State Water Survey Division
METEOROLOGY SECTION
AT THE
UNIVERSITY OF ILLINOIS

Illinois Department of
Energy and Natural Resources

SWS Contract Report 286

THE ASSESSMENT OF STATISTICAL-PHYSICAL TECHNIQUES FOR THE EVALUATION OF WEATHER MODIFICATION OPERATIONS

Volume 3 of the
OSET Final Reports

prepared by

Chin-Fei Hsu, Stanley A. Changnon, Jr.,
*Floyd A. Huff, and K. Ruben Gabriel**

to

National Science Foundation
NSF ATM79-05007

S. A. Changnon, Jr.
Principal Investigator

Champaign, Illinois
October 1981

*Department of Statistics, University of Rochester

TABLE OF CONTENTS

Page

ABSTRACT vii

KEYWORDS vii

ACKNOWLEDGEMENTS viii

1. INTRODUCTION 1

   1. Objectives of Research 1
   2. General Approach to Problem 2

2. STATISTICAL EVALUATION TECHNIQUES 9

   1. Power of Statistical Tests and Its Evaluation 9

3. SIMULATION STUDIES 12

   1. Simulation Procedure 13
   2. Kansas Results 13
   3. Illinois Results — Month as Unit (ILL-EC) 14
   4. Montana Results 19
   5. Illinois Results — Storm as Unit (ILL-ST) 24
   6. Illinois Results —'48-hour as Unit (ILL-48) 31

4. TESTING OF THE TECHNIQUES 36

   1. The Muddy Road Project 36
   2. Illinois Projects 43
   3. Texas Panhandle Hail Suppression Project 44

5. PRINCIPAL COMPONENT REGRESSION 47

   1. Number of Components 47
   2. Biased Regression 50

6. METEOROLOGICAL COVARIATES 53

   1. Use as Forecasters 54
   2. Use as Evaluators 61

7. VALIDITY OF HISTORICAL COMPARISON 67

   1. Problems of Comparison 67
   2. The Study of Illinois Data 69

8. MISCELLANEOUS TOPICS 76

   1. Piggyback Experiment 76
   2. Operational Criteria 76

9. SUMMARY 78

REFERENCES 82

LIST OF PROJECT REPORTS AND PUBLICATIONS 88

APPENDICES 91

A. Statistical Techniques A1
B. Power Curves of High Power Test Statistics B1

LIST OF TABLES

Page

Table 3.1 Data and Evaluation Elements Used in the Simulation Studies 12

Table 3.2 Summary of High Power Statistics for Simulated Rain Modification, Kansas, 5% Nominal Significance Level 14

Table 3.3 Ranks of Test Statistics by Powers, at 5% Nominal Significance Level, ILL-CE 15

Table 3.4 Summary of High Power Statistics for Simulated Rain Modification, ILL-EC, 5% Nominal Significance Level 18

Table 3.5 High Power Statistics Common to Both Kansas and ILL-CE Simulations 19

Table 3.6 High Power Statistics in the Long-Term Rainfall Enhancement Simulation, 5% Significance Level .... 19.

Table 3.7 Ranks of Test Statistics by Powers, at 5% Significance Level, Montana, Hail Loss-Cost, 3 Seeded Years 21

Table 3.8 Ranks of Test Statistics by Powers, at 5% Significance Level, Montana, Hail Loss-Cost, 6 Seeded Years 23

Table 3.9 High Power Statistics in the Montana Hail Suppression Simulation, 5% Significance Level 24

Table 3.10 Percentage of June-August Rainfall for Selected Subsets of Storms with Identifiable Motion, METROMEX 26

Table 3.11 Powers at 5% Significance Level, ILL-ST Simulation 27

Table 3.12 Powers at 10% Significance Level, ILL-ST Simulation 28

Table 3.13 Ranks of Test Statistics by Powers at 5% Significance Level, ILL-ST Simulation, Total Rain 29

Table 3.14 High Power Statistics in the Illinois Short-Term Rainfall Enhancement Simulation, 5% Significance Level, Constant Seeding Effect Assumed 30

Table 3.15 Varying Seeding Effect Model 30

Table 3.16 High Power Statistics in the Illinois Short-Term Rainfall Enhancement Simulation, 5% Significance Level, Varying Seeding Effect Assumed , Storm as Unit 31

Table 3.17 Mean and Standard Deviation of Imposed Precipitation Changes, 500 Runs 31

Table 3.18 Powers at 5% and 10% Significance Levels, ILL-48 Simulation 34

Table 3.19 Ranks of Test Statistics by Powers at 5% Significance Level, ILL-48 Simulation, Total Rain . . . 35

Table 4.1 Mean Difference and 1-Sided Permutational Significance Level, Hail Loss-Cost . . . 39

Table 4.2 Mean Difference and 1-Sided Permutational Significance Level, Seasonal Rainfall . . . 41

Table 4.3 Mean Difference and 1-Sided Permutational Significance Level for Monthly Rainfall . . . 42

Table 4.4 General Effects of Seeding on Rainfall in the Target Area, Illinois . . . 43

Table 4.5 Factor Loading Matrix, Varimax Rotation, 7 Factors Retained, Texas Hail Loss-Cost . . . 46

Table 4.6 Testing of Factor Scores . . . 46

Table 5.1 Eigenvalues of the Covariance Matrix of Independent Variables, 1936-1970, Kansas . . . 48

Table 5.2 Differences of Power, PCR[1]-PCR[3], D as Test Statistic . . . 49

Table 6.1 Surface Predictor Variables Selected by First-Stage Stepwise Regression . . . 55

Table 6.2 Descriptive Statistics of Coefficient of Determination (R^2) and Averaged Difference (D) . . . 62

Table 6.3 Powers, Principal Component Regression, Upwind Controls without Meteorological Covariates, ILL-ST, Total Rain . . . 63

Table 6.4 Powers, ILL-ST with Meteorological Covariates, Total Rain . . . 65

Table 6.5 Ranks of the Statistics D by Powers at 5% and 10% Significance Levels, Total Rain . . . 66

Table 7.1 F-Ratios for between/within Groups of Years . . . 70

Table 7.2 Detailed Analysis of Dubuque vs. Moline Decennial Experiments . . . 72

Table 7.3 Chi-Square Tests on Uniformity of P-values, Comparisons of 5 'Seeded' vs 5 'Unseeded' Years . . . 74

Table 7.4 Chi-Square Tests of Uniformity of P-values, Comparisons of 10 'Seeded' vs 10 'Unseeded' Years . . . 75

LIST OF FIGURES

		Page
Fig. 1.1	West-Central Kansas Simulation Study Area	4
Fig. 1.2	Central Montana Simulation Study Area	5
Fig. 1.3	ILL-48 Simulation Study Area	6
Fig. 1.4	East-Central Illinois Simulation Study Area	7
Fig. 3.1	Illinois-Storm Simulation Study Area	25
Fig. 3.2	Number of Rains Occurring at Each Hour Sharp, METROMEX Network, 1971-1975	33
Fig. 4.1	Muddy Road Project Area	37
Fig. 4.2	Ratio of Hail Loss-Cost, 1975-1979 Average to 1948-1971 Average	38
Fig. 4.3	Ratio of Seasonal Rains, 1975-1979 Average to 1948-1971 Average	38
Fig. 4.4	Hail Suppression Project Area, Texas	45
Fig. 6.1	Point-Covariates Selected by the Stepwise Regression, Total Areal Rain as Response Variable, 1971-1975	56
Fig. 6.2	Pattern of Loading Matrix, Sky Cover	58
Fig. 6.3	Coefficient of Determination, R , and Cp. (a) Principal Components, (b) Point-Covariates	60

ABSTRACT

This report covers the last 2 years of a 3.5-year research project dealing with the evaluation of weather modification operations. A collection of statistical-physical evaluation techniques was compared through a series of simulation studies using 5 data sets covering a broad range of weather regimes. Rainfall enhancement and hail suppression experiments were simulated by superimposing seeding-induced changes onto designated 'target' seed observations. Several past operational weather modification projects were selected for testing the evaluation techniques developed. Meteorological covariates were studied for their usefulness in aiding the evaluation; however, because of reduced funding from NSF during the last 2 years the meteorology covariate studies were only partially completed. Relevant issues to the operational projects, including historical comparison, piggyback experiments, and operational criteria, were also investigated.

KEYWORDS

Weather modification; precipitation enhancement; rainfall; METROMEX; evaluation; statistics; operational (commercial) project; hail suppression; power of test; principal component regression; trend; piggyback; storm; simulation; regression; sum of rank power test; two regressions; double ratio; covariates; historical comparison; operational criteria.

ACKNOWLEDGEMENTS

This work was supported by grants from the National Science Foundation, ENV 77-01103 and ATM 79-05007. Paul Rosenzweig and Julia Chen provided substantial assistance in the computer programming and data management; without their able help, it would have been impossible to carry out the simulation studies successfully. Nancy Chen, Sue Hsu, and Melody Cheng wrote part of the programs for statistical techniques. Herbert Yuen prepared the METROMEX data and helped in plotting the power values. The meteorological covariates were calculated by Gary L. Achtemeier. The program used in the computation of biased regression was modified from a version kindly provided by Prof. S. G. Carmer. Students involved in this work included Robin Toomey, Lynn Minton, Valda Lemons, Yoonyee You, Karen Jones, Victoria Borre, Alfred Cheng, and D. Petrondas. Appreciation is also extended to Gail Taylor who meticulously reviewed and edited the manuscript.

1. INTRODUCTION

This report summarizes the results of Part II of the NSF-sponsored research (Grant ATM79-05007) relating to the development of techniques to evaluate operational weather modification projects. It is the third volume of a 3-volume set of final reports. Volume 1 (Achtemeier, 1981) contained the results of research on the surface meteorological covariates not included in this report. Volume 2 (Hsu, 1981a) contained the results of a literature search on the general issues of evaluation, statistical techniques, and designs of weather modification efforts. This report (Volume 3) addresses the development of statistical-physical evaluation techniques, their testing on a number of operational projects, and other topics related to the evaluation of operational projects. The project was a 2-year effort starting in June 1979, and is a continuation of research carried out earlier under an 18-month grant (NSF ENV 77-01103) spanning the period from June 1977-December 1978. A final report on the earlier work was submitted to NSF in January 1979.

It is important to recognize that an enormously complex, multi-faceted problem was faced in this research on £perational Seeding evaluation techniques (referred to hereafter as OSET). With the limitations imposed by funding, it was not possible to address all of the issues nor to solve all the problems in weather modification evaluation in the 3.5 years devoted to this project. Therefore, an early decision supported by our Advisory Panel (Schickedanz et al., 1978) was to limit our investigation to the development and testing of statistical-physical evaluation techniques that are applicable to the modification of convective precipitation (rain and hail) during the warmer part of the year. Agriculture is the major beneficiary of weather modification, so that demands for rain enhancement and hail suppression are normally greatest in the May-September period over much of the country.

1.1 Objectives of Research

The primary objective of OSET has been to develop statistical-physical evaluation techniques for future operational projects, including both the usual non-randomized operations (commercial type) and those employing some degree of randomization, such as the piggyback type recommended by the Weather Modification Advisory Board in their 1978 reports. Enhancement of growing season rainfall and suppression of hail are the two major applications of weather modification over much of the country. These present a greater evaluation problem than orographic precipitation. Consequently, the utility of weather modification in convective precipitation is not as well-defined as orographic seeding, which has been employed largely for snowpack augmentation in the western part of the U.S.

In developing the statistical-physical evaluation techniques, a strong effort has also been devoted to evaluating the utility of meteorological covariates (predictor variables), both in the verification of seeding results and as forecasting aids in scheduling and carrying out seeding operations. That is, the role of covariates for both evaluation and prediction has been assessed. Because of the size of the task and the restricted NSF funding, this phase of the research was limited to storm rainfall enhancement. However, results should also help determine the use of meteorological covariates in hail suppression operations.

The third objective of the OSET research has been the testing of the statistical-physical techniques developed under the project. This has been done by application to several past seeding projects of the commercial type which were considered suitable for this purpose in terms of available data and information.

The fourth major objective of this research has been the development of operational criteria. These involve design of the seeding operations, determination of seeding criteria, conduct of seeding missions, and the collection and recording of data for subsequent evaluation of project results. Without satisfactory operational criteria, assessment of seeding effects is severely hampered and sometimes impossible. This has been a major problem in attempting to assess past seeding operations. Results of this phase of the research have been covered in a separate OSET report (Huff and Changnon, 1980).

The fifth objective involves the transfer of the results from the various phases of the research to the scientific community and to the user community interested in weather modification. This has been and continues to be accomplished primarily through technical reports, papers presented at scientific meetings dealing with weather modification, and published papers in professional journals which have a large audience among those interested in weather modification.

Some changes in emphasis on objectives resulted not only from the findings of the first 18 months and available fundings, but also from input from the project's advisory team (Schickedanz et al., 1978), and from the recommendations of the national Weather Modification Advisory Board (1978a) and its Statistical Task Force (WMAB, 1978b). These groups pointed to specific informational needs and desirable operational approaches for the evaluation of operational weather modification efforts. These were incorporated into our research to the extent feasible with existing funding.

1.2 General Approach to Problem

The development of statistical-physical techniques involved two highly coordinated investigations. The first and more important of the two was the testing of numerous statistical evaluation techniques to ascertain which are the most applicable for verification of operational projects. Those tested were initially selected from a large number of statistical candidates as having characteristics which make them potentially useful in evaluating weather modification. The second part of the investigation involved the selection and testing of various meteorological factors which were considered potentially useful as covariates (predictor variables) in the evaluation of operations and/or the prediction of weather conditions for seeding operations. These two investigations were aimed towards providing the best combination of verification reliability and minimum sample size requirements in the evaluation of operational projects.

Following recommendations received from consultation with our Advisory Panel members, the evaluation of statistical techniques was accomplished primarily through extensive simulation testing of assumed weather modification effects superimposed upon natural precipitation distributions. This was done for both rain and hail. The hail simulations utilized crop-hail insurance records which provide data on annual hail liability and loss-cost values by county. The rain simulations involved storm, 48-hour, monthly, and seasonal rainfall. The simulation testing was restricted to warm season and convective precipitation. Fixed target and control areas were used in the hail simulations and for 48-hour, monthly and seasonal rainfall analyses. A moving target-control approach was used in the storm rainfall simulations, in which individual storm motions could be taken into account.

Three areas were originally selected for the simulation studies. Selection was based upon absence of any past weather modification efforts in these areas, their potential for future application of weather modification, and the availability of reliable data over a sufficient period of time to permit effective simulation testing. The areas selected were a 10-county region in west central Kansas (Fig. 1.1), a 16-county area in western Montana (Fig. 1.2), and an area encompassing a dense raingage network in southwestern Illinois and eastern Missouri (Fig. 1.3), which was operated as part of the Metropolitan Meteorological Experiment commonly referred to as METROMEX (Changnon et al., 1977).

After simulation studies of various statistical evaluation techniques had been partially completed, results suggested the need to test the spatial stability of the 'best' techniques. For example, is the technique which proved best for warm-season rainfall evaluations in Kansas the best throughout the Midwest where the precipitation climate is generally similar during May-September? In order to clarify this situation, an area in east central Illinois was selected (Fig. 1.4), and the Kansas simulation studies were repeated. The Illinois test area was similar in size to the Kansas area, and the same period of precipitation records was used in the monthly and seasonal simulations. Also, the same target-control tests were used.

The role of meteorological covariates was investigated using data collected in the METROMEX studies. Potentially, covariates can lead to improvement of predictions for seeding operations and can expedite the evaluation of seeding results. The integration of the meteorological covariates into the statistical evaluation of seeding effects must be done on a storm or daily basis, since the covariates must be determined from existing synoptic weather conditions which vary greatly in time and space. Hence, the covariate research was carried out only in conjunction with the METROMEX network simulations. Furthermore, because of the size of the task and the funds allotted for this phase of the work, the covariate research had to be limited to the evaluation of surface meteorological variables.

Past seeding projects of the commercial type were reviewed to determine which were most suitable for testing of the statistical-physical techniques developed under the OSET research. Suitability was based upon location (climatically), length of project, goal of seeding (rain enhancement and/or hail suppression), and adequacy and availability of data. For testing of the hail techniques developed from the Montana study, a hail suppression project carried out in the Texas Panhandle during 1970-1976 was selected. Rain enhancement projects selected for testing included several small-scale Illinois seeding projects operated within the past 5 years. Also, a combined hail suppression and rain enhancement project during the warm seasons of 1975-1979 (the Muddy Road Project) in southwestern Kansas was evaluated. This relatively large-scale project encompassed 15 target counties.

Originally, it had been intended to evaluate the results of the Whitetop experimental project in Missouri during 1961-1965 (Braham, 1966), based on

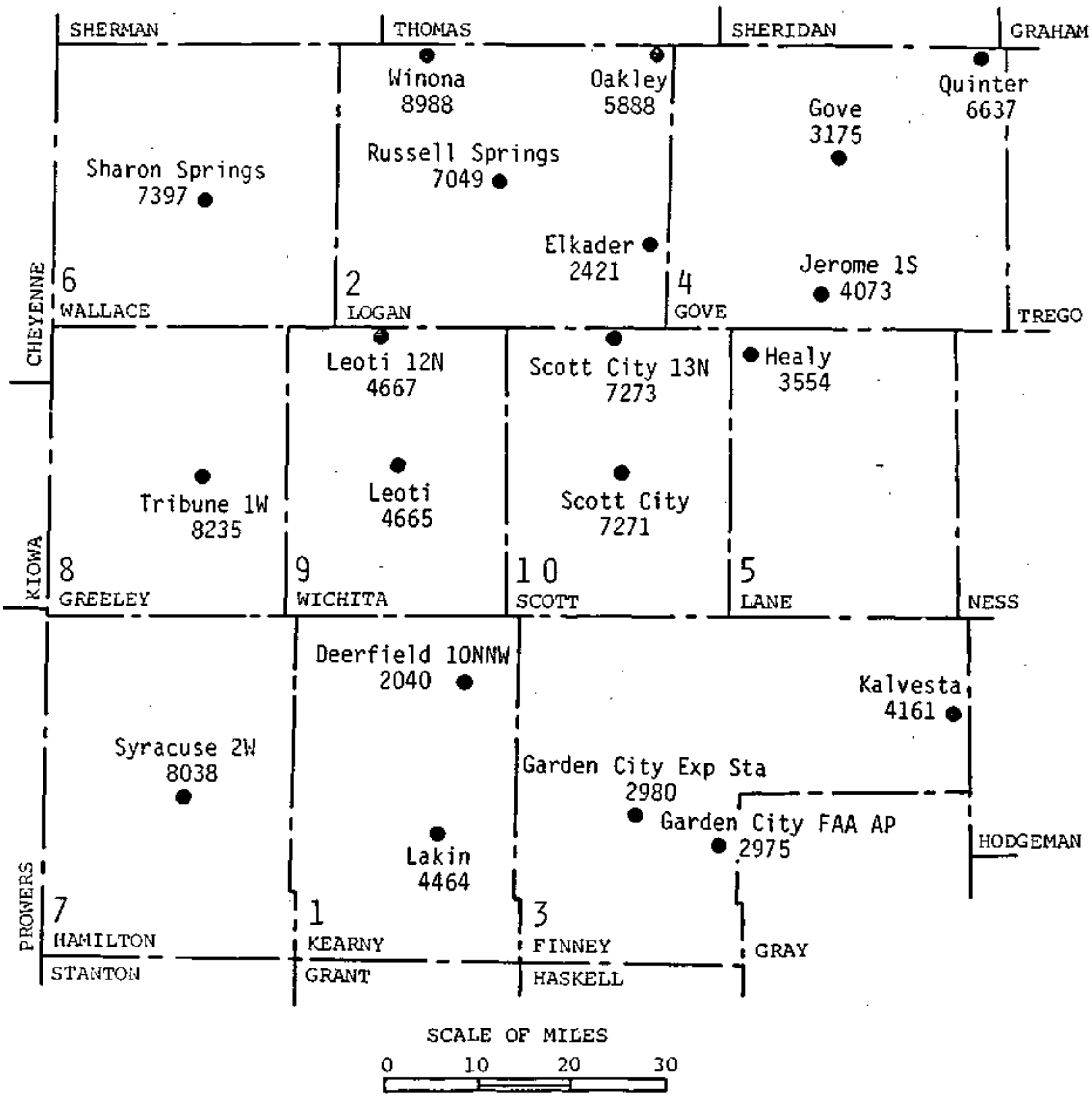


Figure 1.1 West-Central Kansas Simulation Study Area

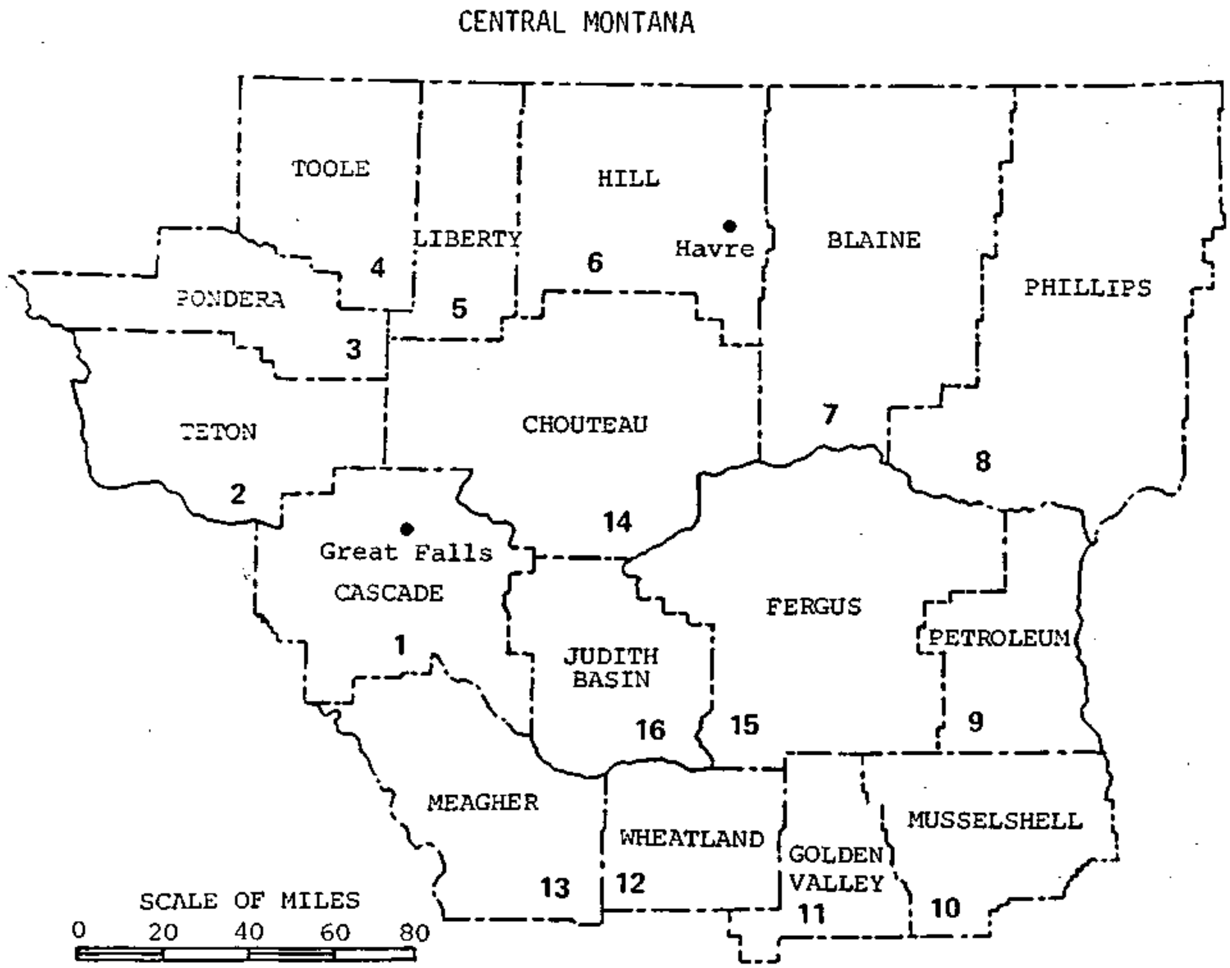


Figure 1.2 Central Montana Simulation Study Area

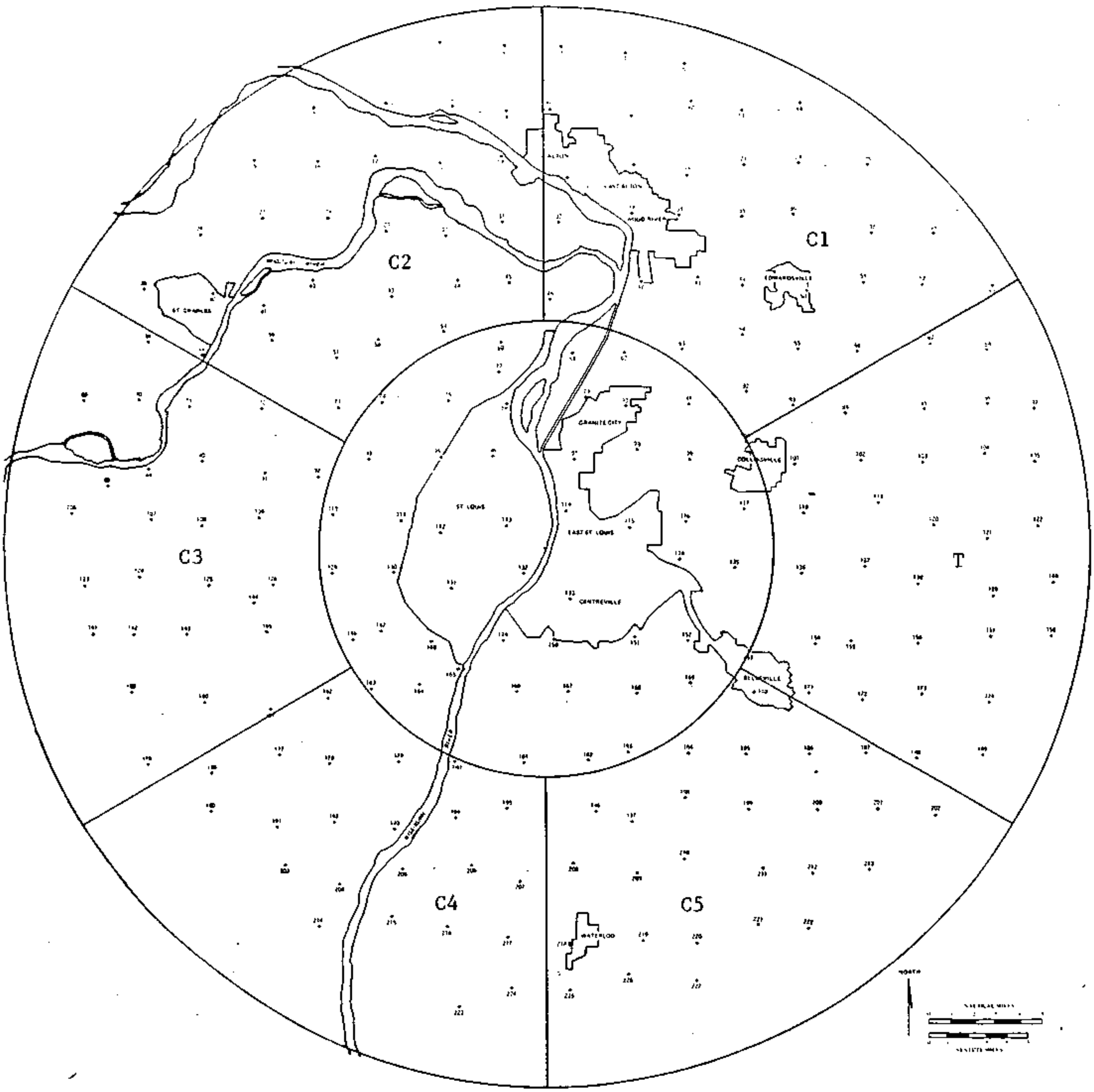


Figure 1.3 ILL-48 Simulation Study Area

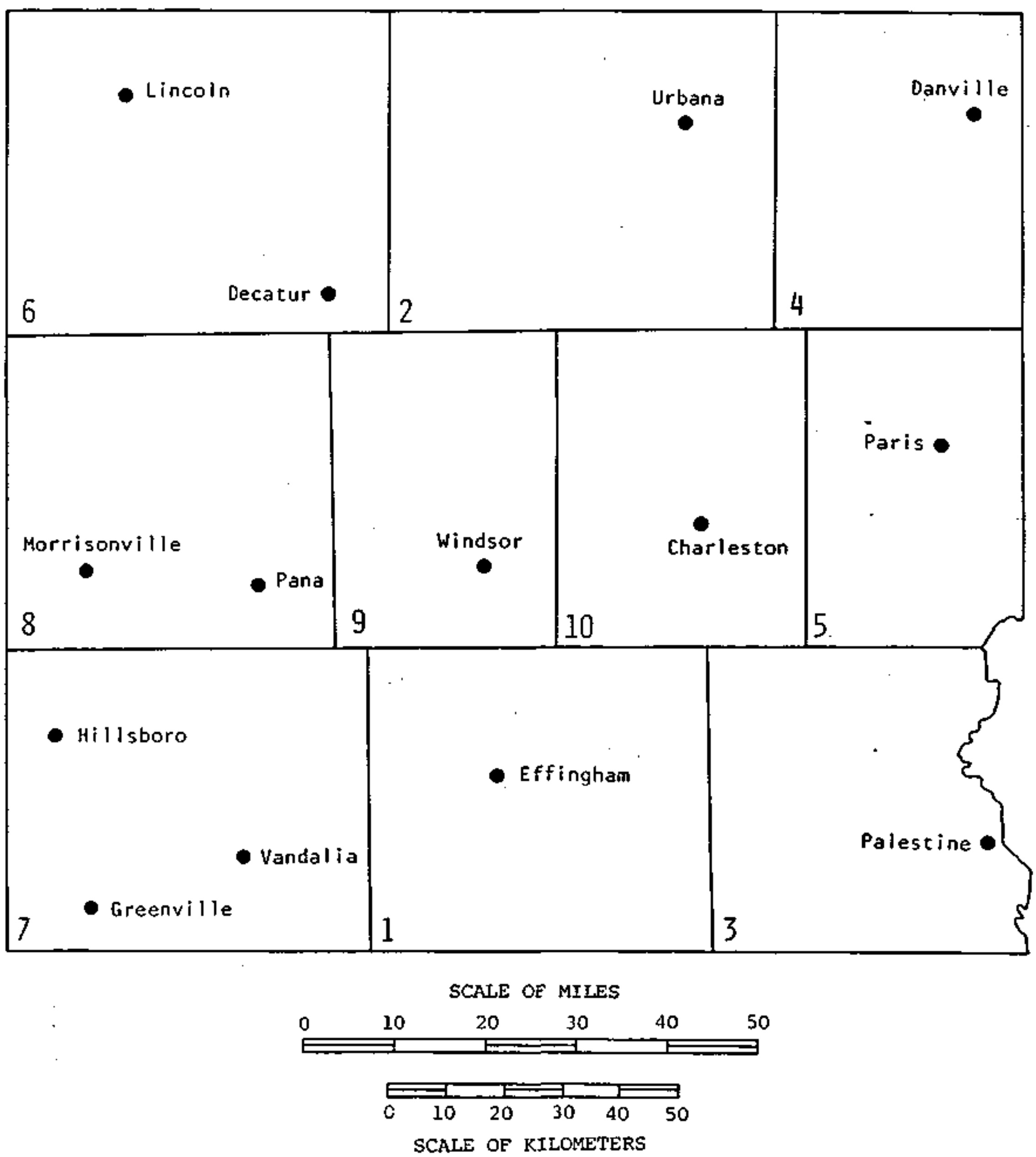


Figure 1.4 East-Central Illinois Simulation Study Area

techniques evolving from the METROMEX network simulations. Later, it was decided to omit this task, because some of our Advisory Panel members questioned the value of this undertaking, and a need arose to carry out more simulation work to define the spatial representativeness of the statistical-physical techniques developed during the research.

This report deals with statistical evaluation techniques, meteorological covariates, historical comparison, and other relevant evaluation issues. The sections on statistical techniques include a description of the techniques, a discussion of statistical power evaluation, summaries of simulation studies, summaries of the evaluations of several operational projects, and studies of principal component regression. The following sections summarize the studies on " the meteorological covariates, studies on the validity of historical comparisons, piggyback experiments, and operational criteria for successful evaluation.

2. STATISTICAL EVALUATION TECHNIQUES

Many statistical-physical techniques have been used to evaluate weather modification projects in the past (Hsu, 1981a). The number of techniques used has become so large and diversified that there is a need to choose among them the most appropriate to use under different weather regimes and various precipitation response variables.

A number of statistical techniques were selected for simulation studies to compare their performance in assessing modification effects of both rainfall-enhancement and hail suppression. Techniques investigated included multiple regression (MR), two simple regressions (2Reg), principal component regression (PCR), double ratio (DR), sum of rank power tests (SRP), and, to a lesser extent, factor analysis (FA) and canonical correlation analysis (CC). Detailed descriptions and relevant issues of these techniques appear in Appendix A.

For multiple regression, principal component regression, and canonical correlation analysis, the following statistics were used:

D = mean of differences between observed and predicted seeded values

W = positive rank sum statistic computed from differences

T = t-statistics derived from differences

These techniques were compared through simulation studies by using five data sets, which cover various weather regimes and precipitation response variables.

2.1 Power of Statistical Tests and Its Evaluation

The evaluation of power of statistical tests was confronted in carrying out the simulation studies. The need to find an appropriate method of computation required that the topic be studied in greater detail. In the following sections two methods of evaluating statistical power will be discussed and compared through numerical examples as well as approximation formulas.

R. A. Fisher(1935) introduced the idea of a permutation test (or randomization test) as an alternative technique to the ordinary t-test for two sample problems. Since then it has been used in various applications, but its properties and its comparison with other statistical techniques have not yet been as widely explored as they should have been. One probable reason for this delay is the excessive computation effort involved in calculating permutation significance values. Available literature usually deals only with data of small sample sizes. Examples can be found in Kempthorne (1952), who discussed usage of permutation tests, in addition to the F-test, for several designs. Cox and Kempthorne (1963) applied permutation tests to compare survival curves. Kempthorne and Doerfler (1969) gave a detailed description of the methodology of permutation tests and compared them with the sign test and the Wilcoxon test. In the same paper, they also demonstrated using re-randomization to compute power. Renewed interest in the permutation tests, coupled with lowered computer costs in recent years, have accelerated study of this useful technique.

Evaluation of Power. The exact method to compute power, herein called Method II, is as follows: First compute from the raw observations an observed value of a certain test statistic. Next, by permuting observations, new values of the test statistic are computed. This can be achieved either through a reference set of all possible permutations, or a randomly selected subset of permutations (Dwass, 1957). A p-value is then computed as the proportion of those new values which are larger than or equal to the observed value (1-sided testing). In testing between certain null and alternative hypotheses, power is then computed as follows. The observations are first adjusted by the effect of alternative hypotheses through a permutation in the reference set. A p-value is then computed from these adjusted observations as described above. This process is repeated for each permutation in the reference set, so that a distribution of p-values is obtained. Power is then the proportion of p-values which are larger than or equal to a (given) nominal significance level.

An alternative method to compute power, herein called Method I, for the same null and alternative hypotheses is as follows. From the raw observations, values of test statistics are computed according to permutations in the reference set, so that a 'null' distribution of the test statistic is obtained. Next, observations are adjusted by the effect of alternative hypotheses for each permutation in the reference set, and values of the test statistics are computed accordingly, so that an 'alternative' distribution of the test statistic is obtained. A critical point is determined from the null distribution at a (given) nominal significance level. Power is then the proportion of values in the alternative distribution which are greater than or equal to the critical point (as in a parametric one-sided test).

Use of Method II to compute power requires a two-stage randomization: first for computing p-values, and second for deriving powers. On the other hand, Method I requires only a one-stage randomization. The saving factor of Method I over Method II is thus M/2, where M is the number of permutations in the reference set (see also Gabriel, 1979). If M is large, say 1000, this would represent roughly a 500-fold saving of computation cost. This kind of saving is certainly desirable for large scale and complex simulation studies, such as those in weather modeling or weather modification. Desire to reduce this tedious effort of computation was also reflected by many efforts to derive efficient computer programs.

Permutation Test and Weather Modification. It has been noted by many that weather events, such as precipitation, have considerably more irregular variability in both space and time than observations obtained in physics, chemistry, agriculture, or medical laboratories (Changnon and Huff, 1967). Due to the difficulties encountered in applying parametric inferences and the largely unknown variability of weather events (in terms of physical and meteorological relationships), earlier attempts to evaluate weather modification contained some examples utilizing permutation tests. Those using ratio as test statistics included Adderley (1961), Gabriel and Feder (1969), and Elliott and Brown (1971). Those using nonparametric techniques included Adderley (1961), Gabriel and Feder (1969), and Dennis (1975). Those using regressions included Adderley (1961), and Smith et al. (1977).

A report by the Statistical Task Force to the Weather Modification Advisory Board (1978b) urged the usage of permutation tests to evaluate weather modification projects. Gabriel (1979) discussed the advantages of using permutation tests over classical parametric tests. Unless a major breakthrough in understanding weather processes occurs, so that better models of the precipitation process are available, permutation tests are likely to be. used more frequently in evaluating weather modification. However, the excessive efforts required in carrying out Method II to compute power are a hindrance to their wider usage. In the following, powers computed by Method I will be compared with those computed by Method II.

Monte Carlo Studies. The numerical example mimics a rainfall-enhancing weather modification project by randomly superimposing mutiplicative seeding effects (se = 1.1, 1.2, 1.3, and 1.4) onto 5 rainfall totals in west-central Kansas out of the 35 summers (1936-1970) during which no weather modification activity was reported. In statistical terms, the null hypothesis to be tested is H_0 : se = 1.0, and the alternative hypothesis is H_1 : se = 1.1, 1.2, 1.3, or 1.4, respectively. The data consisted of monthly (May to September) and seasonal average rainfall for 10 counties in west central Kansas (Fig. 1.1). The middle two counties were designated as 'targets' and the rests as 'controls'. For each month, 5 of the 35 summers were selected according to a permutation in the reference set as 'seeded,' and the other 30 as 'nonseeded.' A hypothetical seeding effect was superimposed onto these 'seeded' target rainfall. Results using double ratio as a test statistic were reported by Hsu (1979b), and additional results using multiple regression and sum of rank power test were reported in Gabriel and Hsu (1981).

A 'restricted' reference set of 100-500 permutations, instead of all possible permutations, was used. This reference set of permutations was randomly selected at the beginning of the Monte Carlo studies, and then used in all subsequent randomizations, whether using Method I or II.

Findings indicated that both at the 5% and 10% nominal significance levels, powers computed by Method I were slightly larger than powers computed by Method II. Discrepancies were small, usually less than or equal to .05. When the target average was used, discrepancies were even smaller.

Approximation for Power. Gabriel and Hsu (1981) derived normal approximations for the power computations of both Method I and Method II. It was shown from these approximations that Method I tended to overestimate power more than Method II. However for large samples, the difference approached zero. Moreover, for larger seeding-induced effects, the convergence to zero was faster. In addition, a number of theoretical and empirical re-randomization distributions were explored to justify the use of these approximations. It was shown that approximation of Method II usually overestimated the exact power slightly and the approximation of Method I was even a little higher. It was concluded that for all but very small experiments both approximations come reasonably close to true power.

3. SIMULATION STUDIES

To achieve the objective of comparing the performance of numerous statistical evaluation techniques, extensive simulation studies were carried out by superimposing assumed weather modification effects upon natural precipitation distributions. Five data sets were used (Table 3-D.

Table 3.1 Data and Evaluation Elements Used in the Simulation Studies

Evaluation Element	Kansas.	ILL-EC*	Montana	ILL-48*	ILL-ST*
Precipitation Type	rain	rain	hail	rain	rain
No. Years					
Seeded	5	5	3 or 6	1	1
Unseeded	30	30	26 or 23	4	4
Unit	month	month	year	48-hr	storm
Design (T-C)	fixed	fixed	fixed	fixed	moving
Target Area (sq. km)	2000-4000	2000-4000	5000-25000	800	800
Seeding Effect Model	const.	const.	const.	const,	const./varying
Predictor	no	no	no	no	yes/no
No. Runs	500	500	1000	500	500

* ILL-EC : east central Illinois; ILL-48 : 48-hour rainfall; ILL-ST : storm rainfall

These sets represent a broad range of data commonly employed in the evaluation of weather modification projects. Two of them (Kansas and Illinois-East Central) mimicked long-term (5 years) summer operational rainfall enhancement projects. Another data set (Montana) simulated a hail suppression project. The fourth (ILL-48) mimicked a short-term (1 year) operational project, and the last one (ILL-Storm) represented an experimental project with observations from a dense raingage network as well as surface meteorological covariates. Table 3»1 also shows various evaluation elements used in the simulation studies.

3.1 Simulation Procedure

For each data set, the simulation investigation was carried out for 500-1000 runs (Table 3.1). A fraction of the observations was set aside as 'seeded' according to a permutation out of a pre-chosen reference set of 500-1000 permutations, and the rest as 'unseeded.' The Cyber Fortran function, RANF, was the main random number generator used in creating the reference sets. In each run, assumed multiplicative weather modification effects, either constant or varying, were superimposed onto the 'seeded' target rainfall to form a changed sample. Test statistics were calculated for the unchanged sample (Null), and for each of. the superimposed samples (Alternative). A null distribution, and four alternative distributions of the test statistics (eight in the ILL-ST study) were then obtained. Power values were then derived by comparing the null distribution with the alternative distribution using Method I.

Next the test statistics were ranked by their powers at the 5% or 10% nominal significance levels, respectively, for each seeding effect imposed, each target-control setup, and/or each month. Findings of the simulation studies are described below.

3.2 Kansas Results

Monthly and seasonal rainfall totals, May to September, from 1935 to 1970 for a 10-county area in western Kansas (Fig. 1.1) were obtained from the National Weather Service (NWS). During this period, there was no cloud seeding being conducted in this area. The county rainfall value was computed by averaging the rains of available NWS stations. There are no missing values in this data set. Each county rainfall was used as a variable. The ten counties consist of Finney, Gove, Greeley, Hamilton, Kearny, Lane, Logan, Scott, Wallace and Wichita. This area is located in the Great Plains, and is typically in need of more rain than nature can supply during the growing season. None of the monthly rainfall distributions was significantly different from normal distribution at the 5% level by the Komogorov-Smirnov goodness-of-fit test.

The Kansas study utilized fixed target-control and historical data from a 35-year period (1936-1970). Fixed target-control and historical data are important sources of information that are most applicable in evaluating the commercial-type, non-randomized operation in which efforts are usually made to seed every situation considered amenable to rain enhancement. Monthly and seasonal seeding-induced changes (enhancement or suppression) have been most commonly used in the past in evaluating non-randomized seeding operations. This type of evaluation will continue to have much usage in the future, since precipitation increases over monthly and seasonal periods, rather than in specific storms, are of prime interest in agriculture and municipal water supply applications of weather modification. The two center counties (Scott and Wichita) were designated as 'targets,' and the other surrounding counties as 'controls.' Three counties - Kearny (county 1), Finney (county 3), and Hamilton (county 7) - are located in the upwind sector of this area in the summer season with respect to prevailing winds.

Findings from the simulations indicated that principal component regression was one of the most powerful techniques for various summer months and for target-control designs (Hsu, 1979a; Changnon et al., 1979). Table 3.2 summarizes the Kansas simulation results. For each simulation, if the powers of other techniques were within a few (1 to 5) percent from the highest power, these were also listed. Power curves of the highest power test statistics in the Kansas simulations can be found in an earlier report by Changnon et al. (1979).

Table 3.2. Summary of High Power Statistics for Simulated Rain Modification, Kansas, 5% Nominal Significance Level

Month	Average Target	Target West	Target East	Month-wise
May	PCR[1],DR,2Reg	PCR[1],SRP	PCR[1],DR	PCR[1],DR
June	DR,PCR[1]	PCR[1]	PCR[1]	PCR[1]
July	PCR[1]	PCR[1],DR,MR	SRP	PCR[1],SRP
August	PCR[1]	PCR[1],2Reg	PCR[1]	PCR[1]
September	PCR[1],2Reg	PCR[1],SRP	PCR[1],MR	PCR[1]
Sea. Avg.	DR,PCR[1],SRP, MR,2Reg	PCR[1]	MR,2Reg	PCR[1],MR, 2Reg
Target-wise	PCR[1],DR,2Reg	PCR[1],SRP	PCR[1],SRP,MR	PCR[1]

3.3 Illinois Results - Month as Unit (ILL-EC)

An area similar in shape and size to those of Kansas was selected in east central Illinois (Fig. 1.4). Identical target-control configuration (Figs. 1.1 and 1.4), time period (1936-1970), and sampling units (month and season) were used to repeat the Kansas simulation; and ten statistics which were found to be most powerful in the Kansas simulation were ranked (Table 3.3). They included D, the average of differences of MR (multiple regression) and PCR[1] (principal component regression with the first component retained), double ratio (DR), T_2 and T3 of the two regressions (2Reg), and A_1, A_2, A_3, C_2, and C_3 (see Appendix A for details) of the sum of rank power test (SRP). Power curves for high power statistics in the ILL-EC simulation are shown in Appendix B. A summary of high power statistics at the 5% nominal significance level is shown in Table 3.4. The techniques of double ratios and principal component regression were generally the most powerful. The technique of two regressions was the next most powerful. The technique of principal component regression still worked well in the ILL-EC simulation in all months except June and August, when the technique of double ratio worked better.

Table 3.3. Ranks of Test Statistics by Powers, at 5% Nominal Significance Level, ILL-CE*

a. County 9 as Target

Month	se	PCR[1]†	DR	MR†	T2	T3	A1	A2	A3	C2	C3
May	1.1	8	9	10	7	6	5	2	1	4	3
	1.2	10	8	9	6.5	6.5	5	2	1	4	3
	1.3	10	9	8	6.5	6.5	5	2	1	4	3
	1.4	9	10	7	7	7	5	2	1	4	3
	Total	37	37	34	27	26	20	8	4	16	12
June	1.1	5	9	2	7	4	1	3	6	8	10
	1.2	6	10	3	7	5	1	2	4	8	9
	1.3	6	8	2	7	5	1	3	4	9	10
	1.4	6	8	1	7	5	2	3	4	9	10
	Total	23	35	8	28	19	5	11	18	34	39
July	1.1	9	7	2	7	7	4	5	10	3	1
	1.2	9.5	9.5	3	7	8	2	4.5	6	4.5	1
	1.3	9	10	6	7	8	2	4	5	3	1
	1.4	9.5	9.5	6	7	8	2	4	5	3	1
	Total	37	36	17	28	31	10	17.5	21	13.5	4
Aug	1.1	7	7	9.5	7	9.5	5	4	2	3	1
	1.2	7.5	10	9	6	7.5	5	4	2	3	1
	1.3	7	9	9	6	9	5	4	3	2	1
	1.4	7.5	7.5	7.5	7.5	10	5	3.5	3.5	2	1
	Total	22	33.5	35	26.5	36	20	15.5	10.5	10	4
Sept	1.1	9.5	3.5	9.5	5.5	3.5	7.5	2	1	7.5	5.5
	1.2	8.5	8.5	1	4	3	5.5	2	5.5	10	7
	1.3	7.5	7.5	1	3	3	3	5	6	9	10
	1.4	9	10	1.5	5.5	5.5	4	1.5	3	7	8
	Total	34.5	29.5	13	18	15	20	10.5	15.5	33.5	30.5
SA	1.1	5	7	1	2.5	2.5	9.5	6	4	9.5	8
	1.2	7	10	3	5	7	4	2	1	7	9
	1.3	3	8.5	1	4.5	8.5	10	6.5	2	6.5	4.5
	1.4	6	6	1	6	6	6	6	6	6	6
	Total	21	31.5	6	18	24	29.5	20.5	13	29	27.5

Table 3.3. (continued)

b. County 10 as Target

Month	se	PCR[1]†	DR	MR†	T2	T3	A1	A2	A3	C2	C3
May	1.1	10	9	6	8	6	6	4	2.5	2.5	1
	1.2	10	9	3.5	7.5	7.5	6	5	3.5	2	1
	1.3	10	9	5.5	7.5	7.5	6	5.5	2	3	1
	1.4	10	9	3	7.5	7.5	4.5	6	4.5	2	1
	Total	40	36	18	30.5	28.5	22.5	20.5	12.5	7.5	4
June	1.1	1.5	7	5	1.5	3	8	5	9	10	5
	1.2	7.5	10	9	6	7.5	5	4	3	2	1
	1.3	6	10	9	7.5	7.5	5	3	4	2	1
	1.4	6	10	9	8	7	3.5	2	5	1	3.5
	Total	21	37	32	23	25	21.5	14	21	15	10.5
July	1.1	7.5	10	2.5	7.5	7.5	7.5	5	1	4	2.5
	1.2	9.5	9.5	1	7	5	6	3	2	4	8
	1.3	10	9	1	6	3.5	7.5	3.5	2	5	7.5
	1.4	9	10	1	3	2	6	7	5	8	4
	Total	36	38.5	5.5	23.5	18	27	18.5	10	21	22
Aug	1.1	9	9	6	9	6	6	3	4	2	1
	1.2	9.5	9.5	6	8	7	5	3	4	2	1
	1.3	10	9	5	8	7	3	4	6	1	2
	1.4	9	10	3	7.5	7.5	6	5	4	2	1
	Total	37.5	37.5	20	32.5	27.5	18	15	18	7	5
Sept	1.1	9	8	10	6	7	4	5	3	1	2
	1.2	8.5	8.5	10	6	7	5	4	3	2	1
	1.3	9	8	10	6	7	5	4	3	2	1
	1.4	9	8	10	6	7	5	4	3	2	1
	Total	35.5	32.5	40	24	28	19	17	12	7	5
SA	1.1	7	10	9	7	7	3	1	4	2	5
	1.2	8.5	10	5	7	8.5	4	3	6	1	2
	1.3	8	10	4.5	8	8	1	2	6	3	4.5
	1.4	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5
	Total	29	35.5	24	27.5	30	13.5	11.5	21.5	11.5	17

Table 3.3. (continued)

c. Avg. of Counties 9 and 10 as Target

Month	se	PCR[1]†	DR	MR†	T2	T3	A1	A2	A3	C2	C3
May	1.1	10	9	6.5	8	6.5	5	4	3	1	2
	1.2	10	8	6	8	8	5	4	3	1	2
	1.3	9	10	5	7.5	7.5	6	4	3	1	2
	1.4	8	10	4	8	8	6	5	3	1	2
	Total	37	37	23	31.5	30	22	17	12	4	8
June	1.1	1	7	6	5	4	10	9	8	2	3
	1.2	2	8	4.5	4.5	3	7	10	9	1	6
	1.3	2.5	7.5	2.5	7.5	4	5	6	9	1	10
	1.4	2.5	7.5	2.5	7.5	4	6	5	9	1	10
	Total	8	30	15.5	24.5	15	28	30	35	5	29
July	1.1	9	10	4	6.5	8	6.5	5	3	1	2
	1.2	10	9	6	7	8	5	3	2	1	4
	1.3	9	10	5	8	7	6	4	3	1	2
	1.4	10	9	4.5	7.5	7.5	6	4.5	3	1	2
	Total	38	38	19.5	29.5	30.5	23.5	16.5	11	4	10
Aug	1.1	8.5	8.5	10	6	7	5	4	2.5	1	2.5
	1.2	9.5	9.5	8	4	6.5	5	3	6.5	1	2
	1.3	8	9	6	4	5	7	3	10	1	2
	1.4	8	9.5	4	6.5	6.5	5	3	9.5	1	2
	Total	34	36.5	28	20.5	25	22	13	28.5	4	8.5
Sept	1.1	10	8	9	6.5	6.5	4	3	5	1	2
	1.2	10	9	8	6.5	6.5	5	4	3	1	2
	1.3	10	9	8	6	7	5	4	3	1	2
	1.4	9	10	8	6	7	4	5	3	1	2
	Total	39	36	33	25	27	18	16	14	4	8
SA	1.1	9	10	6	7.5	7.5	5	4	3	1	2
	1.2	7.5	9.5	5	7.5	9.5	3	4	2	1	6
	1.3	5	5	5	5	5	5	5	5	1	5
	1.4	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5
	Total	27	30	21.5	25.5	27.5	18.5	18.5	15.5	8.5	18.5

*: Most powerful statistic was assigned rank 10 and so on.
†: D was used as the test statistic.

Table 3.4. Summary of High Power Statistics for Simulated Rain Modification, ILL-EC, 5% Nominal Significance Level

Month	Average Target	Target West	Target East	Month-wise
May	PCR[1],DR, 2Reg	PCR[1],DR, MR	PCR[1],DR, 2Reg	PCR[1],DR 2Reg
June	DR,SRP	DR,SRP	DR,MR	DR,SRP
July	PCR[1],DR, 2Reg	PCR[1],DR 2Reg	PCR[1],DR	PCR[1],DR 2Reg
August	PCR[1],DR	MR,DR, 2Reg	PCR[1],DR, 2Reg	DR,PCR[1] 2Reg
September	PCR[1],DR, MR	PCR[1],DR	PCR[1],MR	PCR[1],DR MR
Sea. Avg.	DR,PCR[1], 2Reg	DR,PCR[1] 2Reg,SRP	DR,PCR[1] 2Reg	DR,PCR[1], 2Reg
Target-wise	PCR[1],DR, (2Reg)	DR,PCR[1], (2Reg)	PCR[1],DR (2Reg)	DR,PCR[1] 2Reg

Comparison of Kansas and ILL-EC Simulations. The results of the ILL-EC simulation were compared with those of the Kansas simulation. Statistics which had high powers in both simulations are shown in Table 3.5. The technique of principal component regression had high powers in both simulations in every month except in June, when only the double ratio had high power in the average target simulation. Table 3.6 further summarizes the comparison. For each month, if the statistic appeared in 2 or more testing categories, it was listed. More comparisons on the PCR and DR can be found in the subsequent sections, where several short-term Illinois operational projects are evaluated.

Table 3.5. High Power Statistics Common to Both Kansas and ILL-CE Simulations

Month	Average Target	Target West	Target East
May	PCR[1],DR	PCR[1]	PCR[1]
June	DR	-*	-*
July	PCR[1]	PCR[1],DR	-*
August	PCR[1]	2Reg	PCR[1]
September	PCR[1]	PCR[1]	PCR[1],MR
Sea. Avg.	PCR[1],DR, 2Reg	PCR[1]	2Reg

* In June, PCR[1] had high power in the Kansas simulation; while DR had high power in the ILL-EC simulation;
In July (Target West), SRP had high power in the Kansas simulation; while PCR[1] and DR had high power in the ILL-EC simulation.

Table 3.6. High Power Statistics in the Long-Term Rainfall Enhancement Simulation, 5% Significance Level

Month	Kansas	ILL-EC
May	PCR[1],DR	PCR[1],DR,2Reg
June	PCR[1]	DR,SRP
July	PCR[1],SRP	PCR[1],DR,2Reg
August	PCR[1]	DR,PCR[1],2Reg
September	PCR[1]	PCR[1],DR,MR
Sea. Avg.	PCR[1],MR,2Reg	PCR[1],DR,2Reg
Overall	PCR	PCR,DR,2Reg

3.4 Montana Results

Hail suppression simulation was carried out in a 16-county area of western Montana (Fig. 1.2) through use of annual crop loss data. The test period was 1948-1976, for which suitable crop-hail loss data were available, and during which no evidence of weather modification activity was found. This area is subject to relatively large crop losses from hail damage. Annual values of liability and loss-cost ratios (100 x loss/liability) were furnished by the Crop-Hail Insurance Actuarial Association.

Three counties with high liability (Chouteau, Fergus, and. Judith Basin) were designated as targets, and the 13 surrounding counties as controls (Fig. 1.2). Variances of the hail loss-cost are generally higher than those of the rainfall variables. One target area 25,000 sq km in size and three smaller target areas (A, B, C) 5,000 sq km in size were used (see footnotes in Table 3.7). Because the correlation coefficients of loss-cost between counties decrease more rapidly as a function of distance than those of rainfall, closeness becomes a critical factor. Therefore, only immediate neighboring counties were used as controls. Either 3 or 6 years were randomly selected to form a seeded sub-sample. The corresponding non-seeded sub-sample had sizes of 26 and 23 years respectively. Because of the larger variation in the loss-cost values, 1000 runs were carried out. Ranks of the more powerful test statistics are summarized in Table 3.7 for a simulation of 3 seeded years, and in Table 3.8 for 6 seeded years. Power curves of high power statistics are shown in Appendix B.

Table 3.7. Ranks of Test Statistics by Powers, at 5% Significance Level, Montana, Hail Loss-Cost, 3 Seeded Years*

T-C	se	PC[V][†]	DR	MR[††]	PC[3]	PC[6]	A1	A2	A3	C2	C3
9999**	0.8	8	5	7	10	9	3	1.5	1.5	4	6
	0.6	8	3.5	7	10	9	3.5	2	1	5	6
	0.4	8	4.5	3	9	10	6	2	1	4.5	7
	0.2	2	4	1	8	4	8	8	8	8	4
	Total	26	17	18	37	32	20.5	13.5	11.5	21.5	23
1499	0.8	8	4	7	10	9	6	1.5	1.5	4	4
	0.6	8	6	7	10	9	5	3	3	3	1
	0.4	8	6	7	10	9	5	3	4	1.5	1.5
	0.2	6	8.5	1	10	8.5	7	5	4	3	2
	Total	30	24.5	22	40	35.5	23	12.5	11.5	12.5	8.5
1599	0.8	9	6	7.5	10	7.5	4.5	2.5	4.5	2.5	1
	0.6	8	6	7	10	9	5	2.5	2.5	2.5	2.5
	0.4	8	7	1	10	9	6	2	3	5	4
	0.2	2	5.5	1	4	3	9	9	9	7	5.5
	Total	27	24.5	16.5	34	28.5	24.5	16	19	17	13
1699	0.8	9	2	7	8	10	3.5	3.5	2	5.5	5.5
	0.6	9	4	7	8	10	3	1.5	1.5	5	6
	0.4	9	6	7	8	10	4	1.5	1.5	5	3
	0.2	3.5	5	1	10	9	8	7	3.5	6	2
	Total	30.5	17	22	34	39	18.5	13.5	8.5	21.5	16.5
1494	0.8	9	6	8	10	-	4	2.5	2.5	6	6
	0.6	9.5	7	8	9.5	-	5	3	2	5	5
	0.4	9	7	8	10	-	6	3	4.5	4.5	2
	0.2	5	10	2	7.5	-	6	7.5	9	4	3
	Total	32.5	30	26	37	-	19	16	18	19.5	16
1595	0.8	9.5	7	8	9.5	-	4.5	3	2	6	4.5
	0.6	9	7	8	10	-	6	3	2	5	4
	0.4	8	9	3.5	10	-	7	6	2	5	3.5
	0.2	3	8	2	4	-	8	8	5	8	8
	Total	29.5	31	21.5	33.5	-	25.5	20	11	24	20
1696	0.8	9	6.5	8	10	-	6.5	4	2	4	4
	0.6	10	7	8	9	-	5.5	5.5	3.5	3.5	2
	0.4	9	7	8	10	-	6	4.5	3	4.5	2
	0.2	9.5	8	6	9.5	-	4	3	2	6	6
	Total	37.5	28.5	30	38.5	-	22	17	10.5	18	14

Table 3.7. (continued)

*: The most powerful statistic was assigned rank 10 and so on.
†: A varying number of components was used.
††: W was used as the test statistic.
**: First 2 digits refer to target, the next 2 digits to controls.
They denote respectively
Target : 99 = (14+15+16)/3,
Control : 99 = Average of 1, 2,_____, 13,
94 = (1+2+3+5+6+7+15+16)/8
95 = (7+8+9+10+11 + 12+14+16V8
96 = (1+12+13+14+15)/5

Table 3.9 further summarizes the simulation findings. For the larger target, the principal component regression with 3 components (PCR[3]) was the most powerful. For smaller targets, PCR[3] worked well in the 3 seeded years study. DR was most powerful in the 6 seeded years study, followed closely by PCR[3] and SRP. The technique of two regressions was not compared in the 3-year study, but was compared in the 6-year study. Its powers were rather poor relative to other techniques. The technique of SRP had poor powers in the 3-year study except when the assumed seeding effect was large.

Table 3.8. Ranks of Test Statistics by Powers, at 5% Significance Leve, Montana, Hail Loss-Cost, 6 Seeded Years.*

T-C	se	PC[V]†	DR	MR††	PC[3]	PC[6]	A1	A2	A3	C2	C3
9999**	0.8	8	7	3	10	9	3	1	3	5	6
	0.6	5	9.5	1	8	9.5	4	2	3	6	7
	0.4	2	9	1	10	5	3.5	3.5	7	7	7
	0.2	2	7	1	7	3	7	7	7	7	7
	Total	17	32.5	5	35	26.5	17.5	13.5	20	25	27
1499	0.8	9	8	1	10	5	3.5	6.5	6.5	3.5	2
	0.6	6	9	1	10	5	4	7	8	3	2
	0.4	5	10	1	7	3	6	8	9	4	2
	0.2	4	9	2	6	1	7	9	9	5	3
	Total	24	36	5	33	14	20.5	30.5	32.5	15.5	9
1599	0.8	7	10	1	8.5	8.5	3.5	3.5	6	3.5	3.5
	0.6	2	10	1	9	7	7	5	3	7	4
	0.4	2	10	1	4	3	6.5	6.5	6.5	9	6.5
	0.2	2	7.5	1	3	4	7.5	7.5	7.5	7.5	7.5
	Total	13	37.5	4	24.5	22.5	24.5	22.5	23	27	21.5
1699	0.8	8	10	3.5	2	9	6.5	3.5	1	6.5	5
	0.6	8	10	2.5	2.5	9	5	4	1	6.5	6.5
	0.4	6	10	1	9	7.5	5	4	2	7.5	3
	0.2	2	8	1	4	3	8	8	6.5	6.5	5
	Total	24	38	8	17.5	28.5	24.5	19.5	10.5	27	19.5
1494	0.8	10	8	2	4.5	-	6	7	9	4.5	3
	0.6	6	10	2	3	-	7	8	9	5	4
	0.4	4	10	2	3	-	7	8	9	6	5
	0.2	4	9	2.5	2.5	-	7	9	9	6	5
	Total	24	37	8.5	13	-	27	32	36	21.5	17
1595	0.8	7.5	10	3	7.5	-	7.5	3	3	7.5	5
	0.6	4.5	10	2	7	-	9	4.5	6	8	3
	0.4	3	10	2	4	-	9	8	5	7	6
	0.2	3	7.5	2	4	-	7.5	7.5	7.5	7.5	7.5
	Total	18	37.5	9	22.5	-	33	23	21.5	30	21.5
1696	0.8	10	8	2	9	-	7	5.5	3.5	5.5	3.5
	0.6	9	8	3	10	-	7	4	2	6	5
	0.4	8.5	10	3	8.5	-	5	4	2	6.5	6.5
	0.2	3.5	7	2	3.5	-	7	7	5	9.5	9.5
	Total	31	33	10	31	-	26	20.5	12.5	27.5	24.5

See Table 3.7 for footnotes.

Table 3.9. High Power Statistics in the Montana Hail Suppression Simulation, 5% Significance Level

Target Size (sq km)	No. of Seeded and Unseeded Years 3 vs 26	6 vs 23
25,000	PCR[3],PCR[6]	PCR[3],DR
5,000:		
A	PCR[3],DR	DR,SRP,PCR[3]
B	PCR[3],DR	DR,SRP
C	PCR[3],MR	DR,PCR[3]

3.5 Illinois Results - Storm as Unit (ILL-ST)

The third data set used for simulation involved an area of approximately 5200 sq km centered on St. Louis, Missouri, which contained a network of 225 recording raingages during the 5-year period, 1971-1975 (Fig. 3.1). This was the site of comprehensive research on urban effects on precipitation known as METROMEX (Changnon et al., 1977) and, consequently, provided a large sample of analyzed, high-quality, meteorological data for use in the OSET studies. Simulation studies were undertaken to ascertain the best statistical techniques for use in evaluating seeding-induced effects in individual storms, as well as in units of 48 hours, which might include several individual storms, but usually involved a single synoptic weather situation.

Moving target-control areas, dictated by storm motion, were employed in the ILL-ST simulations. This approach permits more accurate assessment of seeding effects than fixed target-control areas, since it minimizes contamination of designated controls by the seeding agent. Simulation was performed on summer data (June-August), because this is the period of greatest need for weather modification by agriculture, the major beneficiary in the central and eastern parts of the country (WMAB, 1978a). Although users may be primarily interested in the net effect of rain enhancement or hail suppression over an extended period of time (months, seasons), seeding success is dependent upon what can be accomplished in specific seeding situations: that is, on a storm (rain event) or daily basis under various types of synoptic weather conditions.

For each storm, a target was defined as the area in the downwind side of the network according to the storm motion (Fig. 3.1). Upwind controls were similarly defined. A smaller circular area centered at the network center was used as a buffer, and, thus, not used in the simulations. In addition, for a storm to be included in the simulation, it must also satisfy a minimum rainfall condition, that is, the maximum raingage storm rainfall in the target and in at least one of the three opposite controls must be equal to or greater than 0.10 inch. The reason for imposing this condition is that there were a considerable number of storms during the 5-year period that either just grazed the METROMEX network or were stationary storms, which either did not produce rains over the target area or rendered the target-control comparison difficult. In all there were 132 storm units which had an identifiable storm motion and satisfied the minimum rainfall condition. The rainfall totals of these 132 storms indicated that at most 15% of

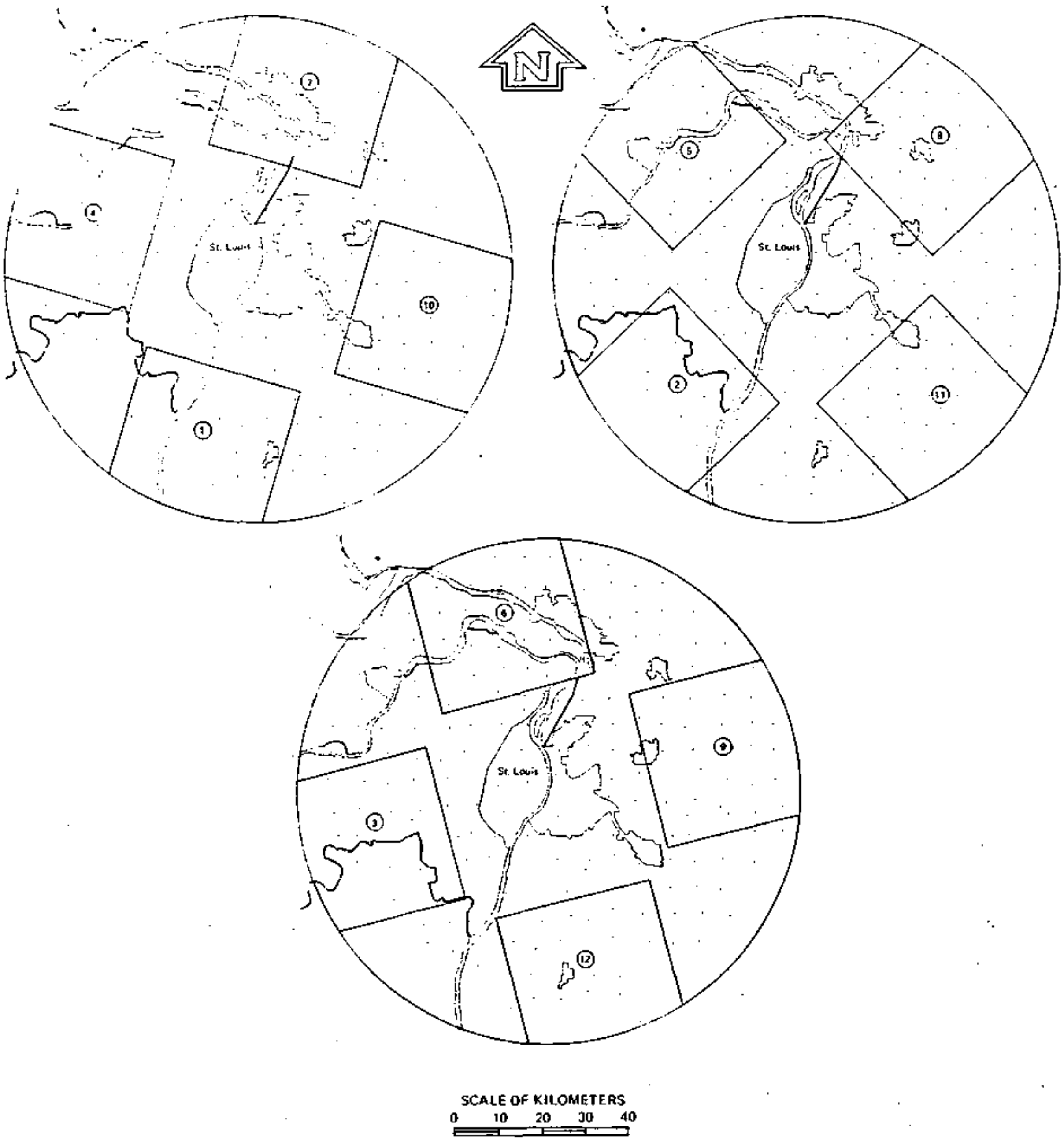


Figure 3.1 Illinois-Storm Simulation Study Area

rain was deleted from all rains falling in the network each year (Table 3.10). In other words, approximately 200 storms which did not satisfy the minimum rainfall condition contributed very little to the rains falling over the METROMEX network during the 1971-1975 period.

Table 3.10. Percentage of June-August Rainfall for Selected Subsets of Storms with Identifiable Motion, METROMEX (Number of storms in parentheses)

	Year					
Subset	71	72	73	74	75	71-75
All Storms	100.00 (47)	100.00 (69)	100.00 (65)	100.00 (80)	100.00 (69)	100.00 (330)
Max. rains in at least one control greater than 0"	98.21 (38)	99.59 (53)	99.91 (50)	93.60 (65)	99.66 (52)	98.23 (258)
Max. rains in at least one control and target greater than 0"	96.50 (3D	97.50 (34)	99.34 (39)	90.83 (38)	98.52 (39)	96.63 (181)
Max. rains in at least one control and target greater than 0.1"	90.77 (21)	95.12 (24)	90.99 (24)	87.96 (28)	96.45 (35)	92.44 (132)

Three rainfall variables were used in the simulation: total storm rainfall volume over the area (Total Rains), maximum point (storm) rainfall total over the area (Max. Rains), and mean point (storm) rainfall total over the area (Avg. Rains). The correlation coefficients between the target and controls for Total Rains were in the range of 0.7 to 0.9 with the exception of 1971, when it was .54. There were fewer storms in 1971 than other years (Table 3-10) which might render a smaller correlation coefficient. A similar range of correlation coefficients was found for Avg. Rains. However, for Max. Rain the correlation coefficients were generally lower. The goodness-of-fit tests for these rainfall variables in each area revealed that Max. Rains and Avg. Rains in the 3 controls fitted the lognormal distribution well but Total Rains in the controls fitted the gamma distribution better. Max. Rains in the target fitted the gamma distribution well, but Total Rains and Avg. Rains fitted the lognormal distribution better than the gamma distribution.

Approximately one-fifth, 26 out of 132 units, were randomly selected to form a 'seeded' sample. Both constant and varying seeding-induced changes were used in the simulations. Results of simulations incorporating meteorological covariates are reported later. Powers at the 5% and 10% nominal significance levels of MR, PCR[1], and DR, the high power statistics, are shown in Tables 3.11 and 3.12. Ranks of the more powerful test statistics are shown in Table 3.13. Their power curves are shown in Appendix B.

Table 3.11. Powers at 5% Significance Level, ILL-ST Simulation

se	MR W	MR D	MR T	PCR[1] W	PCR[1] D	PCR[1] T	DR
			Total Rains				
1.1	.108	.152	.144	.128	.130	.128	.118
1.2	.180	.300	.282	.238	.288	.272	.226
1.3	.236	.486	.458	.372	.450	.436	.344
1.4	.318	.650	.622	.462	.602	.584	.516
A	.324	.356	.322	.404	.332	.302	.274
E	.640	.654	.622	.692	.608	.574	.508
C	.072	.034	.034	.110	.028	.032	.072
M	.174	.344	.320	.240	.316	.302	.262
			Max. Rains				
1.1	.118	.170	.148	.108	.162	.148	.160
1.2	.234	.352	.306	.218	.338	.300	.308
1.3	.358	.588	.544	.368	.582	.548	.484
1.4	.468	.786	.722	.472	.750	.720	.654
A	.498	.646	.582	.534	.640	.588	.528
E	.834	.924	.890	.828	.904	.882	.800
C	.098	.106	.090	.078	.086	.080	.110
M	.226	.386	.334	.212	.370	.342	.322
			Avg. Rains				
1.1	.138	.134	.132	.136	.134	.132	.130
1.2	.248	.300	.282	.270	.300	.294	.262
1.3	.344	.496	.476	.436	.510	.496	.482
1.4	.492	.698	.662	.578	.682	.656	.642
A	.558	.438	.400	.568	.430	.412	.402
E	.868	.772	.746	.858	.774	.738	.730
C	.125	.030	.036	.150	.030	.036	.058
M	.236	.342	.328	.274	.354	.330	.298

Table 3.12. Powers at 10% Significance Level, ILL-ST Simulation

	MR			PCR[1]			DR
se	W	D	T	W	D	T	
				Total Rains			
1.1	.190	.264	.244	.220	.254	.228	.208
1.2	.274	.454	.426	.332	.438	.422	.332
1.3	.384	.628	.610	.472	.608	.574	.524
1.4	.478	.784	.758	.586	.736	.716	.678
A	.464	.528	.506	.504	.488	.470	.392
E	.772	.826	.786	.792	.770	.744	.682
C	.138	.086	.080	.186	.088	.086	.104
M	.276	.508	.476	.344	.486	.460	.388
				Max. Rains			
1.1	.238	.232	.240	.220	.264	.256	.244
1.2	.400	.470	.458	.374	.478	.464	.404
1.3	.542	.682	.674	.558	.700	.678	.598
1.4	.662	.832	.828	.694	.840	.826	.758
A	.696	.746	.730	.712	.758	.738	.634
E	.926	.964	.962	.922	.956	.948	.882
C	.204	.166	.172	.186	.176	.172	.182
M	.398	.492	.490	.372	.516	.486	.428
				Avg. Rains			
1.1	.216	.246	.242	.222	.246	.242	.232
1.2	.326	.464	.444	.396	.474	.464	.444
1.3	.478	.662	.640	.572	.646	.634	.634
1.4	.620	.814	.796	.710	.788	.772	.778
A	.672	.608	.588	.704	.614	.598	.584
E	.924	.906	.892	.924	.888	.880	.832
C	.188	.100	.096	.238	.100	.104	.122
M	.322	.500	.484	.390	.510	.502	.500

Table 3.13. Ranks of Test Statistics by Powers at 5% Significance Level, ILL-ST Simulation, Total Rain*

Variable	se	PCR[1]†	DR	MR†	T2	T3	A1	A2	A3	C2	C3
Total Rain	1.1	9	6	10	2.5	2.5	6	6	6	6	1
	1.2	9	6	10	8	7	5	3	2	4	1
	1.3	9	6	10	7.5	7.5	2	3.5	3.5	5	1
	1.4	9	6	10	7.5	7.5	4	5	3	2	1
	Total	36	24	40	25.5	24.5	17	17.5	14.5	17	4
	A	4	1	5	2.5	2.5	10	9	7	8	6
	E	4	1	5	3	2	10	8	7	9	6
	C	2.5	5	2.5	2.5	2.5	9	6	7	10	8
	M	9	6	10	7.5	7.5	4	3	2	5	1
	Total	20.5	13	22.5	15.5	14.5	33	26	23	32	21
Max Rain	1.1	8	6	10	6	6	9	3.5	1	3.5	2
	1.2	9	8	10	6.5	6.5	4	2	1	5	3
	1.3	9	6	10	8	7	2	4	3	1	5
	1.4	9	6	10	7	8	4	5	2	3	1
	Total	35	26	40	27.5	27.5	19	14.5	7	12.5	11
	A	5	1	6	3.5	3.5	10	7	2	9	8
	E	5	1	9	6.5	6.5	10	2	6	8	4
	C	1	3	2	4.5	4.5	8	10	7	9	6
	M	9	6	10	7.5	7.5	3	5	2	4	1
	Total	20	11	27	22	22	31	24	17	30	21
Avg Rain	1.1	9.5	7	9.5	3.5	5.5	3.5	2	8	5.5	1
	1.2	9.5	5	9.5	7.5	7.5	2	4	6	3	1
	1.3	10	7	9	6	8	2.5	2.5	4.5	4.5	1
	1.4	9	6	10	7	8	2.5	5	2.5	4	1
	Total	38	25	38	24	29	10.5	13.5	21	17	4
	A	3	1	5	3	3	10	7	6	9	8
	E	3	1	2	4.5	4.5	9.5	7	6	9.5	8
	C	1.5	5	1.5	3.5	3.5	10	7	4	9	8
	M	10	6	9	7	8	1	4	5	3	2
	Total	17.5	13	17.5	18	19	30.5	25	21	30.5	26

*: Most powerful statistic was assigned rank 10 etc.
†: D was used as the test statistic.

Results for constant seeding-induced increases indicated that MR and PCR[1] were the most powerful techniques (Table 3.14).

Table 3.14. High Power Statistics in the Illinois Short-Term Rainfall Enhancement Simulation, 5% Significance Level, Constant Seeding Effect Assumed

Rainfall Response Variable	Unit: Storm	48-Hr
Total Rain	MR,PCR[1]	MR,PCR[1]
Max. Rain	MR,PCR[1]	MR,PCR[1],DR
Avg. Rain	MR,PCR[1]	MR,DR,2Reg

In addition to constant seeding-induced changes, four models (A, E, C, M) of varying seeding-induced changes (Table 3.15) were used in the ILL-ST simulation.

Table 3.15. Varying Seeding Effect Model

Gage Average (inches)	Model A	E	C	M
0.00-0.09	100	150	50	10
0.10-0.25	50	75	20	15
0.26-0.50	50	75	20	20
0.51-1.00	20	30	0	25
greater than 1.00	0	10	-10	25

Simulation results using varying changes were different from those using constant changes. Power at the 5% and 10% nominal significance levels are shown in Tables 3.11 and 3.12. Ranks of the more powerful test statistics are shown in Table 3.13. Their power curves are shown in Appendix B. The SRP was the most powerful when seeding effect models A, E, and C were assumed (Table 3.16); while MR and PCR[1] were the most powerful when model M was assumed. A distinction among the four models is that in models A, E, and C seeding-induced rainfall changes were inversely proportional to rainfall amounts; but, in model M they were proportional to rainfall amounts. As a matter of fact, model M is rather similar to the constant-effect models.

Table 3.16. High Power Statistics in the Illinois Short-Term Rainfall Enhancement Simulation, 5% Significance Level, Varying Seeding Effect Assumed , Storm as Unit

Rainfall Response Variable	Model A	E	C	M
Total Rain	SRP	SRP	SRP	MR,PCR[1]
Max. Rain	SRP	SRP,MR	SRP	MR,PCR[1]
Avg. Rain	SRP	SRP	SRP	PCR[1],MR

The means and standard deviations of precipitation changes of 500 'seeded' samples for each model are shown in Table 3.17. Not surprisingly, model E generated the greatest precipitation increases in all rainfall response variables, model A generated the next greatest precipitation increases, and model C generated very small precipitation increases, which explained its rather poor powers in the simulation. Model M generated precipitation increases with magnitude similar to those of model A. Interestingly, model M had a smaller standard deviation than models A, E, or C. In addition, mean precipitation increases of each model (Table 3.17) corresponded roughly to the changes between the category of .26-.50 and the category of .51-1.00 (Table 3.15).

Table 3.17. Mean and Standard Deviation of Imposed Precipitation Changes, 500 Runs

	Model A	E	C	M
Total Rain	1.242	1.400	1.003	1.225
	.060	.077	.049	.008
Max. rain	1.325	1.510	1.066	1.212
	.053	.072	.041	.009
Avg. rain	1.272	1.441	1.025	1.220
	.061	.080	.049	.009

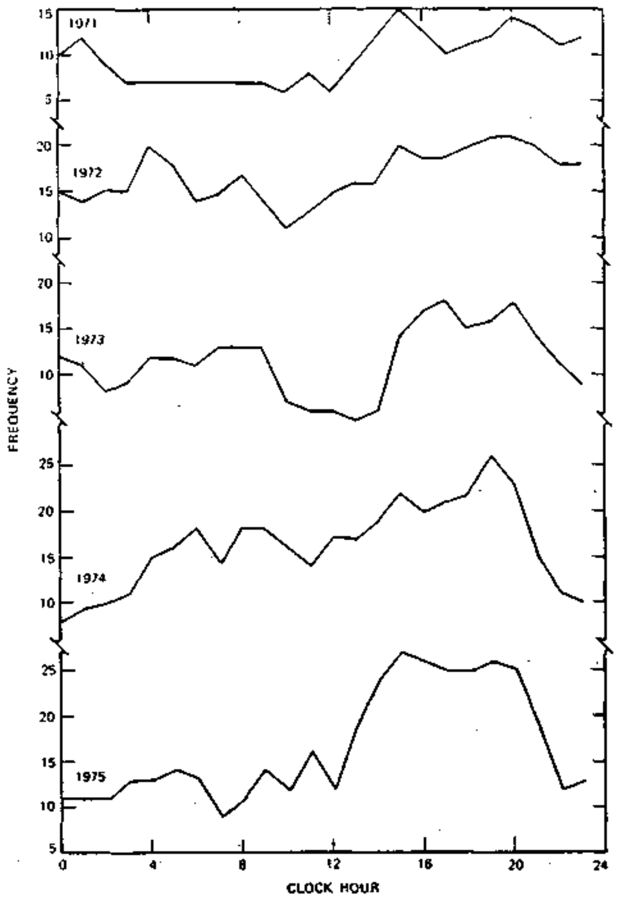
3.6 Illinois Results - 48-hour as Unit (ILL-48)

In evaluating an operational project, generally one does not have precipitation data in the historical period which would contain as much detail as the METROMEX project raingage data. Most frequently only the daily or monthly precipitation data from the National Weather Service stations are available. Therefore, one has to use daily values or multi-day values. The unit of 48 hour was selected over the unit of 24 hour mainly to avoid splitting a natural storm (rain event) into 2 units (Huff and Semonin, 1960).

The 48-hour unit was derived from the same basic METROMEX data as in the ILL-ST simulation study. In order that as many storms as possible be included in one unit, the number of rain events occurring at each clock hour, 0, 1, ---, 23, was tallied (Fig. 3.2). Rains occurred with least frequency at both 0200 and 1000. A secondary minimum was at 0700. Because of the NWS practice of taking observations at either 0700 or 1900, it was decided to use 0700 as the starting time of a 48-hour unit. The 48-hour unit was defined to be the period starting at 0700 under the condition that there must be rain in the first 24-hour period of the unit. There were 129 units thus defined during the period 1971-1975. A fixed target in the general downwind direction and five fixed control areas were defined (Fig. 1.3). Each has an area of 800 sq kms. Furthermore, units which did not have a minimum of .01 inch rain in the target were excluded from the simulation. In all, there were 122 units used in the ILL-48 simulation.

Three rainfall variables were used in the simulation. They were: total rainfall volume over the area (Total Rains), maximum point rainfall total over the area (Max. Rains), and the mean point rainfall total over the area (Avg. Rains). The distributions of these rainfall variables were highly skewed. The goodness-of-fit tests for these variables in each area revealed that all rainfall variables were well fitted by the gamma distribution, but were badly fitted by the normal distribution, and fitted marginally by the lognormal distribution.

Approximately one-fifth, 24 of 122 units, were randomly selected to form a 'seeded' sample. The evaluation design used is historical continuous target-control. Powers at the 5% and 10% nominal significance levels of MR, PCR[1], PCR[3], and DR, the high power statistics, are shown in Table 3.18. Ranks of the more powerful test statistics are shown in Table 3.19. Their power curves are shown in Appendix B. A summary of simulation when constant seeding-induced increases (10-40%) were assumed is shown in Table 3-14. The multiple regression was the most powerful technique in all cases; the principal component regression with 1 component (PCR[1]) was a close second. The double ratio performed well, too.



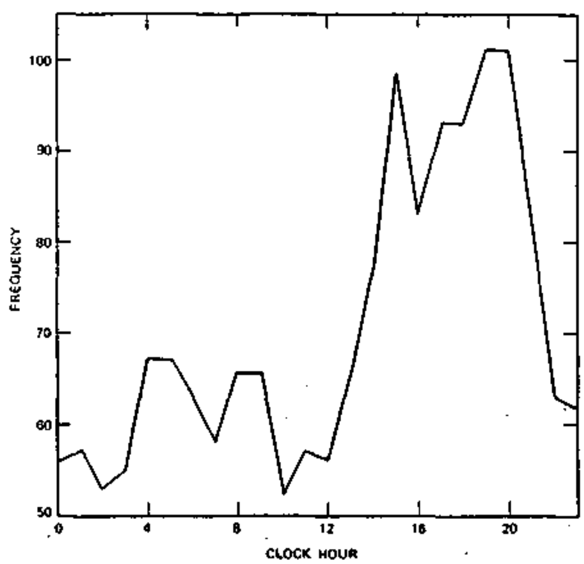


Figure 3.2 Number of Rains Occurring at Each Hour Sharp, METROMEX Network, 1971-1975

Table 3.18. Powers at 5% and 10% Significance Levels, ILL-48 Simulation

Seeding Effect	MR W	MR D	MR T	PCR[1] W	PCR[1] D	PCR[1] T	PCR[3] W	PCR[3] D	PCR[3] T	DR
					Total Rains, 5%					
1.1	.150	.198	.200	.142	.166	.164	.150	.192	.174	.164
1.2	.298	.466	.458	.296	.360	.334	.294	.462	.408	.338
1.3	.472	.700	.686	.486	.560	.522	.502	.688	.648	.528
1.4	.638	.866	.856	.608	.734	.710	.680	.842	.804	.720
					Max. Rains, 5%					
1.1	.184	.190	.170	.166	.162	.158	.180	.172	.162	.188
1.2	.416	.446	.388	.364	.412	.362	.414	.398	.350	.390
1.3	.622	.706	.682	.546	.658	.622	.598	.684	.630	.642
1.4	.776	.846	.828	.674	.820	.792	.746	.830	.804	.788
					Avg. Rains, 5%					
1.1	.144	.236	.230	.138	.182	.152	.158	.204	.190	.212
1.2	.310	.534	.510	.316	.388	.364	.364	.470	.448	.424
1.3	.508	.772	.752	.534	.600	.574	.572	.722	.692	.654
1.4	.708	.908	.894	.666	.786	.748	.762	.874	.866	.826
					Total Rains, 10%					
1.1	.244	.294	.292	.238	.246	.236	.266	.274	.254	.278
1.2	.438	.590	.572	.460	.468	.456	.504	.554	.526	.484
1.3	.622	.798	.788	.638	.678	.656	.674	.756	.740	.686
1.4	.778	.900	.894	.790	.810	.800	.836	.886	.868	.854
					Max. Rains, 10%					
1.1	.292	.292	.274	.296	.292	.270	.326	.256	.244	.270
1.2	.560	.588	.560	.528	.568	.546	.576	.540	.512	.516
1.3	.748	.784	.770	.680	.786	.762	.738	.780	.762	.740
1.4	.878	.902	.886	.812	.882	.864	.864	.886	.870	.854
					Avg. Rains, 10%					
1.1	.254	.320	.314	.236	.276	.260	.292	.300	.306	.290
1.2	.492	.644	.638	.484	.520	.512	.554	.600	.594	.520
1.3	.698	.844	.846	.680	.728	.708	.752	.816	.806	.742
1.4	.852	.934	.930	.820	.872	.852	.878	.916	.908	.886

Table 3.19. Ranks of Test Statistics by Powers at 5% Significance Level, ILL-48 Simulation, Total Rain*

Variable	Seeding Effect	1PC†	DR	MR†	T2	T3	A1	A2	A3	C2	C3
Total Rain	1.1	9	8	10	6	7	5	3	2	1	4
	1.2	9	8	10	6.5	6.5	4	5	3	1	2
	1.3	9	6	10	7	8	5	3	4	1	2
	1.4	9	6	10	7.5	7.5	3	5	4	1	2
	Total	36	28	40	27	29	17	16	13	4	10
Max Rain	1.1	8	10	9	6.5	6.5	2.5	4.5	4.5	2.5	1
	1.2	9	8	7	4	3	1	6	10	5	2
	1.3	9	7	10	4	5.5	1	5.5	8	3	2
	1.4	9	7	10	4	5	1	6	8	2	3
	Total	35	32	36	18.5	20	5.5	22	30.5	12.5	8
Avg Rain	1.1	7	9	10	8	6	2	3.5	5	3.5	1
	1.2	7	9	10	8	6	1	4	5	3	2
	1.3	6	9	10	8	7	1	4	5	3	2
	1.4	5.5	9	10	8	7	1	2	5.5	3	4
	Total	25.5	36	40	32	26	5	13.5	20.5	12.5	9

*: Most powerful statistic was assigned rank 10 etc.

†: D was used as the test statistic.

4. TESTING OF THE TECHNIQUES

A number of past seeding projects of the commercial type were selected for testing of the statistical-physical techniques developed. They included a large-scale combined hail suppression and rain enhancement project in southwestern Kansas (the Muddy Road Project), several small-scale rainfall enhancement projects in Illinois, and a hail suppression project carried out in the Texas Panhandle.

4.1 The Muddy Road Project

The evaluation of operational projects which extend over relatively large areas (10,000 sq km or more) produces complex spatial and temporal control problems relating to climatic homogeneity and temporal variability. Large-area seeding projects have become more common and will undoubtedly contine to be so in the future as weather modification becomes more widely accepted. Such a large-area seeding project, the Muddy Road Project, was selected for statistical evaluation to address the objective of testing the techniques developed.

The Muddy Road Project was conducted in southwestern Kansas and encompassed a target area of 12-15 counties (Fig. 4.1). The project was for both rainfall enhancement and hail suppression during the warm season, April to September, from 1975 to the present. The period of 1975-1979 was selected for evaluation. Data sets employed consisted of (1) monthly and seasonal rainfall totals, 1931-1971, and 1975-1979, derived from the observations of the National Weather Service stations; and (2) annual hail insurance loss-cost ratios (L/C), defined as 100 x hail damage / insurance liability, 1948-1971, and 1975-1979, furnished by the Crop Hail Insurance Actuarial Association. The years 1972-1974 were excluded from consideration mainly for the reason that there existed cloud seeding activities performed by other operators during this period either inside or to the south of the target area.

Neighboring counties were used as area controls and were grouped into areas of roughly the same size as the west and east sub-targets (Fig. 4.1). The controls were further divided into near-upwind (N-U), mid-upwind (M-U), far-upwind (F-U), and downwind (D) regions according to their distances from the target area.

Evaluation of Hail Suppresion. The correlation coefficients between the sub-targets and controls varied from 0.0 to 0.7 according to the distances (Hsu and Chen, 1981a). Ratios of seeded average L/C (1975-1979) to historical average L/C (1948-1971) show that most of the target ratios were less than 0.5. Controls to the south and west also were less than 0.5 (Fig. 4.2). The target ratios were all less than 1.0 except the northwestern and southeastern corners, where the ratios were between 1.0 and 2.0. A portion of this low in the target was significant at the .10 level using a 2-sample Wilcoxon test. Some control ratios were also significant at the .10 level.

The techniques of multiple regresion (MR) and principal component with 3 components (PCR[3]) were applied to the L/C data. The mean differences between the estimated and observed seeded values, and their permutational significances are shown in Table 4.1. All the estimated mean differences were negative with the east sub-target showing more reduction than the west sub-target. When the

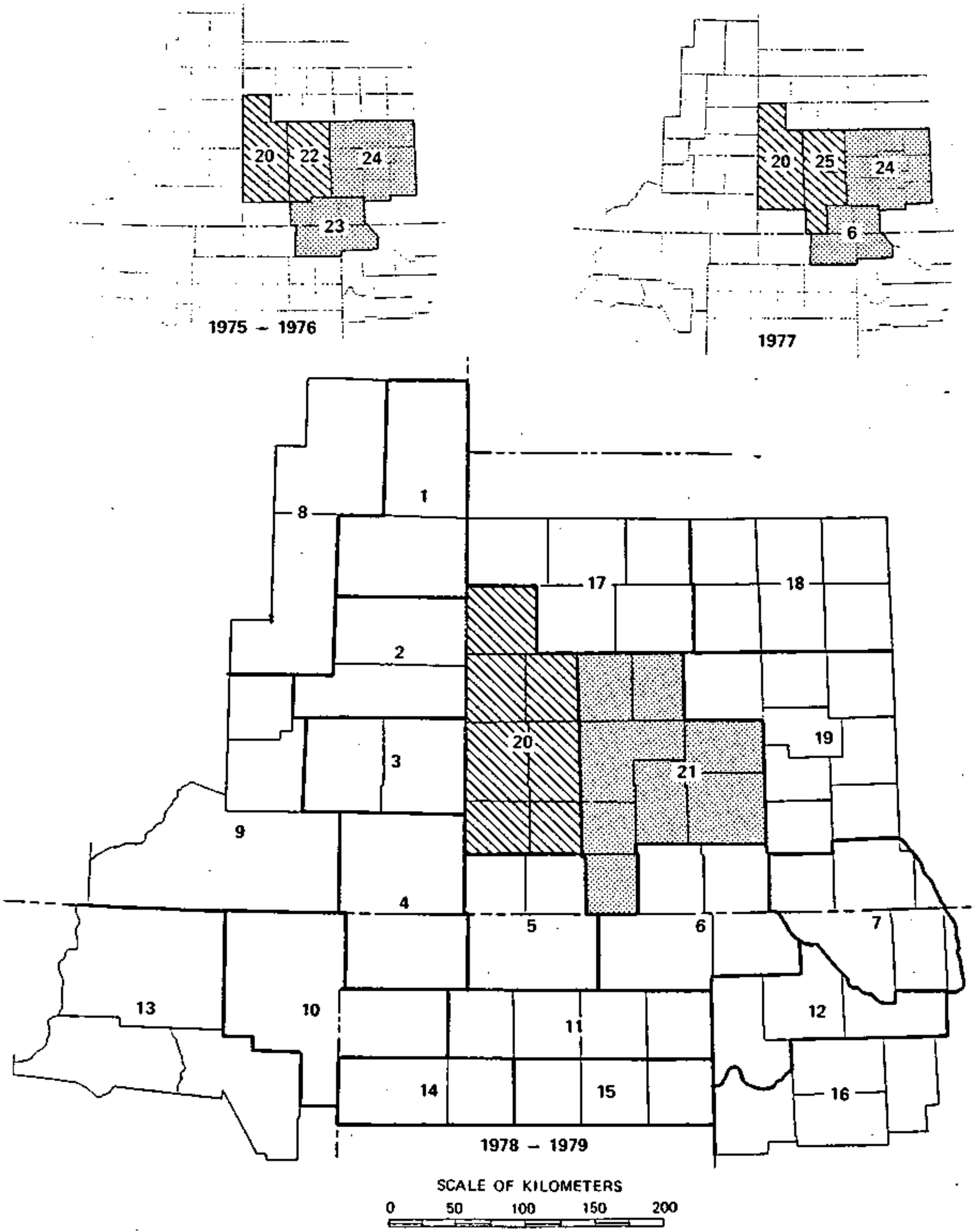


Figure 4.1 Muddy Road. Project Area

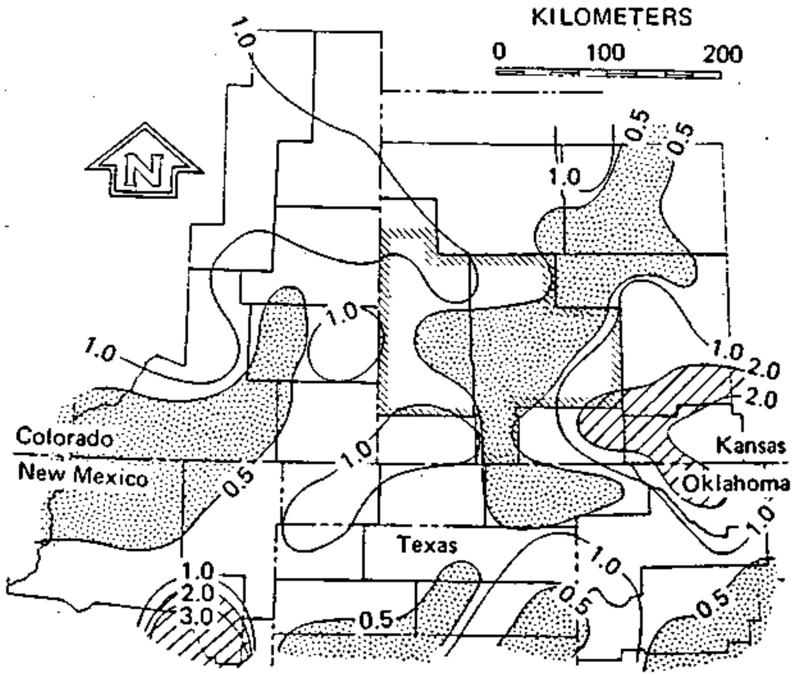


Figure 4.2 *Ratio of Hail Loss-Cost 1975-1979 Average to 1948-1971 Average.*

near-upwind and mid-upwind controls were used, the estimated seeding effects were more pronounced and significant at higher level. Generally the multiple regression values showed slightly more reduction in hail loss-cost than did the principal component regression values. However, the results by PCR were significant at higher level.

Table 4.1. Mean Difference and 1-Sided Permutational Significance Level, Hail Loss-Cost

Target	Control	MR		PCR	
West	N-U	-1.09	(.33)	-1.70	(.23)
	N-U & M-U	-1.94	(.30)	-1.76	(.26)
	All	-1.16	(.41)	-0.75	(.39)
East	N-U	-3.79	(.14)	-4.39	(.06)
	N-U & M-U	-6.09	(.09)	-3.98	(.09)
	All	-4.97	(.16)	-2.62	(.16)

Evaluation of Rainfall Enhancement. Seasonal average rainfall was computed as the mean of May-August monthly rains. The correlation coefficients between the seasonal rains of sub-targets and the controls were in the range of 0.5 to 0.9 (Hsu and Chen, 1981a). Ratios of seeded average seasonal rains (1975-1979) to historical average seasonal rains (1948-1971) show that most of the target ratios were near 1.0, with the eastern sub-target above 1.0, and the northwestern corner and southern portion below 1.0 (Fig. 4.3). Larger rain ratios occurred in Oklahoma and Colorado than in the target area. The rain ratios were generally not different from 1.0 except one high ratio area in the southeastern corner, whose ratio was close to 1.4. Ratios in the downwind half of the target area were higher than those in the other half.

The techniques of multiple regresion (MR) and principal component with 3 components (PCR[3]) were applied to the seasonal and monthly rains. The mean differences between the estimated and observed seasonal seeded values, and their permutational significances are shown in Tables 4.2 and 4.3. All the estimated mean differences were negative, but not statistically significant. The smallest rain decrease in the west sub-target, -0.10, amounted to 4% of the 1931-1971 mean (2.54 inches); while that in the east sub-target, -0.08, amounted to 3% of the historical mean (2.54 inches).

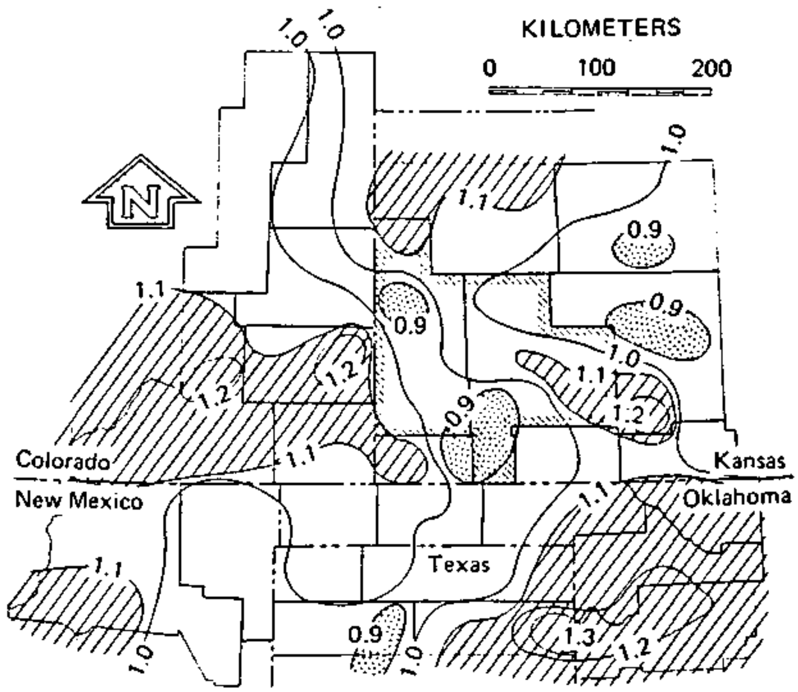


Figure 4.3 Ratio of Seasonal Rain, 1975-1979 Average to 1931-1971 Average.

Table 4.2. Mean Difference and 1-Sided Permutational Significance Level, Seasonal Rainfall

Target	Control	MR		PCR[3]	
West	M-U	-.14	(.79)	-.11	(.76)
	N-U & M-U	-.10	(.68)	-.14	(.79)
	All	-.28	(.88)	-.12	(.73)
East	N-U	-.18	(.76)	-.21	(.85)
	N-U & M-U	-.08	(.61)	-.24	(.84)
	All	-.19	(.82)	-.24	(.88)

Results for the monthly rainfall are shown in Table 4.3. Most estimated rain changes were small and statistically non-significant except for April in the East sub-target (rain increase), April in the West sub-target (rain decrease), and May in the East sub-target (rain decrease). In general, the technique of PCR indicated more increases or less decreases than the MR, except in the months of July and August. Overall, the East sub-target received more rainfall increases than the West sub-target except in the months of May and September. When using PCR as an evaluation technique, the utilization of both near- and mid-upwind controls produced more favorable results than using only near-upwind controls. However, the comparison of using near- and mid-upwind controls with using all controls revealed no preference.

In conclusion, the evaluation on the hail suppression indicated that there was a reduction of hail loss-cost values during the 1975-1979 seeded period; however, only the reduction in the East sub-target was significant at the 10% level. This example also demonstrated that the principal component regression (PCR) is a better technique for evaluating hail suppression than the multiple regression (MR). On the other' hand, the statistical evaluation on the rainfall observations indicated that there was a non-significant reduction of rainfall in the target area during the seeded period.

Table 4.3. Mean Differences and One-Sided Permutational Significance Level, Monthly Rainfall.

Month	West Sub-Target vs N-U	West Sub-Target vs N-U & M-U	West Sub-Target vs All	East Sub-Target vs N-U	East Sub-Target vs N-U & M-U	East Sub-Target vs All
			Multiple Regression			
April	-.54	-.65	-.80	.58	.27	.07
	(.95)	(.94)	(.96)	(.02)	(.16)	(.36)
May	-.03	.02	-.08	-.76.	-1.09	-.83
	(.54)	(.49)	(.58)	(.96)	(1.00)	(.97)
June	-.10	-.30	-.40	.19	-.03	-.07
	(.60)	(.76)	(.84)	(.32)	(.55)	(.63)
July	-.28	-.07	.03	-.15	-.07	.11
	(.82)	(.61)	(.47)	(.61)	(.57)	(.41)
Aug	.07	.09	.32	.32	.13	.22
	(.39)	(.35)	(.16)	(.31)	(.32)	(.21)
Sept	-.19	-.13	-.43	-.19	-.24	-.47
	(.72)	(.67)	(.93)	(.70)	(.71)	(.94)
			Principal Component Regression			
April	-.34	-.11	-.03	.63	.83	.84
	(.87)	(.59)	(.47)	(.00)	(.00)	(.00)
May	.02	.23	.23	-.75	-.50	-.44
	(.50)	(.25)	(.25)	(.97)	(.86)	(.82)
June	.09	.10	.06	.13	.14	.01
	(.40)	(.42)	(.47)	(.35)	(.34)	(.49)
July	-.48	-.36	-.33	-.23	-.10	-.03
	(.92)	(.89)	(.87)	(.69)	(.57)	(.50)
Aug	.03	-.06	-.16	.30	.16	-.04
	(.44)	(.55)	(.67)	(.30)	(.32)	(.50)
Sept	-.19	-.18	-.15	-.27	-.21	-.13
	(.73)	(.69)	(.67)	(.74)	(.67)	(.61)

* N-U, M-U denote repspectively near- and raid-upwind controls, All denotes all controls.

4.2 Illinois Projects

During the 1976-1980 period, there were eight 1-summer weather modification projects in east and central Illinois, each attempting to increase summer rainfall through cloud seeding with silver iodide. Basically they utilized the same seeding approaches and facilities (Changnon and Hsu, 1981). They included a five-county project centered on Coles County (1975 and 1976), a project in Vermilion County (1977), operations in McLean County (1977 and 1978), and a project in southeastern Illinois (1978 to 1980). These projects did not extend for long periods of time, all being two months or less. Over the past several years there have been preliminary, statistically-focused studies on five of these projects (Changnon and Towery, 1977; Changnon, Hsu, and Towery, 1979; Changnon and Hsu, 1980; and Hsu and Changnon, 1981a, 1981b).

In four of the five projects evaluated, specialized networks of non-recording raingages were installed and operated by resident observers during the projects. Also, in all of the projects the cloud seeding firms routinely traced and/or photographed the radar scope to provide a source of echo data. However, the quality of the radar data was frequently poor, limiting the extent of the radar analyses (Changnon and Hsu, 1981). The daily and monthly rainfall values from the weather stations of the National Weather Service became the main data sources used in the evaluations. The basic approach used in the evaluations of these Illinois projects involved a target vs control evaluation design, plus a seeding period vs historical period comparison in two of the projects. Control areas equivalent in size to the target area were defined to the north, west, south, and east of the target area before the projects began. The techniques of PCR, MR, and DR were used to evaluate these projects, and their permutational significance levels were derived. Results revealed that the PCR gave the most significant results among the three techniques compared.

The general tendencies found in the target rainfall and echo characteristics are summarized in Table 4.4.

Table 4.4. General Effects of Seeding on Rainfall in the Target Area, Illinois

Year	Target Rainfall	Target Radar Echoes
1976	not studied	+
1977	0 to weak +	poor data
1978		
1979	+	not studied
1980	0 to weak +	poor data

In general, the results are mixed and inconclusive. Two of the projects (years) indicated increases, signified by pluses (1976 and 1979), in the target rainfall and/or echoes. One year (1978) indicated a rain decrease. The target echo results are also mixed. In all instances, the 1-year (usually one or two months) projects were too short, regardless of the apparent increases or decreases of rainfall or echo in the target areas, to draw any conclusions that have statistical or physical significance when taken alone.

4.3 Texas Panhandle Hail Suppression Project

A third operational project which dealt with hail suppression was selected for evaluation. The project was located in the Texas Panhandle with a target 5,000 sq kms in size (Fig. 4.4) during the May-October periods of 1970-1976. The project has been evaluated by Henderson and Changnon (1972) and by Schickedanz (1974; 1975; 1977). These results used either hailfall data or crop-hail insurance data. Results reported herein were obtained using approaches different from the ones in these previous studies.

The data employed consisted of the annual crop-hail insurance data on a county basis, and were furnished by the Crop-Hail Insurance Actuarial Association (CHIAA). The annual loss-cost (losses divided by liability times 100) was obtained for each county. The period of 1947-1969 was used as the historical control. This was the period when the annual liability was greater than $100,000 in both target counties. During the seeded period, five of the control counties (Swisher, Hockley, Lubbock, Floyd, and Crosby) had liabilities that were at least 2555 of those during the historical period. This set of counties was designated as high liability control counties. Castro County was seeded during 1975-1976.

The technique of factor analysis was applied to the 12-county data set of 1947-1976. The rotation Varimax was used and 7 factors were retained (Morrison, 1976). The resulting factor loading matrix is shown in Table 4.5. The seven factors explained 91% of the total hail loss-cost variance. From the loading matrix it 3hows that the target counties, Hale and Lamb, were both heavily loaded on Factor 4. Factor 1 represented counties in the northwestern corner, and Factor 3 represented counties in the southeastern corner. Both Welch's t-test and Mann-Whitney tests show that only Factor 2 and Factor 4 (target) display significant differences at the 5% level between the historical and seeded scores (Table 4.6). Factor 2 represented Cochran County and Lubbock County, both located south of the target. This indicated that the two target counties together showed a significant change of hail loss-cost between the historical and seeded period. Except for part of the southern counties, most control counties did not show any significant difference of loss-cost values between the two periods.

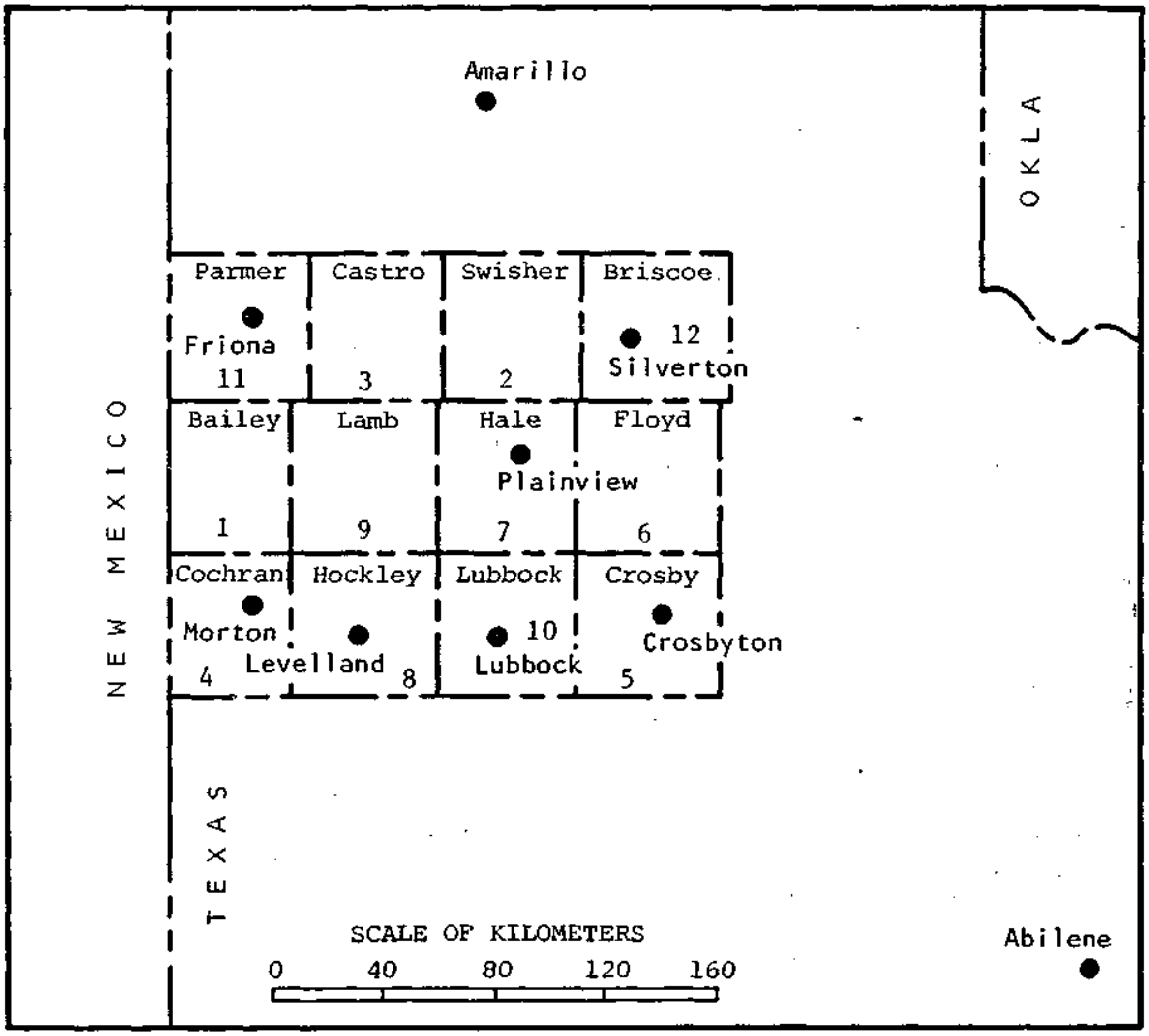


Figure 4,4 Hail Suppression Project Area, Texas

Table 4.5. Factor Loading Matrix, Varimax Rotation, 7 Factors Retained, Texas Hail Loss-Cost

County	Factor 1	2	3	4	5	6	7
Bailey							
Brisco					.956		
Castro	.863						
Cochran		.934					
Crosby			.924				
Floyd			.839				
Hale				.782			
Hockley							.871
Lamb				.691			
Lubbock		.758					
Parmer	.866						
Swisher						.937	
Variance Explained	2.084	1.809	1.783	1.423	1.361	1.357	1.154

Table 4.6. Testing of Factor Scores

	Factor 1	2	3	4	5	6	7
. Mean, 1947-1969	-.01	.16	.03	.17	.07	-.13	-.15
Mean, 1970-1976	.03	-.52	-.04	-.57	-.24	.41	-.49
t-test	-.06	2.41	.03	2.90	.72	-1.28	.97
5% sig.	*			*			
Mann-Whitney test 5% sig.	*			*			

5. PRINCIPAL COMPONENT REGRESSION

The technique of principal component regression (PCR) was found generally to be one of the most powerful in various simulation studies. Because PCR was so useful, it was examined further in more detail. In the previous simulation studies, the target was surrounded by controls from four sides, and usually principal component regression retaining only the first principal component (PCR[1]) would be as powerful as other techniques. In the following it is shown that when only the upwind controls were used, regression using the first 3 principal components performs better than using just the first component. Next, the possibility of improving the prediction of principal component regression by retaining and shrinking the components with smaller eigenvalues, instead of discarding them, is explored. In other words, the regression coefficient vector was estimated by the so-called biased method. The results were then compared with those obtained from the least squares method.

5.1 Number of Components

The selection of data for this study was motivated by the evaluation of weather modification projects, in which there usually was a 'seeded' period and an 'historical unseeded' period. Observations, usually precipitation or closely related meteorological variables, were taken during both periods and were compared to assess seeding effect, if any. Monthly and seasonal rainfall totals, May to September, during the period from 1935 to 1970 for a ten-county area in western Kansas (Fig. 1.1) were used. Among the ten counties, Scott and Wichita are located in the center and surrounded by the other eight counties; Gove County is located in the northeast corner; and Wallace County is located in the northwest corner. The latter two counties are located in the general downwind side during the summer season.

Depending on the analysis, either (1) the center two counties, Wichita and Scott, were used as dependent variables, and the other eight counties as independent variables; (2) the NW corner county, Wallace, was used as the dependent variable, and the other eight counties (except Gove) as the independent variables; or (3) the NE corner county, Gove, was used as the dependent variable, and the other eight counties (except Wallace) were used as the independent variables. A preliminary Kolmogorov-Smirnov test for each variable revealed no significant departure from normality. When the two center counties were used as the dependent variables, the correlation coefficients (for the 1936-1970 data) among the independent variables were high, mostly between 0.5 to 0.8 (Hsu, 1978); when the corner county was used as the dependent variable, the correlation coefficients were also high, mostly between 0.6 to 0.8. The eigenvalues of the corresponding independent variables are shown in Table 5.1. The first (and the largest) eigenvalue accounts for more than 60% of the variance in all months. The first eigenvalues with corner counties as the dependent variables were generally greater than those with center counties as the dependent variables; however, the reverse was true for the other eigenvalues except the sixth.

Table 5.1. Eigenvalues of the Covariance Matrix of Independent Variables, 1936-1970, Kansas

	Eigenvalues							
Month	1	2	3	4	5	6	7	8
	Center County as Dependent Variable							
May	16.833	3.133	2.008	.874	.734	.413	-313	.206
June	34.357	2.854	1.795	1.385	-958	.604	.447	-367
July	18.716	2.501	2.313	1.253	1.069	.628	.513	.386
Aug.	10.597	2.943	1.272	.954	.646	.479	.452	.353
Sep.	8.991	2.098	.807	.649	-397	.281	.242	.108
S.A.	5.192	.726	.429	.185	.156	.116	.084	.071
	Corner County as Dependent Variable							
May	19.405	2.211	1.584	.799	.723	.576	.290	.195
June	34.595	3-050	1.231	1.042	.751	.633	.456	.347
July	21.489	2.222	1.723	1.163	.714	.668	.497	.240
Aug.	10.837	1.714	1.057	.937	.678	.522	.448	.252
Sep.	8.653	1.344	.818	.437	.376	.276	.159	.087
S.A.	5.187	.526	.289	.189	.135	.118	.093	.072

Five out of the 35 years were randomly chosen as 'seeded' with the other 30 years as 'unseeded.' The CDC CYBER Fortran function RANF was the basic random number generator used. Assumed (multiplicative) seeding effects of 10, 20, 30, and 40 percent, respectively, were superimposed on the 'seeded' rains of the dependent variable. For each month (including seasonal average) the principal component regression retaining either 1 principal component (PCR[1]), or 3 principal components (PCR[3]), was fitted to the 30-year 'unseeded' data set depending on whether the two center counties or the corner counties were used as dependent variables. The fitted regression equation was then used to predict the five 'seeded' observations of the dependent variable. The average (D) of the five differences between the changed and predicted observations was used as test statistics.

Five hundred runs were executed to form a null and four alternative distributions of the statistic D. Power curves were then derived by comparing the null and the alternative distributions. Powers corresponding to the five percent and the ten percent nominal significance levels were the main indexes used in comparing the usage of PCR[1] with PCR[3], as well as comparing the usage of center counties or corner counties as dependent variables.

Table 5.2. Differences of Power, PCR[1]-PCR[3], D as Test Statistic

		5%					10%				
		Center*			Corner		Center			Corner	
Month	se	1	2	Avg	1	2	1	2	Avg	1	2
May	1.1	-.07	.03	.01	-.06	-.03	-.09	.02	.02	-.02	-.04
	1.2	-.11	.06	.05	-.08	-.06	-.06	.06	.02	-.05	-.14
	1.3	.00	.09	.07	-.09	-.13	.00	.06	.06	-.07	-.16
	1.4	.01	.09	.16	-.09	-.14	.05	.04	.09	-.07	-.16
June	1.1	.04	.01	.02	.02	.02	.01	.03	-.03	.03	.01
	1.2	.06	.01	.00	.03	.03	.06	-.01	.12	.04	.03
	1.3	.03	-.03	.08	.03	.04	.02	-.02	.04	.05	.05
	1.4	.02	-.04	.02	.05	.06	-.02	.00	.01	.04	.03
July	1.1	-.03	-.03	-.05	-.07	.00	-.08	-.06	-.07	.02	-.03
	1.2	-.07	-.03	-.04	-.08	-.01	-.06	.01	.01	-.03	-.01
	1.3	-.05	.03	-.01	-.13	-.01	-.07	-.03	-.02	-.08	-.03
	1.4	-.06	.01	-.02	-.16	-.01	-.06	-.04	.00	-.08	-.01
Aug.	1.1	.00	.07	.03	-.02	-.03	.02	.02	.06	-.02	.02
	1.2	.00	.04	.10	-.04	-.04	.03	.04	.05	-.10	.02
	1.3	.05	.07	.06	-.10	-.03	.08	.03	-.01	-.11	.00
	1.4	.03	.05	.01	-.12	-.04	.05	-.01	.01	-.11	.00
Sep.	1.1	.01	.00	.04	-.01	-.03	.03	-.02	.07	-.01	-.03
	1.2	.01	-.08	.00	-.04	-.04	-.06	-.03	.05	-.01	-.08
	1.3	-.10	-.09	.00	-.03	-.07	-.07	-.06	-.04	-.03	-.08
	1.4	-.08	-.09	-.01	-.04	-.11	-.12	-.11	-.02	-.05	-.11
S.A.	1.1	-.03	.01	.07	-.13	-.01	-.05	.09	.15	-.11	-.05
	1.2	-.02	.04	-.01	-.23	-.05	-.01	-.02	-.01	-.14	-.08
	1.3	.02	-.04	-.01	-.15	-.10	-.01	-.03	-.02	-.08	-.05
	1.4	-.01	.00	.00	-.05	-.05	.00	.00	.00	-.02	-.04
Mo. Neg.		11	8	7	20	19	13	11	7	19	16
No. Abs. >0.2		14	18	10	21	18	14	6	9	13	10
No. -.2		9	8	2	17	15	10	3	1	12	9
Ratio		.64	.44	.20	.81	.83	.71	.50	.11	.92	.90

* Center 1 denotes Wichita County, Center 2 Scott County, Center Average the average of Wichita and Scott; Corner 1 denotes Gove County, Corner 2 Wallace County.

The differences of power between PCR[1] and PCR[3] are shown in Table 5.2. When the corner counties (Gove and Wallace) were used as dependent variables, using three PCs gave larger power than using one PC. For example, the number of negative differences (meaning that the power of PCR[3] was larger than that of PCR[1]) when Gove County was used as the dependent variable was 20, with p=0.003. However, when the center counties (Scott and Wichita) were used as dependent variables, the differences of power were not as significant.

Some of the small differences may be strictly due to the random fluctuation of power computation (Gabriel and Hsu, 1980, 1981). Hence, looking only at larger differences, the ratio of large negative differences (defined as less than -.02) to the number of large differences (absolute value larger than .02) was tabulated (Table 5.2). The ratio of large positive differences to large differences can be obtained similarly. It is clear that when the two center counties were individually used as dependent variables, power differences between PCR[1] and PCR[3] were not significantly different from zero; when the averaged center counties were used as dependent variables, PCR[1] had larger power than PCR[3] as indicated by the smaller number and smaller magnitude of the negative differences. However, when the corner counties were used as dependent variables, PCR[3] had larger power than PCR[1], as indicated by the larger number and larger magnitude of the negative differences.

5.2 Biased Regression

Meteorological variables of many nearby stations (or variables), because of the persistence of underlying physical factors, usually contain substantial amounts of multicollinearity. The effects of multicollinearity of one such variable, rainfall, over the multiple regression modeling and predicting was investigated in a study using real-time rainfall data (Hsu, 1978), in which the least squares method was used.

Alternative methods, other than least squares, to estimate coefficients of regression models have been proposed and investigated by various authors in the recent literature. These estimators are biased (i. e., the mathematical expectation of these estimators is not exactly equal to the population parameter they estimate), but may possess preferable features to the unbiased least squares. Some advantages of using biased estimators over the least squares estimator are smaller mean square error (MSE) of the estimated regression coefficients, and their correct signs (Hoerl and Kennard, 1970a, 1970b; Gunst et al., 1976; Gunst and Mason, 1977). Large MSE of the least squares estimator is partly attributed to the ill-conditioned design matrix, an indication of a high degree of multicollinearity among the regressors.

It is desirable to discern whether any of the biased estimators would be an improvement over the least squares in estimating the regression model and predicting new observations. Besides rainfall of neighboring stations, other meteorological (predictor) variables can also be used as covariates to further improve the prediction. These variables may include pressure tendency, temperature profile, moisture advection, stability, and cloud characteristics (Hsu, 1981b).

The MSE of an estimator for the regression coefficient vector is defined as the square distance between the estimator and the 'true' regression coefficient vector. The MSE of a biased estimator consists of a variance component and a bias component (Hoerl and Kennard, 1970a). Through appropriate procedures, the variance component of certain estimators can be made substantially smaller and introduce only a small bias component. MSE has been used as the main criterion to compare various estimators in several simulation studies (Hoerl and Kennard, 1970b; Gunst et al., 1976; Dempster et al., 1977; Gunst and Mason, 1977; Wichern and Churchill, 1978).

However, their use was primarily restricted to pre-determined models (in simulation studies) or to a single data set; rarely had independent data been used to justify the claimed advantages of these biased estimators. The results presented herein used real-time data to determine how well various biased estimators perform. Then by setting aside part of the data as a testing sample, the estimated regression model was used to predict new observations and to compare them with the actual observations in the testing sample.

Various estimators of regression coefficient vectors include least squares, principal component, shrinkage estimator, ridge estimator, and generalized ridge estimator. Hocking et al. (1976) gave a unified description of properties of these estimators. The method of principal component reduces considerably the variance component of MSE, but may at the same time enlarge the bias component of MSE. Marquardt (1970) proposed a modified principal component regression by shrinking those principal components with small eigenvalues. Hocking et al. (1976) further modified this estimator. It is this approach of shrinking the principal components of small eigenvalues that was explored herein (see also Carmer and Hsieh, 1980).

Numerical Comparison. Twelve biased estimators for the regression coefficient vector were investigated through Monte Carlo studies. (See Hsu (1980) for details of these estimators.) A data set consisting of values of seasonal (May-September) rainfall averages in each of the 10 counties in west central Kansas from 1936 to 1970 was used (Fig. 1.1). Each county was used as a variable. The average of the two center counties was used as the dependent variable and the other eight counties served as independent variables. A preliminary Kolmogorov-Smirnov test for each variable showed no significant departure from normality. The correlation coefficients among the independent variables were high, ranging from .438 to .890 (Hsu, 1978).

The first 30 observations (1936-1965) were used to fit a regression model by various estimation methods, and the resulting model was used to predict rainfall averages in the 1966-1970 period. This method of dividing observations was employed to simulate the evaluation of operational weather modification projects. A 'target-control' functional relationship was fitted to pre-seed observations. This was used to predict seed target observations. Predictions were compared with the actual seed target observations to assess the cloud seeding effects. A predicted residual mean square (PRMS) was then computed and used as the comparison index. Findings, as reported in Hsu (1980), revealed the following:

1) The difference of RMS's among all the biased regressions was minor. A few RMS's of biased regression were smaller than the full-modeled least squares; RMS's of better subsets of least squares were smaller than those of biased regression. However, the magnitude of differences among RMS's was negligibly small, all less than 0.3.

2) The bias component of MSE was larger when the retained principal components were shrunk, than when the retained principal components were not

shrunk and small eigenvalued principal components were shrunk. This indicates an improvement of overall MSE when the principal components with small eigenvalues were shrunk over when the principal components with small eigenvalues were deleted. As more principal components were included in the regression, MSE became smaller, regardless of whether retained principal components or deleted principal components were shrunk.

3) Shrinking retained principal components shows improvement of RMS's and MSE over non-shrinking whenever generalized ridge estimators were employed.

4) The biased methods predict uniformly better than the least squares best subsets, though the PRMS of biased method did not reach the attainable minimum; the latter, however, is of little practical use in prediction.

5) The minimum PRMS was .1127 when three principal components (1, 2, 3) were retained and shrunk. One method of ridge estimator using the same three principal components was a close second, with PRMS .1137.

Overall, biased methods decreased the coefficient of determination R and increased the residual mean square error slightly when compared to the least squares; however, biased methods gained predicting power over least squares. This predicting power is of more importance than R or RMS in the evaluation of weather modification. Slight shrinking on retained principal components or on small eigenvalued principal components shows improvement in terms of predicted residual mean square (PRMS) over non-shrinking.

6. METEOROLOGICAL COVARIATES

The development of a relationship between precipitation and meteorological covariates is important in designing and evaluating weather modification operations. Good meteorological covariates can be useful in reducing the unexplained natural variability of precipitation, and hence can lead to a better estimation of natural precipitation occurring during modification activities. The value of meteorological covariates in evaluating weather modification has long been recognized (Spar, 1957; Sax et al., 1975; Biondini, 1977), and research on their usage has been carried out in a number of weather modification design studies (Ackerman et al., 1976; Schickedanz and Sun, 1977). An important objective of OSET has been to investigate the utilization of meteorological covariates for evaluating weather modification projects.

Meteorological covariates can be classified into two main types according to when their values were taken. Schickedanz and Sun (1977) called those determined from soundings, rainfall, radar, surface observations, etc., prior to the modification attempts as prognostic covariates (PROGSPEC), and those determined during or after the seeding efforts as synoptic covariates (SYNSPEC). Both PROGSPECs and SYNSPECs can be used in aiding the evaluation. For instance, covariates measured in the upwind area are candidate SYNSPECs, although much care should be exercised in assuring that SYNSPECs are not affected by the seeding.

Meteorological covariates can also be classified according to their uses, … such as:

1) Forecasters; Those used to forecast precipitation, quantitatively or qualitatively.

2) Evaluators: Those used to quantitatively evaluate modification effects.

3) Stratifiers: Those used to stratify cases categorically.

The classification is not disjoint. Some forecasters can also be used in evaluation, while others can be used to declare an operational unit. Conversely, certain evaluators can be used as forecasters, and others not. Stratifiers include covariates used in forecasting rain/no rain situations as well as those used in classification of sampling units. The meteorological covariates discussed herein belong to the PROGSPEC type and can be used as either forecasters or evaluators.

The usage of covariates to post-stratify precipitation cases has been most fruitful in delineating situations amenable to modification from non-effective situations. For example, the cloudtop temperature in the Climax experiment (Grant and Elliott, 1971) and echo motion in FACE (Simpson and Woodley, 1975) were found useful. Both the Climax (Colorado) and FACE (Florida) sites have semi-permanent forcing functions that were important in the development of the covariates. However, the Midwest has no unique precipitation forcing functions which can be readily used for the development of covariates or which can be used to restrict the possible number of candidates (Achtemeier, 1981). It is necessary to seek a number of possible triggering mechanisms, or forcing functions, that are related to Midwest convective precipitation.

There were two main sources of data used in this study.

Precipitation Data.. Rainfall data observed from the dense (1 gage per 20 sq km) METROMEX raingage network operated by the Illinois State Water Survey during 1971-1975 were used to identify objective storms (discrete rain events) which occurred over the network (Changnon, 1975). The starting date and time, the ending date and time, the general motion, the total rainfall, the maximum gage rainfall, and the average rainfall (defined similarly as in the ILL-ST simulation study) of each storm were tabulated. Within the circular METROMEX network, a target area in the general downwind direction and three control areas in the upwind direction of each storm were defined, based on the storm motion as in the ILL-ST study. Only storms which had at least 2.54 mm (0.10 inch) total areal rainfall both in the target and in any of the three controls were included. Total areal rainfall in the target alone was used as the response variable in this study. When covariate data were missing, the corresponding storms were excluded from the data set. The number of storms that qualified for the study was thus reduced from the original total of 330 storms to 115 in the 5-year period.

Meteorological Covariates. Extensive literature searches (Ackerman et al., 1976; Westcott, 1979) were made to determine a set of candidate covariates. Then a subset of covariates related to midwestern convective rainfall was selected for further study. Generally, they can be grouped into two classes: surface-derived covariates and upper air-derived covariates. The results herein concentrated exclusively upon the surface-derived covariates, a situation created by limited funding. The 24 surface covariates selected describe moisture patterns and triggering mechanisms of midwestern precipitation (Table 6.1). Detailed descriptions of these covariates can be found in Ackerman et al. (1976) and Achtemeier (1980).

The data set of surface covariates was furnished by the National Severe Storms Forecast Center, and consists of observations for June, July, and August, 1971-1975, from 48 stations located in or near the region shown in Fig. 6.1. The covariates used in the study were those observed 1-3 hours before the starting time of each storm. These are likely to be those most highly correlated with storm rainfall. Covariates measured during 4 to 12 hours prior to storm start were calculated but were not used in this study. The technique of objective analysis was applied to the raw data to generate a data set of 252 grid-points (14 x 18 mesh) with 56 km separation. After all desired covariates were calculated, the grid density was reduced from 252 points to 63 (7 x 9) points (Achtemeier, 1981).

6.1 Use as Forecasters

Lund (1971) used stepwise and stagewise regressions to estimate and predict precipitation in California. Achtemeier (1980, 1981) studied the relation between the precipitation and the same set of 24 covariates as used here for 1-3, 4-6, 7-9, and 10-12 hours before storms. However, he used a different METROMEX target area and set of storms than used here. He found that the correlation coefficients between precipitation and covariates was rather weak; none were larger than 0.40. He then used a (first-stage) stepwise regression (maximum R criterion, 0.5 cutoff significance for entry) on each of the covariate fields (63 points) to regress on the total areal precipitation. This revealed that among the 24 regressions, three were able to explain more than 30% of the

Table 6.1. Surface Predictor Variables Selected by First-Stage Stepwise Regression.

			Prin. Comp.			Point	
			No	Var	R^2	Grid*	R^2
1	MR	Mixing Ratio	3	19%	.08	17,33	.08
2	GW1	Geostr. Wind 90-270	4	15	.22	13,33	.12
3	GW2	Geostr. Wind 135-315	-	-	-		
4	GW3	Geostr. Wind 180-360	-	-			
5	GW4	Geostr. Wind 225-45	9	10	.23	12,25,34	.13
6	OW1	Obs. Wind 90-270	4	25	.16	17,32	.12
7	OW2	Obs. Wind 135-315	4	24	.18	23,39	.16
8	OW3	Obs. Wind 180-360	4	34	.13	12,24	.13
9	OW4	Obs. Wind 225-45	4	17	.18	11,19,32	.15
10	DIV	Divergence	9	12	.32	17,19,46	.17
11	VOT	Vorticity	4	19	.18	25,32,40	.19
12	GMA	Geostr. Moisture Adv.	7	14	.33	12,23,25	.29
13	MA	Moisture Advection	9	10	.23	26,27	.10
14	MD	Moisture Divergence	4	20	.17	19,27,37	.23
15	WBT	Wet B. Potential Temp.	-	-		18,33	.17
16	CL	Cumulative Lift	4	20	.18	17,19,30	.21
17	PTR	Pressure Trough	-	-		20,26	.25
18	PTN	Pressure Tendency	-	-			
19	SC	Sky Cover	4	57	.17	33,37,53	.23
20	CH	Cloud Height	2	44	.08		
21	PR	Pressure	-	-	-	-	
22	TEM	Temperature '	-	-	.07	19,33	.26
23	DP	Dew Point	-	-			
24	SI	Spot Index	2	16	.12	13,17,25	.27

*See Figure61 for location of grid points

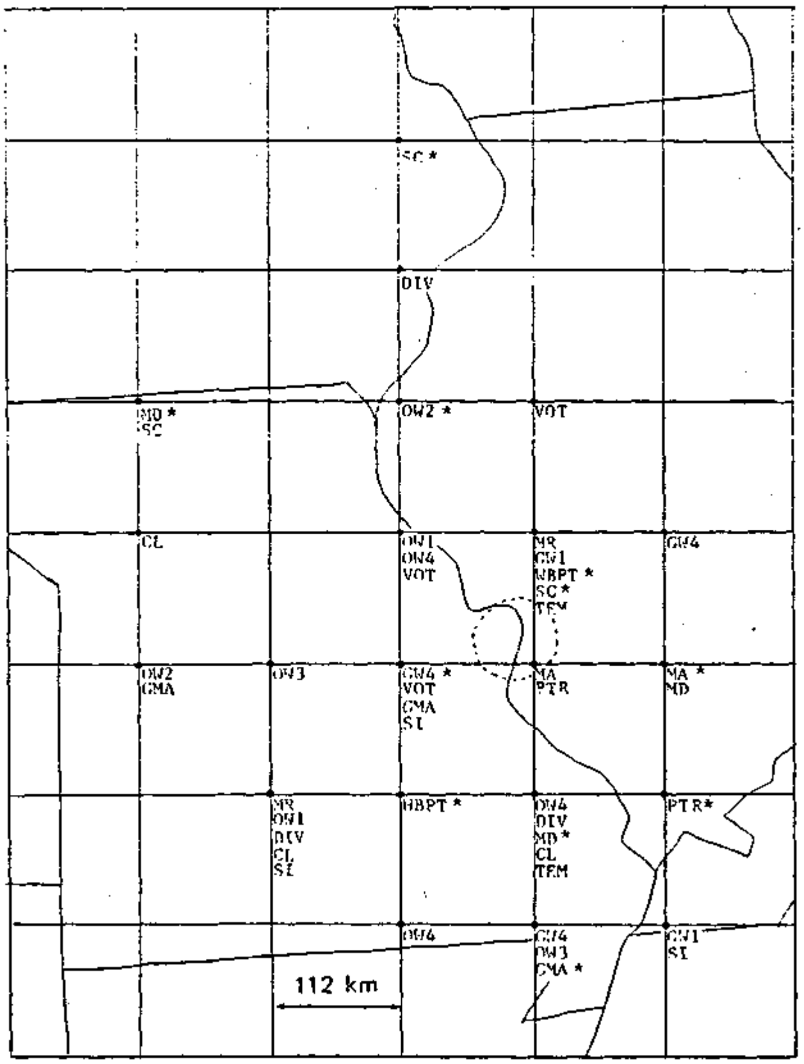


Figure 6.1 *Point-Covariates Selected by the Stepwise Regression, Total Areal Rain as Response Variable, 1971-1975.*

variance of the total rainfall. He further used a second-stage stepwise regression on 144 pooled point-covariates to regress on the total areal precipitation, and was able to explain 53% of the precipitation variance by only 10 point-covariates.

A potential weakness in applying first-stage stepwise regression to point-covariates in predicting precipitation may result from the way the variables were selected. In prediction, generally one would like to include as much relevant information as possible in building up the relationship between precipitation and predictors. Neighboring points of a point well correlated with a precipitation variable are usually also well correlated with the same precipitation variable due to meteorological persistence. However, once a point was selected for use in the regression equation, the chance of its neighboring points being selected by the stepwise method is reduced considerably. If neighboring points were later selected, multi-collinearity could then become a problem.

One method to handle this difficulty is to use principal components instead of point-covariates before the first-stage regression. Points, which are well correlated with the precipitation variable in the same direction and are located closely, usually appear together in the same principal component. By using only those few principal components which are most useful in prediction (see below), one can include in the prediction process as much information as desired, and at the same time avoid the problem of multi-collinearity. Use of both point-covariates and PC-covariates is demonstrated below.

For each covariate (63 points), a principal component analysis was performed using a correlation coefficient matrix. These principal components are linear combinations of point variables with the property that the first component explains a maximal amount of variance of that covariate, the second component explains a next maximal amount of variance and is orthogonal to the first component, etc. These components are then used as independent variables to regress on the precipitation variable.

Variable Selection Procedure. To compare the performance of the PC-covariates and the point-covariates in predicting precipitation, both were investigated and underwent two stages of the variable selection process. For computational accuracy in deriving the covariates, the boundary points of the 7 × 9 mesh (Fig. 6.1) were excluded from further variable selection, i. e., only 35 candidate point-covariates from each covariate were available for selection into the regression. This problem is of less severity for the principal components; hence, all 63 points were used in deriving the principal components.

First-Stage Screening. In the first-stage screening, maximum R^2 was used as a selection criterion for the point-covariates. For the principal components, a cutoff point of .71 was used for the eigenvalues and a minimum correlation coefficient of 0.10 between the component and the precipitation variables was required in order for the component to be included. Additionally, total variance explained by all the components selected for each covariate had. to be greater than 10%; otherwise, the covariate was excluded from further consideration.

Examples of loading patterns (eigenvector) for some selected components of the covariate sky cover are shown in Fig. 6.2. They represent the loadings of the first, eleventh, fourth, and second principal components, in order of their correlation with Target total rainfall. The total variance of sky cover

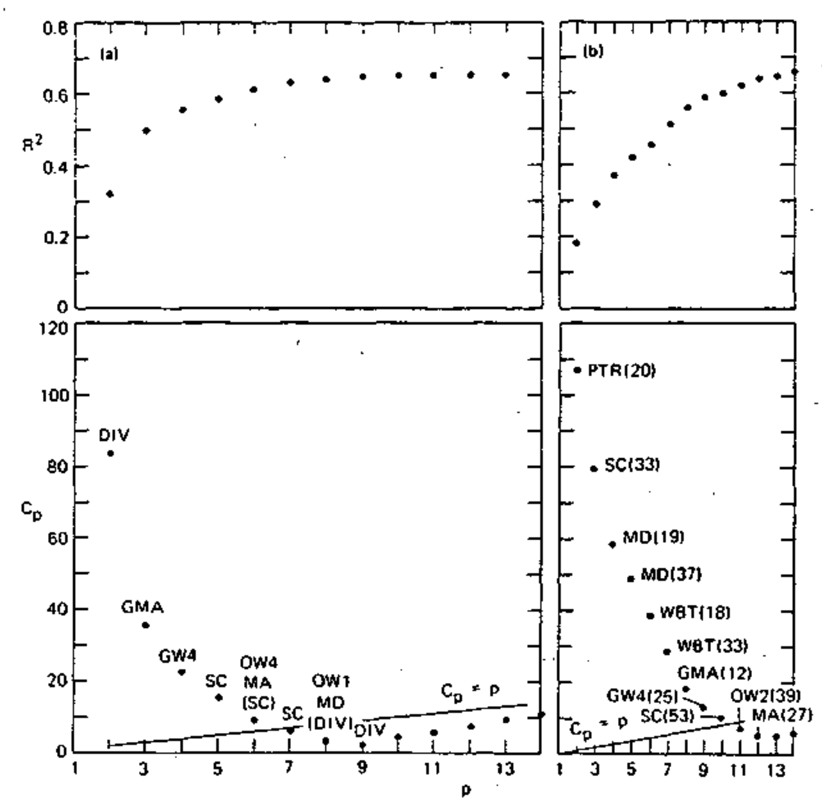


Figure 6.3 *Coefficient of Determination,* R^2 *and* C_p . *(a) Principal Components. (b) Point-Covariates* explained by these four components was 57%, and the variance of the total precipitation explained by them was 17%. It can be seen that areas north, northeast, northwest, and southwest of the target area (first eigenvector) loaded highly with the target area rainfall. The area east of the target area (4th • eigenvector) also contributed to the target areal rainfall variation. The second eigenvector represented a north-south gradient pattern. The eleventh component agreed well with the first component. A physical interpretation of all the components selected was made to avoid inclusion of dubious components.

After the first-stage screening for the principal components, sixteen covariates were retained. The number of principal components selected, total variance explained, and the coefficient of determination are shown in Table 6.1. Coefficients of determination for the selected covariates were in the range of 0.07 to 0.33. For each covariate, the components selected were combined through regression on the target rainfall response variable to form a single variable (PC-covariate) for the second-stage screening.

For point-covariates, the number of points of each covariate selected was restricted to no more than three. All together, 45 point-covariates were retained after the first-stage screening (Table 6.1) and their locations are shown in Fig. 6.1. The range of the coefficients of determination was similar to those of the PC-covariates. Interestingly, a majority of the selected point-covariates was located rather close to the target area, with very few farther than 200 km.

Second-Stage Screening. A second stage screening was then performed using Cp as a selection criterion (Hsu, 1978). Eight PC-covariates (Fig. 6.3a) and 11 point-covariates were retained (Fig. 6.3b). The number inside the parentheses of the point-covariates in Fig. 6.3 refers to the grid point in Fig. 6.1. Grid points are numbered by starting at the lower-left corner (1), across the first row, across the second row, and so on upward to the upper-right corner (63). For example, PTR(20) is located southeast of the METROMEX network. These 11 point-covariates selected after the second-stage screening are marked with an asterisk (*) in Fig. 6.1. Correlation coefficients among the 8 PC-covariates were mostly in the 0.2 to 0.3 range, except the one between divergence and moisture divergence which was 0.61. Correlation coefficients among the 11 point-covariates were mostly less than 0.2. Covariates GW4, GMA, MA, MD, and SC appeared in sets of either 8 PC-covariates or 11 point-covariates; while OW1, 0W4, and DIV appeared only in the set of 8 PC-covariates. 0W2, WMB, and PTR appeared only in the set of 11 point-covariates.

The regression equation using the 8 PC-covariates as independent variables is

$$\begin{aligned} \text{Rain} = & -16.062 + .385\text{GW4} + .302\text{OW1} + .294\text{OW4} \\ & + .264\text{DIV} + .530\text{GMA} + .355\text{MA} + .397\text{MD} \\ & + .338\text{SC} \end{aligned}$$

The F-values for the regression coefficients were all significant at the .10 level. The coefficient of determination of the regression was 0.654.

The regression equation using the 22 point-covariates as independent variables is

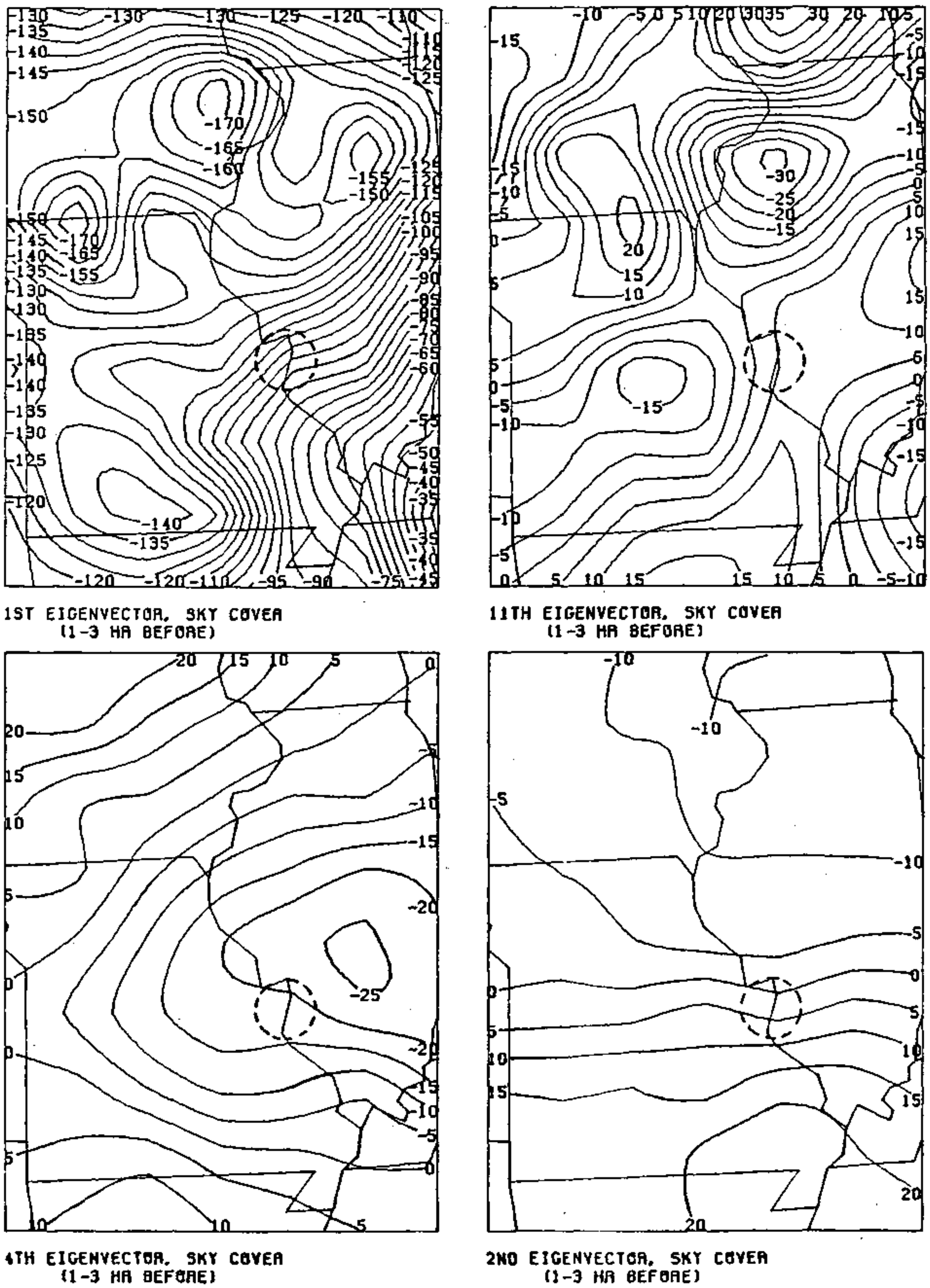


Figure 6.2 Pattern of Loading Matrix, Sky Cover

$$
\begin{aligned}
\text{Rain} = & -162.816 + .836\text{GW4}(25) + .526\text{OW2}(39) \\
& + .515\text{GMA}(12) - .342\text{MA}(27) - .0145\text{MD}(19) \\
& - .097\text{MD}(37) + 2.082\text{WMB}(18) \\
& - 1.566\text{WBT}(33) + 1.920\text{PTR}(20) \\
& + 3.268\text{SC}(33) + 2.407\text{SC}(53)
\end{aligned}
$$

The F-values for the regression coefficients were all significant at the 0.05 level. The coefficient of determination of the regression was 0.637.

Simulation Study. To test how well the selected point-covariates and PC-covariates can be used to predict precipitation, a 500-run simulation study was carried out. In each run, 23 out of 115 storms were randomly set aside as a testing sample, and the remaining 92 storms as . a build-up sample. From the build-up sample, four regression equations were obtained by using as independent variables the 16 PC-covariates, the 45 point-covariates (after the first-stage screening), the 8 PC-covariates, and the 11 point-covariates (after the second-stage screening), respectively. The regression equation was then used to predict storm rainfall for each of the 23 storms in the testing sample.

The key results of this simulation study are shown in Table 6.2. The R^2, when using point-covariates, is higher than the R when using PC-covariates in both stages of screening. The range (max-min) of the R (when using point-covariates) is also wider than that when using PC-covariates. And, of course, the R in the second-stage analysis is lower than that in the first-stage analysis.

In each run, the average (D) of the 23 differences between the observed and the predicted storm rainfall was calculated. The results show that the mean of 500 D-values when PC-covariates were used is closer to zero than when point-covariates were used (Table 6.2). While the second-stage analysis of PC-covariates did not show improvement over the first-stage analysis, that of point-covariates did show considerable improvement. The standard deviation of D values is also smaller when PC-covariates were used.

The advantage of using PC-covariates over point-covariates is most clearly revealed by comparing the maximum and minimum statistics. The extremes are the worst possible situations a prediction could obtain. In other words, they represent the largest possible loss one would encounter by using the above prediction scheme. Using extremes of smallest magnitude, in our case the 8 PC-covariates, would ensure a prediction with a minimax loss (minimum maximal loss). The advantage of using a second-stage analysis over a first-stage anaysis is also obvious by looking at the extremes of D values in Table 6.2.

6.2 Use as Evaluators

In the previous sections, the meteorological covariates were used to predict storm rainfall. In the following sections, the meteorological covariates are used as evaluators to aid the evaluation, and the resulting statistical powers are compared with those without using meteorological covariates. The storm total rains in the 'target' area, as defined in the ILL-ST simulations, were used as the response variables. The same sets of PC-covariates and point-covariates obtained after either the first-stage or second-stage screenings (as above) were used in this study. In addition, rainfall variables in three upwind controls for

Table 6.2. Descriptive Statistics of Coefficient of Determination (R^2) and Averaged Difference (D), 23 Out of 115 Objective Storm Rainfall Totals Predicted, 500 Runs.

	Prin. Comp.		Point-Cov.	
	16 Cov.	8 Cov.	45 Points	11 Points
		R^2		
Mean	.6690	.6548	.7796	.5314
St. Dev.	.0435	.0480	.0326	.0490
Max.	.7518	.7376	.8617	.6281
Min.	.4622	.4475	.5932	.3061
		D		
Mean	- .0087	.0603	.1591	.1016
St. Dev.	1.7737	1.6184	2.4964	1.9567
Max.	5.1553	4.4957	8.9958	6.1245
Min.	-4.5347	-4.2833	-8.2113	-4.8924

each storm, as used in the ILL-ST simulation, were used in the simulation of evaluator studies.

The simulation was carried out similar to that in the predictor study (in the prior sections) except that seeding-induced precipitation changes were superimposed onto the randomly selected 'seeded' sample in each run. A multiple regression was fitted using either PC-covariates or point-covariates, and the mean difference (D) between 23 changed observations and predicted observations was used as the test statistic and the power values were computed. In all, nine simulation studies were carried out. Powers of simulation which employed only the rainfall in the upwind controls without any meteorological covariates are shown in Table 6.3. Powers of the other 8 simulations which all employed meteorological covariates are shown in Table 6.4. These powers were ranked for each change imposed at the 5% and 10 % nominal significance levels (Table 6.5).

Table 6.3. Powers, Principal Component Regression, Upwind Controls without Meteorological Covariates, ILL-ST, Total Rain

Seeding Effect	W	D	T
		5%	
1.1	.116	.156	.164
1.2	.188	.286	.296
1.3	.256	.440	.450
1.4	.316	.604	.606
A	.352	.374	.374
E	.622	.690	.694
C	.098	.050	.054
M	.186	.336	.340
		10%	
1.1	.204	.234	.226
1.2	.282	.386	.386
1.3	.368	.564	.574
1.4	.456	.718	.718
A	.494	.508	.500
E	.728	.764	.770
C	.168	.092	.096
M	.288	.430	.432

Findings indicate that powers of the simulations using meteorological covariates after second-stage screening were greater than those using only upwind controls or using the meteorological covariates after first-stage screening. After the first-stage screening, powers of simulations using the meteorological covariates were not greater than those using only the upwind controls except one case, namely, that of- using both upwind controls and PC-covariates. Secondly, powers of simulations using PC-covariates (PC) out-performed those using point-covariates (SR) whether upwind controls were used or not. Powers of simulation using point-covariates (SR) after either the first-stage or the second-stage screenings were the lowest among all the simulations compared.

After the second-stage screening, powers of simulations at the 5% significance level using upwind controls were greater than those not using upwind controls, and the same was true at the 10% significance level in the case of point-covariates (SR). The differences in powers between using PC-covariates (PC) and point-covariates (SR) diminished after the second-stage screening. A closer look revealed that, at the 5% significance level, PC after the second-stage screening had better powers than SR except for seeding-effect model C; at the 10% significance level both had similar powers. Interestingly, powers of simulations using PC-covariates with upwind controls after the first-stage screening were greater than those using point-covariates without upwind controls even after the second-stage screening. However, powers using PC-covariates or point-covariates without upwind controls after the second-stage screening were generally greater than those with upwind controls after only the first-stage screening. This means that a proper screening of covariates might offset a partial need for upwind controls with an understanding that the inclusion of upwind controls is definitely an advantage after the second-stage screening.

Generally, the use of meteorological covariates improved the powers of the evaluation techniques. A second-stage screening to remove spurious variables was found to be worthwhile; in addition, the use of upwind controls further ensured a greater power. If the degree of spuriousness in the variables is uncertain, then the use of PC-covariates is recommended over point-covariates.

Table 6.4. Powers, ILL-ST with Meteorological Covariates, Total Rain

	Principal Component						Point-Variable					
	Upwind			No Upwind			Upwind			No Upwind		
se	W	D	T	W	D	T	W	D	T	W	D	T
					First-Stage Screening, 5%							
1.1	.108	.158	.156	.120	.138	.132	.092	.118	.110	.100	.100	.092
1.2	.188	.308	.310	.214	.300	.284	.152	.198	.182	.134	.136	.138
1.3	.304	.488	.474	.324	.452	.422	.214	.298	.292	.188	.208	.200
1.4	.408	.638	.620	.446	.582	.578	.288	.482	.450	.240	.330	.288
A	.418	.412	.414	.060	.058	.056	.238	.252	.236	.090	.100	.094
E	.700	.710	.700	.144	.150	.148	.446	.522	.486	.138	.186	.166
C	.100	.048	.048	.002	.002	.002	.058	.052	.056	.028	.014	.014
M	.190	.360	.366	.246	.378	.366	.166	.222	.218	.148	.170	.160
					Second-Stage Screening, 5%							
1.1	.136	.158	.164	.132	.130	.130	.148	.158	.138	.094	.134	.128
1.2	.218	.328	.348	.230	.296	.288	.248	.340	.310	.150	.238	.224
1.3	.354	.540	.542	.342	.484	.466	.394	.514	.470	.228	.392	.370
1.4	.488	.690	.690	.464	.624	.610	.522	.668	.634	.358	.516	.480
A	.468	.436	.444	.454	.404	.398	.488	.434	.402	.336	.322	.298
E	.784	.772	.778	.710	.690	.678	.758	.758	.712	.560	.576	.538
C	.098	.040	.044	.114	.042	.042	.108	.056	.050	.090	.038	.040
M	.222	.382	.394	.244	.350	.348	.256	.380	.362	.150	.274	.258
					First-Stage Screening, 10%							
1.1	.194	.222	.224	.208	.254	.242	.174	.178	.170	.142	.150	.148
1.2	.298	.402	.400	.330	.424	.400	.270	.300	.292	.208	.220	.218
1.3	.452	.578	.566	.472	.574	.560	.362	.488	.452	.266	.360	.346
1.4	.582	.712	.714	.574	.708	.682	.458	.636	.608	.340	.478	.454
A	.592	.514	.498	.132	.116	.108	.408	.410	.374	.142	.164	.160
E	.810	.794	.792	.236	.284	.268	.640	.668	.658	.218	.308	.286
C	.182	.098	.094	.014	.002	.004	.132	.108	.104	.054	.050	.046
M	.304	.448	.440	.398	.502	.480	.282	.340	.318	.230	.270	.244
					Second-Stage Screening, 10%							
1.1	.192	.264	.262	.218	.270	.274	.228	.272	.270	.176	.188	.182
1.2	.340	.458	.454	.342	.464	.448	.376	.450	.446	.302	.354	.340
1.3	.496	.640	.636	.480	.626	.618	.530	.622	.618	.428	.486	.462
1.4	.626	.776	.776	.596	.746	.734	.640	.778	.768	.514	.622	.598
A	.624	.596	.582	.586	.574	.570	.612	.596	.584	.532	.440	.420
E	.842	.850	.856	.820	.826	.822	.854	.864	.852	.720	.688	.660
C	.184	.102	.104	.162	.118	.118	.176	.108	.110	.164	.078	.074
M	.342	.508	.504	.352	.508	.510	.382	.494	.492	.300	.392	.376

Table 6.5. Ranks of the Statistics D by Powers at 5% and 10% Significance Levels, Total Rain*

	Simulation 1	2	3	4	5	6	7	8	9
Upwind Control	x	x	-	x	-	x	-	x	-
Meteor. Cov.	-	x	x	x	x	x	x	x	x
Variables	PC	PC	PC	SR	SR	PC	PC	SR	SR
Screening Stage	-	1	1	1	1	2	2	2	2
No. of Variables	3	19	16	48	45	11	8	14	11
					5%				
1.1	6	8	5	2	1	8	3	8	4
1.2	4	7	6	2	1	8	5	9	3
1.3	4	7	5	2	1	9	6	8	3
1.4	5	7	4	2	1	9	6	8	3
Total	19	29	20	8	4	34	20	33	13
A	5	7	1	3	2	9	6	8	4
E	5.5	7	1	3	2	9	5.5	8	4
C	7	6	1	8	2	4	5	9	3
M	4	6	7	2	1	9	5	8	3
Total	21.5	26	10	7	7	31	21.5	33	14
Grand Total	40.5	55	30	24	11	65	41.5	66	27
					10%				
1.1	5	4	6	2	1	7	8	9	3
1.2	4	5	6	2	1	8	9	7	3
1.3	4	6	5	3	1	9	8	7	2
1.4	6	5	4	3	1	8	7	9	2
Total	19	20	21	10	4	32	32	32	10
A	5	6	1	3	2	8.5	7	8.5	4
E	5	6	1	3	2	8	7	9	4
C	4	5	1	7.5	2	6	9	7.5	3
M	4	5	7	2	1	8.5	8.5	6	3
Total	18	22	10	15.5	7	31	31.5	31	14
Grand Total	37	42	31	25.5	11	63	63.5	63	24

*: Highest power was assigned rank 9 and so on.

7. VALIDITY OF HISTORICAL COMPARISON

Analyses of cloud seeding operations often compare precipitation during operations with precipitation during preceding historical periods. (For references see Hsu, 1981a). For example, rainfall at Santa Clara during 10 years of seeding operations after 1954 has been compared with the rainfall of 10 preceding years (Dennis and Kriege, 1966). Such comparisons implicitly involve the assumption that the difference, if any, between the pre-operational and operational periods reflects mainly the effect of seeding. Though it is acknowledged that random year-to-year variability may also result in differences between periods, tests of significance are used in an attempt to separate the 'true' difference from the random ones, and the former is ascribed to the effect of cloud seeding.

This study has been concerned with the validity of such statistical analyses. It considered the assumptions underlying them and examined precipitation data with a view of verifying the appropriateness of these assumptions. Failing such verification, this study then examined the robustness of standard statistical analyses against the existing divergences from these assumptions. That should indicate what confidence, if any, one may place in historical precipitation data in evaluating cloud seeding operations.

7.1 Problems of Comparison

The present study was not concerned with biases, however important these may be (see for example, Gabriel, 1979), but with the separate questions of whether comparisons of operational with historical periods may validly use standard statistical techniques. Such techniques are usually derived from a series of assumptions, including one which postulates that the observations are based on independent and identically distributed (IID) variables on which the effect of seeding, if any, is superimposed or added. In the present context, this would mean that annual amounts of natural, i.e., unseeded, precipitation were IID. But that surely does not fit known facts exactly. Some persistence and serial dependence of precipitation is known to exist, as are trends over short periods of years. Does the untruth of these assumptions then invalidate the use of standard statistical techniques?

A simple example of the effect that violation of the IID assumption could generate is as follows. Suppose that during a 20-year period annual rainfall increased steadily by an annual increment, so that year i's rainfall could be written $a+ ci$ for some initial amount a and increment c. Now suppose a ten-year seeding operation was launched in year 11 but the seeding had no effect at all on rainfall which remained $a+11c, a+12c,..., a+20c$ during the 10 operational years. The t-statistic for comparing the last 10 'operational' years with the first 10 'historical' ones is found to be 7.39, a very highly significant value. A spurious 'effect of seeding' would be detected, though it consisted entirely of the natural trend in rainfall. A similar, albeit not quite so extreme, result would be found if, more realistically, there were some random variability of precipitation about that linear trend.

Though the assumption of IID precipitation is clearly not correct, and though some deviations from assumptions can invalidate certain analyses (as we have just seen), it does not follow that any deviation invalidates every analysis. It may be that the deviations occurring with precipitation data do not invalidate some, or all, of the standard statistical methods of comparing two samples. Situations can arise in which techniques remain valid, exactly or approximately, even though certain of the assumptions used in deriving them are not valid. For example, Tukey-type simultaneous confidence bounds which were derived for independent means are also valid, with an appropriate adjustment of the variance, for equi-correlated variables. It may well be that certain statistical techniques give perfectly, or approximately, valid inferences when applied to precipitation data even though some deviation from the IID assumption exists.[1]

An alternative set of assumptions which often yields similar distributions of statistics, at least asymptotically, is that of randomized selection of treatment units from among all available units. Strictly speaking, such selections ought to be analyzed by permutation (i.e., re-randomization) tests, but the known similarity with IID methods often permits the use of standard analyses. However, in the case of the operational vs. pre-operational comparisons the assumption of randomization is patently untrue; in an operation the treatment years are surely not chosen at random. The only way one could conceptualize such randomness would be if nature were assumed 'to deal a random deck,' but then we would be back in the IID situation.

It seems reasonable, on a very cursory examination of the evidence, to assume that some sort of serial dependence of precipitation exists from year-to-year but that it is not very strong. It also seems reasonable to assume that compatible trends co-exist in neighboring areas in sequences of say, 20 years or less. The practical problem we are addressing is whether the small existing order of dependence and trends may affect the operating characteristics of standard statistical techniques sufficiently to invalidate their inferences.

The issue is one of robustness of statistical techniques against nature's violation of randomness. One way to study this would be to model natural precipitation as a time series and then use analytical methods to assess the robustness of given techniques under the appropriate model. Another way is to examine the behavior of the statistical techniques when applied to natural, i.e., unseeded, precipitation data, and to see how far that behavior deviates from what would have been predicted from the IID assumptions, i.e., from standard statistical theory.

The first kind of robustness study would require adequate time series modelling of precipitation data - something that does not seem to have been done. Even with such models, the derivation of robustness properties might not be easy. We have therefore chosen the second method of study and applied a number of statistical tests to successive samples of years of precipitation data to check how far the observed distribution of these test statistics differs from that predicted by the standard theory for IID variables.

The objective of this study was to allow informed assessments of the validity of standard statistical comparisons of precipitation during operations with historical records of precipitation. If test statistics applied to natural precipitation data were distributed very differently from what IID assumptions would have indicated, then one should have been warned against the use of such statistics for operational vs. historical comparisons. If, on the other hand, the statistics had been found to be reasonably robust and to behave much as though they came from IID variables, then one might have had some confidence in the validity of such analysis of cloud seeding operations.

It must be understood that confidence in the applicability of statistical techniques does not ensure the elimination of other biases. Even if the present study had supported the robustness of standard methods and would therefore have increased our confidence in standard tests of operational/historical comparisons, that should not in any way have reduced the vigilance of critics in the matter of biases which might creep in. Biases have to be guarded against even if the statistical methods are valid.

7.2 The Study of Illinois Data

To study the distribution of statistics on natural precipitation, it was necessary to assemble such data for reasonably long time periods at several locations. As a beginning study, 100 years of records of annual precipitation, 1879-1978, were obtained for several stations in Illinois.

These Illinois data were used to simulate the analysis of short cloud-seeding 'experiments.' Every 100-year series was broken into 10 decades, each decade being considered as one 'experiment,' its first 5 years as 'unseeded,' the last 5 as 'seeded.' Data for precipitation were used as observed, without imposing or adding any 'seeding effect.' The analyses were, therefore, run under null hypothesis conditions. In this way, ten 'experiments' were simulated from the 100 years' data.

The same data were also divided into sets of 20 years for comparisons of 10 'seeded' years with 10 preceding 'unseeded' years. Again, the logic was the same as for the shorter comparisons, but only 5 such 'experiments' could be simulated from 100 years' data.

Comparisons with longer 'unseeded' periods might have simulated more realistic analyses of operations but would have reduced the number of 'experiments' even more. Overlapping choices of decades, or double decades, would have increased the number of 'experiments' at the cost of introducing dependence, e.g., if 'experiment 1' ran during 1879-1888, 'experiment 2' could have run during 1880-1889, etc., but the nine-year overlap would have caused statistical dependence. We therefore stayed with 10 decades and 5 double decades. (See, however, Gabriel and Petrondas, 1981.)

Analyses of seeding operations usually relate a 'target' area to a 'control' area which is upwind of the target and is correlated with it, but is assumed to be unaffected by seeding. To simulate such a design, eight Illinois stations were paired; the more westerly or northerly station was considered as the 'target' and the other station as the 'control.' For example, Chicago was considered to be a 'target' and Marengo its 'control.' Real operations are not usually analyzed in terms of a single station in each area, but in this study it was impractical to simulate a multiplicity of nearby stations in each of the 'target' and 'control' areas. Adequate historical records were not available. Also, it seemed unlikely that use of a multiplicity of stations would have had a meaningful impact. It would presumably have reduced the intra-area variability for each year, but it is unlikely that it would have affected the year-to-year variation in any interesting manner. This issue was therefore not considered further.

As a preliminary to considering the 'seeded' vs. 'unseeded' comparisons, we briefly considered the variation within and between successive groups of years.

Table 7.1 shows F-ratios of variances between means of groups to pooled variances within groups. Thus, in the top panel of the Table, the F-ratios serve to compare the variance of the 10 decade means with the pooled variance within decades. Similarly, the bottom panel compares the variance between the 20 means of quinquennia with the pooled variance within quinquennia. Considering individual stations (appearing as X or Y in Table 7.1), we found Dubuque, Moline, and St. Louis to have significantly greater between-period variability than within periods. For paired station differences, Dubuque-Moline and St. Louis-Cairo showed significantly greater period-to-period variability, This indicated that, at least in parts of Illinois, there was systematic rather than purely random variation over time - contrary to the IID assumption. That finding made the use of standard techniques prima facie suspect and called for an investigation of their actual performance in 'experiments' simulated by taking decennial data from rainfall records and splitting them up into 'unseeded' and 'seeded' periods.

Table 7.1. F-Ratios for between/within Groups of Years

	Dubuque (Y) vs Moline (X)	St. Louis (Y) vs Cairo (X)	Chicago (Y) vs Marengo (X)	Peoria (Y) vs Springfield (X)
		10 vs 10 F(9, 90)		
X	3-095	2.336	1.488	1.117
Y	4.970	1.115	1.845	0.591
Y-X	4.474	5.674	0.573	1.464
		5 vs 5 F(19, 80)		
X	2.603	1.837'	0.989	0.896
Y	2.770	0.913	1.145	0.682
Y-X	2.550	3.933	0.529	1.070

A number of statistics were computed for each simulated experiment. These included t-tests on the 'target' itself, on the 'target' adjusted for regression on 'control,' and on 'target-control' differences. They further included double ratios, i.e., (seeded target total/unseeded target total) / (seeded control total/unseeded control total), and transformations of these ratios. Non-parametric test statistics were also computed, i.e., the median test, the Mann-Whitney test, and the squared-rank-sum test.

The P-value of each statistic was then evaluated by standard methods which assume IID precipitation or, at least, randomized allocation of seeding to 5 out of 10 given years (or 10 out of 20 years). Since these 'experiments' were applied to natural precipitation data without superimposition of any 'seeding effect,' a valid statistical technique should have produced P-values distributed uniformly between 0 and 1. In other words, the probability that the P-value should be less than any number P $(0<P<1)$ should have been exactly P. The P-values of the simulated 'experiments' were therefore examined to see if they could have arisen from such a uniform distribution. If they had done so, the statistical techniques yielding these P-values could be considered to yield valid inferences from operational vs. historical comparisons.

If, on the other hand, the simulated P-values would have been found to be smaller (larger), one would have been led to suspect that this statistical technique might lead to radical (conservative) inferences, i.e., might result in too many (too few) type I errors. Such findings would have made the analysis of cloud seeding operations with this technique suspect. One would suspect too many false decisions on whether seeding was (or was not) effective.

As an example, consider the 10 decade 'experiment' with the Dubuque 'target' and Moline 'control,' and consider the t-statistic for Y - X, where Y and X are 'target' and 'control' precipitations, respectively. The statistics and P-values for this example are shown in Table 7.2 so it may be judged whether these ten P-values deviate significantly from the uniform (0,1) distribution. No clear deviation is evident. The calculations were made of the four statistics,

$$X_1^2 = -2 \sum_{i=1}^{10} \ln Pi; \qquad X_2^2 = -2 \sum_{i=1}^{10} \ln (1 - Pi);$$

$$X_3^2 = -2 \sum_{i=1}^{10} \ln (1 - 2\,|Pi-0.5|); \qquad X_4^2 = -2 \sum_{i=1}^{10} \ln (2\,|Pi-0.5|)$$

each of which has a chi-square distribution with 20 degrees of freedom under the null hypothesis. X_1^2 and X_3^2 are likelihood ratio tests; $X_2^1$and X_4^2 are two versions of the test developed by Pearson and advocated by Fisher. The alternatives indicated by high and low values of these statistics are listed in Table 7.2. The example shows one 5% significant (one-tailed), statistic (since $X_{(20)},.95= 31.41$) and thus provides slight evidence of less dispersion than in the uniform case.

Table 7.2. Detailed Analysis of Dubuque vs. Moline Decennial Experiments

Decade	t statistics	P-value*
1879-1888	-0.171	0.566
1889-1898	-0.001	0.500
1899-1908	-0.951	0.815
1909-1918	-0.715	0.752
1919-1928	-1.609	0.927
1929-1938	1.427	0.096
1939-1948	0.016	0.494
1949-1958	1.044	0.164
1959-1968	-0.856	0.791
1969-1978	2.276	0.026

Test statistics (HQ : P-distribution is Uniform (0,1))

	Likelihood Ratio	Pearson-Fisher
Against a shift alternative	21.1**	19.6
(+ shift as indicated by	small values	large values)
(- shift as indicated by	large values	small values)
Against a dispersion alternative	20.7	31.7
(less dispersion about 1/2 is indicated by	small values	large values)
(more dispersion about 1/2 is indicated by	large values	small values)

* 8 d.f., one-sided

** All four statistics have a chi-square distribution with 20 d.f.

Comparisons of this kind were carried out on all four pairs of stations, for each of a selection of statistics and separately for 10 decennial 'experiments' and 5 duodecennial 'experiments.' These are not quite independent because annual precipitation at the various Illinois stations was correlated although inter-station differences Y-X were probably less correlated. Hence, no significance tests were run on these 'mixed' samples, but only on samples from a single station pair. The same proviso applies to mixing the P-values of 5 duodecennial 'experiments' from each of four station pairs.

Chi-square tests of significance of uniformity of P-value distribution were run separately for each of the four station pairs. The four tests - see above and Table 7.2 - were run separately for 5 vs. 5 year 'experiments' (Table 7.3) and for 10 vs. 10 year 'experiments' (Table 7.4). Most of the P-values were based on statistical techniques comparing the location of the 'seeded' with the 'unseeded' set of years to see if the former were larger, i.e., one-sided tests. P-values for slope and regression techniques were somewhat different since these compare Y on X regressions rather thean the 'effects' of seeding on location. However, they were included in this study because such tests are also commonly run.

No striking evidence of departures from uniformity is apparent from Table 7.3. Very few of the chi-squares are significant even at the one-tailed, 5% level test, i.e., at a 10 % two-tailed level. At most, there is a very vague suggestion of a tendency to smaller P-values than expected from uniformity. Table 7.4, on the other hand, shows high significance for too large P-values and excessive dispersion of P-values. It is difficult to reconcile these two bits of evidence.

It is difficult to know what to make of these findings. More study is needed to resolve these issues. The 5 vs. 5 year comparisons seem to confirm the validity of the statistical techniques for location comparisons; if anything, they were perhaps a little radical, i.e., resulting in too many type I errors. The 10 vs. 10 years comparisons, on the other hand, strongly suggest that these tests are conservative, i.e., have too few type I errors and, hence, also too low power. It could, of course, be that precipitation distributions affect the performance of these techniques differently for experiments of different lengths, but that would seem somewhat surprising, and one would wish for more evidence before reaching even tentative conclusions (see Gabriel and Petrondas, 1981).

As to slope comparisons, Tables 7.3 and 7.4 suggest that standard statistical techniques may not be valid with precipitation experiments. However, here again, the evidence from the two tables is contradictory. The 5 vs. 5 year comparisons (Table 7.3) suggest that the standard tests are radical, whereas 10 vs. 10 year comparisons (Table 7.4) yield apparently conservative tests. Again, we can only conclude that the evidence is equivocal and cannot make definite recommendations.

Conclusions. The present study of 100 years of Illinois precipitation data has not resolved the issue which it addressed. At best, we may conclude that the standard statistical techniques of comparing operational with historical precipitation are not blatantly invalid. But it is impossible to say whether their error rates are very close to the true ones or whether they deviate conservatively or radically. More study is needed.

The main reason for the paucity of results is that the present study analyzed only 10 'experiments' of 5 'seeded' vs. 5 'unseeded' years (or 5 'experiments' of 10 vs. 10 years). This is a very small number, but is all one can get from 100 years' data. To some extent we tried to augment the data by concurrently studying experiments at four different station pairs, but since they were all in Illinois, and well correlated, this could not really be considered to be replication. For the same reason, we did not 'replicate' the 'experiments' further by studying all 91 possible 10 year 'experiments,' i.e., 1879-1888,1880-1889,1881-1890,...,1968-1977, 1969-1978. These 91 overlapping 'experiments' would have been likely to be highly correlated.

Table 7.3. Chi-Square Tests on Uniformity of P-values, Comparisons of 5 'Seeded' vs 5 'Unseeded' Years (Tests as in Table 7.2)

		Dubuque (Y) vs Moline (X)		St. Louis (Y) vs Cairo (X)		Chicago (Y) vs Marengo (X)		Peoria (Y) vs Springfield (X)	
		LR	P-F	LR	P-F	LR	P-F	LR	P-F
X : t-test	Loc	22.5	23.0	23.7	18.7	14.7	20.3	19.0	14.3
	Disp	27.4	11.7	23.3	15.0	15.3	15.2	11.9	25.0
Y : t-test	Loc	19.9	21.6	24.7	11.5	16.2	18.0	20.3	15.0
	Disp	22.1	17.0	15.0	23.1	13.1	21.5	14.2	24.2
Y-X : t-test	Loc	21.1	19.6	24.6	18.5	19.3	16.1	21.4	16.1
	Disp	20.7	31.7	16.4	23.6	13.9	28.7	18.1	15.0
$Y-b_cX$: t-test	Loc	23.9	21.2	16.6	22.8	22.9	14.1	23.6	17.0
	Disp	25.6	16.3	19.4	16.2	16.2	27.3	20.9	18.8
ANCOVA, t-test	Loc	16.6	21.1	22.8	15.1	25.0	15.3	23.5	15.1
	Disp	18.6	13.8	18.2	17.2	19.5	26.1	18.0	24.6
b slopes : t-test	Loc	34.8	8.5	20.6	15.4	15.0	14.6	16.0	26.1
	Disp	22.6	22.0	15.0	23.3	6.1	41.7	23.6	12.2
a,b reg.: F-test	Loc	21.4	19.4	14.7	21.8	11.1	30.6	20.7	15.6
	Disp	20.2	22.0	16.5	24.7	22.5	15.9	17.2	13.2
InR : γ-test	Loc	20.5	19.2	24.0	17.6	19.6	15.5	20.6	15.8
	Disp	19.8	23.2	21.7	20.2	13.3	30.5	16.4	16.6
InR : Normal test	Loc	20.4	19.9	23.8	18.0	19.9	15.5	20.6	16.3
	Disp	20.6	21.9	22.1	19.0	13.8	29.1	17.3	15.1
InR : permutation test	Loc	20.1	19.8	24.8	18.0	20.1	15.6	21.0	16.3
	Disp	20.1	22.7	23.2	19.1	14.2	28.3	17.6	15.4
Median test	Loc	26.2	13.1	25.1	21.2	15.6	20.2	22.2	13.6
	Disp	20.1	13.0	28.3	10.1	16.1	14.5	16.1	14.5
Mann-Whitney test	Loc	20.6	16.7	25.8	18.9	17.6	16.3	22.7	15.5
	Disp	16.2	25.8	25.4	17.4	11.8	28.4	18.0	19.3
Squared Ranks test	Loc	19.0	21.9	23.7	17.9	18.2	16.5	22.4	17.1
	Disp	21.5	20.1	22.4	15.2	13.0	32.4	20.1	15.1

Table 7.4. Chi-Square Tests of Uniformity of P-values, Comparisons of 10 'Seeded' vs 10 'Unseeded' Years (Tests as in Table 7.3)

		Dubuque (Y) vs Moline (X)		St. Louis (Y) vs Cairo (X)		Chicago (Y) vs Marengo (X)		Peoria (Y) vs Springfield (X)	
Test		LR	P-F	LR	P-F	LR	P-F	LR	P-F
X : t-test	Loc	5.0	13.1	12.7	6.0	. 9.4	8.2	6.5	12.3
	Disp	7.9	10.6	8.0	11.1	7.8	7.8	9.6	5.2
Y : t-test	Loc	5.4	24.1	12.7	10.9	11.1	12.6	6.5	12.5
	Disp	21.3	2.9	15.3	3.2	14.8	5.0	9.5	7.2
Y-X : t-test	Loc	9.4	26.7	9.2	22.7	7.5	8.7	11.3	6.3
	Disp	26.4	8.6	22.3	16.6	5.0	15.1	7.3	9.5
$Y-b_cX$: t-test	Loc	9.9	28.6	14.2	19.4	8.5	10.4	7.6	7.8
	Disp	29.8	4.0	25.8	2.1	9.5	6.4	4.2	13.4
ANCOVA, t-test	Loc	8.4	28.5	12.2	20.6	8.6	11.2	7.6	9.3
	Disp	28.1	4.6	24.7	2.8	10.0	7.9	6.2	12.5
b slopes :	Loc	9.4	21.1	10.9	9.8	13.6	10.7	8.1	11.9
t-test	Disp	20.3	11.7	10.4	12.9	15.7	4.1	10.3	8.6
a,b reg.:	Loc	34.7	7.3	21.2	3.2	13.4	7.0	7.4	11.2
F-test	Disp	32.1	8.6	14.7	8.1	10.7	18.5	8.6	8.2

In view of the inconclusiveness of the present findings, it is recommended that a few more analyses be made of the Illinois data, such as: (1) Try 3 vs. 3 year 'experiments' as well as 7 vs. 7 year 'experiments' to see if there is consistency in the results for experiments of different lengths; (2) Try overlapping 'experiments' after all. More importantly, we should try to replicate the analyses at other stations, preferably far from Illinois. The above procedures might lead to more conclusive findings (Gabriel and Petrondas, 1981).

8. MISCELLANEOUS TOPICS

Other topics which are important to the evaluation of operational seeding projects are discussed below. The topic of piggyback is relatively recent, and because of its future potential as a viable means of conducting scientific experiments in conjunction with commercial operations, efforts were exerted to obtain a better understanding of the feasibility of piggyback experiments. Also, criteria for weather modification operations and effective evaluation were developed as part of OSET (Huff and Changnon, 1980) in order that a reasonably good bank of information would be available for a latter assessment of the seeding operations.

8.1 Piggyback Experiment

The addition of scientific measurements to operational weather modification projects has been referred to as 'piggyback' science (Weather Modification Advisory Board, 1978b). Some form of randomization must be employed in this approach. Inventive ways to incorporate randomized piggyback research need to be studied. Two types of piggyback projects appear scientifically possible and acceptable to users of operational weather modification. The first type could utilize partial randomization on some (rainfall) occasions before, during, or after the designated operational seeding period. For example, in the period before the users want seeding, the choice of seed or no-seed is made for each occasion. The weather and climate conditions before or after would have to be very similar to the non-randomized seeded period. Also, minimal randomization during the period of user need for modification should be undertaken, if at all possible.

The second type of potential piggyback research would employ randomization only during seeding operations, with sufficient frequency (percentage of seedable situations) to provide adequate statistical data for reliable evaluations. For instance, different seeding agents or difference rates could be used. Combination of both the first and second type piggyback approaches may also be feasible.

Due to restricted funding, a relatively small effort has been made to study various issues relating to piggyback experiments. The results were summarized in a report by Gabriel and Changnon (1981). The idea of piggyback experiments on operational projects was discussed with emphasis on the meteorological aspects. Two examples of possible piggyback experiments and the outlines of experimental designs were explicitly given in the report. Other issues discussed included 'blindness' in various stages of operations, and seeding rates.

8.2 Operational Criteria

An OSET report (Huff and Changnon, 1980) treated the key issues and presented recommendations for weather modification operations. This report provides guidance for achieving effective, reliable evaluation of seeding results, and, consequently, establishing credibility in these evaluations, and providing scientific information leading to better understanding and greater skills in future weather modification operations. Four tasks were discussed--design, selection of seeding criteria, conduct of seeding mission, and collection and recording of data. A number of key issues and recommendations are presented at the end of the report. They included personnel required for operations; seeding criteria; requirements for operations for different types of seeding; needs for radar and other instrumentation; and requirements for detailed documentation of operational activities.

9. SUMMARY

A collection of statistical-physical techniques to evaluate weather modification projects was compared primarily through extensive simulation testing of assumed weather modification effects superimposed upon natural precipitation distributions. Statistical power was the main index used in comparison. The studies on the approximation of power by using two methods indicated that at both 5% and 10% nominal significance levels, powers computed by Method I (naive method) were, in general, slightly larger than those computed by exact Method II. Discrepancies were small, usually less than or equal to .05. Additionally, normal approximation of Method II usually overestimated the exact power slightly and the approximation of Method I was even a little higher. It was concluded that for all but very small experiments, both approximations come reasonably close to true power (only a few percentage points above it). Method I, due to its cost-efficiency in the computations, was employed in the subsequent simulations.

Five data sets from four areas were selected for simulation to compare the effectiveness of the statistical techniques in evaluating weather modification projects. Findings from Kansas rain simulations indicated that the technique of principal component regression retaining the first component (PCR[1]) was one of the most powerful techniques for various summer months and target-control designs. In the east-central Illinois (ILL-EC) rainfall study the techniques of PCR[1] and double ratios (DR) were generally the most powerful; and the technique of two regressions (2Reg) was the next powerful. The results of the ILL-EC simulation, when compared with those of the Kansas simulation, indicated that the technique of PCR[1] had high powers in both simulations in every month except June, when only the double ratio had high power (in the averaged target simulation).

In Montana hail suppression simulations, for the larger target, principal component regression with 3 components (PCR[3]) was the most powerful in both 3 seeded years and 6 seeded years simulations. For smaller targets, PCR[3] worked well in the 3 seeded years study. DR was most powerful in the 6 seeded years study, followed closely by PCR[3] and sum of ranked powers test (SRP). The techniques of two regressions was not compared in the 3-year study, but was compared in the 6-year study. Its powers were rather poor relative to other techniques. The technique of SRP had poor powers in the 3-year study except when the assumed seeding effect was large. In the Illinois-storm simulation, results for constant seeding-induced increases indicated that multiple regression (MR) and PCR[1] were the most powerful techniques. The SRP was the most powerful when varying seeding effect models A, E, and C (see Table 3.15 for details) were assumed; while MR and PCR[1] were the most powerful when model M was assumed. In the Illinois 48-hour simulation, multiple regression was the most powerful technique in all cases; the principal component regression with 1 component (PCR[1]) was a close second. The double ratio performed well, too.

A number of past seeding projects of the commercial type were selected for testing the statistical-physical evaluation techniques developed. A large-scale hail suppression and rain enhancement project, the Mudddy Road Project in southwestern Kansas, was evaluated using monthly rains and annual crop-hail loss-cost data. The evaluation of the hail suppression efforts indicated that there was a reduction of hail loss-cost values during the 1975-1979 seeded period; however, only the reduction in the east sub-target was significant at the

10% significance level. This example also demonstrated that the principal component regression (PCR) is a better technique for evaluating hail suppression than the multiple regression (MR). On the other hand, the statistical evaluation on the rainfall observations indicated that there was a non-significant reduction of rainfall in the target area during the seeded period.

Several small-scale rain enhancement projects in Illinois also were evaluated. In general, the results reflected quite mixed outcomes. Two of the projects (years) indicated increases, signified by pluses (1976 and 1979), in the target rainfall and/or radar echoes. One year (1978) indicated a rain decrease. The target echo results were also mixed. In all instances, the 1-year (usually one or two months) projects were too short, regardless of the apparent increases or decreases of rainfall or echo in the target areas, to draw any conclusions that have any statistical or physical significance when taken alone.

A long-term operational project in the Texas Panhandle which dealt with hail suppression was selected for evaluation. The technique of factor analysis was applied to a 12-county data set for 1947-1976. The Varimax rotation was employed and 7 factors were retained. They explained 91% of the total hail loss-cost variance. From the loading matrix it was shown that the target counties, Hale and Lamb, were both heavily loaded on Factor 4, Factor 1 represented counties in the northwestern corner, and Factor 3 represented counties in the southeastern corner. Both Welch's t-test and Mann-Whitney tests showed that only Factors 2 and Factor 4 (target) displayed differences which were significant at the 5% significance level between the historical and seeded factor scores. Factor 2 represented Cochran County and Lubbock County, both located south of the target. This indicated that the two target counties together showed a significant change of hail loss-cost between the historical and seeded period, and except for part of the southern counties, most control counties did not show any significant difference of loss-cost values between the two periods.

Further investigation of the usage of principal component regression indicated that when corner counties were used as dependent variables, the principal component regression which retained the first 3 components was more powerful than the principal component regression which retained only the first component. Twelve biased methods which shrink the principal components were investigated. The findings revealed first that in the modeling process, the difference of residual mean square (RMS) among all the biased regression was minor. A few RMS's of biased regression were smaller than the full-modeled least squares, but larger than certain least squares best subsets. Shrinking the small-eigenvalued components reduced the biased portion of MSE more than shrinking the retained components, and deleted the small-eigenvalued components. As more principal components were included in the regression, MSE became smaller, no matter whether retained principal components or small-eigenvalued principal components were shrunk. However, shrinking retained principal components shows improvement of RMS and MSE over non-shrinking whenever generalized ridge estimators were employed. In the prediction process, the biased methods predicted uniformly better than the least squares best subsets, though the predicted residual mean square (PRMS) of the biased method did not reach the attainable minimum. Overall, the biased methods decreased the coefficient of determination, R, when compared to the least squares; however, the biased methods gained predicting power over least squares. Slight shrinking on retained principal components or on small-eigenvalued principal components showed improvement in terms of PRMS over non-shrinking.

The usage of surface meteorological covariates as forecasters and evaluators was investigated. In the forecaster study, comparisons were made between the usage of PC-covariates and point-covariates, as well as between first-stage and second-stage variable screenings. The advantage of using PC-covariates over using point-covariates is that by using only those few principal components which are most useful in prediction, we are able to include in the prediction process as much information as desired and at the same time avoid the problem of multi-collinearity. Forty-five point-covariates and 16 PC-covariates were retained after the first-stage screening. The range of the coefficients of determination of the regresssion, using the individual field of point-covariates as the independent variable, was slightly narrower than that using the individual field of PC-covariates as the independent variable. The majority of the selected point-covariates were located rather close to the target area, with very few farther than 200 km. After a second-stage screening, 11 point-covariates and 8 PC-covariates were retained. The results showed that the mean of 500 D (mean difference) values using PC-covariates was closer to zero than using point-covariates both after a first-stage and a second-stage screening. The means and extremes of the D-distributions revealed an advantage of employing a second-stage screening whether using PC-covariates or point-covariates.

In the evaluator study, findings indicate that powers using the meteorological covariates after second-stage screening were greater than those using only the precipitation in the upwind controls as independent variables or those stopped at the first-stage screening. If screening stopped at the first-stage, powers using both upwind controls and the meteorological covariates were greater than those using only the upwind controls, but the inclusion of point-covariates did not improve the powers over using only the upwind controls. Secondly, powers of simulation using PC-covariates (PC) out-performed those using point-covariates (SR) whether upwind controls were included or not. Powers of using point-covariates (SR) were the lowest among all the simulations compared in both the first-stage and the second-stage screenings. After the second-stage screening, powers at the 5% significance level of the simulation which employed upwind controls were larger than those not using upwind controls.

The differences in powers between using PC-covariates (PC) and point-covariates (SR) diminished after the second-stage screening. A closer look revealed that, at the 5% significance level, PC after the second-stage screening had better powers than SR except for seeding-effect model C; at the 10% significance level both had similar powers. Interestingly, powers using PC-covariates with upwind controls after the first-stage screening were greater than those using point-covariates without upwind controls, even after the second-stage screening. Powers of using PC-covariates or point-covariates without upwind controls after the second-stage screening were generally greater than those including upwind controls but stopped at the first-stage screening. This means that a proper screening of covariates might offset a partial need for upwind controls with an understanding that the inclusion of upwind controls is definitely an advantage after the second-stage screening.

Generally, the use of meteorological covariates improved the powers of the evaluation techniques. A second-stage screening to remove spurious variables was found to be worthwhile; in addition, the use of upwind controls further ensured a greater power. If the degree of spuriousness in the variables is unknown, then the use of PC-covariates is recommended over point-covariates.

The validity of using the historical comparison approach to evaluate weather modification projects was studied. A number of statistical tests were employed and the resulting distributions of P-values were compared by using a number of pairs of long-term National Weather Service stations in Illinois. From these distributions of P-values, no striking evidence of departures from uniformity was apparent. Very few of the chi-square statistics were significant even at the one-tailed, 5% level test, i.e., at a 10% two-tailed level. At most, there was a very vague suggestion of a tendency to smaller P-values than expected from uniformity. On the other hand, a high significance for too large P-values and excessive dispersion of P-values was shown. It was difficult to reconcile these two bits of evidence. As to slope comparisons, the findings suggested that standard statistical techniques may not be valid with precipitation experiments; however, the evidence was not conclusive. Five vs. five year comparisons suggested that the standard tests were slightly radical, whereas 10 vs. 10 year comparisons yielded apparently conservative tests. The present study of 100 years of Illinois precipitation data has not resolved the issue which it addressed. At best, we may conclude that the standard statistical techniques of comparing operational with historical precipitation are not blatantly invalid. However, it is impossible to say whether their error rates are very close to the true ones or whether they deviate conservatively or radically. More study is needed to resolve these issues.

REFERENCES

Achtemeier, G. L., P. H. Hildebrand, P. T. Schickedanz, B. Ackerman, S. A. Changnon, Jr., and R. G. Semonin, 1977: Illinois precipitation enhancement program (Phase I) and design and evaluation techniques for High Plains cooperative program. Final Report to Bureau of Reclamation, 14-06D-7197, Illinois State Water Survey, Urbana, 267 pp.

---, 1980: On the development of covariates for the evaluation of operational seeding projects in areas without physiographic influences. J. Wea. Mod., 12(1), 16-23.

---, 1981: Relationships between rainfall and meteorological surface variables: Applications to Midwestern operational weather modification. Final Report, NSF ATM79-05007, Illinois State Water Survey, Champaign, IL, 69 pp.

Ackerman, B., G. L. Achtemeier, H. Appleman, S. A. Changnon, Jr., F. A. Huff, G. M. Morgan, P. T. Schickedanz, and R. G. Semonin, 1976: Design of the High Plains experiment with specific focus on phase 2, single cloud experimentation. Final Report, Bureau of Reclamation, 14-06-D-7197, Illinois State Water Survey, Urbana, 231 pp.

Adderley, E. E., 1961: Non-parametric methods of analysis appled to large-scale cloud seeding experiments. . J. Meteor., 18, 692-694.

Anderson, T. W., 1963: Asymptotic theory for principal component analysis. Ann. Math. Statist., 34, 122-148.

Bernier, J., 1967: On the design and evaluation of cloud seeding experiments performed by Electricite de France. Proc. Fifth Berkeley Symp. on Math. Statist. and Prob., V, 5, 35-54.

Biondini, R., J. Simpson, and W. L. Woodley, 1977: Empirical predictors for natural and seeded rainfall in the Florida area cumulus experiment (FACE), 1970-1975. J. Appl. Meteor., 16, 585-594.

Braham, Roscoe R., Jr., 1966: Project Whitetop: Part I - Design of the experiment, Part II - Summary of operations. Final Report, Dept. of Geophys. Sci., University of Chicago, 156 pp.

Carmer, S. G., and W. T. Hsieh, 1980: A biased regression procedure combining principal component and ridge regression techniques. Paper presented at the spring Regional Meeting of the Biometric Society (ENAR), Charleston, South Carolina, 13 March, 7 pp.

Changnon, S. A., Jr., 1975: Operations of mesoscale networks, illustrated by METROMEX. Bull. Amer. Meteor. Soc, 56(9), 971-977.

---, and F. A. Huff, 1967: The effect of natural rainfall variability in verification of rain modification experiments. Proc. Fifth Berkeley Symp. on Math. Statist, and Prob., V, 177-198.

---, F. A. Huff, P. T. Schickedanz, and J. L. Vogel, 1977: Summary of METROMEX, Volume 1: Weather anomalies and impacts. Bulletin 62, Illinois State Water Survey, Champaign, IL, 260 pp.

---, and N. G. Towery, 1977: Preliminary evaluation of the 1976 rain modification project in central Illinois. J. Wea. Mod., 9, 66-78.

---, C. F. Hsu, and N. G. Towery, 1979: Evaluation of the McLean County rainfall modification projects in 1977 and 1978. Technical Report, Illinois State Water Survey, Champaign, IL, 22 pp.

---, F. A. Huff, C. F. Hsu, G. L. Achtemeier, N. Westcott, and P. Rosenzweig, 1979: Operational Seeding Evaluation Techniques. Final Report, NSF ENV78-01003, Illinois State Water Survey, Champaign, IL, 63 pp.

---, and C. F. Hsu, 1980: Assessment of summer 1979 rainfall in southeastern Illinois with special reference to weather modification effects. Misc. Publ. 56, Illinois State Water Survey, Champaign, IL, 18 pp.

---, and C. F. Hsu, 1981: Evaluation of Illinois weather modification projects of 1976-1980: A summary. Circular 148, Illinois State Water Survey, Champaign, IL, 31 pp.

Cochran, W. G., 1969: The use of covariance in observational studies. Appl. Statist., 18, 270-275.

Cox, D. R., and 0. Kempthorne, 1963: Randomization tests for comparing survival curves. Biometrika, 307-317.

Dempster, A. P., M. Schatzoff, and N. Wermuth, 1977: A simulation study of alternatives to ordinary least squares. J. Amer. Statist. Assoc, 72, 77-91.

Dennis, A. S., D. F. Kriege, 1966: Results of ten-years of cloud seeding in Santa Clara county, California. J. Appl. Meteor., 5, 684-691.

---, J. R. Miller, and R. L. Schwaller, 1975: Evaluation by Monte Carlo tests of effects of cloud seeding on growing season rainfall in North Dakota. J. Appl. Meteor., 14,959-969.

Dwass, M., 1957: Modified randomization tests for nonparametric hypotheses. Ann. Math. Statist., 28, 181-187.

Elliot, R. D., and K. J. Brown, 1971: The Santa Barbara II Project — Downwind effect. Proc. Internat. Conf. on Wea. Mod., Canberra, Australia, 6-11 Sept., 179-184.

Fisher. R. A., 1935 (8th ed., 1971): The design of experiments. Hafner Publ. Co., New York, 245 pp.

Gabriel, K. R., and P. Feder, 1969: On the distribution of statistics for evaluating rainfall stimulation experiments. Technometrics, 11, 149-160.

-, 1979: Some statistical issues in weather modification. Commun. Statist.-Theor. & Meth., A8(10), 975-1015.

---, and C. F. Hsu, 1980: Power studies of re-randomization tests. Third WMO Sci. Conf. on Wea. Mod., Clermont-Ferrand, France, 21-25 July, 507-513.

---, and S. A. Changnon, Jr., 1981: Piggyback weather experiments: superimposing randomized treatment comparisons. Submitted to J. Wea. Mod..

---, and C. F. Hsu, 1981: Evaluation of the power of re-randomization test, with application to weather modification experiments. Submitted to J. Amer. Statist. Assoc.

---, and D. Petrondas, 1981: On using historical comparisons in evaluating cloud seeding operations. Technical Report 81/12 , Dept. of Statistics , University of Rochester, 6 pp.

Grant, L. O., and R. D. Elliott, 1974: The cloud seeding temperature window. J. Appl. Meteor., 13(3), 355-363.

Gunst, R. F., J. T. Webster, and R. L. Mason, 1976: A comparison of least squares and latent root regression estimators. Technometrics, 18(1), 75-83.

---, and R. L. Mason, 1977: biased estimation in regression: An evaluation using mean square error. J. Amer. Statist. Assoc, 72, 616-628.

---, and J. T. Webster, 1978: Deletion of principal components in regression. Technical Report, Department of Statistics, Southern Methodist University, 22 pp.

Henderson, T. J., and S. A. Changnon, Jr., 1972: Results from an applications program of hail suppression in Texas. Third Conf. on Wea. Mod., Amer. Meteor. Soc, Rapid City, S.D., 26-29 June, 260-267.

Hocking, R. R., 1976: The analysis and selection of variables in linear regression. Biometrics, 32, 1-49.

---, F. M. Speed, and M. J. Lynn, 1976: A class of biased estimators in linear regression. Technometrics, 18(4), 425-437.

Hoerl, A. E., and R. W. Kennard, 1970a: Ridge regression: Biased estimation for nonorthogonal problems. Technometrics, 12(1), 55-67.

---, and R. W. Kennard, 1970b: Ridge regression: Applications to nonorthogonal problems. Technometrics, 12(1), 69-82.

Hsu, C. F., 1978: Variable Selection and Forecasting of Regression Models. Proc Statist. Comp. Sec, Amer. Statist. Assoc, Washington, DC, 256-260.

---, 1979a: Monte Carlo studies of statistical evaluation techniques for weather modification. Seventh Conf. on Inadv. and Planned Wea. Mod., Amer. Meteor. Soc, Banff, Canada, 8-12 Oct., J3-J4.

---, 1979b: Two methods of computing statistical powers with application to weather modification. Proc. Statist. Comp. Sec, Amer. Statist. Assoc, Washington, DC, 243-246.

---, 1980: Using biased regression to statistically predict rainfall over many years. Proc. Statist. Comp. Sec, Amer. Statist. Assoc, Washington, DC, 221-226.

---, 1981a: An annotated bibliography on the evaluation and statistical issues of weather modification. Final Report, MSF ATM 79-05007, Illinois State Water Survey, Champaign, IL, 93 pp.

---, 1981b: Using surface meteorological covariates to predict storm areal rainfall 1-3 hours in advance. Seventh Conf. on Prob. and Statist. in Atmos. Sci., Amer. Meteor. Soc, Monterey, California, 2-6 Nov., 217-221

---, and S. A. Changnon, Jr., 1981a: Assessment of summer 1979 weather modification effort in southeastern Illinois. J. Wea. Mod., 13(1), 132-140.

---, and S. A. Changnon, Jr., 1981b: Assessment of summer 1980 weather modification effort in southeastern Illinois. Misc. Publ., Illinois State Water Survey, Champaign, IL.

---, and J. Chen, 1981a: Statistical evaluation of a rain-hail operational project in southwestern Kansas. Eighth Conf. on Inadv. and Planned Wea. Mod., Amer. Meteor. Soc, Reno, Nevada, 5-7 Oct., 124-125.

---, and J. Chen, 1981b: Performance comparison of statistical techniques in evaluating weather modification projects. Eighth Conf. on Inadv. and Planned Wea. Mod., Amer. Meteor. Soc, Reno, Nevada, 5-7 Oct., 128-129.

Huff, F. A., and R. G. Semonin, 1960: An investigation of flood-producing storms in Illinois. Topics in Eng. in Meteor., 4, Meteor. Monog., Amer. Meteor. Soc, 50-55.

---, and S. A. Changnon, Jr., 1980: Criteria for weather modification operations and effective evaluation. Final Report, NSF ATM 79-05007, Illinois State Water Survey, Urbana, 22 pp.

Kempthorne, 0., 1952: The design and analysis of experiments. John Wiley & Sons, New York.

---, and T. E. Doerfler, 1969: The behavior of some significance tests under experimental randomization. Biometrika, 56, 231-248.

Klazura, G. E., and M. J. Schroeder, 1976: Development of prediction variables of areal precipitation characteristics. Second WMO Sci. Conf. on Wea. Mod., Boulder, CO, 2-6 August, WMO Mo. 443, 173-180.

Lund, I. A., 1971: An application of stagewise and stepwise regression procedures to a problem of estimating precipitation in California. J. Appl. Meteor., 10, 892-902.

Marquardt, D. W., 1970: Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. Technometrics, 12(3), 591-612.

Massey, W. F., 1965: Principal components regression in exploratory statistical research. J. Amer. Statist. Assoc, 60, 234-256.

Mielke, P. W. Jr., J. S. Williams, and S. C. Wu, 1977: Covariance analysis technique based on bivariate log-normal distribution with weather modification applications. J. Appl. Meteor., 16, 183-187.

Moran, P. A. P., 1959: The power of a cross-over test for the artificial stimulation of rain. Austral. J. Statist., 1, 47-52.

Morrison, D. F., 1976: Multivariate statistical methods. McGraw-Hill Book Co, second ed., 415 pp.

Meter, J., and W. Wasserman, 1974: Applied linear statistical models. R. D. Irwin, Inc., Homewood, IL.

Potthoff, R. F., 1974: A non-parametric test of whether two simple regression lines are parallel. Ann. Statist., 2, 295-310. .

Sax, R. I., S. A. Changnon, L. 0. Grant, W. F. Hitschfeld, P. V. Hobbs, A. M. Kahan, and J. Simpson, 1975: Weather modification: where are we now and where should we be going? An editorial overview. J. Appl. Meteor., 14(5), 652-672.

Schickedanz, P. T., 1974: Evaluation of the rainfall data in the vicinity of the Texas hail suppression program. Report prepared for Atmospherics Inc., 27 pp.

---, 1975: Evaluation of hail suppression. Preprints, NHRE Symp. on Precip. Anal, for Hydrol. Modeling, Davis, CA., AGU, 101-121.

---, 1977: Evaluation of the rainfall and hailfall data in the vicinity of the Texas hail suppression program -An update. Report prepared for Atmospherics Inc., 15 pp.

---, and R. Y. Sun, 1977: Statistical techniques for the incorporation of covariates into the design and evaluation of HIPLEX. Sixth Conf. on Planned and Inadv. Wea. Mod., Amer. Meteor. Soc, Urbana, IL., 10-13 Oct., 230-233.

---, C. F. Hsu, and S. A. Changnon, Jr., 1978: Report of the 1977 annual meeting of 0SET Advisory Panel. Contract Report, NSF ENV77-01103, Illinois State Water Survey, Champaign, IL, 16 pp.

Simpson, J., and W. L. Woodley, 1975: Florida area cumulus experiments 1970-1973 rainfall results. J. Appl. Meteor., 14, 734-744.

Smith, E. ,J., L. G. Veitch, D. E. Shaw, and A. J. Miller, 1977: A cloud-seeding experiment in Tasmania, 1964-1970. CSIR0, Australia, 115 pp.

Spar, J., 1957: Project SCUD. Meteor. Monog., 2(11), 5-23.

Weather Modification Advisory Board, 1978a: The management of weather resources. Volume I, "Proposals for a national policy and program." Report to the Secretary of Commerce, Dept. of Commerce, Washington, D. C, 229 pp.

---, 1978b: The management of weather resources. Volume II, "The role of - statistics in weather resources management." Report of the Statistical Task Force, Dept. of Commerce, Washington, D. C.

Westcott, N., 1979: Annotated bibliography of predictor variables for weather modification applications. Technical Report, Illinois State Water Survey, Champaign, IL, 117 pp.

Wichern, D. W., and G. A. Churchill, 1978: A comparison of ridge estimators. Technometrics, 20(3), 301-311.

Wilks, S. S., 1962: Mathematical statistics. John Wiley & Sons, Inc., New York, 644 pp.

LIST OF PROJECT REPORTS AND PUBLICATIONS

Achtemeier, G. L., and N. E. Westcott, 1979: Environmental covariates derived from surface field analyses. Sixth Conf. on Planned and Inadv. Wea. Mod., Araer. Meteor. Soc, Urbana, IL., 10-13 Oct., 207-208.

---, 1980: On the development of covariates for the evaluation of operational seeding projects in areas without physiographic influences. J. Wea. Mod., 12(1), 16-23.

---, 1981: Relationships between rainfall and meteorological surface variables: Applications to Midwestern operational weather modification. Final Report, NSF ATM79-05007, Illinois State Water Survey, Champaign, IL, 69 pp.

Changnon, S. A., Jr., 1978: The technical and economic aspects of weather modification: a background for lawyers. Southern Illinois Univ. Law J., 77(2), 326-358.

---, C. F. Hsu, and N. G. Towery, 1979: Evaluation of the McLean County rainfall modification projects in 1977 and 1978. Technical Report, Illinois State Water Survey, Champaign, IL, 22 pp.

---, F. A. Huff, and C. F. Hsu, 1979: On the need to evaluate operational weather modification projects. Bull. Amer. Meteor. Soc, 60(7), 770-774.

---, F. A. Huff, C. F. Hsu, G. L. Achtemeier, N. Westcott, and P. Rosenzweig, 1979: Operational Seeding Evaluation Techniques. Final Report, NSF ENV78-01003, Illinois State Water Survey, Champaign, IL, 63 pp.

---, 1980: Impacts of operational weather modification projects and their implications for state policy. State Government, 52 (1), 10 pp.

---, C. F. Hsu, G. L. Achtemeier, F. A. Huff, and N. E. Westcott, 1980: Techniques to evaluate operational weather modification projects: Part II. Progress Report, NSF ATM 79-05007, Illinois State Water Survey, Champaign, IL, 15 pp.

---, K. R. Gabriel, and C. F. Hsu. 1980: Evaluating operational cloud seeding projects. Third WMO Sci. Conf. on Wea. Mod., Clermont-Ferrand, France, 21-25 July, 493-499.

---, and C. F. Hsu, 1980: Assessment of summer 1979 rainfall in southeastern Illinois with special reference to weather modification effects. Misc. Publ. 56, Illinois State Water Survey, Champaign, IL, 18 pp.

---, and C. F. Hsu, 1981: Evaluation of Illinois weather modification projects of 1976-1980: A summary. Circular 148, Illinois State Water Survey, Champaign, IL, 31 pp.

Gabriel, K. R., 1979: Re-randomization tests on weather experiments. Sixth Conf. on Planned and Inadv. Wea. Mod., Amer. Meteor. Soc, Urbana, IL., 10-13 Oct., J5-J6.

---, and C. F. Hsu, 1980: Power studies of re-randomization tests. Third WMO Sci. Conf. on Wea. Mod., Clermont-Ferrand, France, 21-25 July, 507-513.

---, 1981: On the roles of physicists and statisticians in weather modification experimentation. Bull. Amer. Meteor. Soc, 62(1), 62-69.

---, and C. F. Hsu, 1981: Evaluation of the power of re-randomization test, with application to weather modification experiments. Submitted to J. Amer. Statist. Assoc.

-—, and S. A. Changnon, Jr., 1981: Piggyback weather experiments: superimposing randomized treatment comparisons. Submitted to J. Wea. Mod..

---, and D. Petrondas, 1981: On using historical comparisons in evaluating cloud seeding operations. Technical Report 81/12 , Dept. of Statistics , University of Rochester, 6 pp.

Hsu, C. F., 1978: Variable selection and forecasting of regression models. Proc. Statist. Comp. Sec, Amer. Statist. Assoc, Washington, DC, 256-260.

---, 1979: Monte Carlo studies of statistical evaluation techniques for weather modification. Seventh Conf. on Inadv. and Planned Wea. Mod., Amer. Meteor. Soc, Banff, Canada, 8-12 Oct., J3-J4.

---, 1979: Two methods of computing statistical powers with application to weather modification. Proc Statist. Comp. Sec, Amer. Statist. Assoc, Washington, DC, 243-246.

---, 1980: Using biased regression to statistically predict rainfall over many years. Proc. Statist. Comp. Sec, Amer. Statist. Assoc, Washington, DC, 221-226.

---, 1981: Weather modification activities in Taiwan, 1951-1979. J. Wea. Mod., 13(1), 161-164.

---, 1981: An annotated bibliography on the evaluation and statistical issues of weather modification. Final Report, Illinois State Water Survey, Champaign, IL, 93 pp.

---, 1981: Using surface meteorological covariates to predict storm areal rainfall 1-3 hours in advance. Seventh Conf. on Prob. and Statist, in Atmos. Sci., Amer. Meteor. Soc, Monterey, California, 2-6 Nov., 217-221

---, F. A. Huff, and S. A. Changnon, Jr., 1978: Operational seeding evaluation techniques (OSET). First Interim Report, NSF ENV77-01103, Illinois State Water Survey, Champaign, IL, 6 pp.

---, G. L. Achtemeier, F. A. Huff, and S. A. Changnon, Jr., 1978: Operational seeding evaluation techniques. Second Interim Report, NSF ENV77-01103, Illinois State Water Survey, Champaign, IL, 15 pp.

---, and S. A. Changnon, Jr., 1981: Assessment of summer 1979 weather modification effort in southeastern Illinois. J. Wea. Mod., 13(1), 132-140.

---, K. R. Gabriel, and S. A. Changnon, Jr., 1981: Statistical techniques and key issues for the evaluation of operational weather modification. J. Wea. Mod., 13(1), 195-199.

---, S. A. Changnon, Jr., F. A. Huff, and K. R. Gabriel, 1981: The assessment of statistical-physical techniques for evaluation of weather modification operations. Final Report, NSF ATM79-05007, Illinois State Water Survey, Champaign, IL.

---, and S. A. Changnon, Jr., 1981: Assessment of summer 1980 weather modification effort in southeastern Illinois. Misc. Publ., Illinois State Water Survey, Champaign, IL.

---, and J. Chen, 1981: Statistical evaluation of a rain-hail operational project in southwestern Kansas. Eighth Conf. on Inadv. and Planned Wea. Mod., Amer. Meteor. Soc, Reno, Nevada, 5-7 Oct., 124-125.

---, and J. Chen, 1981: Performance comparison of statistical techniques in evaluating weather modification projects. Eighth Conf. on Inadv. and Planned Wea. Mod., Amer. Meteor. Soc, Reno, Nevada, 5-7 Oct., 128-129.

Huff, F. A., C. F. Hsu, and G. L. Achtemeier, 1978: Development of operational evaluation techniques for weather modification. Fourteenth Conf. on Agric. and Forest Metero., Minneapolis, 2-6 April, Amer. Meteor. Soc, 47-48.

---, and S. A. Changnon, Jr., 1980: Criteria for weather modification operations and effective evaluation. Final Report, NSF ATM 79-05007, Illinois State Water Survey, Urbana, 22 pp.

---, and S. A. Changnon, Jr., 1981: Summary of criteria for weather modification operations and effective evaluation. J. Wea. Mod., 13(1), 236.

Neill, J. C, and C. F. Hsu, 1980: Using non-integer spectral analysis in discerning spatially coherent rainfall periodicities. Time Series Analysis, North-Holland Publ., Co., to appear.

Schickedanz, P. T., C. F. Hsu, and S. A. Changnon, Jr., 1978: Report of the 1977 annual meeting of OSET Advisory Panel. Contract Report, NSF ENV77-01103, Illinois State Water Survey, Champaign, IL, 16 pp.

Westcott, N., 1979: Annotated bibliography of predictor variables for weather modification applications. Technical Report, Illinois State Water Survey, Champaign, IL, 117 pp.

APPENDIX A

Statistical Techniques

Details of the statistical techniques used in the simulation studies are described in this appendix. They include double ratio, multiple regression, principal component regression, two regressions, and sum of rank power tests. These are techniques found to be more promising after the inital Kansas simulation. Two techniques, factor analysis (FA) and canonical correlation analysis (CCA), were not studied as intensively as others due to limited time and funding, and a preliminary simulation using FA and CCA was carried out only in the Kansas simulation. More research on better application of FA and CCA needs to be carried out, and they were not described here.

The assumptions and the hypotheses relevant to the testing and estimating of the seeding effects are discussed. Formulas for test statistics are given, and remarks on their usage are included.

<u>Double Ratio Test</u>

Suppose that X_1, ---, X_n, X_{n+1}, ---, X_{n+m}, and Y_1, ---, Y_n, Y_{n+1}, ----, Y_{n+m}, are two samples collected in a target area and a control area, respectively, where n(m) is the number of time units during the historical (seeding) period.

A double ratio (DR) is defined as

$$DR = \left(\frac{\bar{X}_m}{\bar{X}_n}\right) / \left(\frac{\bar{Y}_m}{\bar{X}_n}\right) \qquad (1)$$

where

$$\bar{X}_m = \frac{1}{m} \sum_{i=1}^{m} X_{n+i} \; , \; \bar{X}_n = \frac{1}{n} \sum_{i=1}^{n} X_i \; ,$$

$$\bar{Y}_m = \frac{1}{m} \sum_{i=1}^{m} Y_{n+i} \; , \; \bar{Y}_n = \frac{1}{n} \sum_{i=1}^{n} Y_i$$

DR can also be expressed as

$$DR = \left(\frac{\bar{X}_m}{\bar{Y}_m}\right) / \left(\frac{\bar{X}_n}{\bar{Y}_n}\right) \qquad (2)$$

In order that DR be used to assess seeding effect, we need to assume implicitly either one of the following two assertions:

(A) Had no seeding been carried out, the temporal relationship of average events in the target area during the historical period and the seeding period would be identical to the corresponding temporal relationship of average events in the control area. (This can be seen from (1). by putting DR = 1.)

(B) Had no seeding been carried out, the areal relationship of average events in the target area and in the control area during the historical period would be identical to the corresponding areal relationship of average events during the seeding period. (This can be seen from (2) by setting DR = 1.)

Hypotheses

H_0 : DR = 1,

H_1 : DR > 1.

Suppose either one of the assertions (A) or (B) holds, if there is no seeding effect, DR is close to one. Therefore, a one-sided test procedure is as follows: Reject H_0, if DR is too large.

Multiple Regression

Suppose that X_1, ---, X_n, X_{n+1}, ---, X_{n+m}, and Y_1^j, ---, Y_n^j, Y_{n+1}^j, ---, Y_{n+m}^j, j=1, ---, k, are samples collected respectively in the target area and in the j^{th} control area, where n(m) is the number of time units during the historical (seeding) period.

Model

$$X_i = \beta_o + \beta_1 Y_i^1 + \beta_2 Y_i^2 + --- + \beta_k Y_i^k + \rho_i, \quad i=1, 2, ---, n \qquad (1)$$

where p_i's are assumed to be independent random variables with zero mean and identical variance. It is assumed implicitly that each Y_i^j is constant, i.e., no measurement error nor random variation. The regression coefficients, β_o, β_i, ---, β_k, are fitted by the usual least squaresmethod for the historical data. In order that the above model can be applied to detect seeding effect, we assume that:

(A) Had no seeding been carried out, the relationships of events between target area and control areas during the seeding period can also be described by (1) with sufficiently high resolution.

Hypotheses

H_o: There is no seeding effect on events in the target area during the seeding period.

H_i: There is a positive seeding effect on events in the target area during the seeding period.

Suppose that assumption (A) holds, then (1) can be used to predict events in the target area during the seeding period, or more explicitly,

$$\hat{X}_i = \beta_o + \beta_1 Y_i^{\,1} + \beta_2 Y_i^{\,2} + \text{---} + \beta_k Y_i^{\,k},\ i=n+1,\ n+2,\ \text{---},\ n+m \tag{2}$$

Under H_0, the predicted event $\hat{X}_i$ differs from the observed event X_i only by a random error. Various tests can then be applied to those m matched pairs, $(X_{n+1}, \hat{X}_{n+1})$, $(X_{n+2}, \hat{X}_{n+2})$, ---, $(X_{n+m}, \hat{X}_{n+m})$ to test whether the observed X_i's and the predicted $\hat{X}_i$'s come from the same population. If this later claim is rejected, then H_0 is rejected.

<u>Note</u>:

(1) $X_i/\hat{X}_i$ can be used as an estimator of the ratio of change due to seeding effects in the $i^{\underline{th}}$ time unit, while the confidence interval of $\hat{X}_i$ can be calculated by assuming normal distribution of p's.

(2) For the validity of using (2) to predict seeded events, see Neter and Wasserman (1974).

(3) In general, control areas are adjacent to target areas; therefore, a certain degree of interdependence (e.g., multicollinearity) seems inevitable for (meteorological) events among control areas. Therefore, the validity of model (1) needs to be established before using the method of multiple regression (Hsu, 1978).

Principal Component Regression

Suppose that X_1, ---, X_n, X_{n+1}, ---, X_{n+m}, and Y_1^d, ---, Y_n^d, Y_{n+1}^d, ----, $Y_n^d + m =$, d=1, 2, ---, k, are samples collected respectively in the target area and in the d^{th} control area, where n(m) is the number of time units during the historical (seeding) period.

Denote by R the sample correlation matrix of Y^1, Y^2, ---, Y^k obtained from the historical data. Suppose that the rank of R is r. Then from R we can obtain a principal component decomposition of Y^j's as follows (cf. Morrison, 1976):

$$Z_i^j = A_{j1} P_{1i} + A_{j2} P_{2i} + \text{---} + A_{jr} P_{ri}, \; i=1, 2, \text{---}, n; \quad j=1, 2, \text{---}, k \tag{1}$$

where Z_i^j is the standardized Y_i^j, and $(P_{\ell 1}, \text{---} P_{\ell n})'$ is the ℓ^{th} principal component.

Model

$$V_i = \beta_o + \beta_1 \frac{P_{1i}}{\sqrt{\lambda_1}} + \text{---} + \beta_s \frac{P_{si}}{\sqrt{\lambda_s}} + e_i, \; i=1, 2, \text{---}, n, \quad s \leq r \tag{2}$$

where V_i. is the standardized X., X. is the ℓ^{th} largest eigenvalue of R_y, and e.'s are assumed to be independent variables with zero mean and identical variance. It is assumed implicitly that each P.. is constant, i.e., no measurement error nor random variation. The number s, which indicates how many principal components are included in the regression model, decides the magnitude of resolution of the above model. Usually, only a small s is required to produce a satisfactory result. The regression coefficients, β_0, β_1, ---, 3 , are fitted by the usual least squares method for the historical data. (2) can be expressed in terras of Z_i^j as follows:

$$V_i = \gamma_o + \gamma_1 Z_i^1 + \gamma_2 Z_i^2 + --- + \gamma_k Z_i^k + e_i \quad (3)$$

In order that the above model can be applied to the seeding period, we assume that:

(A) Had no seeding been carried out, observations in the target area during the seeding period could be described by (3) with sufficiently high resolution.

Hypotheses

H : There is no seeding effect on events in the target area during the seeding period,

H,: There is a positive seeding effect on events in the target area during the seeding period.

Suppose that assumption (A) holds, then (3) can be used to predict observations in the target area during the seeding period, or more explicitly,

$$\hat{V}_i = \gamma_o + \gamma_1 Z_i^1 + \gamma_2 Z_i^2 + --- + \gamma_k Z_i^k, \; i=n+1, \; n+2, \; ---, \; n+m \quad (4)$$

Under H_0, the predicted observation $\hat{V}_i$ differs from the observed V_i only by a random error. Various tests can then be applied to those m matched pairs $(V_{n+1}, \hat{V}_{n+1}), (V_{n+2}, \hat{V}_{n+2})$, ---, $(V_{n+m}, \hat{V}_{n+m})$ to test whether the observed V.'s and the predicted $\hat{V}_i$'s come from the same population. If this later claim is rejected, then H_o is rejected.

Note:

(1) $V_i/\hat{V}_i$ can be used as an estimator of the ratio of change due to seeding effects in the i^{th} time unit. However, the confidence interval of this estimator is not a trial thing to work out (cf. Anderson, 1963).

(2) In the case of meteorological events, data of neighboring areas are often commensurate with each other. So, instead of R_y, one may want to start with S_y, the sampling covariance matrix, and standardize all the observations by subtracting their means only. Then proceed with the rest as above. The advantage of this is that sampling distributions of the regression coefficients β_o, β_1, ---, β_s, are much easier to derive.

(3) If there exists multicollinearity between the observations of control areas, Y's, then principal component regression possesses certain advantages over the usual multiple regression (cf. Massy, 1965).

<u>Two (Simple) Regression Lines</u>

Suppose that X_1,---, X_n, X_{n+1},---, X_{n+m}, and Y_1,---, Y_n, Y_{n+1}, ---, Y_{n+m} are two samples collected in a target area and a control area respectively, where n(m) is the number of time units during the historical (seeding) period, and N, m are not too small.

<u>Model</u>

$$X_i = \beta_o^1 + \beta_1^1 Y_i + e_i \qquad i = 1, 2, ---, n \qquad (1)$$

$$X_i = \beta_o^2 + \beta_1^2 Y_i + e_i \qquad i = n+1, n+2, ---, n+m \qquad (2)$$

where e_i's are assumed to be independent random variables with zero mean and identical variance. The regression coefficients β_o^1 and β_1^1 are fitted by the least squares methods for the <u>historical</u> data, While the coefficients β_o^2 and β_1^2 are fitted for the <u>seeded</u> data.

Several test procedures can be performed to detect whether there is a seeding effect or not. They are described in the following paragraphs. First we discuss some parametric tests, then non-parametric tests.

1) Likelihood Ratio Test

(A) Assume that, for i = 1, 2,____, n, (Xi, Yi) is an identically and independently distributed (i. i. d.) bivariate normal random vector BINORM (m_x, m_y; σ_x^2; σ_y^2; ρ),

with m_x, m_y expected values, σ_x^2, σ_y^2 variance, and p correlation coefficient; and for i = n+1, n+2, ---, n+m, (X., Y.) is i.i.d. BINORM ($m_x + c$, m_y; σ_x^2, σ_y^2; ρ) random vector, where c is a constant. In other words, we assume that the seeding effect is constant and additive.

Hypotheses

H_o : $C = o$

H_1 : $C > o$

Bernier (1967) shows that the likelihood ratio test statistic for the above hypotheses is asymptotically equivalent to the following

$$\lambda = [(m+n)\ S_{ox}^2\ (1-\gamma_o^2)\ /(n\ S_{1x}^2(1-\gamma_1^2)\ + mS_{2x}^2(1-\gamma_2^2))]^{-(m+n)/2} \qquad (3)$$

where S_{1x}^2, S_{2x}^2, and S_{ox}^2 are the m.l.e. variances of X for the historical period, the seeding period, and the two periods combined, respectively; and γ_1, γ_2, γ_o are the sample correlation coefficients similarly defined. For m, n large, $-2 \log_e \lambda$ is distributed as a chi-square distribution with one degree of freedom. Therefore H_o is rejected, if $-2 \log_e \lambda$ is large.

Note:

(1) It is implicitly assumed that the variance of X (Y), σ_x^2 (σ_y^2), as well as the correlation coefficient of x, y are identical during the historical period and during the seeding period. Their equality must be established beforehand.

(2) The assumption of normality may be achieved frequently by suitably transforming X, Y; e.g., square root transformation, logarithmic transformation, etc.

(3) Usually m, the number of time units during the seeding period, is relatively small. In this case, the asymptotical chi-square distribution can not be used; rather, the exact distribution of the likelihood ratio test statistic should be used, although it may not be easy to derive.

(4) Under assumption (A), equations (1) and (2) hold, and $\beta_1^1 = \beta_1^2$. The null hypothesis of testing c = o is then equivalent to the hypothesis of testing $\beta_o^1 = \beta_o^2$. (In other words, constant σ_x^2, σ_y^2, ρ during both time periods implies that the two regression lines are parallel.)

11) t Tests

First we test the parallelism of regression lines (1) and (2), i.e.,

Hypothesis 1

$$H_o = \beta_1^1 = \beta_1^2 \quad (=\beta_1)$$

The statistic T_1 defined below may be used (Bernier, 1967);

$$T_1 = \left[\frac{mn\, S_{1y}^2 \; S_{2y}^2}{n\, S_{1y}^2 + m\, S_{2y}^2} \right]^{\frac{1}{2}} \cdot \frac{\hat{\beta}_1^2 - \hat{\beta}_1^1}{\hat{\sigma}} \qquad (4)$$

where $\hat{\beta}_1^i = \gamma_i \, S_{ix} \; / \; S_{iy}, \quad i = 1, 2$ (5)

$$\hat{\sigma}^2 = (m+n-4)^{-1} \cdot [n \, S_{1x}^2 (1-\gamma_1^2) + m \, S_{2x}^2 (1-\gamma_2^2)] \qquad (6)$$

$S_{1x}^2, S_{2x}^2, S_{1y}^2, S_{2y}^2$ are the m.l.e. variances of X, Y for the historical and seeding periods, respectively; and Λ_1 and Λ_2 are the sample correlation coefficients similarly defined.

(B) Assume that e_u's are i. i. d. normal (o, σ^2).

Then under H_0 and assumption (B) , T_1 has "approximately" a student's t distribution with (m+n-4) degrees of freedom. We reject H_0 if T_1. is large.

Suppose that the above H_0 is not rejected, i.e., $\beta_1^1 = \beta_1^2$. Then next we test whether the intercepts of these two regression lines are identical, i.e.,

<u>Hypothesis 2</u>

$$H_o: \; \beta o^1 = \beta o^2 \; (=\beta o)$$

The statistic T_2 defined below is used (Mielke <u>et al.</u>, 1977)

$$T_2 = \left[\frac{mn}{(m+n)(1+H)}\right]^{\frac{1}{2}} \cdot \frac{\bar{X}_2 - \bar{X}_1 - \hat{\beta}_1(\bar{Y}_2 - \bar{Y}_1)}{S} \qquad (7)$$

$$\text{where} \quad H = \frac{mn}{m+n} \; \frac{(\bar{Y}_2 - \bar{Y}_1)^2}{(mS_{2y}^2 + nS_{1y}^2)} \qquad (8)$$

$$\hat{\beta}_1 = \frac{nS_{1xy} + mS_{2xy}}{nS_{1y}^2 + mS_{2y}^2} \qquad (9)$$

$$S^2 = \left[nS_{1x}^2 + mS_{2x}^2 - \hat{\beta}_1^2 (nS_{1y}^2 + mS_{2y}^2) \right] (m+n-3)^{-1} \qquad (10)$$

$\bar{X}_1$, $\bar{X}_2$, $\bar{Y}_1$, $\bar{Y}_2$ are the sample means of X, Y for the historical and seeding periods, respectively; S_{1x}^2, S_{2x}^2, S_{1y}^2, S_{2y}^2 are defined as before; and S_{1xy}, S_{2xy} are the m.l.e. covariance of X, Y for the historical and seeding periods, respectively. Then under H_0 and assumption (B), T_2 has "approximately" a student's t distribution with (m+n-3) degrees of freedom. We reject H_0 if T_2 is large.

Another test which compares the "central position" of the regression lines is as follows (Bernier, 1967):

<u>Hypothesis 3</u>

$$H_0: \quad \bar{X}_1 - \beta_1^1 \bar{Y}_1 = \bar{X}_2 - \beta_1^2 \bar{Y}_2 \quad \text{and } \beta_1^1 = \beta_1^2 \quad (=\beta_1)$$

Let

$$T_3 = \left[\frac{mn}{(m+n)(1+H)}\right]^{1/2} \frac{\bar{X}_2 - \bar{X}_1 - \hat{\beta}_1(\bar{Y}_2 - \bar{Y}_1)}{\hat{\sigma}} \qquad (11)$$

where $\hat{\beta}_1$ is defined in (.9), $\hat{\sigma}$ in (6). Under H_0 and assumption (B), T_3 has "approximately" a student's t distribution with (m+n-4) degrees of freedom. We reject H_0 if T_3 is large.

<u>Note</u>:

(1) The assumption (B) of normality may be achieved frequently by transforming X.'s.

(2) T, and T_3 are statistically independent (Bernier, 1967, pp. 38). The only difference between T_2 and T_3 is that of s and $\hat{\sigma}$, which is due to the difference of Hypotheses 2 and 3. T_3 is also a maximum likelihood estimator.

(3) In actual application, we often find that not all of the above assumptions are satisfied. Cochran (1969) points out that when some of these assumptions are violated, using only the historical data to estimate the regression coefficients possesses some advantages over using the pooled data. More explicitly, difference estimation methods should be used according to the following three situations:

(i) $\beta_o^2 = \beta_o^1$ + constant

I.e., seeding effect is constant. Pooled data should be used in estimating β_1^1 in (7) or (.11).

(ii) $\beta_o^2 = \beta_o^1$ + constant + random variation

a) If $EY_1 = EY_2$ (here 1 (2) refers to historical (seeding).) No preferred method.

b) If $EY_1 \neq EY_2$, $nm^{-1} < \sigma_1^2 \sigma_2^{-2} - 2$, use historical data, otherwise use pooled data.

(iii) $\beta_o^2(i) = \beta_o^1$ + constant + δY_{i+n} + random variation, i.e., seeding effect in the (i+n)th time unit is proportional to the (i+n)th event in the control area. In this situation, only historical data should be used to estimate the regression coefficients. If pooled data are used, the resulting estimates will be biased.

To sum up, if $\hat{\beta}_1^1$ and $\hat{\beta}_1^2$ differ significantly and if the interpretation in situation (iii) seems reasonable, only historical data should be used to estimate the regression coefficients.

lll) F Tests

The approach used here is that of the linear hypothesis in linear model. Assuming the same model as in (1) and.(2), first we test the parallelism of these two regression lines.

Hypothesis 1

$$H_o: \beta_1^1 = \beta_1^2 \quad (=\beta_1)$$

The statistic F_1 defined below is used (Wilks, 1962),

$$F_1 = \frac{SSE_o - SSE_1}{SSE_o/(m+n-4)} \tag{12}$$

where

$$SSE_1 = \sum_{i=1}^{n}\left[(X_i - \bar{X}_1) - \hat{\beta}_1^1 (Y_i - \bar{Y}_1)\right]^2 + \sum_{i=n+1}^{n+m}\left[(X_i - \bar{X}_2) - \hat{\beta}_1^2 (Y_i - \bar{Y}_2)\right]^2 \tag{13}$$

$$SSE_o = \sum_{i=1}^{n}\left[(X_i - \bar{X}_1) - \hat{\beta}_1 (Y_i - \bar{Y}_1)\right]^2 + \sum_{i=n+1}^{n+m}\left[(X_i - \bar{X}_2) - \hat{\beta}_1 (Y_i - \bar{Y}_2)\right]^2 \tag{14}$$

$\hat{\beta}_1^1$, $\hat{\beta}_1^2$ are defined in (5), $\hat{\beta}_1$ **in (9), and** $\bar{X}_1$, $\bar{X}_2$, $\bar{Y}_1$, $\bar{Y}_2$, similarly defined as in (11).

Under H and assumption (B), F, has an F distribution with (1, m+n-4) degrees of freedom. We reject H_0 if F_1, is large.

Next we test whether the two regression lines are identical or not.

Hypothesis 2

$$H_o \quad \beta_o^1 = \beta_o^2 \ (= \beta_o) \text{ and } \beta_1^1 = \beta_1^2 \ (= \beta_1)$$

Let

$$F_2 = \frac{(SSE-SSE_1)/2}{SSE_1/(m+n-4)} \tag{15}$$

$$\text{where } SSE = \sum_{i=1}^{m+n}\left[X_i - \overline{X}_{n+m} - \hat{\hat{\beta}}_1(Y_i-\overline{Y}_{n+m})\right]^2 \tag{16}$$

$$\hat{\hat{\beta}}_1 = \left[\sum_{i=1}^{m+n} X_iY_i-(m+n)\overline{X}_{n+m}\overline{Y}_{n+m}\right]\Big/\left[\sum_{i=1}^{n+m} Y_i^2 - (n+m)\overline{Y}_{n+m}^{\,2}\right] \tag{17}$$

and $\overline{X}_{n+m}$, $\overline{Y}_{n+m}$ are the sample means of X, Y of the combined samples, respectively. Under H_0 and assumption (B), F_2 has an F distribution with (2, m+n-4) degrees of freedom. We reject H_0 if F_2 is too large.

Note:

(1) As in the above, the assumption (B) of normality may be achieved by making a suitable transformation of X's.

(2) t tests and F tests are closely related in theory. F tests are exact tests, while t tests utilize some estimation in defining test statistics. For large sample sizes m, n, these two kinds of tests probably will not display too much difference, but for small or moderate sample sizes, they might behave differently.

(3) The approach used in this section can easily be extended to the cases of two multiple regression lines, or three or more regression lines.

IV) Non-Parametric Test

Assuming the same model as in (1) and (2), we test the parallelism of these two lines as follows:

Hypotheses

$$H_o : \beta_1^1 = \beta_1^2$$

$$H_1 ; \beta_1^1 < \beta_1^2$$

(C) Assume that no two Y.'s in the historical period are equal and no two Y.'s in the seeding period are equal.

(D) Assume that as $m \to \infty$, $\eta/m \to \infty$ some constant.

(E) See Assumption 5B in Potthoff's paper, p. 302.

Define (Potthoff, 1974)

$$W = \binom{n}{2}^{-1} \binom{m}{2}^{-1} \sum_{i<k}^{n} \sum_{j<\ell}^{m} h(V_{ikj\ell}), \tag{18}$$

where $h(x) = \begin{cases} o & \text{if } x \leq o \\ 1 & \text{if } x > o \end{cases}$

and $V_{ikj\ell} = (X_{n+\ell} - X_{n+j})(Y_{n+\ell} - Y_{n+j})^{-1} - (X_k - X_i)(Y_k - Y_i)^{-1}$

Potthoff shows that, under H_O and assumptions (C), (D), and (E), as m, n large, the statistic

$$NP_1 = \left[W - .5\right] \left(\frac{2m+5}{18m(m-1)}\right)^{-1/2} \tag{19}$$

has a standard normal distribution. We reject H_O, if NP_1, is large.

Note:

(1) Assumption (C) can also be interpreted as that the probability of two Y.'s having the same value is virtually zero. In the real world, this often is the case, provided that measurement precision of the instrument is taken into consideration, no matter how small it is.

(2) For the present test, the requirement of identical variance of e_i's can be lessened so that those e.'s in the historical period have an identical variance, and those e.'s in the seeding period have another identical variance.

(3) Assumptions (D) and (E) are needed only to prove the asymptotic normality of W. If we are interested only in the case of small sample sizes, they are not required.

(4) In the same paper Potthoff also proposed a non-parametric statistic for testing the equality of two intercepts after accepting the parallelism, but its properties have not been fully studied yet.

Overall Remarks:

(1) Depending on the test used, equality of the two residual variances might need to be established before further testing. This can be accomplished by the usual F test.

(2) The independence of e_i's needs to be verified after the fitting. Some test procedures are specifically designed for such verification. For example, the Durbin-Watson test may be performed to test whether there exists a serial correlation between e.'s (cf. Neter and Wasserman, p. 358-361).

(3) Moran (1959) has suggested using X_i-Y_i, and X_i+Y_i instead of X_i, Y_i in fitting the models (1) and (2). In fact this will reduce the residual variance by a factor of $(1-\beta_1)^2$, which is < 1, if the correlation between X and Y is positive. In turn, the estimation of regression coefficients will be more accurate. This substitution may be applied to each one of the above tests.

Sum of Rank Power Test

Suppose that X_i,——, X_n, X_{n+1}, --- X_{n+m}, and Y_1,---, Y_n, Y_{n+1}, ---, Y_{n+m} are two samples collected in a target area and a control area, respectively, where n(m) is the number of time units during the historical (seeding) period.

For i = 1, ---, n + m, let

$R_i = X_i/Y_i$

i.e., R. is the ith target-control ratio.

For each j = 1, ---, m, let a. be the rank of R . in the combined sample of R_1, R_2, ---, R_n, R_{n+1},---, R_{n+j}. A sum of rank power statistic is then defined as

$$A_r = \Sigma (a_i)^r, \text{ for } r=1, 2, 3$$
$$B_r = \Sigma |D_i|^r, \text{ for } r=1, 3$$
$$C_r = \Sigma \text{ SIGN}(D_i)|D_i|^r, \text{ for } r=2, 3$$

where summation is over the seeded sample; D. = a.-(N+1)/2, with N the total number of observations; and SIGN(a)=1, 0, or -1, according to whether a is >0, =0, or <0.

In order to use these statistics to assess a seeding effect, we assume that

(A) R_i, R_2, ---, R_n are independent, identically distributed with distribution function F(x)

(B) R_{n+1}, R_{n+2},---, R_{n+m} are independent, identically distributed with distribution function G(x)

(C) G(x) = F(x-a), a≥0

Hypotheses

H_O: a = 0

H_1: a > 0

Then under assumptions (A)-(C), a test procedure is as follows:

Reject H_o, if the statistic is large.

APPENDIX B

Power Curves of High Power Test Statistics

Power curves of the high power statistics as discussed in the simulations are shown below. Values along the horizontal axis are nominal significance level, and values along the vertical axis are values of power. In each figure, there are four curves. From bottom upward they are power curves corresponding to 10, 20, 30, and 40% seeding-imposed changes, respectively. The only exceptions are those corresponsing to varying changes in the ILL-ST simulation studies, (either with or without meteorological covariates). In these figures, the three solid curves correspond, upward, to powers of seeding effect models C, A, and E, respectively; and the dashed curve corresponds to powers of seeding effect model M. Notations in the figures are self-explanatory except the following:

1) The four-digit number denotes the target-control setup used in the simulation. The first 2 digits represent the county (or area) used as 'target,' the next 2 digits represent the county or counties used as 'control(s).' '99' or '88' generally denote the average of target or control counties (or areas). The county (or area) numbers can be found in the figures displaying the simulation study area.

2) N denotes the number of runs carried out in the simulations.

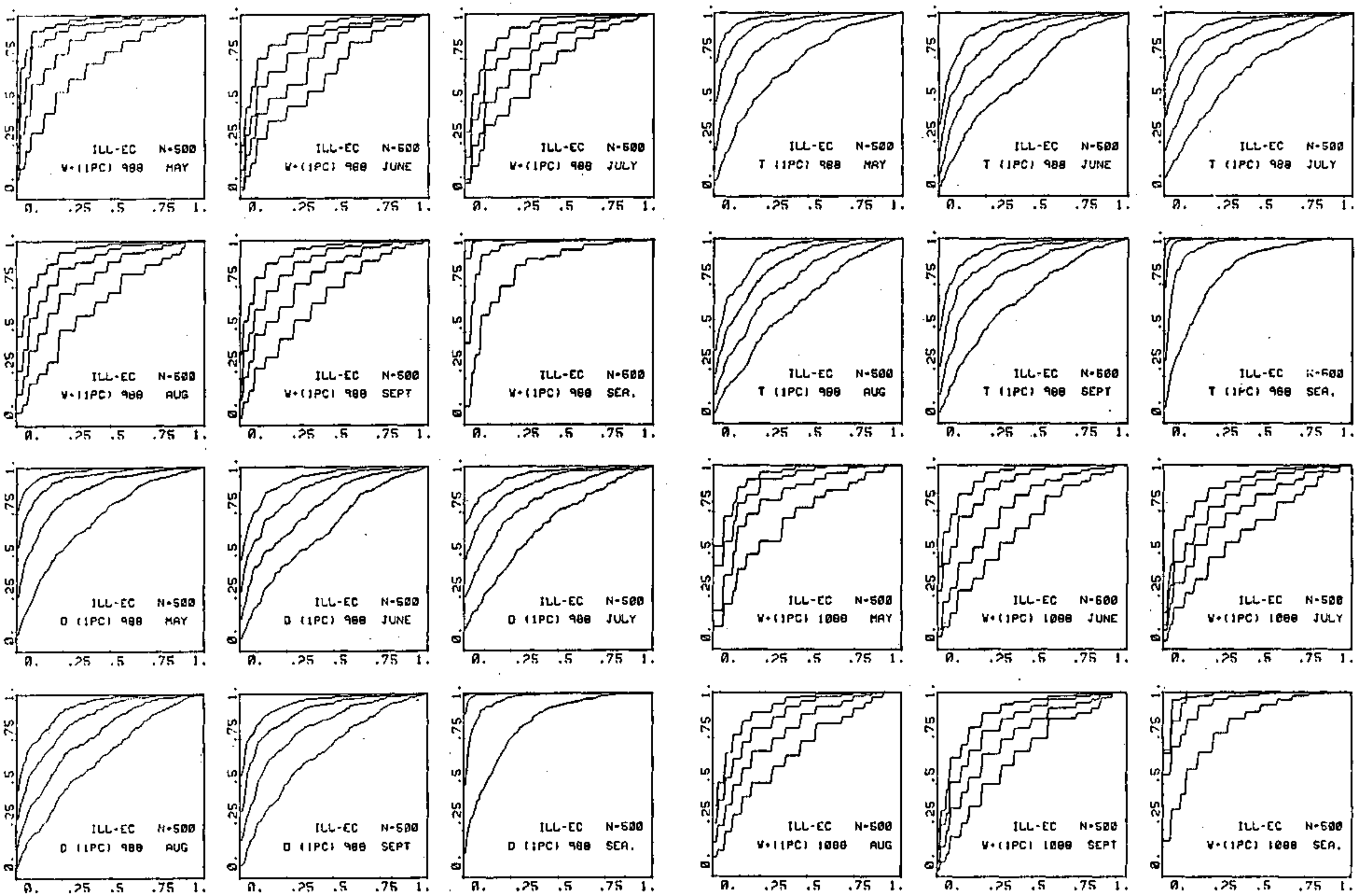
3) In the Montana simulation, M0N(3) denotes that 3 years were selected to form a seeded sample, and similarly M0N(6) denotes that 6 years were selected.

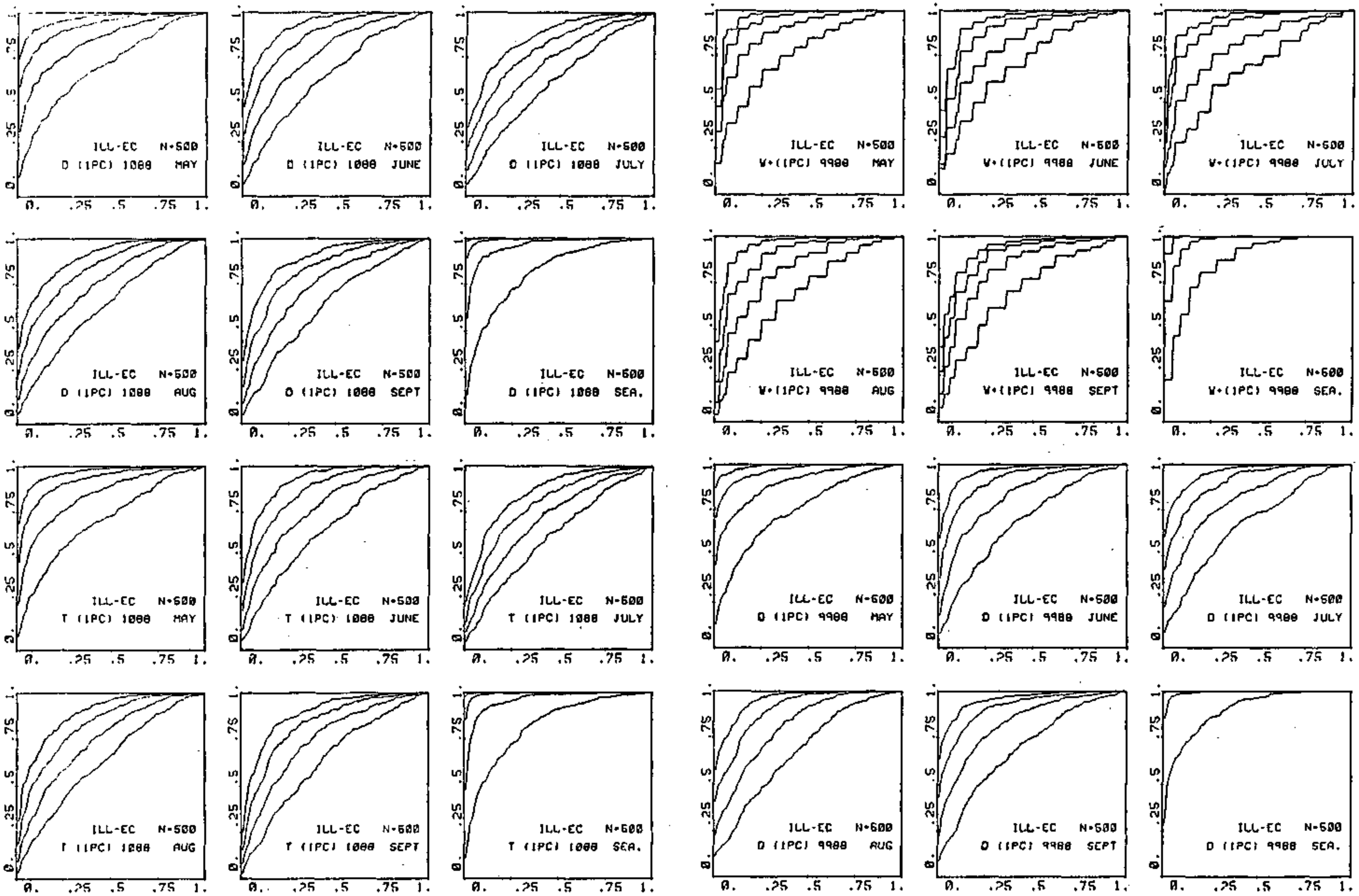
4) In the ILL-ST or Ill-48 simulations, after the 4 digits (sometimes the leading zero was omitted), the characters T, M, A denote, respectively, that total rain, maximum rain, or average rain were used as responsible variables.

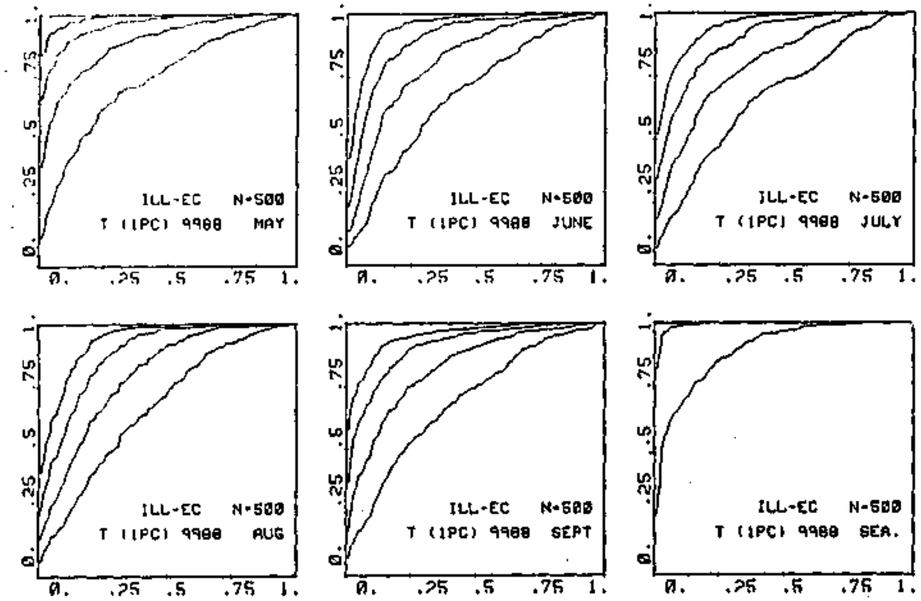
5) 'ILL-ST,V denotes that varying seeding-induced changes were employed in the ILL-ST simulation.

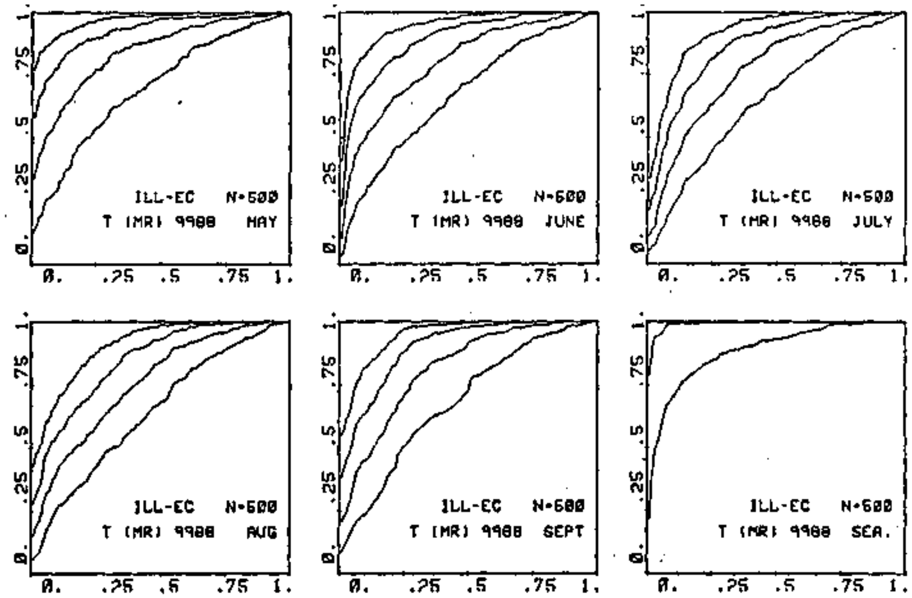
6) Some extra notations after the statistic in the ILL-ST simulation have the following meanings: (PC, PV) denotes that the PC-covariates of the meteorological covariates (or predictor variables) were employed; (SR, PV) denotes that the point-covariates of the meteorological covariates were used and were screened by stepwise regression.

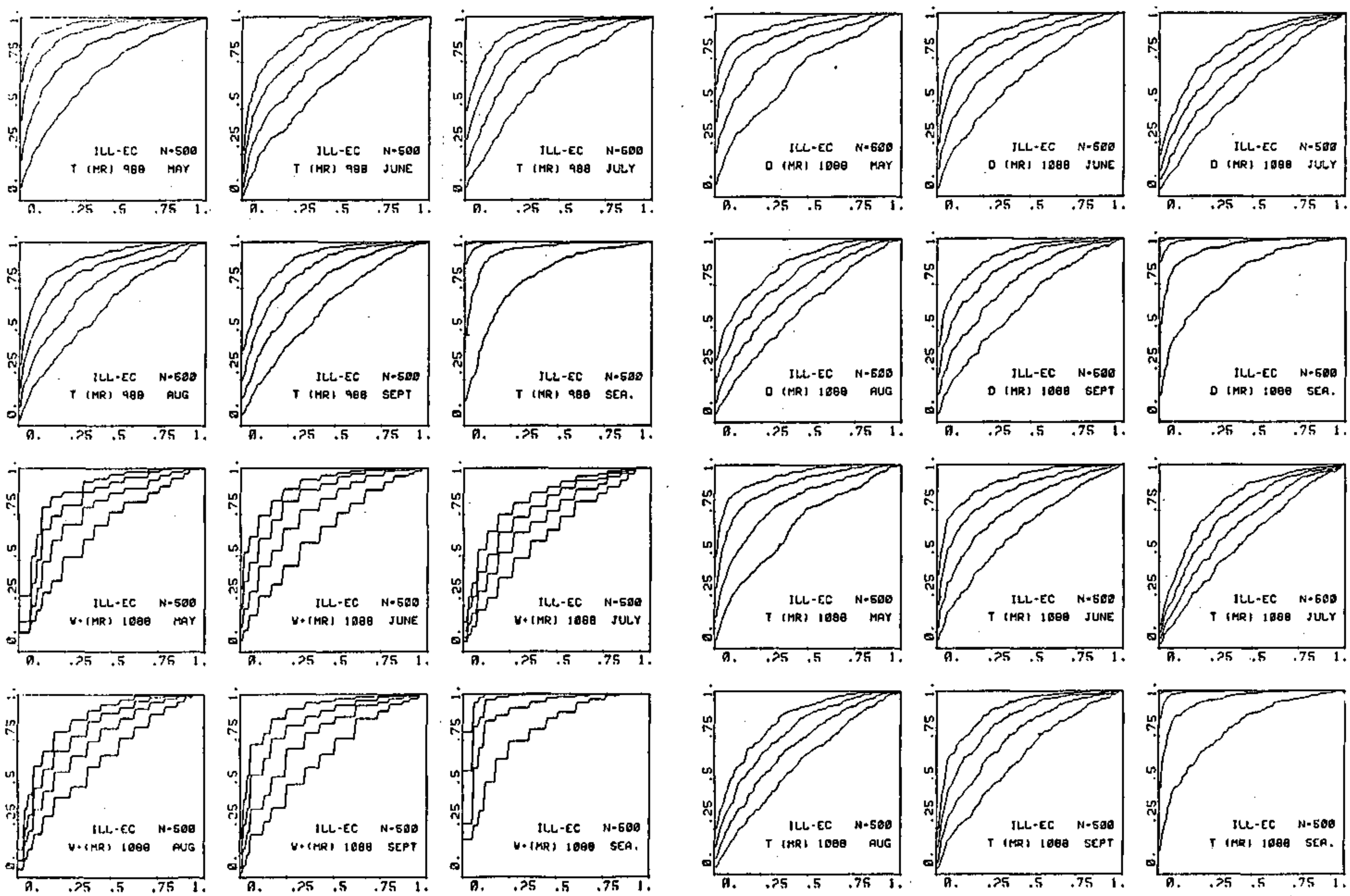
7) 'W and 'W+' both denote the sum of positive ranks (or signed rank test statistic).

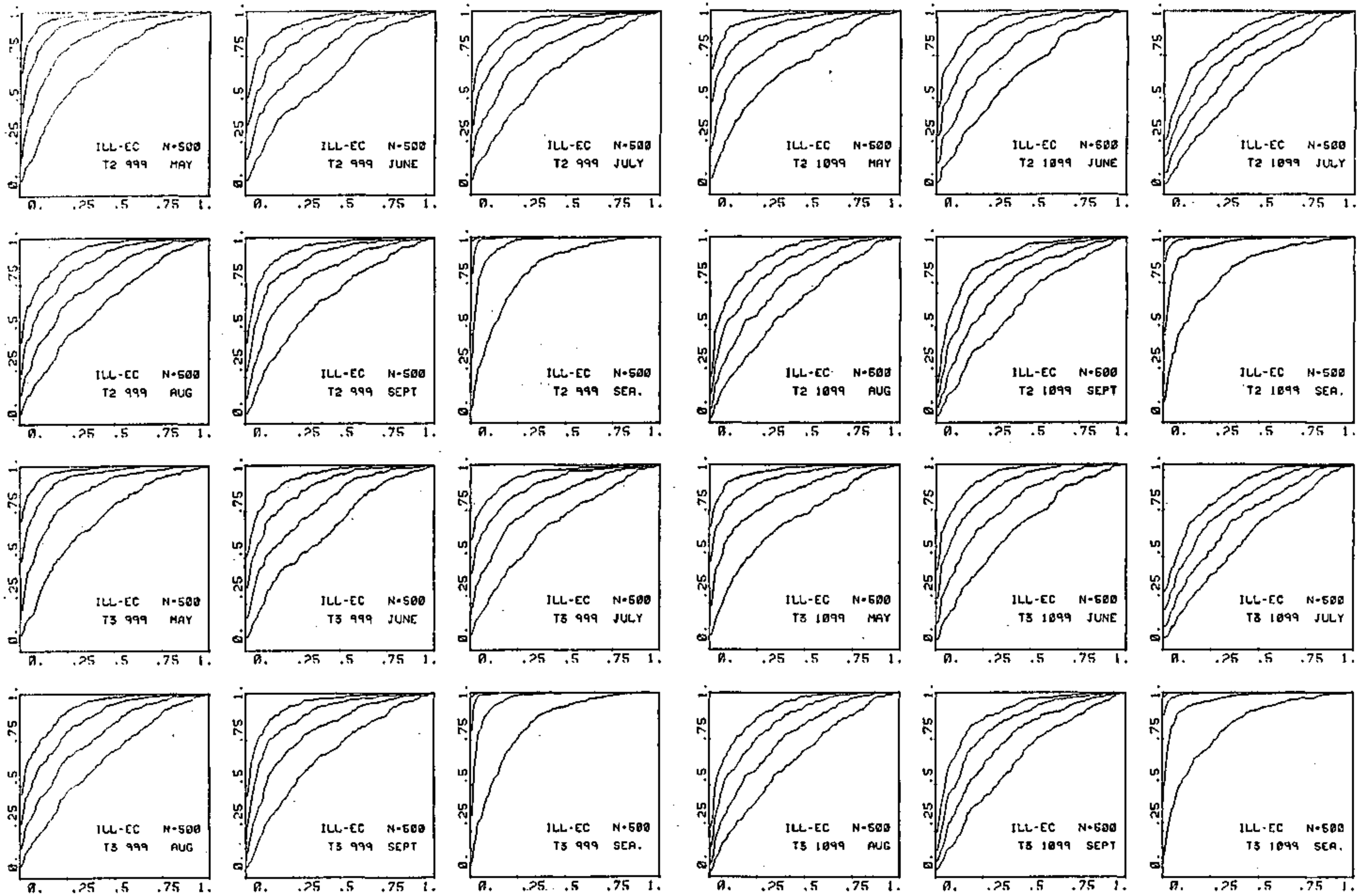

ILL-EC N=500 V+(1PC) 900 MAY
ILL-EC N=600 V+(1PC) 900 JUNE
ILL-EC N=600 V+(1PC) 900 JULY
ILL-EC N=500 T (1PC) 900 MAY
ILL-EC N=600 T (1PC) 900 JUNE
ILL-EC N=500 T (1PC) 900 JULY
ILL-EC N=600 V+(1PC) 900 AUG
ILL-EC N=500 V+(1PC) 900 SEPT
ILL-EC N=600 V+(1PC) 900 SEA.
ILL-EC N=500 T (1PC) 900 AUG
ILL-EC N=600 T (1PC) 900 SEPT
ILL-EC N=600 T (1PC) 900 SEA.
ILL-EC N=500 D (1PC) 900 MAY
ILL-EC N=600 D (1PC) 900 JUNE
ILL-EC N=500 D (1PC) 900 JULY
ILL-EC N=500 V+(1PC) 1000 MAY
ILL-EC N=600 V+(1PC) 1000 JUNE
ILL-EC N=500 V+(1PC) 1000 JULY
ILL-EC N=500 D (1PC) 900 AUG
ILL-EC N=600 D (1PC) 900 SEPT
ILL-EC N=500 D (1PC) 900 SEA.
ILL-EC N=600 V+(1PC) 1000 AUG
ILL-EC N=500 V+(1PC) 1000 SEPT
ILL-EC N=600 V+(1PC) 1000 SEA.


ILL-EC N=600
D (IPC) 1000 MAY
ILL-EC N=600
D (IPC) 1000 JUNE
ILL-EC N=600
D (IPC) 1000 JULY
ILL-EC N=600
V+(IPC) 9900 MAY
ILL-EC N=600
V+(IPC) 9900 JUNE
ILL-EC N=600
V+(IPC) 9900 JULY
ILL-EC N=600
D (IPC) 1000 AUG
ILL-EC N=600
D (IPC) 1000 SEPT
ILL-EC N=600
D (IPC) 1000 SEA.
ILL-EC N=600
V+(IPC) 9900 AUG
ILL-EC N=600
V+(IPC) 9900 SEPT
ILL-EC N=600
V+(IPC) 9900 SEA.
ILL-EC N=600
T (IPC) 1000 MAY
ILL-EC N=600
T (IPC) 1000 JUNE
ILL-EC N=600
T (IPC) 1000 JULY
ILL-EC N=600
D (IPC) 9900 MAY
ILL-EC N=600
D (IPC) 9900 JUNE
ILL-EC N=600
D (IPC) 9900 JULY
ILL-EC N=600
T (IPC) 1000 AUG
ILL-EC N=600
T (IPC) 1000 SEPT
ILL-EC N=600
T (IPC) 1000 SEA.
ILL-EC N=600
D (IPC) 9900 AUG
ILL-EC N=600
D (IPC) 9900 SEPT
ILL-EC N=600
D (IPC) 9900 SEA.
0. .25 .5 .75 1.

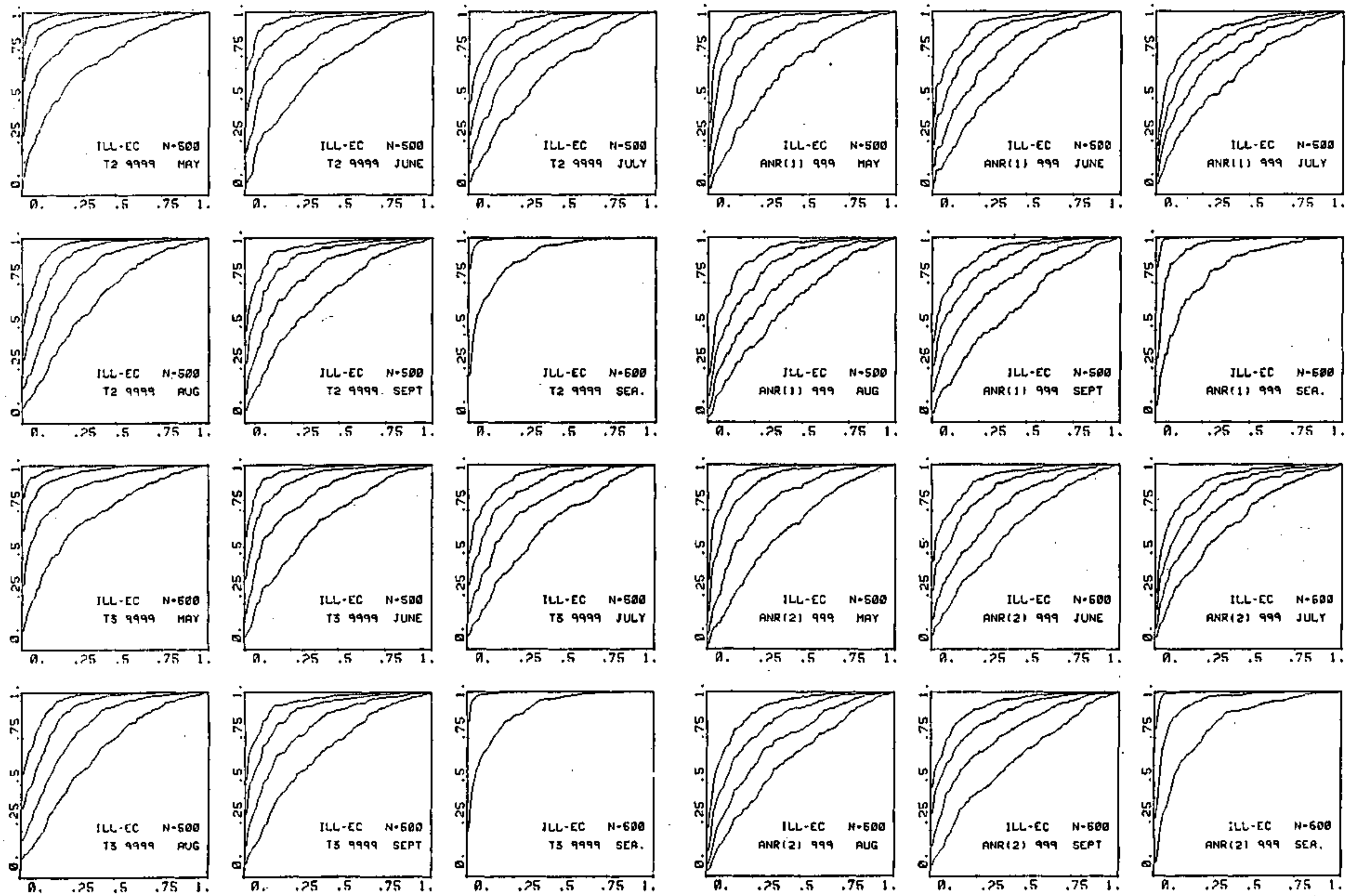

ILL-EC N=500
T (1PC) 9980 MAY
ILL-EC N=500
T (1PC) 9980 JUNE
ILL-EC N=500
T (1PC) 9980 JULY
ILL-EC N=500
T (1PC) 9980 AUG
ILL-EC N=500
T (1PC) 9980 SEPT
ILL-EC N=500
T (1PC) 9980 SEA.
0. .25 .5 .75 1.


ILL-EC N=500
T (MR) 9980 MAY
ILL-EC N=500
T (MR) 9980 JUNE
ILL-EC N=500
T (MR) 9980 JULY
ILL-EC N=500
T (MR) 9980 AUG
ILL-EC N=500
T (MR) 9980 SEPT
ILL-EC N=500
T (MR) 9980 SEA.
0. .25 .5 .75 1.

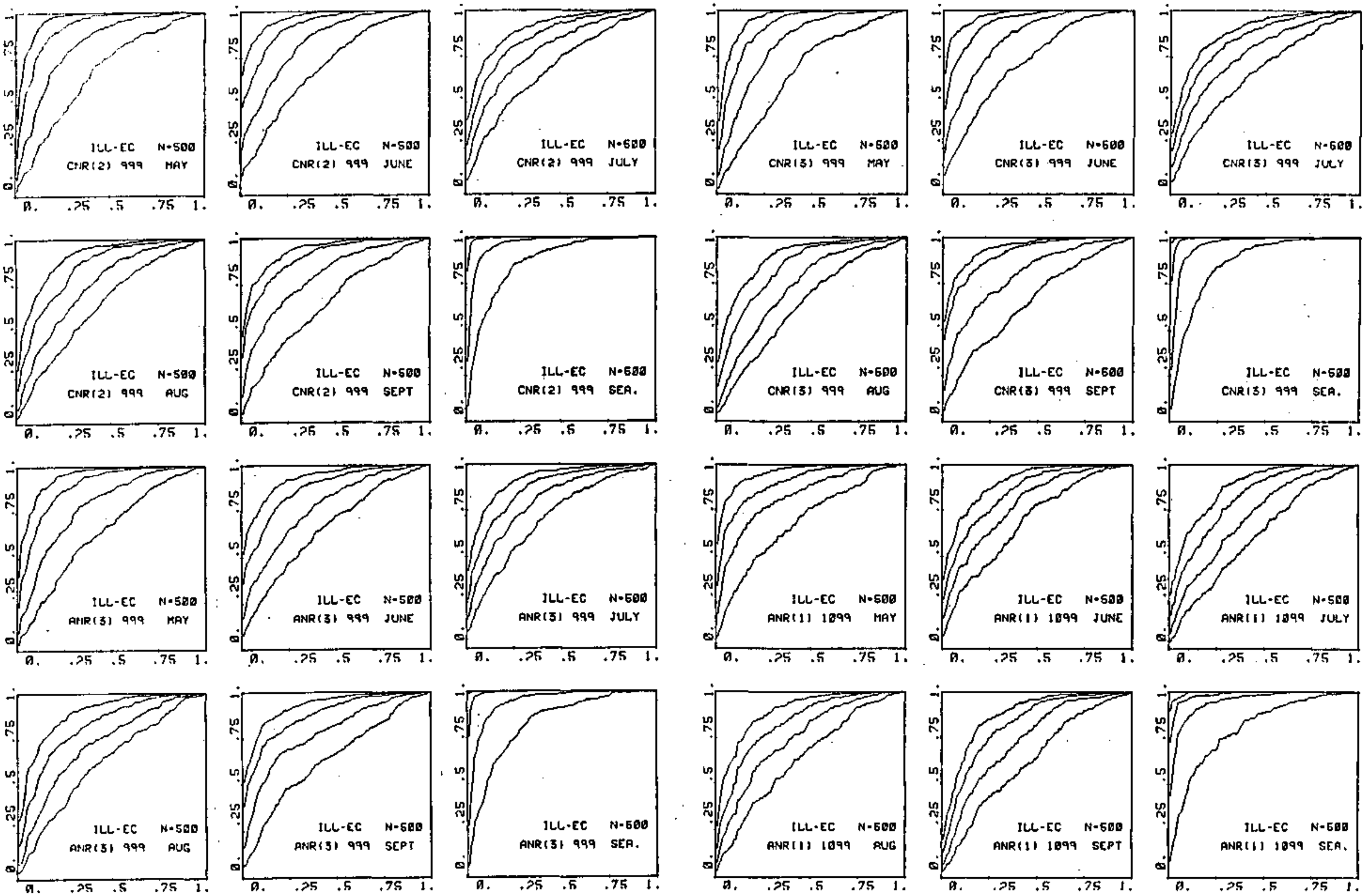

ILL-EC N=500
T (HR) 900 MAY
ILL-EC N=500
T (HR) 900 JUNE
ILL-EC N=600
T (HR) 900 JULY
ILL-EC N=600
D (HR) 1000 MAY
ILL-EC N=600
D (HR) 1000 JUNE
ILL-EC N=500
D (HR) 1000 JULY
ILL-EC N=600
T (HR) 900 AUG
ILL-EC N=500
T (HR) 900 SEPT
ILL-EC N=500
T (HR) 900 SEA.
ILL-EC N=600
D (HR) 1000 AUG
ILL-EC N=600
D (HR) 1000 SEPT
ILL-EC N=600
D (HR) 1000 SEA.
ILL-EC N=500
V+(HR) 1000 MAY
ILL-EC N=500
V+(HR) 1000 JUNE
ILL-EC N=500
V+(HR) 1000 JULY
ILL-EC N=500
T (HR) 1000 MAY
ILL-EC N=600
T (HR) 1000 JUNE
ILL-EC N=600
T (HR) 1000 JULY
ILL-EC N=500
V+(HR) 1000 AUG
ILL-EC N=500
V+(HR) 1000 SEPT
ILL-EC N=600
V+(HR) 1000 SEA.
ILL-EC N=500
T (HR) 1000 AUG
ILL-EC N=500
T (HR) 1000 SEPT
ILL-EC N=500
T (HR) 1000 SEA.

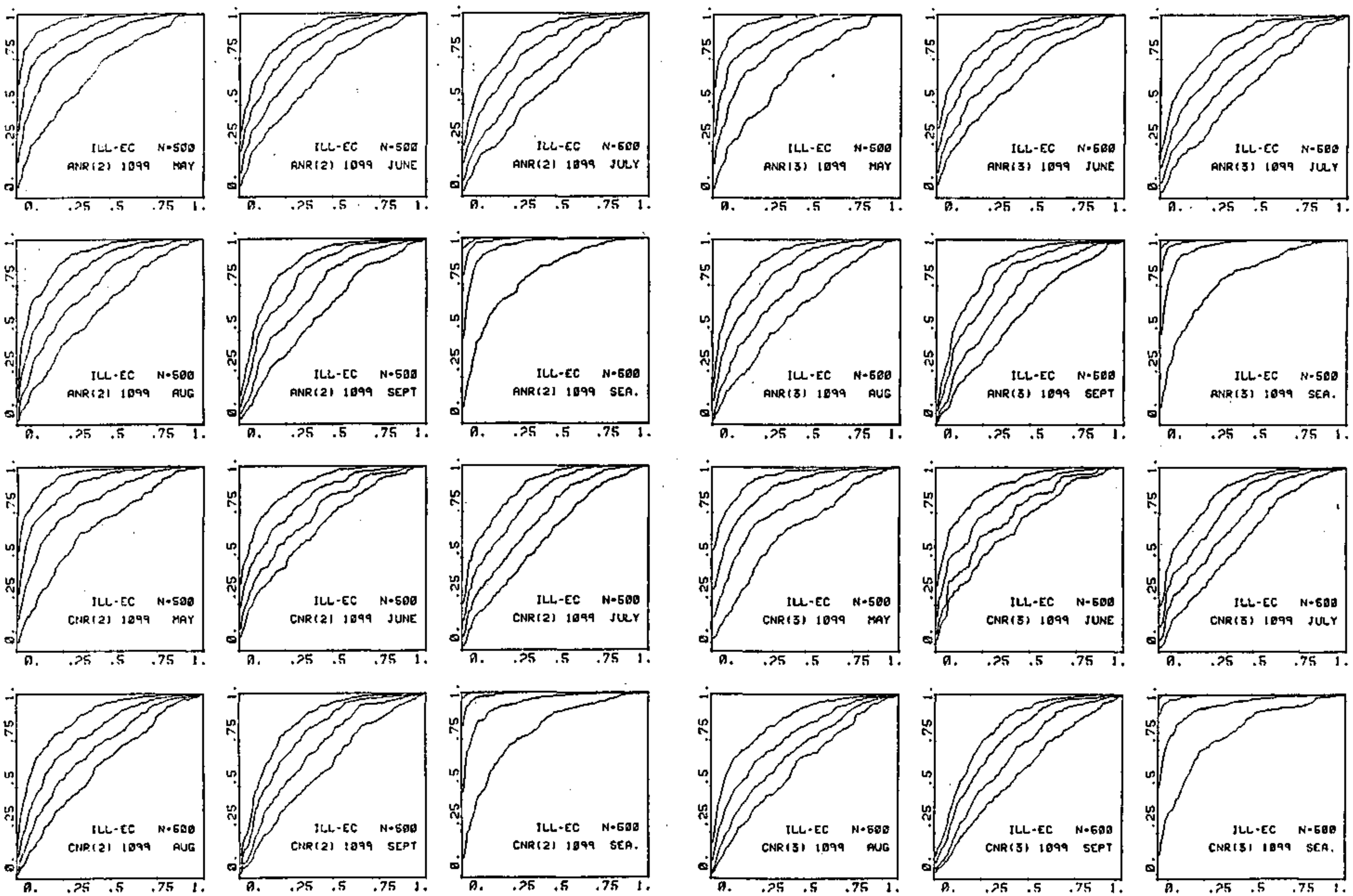


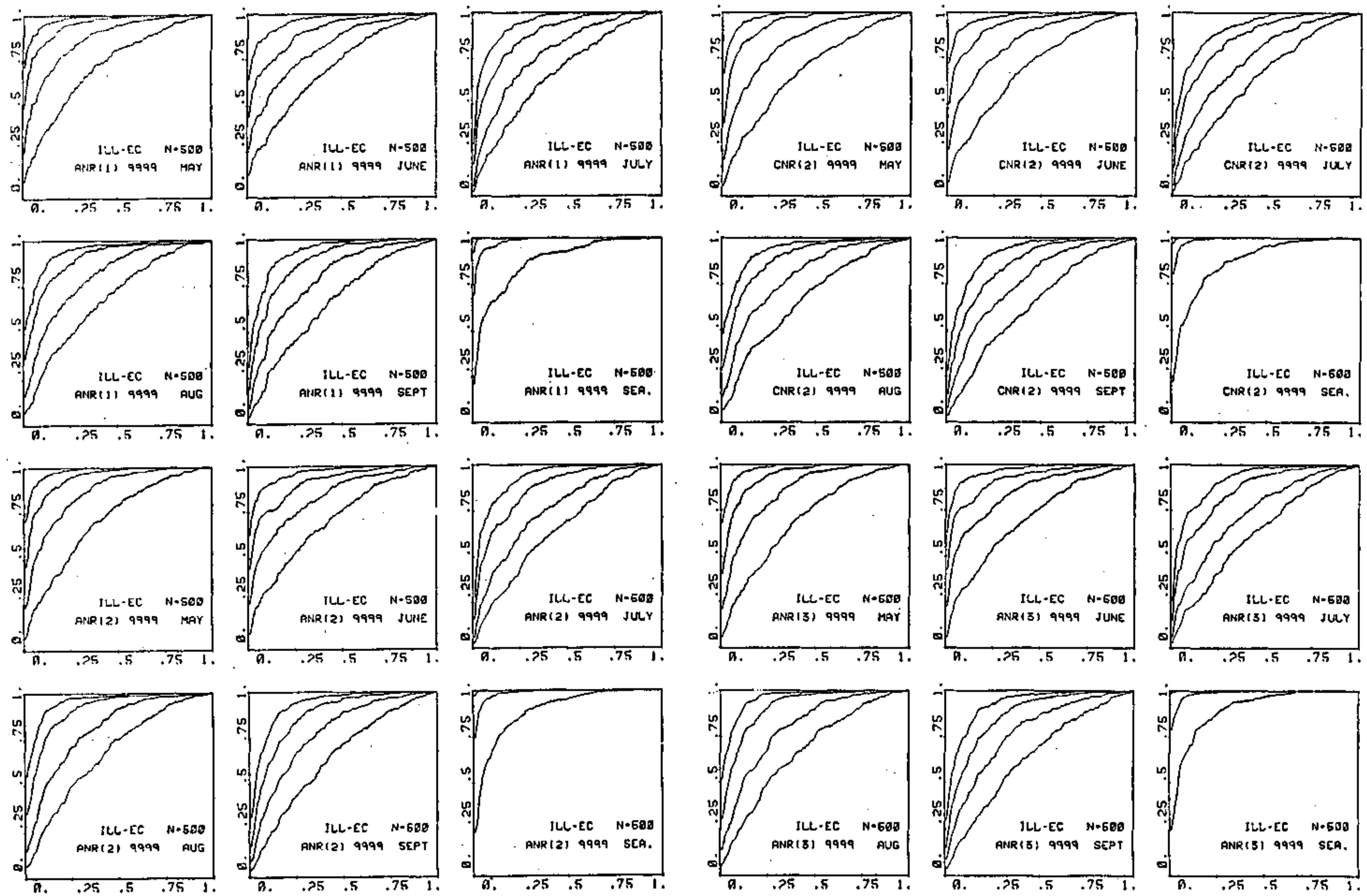
ILL-EC N=500
T2 999 MAY
ILL-EC N=500
T2 999 JUNE
ILL-EC N=500
T2 999 JULY
ILL-EC N=500
T2 1099 MAY
ILL-EC N=500
T2 1099 JUNE
ILL-EC N=500
T2 1099 JULY
ILL-EC N=500
T2 999 AUG
ILL-EC N=500
T2 999 SEPT
ILL-EC N=500
T2 999 SEA.
ILL-EC N=500
T2 1099 AUG
ILL-EC N=500
T2 1099 SEPT
ILL-EC N=500
T2 1099 SEA.
ILL-EC N=500
T3 999 MAY
ILL-EC N=500
T3 999 JUNE
ILL-EC N=500
T3 999 JULY
ILL-EC N=500
T3 1099 MAY
ILL-EC N=500
T3 1099 JUNE
ILL-EC N=500
T3 1099 JULY
ILL-EC N=500
T3 999 AUG
ILL-EC N=500
T3 999 SEPT
ILL-EC N=500
T3 999 SEA.
ILL-EC N=500
T3 1099 AUG
ILL-EC N=500
T3 1099 SEPT
ILL-EC N=500
T3 1099 SEA.

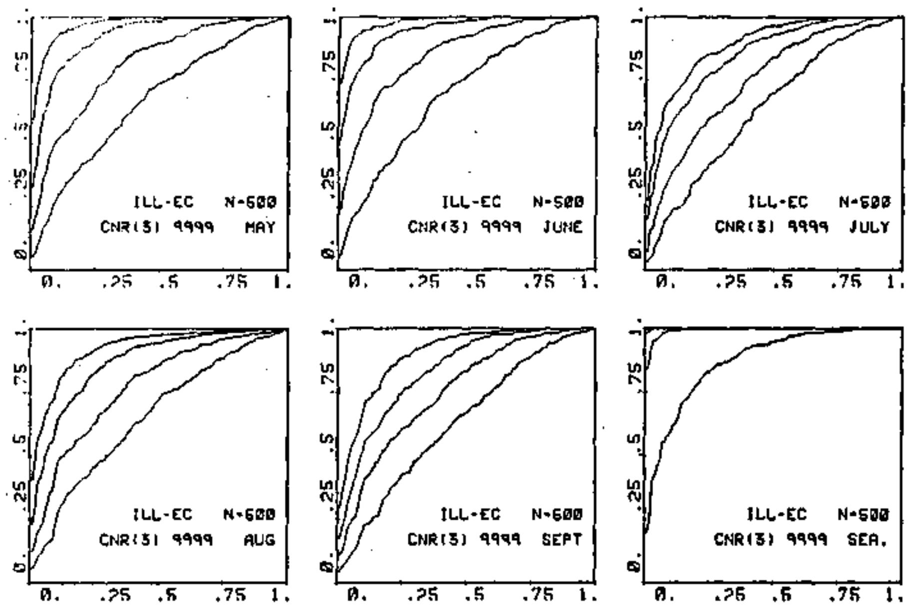


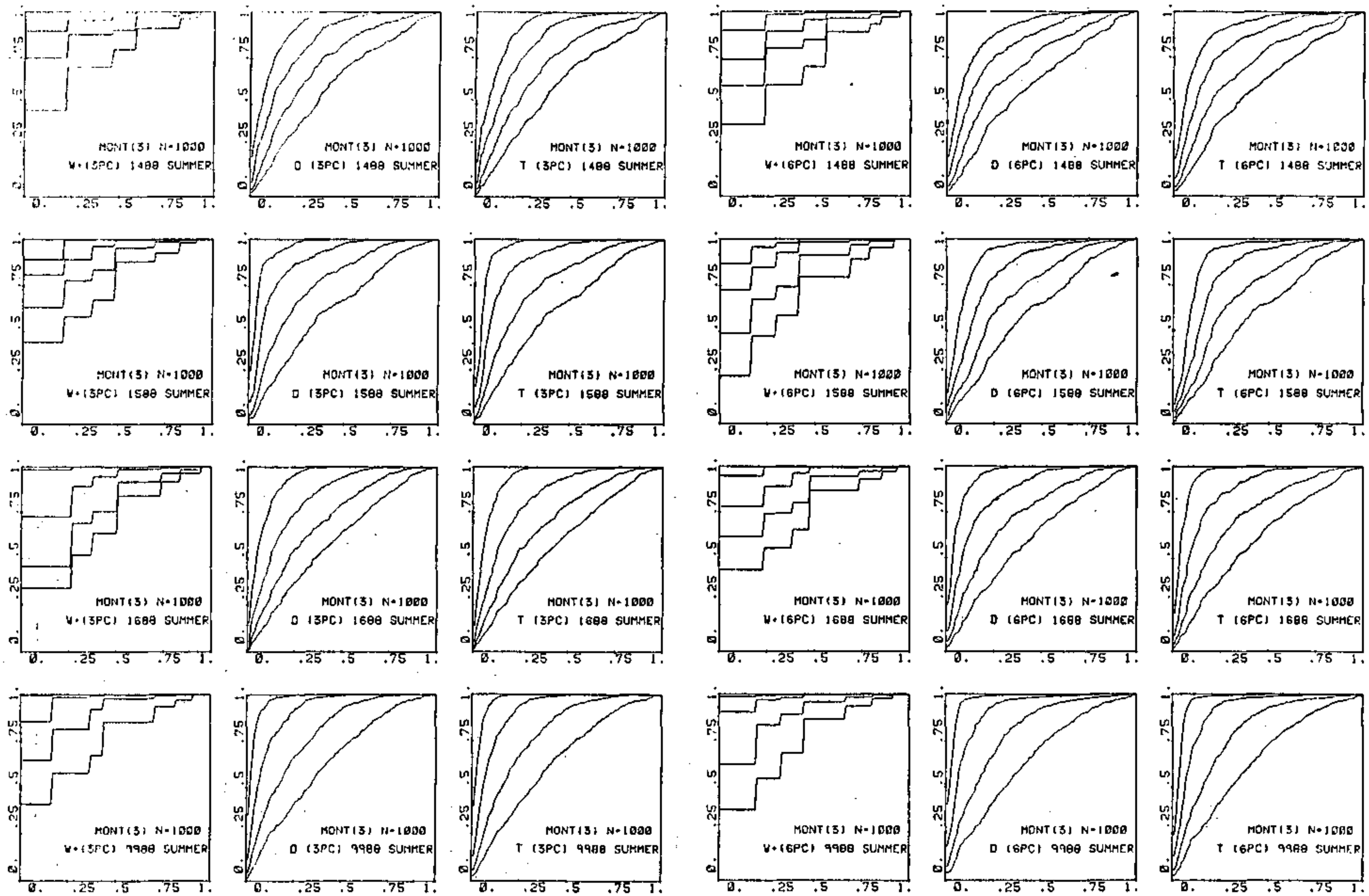
ILL-EC N=500
T2 9999 MAY
ILL-EC N=500
T2 9999 JUNE
ILL-EC N=500
T2 9999 JULY
ILL-EC N=500
ANR(1) 999 MAY
ILL-EC N=500
ANR(1) 999 JUNE
ILL-EC N=500
ANR(1) 999 JULY
ILL-EC N=500
T2 9999 AUG
ILL-EC N=500
T2 9999 SEPT
ILL-EC N=600
T2 9999 SEA.
ILL-EC N=500
ANR(1) 999 AUG
ILL-EC N=500
ANR(1) 999 SEPT
ILL-EC N=600
ANR(1) 999 SEA.
ILL-EC N=500
T3 9999 MAY
ILL-EC N=500
T3 9999 JUNE
ILL-EC N=500
T3 9999 JULY
ILL-EC N=500
ANR(2) 999 MAY
ILL-EC N=500
ANR(2) 999 JUNE
ILL-EC N=500
ANR(2) 999 JULY
ILL-EC N=500
T3 9999 AUG
ILL-EC N=500
T3 9999 SEPT
ILL-EC N=600
T3 9999 SEA.
ILL-EC N=500
ANR(2) 999 AUG
ILL-EC N=500
ANR(2) 999 SEPT
ILL-EC N=600
ANR(2) 999 SEA.

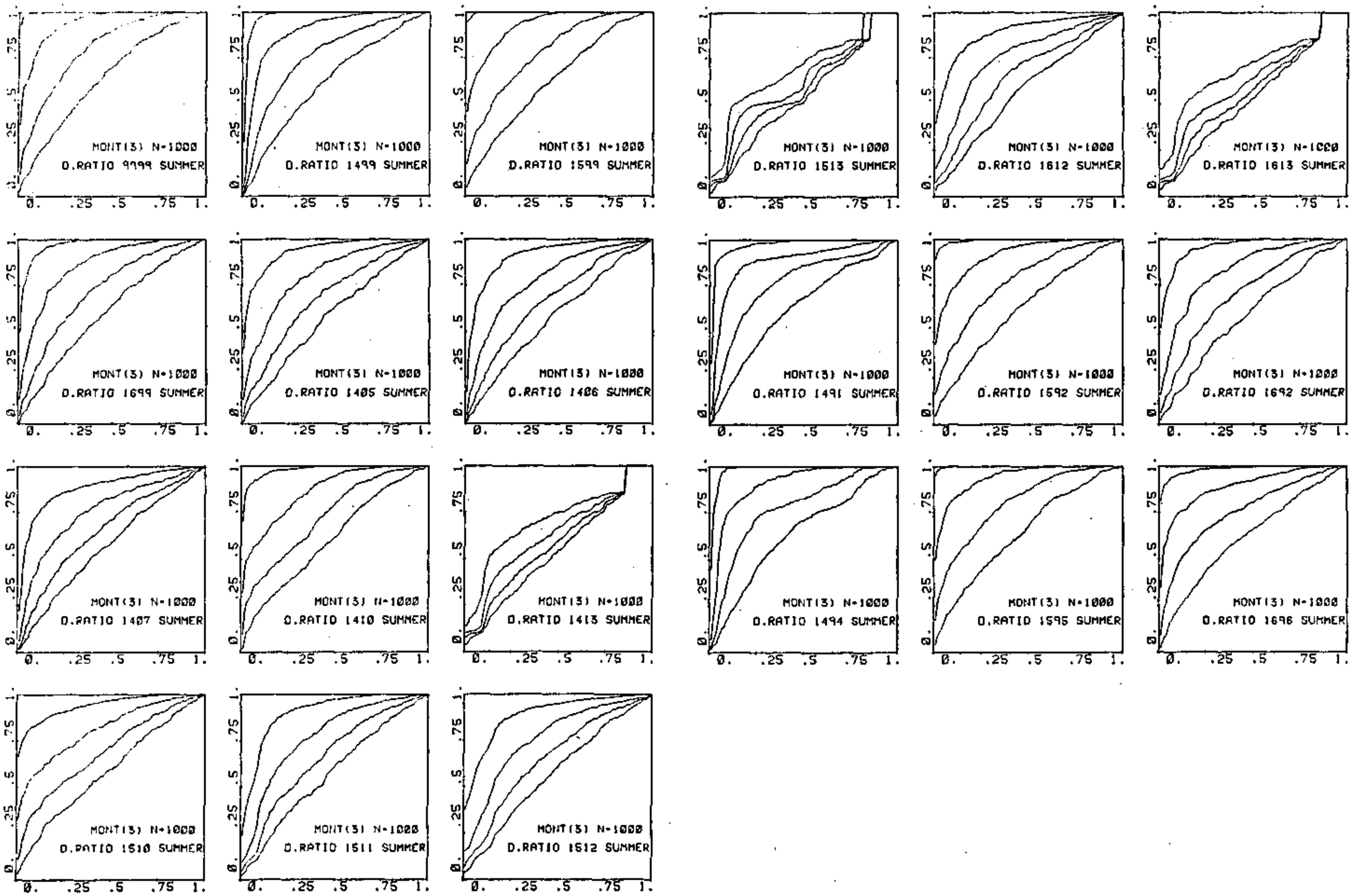

ILL-EC N=500
CNR(2) 999 MAY
ILL-EC N=500
CNR(2) 999 JUNE
ILL-EC N=600
CNR(2) 999 JULY
ILL-EC N=600
CNR(3) 999 MAY
ILL-EC N=600
CNR(3) 999 JUNE
ILL-EC N=600
CNR(3) 999 JULY
ILL-EC N=500
CNR(2) 999 AUG
ILL-EC N=600
CNR(2) 999 SEPT
ILL-EC N=600
CNR(2) 999 SEA.
ILL-EC N=600
CNR(3) 999 AUG
ILL-EC N=600
CNR(3) 999 SEPT
ILL-EC N=500
CNR(3) 999 SEA.
ILL-EC N=500
ANR(3) 999 MAY
ILL-EC N=500
ANR(3) 999 JUNE
ILL-EC N=600
ANR(3) 999 JULY
ILL-EC N=600
ANR(1) 1099 MAY
ILL-EC N=600
ANR(1) 1099 JUNE
ILL-EC N=500
ANR(1) 1099 JULY
ILL-EC N=500
ANR(3) 999 AUG
ILL-EC N=600
ANR(3) 999 SEPT
ILL-EC N=600
ANR(3) 999 SEA.
ILL-EC N=600
ANR(1) 1099 AUG
ILL-EC N=600
ANR(1) 1099 SEPT
ILL-EC N=600
ANR(1) 1099 SEA.
0. .25 .5 .75 1.

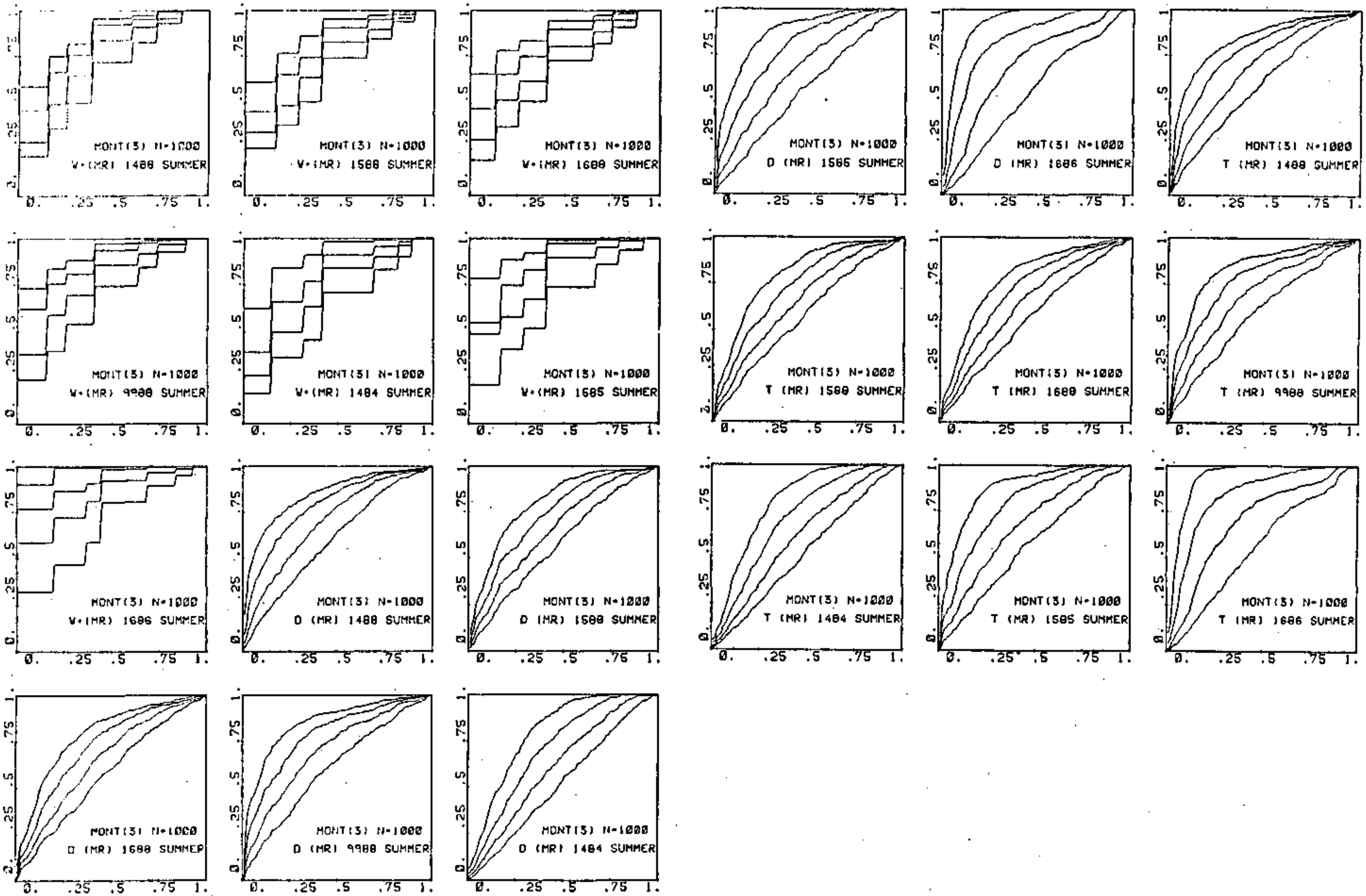

ILL-EC N=500
ANR(2) 1099 MAY
ILL-EC N=500
ANR(2) 1099 JUNE
ILL-EC N=600
ANR(2) 1099 JULY
ILL-EC N=600
ANR(3) 1099 MAY
ILL-EC N=600
ANR(3) 1099 JUNE
ILL-EC N=600
ANR(3) 1099 JULY
ILL-EC N=500
ANR(2) 1099 AUG
ILL-EC N=500
ANR(2) 1099 SEPT
ILL-EC N=600
ANR(2) 1099 SEA.
ILL-EC N=600
ANR(3) 1099 AUG
ILL-EC N=600
ANR(3) 1099 SEPT
ILL-EC N=500
ANR(3) 1099 SEA.
ILL-EC N=500
CNR(2) 1099 MAY
ILL-EC N=500
CNR(2) 1099 JUNE
ILL-EC N=500
CNR(2) 1099 JULY
ILL-EC N=500
CNR(3) 1099 MAY
ILL-EC N=600
CNR(3) 1099 JUNE
ILL-EC N=600
CNR(3) 1099 JULY
ILL-EC N=600
CNR(2) 1099 AUG
ILL-EC N=600
CNR(2) 1099 SEPT
ILL-EC N=600
CNR(2) 1099 SEA.
ILL-EC N=600
CNR(3) 1099 AUG
ILL-EC N=600
CNR(3) 1099 SEPT
ILL-EC N=600
CNR(3) 1099 SEA.

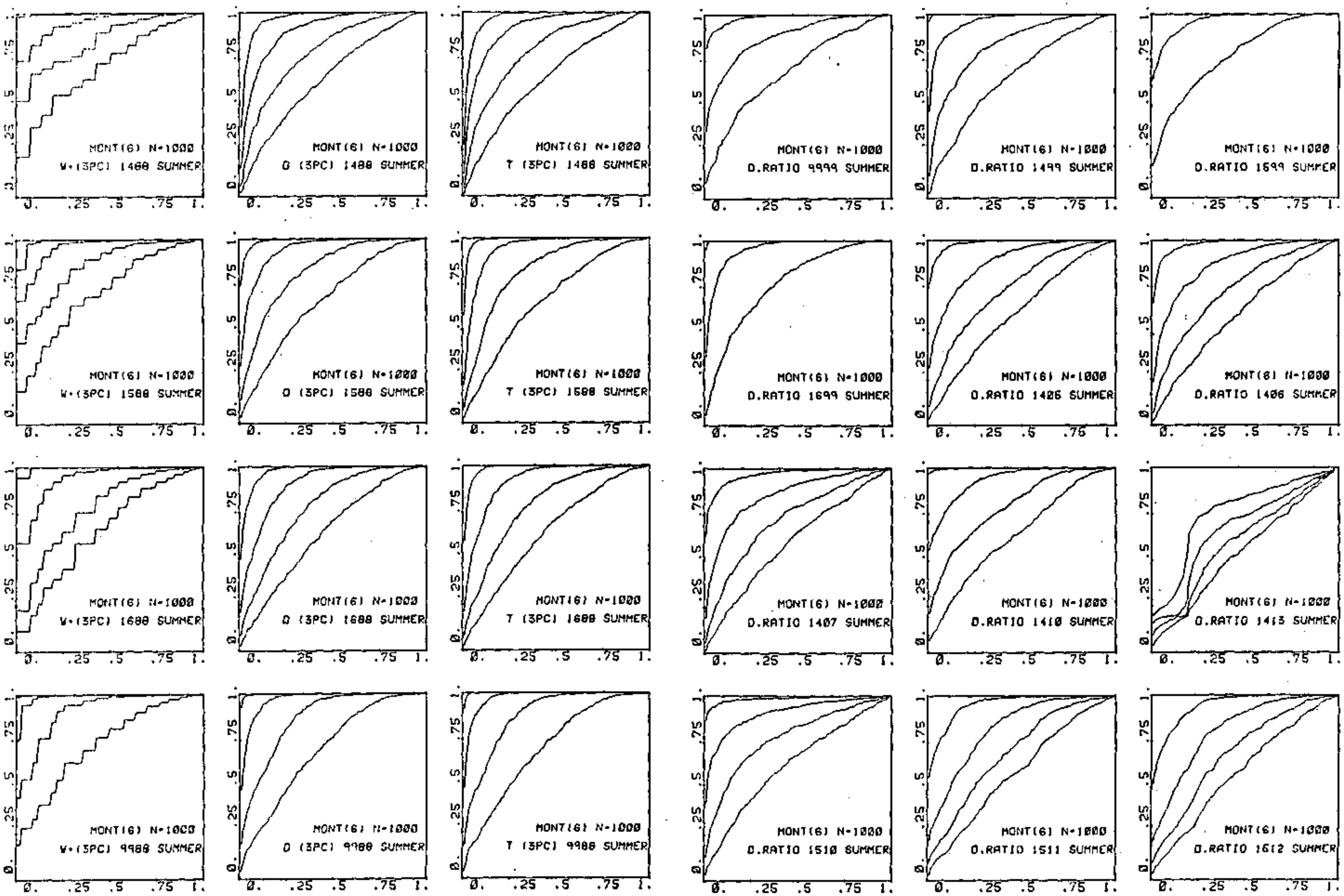

ILL-EC N=500
ANR(1) 9999 MAY
ILL-EC N=500
ANR(1) 9999 JUNE
ILL-EC N=500
ANR(1) 9999 JULY
ILL-EC N=500
CNR(2) 9999 MAY
ILL-EC N=500
CNR(2) 9999 JUNE
ILL-EC N=500
CNR(2) 9999 JULY
ILL-EC N=500
ANR(1) 9999 AUG
ILL-EC N=500
ANR(1) 9999 SEPT
ILL-EC N=500
ANR(1) 9999 SEA.
ILL-EC N=500
CNR(2) 9999 AUG
ILL-EC N=500
CNR(2) 9999 SEPT
ILL-EC N=500
CNR(2) 9999 SEA.
ILL-EC N=500
ANR(2) 9999 MAY
ILL-EC N=500
ANR(2) 9999 JUNE
ILL-EC N=500
ANR(2) 9999 JULY
ILL-EC N=500
ANR(3) 9999 MAY
ILL-EC N=500
ANR(3) 9999 JUNE
ILL-EC N=500
ANR(3) 9999 JULY
ILL-EC N=500
ANR(2) 9999 AUG
ILL-EC N=500
ANR(2) 9999 SEPT
ILL-EC N=500
ANR(2) 9999 SEA.
ILL-EC N=500
ANR(3) 9999 AUG
ILL-EC N=500
ANR(3) 9999 SEPT
ILL-EC N=500
ANR(3) 9999 SEA.
0. .25 .5 .75 1.

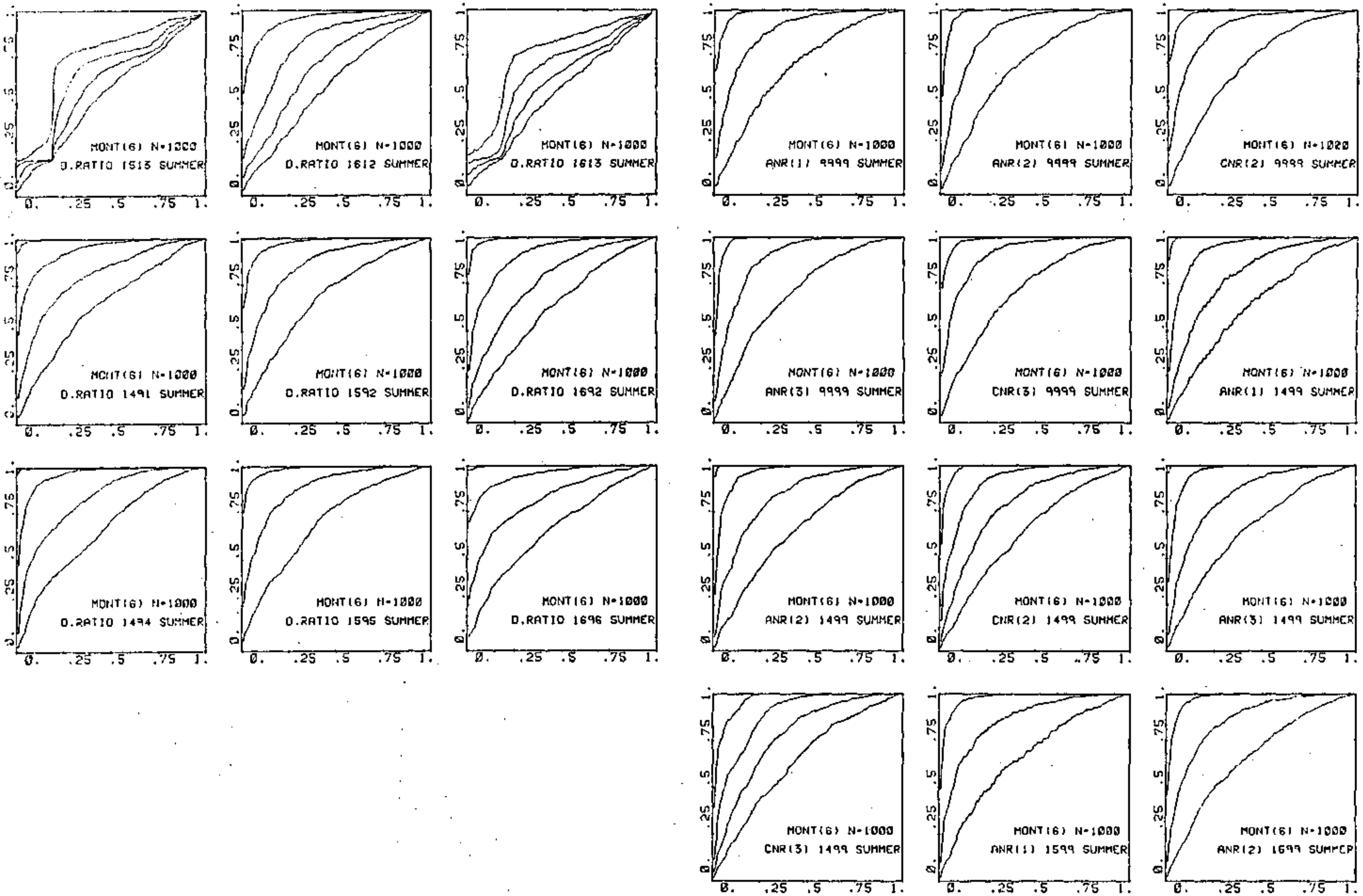

ILL-EC N=600
CNR(3) 9999 MAY
ILL-EC N=500
CNR(3) 9999 JUNE
ILL-EC N=600
CNR(3) 9999 JULY
ILL-EC N=600
CNR(3) 9999 AUG
ILL-EC N=600
CNR(3) 9999 SEPT
ILL-EC N=600
CNR(3) 9999 SEA.
0. .25 .5 .75 1.

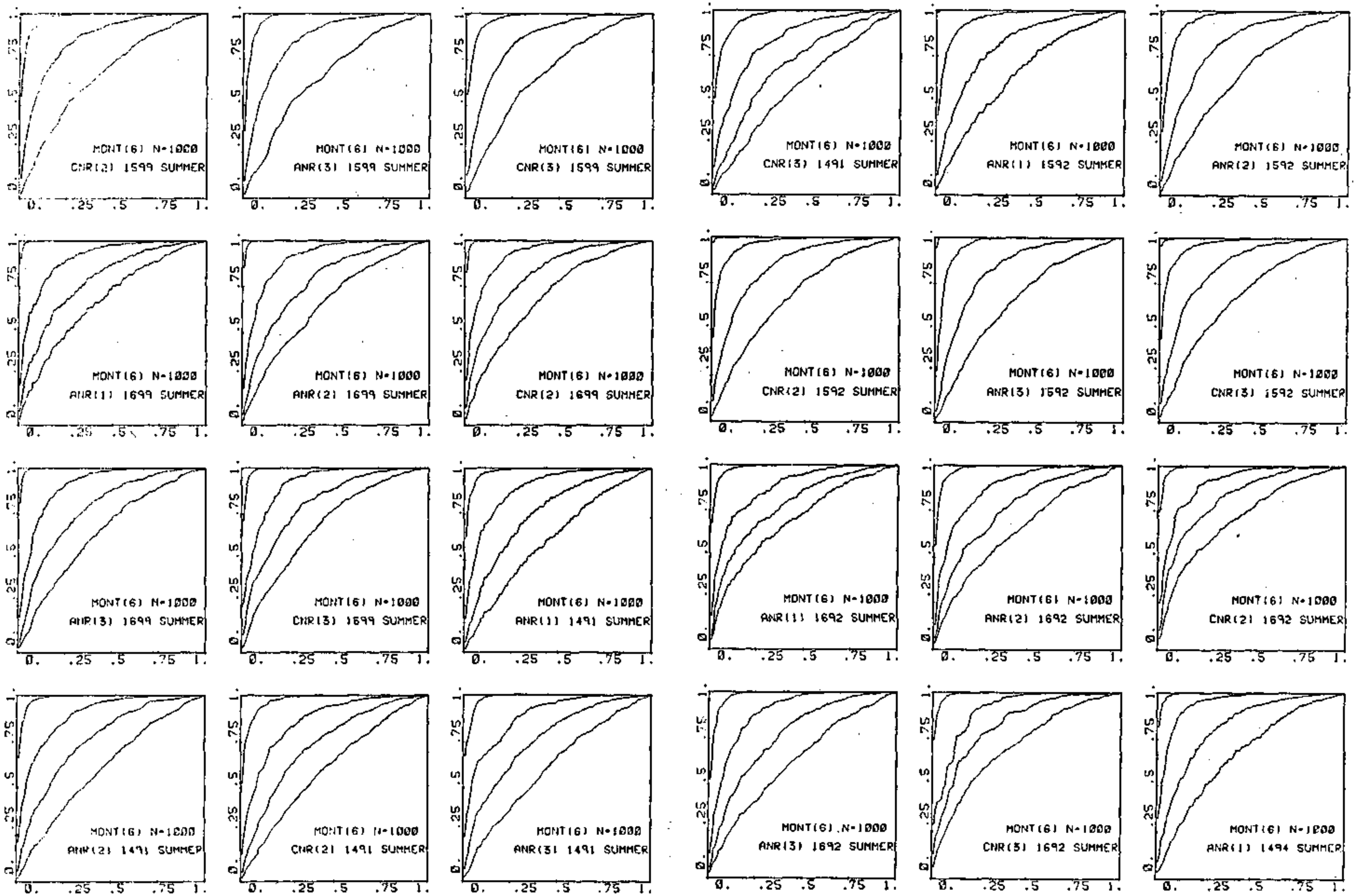

MONT(3) N=1000
W+(3PC) 1400 SUMMER
MONT(3) N=1000
D (3PC) 1400 SUMMER
MONT(3) N=1000
T (3PC) 1400 SUMMER
MONT(3) N=1000
W+(6PC) 1400 SUMMER
MONT(3) N=1000
D (6PC) 1400 SUMMER
MONT(3) N=1000
T (6PC) 1400 SUMMER
MONT(3) N=1000
W+(3PC) 1500 SUMMER
MONT(3) N=1000
D (3PC) 1500 SUMMER
MONT(3) N=1000
T (3PC) 1500 SUMMER
MONT(3) N=1000
W+(6PC) 1500 SUMMER
MONT(3) N=1000
D (6PC) 1500 SUMMER
MONT(3) N=1000
T (6PC) 1500 SUMMER
MONT(3) N=1000
W+(3PC) 1600 SUMMER
MONT(3) N=1000
D (3PC) 1600 SUMMER
MONT(3) N=1000
T (3PC) 1600 SUMMER
MONT(3) N=1000
W+(6PC) 1600 SUMMER
MONT(3) N=1000
D (6PC) 1600 SUMMER
MONT(3) N=1000
T (6PC) 1600 SUMMER
MONT(3) N=1000
W+(3PC) 9900 SUMMER
MONT(3) N=1000
D (3PC) 9900 SUMMER
MONT(3) N=1000
T (3PC) 9900 SUMMER
MONT(3) N=1000
W+(6PC) 9900 SUMMER
MONT(3) N=1000
D (6PC) 9900 SUMMER
MONT(3) N=1000
T (6PC) 9900 SUMMER

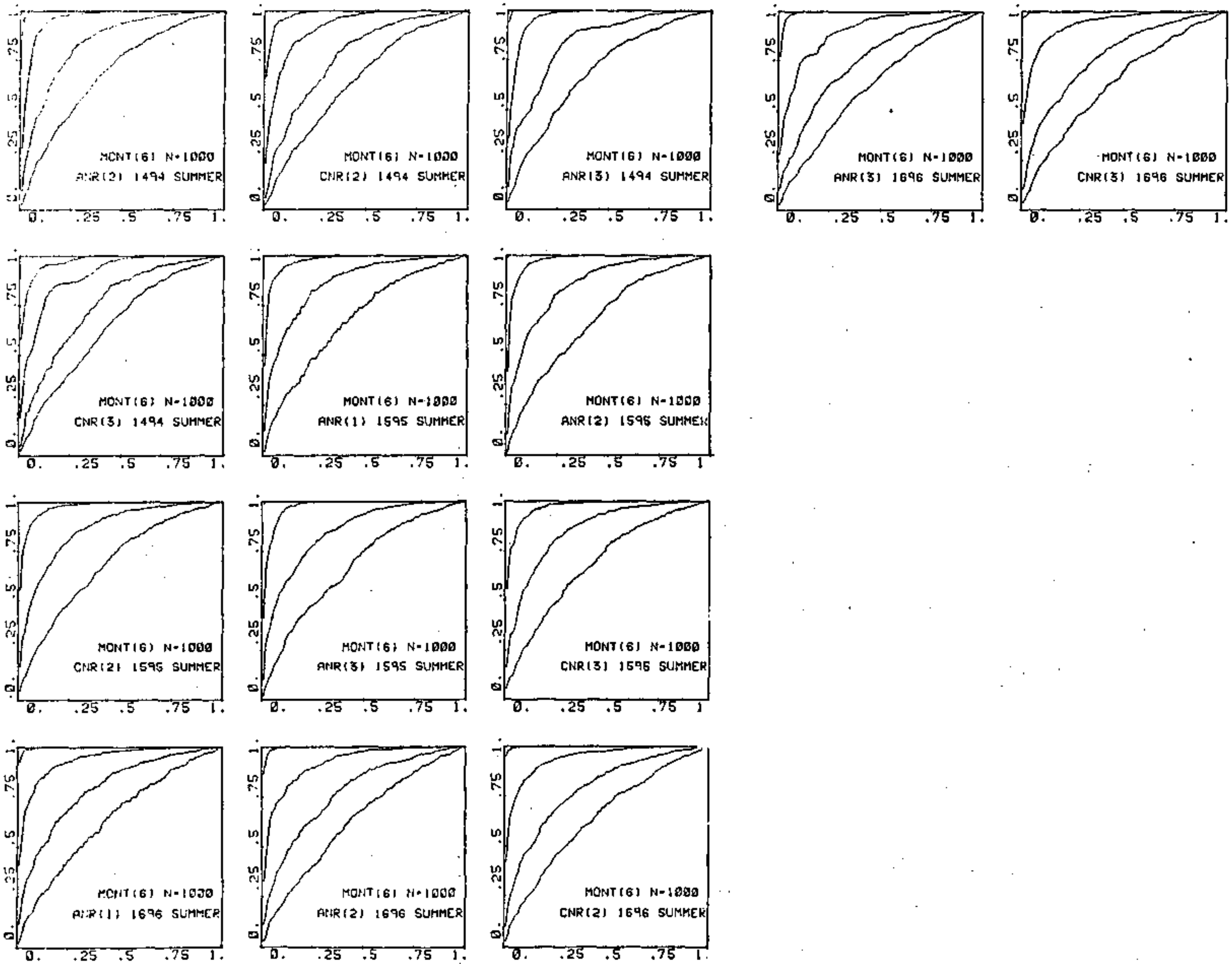

MONT(3) N=1000
D.RATIO 9999 SUMMER
MONT(3) N=1000
D.RATIO 1499 SUMMER
MONT(3) N=1000
D.RATIO 1599 SUMMER
MONT(3) N=1000
D.RATIO 1513 SUMMER
MONT(3) N=1000
D.RATIO 1612 SUMMER
MONT(3) N=1000
D.RATIO 1613 SUMMER
MONT(3) N=1000
D.RATIO 1699 SUMMER
MONT(3) N=1000
D.RATIO 1405 SUMMER
MONT(3) N=1000
D.RATIO 1406 SUMMER
MONT(3) N=1000
D.RATIO 1491 SUMMER
MONT(3) N=1000
D.RATIO 1592 SUMMER
MONT(3) N=1000
D.RATIO 1692 SUMMER
MONT(3) N=1000
D.RATIO 1407 SUMMER
MONT(3) N=1000
D.RATIO 1410 SUMMER
MONT(3) N=1000
D.RATIO 1413 SUMMER
MONT(3) N=1000
D.RATIO 1494 SUMMER
MONT(3) N=1000
D.RATIO 1595 SUMMER
MONT(3) N=1000
D.RATIO 1696 SUMMER
MONT(3) N=1000
D.RATIO 1510 SUMMER
MONT(3) N=1000
D.RATIO 1511 SUMMER
MONT(3) N=1000
D.RATIO 1512 SUMMER

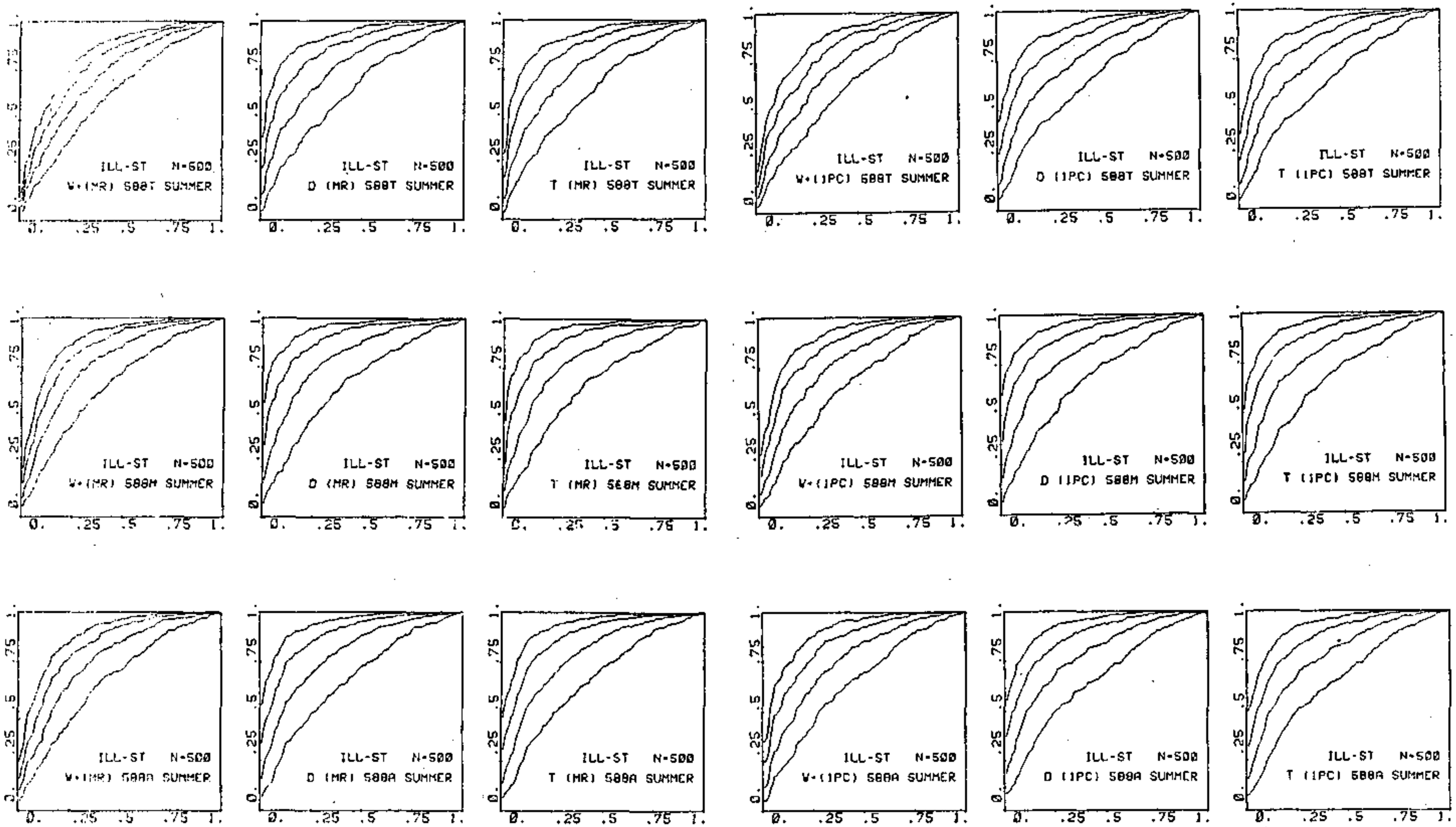

MONT(3) N=1000
V+(MR) 1400 SUMMER
MONT(3) N=1000
V+(MR) 1500 SUMMER
MONT(3) N=1000
V+(MR) 1600 SUMMER
MONT(3) N=1000
D (MR) 1505 SUMMER
MONT(3) N=1000
D (MR) 1606 SUMMER
MONT(3) N=1000
T (MR) 1400 SUMMER
MONT(3) N=1000
V+(MR) 9900 SUMMER
MONT(3) N=1000
V+(MR) 1404 SUMMER
MONT(3) N=1000
V+(MR) 1505 SUMMER
MONT(3) N=1000
T (MR) 1500 SUMMER
MONT(3) N=1000
T (MR) 1600 SUMMER
MONT(3) N=1000
T (MR) 9900 SUMMER
MONT(3) N=1000
V+(MR) 1606 SUMMER
MONT(3) N=1000
D (MR) 1400 SUMMER
MONT(3) N=1000
D (MR) 1500 SUMMER
MONT(3) N=1000
T (MR) 1404 SUMMER
MONT(3) N=1000
T (MR) 1505 SUMMER
MONT(3) N=1000
T (MR) 1606 SUMMER
MONT(3) N=1000
D (MR) 1600 SUMMER
MONT(3) N=1000
D (MR) 9900 SUMMER
MONT(3) N=1000
D (MR) 1404 SUMMER

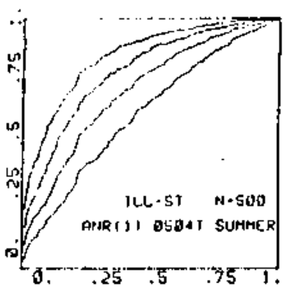

MONT(6) N=1000
W+(3PC) 1400 SUMMER
MONT(6) N=1000
Q (3PC) 1400 SUMMER
MONT(6) N=1000
T (3PC) 1400 SUMMER
MONT(6) N=1000
D.RATIO 9999 SUMMER
MONT(6) N=1000
D.RATIO 1499 SUMMER
MONT(6) N=1000
D.RATIO 1599 SUMMER
MONT(6) N=1000
W+(3PC) 1500 SUMMER
MONT(6) N=1000
Q (3PC) 1500 SUMMER
MONT(6) N=1000
T (3PC) 1500 SUMMER
MONT(6) N=1000
D.RATIO 1699 SUMMER
MONT(6) N=1000
D.RATIO 1406 SUMMER
MONT(6) N=1000
D.RATIO 1406 SUMMER
MONT(6) N=1000
W+(3PC) 1600 SUMMER
MONT(6) N=1000
Q (3PC) 1600 SUMMER
MONT(6) N=1000
T (3PC) 1600 SUMMER
MONT(6) N=1000
D.RATIO 1407 SUMMER
MONT(6) N=1000
D.RATIO 1410 SUMMER
MONT(6) N=1000
D.RATIO 1413 SUMMER
MONT(6) N=1000
W+(3PC) 9900 SUMMER
MONT(6) N=1000
Q (3PC) 9900 SUMMER
MONT(6) N=1000
T (3PC) 9900 SUMMER
MONT(6) N=1000
D.RATIO 1510 SUMMER
MONT(6) N=1000
D.RATIO 1511 SUMMER
MONT(6) N=1000
D.RATIO 1512 SUMMER

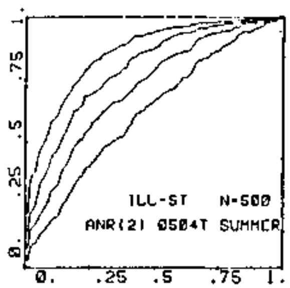

MONT(6) N=1000
D.RATIO 1513 SUMMER
MONT(6) N=1000
D.RATIO 1612 SUMMER
MONT(6) N=1000
D.RATIO 1613 SUMMER
MONT(6) N=1000
ANR(1) 9999 SUMMER
MONT(6) N=1000
ANR(2) 9999 SUMMER
MONT(6) N=1000
CNR(2) 9999 SUMMER
MONT(6) N=1000
D.RATIO 1491 SUMMER
MONT(6) N=1000
D.RATIO 1592 SUMMER
MONT(6) N=1000
D.RATIO 1692 SUMMER
MONT(6) N=1000
ANR(3) 9999 SUMMER
MONT(6) N=1000
CNR(3) 9999 SUMMER
MONT(6) N=1000
ANR(1) 1499 SUMMER
MONT(6) N=1000
D.RATIO 1494 SUMMER
MONT(6) N=1000
D.RATIO 1595 SUMMER
MONT(6) N=1000
D.RATIO 1696 SUMMER
MONT(6) N=1000
ANR(2) 1499 SUMMER
MONT(6) N=1000
CNR(2) 1499 SUMMER
MONT(6) N=1000
ANR(3) 1499 SUMMER
MONT(6) N=1000
CNR(3) 1499 SUMMER
MONT(6) N=1000
ANR(1) 1599 SUMMER
MONT(6) N=1000
ANR(2) 1699 SUMMER

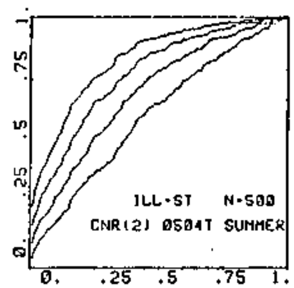

MONT(6) N=1000
CNR(2) 1599 SUMMER
MONT(6) N=1000
ANR(3) 1599 SUMMER
MONT(6) N=1000
CNR(3) 1599 SUMMER
MONT(6) N=1000
CNR(3) 1491 SUMMER
MONT(6) N=1000
ANR(1) 1592 SUMMER
MONT(6) N=1000
ANR(2) 1592 SUMMER
MONT(6) N=1000
ANR(1) 1699 SUMMER
MONT(6) N=1000
ANR(2) 1699 SUMMER
MONT(6) N=1000
CNR(2) 1699 SUMMER
MONT(6) N=1000
CNR(2) 1592 SUMMER
MONT(6) N=1000
ANR(3) 1592 SUMMER
MONT(6) N=1000
CNR(3) 1592 SUMMER
MONT(6) N=1000
ANR(3) 1699 SUMMER
MONT(6) N=1000
CNR(3) 1699 SUMMER
MONT(6) N=1000
ANR(1) 1491 SUMMER
MONT(6) N=1000
ANR(1) 1692 SUMMER
MONT(6) N=1000
ANR(2) 1692 SUMMER
MONT(6) N=1000
CNR(2) 1692 SUMMER
MONT(6) N=1000
ANR(2) 1491 SUMMER
MONT(6) N=1000
CNR(2) 1491 SUMMER
MONT(6) N=1000
ANR(3) 1491 SUMMER
MONT(6) N=1000
ANR(3) 1692 SUMMER
MONT(6) N=1000
CNR(3) 1692 SUMMER
MONT(6) N=1000
ANR(1) 1494 SUMMER
0. .25 .5 .75 1.

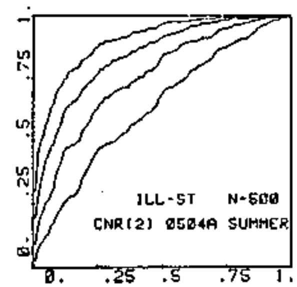

MONT(6) N=1000
ANR(2) 1494 SUMMER
MONT(6) N=1000
CNR(2) 1494 SUMMER
MONT(6) N=1000
ANR(3) 1494 SUMMER
MONT(6) N=1000
ANR(3) 1696 SUMMER
MONT(6) N=1000
CNR(3) 1696 SUMMER
MONT(6) N=1000
CNR(3) 1494 SUMMER
MONT(6) N=1000
ANR(1) 1595 SUMMER
MONT(6) N=1000
ANR(2) 1595 SUMMER
MONT(6) N=1000
CNR(2) 1595 SUMMER
MONT(6) N=1000
ANR(3) 1595 SUMMER
MONT(6) N=1000
CNR(3) 1595 SUMMER
MONT(6) N=1000
ANR(1) 1696 SUMMER
MONT(6) N=1000
ANR(2) 1696 SUMMER
MONT(6) N=1000
CNR(2) 1696 SUMMER

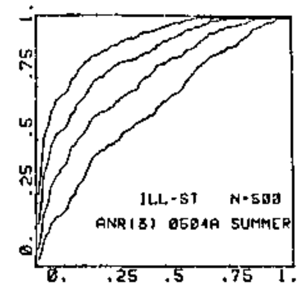

ILL-ST N=500
V+(MR) 500T SUMMER
ILL-ST N=500
D (MR) 500T SUMMER
ILL-ST N=500
T (MR) 500T SUMMER
ILL-ST N=500
V+(1PC) 500T SUMMER
ILL-ST N=500
D (1PC) 500T SUMMER
ILL-ST N=500
T (1PC) 500T SUMMER
ILL-ST N=500
V+(MR) 500M SUMMER
ILL-ST N=500
D (MR) 500M SUMMER
ILL-ST N=500
T (MR) 500M SUMMER
ILL-ST N=500
V+(1PC) 500M SUMMER
ILL-ST N=500
D (1PC) 500M SUMMER
ILL-ST N=500
T (1PC) 500M SUMMER
ILL-ST N=500
V+(MR) 500A SUMMER
ILL-ST N=500
D (MR) 500A SUMMER
ILL-ST N=500
T (MR) 500A SUMMER
ILL-ST N=500
V+(1PC) 500A SUMMER
ILL-ST N=500
D (1PC) 500A SUMMER
ILL-ST N=500
T (1PC) 500A SUMMER

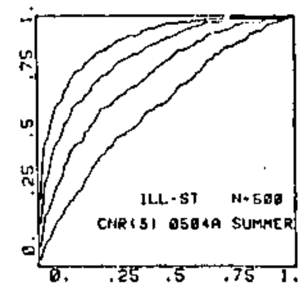

ILL-ST N=500
ANR(1) 0504T SUMMER
0. .25 .5 .75 1.

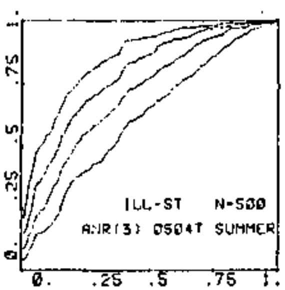

ILL-ST N=500
ANR(2) 0504T SUMMER
0. .25 .5 .75 1.

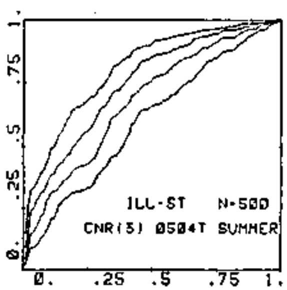

ILL-ST N=500
CNR(2) 0504T SUMMER
0. .25 .5 .75 1.

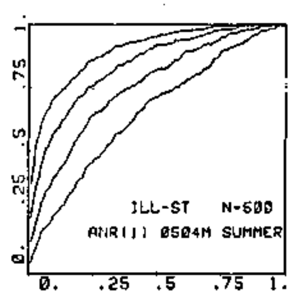

ILL-ST N=600
CNR(2) 0504A SUMMER
0. .25 .5 .75 1.

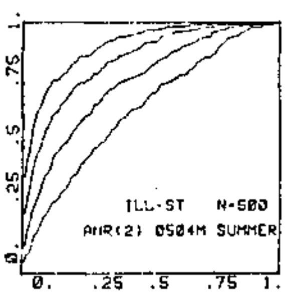

ILL-ST N=500
ANR(3) 0504A SUMMER
0. .25 .5 .75 1.

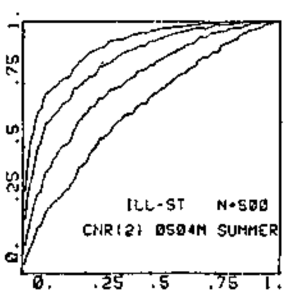

ILL-ST N=500
CNR(3) 0504A SUMMER
0. .25 .5 .75 1.

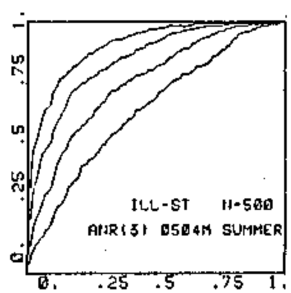

ILL-ST N=500
ANR(3) 0504T SUMMER
0. .25 .5 .75 1.

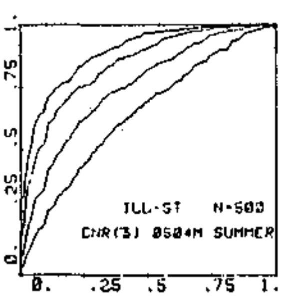

ILL-ST N=500
CNR(3) 0504T SUMMER
0. .25 .5 .75 1.

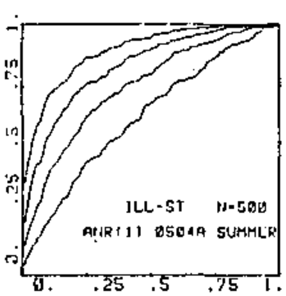

ILL-ST N=600
ANR(1) 0504M SUMMER
0. .25 .5 .75 1.

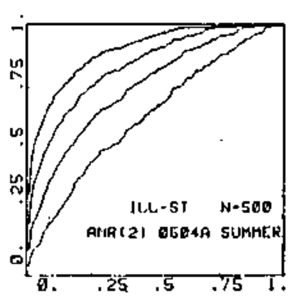

ILL-ST N=500
ANR(2) 0504M SUMMER
0. .25 .5 .75 1.

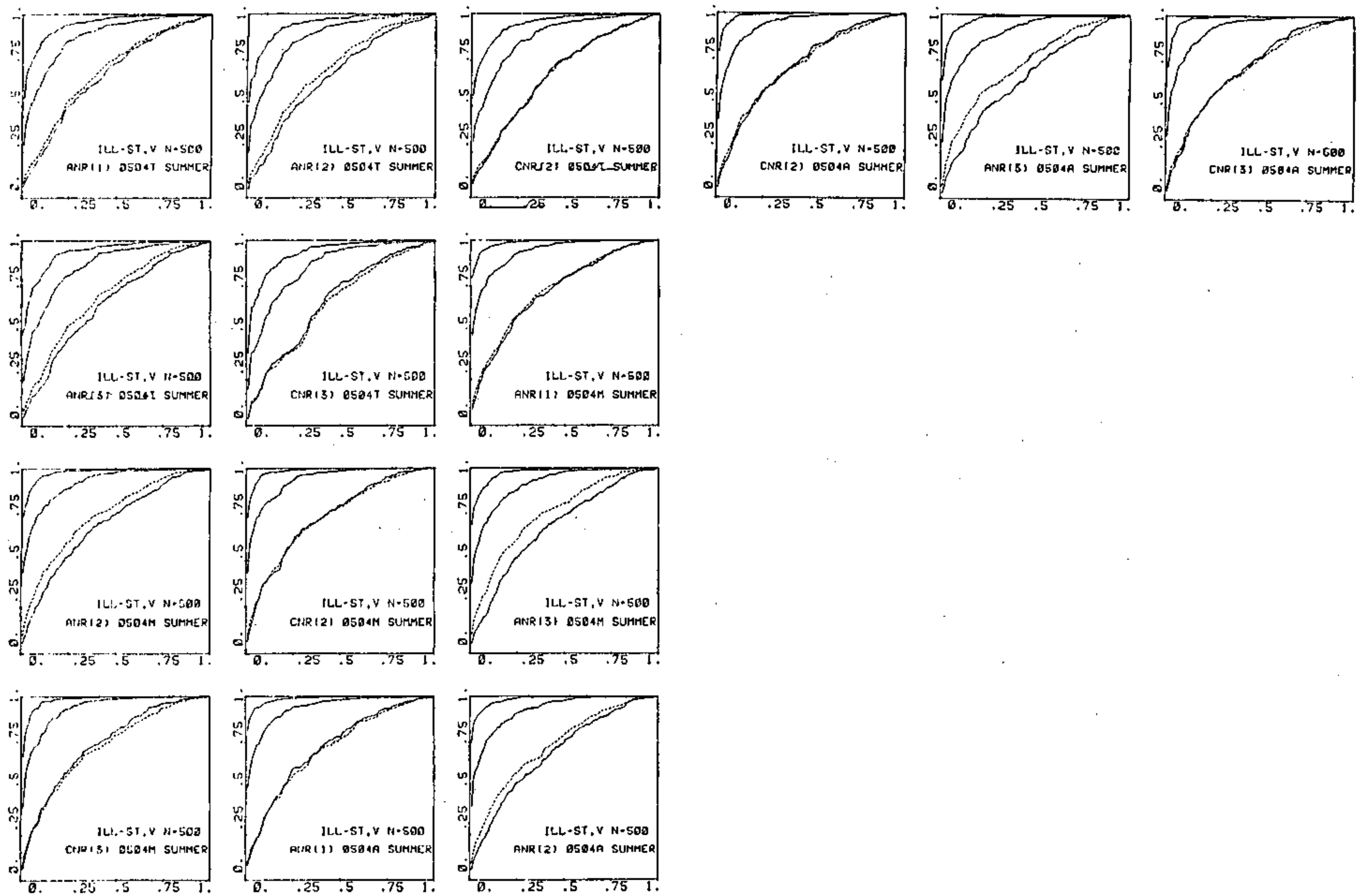

ILL-ST N=500
CNR(2) 0504M SUMMER
0. .25 .5 .75 1.

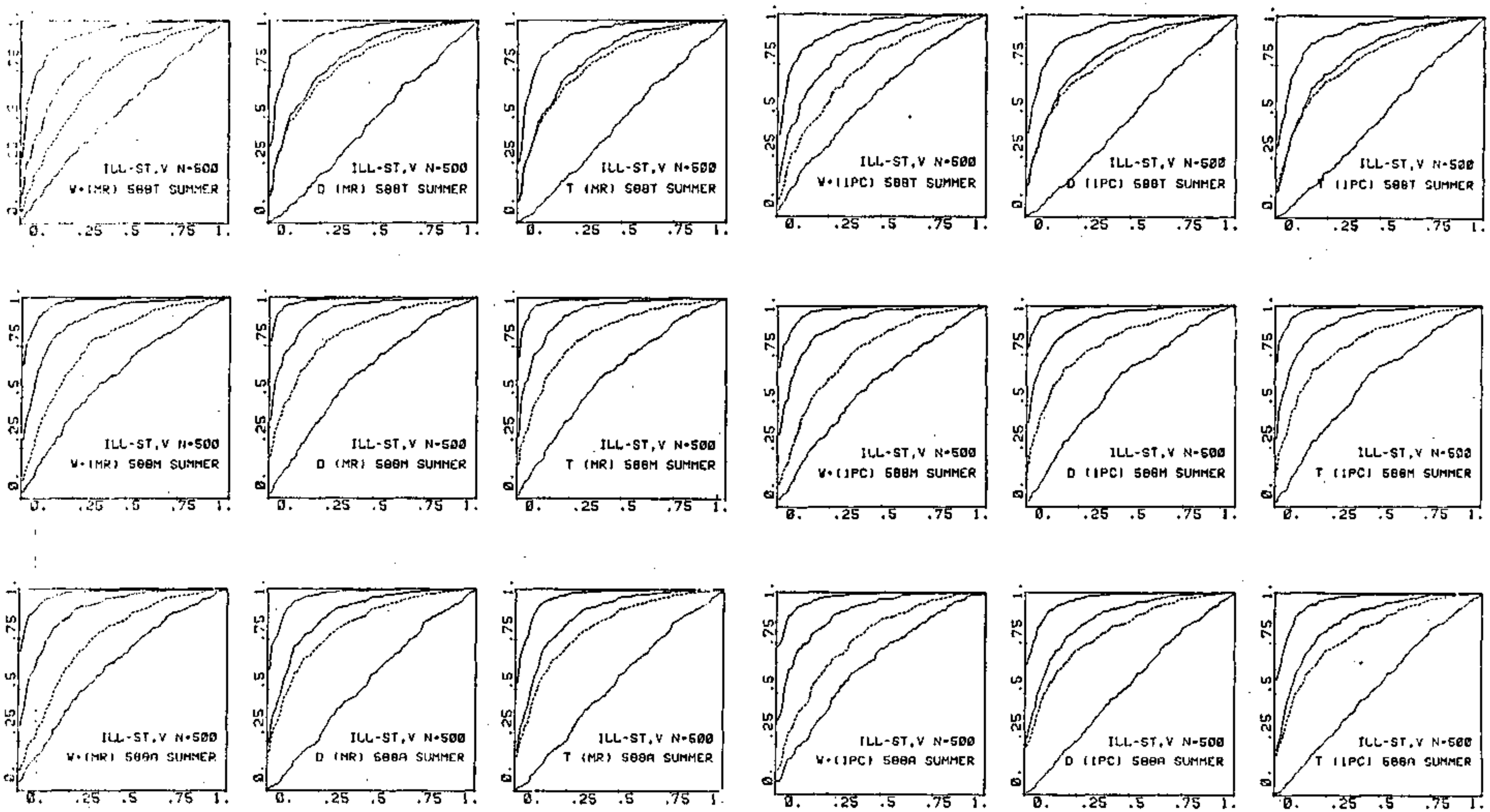

ILL-ST N=500
ANR(3) 0504M SUMMER
0. .25 .5 .75 1.

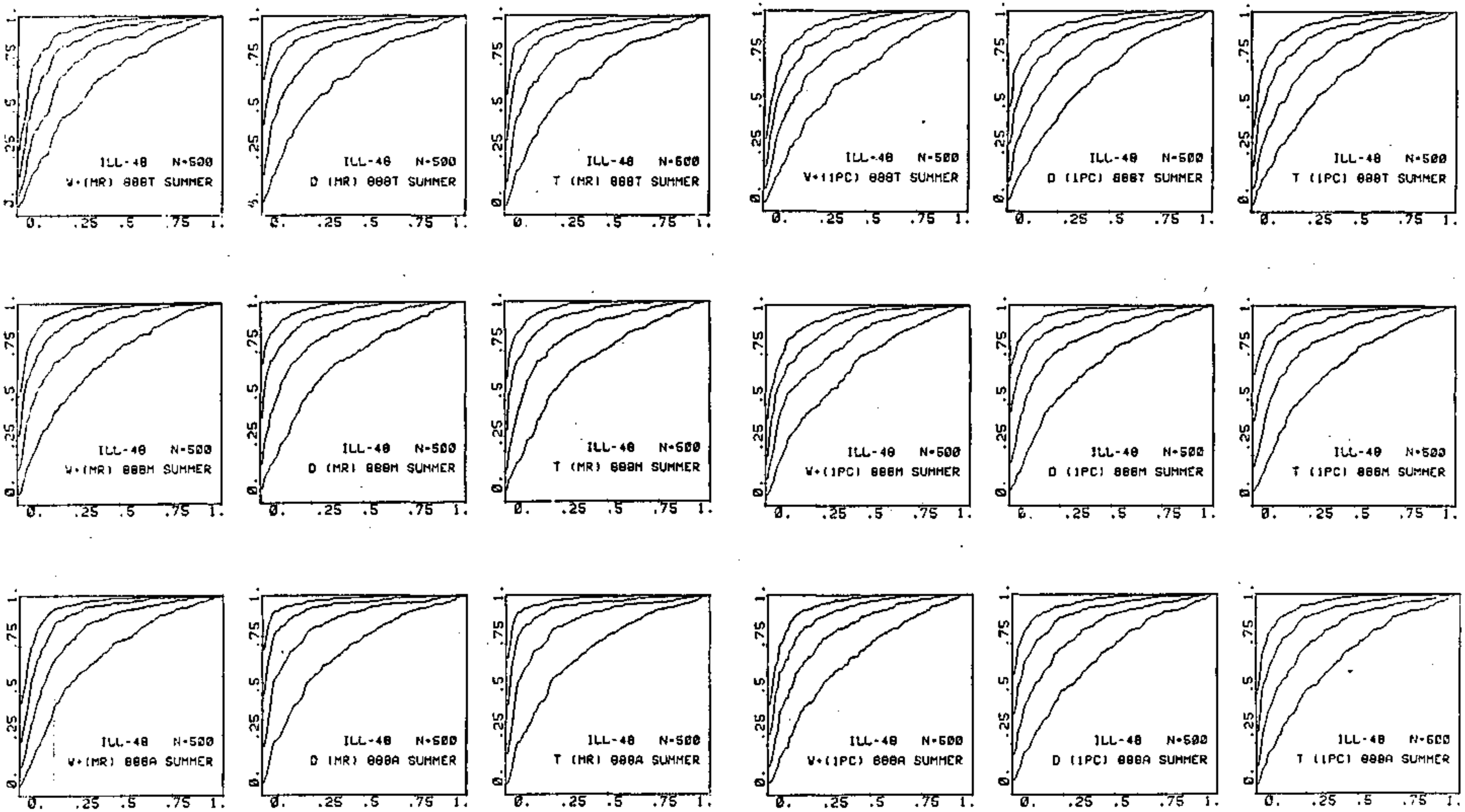

ILL-ST N=500
CNR(3) 0504M SUMMER
0. .25 .5 .75 1.

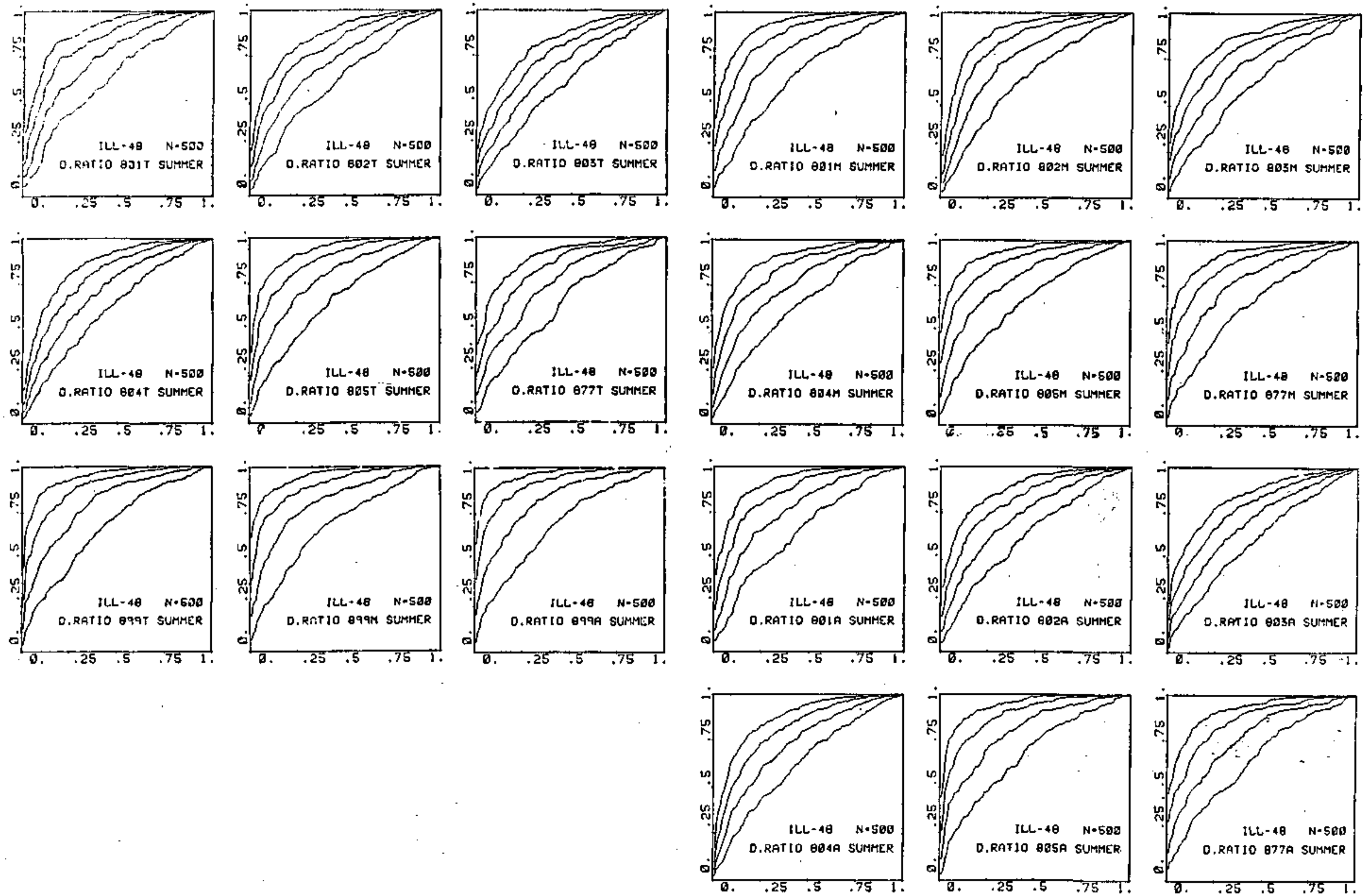

ILL-ST N=500
ANR(1) 0504A SUMMER
0. .25 .5 .75 1.


ILL-ST N=500
ANR(2) 0504A SUMMER
0. .25 .5 .75 1.

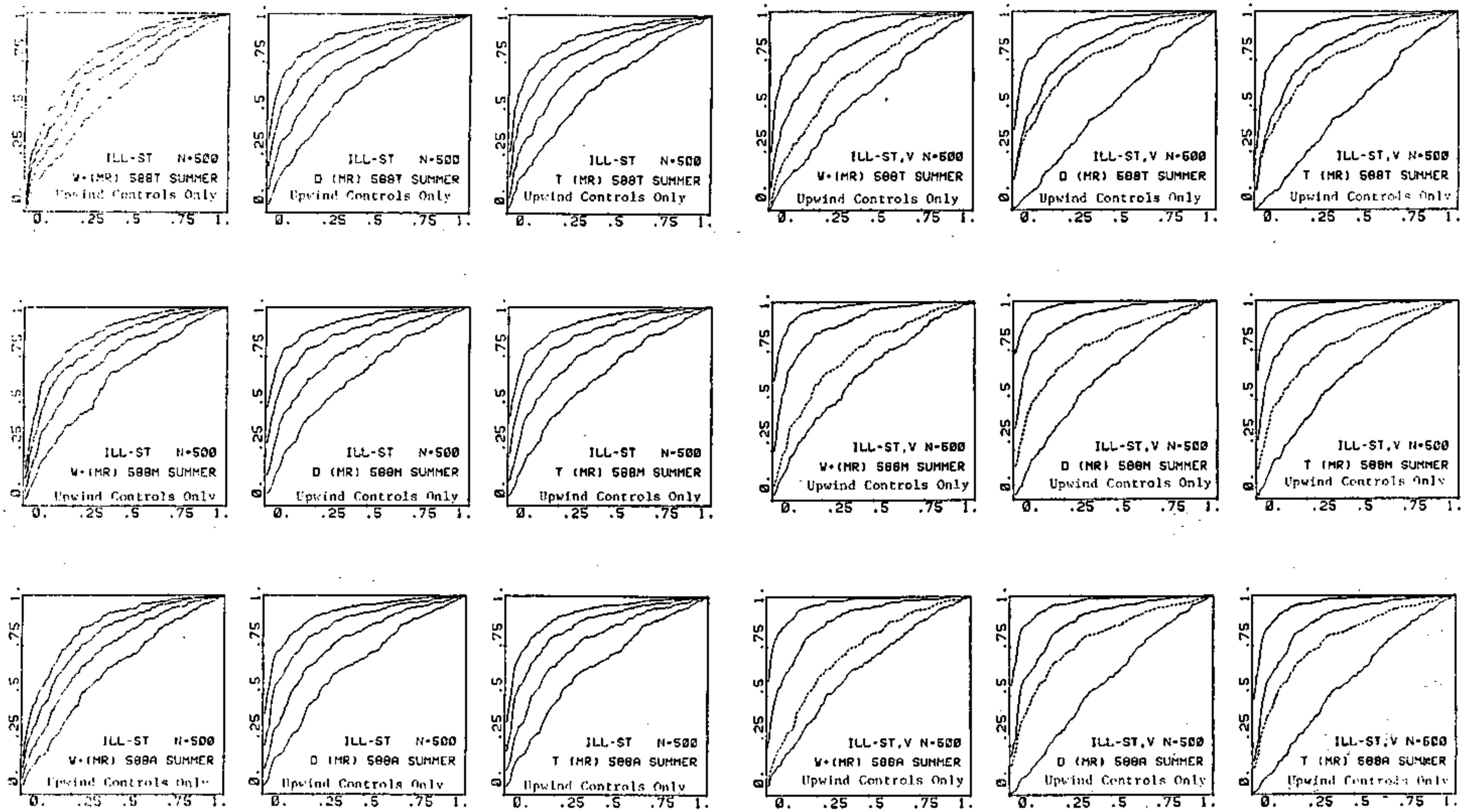

ILL-ST,V N=500
ANR(1) 0504T SUMMER
ILL-ST,V N=500
ANR(2) 0504T SUMMER
ILL-ST,V N=500
CNR(2) 0504T SUMMER
ILL-ST,V N=500
CNR(2) 0504A SUMMER
ILL-ST,V N=500
ANR(3) 0504A SUMMER
ILL-ST,V N=500
CNR(3) 0504A SUMMER
ILL-ST,V N=500
ANR(3) 0504T SUMMER
ILL-ST,V N=500
CNR(3) 0504T SUMMER
ILL-ST,V N=500
ANR(1) 0504M SUMMER
ILL-ST,V N=500
ANR(2) 0504M SUMMER
ILL-ST,V N=500
CNR(2) 0504M SUMMER
ILL-ST,V N=500
ANR(3) 0504M SUMMER
ILL-ST,V N=500
CNR(3) 0504M SUMMER
ILL-ST,V N=500
ANR(1) 0504A SUMMER
ILL-ST,V N=500
ANR(2) 0504A SUMMER

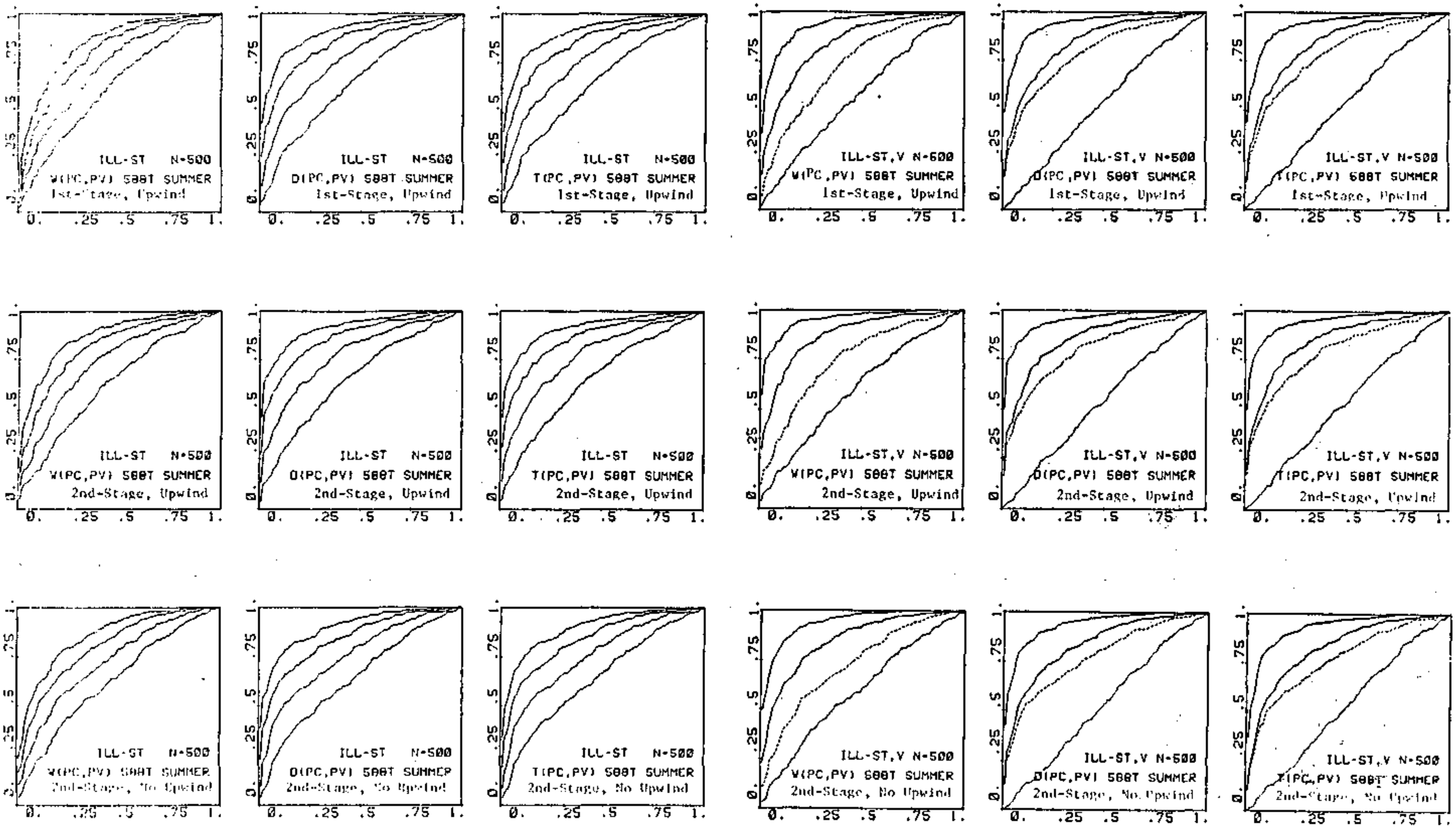

ILL-ST,V N=500
V·(MR) 500T SUMMER
ILL-ST,V N=500
D (MR) 500T SUMMER
ILL-ST,V N=500
T (MR) 500T SUMMER
ILL-ST,V N=500
V·(IPC) 500T SUMMER
ILL-ST,V N=500
D (IPC) 500T SUMMER
ILL-ST,V N=500
T (IPC) 500T SUMMER
ILL-ST,V N=500
V·(MR) 500M SUMMER
ILL-ST,V N=500
D (MR) 500M SUMMER
ILL-ST,V N=500
T (MR) 500M SUMMER
ILL-ST,V N=500
V·(IPC) 500M SUMMER
ILL-ST,V N=500
D (IPC) 500M SUMMER
ILL-ST,V N=500
T (IPC) 500M SUMMER
ILL-ST,V N=500
V·(MR) 500A SUMMER
ILL-ST,V N=500
D (MR) 500A SUMMER
ILL-ST,V N=500
T (MR) 500A SUMMER
ILL-ST,V N=500
V·(IPC) 500A SUMMER
ILL-ST,V N=500
D (IPC) 500A SUMMER
ILL-ST,V N=500
T (IPC) 500A SUMMER

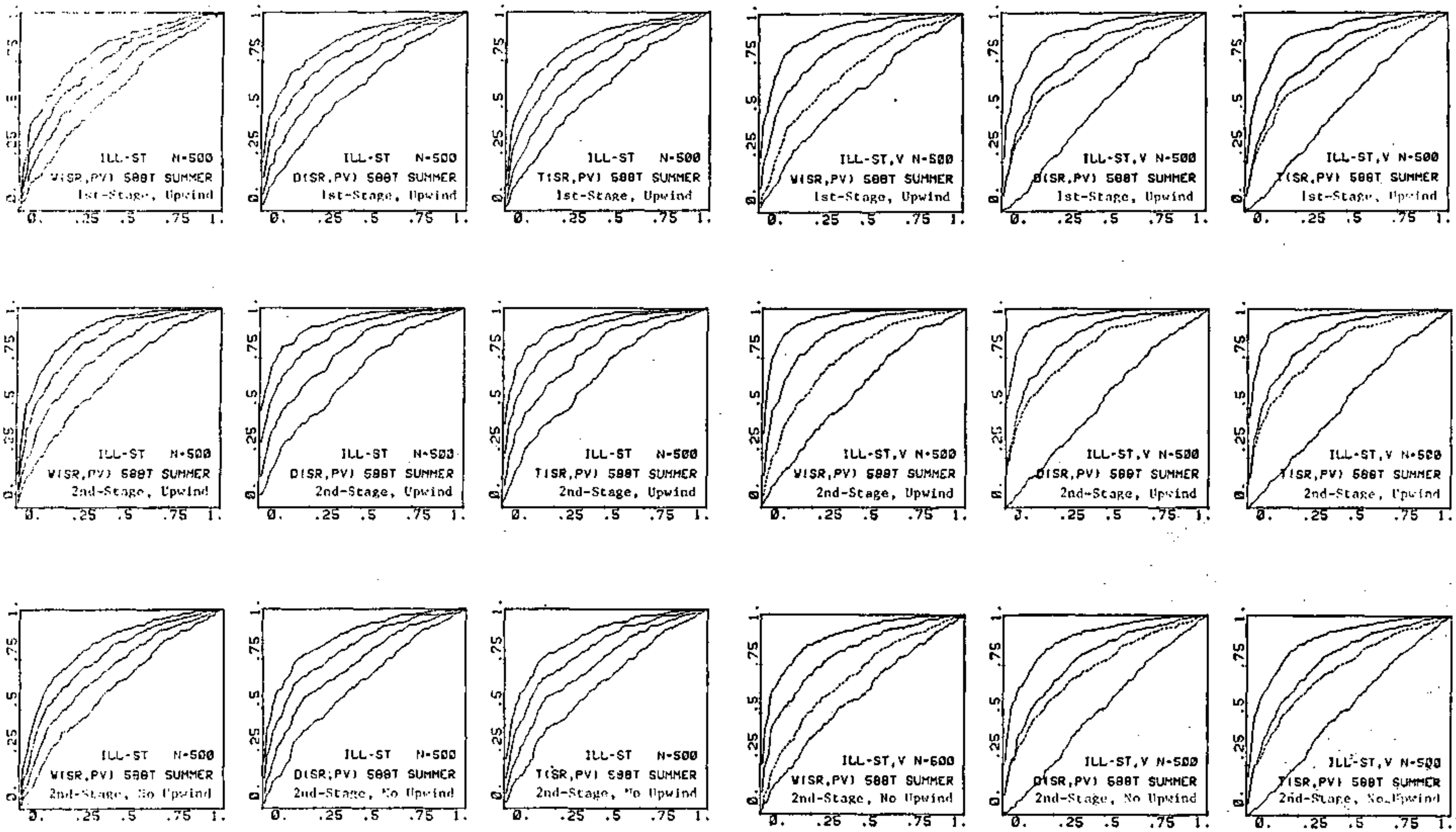

ILL-48 N=500
V+(MR) 888T SUMMER
ILL-48 N=500
D (MR) 888T SUMMER
ILL-48 N=500
T (MR) 888T SUMMER
ILL-48 N=500
V+(1PC) 888T SUMMER
ILL-48 N=500
D (1PC) 888T SUMMER
ILL-48 N=500
T (1PC) 888T SUMMER
ILL-48 N=500
V+(MR) 888M SUMMER
ILL-48 N=500
D (MR) 888M SUMMER
ILL-48 N=500
T (MR) 888M SUMMER
ILL-48 N=500
V+(1PC) 888M SUMMER
ILL-48 N=500
D (1PC) 888M SUMMER
ILL-48 N=500
T (1PC) 888M SUMMER
ILL-48 N=500
V+(MR) 888A SUMMER
ILL-48 N=500
D (MR) 888A SUMMER
ILL-48 N=500
T (MR) 888A SUMMER
ILL-48 N=500
V+(1PC) 888A SUMMER
ILL-48 N=500
D (1PC) 888A SUMMER
ILL-48 N=500
T (1PC) 888A SUMMER
0. .25 .5 .75 1.



ILL-48 N=500 D.RATIO 001T SUMMER
ILL-48 N=500 D.RATIO 002T SUMMER
ILL-48 N=500 D.RATIO 003T SUMMER
ILL-48 N=500 D.RATIO 001M SUMMER
ILL-48 N=500 D.RATIO 002M SUMMER
ILL-48 N=500 D.RATIO 003M SUMMER
ILL-48 N=500 D.RATIO 004T SUMMER
ILL-48 N=500 D.RATIO 005T SUMMER
ILL-48 N=500 D.RATIO 077T SUMMER
ILL-48 N=500 D.RATIO 004M SUMMER
ILL-48 N=500 D.RATIO 005M SUMMER
ILL-48 N=500 D.RATIO 077M SUMMER
ILL-48 N=500 D.RATIO 099T SUMMER
ILL-48 N=500 D.RATIO 099M SUMMER
ILL-48 N=500 D.RATIO 099A SUMMER
ILL-48 N=500 D.RATIO 001A SUMMER
ILL-48 N=500 D.RATIO 002A SUMMER
ILL-48 N=500 D.RATIO 003A SUMMER
ILL-48 N=500 D.RATIO 004A SUMMER
ILL-48 N=500 D.RATIO 005A SUMMER
ILL-48 N=500 D.RATIO 077A SUMMER


ILL-ST N=500
V+(MR) 500T SUMMER
Upwind Controls Only
ILL-ST N=500
D (MR) 500T SUMMER
Upwind Controls Only
ILL-ST N=500
T (MR) 500T SUMMER
Upwind Controls Only
ILL-ST,V N=500
V+(MR) 500T SUMMER
Upwind Controls Only
ILL-ST,V N=500
D (MR) 500T SUMMER
Upwind Controls Only
ILL-ST,V N=500
T (MR) 500T SUMMER
Upwind Controls Only
ILL-ST N=500
V+(MR) 500M SUMMER
Upwind Controls Only
ILL-ST N=500
D (MR) 500M SUMMER
Upwind Controls Only
ILL-ST N=500
T (MR) 500M SUMMER
Upwind Controls Only
ILL-ST,V N=500
V+(MR) 500M SUMMER
Upwind Controls Only
ILL-ST,V N=500
D (MR) 500M SUMMER
Upwind Controls Only
ILL-ST,V N=500
T (MR) 500M SUMMER
Upwind Controls Only
ILL-ST N=500
V+(MR) 500A SUMMER
Upwind Controls Only
ILL-ST N=500
D (MR) 500A SUMMER
Upwind Controls Only
ILL-ST N=500
T (MR) 500A SUMMER
Upwind Controls Only
ILL-ST,V N=500
V+(MR) 500A SUMMER
Upwind Controls Only
ILL-ST,V N=500
D (MR) 500A SUMMER
Upwind Controls Only
ILL-ST,V N=500
T (MR) 500A SUMMER
Upwind Controls Only
0. .25 .5 .75 1.


ILL-ST N=500
V(PC,PV) 500T SUMMER
1st-Stage, Upwind
ILL-ST N=500
D(PC,PV) 500T SUMMER
1st-Stage, Upwind
ILL-ST N=500
T(PC,PV) 500T SUMMER
1st-Stage, Upwind
ILL-ST,V N=500
V(PC,PV) 500T SUMMER
1st-Stage, Upwind
ILL-ST,V N=500
D(PC,PV) 500T SUMMER
1st-Stage, Upwind
ILL-ST,V N=500
T(PC,PV) 500T SUMMER
1st-Stage, Upwind
ILL-ST N=500
V(PC,PV) 500T SUMMER
2nd-Stage, Upwind
ILL-ST N=500
D(PC,PV) 500T SUMMER
2nd-Stage, Upwind
ILL-ST N=500
T(PC,PV) 500T SUMMER
2nd-Stage, Upwind
ILL-ST,V N=500
V(PC,PV) 500T SUMMER
2nd-Stage, Upwind
ILL-ST,V N=500
D(PC,PV) 500T SUMMER
2nd-Stage, Upwind
ILL-ST,V N=500
T(PC,PV) 500T SUMMER
2nd-Stage, Upwind
ILL-ST N=500
V(PC,PV) 500T SUMMER
2nd-Stage, No Upwind
ILL-ST N=500
D(PC,PV) 500T SUMMER
2nd-Stage, No Upwind
ILL-ST N=500
T(PC,PV) 500T SUMMER
2nd-Stage, No Upwind
ILL-ST,V N=500
V(PC,PV) 500T SUMMER
2nd-Stage, No Upwind
ILL-ST,V N=500
D(PC,PV) 500T SUMMER
2nd-Stage, No Upwind
ILL-ST,V N=500
T(PC,PV) 500T SUMMER
2nd-Stage, No Upwind
0.
.25
.5
.75
1.


ILL-ST N=500
V(SR,PV) 588T SUMMER
1st-Stage, Upwind
ILL-ST N=500
D(SR,PV) 588T SUMMER
1st-Stage, Upwind
ILL-ST N=500
T(SR,PV) 588T SUMMER
1st-Stage, Upwind
ILL-ST,V N=500
V(SR,PV) 588T SUMMER
1st-Stage, Upwind
ILL-ST,V N=500
D(SR,PV) 588T SUMMER
1st-Stage, Upwind
ILL-ST,V N=500
T(SR,PV) 588T SUMMER
1st-Stage, Upwind
ILL-ST N=500
V(SR,PV) 588T SUMMER
2nd-Stage, Upwind
ILL-ST N=500
D(SR,PV) 588T SUMMER
2nd-Stage, Upwind
ILL-ST N=500
T(SR,PV) 588T SUMMER
2nd-Stage, Upwind
ILL-ST,V N=500
V(SR,PV) 588T SUMMER
2nd-Stage, Upwind
ILL-ST,V N=500
D(SR,PV) 588T SUMMER
2nd-Stage, Upwind
ILL-ST,V N=500
T(SR,PV) 588T SUMMER
2nd-Stage, Upwind
ILL-ST N=500
V(SR,PV) 588T SUMMER
2nd-Stage, No Upwind
ILL-ST N=500
D(SR,PV) 588T SUMMER
2nd-Stage, No Upwind
ILL-ST N=500
T(SR,PV) 588T SUMMER
2nd-Stage, No Upwind
ILL-ST,V N=500
V(SR,PV) 588T SUMMER
2nd-Stage, No Upwind
ILL-ST,V N=500
D(SR,PV) 588T SUMMER
2nd-Stage, No Upwind
ILL-ST,V N=500
T(SR,PV) 588T SUMMER
2nd-Stage, No Upwind