value of Bayes' strategy:

$$778.05 \times 0.097762 + 758.72 \times 0.511891 + 769.81 \times 0.366249 + 1000.98 \times 0.024198 = 770.60$$

Expected value of prior optimum: 770.93

Expected value of information: 0.33

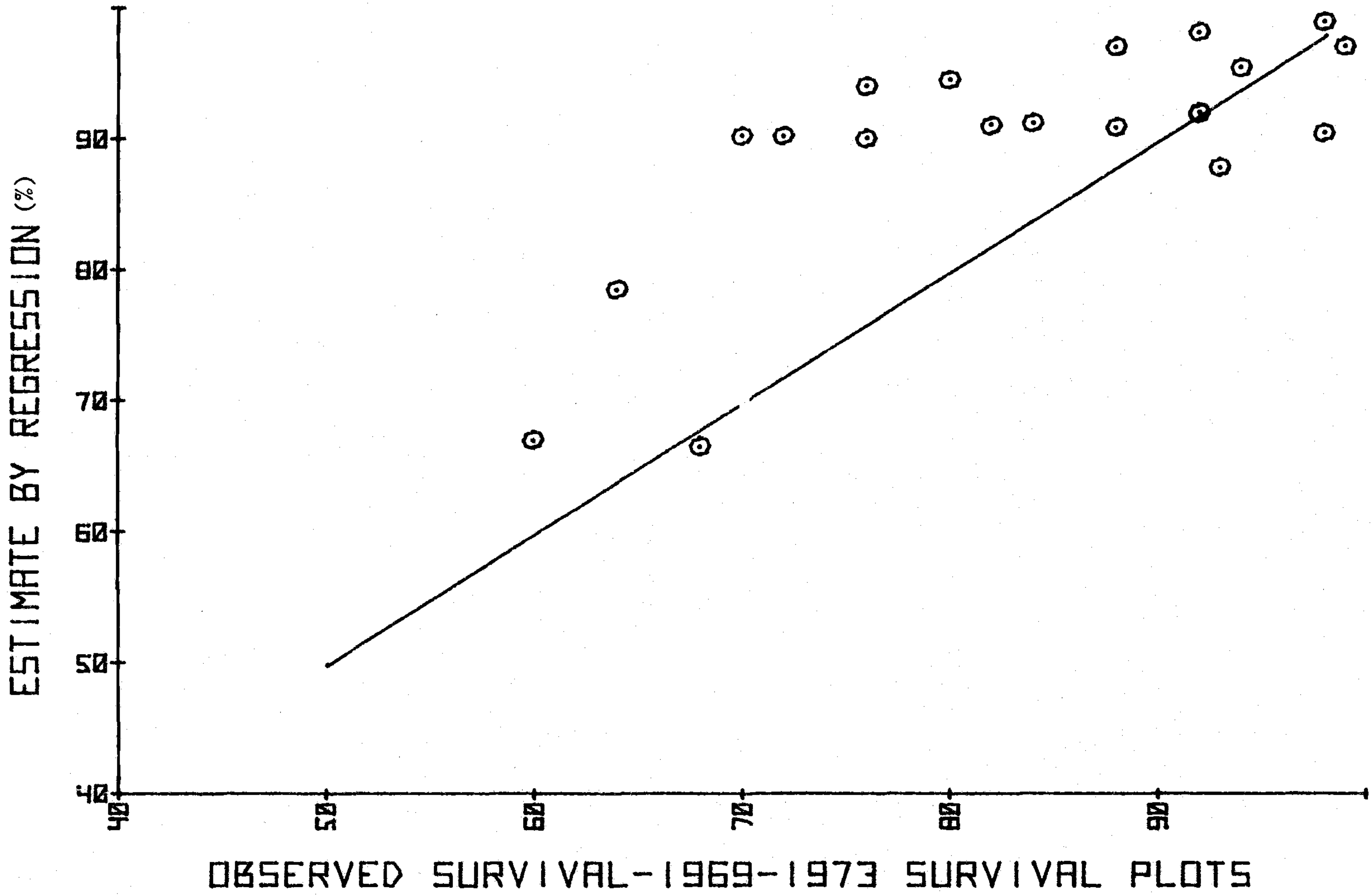


FIGURE 27. Comparison of actual and predicted survival for some operational survival plots established 1969 to 1973.

acre less than the corresponding prior value. Hence, up to $10 may be spent to look up site class of an average clearcut of 30 acres prior to planting. Table 26 points out reasons for this low value.

Imperfect Survival Predictions with Perfect Knowledge of Site Class: Bayes' Strategy and Value of Field Information

In the form of a preplanting survey, managers can obtain perfect information on site class and additional information about prospective survival. Compared to a simple site map check, will added returns outweigh the cost of field work? How does the information translate into management prescriptions?

For each site class at a time, we carry out preposterior analysis: For each message and planting density we compute an expected cost. Actions with minimal cost for each forecast represent Bayes' strategy (Table 27). Weighting each act in the strategy by the respective forecast probabilities, we arrive at the expected value of Bayes' strategy for each site class. The final step in calculations is illustrated in Table 27, which lists the expected values of both site class and survival information separately. The low overall value of information does not surprise: Table 27 indicates that, overall, site information will not change the optimal planting density often; in most cases, we would adhere to the optimal prior act of planting 650 trees to the acre.

This concludes preposterior analysis. What have we accomplished? We have not established "THE" value of site information for reforestation in Northwestern Oregon. We have merely determined, *a priori*, that is, before collecting any information, a prospective value of site information to one ownership in this region. This expected value is conditional on an existing regeneration policy predetermined costs and revenues, subjectively assessed probability distributions, and a neutral attitude towards risk. Conditional on these same subjective beliefs and

TABLE 26. Computation of the Expected Value of Soil Map Information for Tillamook (from Table 23)

Forecast	Predictive Probability	Bayes' Strategy	Posterior E.V. of Prior Optimum	Posterior E.V. of Posterior Optimum	Value of Information
Z_1	0.097762	750	780.83	778.05	2.78
Z_2	0.511891	650	758.72	758.72	0
Z_3	0.366249	650	769.81	769.81	0
Z_4	0.024198	750	1003.55	1000.98	2.57

Expected value of information:

$$0.097762 \times 2.78 + 0.024198 \times 2.57 = 0.33$$

TABLE 27. Bayes' Strategy and Combined Value of Site Information in Tillamook

Site Class	Probability	Prediction	Probability	Optimal Density	Expected Cost	Expected Value of Strategy	Expected Cost with Perfect Site Class Information Only	Marginal Expected Value of Survival Prediction
1	0.0944	Y_1	.20493	650	631.42	770.11	777.92	7.81
		Y_2	.79507	850	805.86			
		Y_3	.00000	-	-			
		Y_4	.00000	-	-			
2	0.5538	Y_1	.12808	650	619.60	755.58	755.58	0
		Y_2	.33752	650	671.81			
		Y_3	.25667	650	761.81			
		Y_4	.27780	650	915.11			
3	0.3345	Y_1	.00000	-	-	771.87	772.47	0.60
		Y_2	.36439	650	645.95			
		Y_3	.21033	650	719.06			
		Y_4	.42488	550	906.73			
4	0.0173	Y_1	.00000	-	-	1139.49	1140.07	0.58
		Y_2	.06861	750	718.87			
		Y_3	.13886	850	813.26			
		Y_4	.79254	750	1233.06			

Expected value of perfect site class information (Table 10) = 0.86

Marginal expected value of survival information

0.0944 x 7.81 + 0.5538 x 0 + 0.3345 x 0.60 + 0.0173 x 0.58 = 0.95

Expected value of combined information = 1.81

preferences, we have identified optimal strategies for various sources and intensities of site information. Which information should the ownership select?

Selecting and Aggregating Sources of Information

Should district foresters rely on the prior optimal policy, or should they try to retrieve further information? Which source of information should they choose? Does it pay to amass information systematically or just in selected cases?

The agency already owns the soil map. Perceptible, additional costs will arise neither in looking up the information, nor in implementing strategies. Therefore, as a first step, managers should rely on their soil map; resulting net gains from information will amount to only 33 cents per acre over all possible predictions. On predicted site classes two and three, they will gain nothing; on site classes one and four net gains of $2.78 and $2.57, respectively, or approximately $80 per 30-acre clearcut, will will result (Table 26).

Could foresters improve this result by, instead, systematically collecting field site information for every project? For those areas of the forest which are actually covered by the soil map--not all are--such an effort will pay if, on the average, marginal costs for material, travel, labor and administration do not exceed the marginal revenue, namely approximately $1.48 (1.81-0.33) per acre, or about $44 per project.

Soil parameters must be assessed by trained personnel, and the ownership employs only one soils specialist for all districts. Routine, large-scale, preplanting site mapping does not appear to be justified economically, or even practically feasible. By embarking on such a policy, the ownership would essentially venture a game of chance: In some instances, the information retrieved would reduce costs substantially. In most cases, information would not influence actions, and hence would be worthless.

Why could one not "load the dice" in this game of chance? Could one not improve the odds of obtaining those signals which will lead to a payoff?

Foresters in Tillamook may formally eliminate areas where site investigations are unlikely to produce payoffs. The questicn is not whether to apply the soil map, or whether to collect field data. Rather, one should try to aggregate information.

After a soil map prediction of site class, prior probabilities change to posterior probabilities, each conditional on a specific site class prediction. In a stepwise Bayesian analysis, we now consider these posterior distributions as prior probabilities for the valuation of subsequent information. Given that the soil map predicts a site class, does it pay to obtain additional information in the field?

Based on the likelihoods for site map predictions (Table 19), we compute posterior probabilities for each site class by applying Bayes' theorem. Table 28 summarizes calculations. Practical recommendations follow.

Practical Recommendations

Overall, the following policy appears indicated for Tillamook conditions:

The district should not embark on systematic site mapping on all reforestation projects. Instead, foresters should first consult their soil map.

Whenever the soil map indicates site classes two or three, the prior optimal act, 650 trees to the acre, is indicated (Table 25). Here, field work will probably not pay in most instances (Table 28).

For map predictions of site classes one and four, field

TABLE 28. Expected Value of Field Site Information after Soil Map Prediction of Site Class.

Site Class	Expected Cost of Bayes' Strategy with Imperfect Survival Forecasts but Known Site Class (from Table 27)	Posterior Probabilities for Site Class after Soil Map Prediction			
		Z_1	Z_2	Z_3	Z_4
1	770.11	0.8695	0.0184	0.0000	0.0000
2	755.58	0.1133	0.8655	0.2646	0.1146
3	771.87	0.0171	0.1143	0.7307	0.2768
4	1139.49	0.0000	0.0017	0.0047	0.6086
Expected costs of Bayes' strategy under posterior distribution		768.43	758.32	769.29	993.75
Expected cost where only site class is known with certainty under posterior distribution		775.23	758.53	769.74	994.27
Expected value of additional survival information		6.80	0.21	0.45	0.52
Expected cost with soil map prediction only (from Table 23)		778.05	758.72	769.81	1000.98
Expected value of field site mapping (imperfect survival, perfect site class information)		9.62	0.40	0.52	7.23
Expected value of soil map prediction (from Table 25)		2.78	0.00	0.00	2.57
Expected value of aggregated information from soil map and field site mapping		12.40	0.40	0.52	9.80
Expected value of aggregated information over all predictions		1.81			

investigation of site class and prospective survival promises returns (Table 28), as long as costs do not surpass \$9.62 and \$7.23, respectively. Table 27 lists Bayes' strategy, and Figure 28 facilitates decisions.

Summary of the Tillamook Study

Reforestation practices in the Tillamook District of the Oregon State Department of Forestry served as subject for a case study on the valuation and use of site information for Douglas-fir reforestation by Bayesian decision analysis.

After an analysis of reforestation operations, based on available records, a simulation model compiled economic and operational consequences for each initial planting density, and each joint occurrence of site class and first-year survival.

During the prior analysis phase of the decision model, this existing information was used to find an overall, optimal planting rate _a priori_, that is, without any site information. After a check on the potential maximum value of further information about the main sources of uncertainty, survival and site class, an ecological predictor for survival was established. It relies on site information. An existing forecast model for site class was adopted, and the accuracy of both regression models assessed subjectively.

In the preposterior analysis, forecasts were valuated, again strictly subjectively, based on the prospective reduction of expected reforestation costs.

As a case study, the investigation produced practically tangible results for the ownership, insights into the ecological determinants of survival and productivity and, finally, theoretical knowledge about potential and weaknesses of decision analysis in forestry.

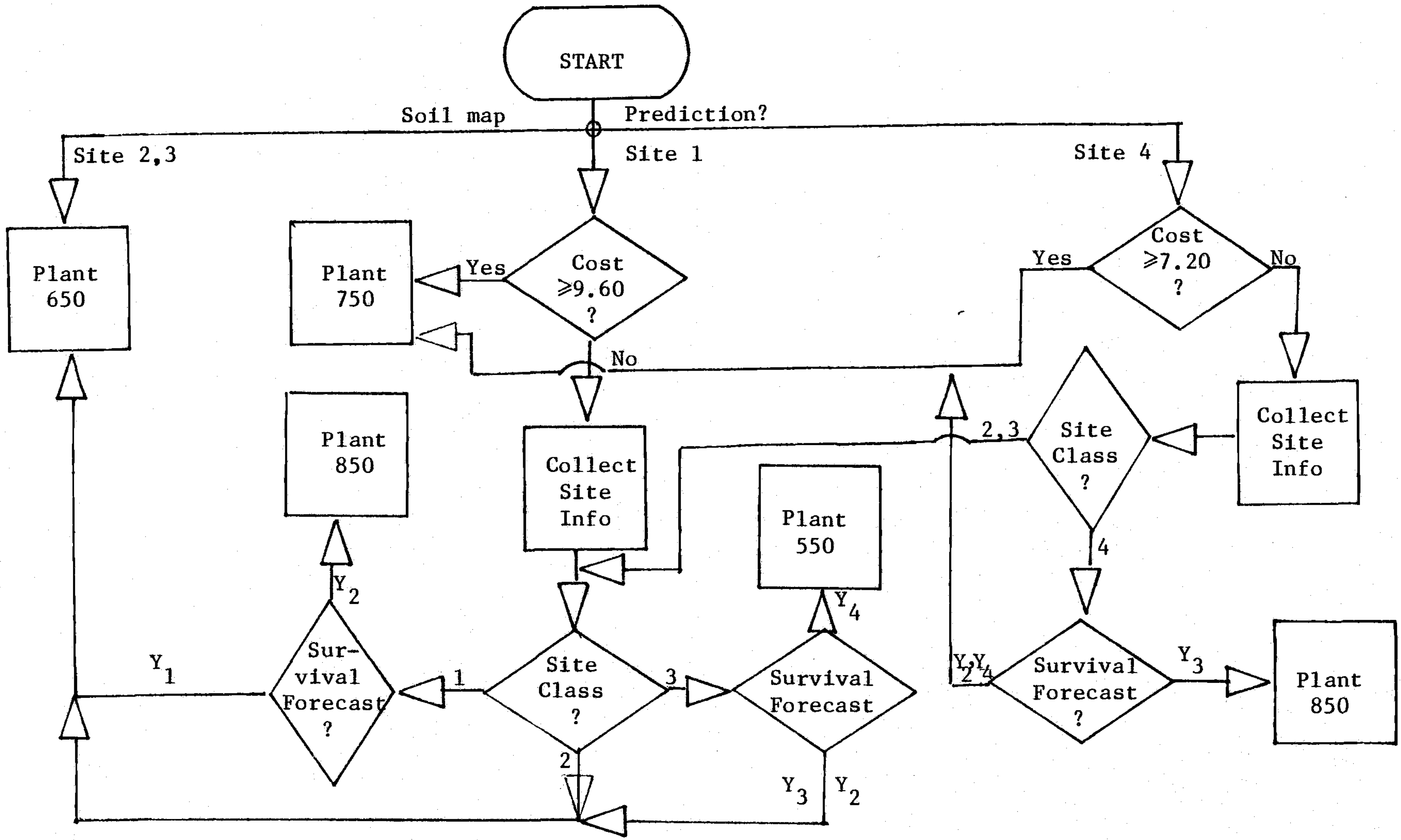


FIGURE 28. Decision diagram for areas contained in the soil map. (Costs are for gathering information in $ per acre.) Tillamook Case Study.

Assuming present policies are continued, the ownership should raise planting densities from the present 450 to 650 trees per acre, even without or before collecting site information. With few modifications, an existing regression model will predict average site class of an area with certainty. Site variables can serve to predict poor and excellent survival rather successfully. Intermediate survival rates cannot be anticipated reliably, due to annually changing, uncontrollable inputs. The district's soil map, while not perfect, appears to produce reasonably accurate and unbiased site class ratings. Its average value for reforestation purposes was subjectively assessed at 33 cents per acre. The map achieves its greatest value for reforestation as a useful device to screen all sites, and limit site mapping to areas where, by aggregation, high returns to further information are likely. Practical results culminate in a detailed strategy for collecting site information and adjusting planting densities.

In the ecological part of the study, a field index for the available-water capacity of Tillamook soils was established. Its role, and the influence of further site variables in seedling survival, is quantified in a subjective prediction model.

The greatest potential tangible benefit of this study for the ownership, an increase in expected revenues of $50 per acre, emerged from the prior analysis. It is merely a consequence of logically combining existing, *a priori* information, contained in reforestation records. The importance of maintaining such records became evident in the initial operations analysis, the establishment of the simulation model, the assessment of prediction likelihoods, and, generally, throughout the study.

In the absence of such historical evidence, Bayesian decision analysis is still possible. However, without records or the true expertise which results from their critical evaluation, decision analysis may resemble Baron von Münchhausen's attempt to leave the fabled swamp.

With an average value of approximately \$2 per acre, the added ecological information on prospective survival and site class is worth relatively little in the overall management of the study area. In essence, few site- and survival classes dominate, and prior analysis adjusts actions to match these prevalent states of nature. For some small strata within the forest, established by means of a soil map, the ownership could spend up to approximately \$10 per acre for site information; for others any returns to information are unlikely.

Overall, Bayesian decision analysis succeeded in effectively using _a priori_ information to its full potential; it appears well-suited to translate ecological findings consistently into economically optimal management decisions.

VII. RESULTS AND DISCUSSION: THE ROSEBURG CASE STUDY

For reasons of continuity and clarity, both case studies have been kept separate. The Roseburg analysis, however, is by no means independent. Rather, it should be seen as a contrast to Tillamook and, hence, results are presented deliberately against this background.

The reader will find frequent cross-references and comparisons, whenever they appeared possible, particularly illustrative or throught-provoking.

On the other hand, familiarity with decision analysis in general, and with its application in the preceding study, is presumed.

The Natural and Organizational Environment for Reforestation

While environmental conditions, in general, favor regeneration in the Tillamook area, reforestation problems abound in the South Umpqua Resource Area of the Roseburg BLM, and in Southwestern Oregon. They have received the attention of foresters and researchers, as well as that of the general public.

Bedrock may vary from sedimentary silt-and sandstones over igneous basalt, andesite, tuffs, diorite and granite to metamorphic gneiss and graywacke. Serpentine rocks represent a particularly interesting feature. Associated topography and soils show similar variability. Soil texture may range from pure clays to loamy sands; Figure 29 depicts sample textures from the survival plots. There are soils with pure pebble overlays and others, where the heavy clay surface cracks in the summer, and dries to a bricklike consistency. These sites support a variety of tree species and, unfortunately, a multitude of aggressive,

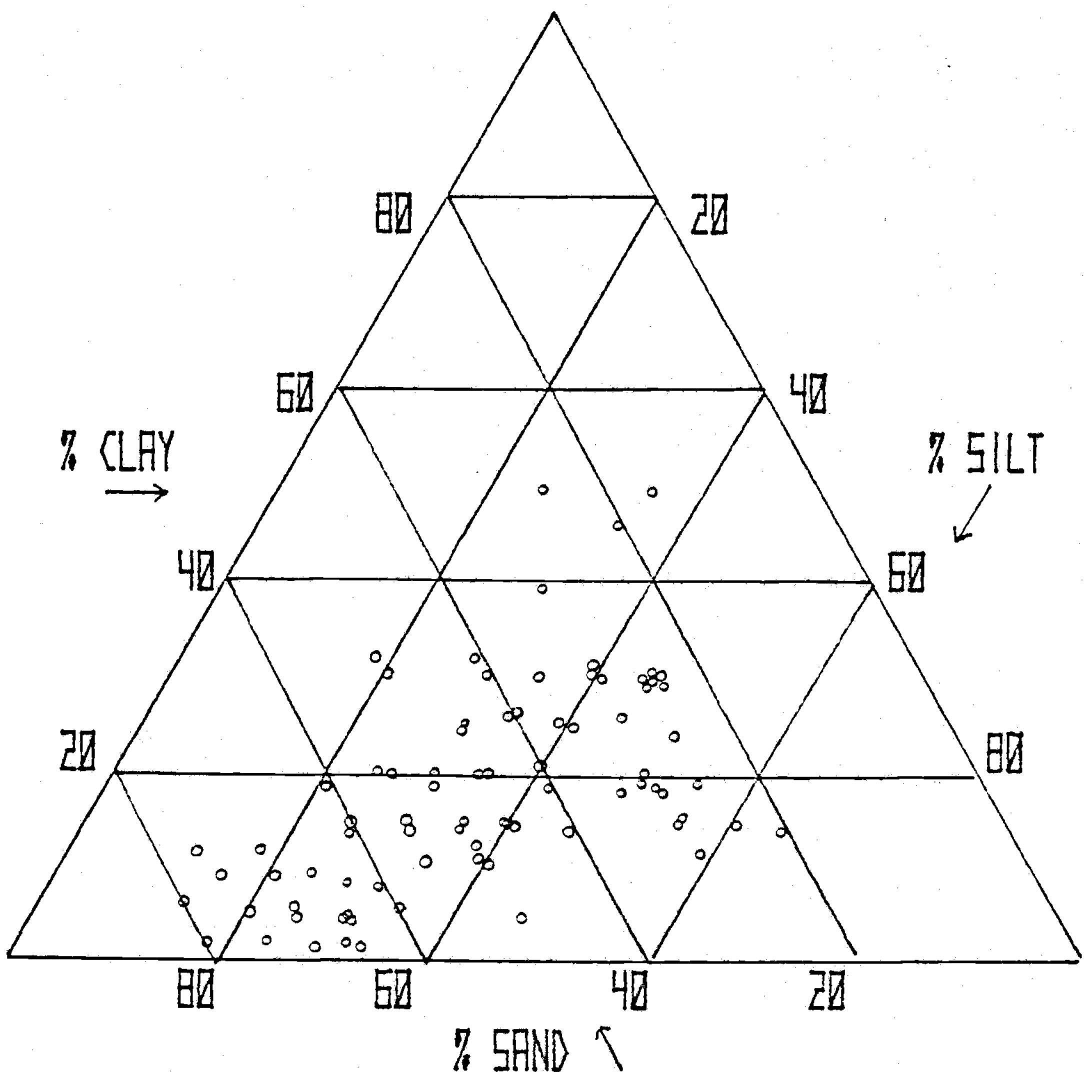


FIGURE 29. Sample soil textures for the Roseburg study.

sclerophyllous, brushy vegetation. Steep slopes, stony surface horizons and logging residue combine to create a serious ravel problem in some places. Seedlings on a few survival plots were simply buried in this dry ravel; in two other instances, entire plots moved downhill as a consequence of landslides. On the brighter side, animal damage is less of a problem than in Tillamook.

Annual precipitation rises from a low of 25 inches near Canyonville to a maximum of approximately 45 inches East of Tiller (Soil Conservation Service, 1964). Only about 20 percent of this moisture falls during the most active season for plant growth, and only zero to six percent during June to August. Clear sky radiation is high, and relative humidity low. Striking contrasts to Tillamook's climate become particularly apparent in climatograms (Loy et al., 1976). Unfortunately, isohyetal maps do not display seasonal rainfall figures, which can be expected to be immensely more meaningful than annual averages.

Attempts have been made to improve survival by shading (Lewis et al., 1978; Hobbs et al., 1980) or mulching. The need to identify areas with overwhelming reforestation problems before cutting has become evident. Scientifically, Carkin and Minore (1974) have developed a stocking prediction aid, based on soil, aspect, elevation, slopes, and an index for moisture and temperature which is calculated from indicator plant species. Foresters themselves have operationally mapped areas where they anticipate reforestation problems, in order to delay further cutting for the time being, or to withdraw these areas from the land base for the allowable cut.

District organization, too, reflects concern with the ecological constraints to management: Resource areas are staffed with soils specialists, and an admirable soils inventory elaborates on management implications. Unfortunately, its scale precludes identification of site classes for a specific parcel of land on the ground.

Reforestation policies, too, implicitly appear to acknowledge the overriding influence of the site: In a flexible response to repeated failures, management guidelines stepwise lower minimum acceptable stocking on these sites (Table 29).

In another deviation from policies in Tillamook, target and minimum stocking, as well as the desirable density after a precommercial thinning vary by site class. Special problems exist in Roseburg with respect to site class ratings, however. They are outlined in Appendix A, which also contains the marginal distribution of site classes. Before attempting the prior analysis in the following, the reader is cautioned against some comparisons of results in both case studies: Besides different reforestation policies, different target and minimum stocking, both ownerships operate with different management and opportunity costs, and they do not employ the same system of site classes.

Some Operating Characteristics of the Reforestation System

Plantations remain in the reforestation system until they are rated "stocked and established," or until no further effort appears justified. In the latter case, areas may be withdrawn from the timber production base.

Figure 30 reveals that, historically, plantations have spent as much as 20 years in the rehabilitation phase without being established yet. Fill-plantings are the rule rather than the exception (Figure 31). Only approximately one-third of all plantations during the period from 1970 to 1976 did not require interplanting, in spite of lower acceptable stocking and higher planting densities than in Tillamook. Due to a more flexible policy, no more than four interplants occurred at any one site. As in Tillamook, herbicide use tends to increase with the number of establishment attempts (Figure 32), but, compared to Tillamook (Figure 6) some restraint appears visible. Foresters have sought to curb

TABLE 29. Replanting and Precommercial Thinning Policy in the Roseburg District

Unit's Age	Site Class	Target Stocking (effective trees)	Corresponding Number of Trees per Acre Age 15	Minimum Stocking (effective trees)	Corresponding Number of Trees per Acre Age 15
t ⩽ 3	2	320	585	320	585*
	3	280	465	280	465*
	4	245	371	245	371*
	5	200	266	200	266*
t > 3 t < 6	2	Note: In all other respects, reforestation policies in Roseburg equal those in Tillamook (Table 7).		250	384
	3			220	311
	4			200	266
	5			100	100
t ⩾ 6	2			150	170
	3			150	170
	4			150	170
	5			100	100

*desirable densities after precommercial thinning.

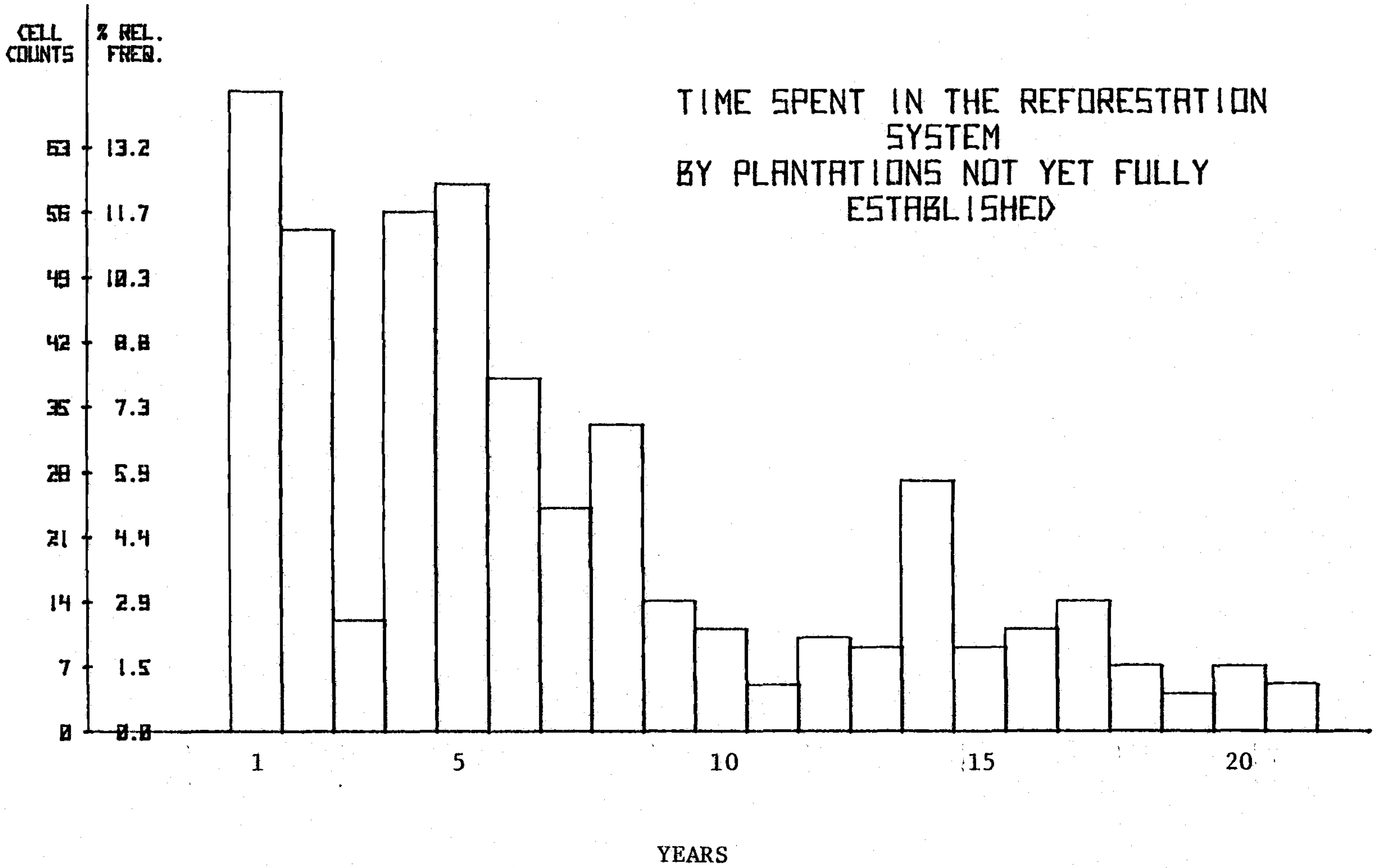


FIGURE 30. Histogram of the time spent in the Roseburg reforestation system by plantations that were not yet considered fully established in 1980.

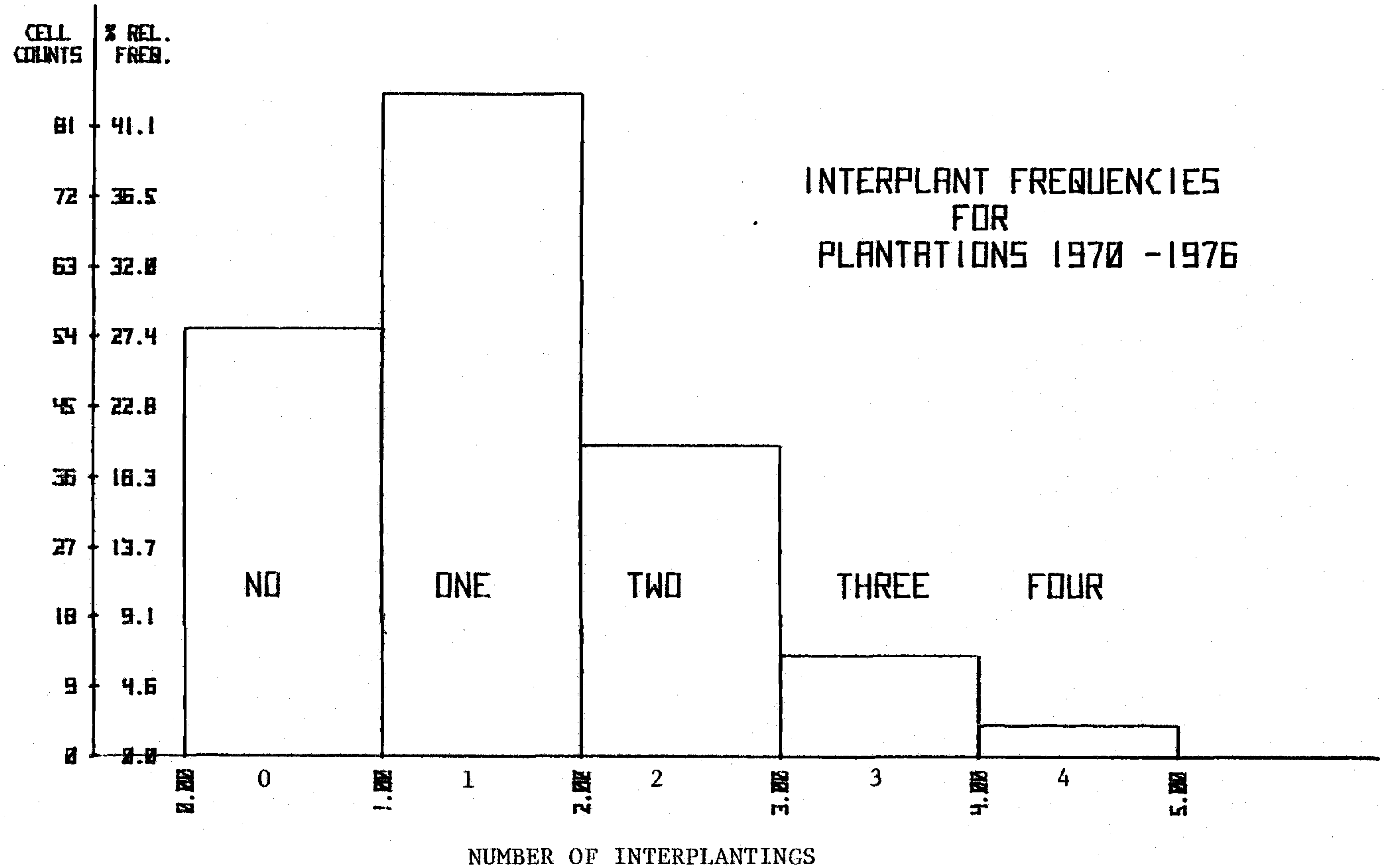


FIGURE 31. Histogram of the number of interplantings in plantations 1970 to 1976 in Roseburg.

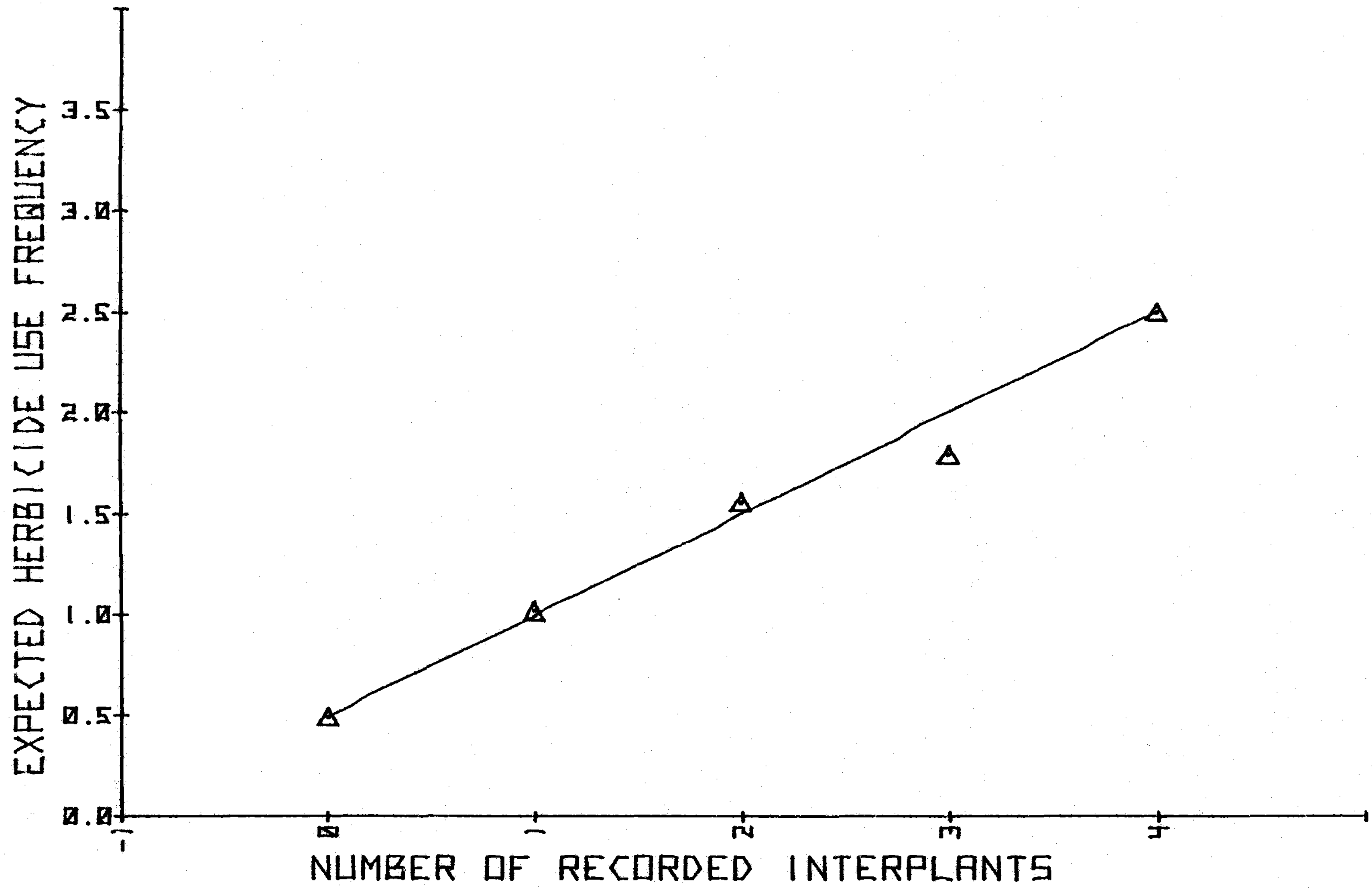


FIGURE 32. Average number of herbicide treatments as a function of the number of recorded fill plantings in Roseburg.

troublesome interplantings by steadily raising planting densities (Figure 33), from ten feet by ten feet before 1970, to six by six feet more recently. As a consequence, "stocking," found during first-year surveys, has risen (Figure 34).

The district's survey procedures focus on achieving acceptable stocking, and report it in terms of "effective, well-spaced trees." This estimate is based on occupancy of circular plots of predetermined radius with at least one acceptable tree; no record is kept of the actual tree count on the sample plot. The method underestimates the actual number of trees.

For the year 1979, both regular, operational stocking survey reports and the results of my own survival plots were available, and provided an opportunity for calibration. I could compare both estimates and establish the following regression (R = 0.89).

$$a = (3.23 + 0.06548\ b)^2$$

where a = actual number of trees

b = "effective trees" from stocking surveys.

Figure 35 facilitates transformation.

The district records show a trend toward improved reforestation practices. Stocking standards have been raised repeatedly. In addition, a new technique, shading, has recently been applied at "problem" sites.

The sampling distribution of survival percentages for entire plantations during the 1974 to 1979 period reflects the harsh environment (Figure 36). Clearly, we cannot simply smooth relative frequencies in order to obtain our desired distribution of first-year survival. Not all of the plantations, 196 in all, had been burnt prior to planting; moreover, we have established above that reforestation techniques have changed. We would expect a shift toward higher survival rates in the future.

Survival frequencies for 127 study plots of 15 trees each appear in Figure 37. In an interesting extrapolation from the previous case study, average survival has decreased to 68 percent

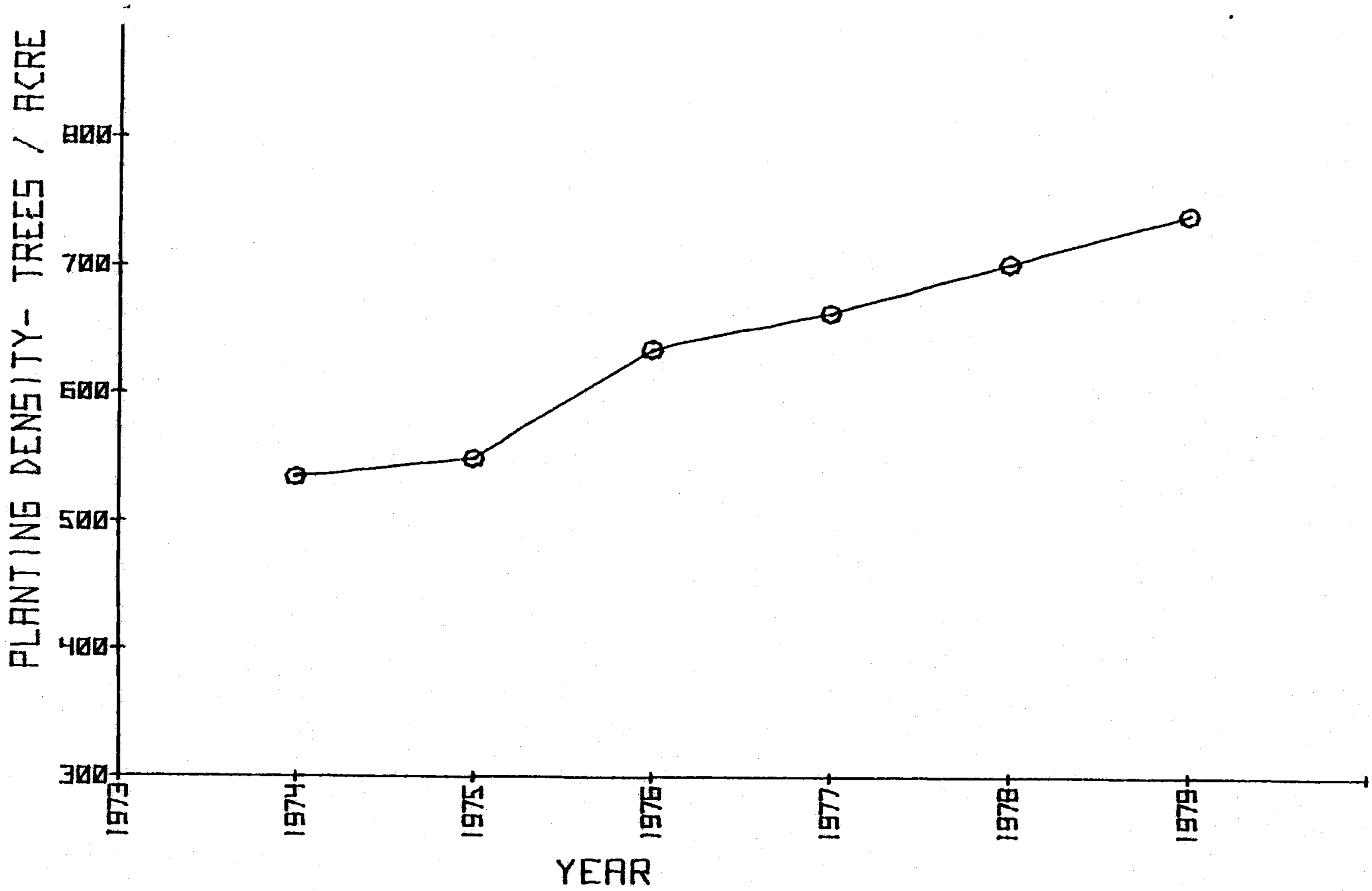


FIGURE 33. Development of average planting densities from 1973 to 1979 for the South Umpqua district.

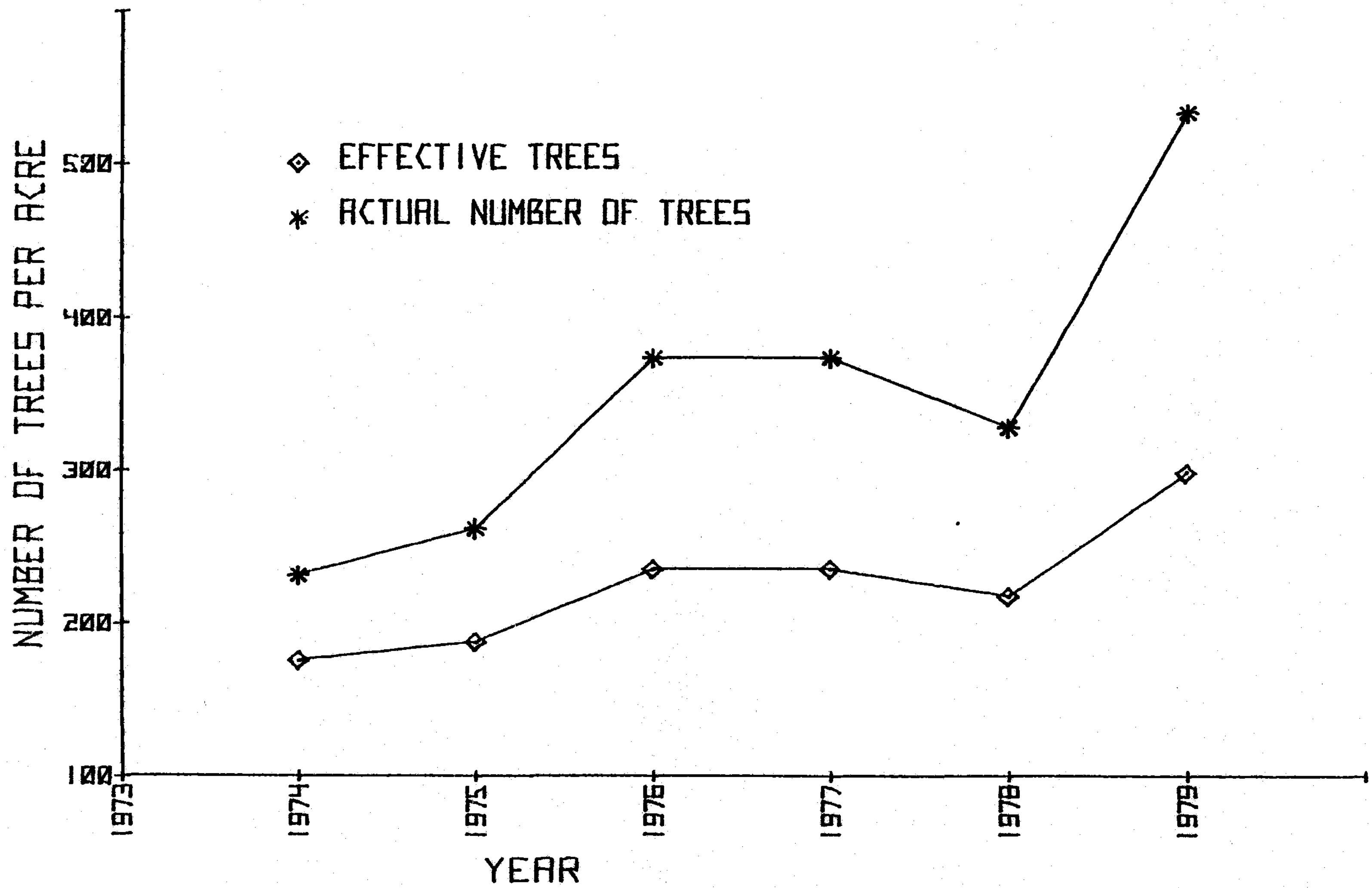


FIGURE 34. Development of average stocking survey results during the years 1973 to 1979 in Roseburg.

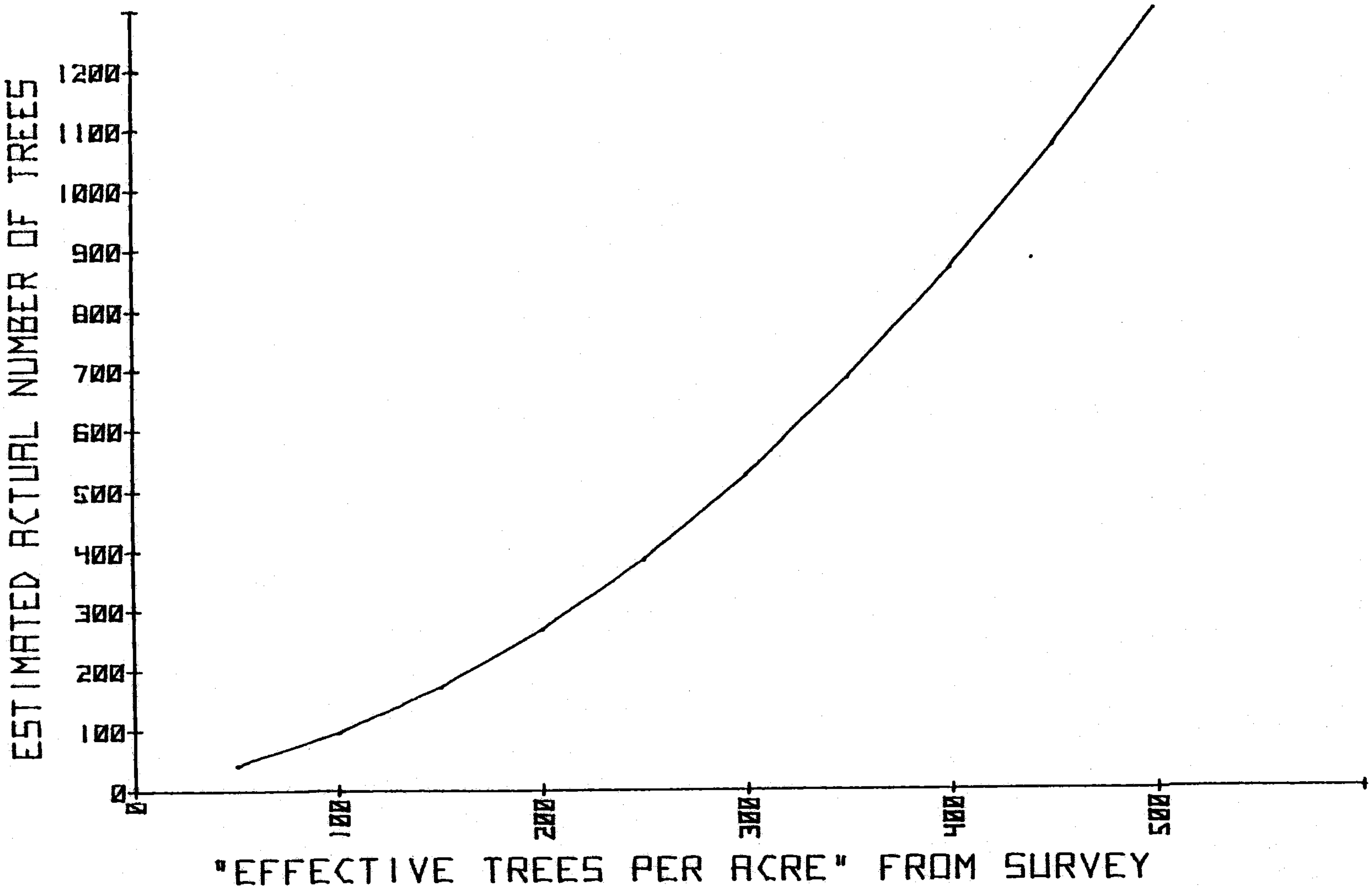


FIGURE 35. Estimation aid for actual number of trees, from survey results reported as effective trees per acre.

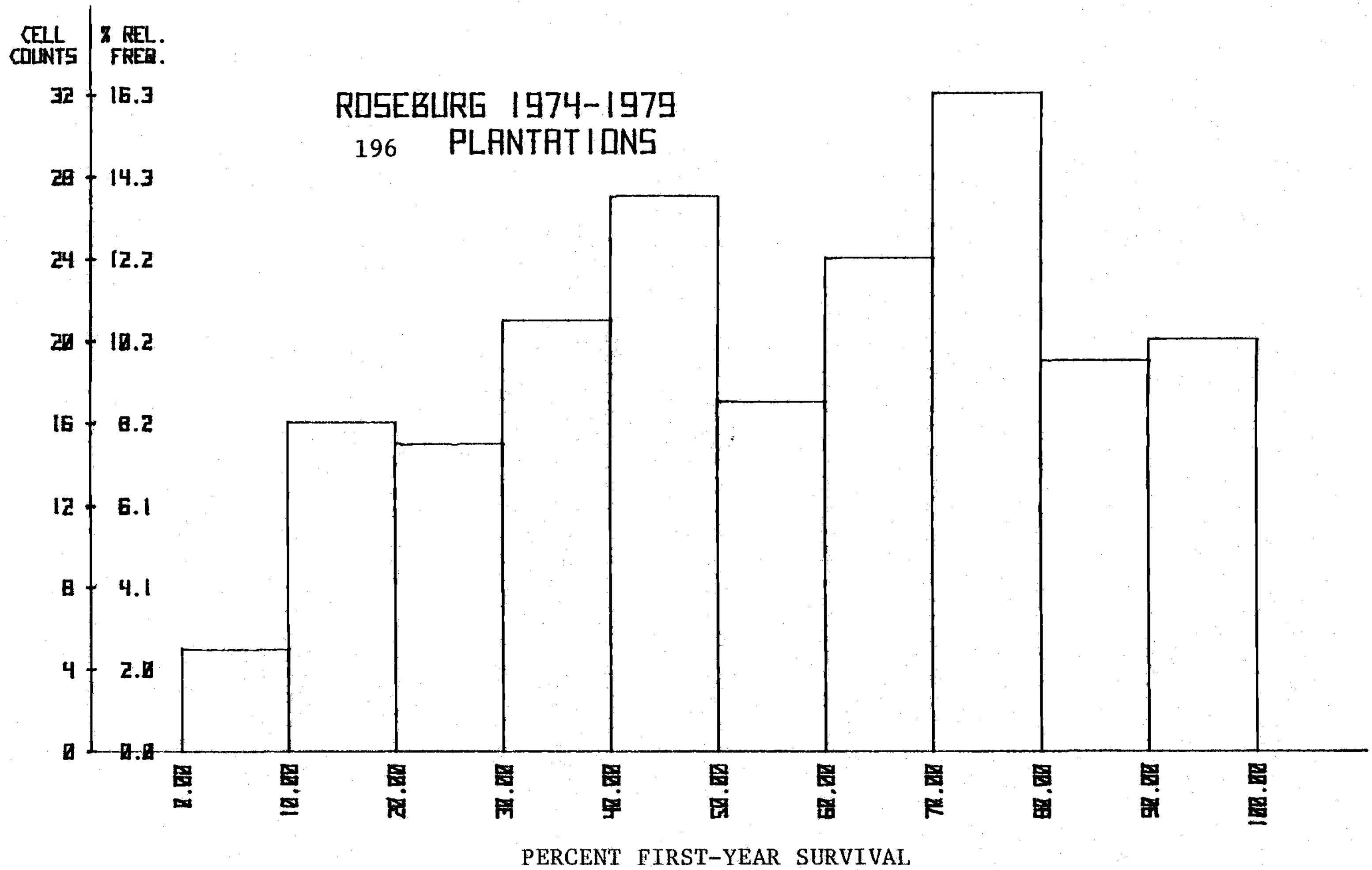


FIGURE 36. Histogram of estimated first-year survival in plantations 1974 to 1979 in Roseburg.

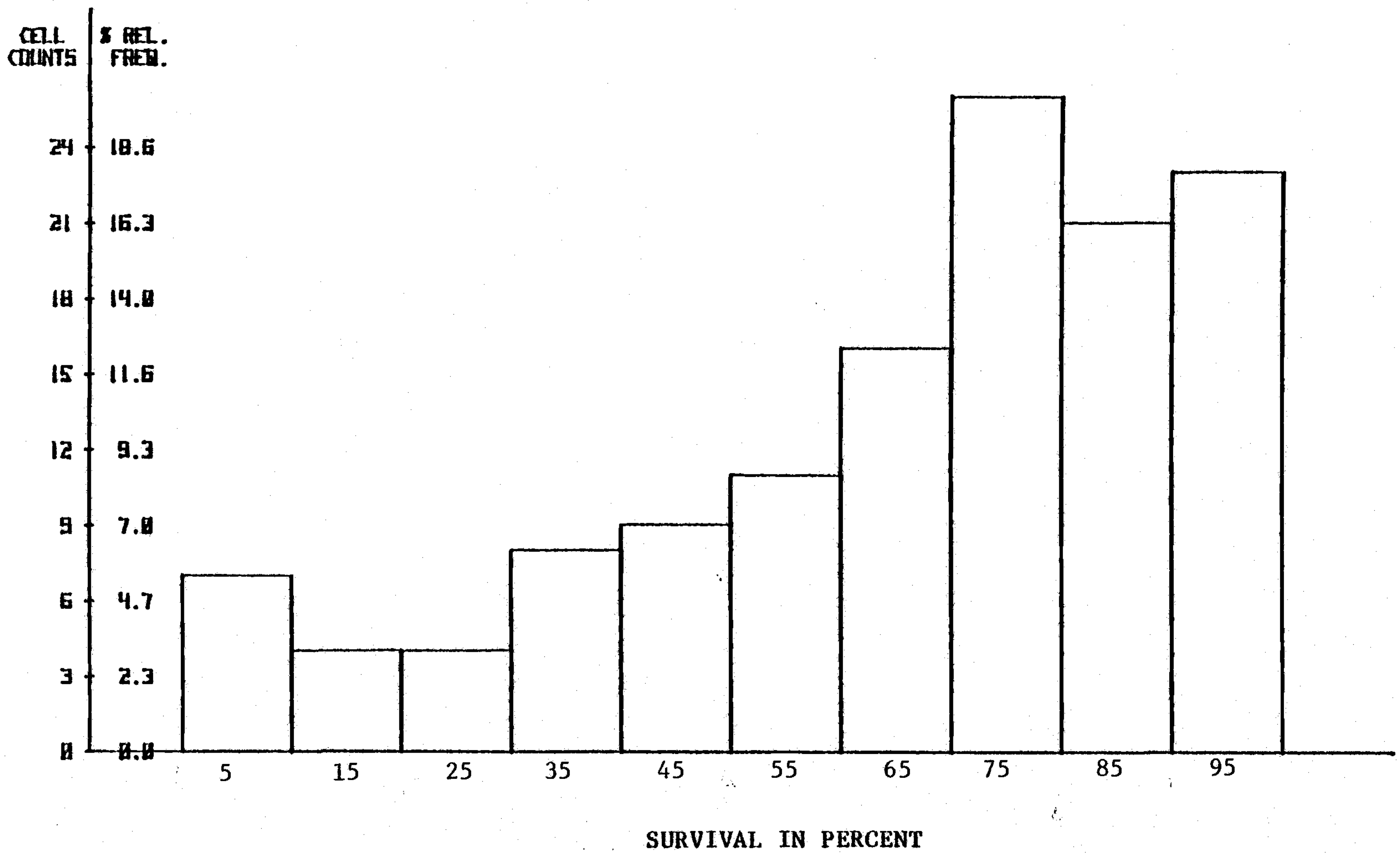


FIGURE 37. Frequency distribution of first-year survival for 127 study plots of 15 trees each in Roseburg.

from 78 in Tillamook. Simultaneously, its variance has increased. Figure 38 was obtained by combining individual survival plots within uniform strata of the clearcuts. Is this 1979 distribution more representative than the historical survival distribution (Figure 36)?

According to records (U.S. Department of Commerce, 1974 to 1979), the Roseburg area received 2.21 inches of rain in 1979 during the May to August period, much more than the average for the preceding five years, namely 1.62 inches. As in Tillamook (Figure 10), summer rainfall clearly affects average survival (Figure 39), and 1979 was not an average year in Roseburg.

A typical, representative distribution of first-year survival in Roseburg would be an intermediate between distributions depicted in Figures 36 and 38. Purely subjectively the following distribution for first-year survival in Roseburg was assessed (Figure 40). Roughly, it corresponds to a weighted average between the historical distribution and the 1979 sample results, where the former received a weight of four, and the latter a weight of three. The distribution represents survival over all site classes.

When a rough productivity index was calculated for each survival plot from site data (Appendix A), stratification of survival by sites with low, average and high productivity produced strikingly different distributions (Figure 41). Not surprisingly, and as in Tillamook, survival will vary by productivity.

Judgmental distributions for first-year survival for each site class were assessed on the basis of Figure 41. They were chosen to sum to the previously selected average prior distribution over all sites.

In the absence of permanent, operational survival plots, these distributions are clearly much more tentative than those in Tillamook. The same applies to the distributions for survival in subsequent years, which are based on 51 sample plots of CADS (Black et al., 1979). As in Tillamook, mortality subsides within the first

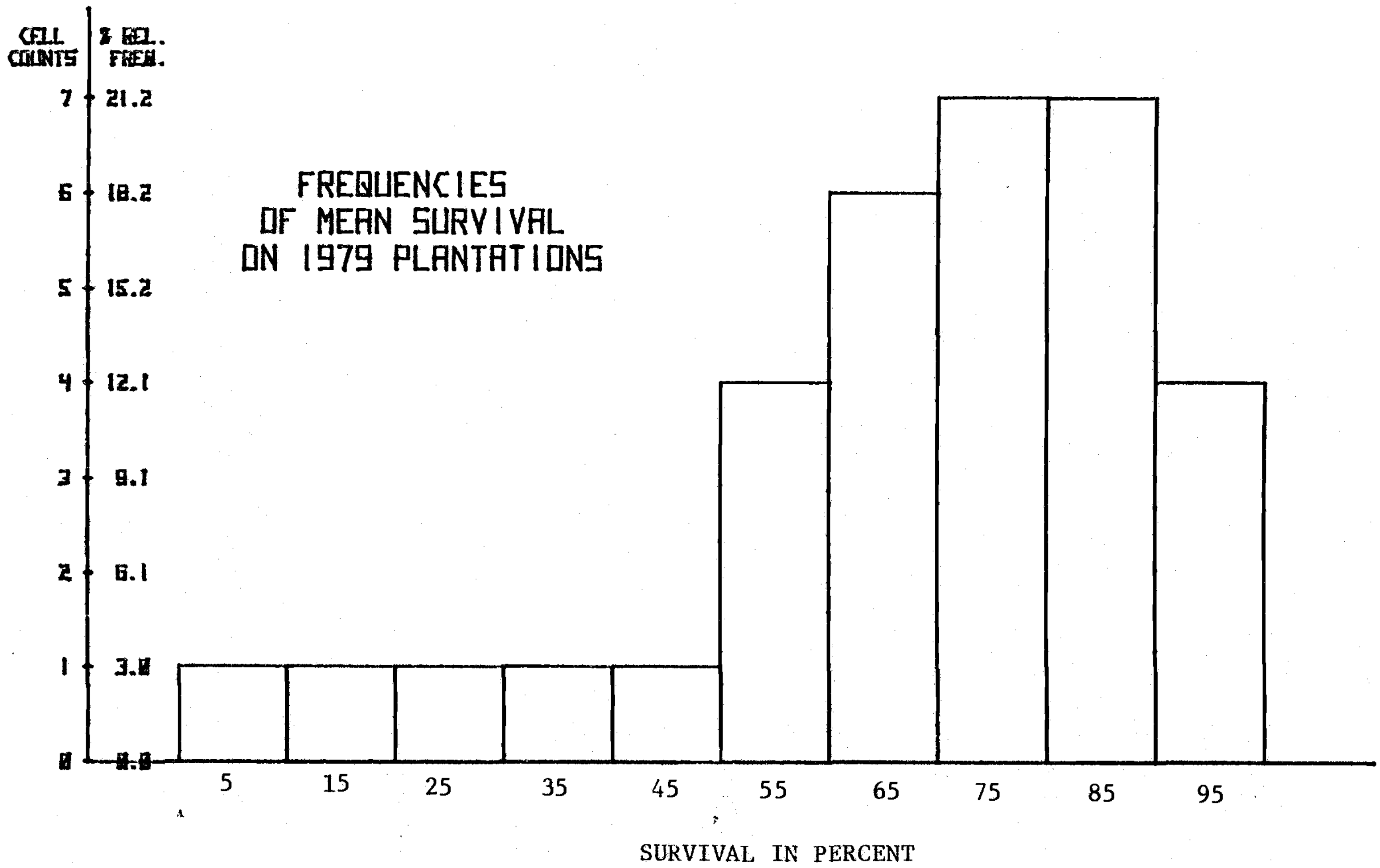


FIGURE 38. Frequency distribution of average first-year survival for study plots combined by uniform sites within clearcuts in Roseburg.

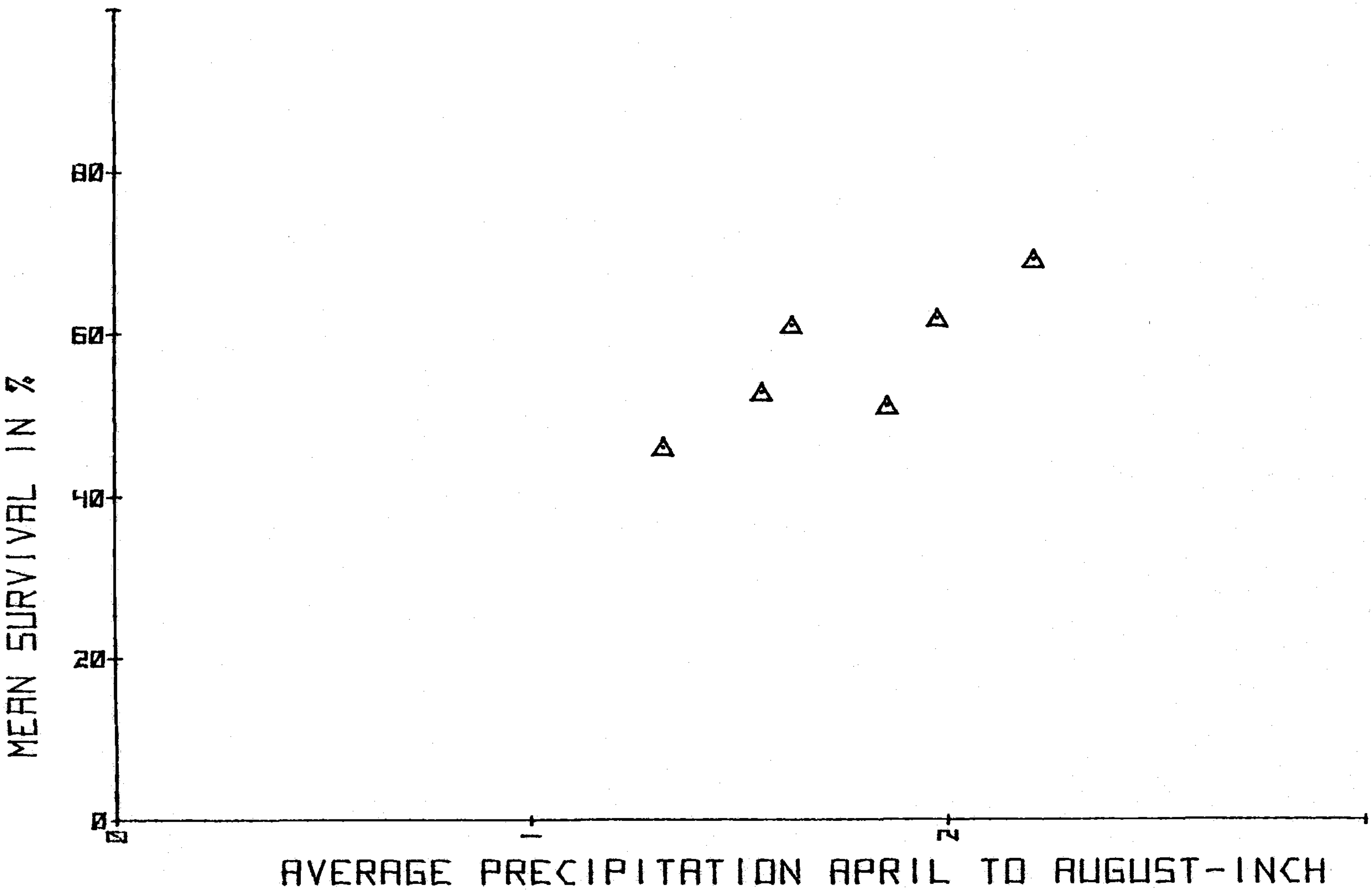


FIGURE 39. Mean survival of plantations 1974 to 1979 as a function of precipitation from May to August in Roseburg.

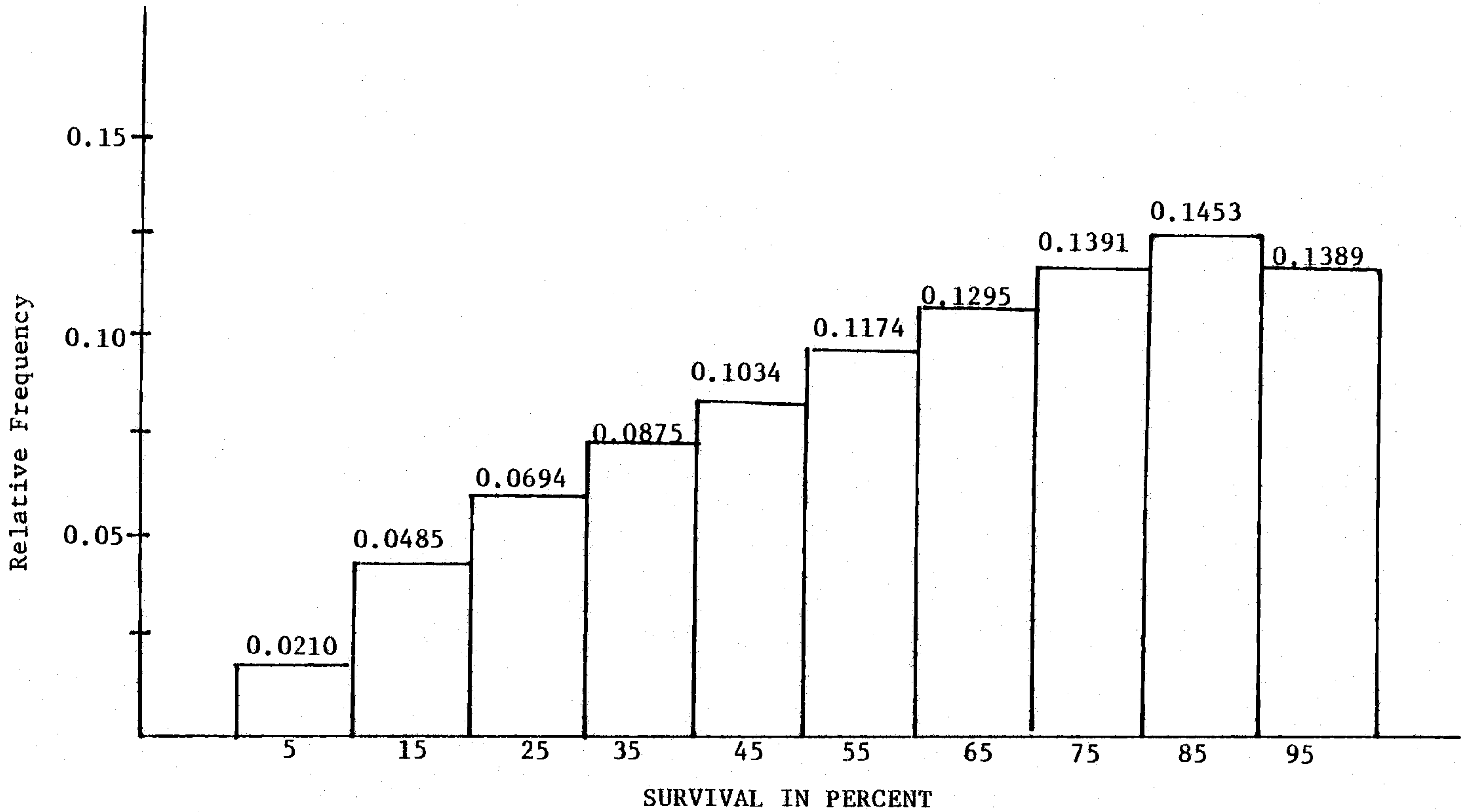


FIGURE 40. Subjective prior distribution of first-year survival over all site classes in Roseburg.

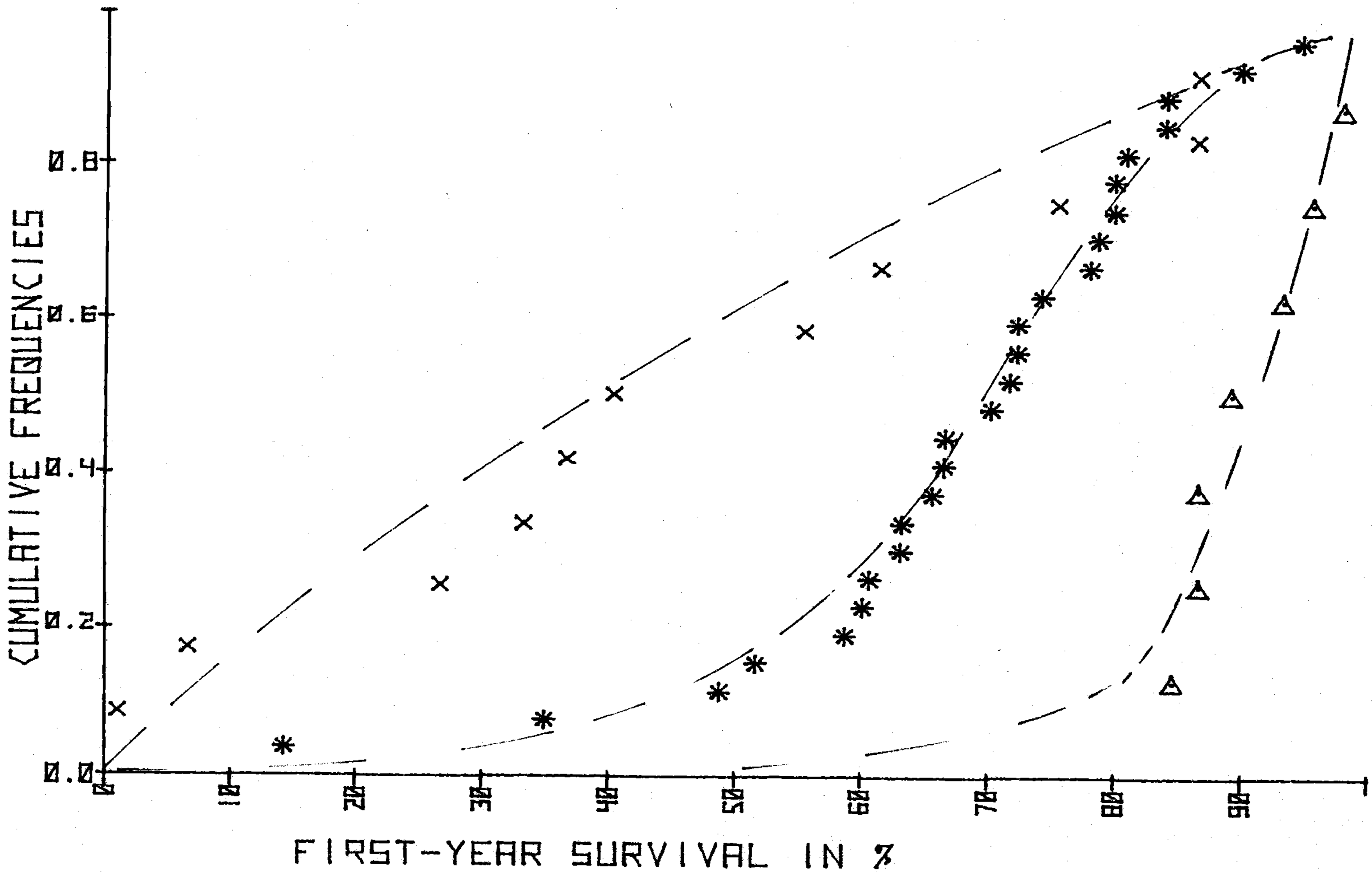


FIGURE 41. Cumulative distribution functions of first-year survival for sites with low (x), medium (*) and high (Δ) productivity in Roseburg.

five years, and second-year marginal survival depends stochastically on first-year survival. Parameters for all distributions are provided in Appendix D. Shapes correspond generally to those in Tillamook (Figures 16 to 18).

We have now completed an analysis of reforestation in Roseburg. Environmental features pointed to a generally much harsher environment than that in Tillamook, and the operating characteristics of the system clearly reflected this. In its organization and its policies, the district has distinctly responded, and attempted to meet this challenge by nature. Overall, prior distributions of site class and survival represent much more judgment, and less "hard" evidence than in Tillamook. Results of the prior analysis, our next step, are clearly conditional on this subjective judgment, and much more tentative than in Tillamook.

Prior Analysis

Results of the prior analysis (Table 30) indicate that, in the absence of any site or survival information, managers should plant 650 trees to the acre in order to minimize total expected costs. While, by chance, optimal planting densities in Tillamook and Roseburg coincide, corresponding expected costs do not (Tables 30 and 9). Several factors account for lower overall costs in Roseburg: Direct management expenses, provided in both instances by the ownerships, are generally lower in Roseburg (Table 31) for reasons unknown. While the Tillamook policies adhere to one target and minimum stocking goal throughout the reforestation phase for the intensive management regime considered there, standards are less rigid in Roseburg. They are successively lowered as time advances (Table 29). Site class definitions vary between both operations; however, average site class in Tillamook exceeds corresponding figures in Roseburg by far. Hence, opportunity losses due to reforestation lag and understocking are much higher in Tillamook. Given they accept a profit maximization goal, with linear utility for

TABLE 30. Prior Analysis for the Roseburg Case Study (Matrix entries represent total expected discounted costs in $ per acre)

PRIOR ANALYSIS
$$$$$$$$$$$$$$

Number of Trees Planted

Site Class	Sur-vi-val	550	650	750	850	950	1050	1150	PRIOR PROB-ability
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
0	0	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	99999.00	0.000000
2	95	429.66	330.60	387.39	415.68	438.36	471.65	486.15	.012350
2	85	448.21	439.37	414.01	416.32	446.94	465.79	492.08	.007650
2	75	506.30	490.37	492.01	472.93	468.86	479.08	490.33	.004590
2	65	540.32	524.70	525.41	548.77	550.86	550.63	524.60	.002600
2	55	591.88	572.50	571.27	588.75	616.60	653.59	628.14	.001360
2	45	631.40	593.25	607.99	631.42	650.57	677.47	712.72	.000630
2	35	675.88	654.68	640.84	663.75	688.99	705.64	728.67	.000240
2	25	702.17	690.69	681.11	692.45	725.64	747.01	746.10	.000060
2	15	722.59	706.87	682.47	710.66	732.74	752.97	766.04	.000010
2	5	796.41	728.51	741.60	757.66	791.86	790.39	798.04	0.000000
3	95	337.68	349.79	375.83	407.77	427.96	456.50	481.33	.065220
3	85	382.66	367.50	375.38	404.30	430.28	456.62	478.31	.099220
3	75	421.79	415.37	398.03	414.04	436.05	458.15	483.03	.095170
3	65	464.81	456.42	467.80	467.18	455.81	476.83	493.38	.077790
3	55	515.91	506.65	520.75	526.48	540.49	530.45	532.39	.056360
3	45	567.20	553.59	566.45	593.30	621.60	603.90	597.38	.036020
3	35	607.63	587.33	596.99	619.46	644.55	675.18	693.92	.019550
3	25	637.66	618.43	646.76	651.69	691.43	686.57	705.75	.008280
3	15	695.51	630.84	684.69	696.17	701.72	720.92	729.20	.002210
3	5	728.98	705.18	742.37	728.05	734.34	737.66	759.29	.000220
4	95	319.90	346.84	377.59	400.91	428.17	458.42	482.77	.031500
4	85	331.42	343.78	372.41	405.01	424.16	453.23	479.92	.049410
4	75	364.36	361.26	381.00	404.24	427.65	452.75	479.07	.056650
4	65	423.16	391.98	408.57	413.13	434.23	456.06	480.00	.059310
4	55	476.93	482.88	447.45	442.26	460.17	468.53	492.01	.058860
4	45	524.14	518.79	540.20	533.75	526.55	506.67	517.33	.055760
4	35	561.97	574.75	578.68	604.68	625.64	651.00	605.99	.050310
4	25	610.92	599.78	640.09	630.64	649.99	674.68	683.70	.042300
4	15	675.28	668.36	633.95	676.36	689.23	675.00	690.33	.031230
4	5	682.79	706.35	721.35	716.05	723.30	723.36	741.98	.014670
5	95	314.99	342.37	372.61	400.31	429.91	458.56	487.83	.000310
5	85	309.10	339.41	366.19	395.43	423.40	451.34	480.42	.001190
5	75	305.06	332.86	361.94	388.74	416.61	444.34	472.66	.002290
5	65	308.27	328.52	354.16	384.23	410.56	436.99	463.99	.003540
5	55	337.11	336.62	360.47	379.88	403.36	430.16	456.28	.004910
5	45	477.00	382.75	335.62	398.67	412.28	434.97	457.63	.006380
5	35	545.46	540.38	557.43	447.90	452.74	466.80	480.73	.007910
5	25	619.29	617.36	605.22	611.63	635.15	634.26	536.79	.009510
5	15	755.39	711.97	685.70	682.67	685.92	683.45	680.25	.011160
5	5	812.38	818.79	771.53	778.07	785.76	763.79	760.20	.012790
EXPECTED VALUES OF ACTS:		469.43	464.66	471.30	484.99	501.48	516.52	530.15	

TABLE 31. Direct management expenses for reforestation and assumed revenues in the Roseburg case study.

REFORESTATION ACTIVITIES SIMULATION FOR YEAR 1 TO YEAR 10

```
INTEREST RATE IS: .0300
$$$$$$$$$$$$$$$$$$

THE FOLLOWING COST FIGURES WERE USED:
VARIABLE COST PER SEEDLING:
----------------------------
SEEDLING COST:  .11
ORIGINAL PLANTING COST:  .13
INTERPLANTING COST:
     UP TO 200/ACRE:  .30
     UP TO 350/ACRE:  .25
     OVER 350/ACRE:  .19

FIXED COST PER ACRE:
--------------------
BURNING:96.00

COST FOR PRECOMMERCIAL THINNINGS:
     500-600 TREES/ACRE: 70.0
     600-800 TREES/ACRE: 90.0
     800-1000 TREES/ACRE:110.0
     OVER 1000 TREES/ACRE:130.0
SURVEY COSTS:  2.4
ADMINISTRATIVE COSTS:  7.0
HERBICIDE: 60.0
CAPITALIZED RETURNS PER SITE CLASS:
-----------------------------------

SITE 1:       -
SITE 2:   4500.00
SITE 3:   2850.00    $ per acre
SITE 4:   1638.00
SITE 5:    800.00
```

money, and, barring a multidimensional utility function, managers of the South Umpqua study area should lower planting densities from the present level (1200 trees in an approximate six foot by six foot pattern), to an approximate eight-foot-square pattern. (Since unplantable spots usually occur in clearcuts, actual stocking per acre may be less.) Expected cost reductions amount to $65.00 per acre,approximately (530.15 - 464.66).

The Expected Value of Perfect Information

At this point, the initial hypothesis, that the potential value of site information for reforestation will change as a function of environmental quality and diversity, should be tested. One would expect that the harsh natural environment and the ecological diversity of the South Umpqua Resource Area would create a higher potential for the use of site information, in spite of somewhat lower management intensity.

Actually, the expected value of perfect information on site class and survival in Roseburg, calculated again as the expected minimum regret (Tables 32 and 33), exceeds corresponding values in Tillamook by very little. Table 34 indicates an optimal strategy for perfect knowledge of site class, which, again, bears resemblance to Tillamook results. For those strata with a high prior probability, prior and posterior optimal act coincide.

By selecting two ownerships with widely varying ecological, economic and organizational situations, we had hoped to capture the range of the expected value of site information for the reforestation alternatives considered here. By chance this did not happen. It appears more likely that we found a representative average.

An Attempt to Extrapolate: Site Mapping Priorities in Western Oregon

What would happen if marginal variable costs, such as seedling-, planting-, or protection costs were allowed to rise? None

TABLE 32. Regret Table for the Roseburg Case Study. (Matrix entries represent regrets in $ per acre.)

REGRET TABLE

Site Class	Survival	Planting Density: 550	650	750	850	950	1050	1150
2	95	49.06	0.00	6.79	35.08	57.76	91.05	105.55
2	85	34.20	25.36	0.00	2.31	32.93	51.78	78.07
2	75	37.44	21.51	23.15	4.07	0.00	10.22	21.97
2	65	15.72	.10	.81	24.17	26.26	26.03	0.00
2	55	20.61	1.23	0.00	17.48	45.33	82.32	56.87
2	45	38.15	0.00	14.74	38.17	57.32	84.22	119.67
2	35	35.04	13.84	0.00	23.11	48.15	64.80	87.83
2	25	21.06	9.58	0.00	11.34	44.53	65.90	64.99
2	15	40.12	24.40	0.00	28.19	50.27	70.50	83.57
2	5	67.90	0.00	13.09	29.15	53.35	61.88	69.53
3	95	0.00	12.11	38.15	70.09	90.28	118.82	143.65
3	85	15.16	0.00	7.88	36.80	62.78	89.12	111.31
3	75	23.76	17.34	0.00	16.01	38.02	60.12	85.00
3	65	9.00	10.61	11.99	11.37	0.00	21.02	37.57
3	55	9.26	0.00	14.10	19.83	33.84	23.80	25.74
3	45	13.61	0.00	12.86	39.71	68.01	50.31	43.79
3	35	20.30	0.00	9.66	32.13	57.22	87.85	106.59
3	25	19.23	0.00	28.53	33.26	73.00	68.14	87.32
3	15	14.67	0.00	3.85	15.33	20.88	40.08	48.36
3	5	23.80	0.00	37.19	22.87	29.16	32.48	54.11
4	95	0.00	26.94	57.69	81.01	108.27	138.52	162.37
4	85	0.00	12.36	40.99	73.59	92.74	121.81	148.50
4	75	3.10	0.00	19.74	42.98	66.39	91.49	117.81
4	65	31.18	0.00	16.59	21.15	42.25	64.08	88.02
4	55	34.67	40.62	5.19	0.00	17.91	26.27	49.75
4	45	17.47	12.12	33.53	27.08	19.88	0.00	10.66
4	35	0.00	12.78	16.71	42.71	63.67	89.03	44.02
4	25	11.14	0.00	40.31	30.86	50.21	74.90	83.92
4	15	41.33	34.41	0.00	42.91	54.28	41.05	56.93
4	5	0.00	23.56	38.56	33.26	40.51	41.07	59.19
5	95	0.00	27.38	57.62	85.32	114.92	143.57	172.34
5	85	0.00	30.31	57.09	86.33	114.30	142.74	171.32
5	75	0.00	27.80	56.88	83.68	111.55	139.78	167.60
5	65	0.00	20.25	45.89	75.96	102.29	128.72	155.62
5	55	.49	0.00	23.85	43.26	66.74	93.54	119.66
5	45	94.25	0.00	2.87	15.92	29.53	52.22	74.88
5	35	97.56	92.48	109.53	0.00	4.84	18.90	32.83
5	25	82.51	80.58	68.44	74.85	98.37	97.48	0.00
5	15	75.14	31.72	5.45	2.42	5.67	3.20	0.00
5	5	52.18	58.59	11.33	17.87	25.56	8.59	0.00

EXPECTED REGRETS

		550	650	750	850	950	1050	1150
		17.71	12.93	19.57	33.26	49.75	64.79	78.42

TABLE 33. The Expected Value of Perfect Information in Tillamook and Roseburg

	Roseburg ($ per acre)	Tillamook
Perfect site class information	2.40	0.86
Perfect survival information	10.53	11.27
Perfect information	12.93	12.13

TABLE 34. Optimal Strategy and Expected Costs for Known Site Classes in Roseburg

	Site Class			
	2	3	4	5
Marginal probability	0.03	0.46	0.45	0.06
Optimal density (trees per acre)	750	650	650	850
Expected cost ($ per acre)	437.86	435.75	476.66	569.83

of these changes would affect the physical fate of the plantations, since reforestation policies and survival distributions remain in place. Cost differences between planting densities for a given state of nature, however, must necessarily increase. The regrets reflect these differences. Hence, the expected regret of the prior optimum, which is identical to the expected value of perfect information, must also increase by necessity, all other things remaining the same.

In calculating the expected regret of the prior optimum, each regret is weighted by its associated prior probability. As prior distributions become more diffuse, these individual weights increase. Hence, ceteris paribus, perfect information will have a high value if the prior distribution contains much uncertainty.

Using a concept from information theory (Winkler and Hays, 1975), one can verify that the Roseburg prior distribution contains more uncertainty than the corresponding one in Tillamook (Table 35). for the joint states. On the other hand, average regrets in Tillamook ($56.08/acre) exceed those in Roseburg ($42.94 per acre). By chance, both factors interact, to create very similar expected values of information. Site information would have a greater potential value in Roseburg, if marginal, variable establishment costs equaled those in Tillamook.

Efforts to collect site information promise highest returns for Western Oregon ownerships, whenever sites are highly variable, and whenever reforestation activities are characterized by high marginal variable costs.

The Ecological Models

Soil Parameters

The laboratory analysis of 17 selected South Umpqua soils (Table 36) illustrates striking differences to corresponding data

TABLE 35. Average Amounts of Uncertainty (H)* for the States of Nature in Roseburg and Tillamook and for a completely diffuse, uniform prior distribution

Amount of Uncertainty with Respect to	Roseburg		Tillamook		Uniform	
	H	%	H	%	H	%
Site Class	0.99	71.4	0.98	71.2	1.3863	100
Survival Class	2.19	95.3	1.88	81.78	2.3020	100
Joint States	3.05	82.7	2.83	76.7	3.6880	100
Survival for Known Site Class	2.05	87.1	1.84	79.9	2.3020	100
Reduction in Uncertainty from Known Site Class	--	6.6	--	2.2	--	--

* H stands for entropy, a concept from information theory, used to measure the average amount of uncertainty contained in a probability distribution. H attains a maximum value for a uniform distribuion.

TABLE 36. Laboratory Analysis of South Umpqua Surface Soils (water content determinations are means of duplicate measurements)

Area Name	Particle Sizes: Sand	Silt	Clay	Textural Class	Organic Matter	Water Content at 1/3 atm	15 atm	Water Capacity
	(percent oven dry weight)				(percent oven dry weight)			
Brushy Butte	34.3	46.1	19.6	loam	4.43	29.40	13.20	16.20
Sandy Springs	69.2	24.7	9.1	sandy loam	1.07	13.20	10.30	2.90
Sandy Springs	82.9	16.1	1.0	loamy sand	7.31	25.10	11.50	13.60
Sandy Springs	74.5	23.4	2.1	loamy sand	6.29	21.50	10.80	10.70
Shively Creek	47.7	33.7	18.6	loam	2.40	25.70	7.50	18.20
Turkey Creek	52.6	29.8	17.6	sandy loam	3.20	28.30	8.30	20.00
Shively Creek	49.1	36.5	13.4	loam	2.13	28.80	6.20	22.60
Shively Creek	35.2	41.0	23.8	loam	2.19	31.00	8.70	22.30
Dompier Slide	40.2	42.1	17.7	loam	2.93	30.20	10.30	19.90
Dompier Slide	35.0	26.5	38.5	clay loam	6.72	39.00	24.90	14.10
Turkey Creek	39.5	45.0	15.5	loam	2.29	32.80	7.10	25.70
Shively Creek	49.1	39.3	11.6	loam	8.21	34.30	9.90	24.40
Brushy Butte	58.2	26.0	15.8	sandy loam	5.92	29.20	12.40	16.80
Shively Creek	30.4	43.9	25.7	loam	5.97	34.80	10.70	24.10
Dompier Slide	43.7	25.3	31.0	clay loam	14.67	46.50	26.50	20.00
Sandy Springs	54.5	30.7	14.8	sandy loam	2.67	24.50	7.90	16.60
Uncle Billy	60.0	27.4	12.6	sandy loam	5.49	24.40	9.40	15.00
Mean					4.93	29.33	11.50	17.83

in Tillamook (Table 12). Textures vary widely (Table 36; Figures 29 and 3). They reach from coarse, sandy soils into heavy clays. Soils contain conspicuously less organic matter, as well as appreciably less water at both ends of the range of availability. Somewhat surprisingly, corresponding gravimetric contents of available moisture resemble those in Tillamook. Since Southwestern Oregon soils are known for their higher volume weights, South Umpqua soils will contain, ceteris paribus, potentially more available water than those in Tillamook. To some extent, this phenomenon may help to counteract atmospheric demand for plant water which can be expected to be much higher than in the Northwestern Oregon area.

During regression analysis, it became apparent again that textural class, per se, was a poor classification factor for available moisture. In medium soils, defined here as possessing more than 25% silt and less than 20% clay, silt content explained much of the variability. The AWC of coarse-textured soils, with a silt content of at most 25%, varied as a function of organic matter. Above 20% clay, approximately, in fine soils, an increase in clay led to a decrease of AWC. Observations in the "coarse" and "fine" strata were few.

Instead of a formal regression, the following approach was chosen: Measured AWC was entered into the conventional textural triangle by plotting it against texture. Similar levels of AWC were then connected by lines, contour lines which resemble isohyetes. They were subjectively smoothed and extrapolated. Thus, Figure 42, a preliminary "contour map" for the available-water capacity of soils from the South Umpqua area, was derived. It eliminates the difficulties and inaccuracies that result from listing AWC by textural class and not by texture.

For coarse soils, the third dimension, representing organic matter, would be necessary. Hence, estimates from a regression equation must be substituted here. From data contained in Table 36, the following equation was estimated: AWC = 1.02 + 1.643 · Organic matter %. A comparison of model predictions with an independent

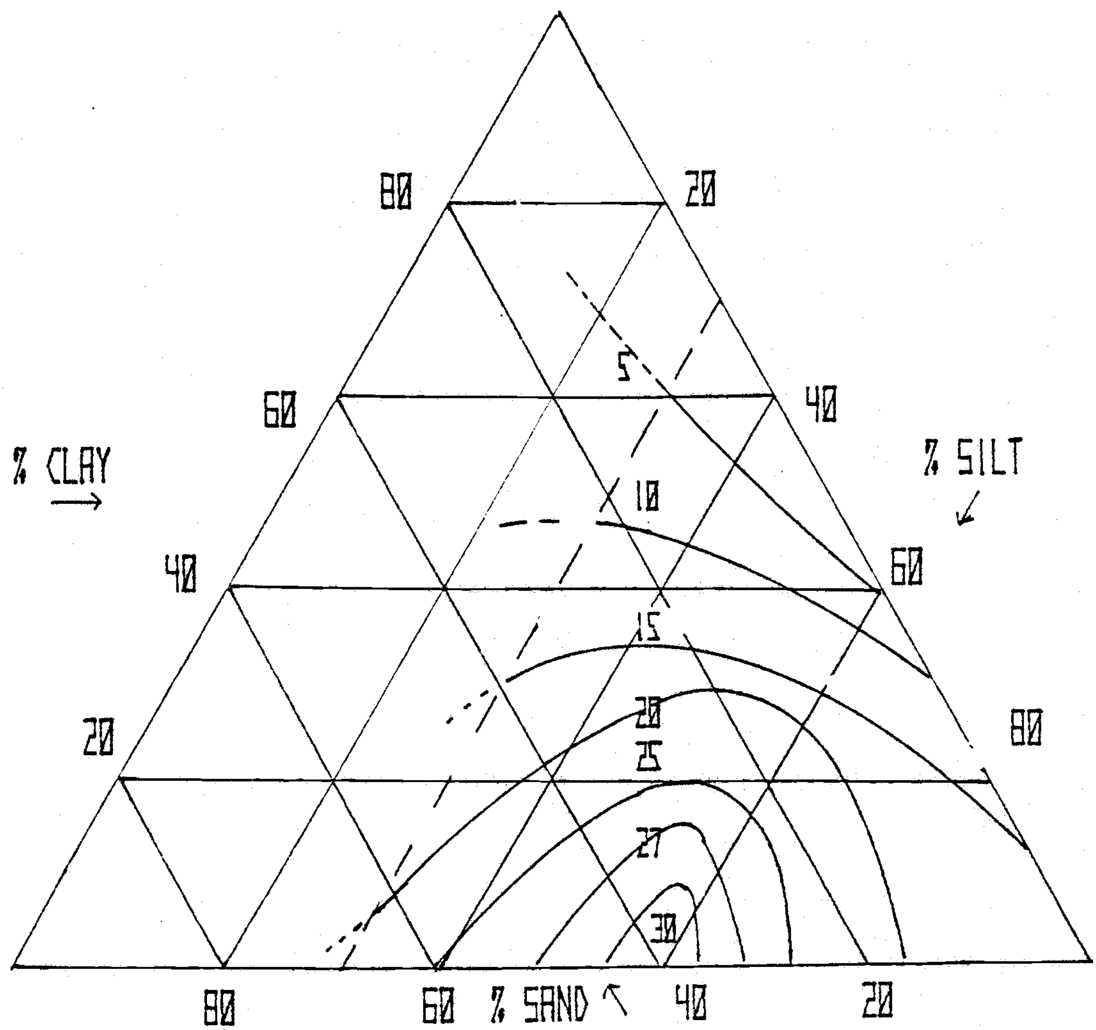


FIGURE 42. Contour lines for the available water capacity of South Umpqua surface soils.

set of measurements listed in the Roseburg Soil Inventory produced the results shown in Figure 43.

An Estimation Aid for First-year Survival

Among those environmental variables which partially explain variability of first-year survival among individual plots (R^2 = 0.616) (Tables 37 and 38), aspect predominates and reveals particularly interesting patterns. Chosen aspect classes, their definitions, and striking differences between corresponding mean survival appear in Figure 44.

As in Tillamook, and in agreement with findings by Brodie et al. (1979), Depta (1975), and Sullivan (1976), survival on north, east, and west exposures surpasses that of southerly aspects. Again, survival figures on gentle terrain of less than 30 percent inclination approximate those of southerly aspects.

Inclination, which appeared to promote survival in earlier findings (Brodie et al., 1979), correlates positively with overall survival (Table 37). On southerly aspects, however, the correlation turned to negative (R = -0.32) in this study.

The concern of Roseburg managers with vegetation management seems understandable in the light of lowered survival with an increasing density of vegetative cover. Particularly on southern aspects, poor survival appeared to occur on sites with dense vegetation (R = -0.5). Of course, no causal mechanism is proven; conceivably, sunny slopes could revegetate more rapidly than cooler, northerly aspects.

The role of altitude in Tillamook depends on location in relation to the coastline (Figure 25). In Roseburg, survival seems practically independent of elevation on north and west exposures (R ≈ 0.13). On south slopes and on level ground, however, high altitude appears to coincide with high mortality, possibly as a result of higher radiation loads, and incrased atmospheric demand for water.

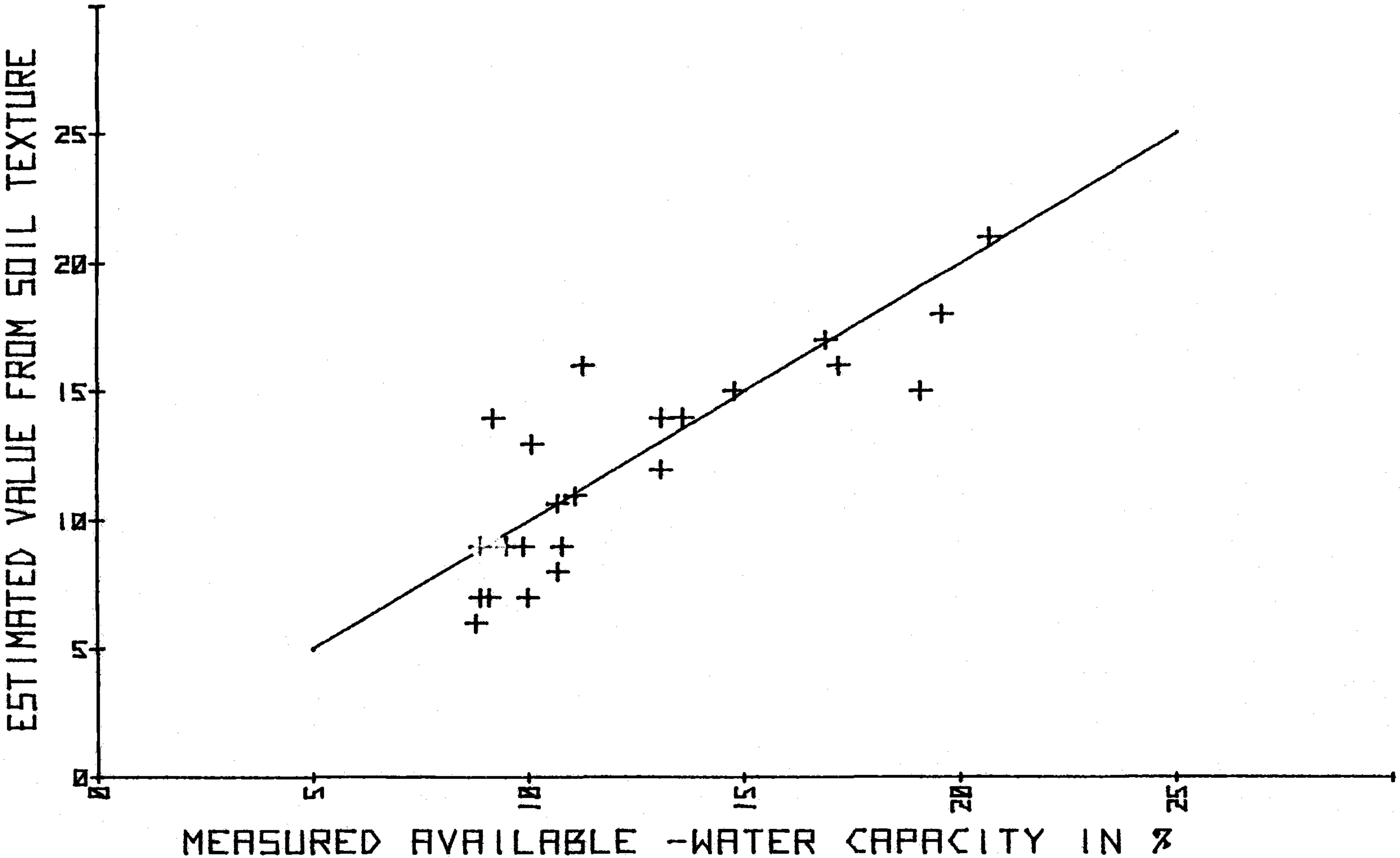


FIGURE 43. Comparison of predicted AWC and actual measurements listed in the Roseburg Soils Inventory.

TABLE 37. Simple Correlations for First-Year Survival in Roseburg with Environmental Variables

Variable	Definition	R
AWC	Available-water capacity of the surface soil in mm/dm, liter per m^2, or mm precipitation	+ 0.395
CLAY	Indicator available for soils with a clay content 20% and above	- 0.263
DEPTH	Total soil depth in cm, determined by the use of the "Pürckhauer" probe	+ 0.398
ALTIT	Altitude as read from a topographic map in feet	- 0.267
SLOPE	Slope, measured by means of clinometer in %	+ 0.322
VEG	Vegetative cover, estimated as 1.0 for closed canpy above seedlings, 0.0 on bare soil	- 0.316
EFFAWC	Available-water storage in the entire profile (DEPTH x AWC x (1 - ROCK/100), where ROCK corresponds to estimated coarse fragment content in percent	+ 0.341
NORTH,	Indicator variables, defined	+ 0.451
ESE,	according to Figure 44 -	0.046
SE,	Inclinations below 30% by definition,	- 0.204
SW	are considered level ground without	- 0.332
WEST	any aspect	0.089
WESTVEG	Interaction of VEG and WEST	+ 0.029
SEVEG	Interaction of VEG and SE	- 0.271
NORTHVEG	Interaction of VEG and NORTH	+ 0.242
SWVEG	Interaction of VEG and SW	- 0.355
RAIN	Annual precipitation as read from isohyetal map	- 0.150

TABLE 38. Prediction aid for first-year survival in Roseburg from soil and site variables (variables defined as in Table 37).

LOGIT =

.140235	AWC
.361171E-01	DEPTH
-.167342E-01	SLOPE
-.813909E-01	RAIN
-1.73278	VEG
1.72506	NORTH
.851883	ESE
2.23218	WEST
-1.54586	SEVEG
-3.97625	WESTVEG

ANALYSIS OF VARIANCE TABLE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
TOTAL	127	6429.76	50.6280
REGRESSION	10	4579.48	457.948
RESIDUAL	117	1850.28	15.8143

$R^2 = 0.616$

VARIABLE	S.E. OF REGR. COEF	T	P
AWC	.21942E-01	6.391	.0000
DEPTH	.68760E-02	5.253	.0000
SLOPE	.64112E-02	-2.610	.0102
RAIN	.13463E-01	-6.045	.0000
VEG	.39042	-4.438	.0000
NORTH	.28623	6.027	.0000
ESE	.33366	2.553	.0120
WEST	.74206	3.008	.0032
SEVEG	.82021	-1.885	.0619
WESTVEG	2.4646	-1.613	.1094

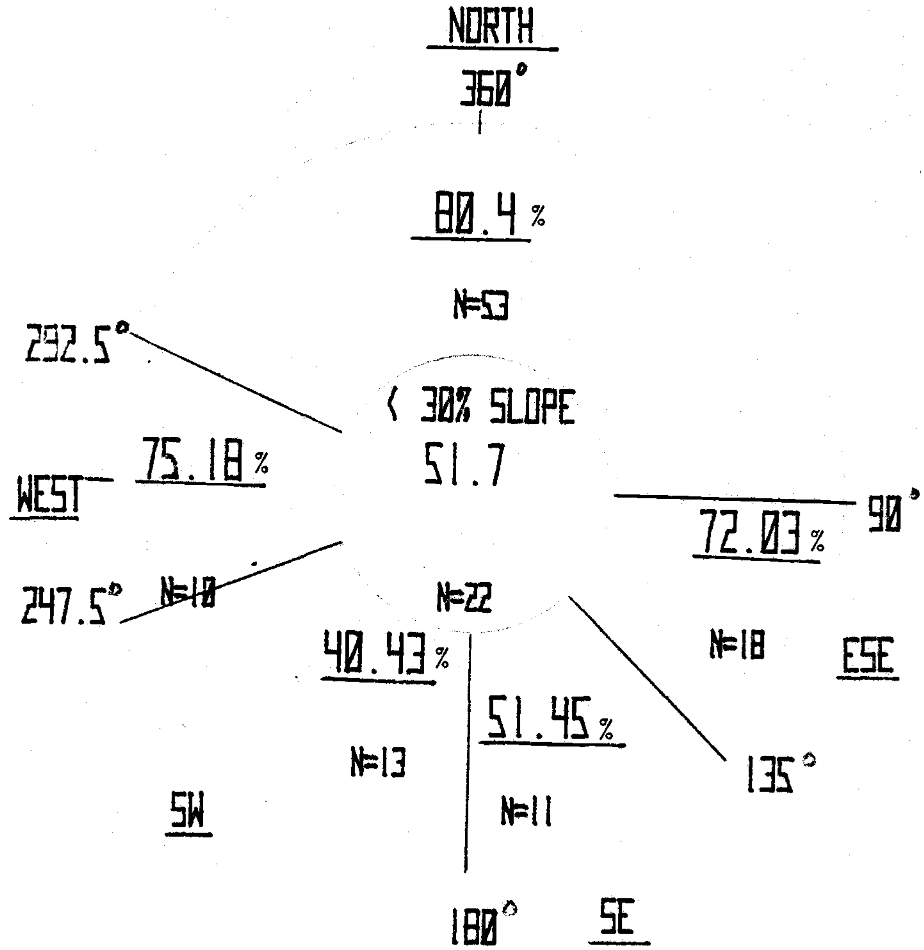


FIGURE 44. Definition of aspect classes with corresponding mean survival and sample size (N) in Roseburg.

On the supply side of soil and plant water, profile depth and the available water capacity predominate (Table 37), corroborating results in Tillamook, as well as those found by Carkin and Minore (1975) and Wert et al. (1977).

Once individual plots within one clearcut are combined for uniform sites, fit of the model appears satisfactory (Figure 45).

So far, we have not tested our prediction aid against an independent data set and, unfortunately, no such set is available. Informally, however, one may judge performance by, ex post, calculating mean survival for those 1977/78 plantations included in the sample (Table 4). If one excludes factors which are not contained in the regression model, such as a "gley"-surface horizon, or severe ravel, none of the plantations with a high predicted survival was interplanted operationally. On the other hand, the model would have predicted low survival for virtually all units that had needed interplants (Table 39).

Figure 46 depects survival for plots which had been shaded operationally. In the immediate vicinity of four of these plots, shingles were removed and control plots established. In all cases, the prediction model underestimates survival on shaded plots, but the underestimate appears largest and, hence, the benefit of shade highest, where anticipated survival is lowest.

Overall, in the more stringent Roseburg environment, a somewhat clearer picture of the survival function emerges. Definite ecological factors appear to override much of the apparently random variability met in Tillamook. Still, care must be exercised in model use: Traditional regression procedures assume that independent variables are observed without error. In our case, many are mere subjective estimates. Moreover, the model is based on survival in one year only, and on a mere accessibility sample of clearcuts. On the other hand, all parameters agree well with earlier results, with experiences in Tillamook, and with ecological theory.

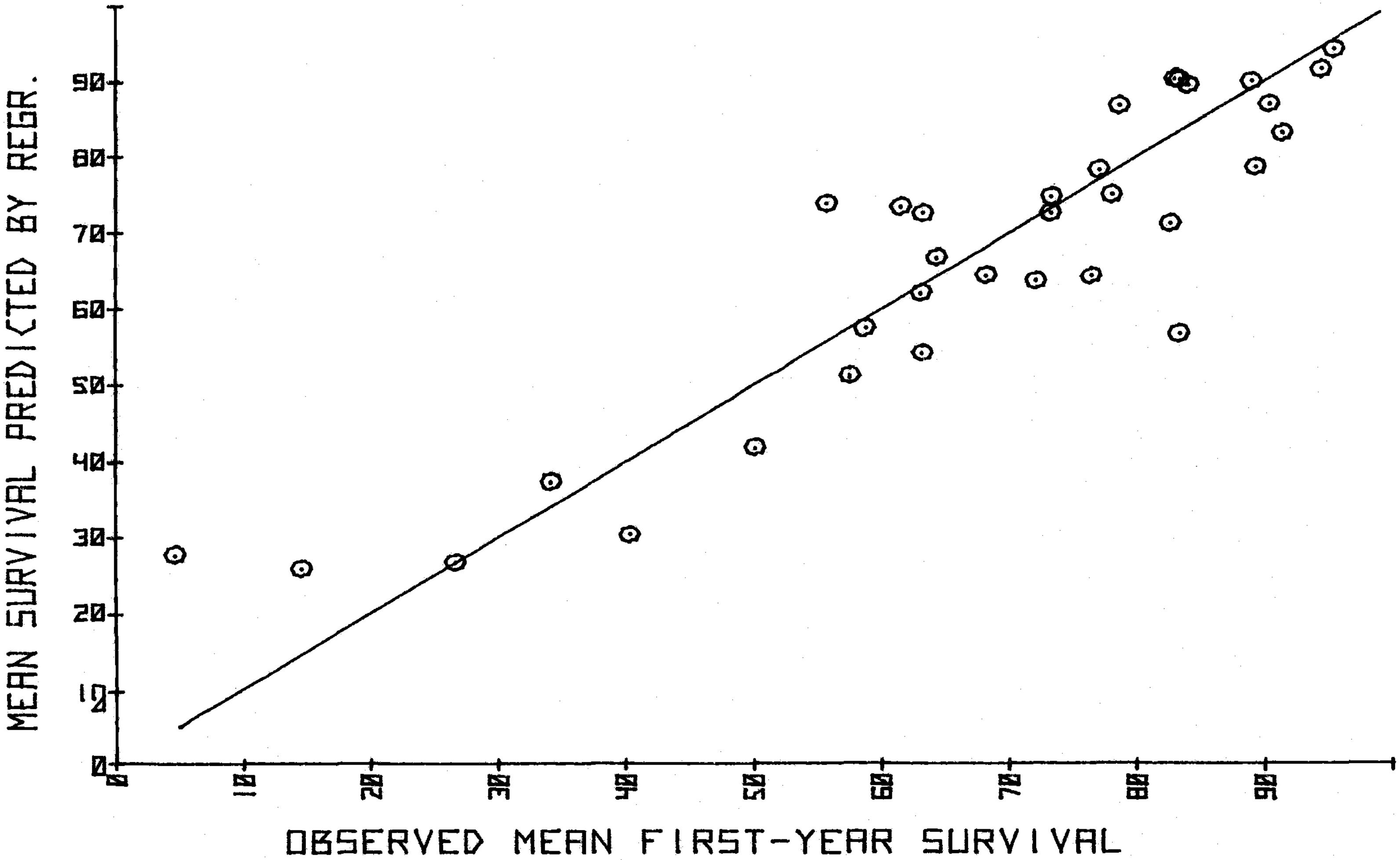


FIGURE 45. Comparison of predicted mean survival for plots on uniform sites with regression estimate in Roseburg.

TABLE 39. Comparison of Survival Prediction Model and Success of 1977/78 Plantations of the South Umpqua District

Survival Prediction	Interplanted after Poor Survival	Interplanted after Moderate Survival	Not interplanted - Good Survival
81 - 100			3
61 - 80		1	2
41 - 60		4	
< 40	5	1	

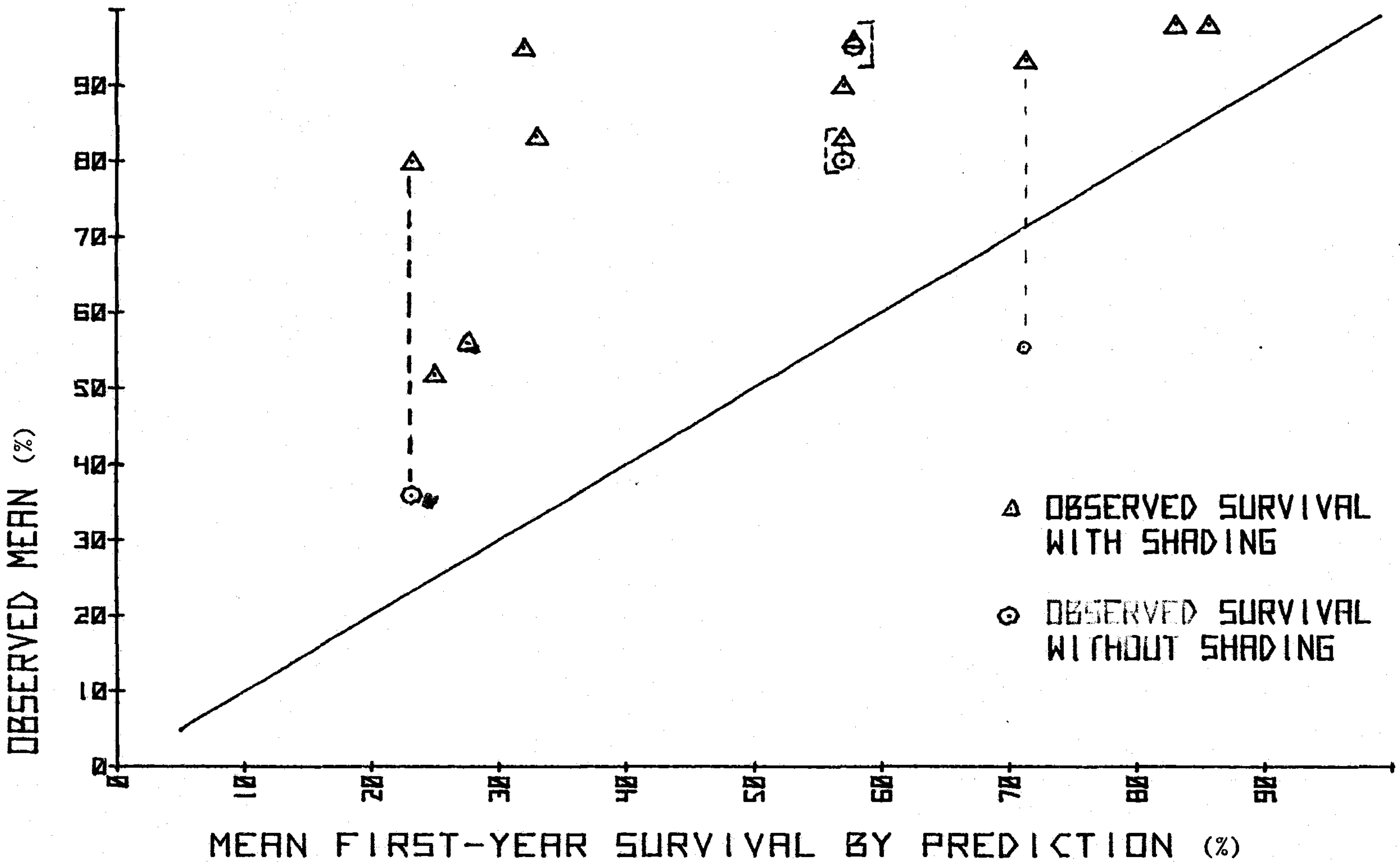


FIGURE 46 . A comparison of observed survival on shaded plots with predictions from the survival model for unshaded seedlings. (Dashed lines connect plots with unshaded control.)

Assessment of Likelihoods for Survival Predictions

Survival forecasts are grouped into four prediction categories. Their boundaries, and a cross-tabulation of the relationship between observed mean survival and model predictions, which has been presented graphically in Figure 45, appear in Table 40, together with actuarial probabilities. Even more so than in Tillamook, no reliable assessment of likelihoods is possible at present, since there is no experience with predictive accuracy at all.

The likelihoods listed in Table 41 parallel actuarial probabilities in Table 40. They reflect the belief that actual predictions for an independent sample will be less accurate than indicated in Figure 45, and they mirror the fact that average summer rainfall in 1979 exceeded the long-run average. Hence, particularly on poor site classes, where seedlings are likely to exist in the transition zone of the survival function, the likelihoods were chosen with a growing tendency for overestimates by the prediction aid.

Otherwise, these probabilities are provisional and represent one thing only: The author's personal, subjective and biased judgment.

Preposterior Analysis

Bayes' Strategy and the Expected Value of Site Information

Preposterior analysis in Roseburg follows procedures established and explained in the Tillamook study, hence results only are displayed in Table 42.

Unfortunately, we cannot assume that site class is known from site data with certainty (Appendix A). Hence, Roseburg managers can adopt Bayes' strategy only in instances where site class is known for sure from extraneous sources; for instance, an inventory

TABLE 40. Cross-tabulation of Predicted Survival Class for Uniform Sites versus Actually Observed Survival Class for the 1979 Survival Plots in Roseburg

Actually Observed Survival	PREDICTION CATEGORY:			
	Y_1 = Excellent (> 90%)	Y_2 = Good (71 - 90%)	Y_3 = Medium (51 - 70%)	Y_4 = Poor (≤ 50%)
Excellent	2 (0.67)	1 (0.33)	--	
Good	--	11 (0.79)	3 (0.21)	
Medium	--	3 (0.33)	6 (0.67)	
Poor	--	--	--	6 (1.0)

*Numbers in parenthesis represent actuarial probabilities.

TABLE 41. Subjective Likelihoods for Survival Predictions in Roseburg.

First Year Survival	LIKELIHOODS - Site Class 2 Y_1	Y_2	Y_3	Y_4	LIKELIHOODS - Site Class 3 Y_1	Y_2	Y_3	Y_4
95	.600000	.400000	0.000000	0.000000	.700000	.300000	0.000000	0.000000
85	.100000	.800000	.100000	0.000000	.200000	.750000	.050000	0.000000
75	.050000	.750000	.200000	0.000000	.100000	.750000	.150000	0.000000
65	0.000000	.300000	.650000	.050000	.010000	.300000	.650000	.040000
55	0.000000	.150000	.650000	.200000	0.000000	.200000	.650000	.150000
45	0.000000	0.000000	.250000	.750000	0.000000	.020000	.280000	.700000
35	0.000000	0.000000	.200000	.800000	0.000000	0.000000	.250000	.750000
25	0.000000	0.000000	.150000	.850000	0.000000	0.000000	.200000	.800000
15	0.000000	0.000000	.100000	.900000	0.000000	0.000000	.150000	.850000
5	0.000000	0.000000	.030000	.970000	0.000000	0.000000	.050000	.950000

First Year Survival	LIKELIHOODS - Site Class 4 Y_1	Y_2	Y_3	Y_4	LIKELIHOODS - Site Class 5 Y_1	Y_2	Y_3	Y_4
95	.800000	.200000	0.000000	0.000000	.900000	.100000	0.000000	0.000000
85	.250000	.700000	.050000	0.000000	.300000	.650000	.050000	0.000000
75	.150000	.700000	.150000	0.000000	.200000	.700000	.100000	0.000000
65	.030000	.400000	.550000	.020000	.080000	.450000	.450000	.020000
55	.020000	.300000	.580000	.100000	.050000	.400000	.500000	.050000
45	0.000000	.050000	.350000	.600000	0.000000	.100000	.400000	.500000
35	0.000000	0.000000	.300000	.700000	0.000000	.050000	.350000	.600000
25	0.000000	0.000000	.250000	.750000	0.000000	0.000000	.300000	.700000
15	0.000000	0.000000	.200000	.800000	0.000000	0.000000	.250000	.750000
5	0.000000	0.000000	.100000	.900000	0.000000	0.000000	.150000	.850000

TABLE 42. Bayes' Strategy for Roseburg by Site Class

Site Class	Prior Probability	Prediction	Probability	Optimal Density	Expected Cost	Expected Cost of Bayes' Strategy	Value of Survival Information
2	0.03	Y_1	0.2902	650	388.66	436.64	1.22
		Y_2	0.5231	750	429.98		
		Y_3	0.1491	750	513.03		
		Y_4	0.0376	650	596.71		
3	0.46	Y_1	0.1655	550	361.32	435.33	0.42
		Y_2	0.4381	650	398.32		
		Y_3	0.2687	650	482.54		
		Y_4	0.1277	650	558.93		
4	0.45	Y_1	0.1089	550	338.03	474.86	1.80
		Y_2	0.2771	650	382.27		
		Y_3	0.2903	650	486.46		
		Y_4	0.3237	550	589.76		
5	0.06	Y_1	0.0269	550	313.07	556.68	13.15
		Y_2	0.1166	550	344.54		
		Y_3	0.2871	850	515.98		
		Y_4	0.5693	1150	627.16		

Expected cost of Bayes' strategy:	460.44
Expected cost of prior optimal act:	464.66
Expected value of perfect knowledge of site class and of imperfect survival predictions, combined:	4.22
Expected value of survival information alone:	1.82
Expected value of perfect site class information:	2.40

or a presale cruise. In the absence of such information, must they cling to the optimal prior act, in spite of the fact that survival predictions are possible? Or, could they conceivably react to survival predictions alone?

For a forecast "excellent survival," for instance, foresters should plant 550 trees to the acre, unless site class is two, in which case 650 trees would be the better choice (Table 42). However, the incidence of site class two is low. Hence, intuitively, they should plant 550 trees irrespective of site class.

Table 43 formalizes the analysis, and depicts a strategy which managers might follow with survival, but without site class predictions (Figure 47).

Whether they actually collect field site information in order to predict survival will depend on the cost of retrieving such information. On the average, they could afford to spend up to $1.82, approximately, that is, almost double the amount indicated in Tillamook.

Summary and Conclusions for the Roseburg Study

The Roseburg case study, designed specifically as a contrast to the Tillamook study, was included to investigate the effects of a very different environment on the potential for site information, and to determine possible priorities for site mapping within Western Oregon. Methods closely paralleled patterns established in Tillamook.

A priori, there were reasons to expect a higher potential for site information in the difficult and diverse Roseburg environment. The analysis of the reforestation system and of the general setting did indeed uncover evidence for an environment, which is harsh and complicated in more than one sense: Ecological diversity and rigorous climatic conditions were reflected in less consistent

TABLE 43. Bayes' Strategy for Roseburg by Survival Forecast without Knowledge of Site Class

Survival Forecast	Site Class	Joint Probability	Conditional Probability for Site Class	Optimal Act: Plant	Expected Cost
Y_1 (Excellent)	2 3 4 5	0.008706 0.076130 0.049005 0.001614	0.06427 0.56203 0.36178 0.01192	500	356.94
		0.135407	1.00000		
Y_2 (Good)	2 3 4 5	0.015093 0.201526 0.124695 0.006996	0.04500 0.57760 0.35730 0.02010	650	393.86
		0.348910	1.00000		
Y_3 (Medium)	2 3 4 5	0.004473 0.123602 0.130635 0.017226	0.01630 0.44790 0.47340 0.06240	650	488.32
		0.275936	1.00000		
Y_4 (Poor)	2 3 4 5	0.001128 0.058742 0.145665 0.034158	0.00470 0.24510 0.60770 0.14250	650	593.82
		0.239693	1.00000		
Expected cost:					462.84
Prior optimal cost:					464.66
Expected value of survival information:					1.82

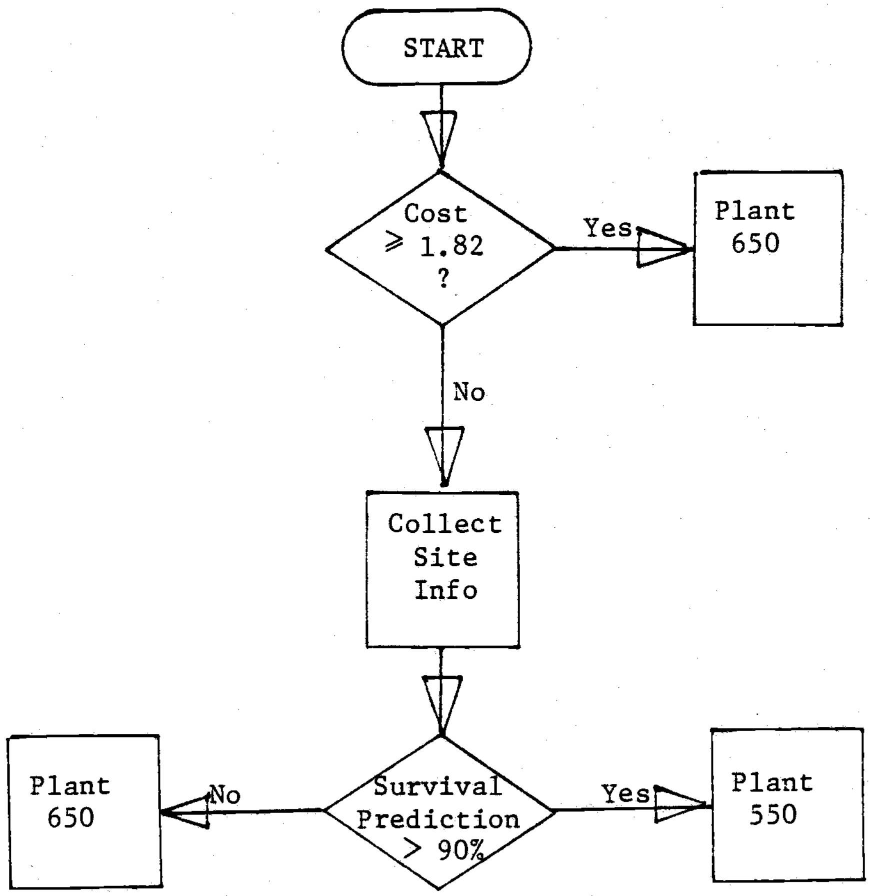


FIGURE 47. Decision diagram for Roseburg

(Costs are in $ per acre for gathering site information.)

reforestation success and lowered site classes. Reaction of the public at-large, and of special-interest groups affected reforestation goals. In its organizational structure, in flexible reforestation standards, by innovative techniques, and clearly visible improvement efforts, the ownership has adapted to the ecological and political challenge. Because of these shifts in past reforestation practices and because of non-representative climatic conditions during the year of this study, historical survival distributions had to be adjusted purely subjectively, and are less well-defined than in Tillamook.

Contingent on the acceptance of a mere profit maximization goal, present planting densities should be lowered to 650 trees per acre in the absence of any site information. This, by chance, is identical to the optimal prior act in Tillamook. Potential savings amount to $65.00 per acre. As in Tillamook, the greatest financial benefit resulted from the prior analysis.

Contrary to expectations and the initial hypothesis, the maximum potential for site information in Roseburg did not exceed that in Tillamook appreciably. This is caused by an interaction of several determinants of the value of perfect information. It is true that the prior distribution of the joint states of nature contains more uncertainty in Roseburg, particularly with respect to the marginal distribution of first-year survival. However, the regrets for not having perfect information do not reach Tillamook levels. Marginal, variable reforestation costs are considerably lower; guidelines define stocking standards less rigorously and, because of lower productivity and different stocking targets, reforestation lag and understocking represent smaller opportunity losses.

The ecological part of the study estimated values of the available-water capacity of Roseburg soils as an index of soil water supply. Values correlated positively with first-year survival. Among additional determinants of reforestation success, aspect, soil depth, and vegetative cover predominated. Overall, mortality in Roseburg appeared to occur less randomly, and more in response to definite site variables than in Tillamook.

Unfortunately, only informal checks of the model's predictive ability were possible. The likelihoods represent pure personal judgment.

With a value of $1.82 per acre on the average, the expected value of survival predictions exceeds Tillamook estimates by 100 percent. Since preplanting surveys are routine in Roseburg anyhow, site investigations appear financially feasible. They would be even more attractive if foresters could only predict site class from site data at the same time. Unfortunately this seems impossible now, since none of the existing height growth models appears to capture actual growth trends in Roseburg.

For comparable marginal variable costs, the potential for site information in Roseburg would exceed expectations in Tillamook.

VIII. FOREST MANAGEMENT DECISIONS, FOREST SITE AND BAYESIAN DECISION ANALYSIS: A SYNOPSIS

Are forestry and Bayesian decision analysis compatible? Should the technique be assimilated into the formal body of knowledge that constitutes forestry? Can it assume a useful role in the management of our forest resource?

It is a particularly useful feature that Bayesian decision analysis can account for the typical uncertainties of the forest production process by replacing deterministic point estimates with expected values. During the prior analysis, without site information, it establishes a decision rule, which is virtually as old as forestry: Almost 200 years ago, Georg Ludwid Hartig named it the "General Rule," a simple strategy which works best on the average and, besides, is easy to implement.

Neither forest history nor decision analysis stop here: Wilhelm Pfeil's site-specific management adjusts the general rule to the "Law of Site." The corresponding transition in Bayesian decision analysis replaces the prior solution with the posterior, site-specific solution. During both stages of the analysis, decision theory merely substitutes more quantitative methods for traditional intuition. In the latter stage, the technique emphasizes the duality of ecology and economics in forestry. In a particularly useful manner, it translates ecological knowledge directly into managerial action, provided that forest scientists supply managers not only with summary measures, but rather with entire distributions.

How should decision analysis be implemented? Due to the use of subjective probabilities and preferences, one can always produce solutions with Bayesian analysis. If these are based on unsubstantiated, diffuse and possibly confused subjective guesses, the analysis may be as useful as Baron von Münchhausen's attempts to extricate himself from the swamp by a tug at his own hair. Besides, the process may be expensive. On the other hand, iron-clad, objective knowledge about the forest's response to management will typically be lacking, and is unlikely to be available ever.

There is an escape from this dilemma: systematic accumulation and evaluation of operational records. The traditional control method has long adapted management to specific environments by gathering information on the spot, inductively, by recording and monitoring responses of the forest. When we free this old idea from its original narrow confinement to silviculture and mensuration, and augment it with statistical, economic and computational refinements, then old and new concepts merge. Among the maze of states, acts, payoffs, prior and posterior distributions, likelihoods, Bayes' and other formulae, foresters will discern a familiar face: Now decision analysis presents itself as nothing else but the extended, updated equivalent of Biolley's control method. It merely fills established concepts in forestry with new methods and meaning. In my opinion, Bayesian decision analysis deserves a place in the theory of forestry and in the practical management of our forests.

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APPENDICES

APPENDIX A

APPENDIX A

Site Class Rating and the Marginal Distribution of Site Classes in Roseburg

Site class ratings by the site index concept have meaning only in reference to specific site index curves, and they imply that actual height growth of stands follows the patterns established in the model. Unfortunately, neither presumption is clearly met in Roseburg.

The district generally expresses productivity in terms of a 100-year index proposed by McArdle et al. (1949). The soils inventory, on the other hand, provides a 50-year index (King, 1966), and translates it into McArdle's index based on an approximate conversion. Since growth trends for both models differ, the conversion varies with age.

An even more serious problem stems from the observation that neither set of site index curves appears to match actual growth trends. Site index appears to decline with age (Figure 48). This apparent decline of site index does not come as a surprise: Tree growth in a warm, dry environment usually does not follow growth trends observed in cool, moist, maritime climates (Assmann, 1961; Schober, 1960; Kramer, 1962; Eder, 1980); instead, height growth levels off as stands grow older. Neither set of site index curves (King, 1966; McArdle et al., 1949) was based on samples South of Roseburg.

Productivity ratings in general and site class estimates for soil series in particular appear problematic in Roseburg. One cannot derive the marginal distribution of site classes from the corresponding distribution of soil series. Instead, I used relative frequencies of site classes from a large, systematic sample of permanent inventory plots to assess the following distribution:

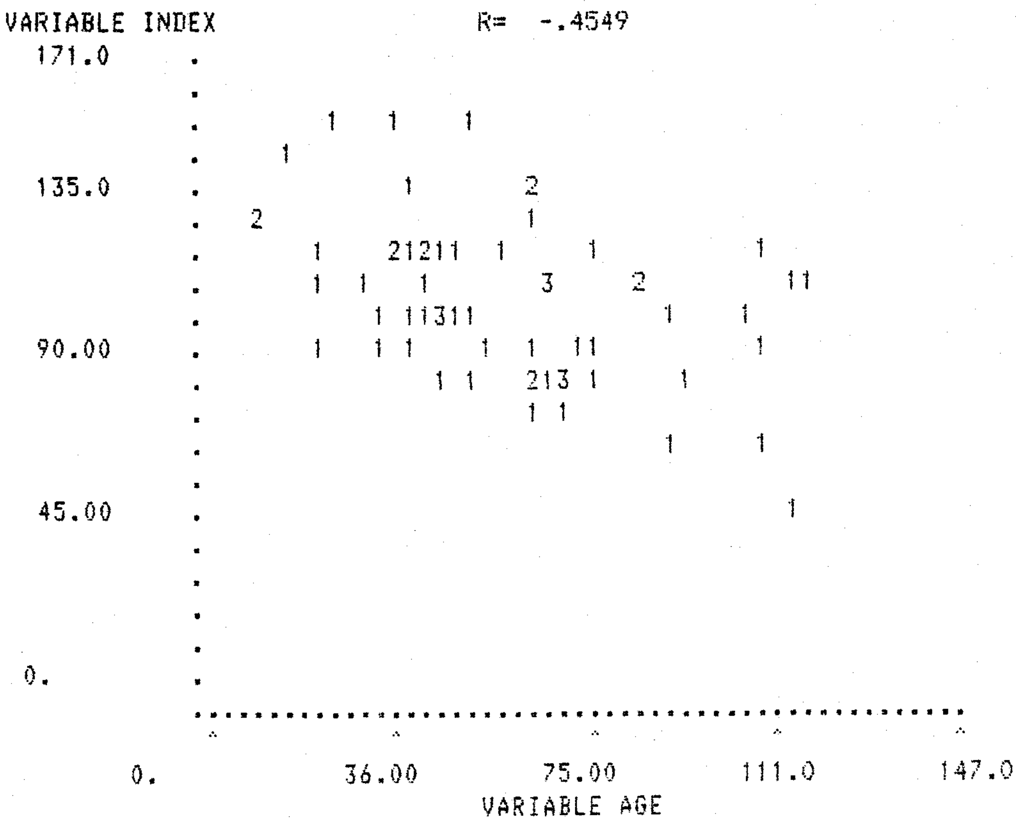


FIGURE 48. McArdle's site index of sample stands from the Roseburg soils inventory as a function of stand age

McArdle's Site Class	1	2	3	4	5
Proportion	0	0.03	0.46	0.45	0.06

In order to assess subjective distributions of first-year survival for each site class, I estimated productivity, based on site variables for each survival plot; I developed a simple, preliminary regression model from sample tree measurements, and corresponding soils descriptions in the soils inventory (Wert et al., 1977).

Simple correlations between site index (age 100) and individual soils variables revealed anticipated relationships: As in Tillamook, productivity tends to increase with the amount of available water in the solum and the thickness of the "A"-horizon. It decreases with altitude and, due to the lack of an applicable set of site index curves, declines with age. Table 44 provides these partial correlation coefficients.

After the preceding discussion, we cannot hope to obtain a valid prediction model for "site class" in Roseburg, but we need at least a crude model to assign a rough productivity index to each survival plot in the 1979 sample. The model finally adopted has low precision (R = 0.62) (Table 45). It is used only to stratify survival plots roughly into areas of high, medium and low productivity.

TABLE 44. Simple Correlations between McArdle's Site Index and Selected Site Variables in Roseburg

Symbol	Definition	Partial Correlation
EFFAWC	Available water in the rooting zone in inches	+ 0.37
ALT	Altitude in feet	- 0.30
SLOPE	Slope in percent	- 0.22
AH	Depth of the "A"-horizon in inches	0.36
INDUP	Binary indicator variable for upper slope position	- 0.16
INDL	Indicator for position on lower slope	+ 0.13
INDSOUTH	Binary indicator variable for position on south aspect	- 0.40
INDN	Binary indicator for position on north slope	+ 0.34
AGE	Age of stand at time of observation	- 0.45
EFFAGE	Interaction term of EFFAWC and AGE	+ 0.01
INDEX	McArdle's site index, the dependent variable	--

TABLE 45. Preliminary regression model for site index (variable symbols as in Table 44)

```
INDEX   =
  122.321      (CONSTANT)
 -.376654E-02  ALT
 -.306259      AGE
  .913014      AH
 -10.0358      INDSTH
  .138715E-02  EFFAGE
```

ANALYSIS OF VARIANCE TABLE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
TOTAL	64	29799.0	465.609
REGRESSION	5	11505.9	2301.18
RESIDUAL	59	18293.1	310.052

R SQUARED = .3861

APPENDIX B

APPENDIX B

Non-monetary Consequences of Varying Planting Densities in Tillamook

We have accepted cost minimization as the single criterion for optimality in this approach. Managers, on the other hand, are invariably interested in other consequences of the optimal act, too. Will young stands become overly dense? Will we have to pre-commercially thin all our young stands in the future? How many more seedlings will we have to order from the nursery? Will the higher rate of planting eliminate inter- and replantings and under-stocked stands?

Managerially inclined readers are invited to find answers to these and other questions in the following graphs (Figures 49 to 52), which condense and illustrate additional output of the simulations. They speak for themselves, and are presented without comment.

While these figures depict only averages, one might well be also interested in entire distributions, the range, or the variance of criteria. Tables 46 to 49 provide sample output. What is the probability of having to spend more than $700 when planting 450, 650, or 850 trees per acre (Table 46)? By how much can we reduce the probability of having to interplant at least once by planting 200 seedlings more than the prior optimum (Table 48)? What are the odds of successfully rehabilitating a site within 10 years if we plant 650 trees per acre? 850 trees per acre? (Table 49)

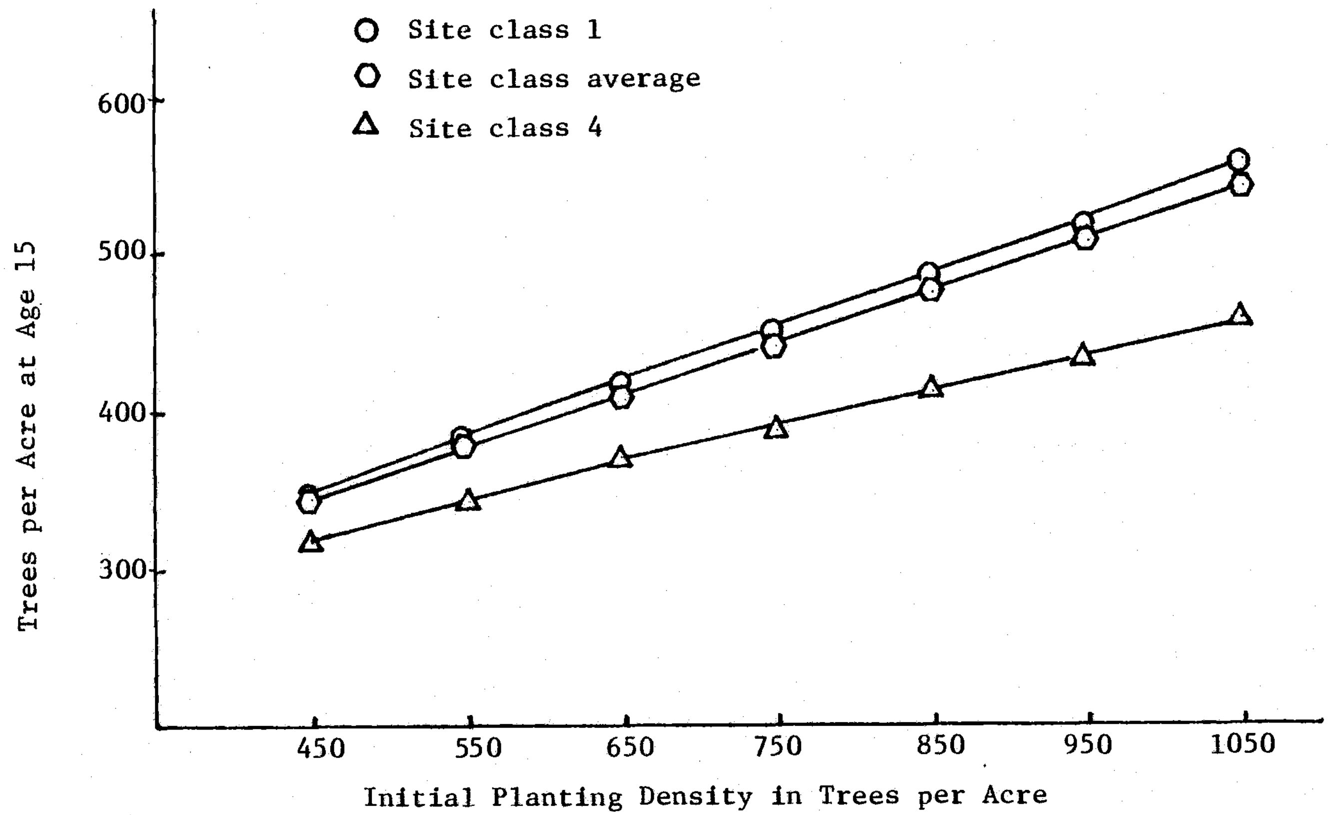


FIGURE 49. Expected number of surviving trees per acre at age 15 as a function of initial planting density in Tillamook

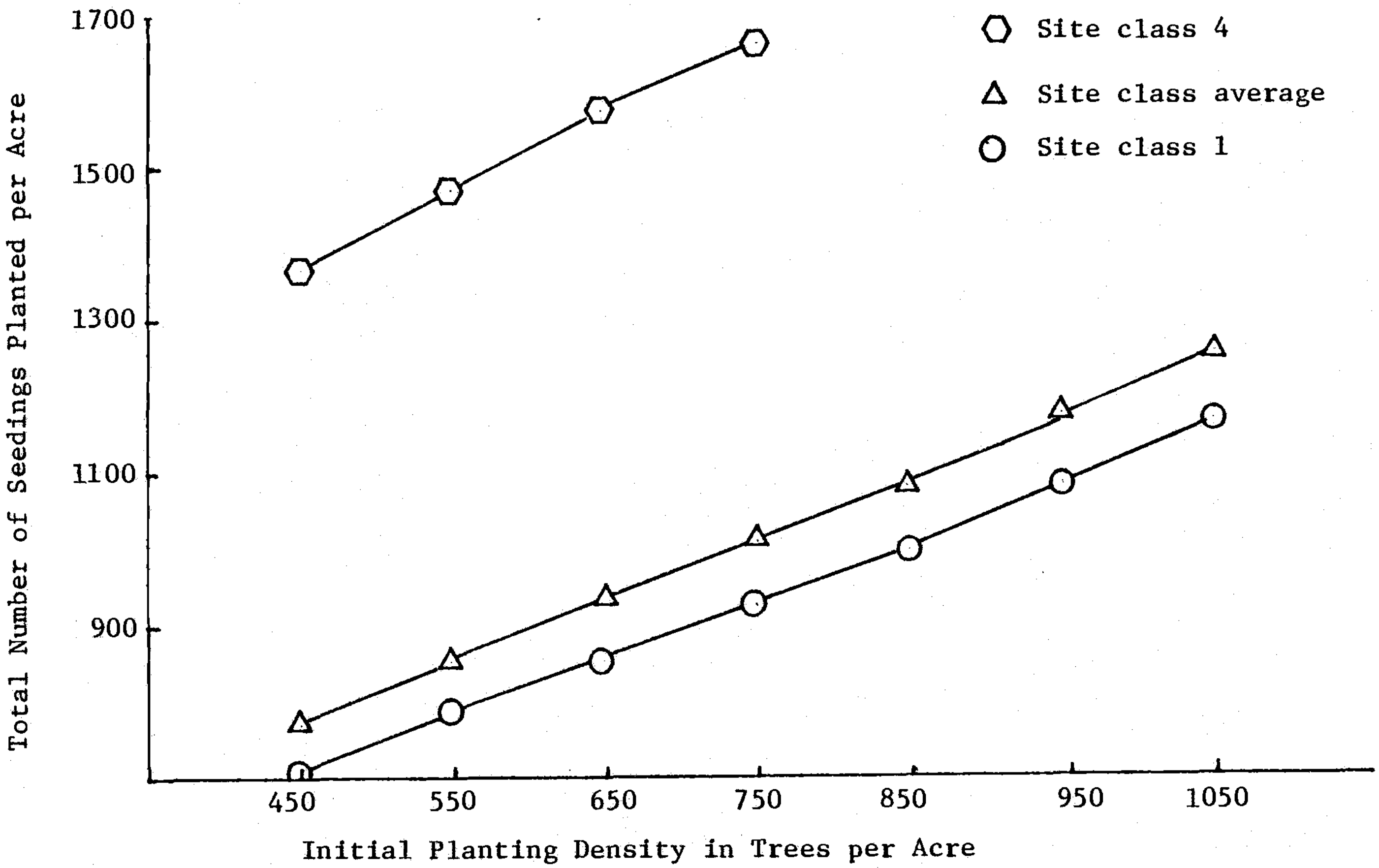


FIGURE 50. Expected total number of seedlings used during reforestation as a function of initial planting density in Tillamook.

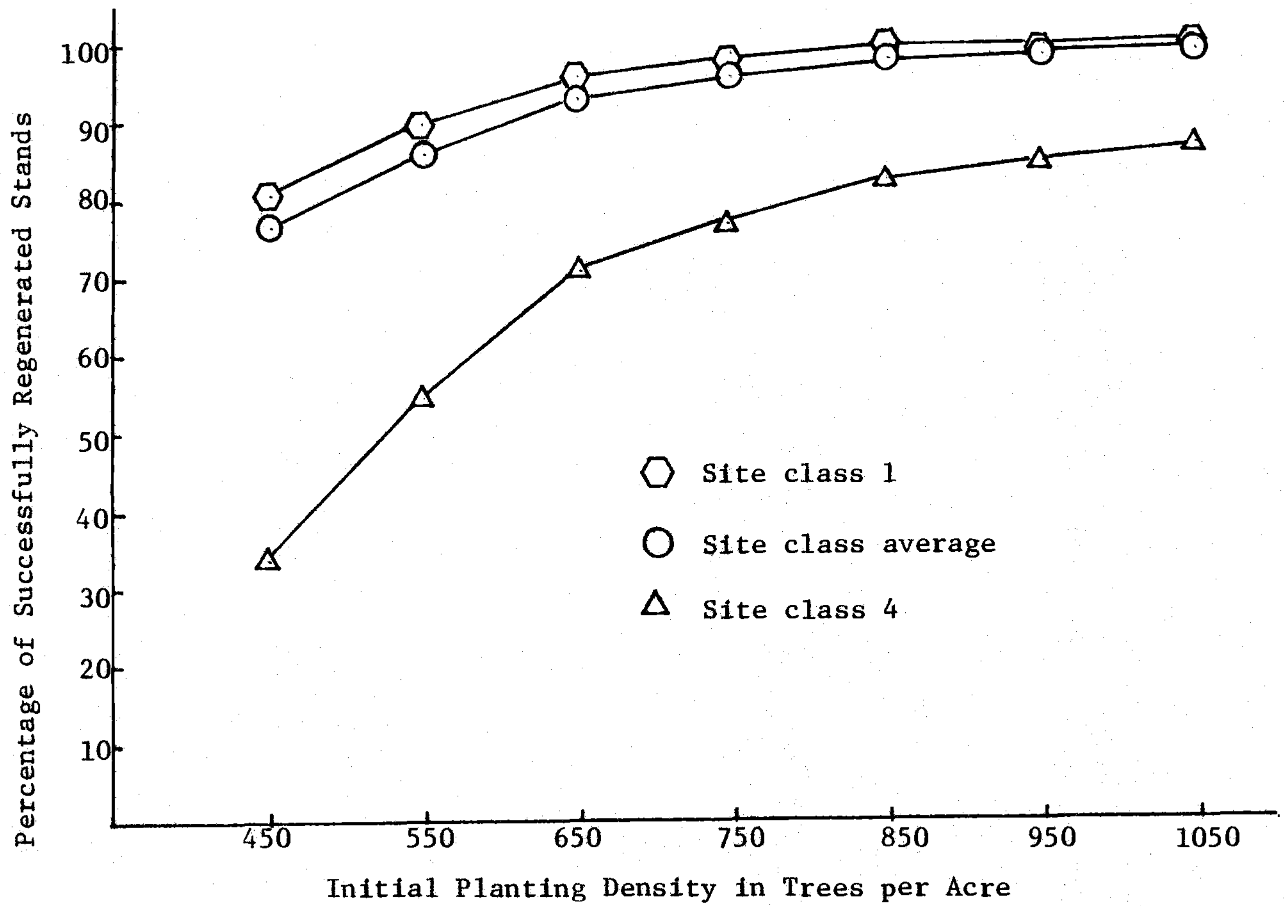


FIGURE 51. Expected percentage of plantations established successfully during the reforestation phase in Tillamook

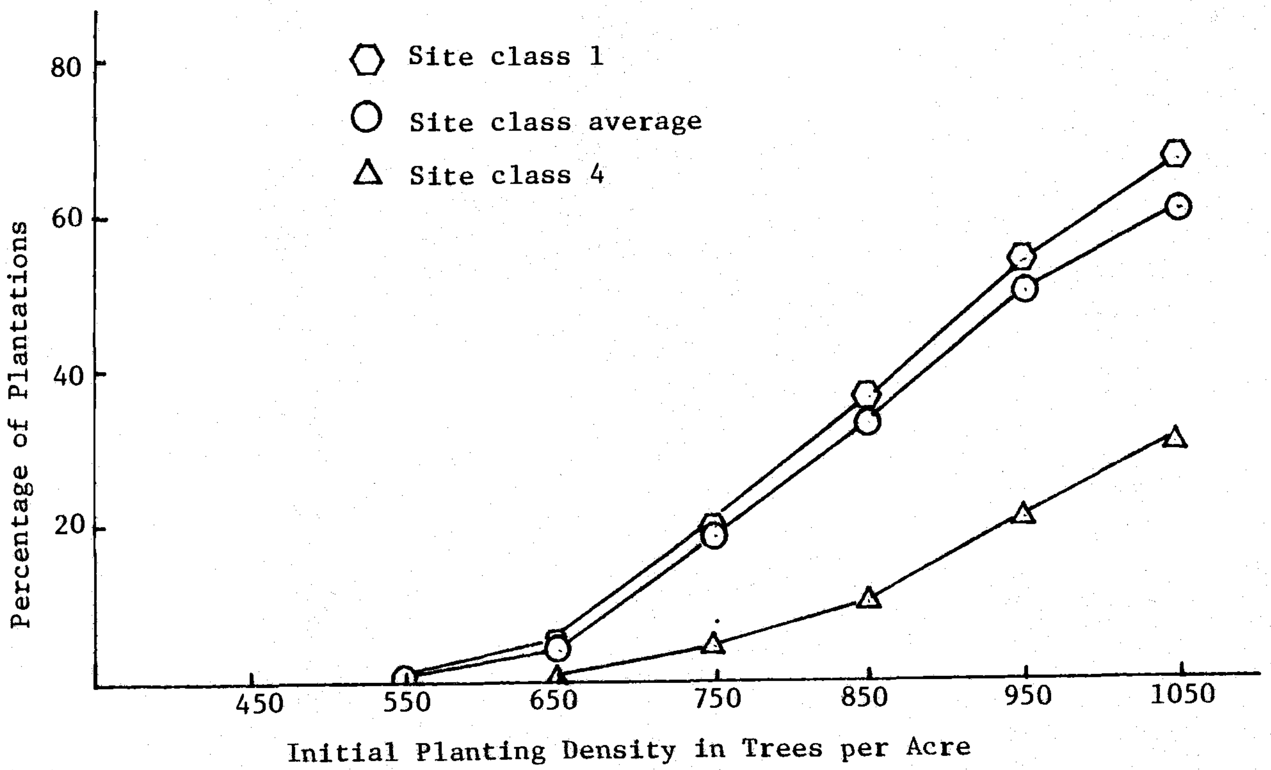
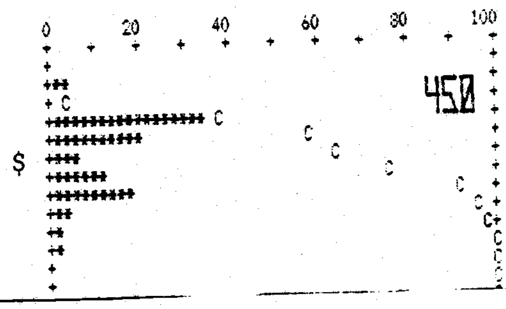


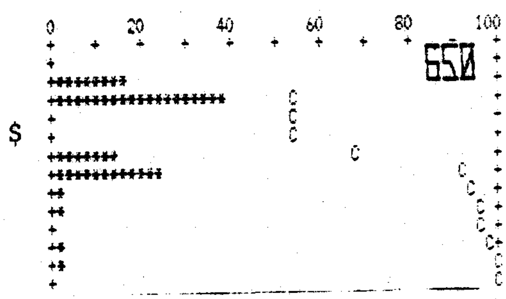
FIGURE 52. Expected percentage of plantations in need of pre-commercial thinning as a function of initial planting density

TABLE 46. Distribution of Total Costs in $ per Acre for Planting Densities of 450, 650, 750 and 850 in Tillamook for Site Class Two and Average First-year Survival

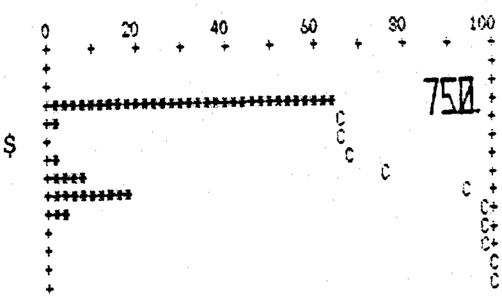
OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
0	0.000	0.000	.4000E+03
7	.047	.047	.5000E+03
0	0.000	.047	.6000E+03
50	.333	.380	.7000E+03
29	.193	.573	.8000E+03
9	.060	.633	.9000E+03
18	.120	.753	.1000E+04
26	.173	.927	.1100E+04
5	.033	.960	.1200E+04
3	.020	.980	.1300E+04
2	.013	.993	.1400E+04
1	.007	1.000	.1500E+04
0	0.000	1.000	.1600E+04



OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
0	0.000	0.000	.4000E+03
25	.167	.167	.5000E+03
57	.380	.547	.6000E+03
0	0.000	.547	.7000E+03
0	0.000	.547	.8000E+03
20	.133	.680	.9000E+03
35	.233	.913	.1000E+04
4	.027	.940	.1100E+04
3	.020	.960	.1200E+04
1	.007	.967	.1300E+04
2	.013	.980	.1400E+04
2	.013	.993	.1500E+04
1	.007	1.000	.1600E+04



OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
0	0.000	0.000	.4000E+03
0	0.000	0.000	.5000E+03
97	.647	.647	.6000E+03
2	.013	.660	.7000E+03
0	0.000	.660	.8000E+03
2	.013	.673	.9000E+03
13	.087	.760	.1000E+04
27	.180	.940	.1100E+04
6	.040	.980	.1200E+04
0	0.000	.980	.1300E+04
1	.007	.987	.1400E+04
1	.007	.993	.1500E+04
1	.007	1.000	.1600E+04



OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
0	0.000	0.000	.4000E+03
0	0.000	0.000	.5000E+03
28	.187	.137	.6000E+03
90	.600	.787	.7000E+03
0	0.000	.787	.8000E+03
0	0.000	.787	.9000E+03
2	.013	.800	.1000E+04
13	.087	.887	.1100E+04
13	.087	.973	.1200E+04
2	.013	.987	.1300E+04
0	0.000	.987	.1400E+04
0	0.000	.987	.1500E+04
2	.013	1.000	.1600E+04

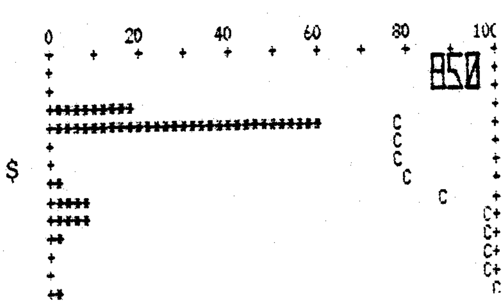


TABLE 47. Distribution of the Total Number of Seedlings per Acre used in Tillamook for Initial Densities of 450, 650, 750 and 850, Site Two, and Average Survival

OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
7	.047	.047	.4500E+03
0	0.000	.047	.5500E+03
45	.300	.347	.6500E+03
37	.247	.593	.7500E+03
18	.120	.713	.8500E+03
32	.213	.927	.9500E+03
5	.033	.960	.1050E+04
4	.027	.987	.1150E+04
2	.013	1.000	.1250E+04
0	0.000	1.000	.1350E+04
0	0.000	1.000	.1450E+04
0	0.000	1.000	.1550E+04
0	0.000	1.000	.1650E+04
0	0.000	1.000	.1750E+04
0	0.000	1.000	.1950E+04
0	0.000	1.000	.1950E+04
0	0.000	1.000	INF
150			
0	0.000	0.000	.4500E+03
0	0.000	0.000	.5500E+03
82	.547	.547	.6500E+03
0	0.000	.547	.7500E+03
0	0.000	.547	.8500E+03
0	0.000	.547	.9500E+03
32	.213	.760	.1050E+04
23	.153	.913	.1150E+04
4	.027	.940	.1250E+04
2	.013	.953	.1350E+04
2	.013	.967	.1450E+04
4	.027	.993	.1550E+04
1	.007	1.000	.1650E+04
0	0.000	1.000	.1750E+04
0	0.000	1.000	.1850E+04
0	0.000	1.000	.1950E+04
0	0.000	1.000	INF
150			
0	0.000	0.000	.4500E+03
0	0.000	0.000	.5500E+03
0	0.000	0.000	.6500E+03
99	.660	.660	.7500E+03
0	0.000	.660	.8500E+03
0	0.000	.660	.9500E+03
0	0.000	.660	.1050E+04
0	0.000	.660	.1150E+04
28	.187	.847	.1250E+04
17	.113	.960	.1350E+04
3	.020	.980	.1450E+04
0	0.000	.980	.1550E+04
0	0.000	.980	.1650E+04
1	.007	.987	.1750E+04
1	.007	.993	.1850E+04
0	0.000	.993	.1950E+04
1	.007	1.000	INF
150			
0	0.000	0.000	.4500E+03
0	0.000	0.000	.5500E+03
0	0.000	0.000	.6500E+03
0	0.000	0.000	.7500E+03
118	.787	.787	.8500E+03
0	0.000	.787	.9500E+03
0	0.000	.787	.1050E+04
0	0.000	.787	.1150E+04
0	0.000	.787	.1250E+04
0	0.000	.787	.1350E+04
16	.107	.893	.1450E+04
13	.087	.980	.1550E+04
1	.007	.987	.1650E+04
0	0.000	.987	.1750E+04
0	0.000	.987	.1850E+04
0	0.000	.987	.1950E+04
2	.013	1.000	INF
150			

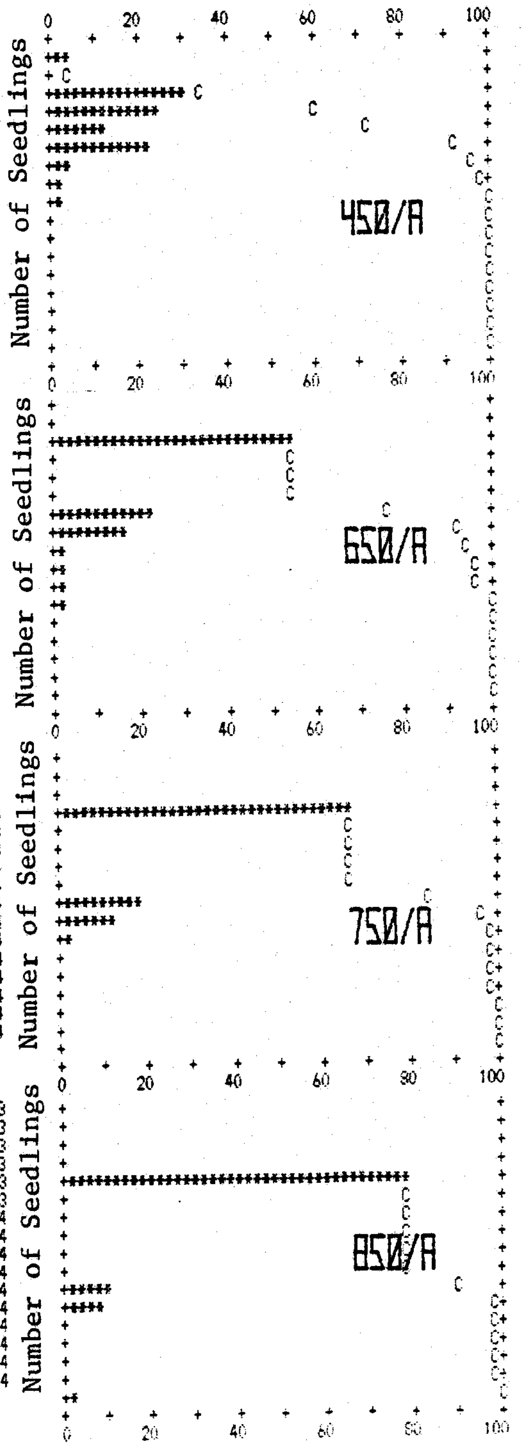


TABLE 48. Distribution of the Number of Interplants for Planting Densities of 450, 650, 750, 850 in Tillamook for Site Class Two and Average Survival

OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
11	.073	.073	0.
89	.593	.667	.1000E+01
47	.313	.980	.2000E+01
3	.020	1.000	.3000E+01
0	0.000	1.000	.4000E+01
0	0.000	1.000	.5000E+01
0	0.000	1.000	.6000E+01
0	0.000	1.000	.7000E+01
84	.560	.560	0.
59	.393	.953	.1000E+01
7	.047	1.000	.2000E+01
0	0.000	1.000	.3000E+01
0	0.000	1.000	.4000E+01
0	0.000	1.000	.5000E+01
0	0.000	1.000	.6000E+01
0	0.000	1.000	.7000E+01
99	.660	.660	0.
48	.320	.980	.1000E+01
3	.020	1.000	.2000E+01
0	0.000	1.000	.3000E+01
0	0.000	1.000	.4000E+01
0	0.000	1.000	.5000E+01
0	0.000	1.000	.6000E+01
0	0.000	1.000	.7000E+01
118	.787	.787	0.
30	.200	.987	.1000E+01
2	.013	1.000	.2000E+01
0	0.000	1.000	.3000E+01
0	0.000	1.000	.4000E+01
0	0.000	1.000	.5000E+01
0	0.000	1.000	.6000E+01
0	0.000	1.000	.7000E+01

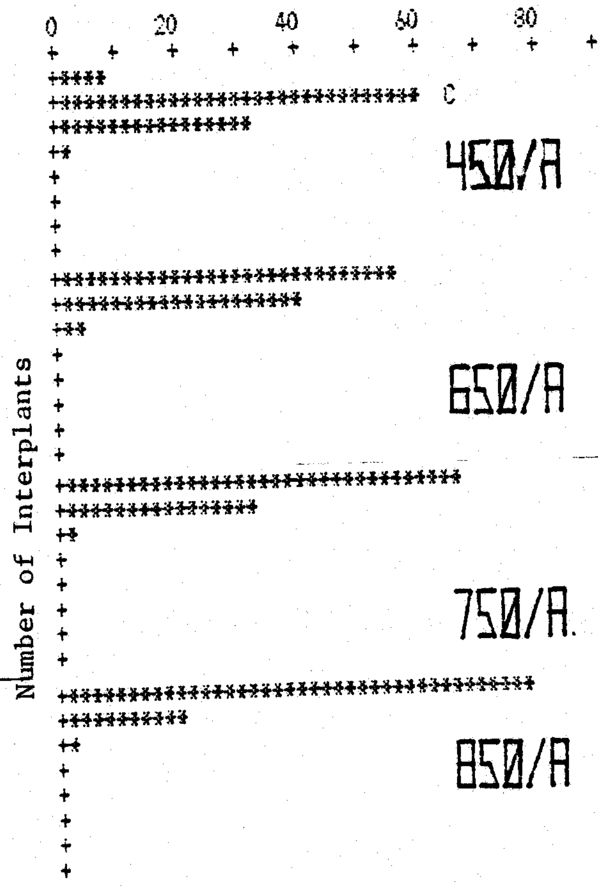
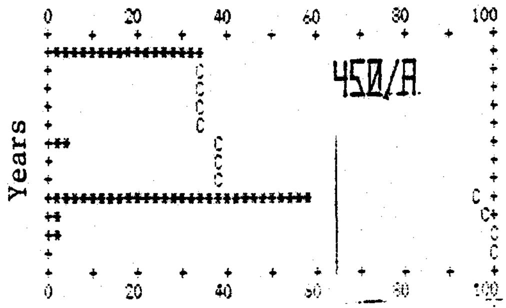
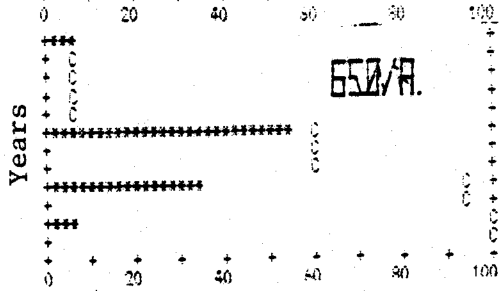


TABLE 49. Distribution of the Time Spent in the Tillamook Reforestation System by Plantations until Successful Establishment or Failure in Year 10 (Length "zero" indicates that the unit was still in need of interplanting at the end of year 10)

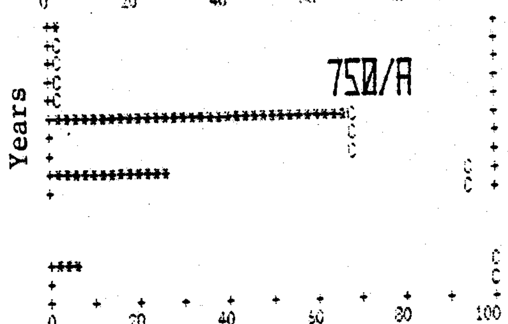
OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
51	.340	.340	0.
0	0.000	.340	.1000E+01
0	0.000	.340	.2000E+01
0	0.000	.340	.3000E+01
0	0.000	.340	.4000E+01
7	.047	.387	.5000E+01
0	0.000	.387	.6000E+01
0	0.000	.387	.7000E+01
87	.580	.967	.8000E+01
3	.020	.987	.9000E+01
2	.013	1.000	.1000E+02
0	0.000	1.000	INF
150			



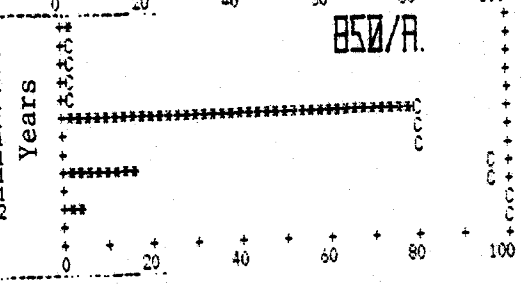
OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
8	.053	.053	0.
0	0.000	.053	.1000E+01
0	0.000	.053	.2000E+01
0	0.000	.053	.3000E+01
0	0.000	.053	.4000E+01
82	.547	.600	.5000E+01
0	0.000	.600	.6000E+01
0	0.000	.600	.7000E+01
51	.340	.940	.8000E+01
0	0.000	.940	.9000E+01
9	.060	1.000	.1000E+02
0	0.000	1.000	INF
150			



OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
3	.020	.020	0.
0	0.000	.020	.1000E+01
0	0.000	.020	.2000E+01
0	0.000	.020	.3000E+01
0	0.000	.020	.4000E+01
99	.660	.680	.5000E+01
0	0.000	.680	.6000E+01
0	0.000	.680	.7000E+01
38	.253	.933	.8000E+01
0	0.000	.933	.9000E+01
10	.067	1.000	.1000E+02
0	0.000	1.000	INF
150			



OBSV FREQ	RELA FREQ	CUML FREQ	UPPER CELL LIMIT
2	.013	.013	0.
0	0.000	.013	.1000E+01
0	0.000	.013	.2000E+01
0	0.000	.013	.3000E+01
0	0.000	.013	.4000E+01
118	.787	.800	.5000E+01
0	0.000	.800	.6000E+01
0	0.000	.800	.7000E+01
24	.160	.960	.8000E+01
0	0.000	.960	.9000E+01
6	.040	1.000	.1000E+02
0	0.000	1.000	INF
150			



APPENDIX C

APPENDIX C

Some Additional Consequences of Varying Planting Densities in Roseburg

Figure 53 to 58 display added consequences of varying planting density under the stated reforestation guidelines. In their interpretation the reader is reminded that survival targets, and the stocking levels which trigger predommercial thinnings, vary by site class and that this analysis does not assume a quality or productivity premium after such an early thinning of Douglas-fir. In interpreting Figure 56, and comparing it with corresponding Tillamook results (Figure 51), one should keep in mind that, after a time of over six years, even modest stockings represent a "success" (Table 29). Additional output, such as the frequency distribution of the number of interplants, or of the rehabilitation time (Tables 46 to 49) is available from the simulator, but not on display here.

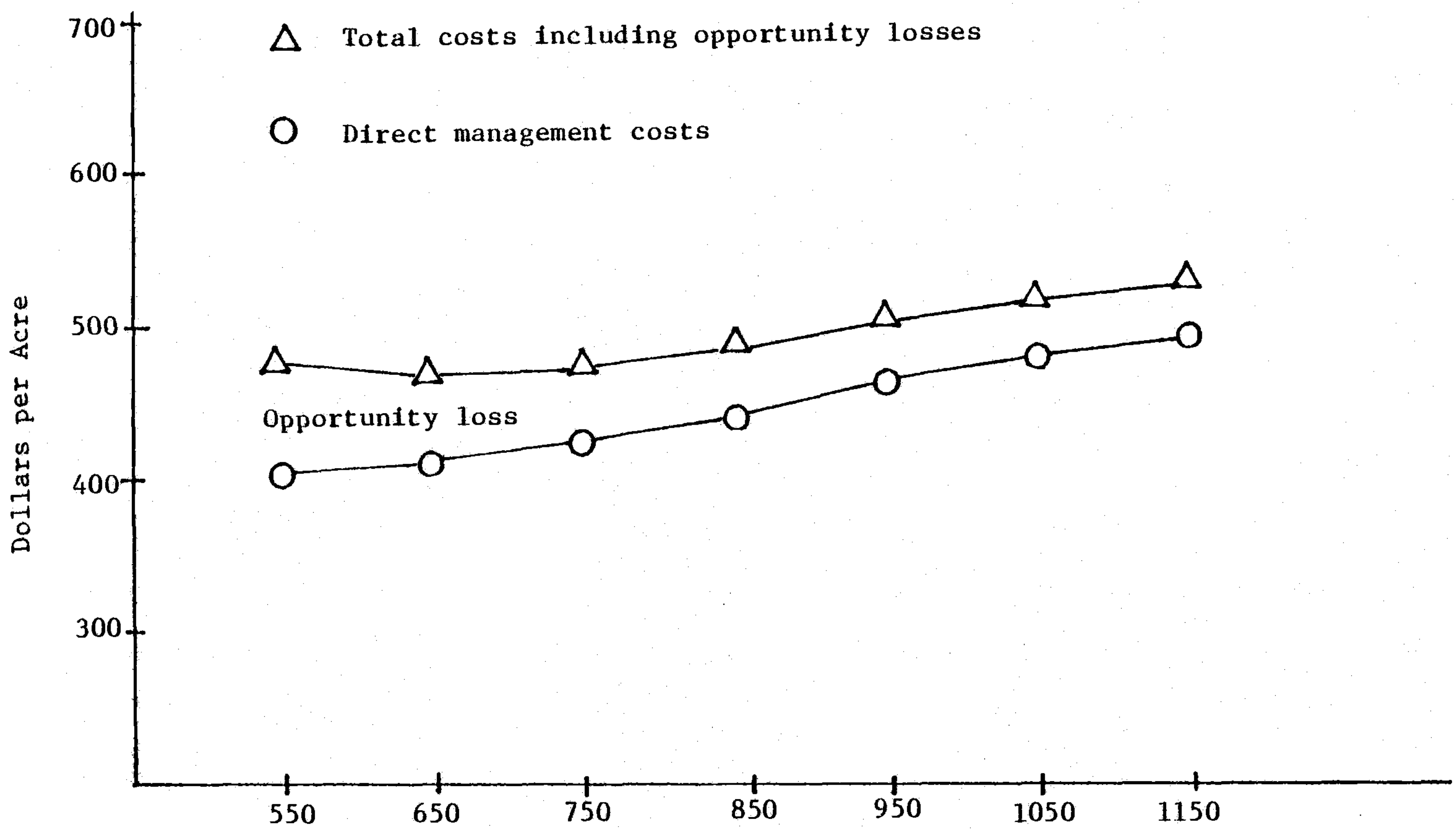


FIGURE 53. Total expected costs and direct management costs as a function of initial planting density in Roseburg

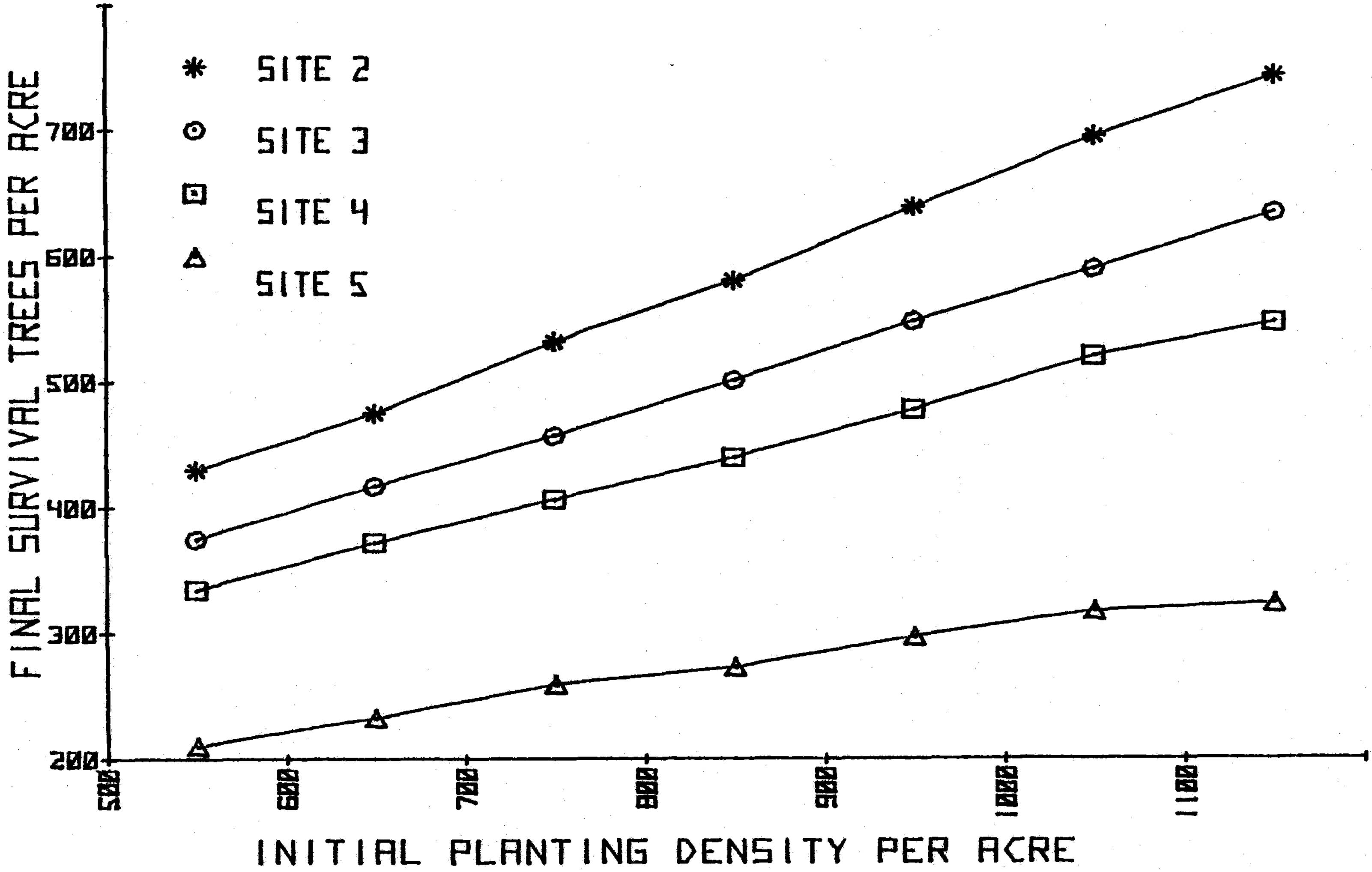


FIGURE 54. Surviving trees at age 15 as a function of initial planting density by site class in Roseburg.

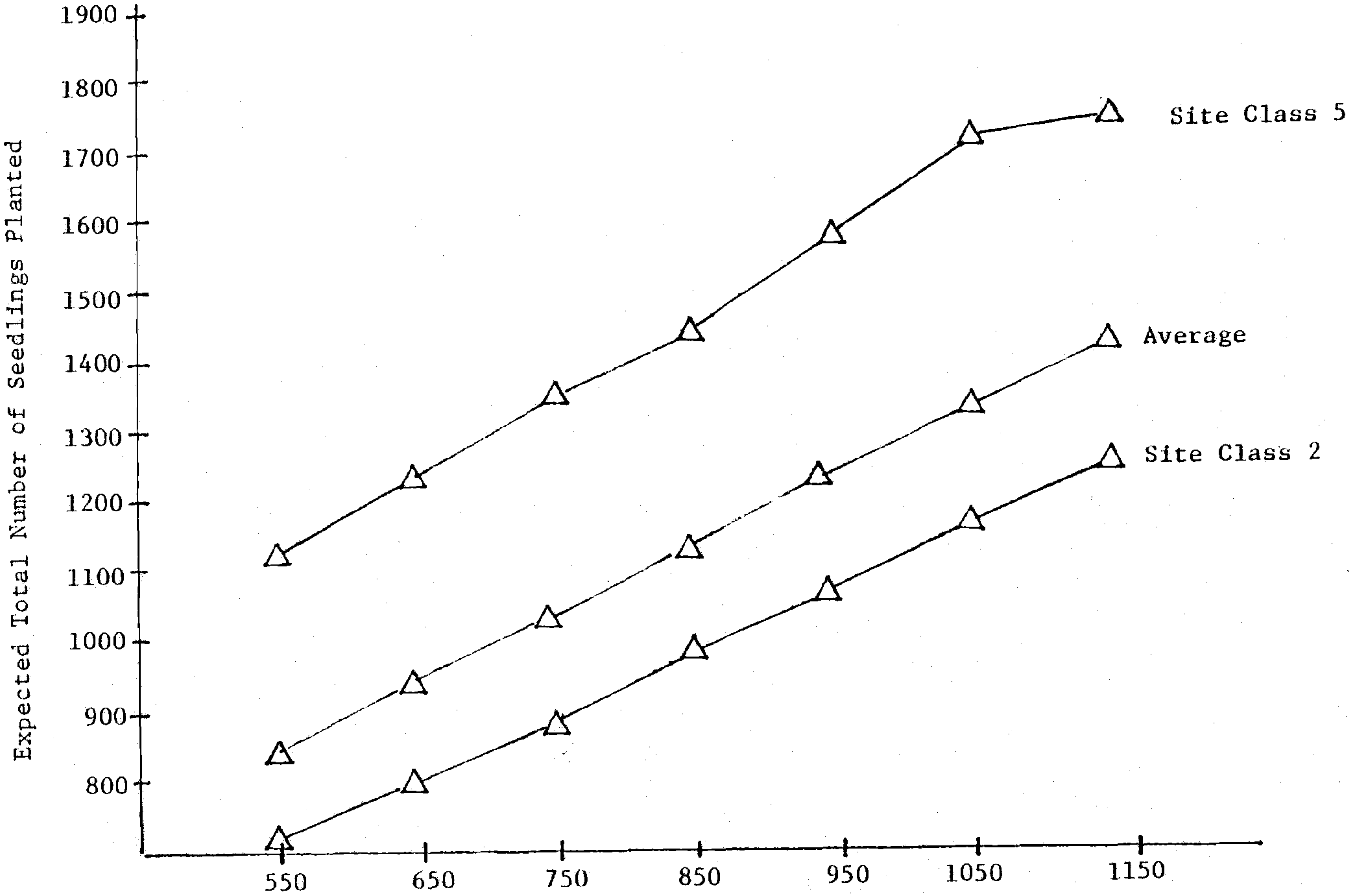


FIGURE 55. Expected total number of seedlings used during the reforestation period as a function of initial planting density in Roseburg.

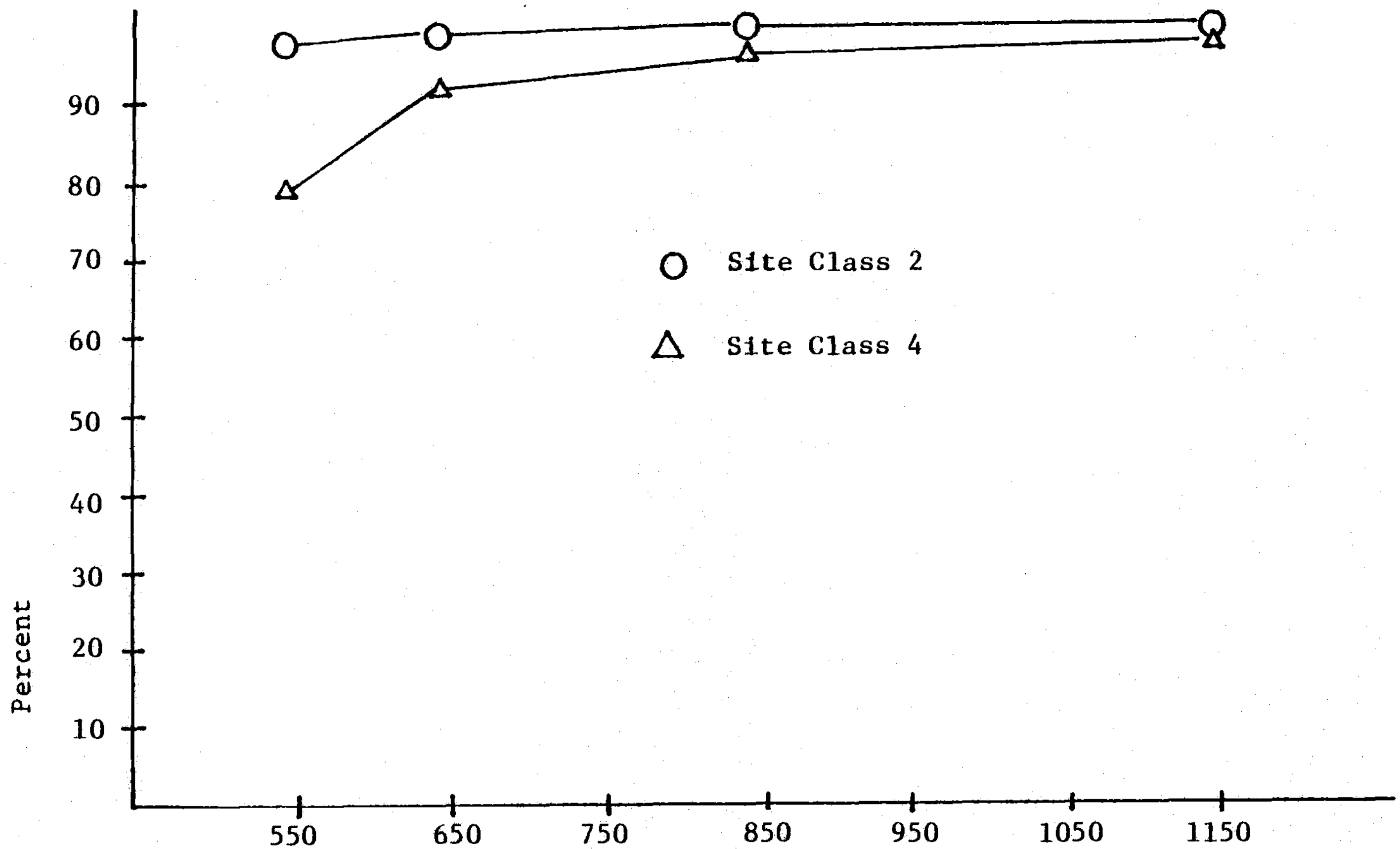


FIGURE 56. Expected percentage of plantations "successfully" rehabilitated during a ten-year reforestation phase in Roseburg.

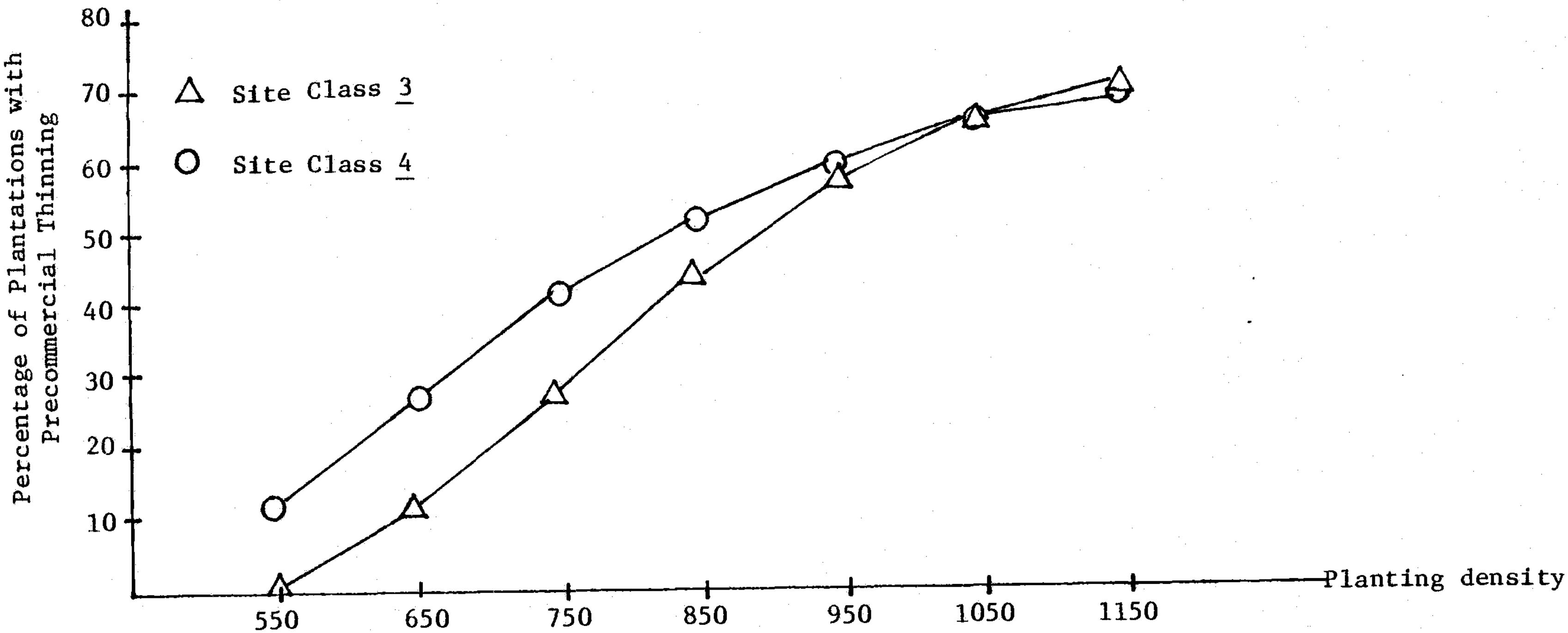


FIGURE 57. Expected percentage of plantations in need of precommercial thinning as a function of initial planting density for site classes three and four in Roseburg.

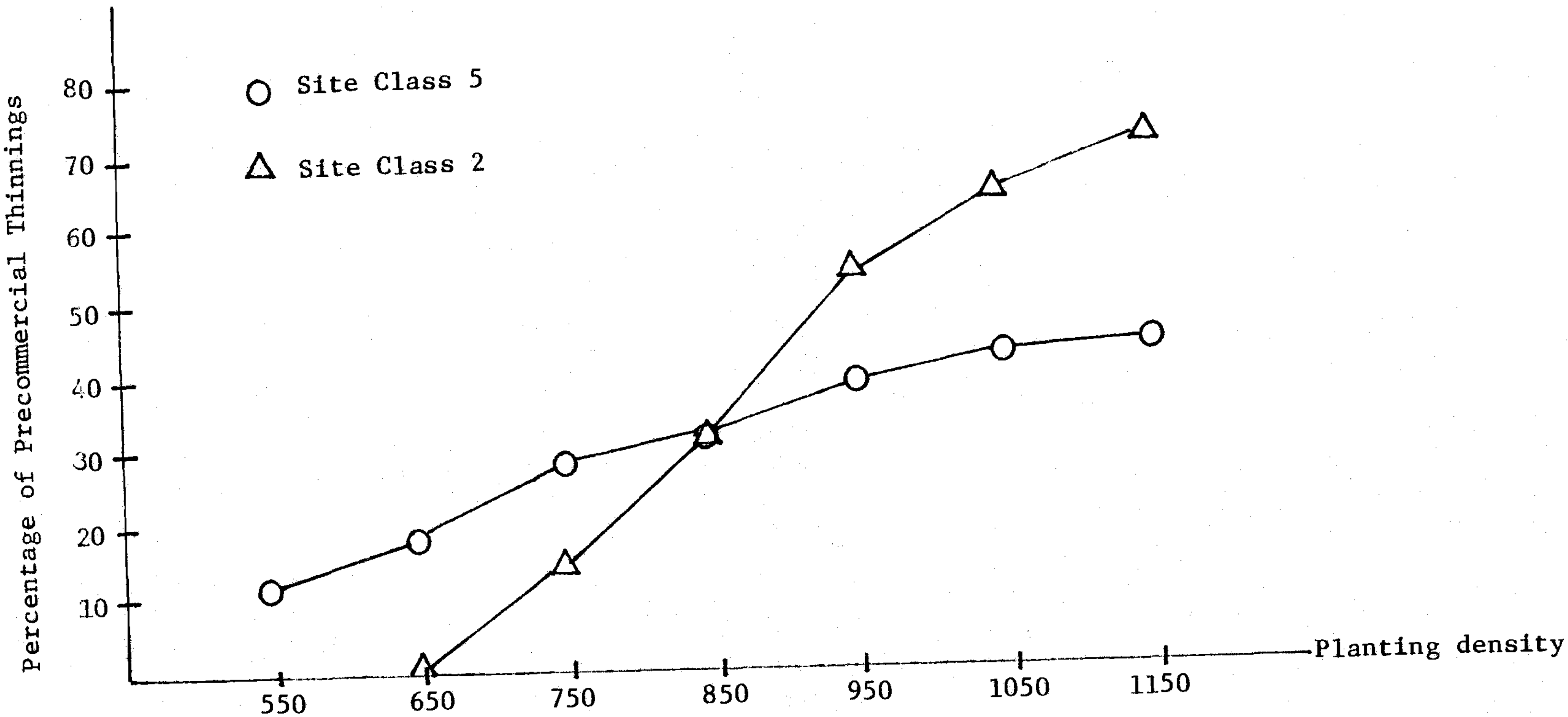


FIGURE 58. Expected percentage of plantations in need of precommercial thinning as a function of initial planting density in Roseburg for site classes two and five.

APPENDIX D

APPENDIX D

Functional Form of Survival Distributions

Tillamook Case Study

Marginal Survival in year	Site Class	Type of Distribution	Mean	Variance
1	1	Beta	0.7820	0.0161
1	2	Beta	0.7415	0.0253
1	3	Beta	0.6811	0.0366
1	4	Beta	0.4000	0.0559
2	all	Normal	0.0000*	1.1989
3	all	Beta	0.8351	0.0289
4	all	Beta	0.9613	0.0042
5	all	Beta	0.9704	0.0039

Roseburg Case Study

Marginal Survival in year	Site Class	Type of Distribution	Mean	Variance
1	2	Beta	0.8375	0.0201
1	3	Beta	0.7062	0.0379
1	4	Beta		
1	5	Beta	0.3040	0.0639
2	all	Normal	0.0000*	1.1989
3	all	Beta	0.9142	0.0091
4	all	Beta	0.9172	0.0128
5	all	Beta	0.9406	0.0192

*Note: Average second-year marginal survival percent was obtained as a function of first-year survival, through the regression equations:

$$Y = 0.2017 + 0.0247 \cdot X \text{ (Tillamook)}$$

$$Y = 0.0131 + 0.0356 \cdot X \text{ (Roseburg)}$$

where Y = logit function of second-year marginal survival as a fraction

X = first-year survival in percent

The given second-year marginal survival distribution corresponds to the normal distribution of residuals about this estimate of average, second-year, marginal survival