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Methods for the Evaluation of Real-Time Weather Data for use in Crop Yield Models: An Application to North Dakota

IN COOPERATION WITH THE STATISTICS DEPARTMENT OF THE UNIVERSITY OF MISSOURI

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METHODS FOR THE EVALUATION OF REAL-TIME WEATHER DATA FOR USE IN CROP YIELD MODELS: AN APPLICATION TO NORTH DAKOTA. By Mark Kaiser and Jeanne L. Sebaugh, Ph.D., Statistical Research Division, Statistical Reporting Service, U. S. Department of Agriculture, Columbia, Missouri 65201; April 1984

ABSTRACT

A problem with the operational use of many crop yield models is a time delay in obtaining current values for the required weather data. Real-time estimates of subsequently published weather values (considered the standard) are often used. A procedure for evaluating these real-time estimates is developed through two approaches. One approach directly compares real-time data with the standard set using statistical analysis. The other approach uses each set of data in a crop yield model and compares the results. Strengths and weaknesses of these approaches are illustrated using weather data and barley yield models for North Dakota.

Key Words: Weather data, real-time data, data evaluation, crop yield models.

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*AgRISTARS is an acronym for Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing. It is a multi-agency research program to meet some current and new information needs of the U. S. Department of Agriculture.

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INTRODUCTION

A major objective of the AgRISTARS Program has been to develop and evaluate models which predict seasonal yields for a variety of crops and geographical areas. These are often regression models which consist of one or more linear trend terms (used as surrogate variables for technological advances), and a number of weather related variables. For simple models the weather variables are typically derived from monthly average temperature and total precipitation values. As many as twenty-five years of historical values may be required to develop models and estimate regression coefficients for use in the current year. Often these historical weather data have been climate division (CD) monthly values available from the National Climatic Data Center (NCDC) in Asheville, North Carolina. NCDC values are averages over many reporting weather stations within each CD. A problem with real-time use of these CD values has been a delay in obtaining published data from NCDC. However, there are sources of real-time weather data for some individual stations, and a number of procedures for converting these station data to climatic division values could potentially be used to provide input variables for operational crop-yield models. Given a source of real-time station data and a process by which those data are converted to CD level values, a fundamental concern is the compatibility of weather values produced by that process with the historical data base used to develop the model. More specifically, the question becomes "will the use of a real-time process to estimate weather values in the current year affect the performance of a crop-yield prediction model?" Several approaches to addressing this question have been taken by different authors. Sakamoto et al. (1977) used plots and histograms to compare monthly temperature and precipitation data from two sources, and computed correlations between crop-yield predictions produced by using those data sources. Perry, Rogers and Ritchie (1982) used components of variance and other techniques to compare satellite-derived estimates of daily minimum and maximum temperatures, precipitation, and solar radiation values to ground measured values. Willmott and Wicks (1980) partitioned the root mean square error obtained from regressing estimated monthly precipitation values on observed values for a set of weather stations in California.

The objective of this study was to develop methods and a generalized procedure for evaluating real-time weather data. Two approaches were used. One approach involved the direct comparison of real-time data with a standard set of values. The other approach involved an empirical investigation of the effect of estimated weather values on the predictive ability of two crop yield models.

Conducting an analysis of real-time data sources for one state was a convenient way to limit the project to a manageable geographic region. North Dakota was selected because (1) Climatic Division (CD) and Crop Reporting District (CRD) boundaries coincide in North Dakota, (2) barley and spring wheat are major crops in North Dakota, and models for these crops have been developed and evaluated as part of the AgRISTARS Program (Motha, 1980; Barnett, 1981; LeDuc, 1981; Sebaugh, 1981), and (3) data from both a real-time source and the historical data base used to develop models are readily available for North Dakota. A description of real-time point-source data available in North Dakota and methods of converting those data to CD level values may be found in Appendix A. The criteria used to evaluate real-time data were:

1. Timeliness. Are the data available on a time scale that permits weekly or monthly use of prediction models?

2. Availability and cost. Are data available in a usable form that permits economic derivation of model weather variables?

3. Accuracy and precision. How well do data estimate historical values used in model development?

The first two criteria are discussed in Appendix A. The remainder of this report focuses on criterion 3.

Historical weather values calculated by NCDC and used to develop crop yield models are considered to be "true" values in this report. The use of estimates in the current year which may deviate from these true values has a potentially great, but unknown, impact on the crop yield forecast of a model. In the first portion of this report we adopt the approach that any deviation of an estimated weather value from the "true" values subsequently reported by NCDC is undesirable. In the second portion of the report, we address the question of how deviations from NCDC values affect the predictive quality of barley models for North Dakota.

EVALUATION OF A REAL-TIME DATA SOURCE

A detailed evaluation was conducted on North Dakota temperature and precipitation values derived by NOAA, Climatic Impact Assessment Division, Climate Assessment Division, Climate Assessment Branch (CAB) in Washington, D.C. Values derived by CAB are subjective estimates based on weather maps containing isolines (see Appendix A). This particular data source was selected for further study because the subjective estimates were similar to NCDC values in form (i.e., one average temperature and total precipitation value per month per CRD). Thus CAB values could be used directly in crop yield models if they proved sufficiently accurate and precise. CAB estimates were available for the period February 1979 to December 1982. Differences between CRDs in the number of values reported in subsequent tables are due to missing values. To facilitate presentation of charts and figures, only CRDs 30 and 70 are included in the body of this report. Charts and figures for the other CRDs are included in Appendix B. In recent years CRD 30 reported the highest average area harvested for both barley and spring wheat, while CRD 70 provided a geographic and climatic contrast to CRD 30 (Table 1).

Tests of Central Tendency

Temperature values followed a well defined annual cycle in all North Dakota CRDs, but precipitation values did not appear to follow a consistent pattern (Fig. 1). Also, the range in temperature values reported since 1979 by both CAB and NCDC was consistent across CRDs, while the range in precipitation values changed between CRDs. Because CAB and NCDC values are reported for the same time periods, they are correlated and should be compared in a pairwise manner. For this purpose a variable called YR_MONTH was constructed by juxtaposing year numerals with numeric month values. Thus 7901 was the value assigned to January, 1979, 7902 was assigned to February, 1979, etc. This variable matches the CAB and NCDC values according to time of observation and was used to account for differences between years as well as differences between the months within a year. If only the month were taken into consideration, values for the different years would be averaged for each month and these averages compared instead of the individual monthly observations. Because of the unstable annual cycle of precipitation, the use of the variable YR_MONTH as a blocking factor was probably more important for precipitation values than for temperature values.

Because it was desired to compare NCDC and CAB values in a pairwise fashion, the distribution of difference values (CAB-NCDC) was important. Assumptions of normality necessary for most parametric tests of location with pairwise data could be met in only 2 of 9 CRDs, CRD 10 and CRD 40, for temperature and none for precipitation differences when tested with a Shapiro-Wilk statistic (Appendix C). Although the parametric procedure used is sometimes considered robust enough to ignore such conditions (Box 1953), both parametric and nonparametric analysis of variance (ANOVA) procedures were used to test for differences between data sources to protect against possible errors in the resulting inference (Geary 1947; Tukey 1948). The variable YR_MONTH was used as a blocking factor, resulting in a randomized complete block design with two treatments per block. The model tested for each CRD was:

$$Y_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij}$$

where μ = grand mean over both data sources

α_i = main fixed effects for data source

β_j = main effects for year and month (YR_MONTH), and

ε_{ij} = independent error effects $(N(0,\sigma^2))$.

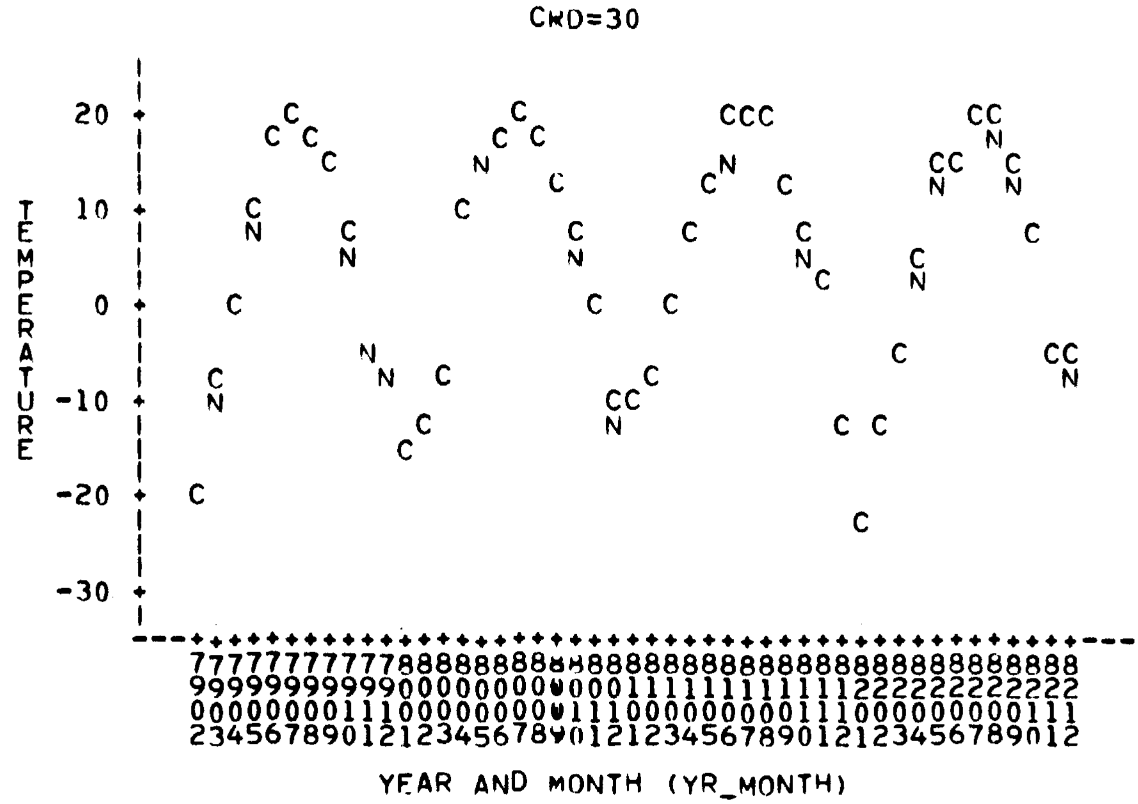
The two-way ANOVA by ranks, or Friedman Ranks test, is the direct nonparametric analog of the parametric randomized complete block design and was used to test the null hypothesis that the data source effects are identical.

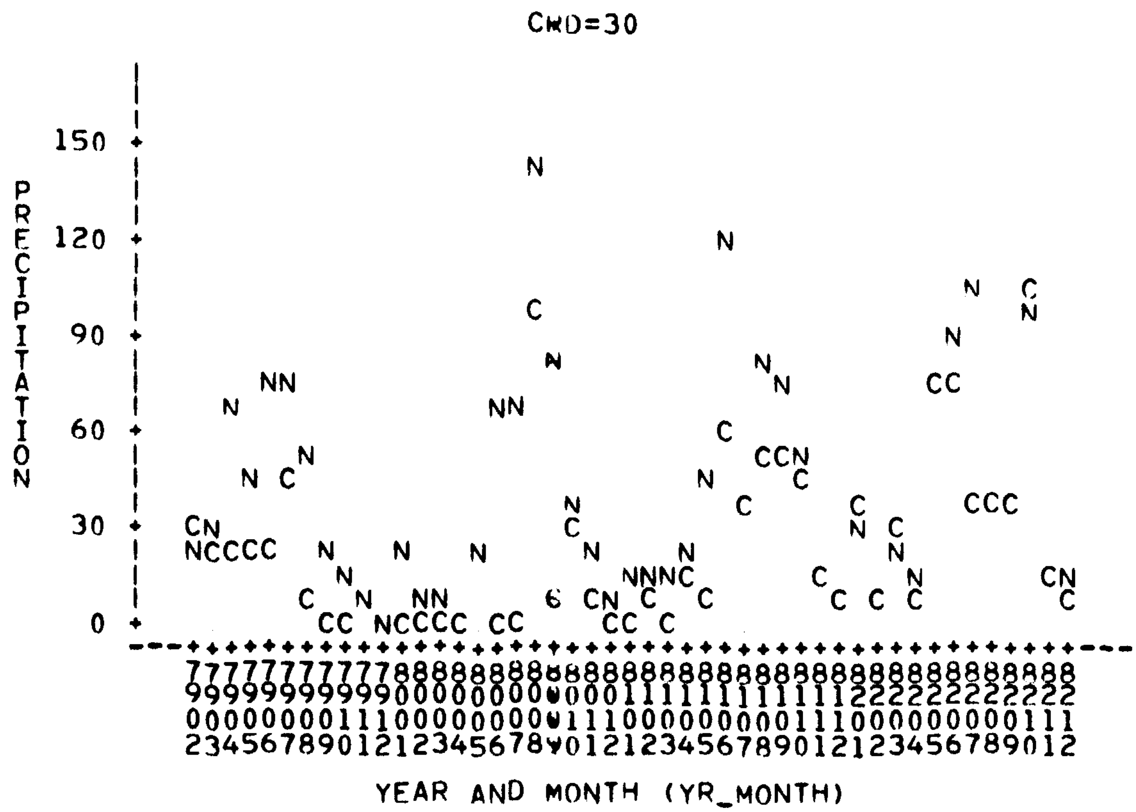
For only two data sources, these parametric and nonparametric procedures are equivalent to paired "t" and Wilcoxon matched-pairs signed-rank tests, respectively. However, they were employed because of their applicability when more than two data sources are to be compared.

Table 1. North Dakota CRD values for average percent of statewide production (barley and spring wheat), 1970-1979, and average January temperature and annual precipitation, 1951-1980

CRD	Average Percent of N.D. Production		Average January Temp. (C)	Average Annual Precipitation (mm)
	Barley	Spring Wheat		
10: Northwest	5.7	16.5	-14.9	400
20: North central	10.3	10.6	-16.3	427
30: Northeast	34.3	21.7	-16.4	458
40: West central	2.5	7.6	-10.9	418
50: Central	7.2	10.3	-14.8	444
60: East central	24.6	12.6	-15.2	490
70: Southwest	3.4	7.2	-11.6	406
80: South central	2.2	4.8	-13.0	412
90: Southeast	9.9	8.7	-11.2	494

Figure 1. Plots of reported temperature and precipitation values over time by CRD. Values from NCDC (Asheville) are represented by N; values from CAB by C.





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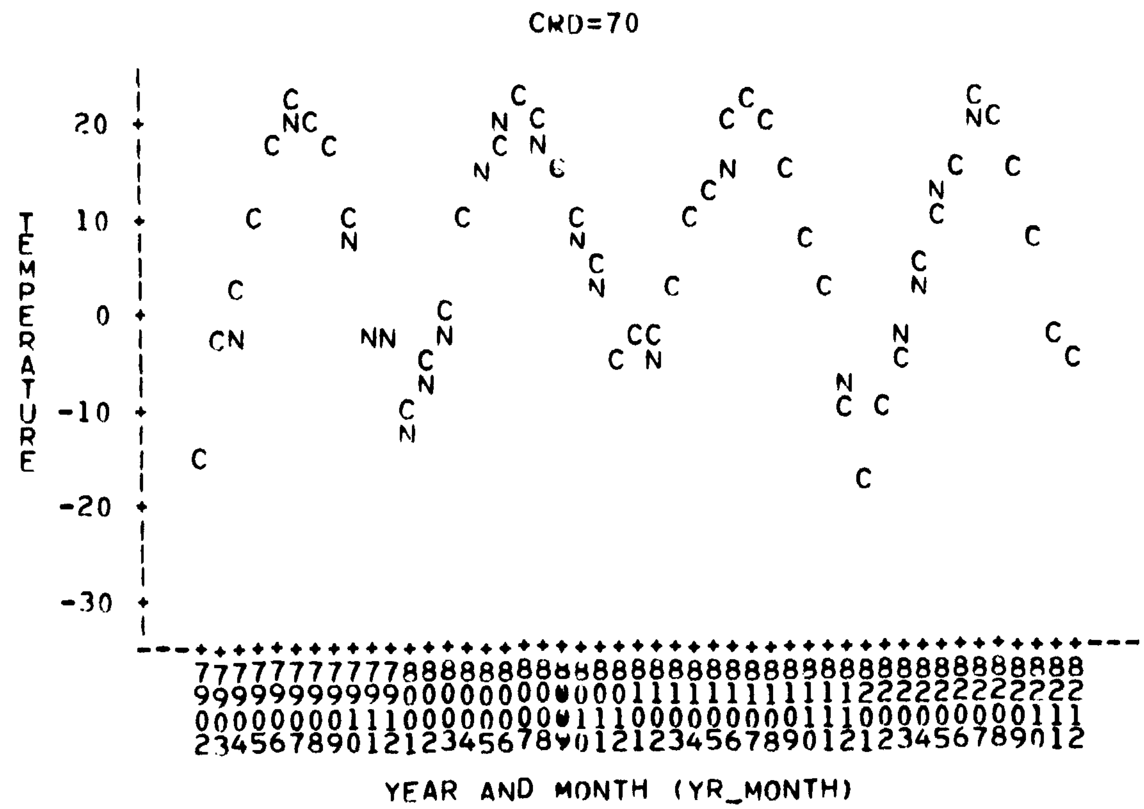
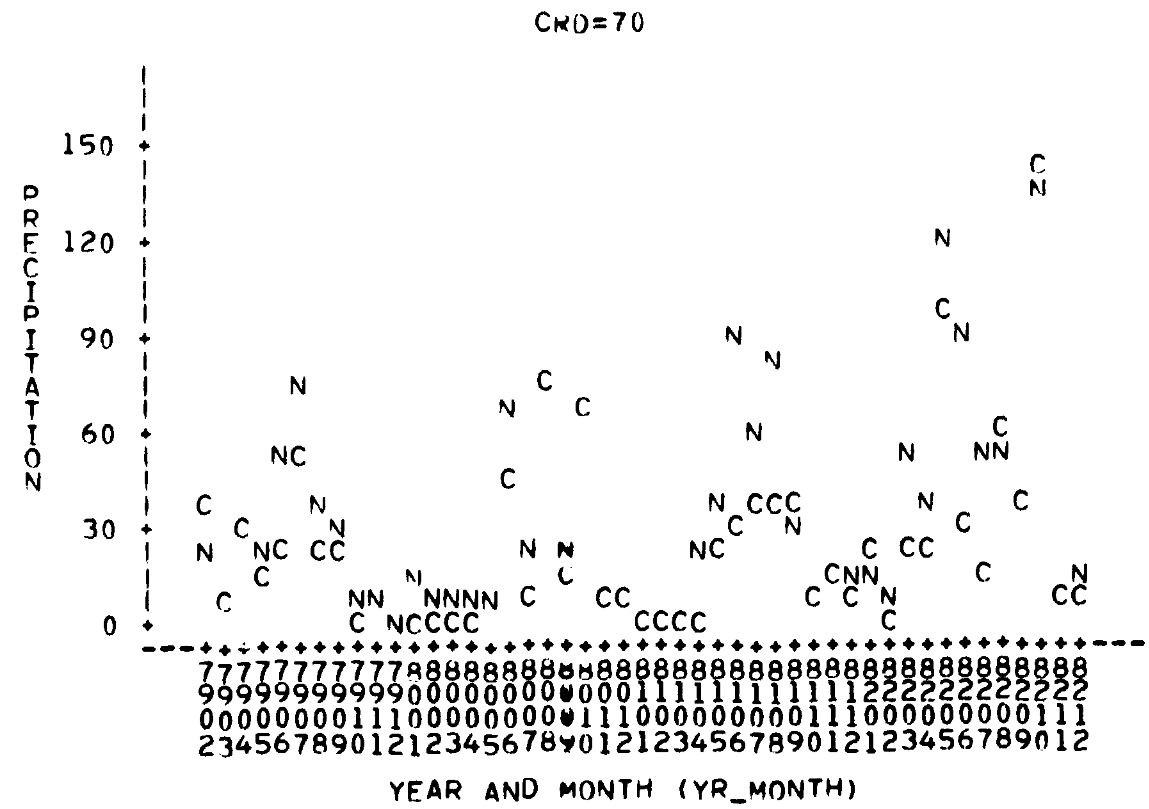




Both the parametric and nonparametric procedures were run for each CRD, and differences between data sources were tested at the 0.05 and 0.10 significance levels, respectively. Significant data source effects were found in 8 out of 9 CRDs for temperature and in all CRDs for precipitation with both the parametric and nonparametric procedures (Table 2).

Difference values were calculated for each month (by CRD) by subtracting the NCDC value from the CAB value. The mean difference in temperature values ranged over CRDs from 0.12 C° to 0.98 C°, while mean precipitation differences ranged from -19.9 mm to -5.3 mm (Table 3). Values reported by CAB appeared to overestimate true temperature values (mean differences positive for all CRDs), and underestimate true precipitation values (all mean differences negative). Plots of temperature and precipitation differences (Figure 2) also showed a fairly consistent overestimation of temperature values by CAB. Precipitation values generally were slightly underestimated by CAB early and late in the year and grossly underestimated during the summer months. In addition, difference values farthest from 0 (thus representing the worst predictions by CAB) were consistently the same year and month across CRDs for temperature but varied for precipitation; the least accurate CAB temperature estimate in the 47 months of data was the June 1981 value, and this was true for all CRDs (see Figure 2 and Appendix B). The least accurate CAB precipitation estimates varied from CRD to CRD but generally occurred between May and August.

Measures of Reliability

The two ANOVA procedures (parametric and nonparametric) used to test for differences between CAB and NCDC values were both tests of central tendency, that is, they determined if the CAB and NCDC values were centered around the same point after taking into account differences between years and month[illegible] problem with these procedures is that overestimates and underestimates may counteract each other such that the mean difference between CAB and NCDC values is close to zero but the CAB value is not a good estimate of the NCDC value in any given year and month. Thus, a number of poor estimates may "cancel" each other's effect on the outcome of tests of location, yet alter the performance of a crop-yield model if they are used as real-time weather values. It is desirable that CAB weather values be good estimates of the true value not only on the average but also in any given year and month. The closer a set of real-time weather values is to the set of true values when compared retrospectively in a pairwise fashion, the more reliable that real-time data source is considered to be. A set of descriptive statistics, originally developed for the evaluation of crop yield models, is also appropriate for the comparison of a real-time data source to a standard. These statistics are called indicators of reliability, are described in Wilson and Sebaugh (1981), and formulas are given in Appendix D. In this report, the following indicators of reliability are used:

Bias
Relative Bias
Root Mean Square Error
Relative Root Mean Square Error
Standard Deviation
Relative Standard Deviation
Percent of Absolute Difference Values Greater than 1°C or 10 mm
Largest Positive Difference

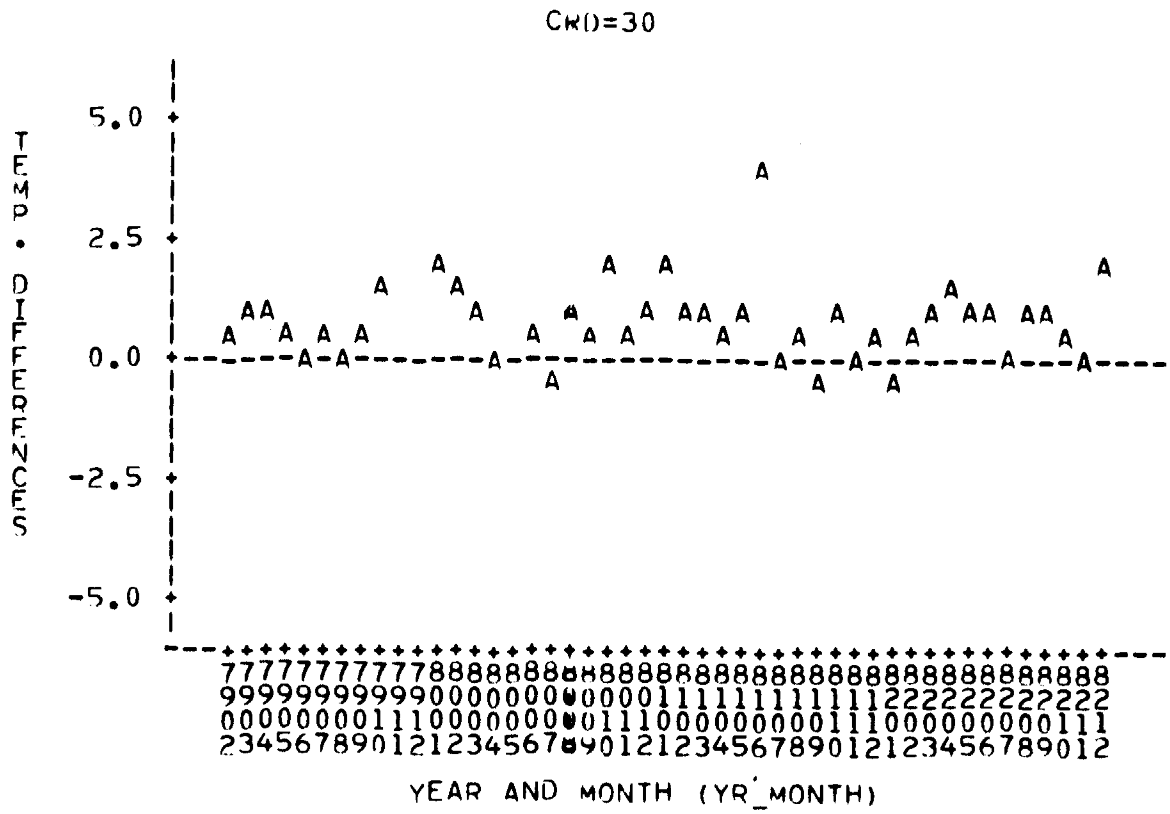
Table 2. Observed significance levels for parametric and non-parametric tests of data source effects on weather values

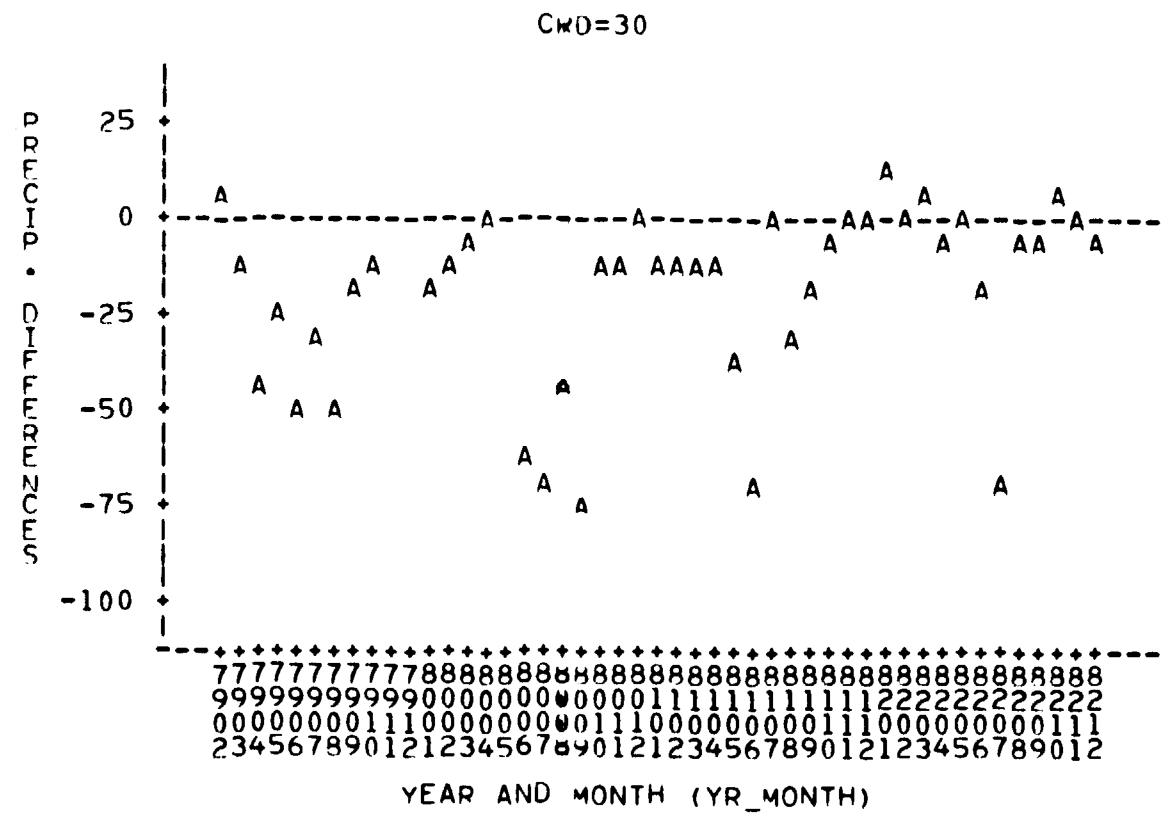
CRD	Temperature		Precipitation	
	Parametric	Non-parametric	Parametric	Non-parametric
10	.0001	.0001	.0407	.0065
20	.0001	.0001	.0001	.0001
30	.0001	.0001	.0001	.0001
40	.0001	.0023	.0001	.0001
50	.0008	.0007	.0001	.0001
60	.0172	.0007	.0001	.0001
70	.0001	.0001	.0001	.0001
80	.5445	.5430	.0001	.0002
90	.0001	.0001	.0011	.0166

Table 3. Mean differences in temperature and precipitation data between CAB and NCDC sources, 1979-1982

CRD	Mean Difference (CAB-NCDC)				Standard Deviation	
	n	Temperature (C^{o})	n	Precipitation (mm)	Temperature (C^{o})	Precipitation (mm)
10	47	0.98	47	-5.3	.787	17.07
20	45	0.93	45	-19.9	.688	25.11
30	46	0.82	47	-18.7	.803	22.56
40	46	0.56	47	-10.9	1.114	18.71
50	47	0.43	47	-17.3	.791	22.07
60	47	0.36	47	-10.4	.968	17.08
70	47	0.70	47	-10.4	1.091	15.44
80	47	0.12	47	-6.9	1.15	10.37
90	44	0.67	45	-8.2	1.125	16.93

Figure 2. Plots of differences between CAB and NCDC temperature and precipitation values (CAB-NCDC) over time by CRD.





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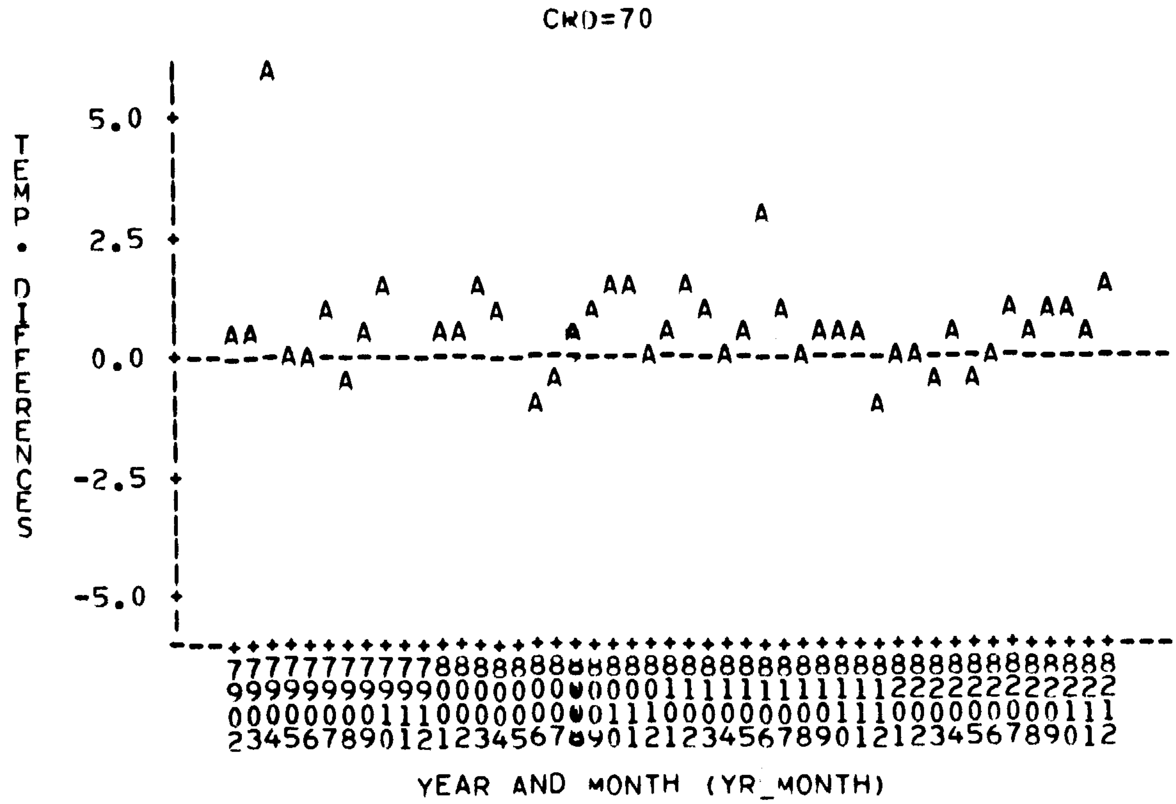
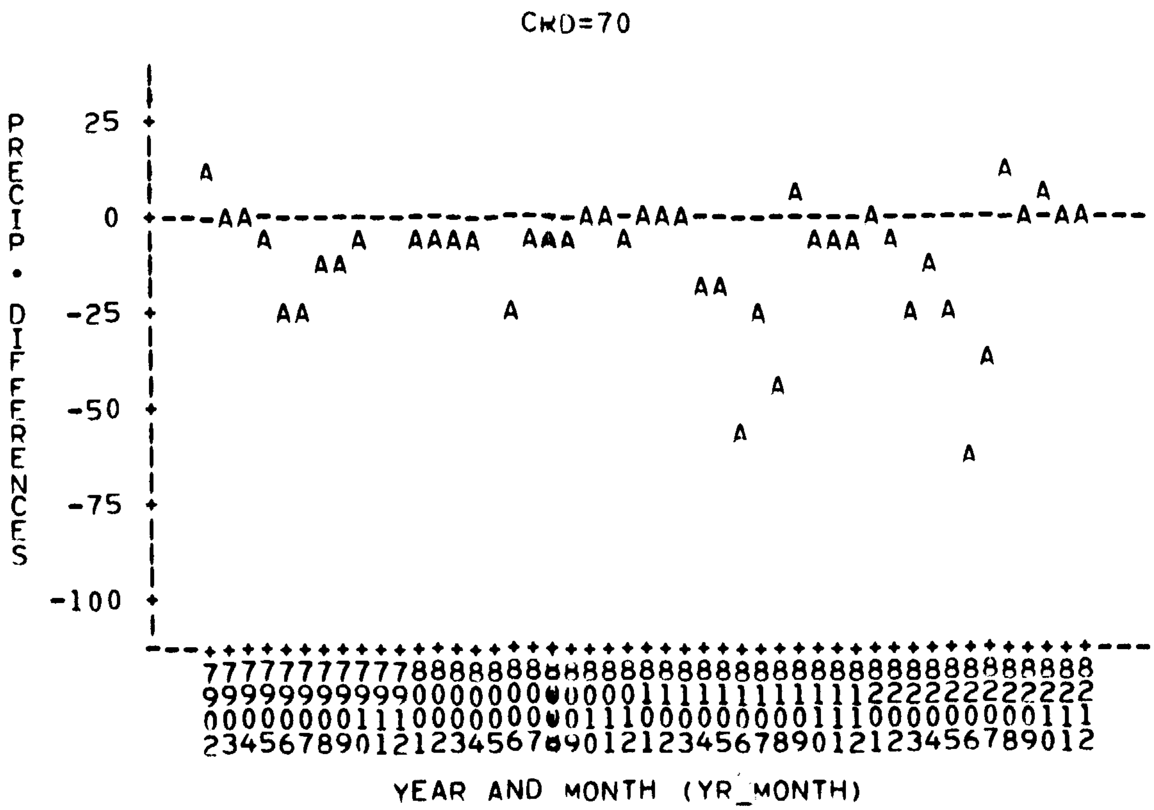




Largest Negative Difference
Direction of Change from Previous Value
Pearson Correlation Coefficient

Measures of reliability are presented in Table 4. Overestimation of temperature values and underestimation of precipitation values by CAB are again seen in the consistently positive and negative bias terms, respectively. It should be noted that many of the quantities presented in Table 4 were calculated on the difference values (CAB-NCDC), not the original CAB estimates. Thus while the variance of CAB precipitation estimates should be large to reflect the true variance in precipitation, the variance of the set of precipitation differences should be small for a high level of reliability. The calculated measures indicate that CAB temperature estimates were more reliable predictors of the true values than were CAB precipitation estimates. This difference in reliability is seen in the lower relative bias, relative RMSE, and relative standard deviation of temperature differences, as well as the percent of YR_MONTHS for which the direction of change was correct (Table 4). The percent of YR_MONTHS for which absolute difference values were greater than the specified limits of 1° C or 10 mm averaged 43.4% and 35.4% across the 9 CRDs respectively. Although the Pearson correlation coefficients between CAB and NCDC values also indicated that CAB temperature estimates were better predictors of NCDC values than were CAB precipitation estimates, the correlation coefficient is not a sensitive measure of reliability; the correlation coefficient measures the tendency of two sets of values to vary in the same fashion, but not necessarily on the same scale. Thus the correlation coefficient for CAB pr cipitation estimates is fairly high even though these estimates have extremely large relative standard deviations and are off by more than 10 mm in about 45% of the observations (Table 4, Appendix B).

Investigation of Differences

An important aspect of studying temperature and precipitation difference values (CAB value-NCDC value) was to determine if the observed statistical difference between CAB and NCDC estimates could be explained. If so, these explanations might indicate consistent flaws in the CAB process. Consistent flaws may, of course, be more easily corrected than inconsistent flaws. The search, then, was for systematic patterns in the deviation of CAB values from the "true" NCDC values.

In order to investigate whether the degree of difference in the weather values was related to geographic location, a randomized complete block ANOVA was used to test for significant CRD effects. The model tested was:

$$Y_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij} ,$$

where μ = grand mean difference over all CRDs,

α_i = main fixed effects for CRD,

β_j = main effects for year and month (YR_MONTH), and

ε_{ij} = the independent error effects $N(0,\sigma^2)$.

Table 4. Measures of reliability for CAB weather values estimates

Measure	CRD 30 Temperature	CRD 30 Precipitation	CRD 70 Temperature	CRD 70 Precipitation
Bias = B (C^{o}) or (mm)	0.82	-18.69	0.70	-10.36
Relative Bias = RB (%)	19.2	-44.8	11.2	-30.5
Root Mean Square Error = RMSE (C^{o}) or (mm)	1.14	29.12	1.29	18.46
Relative RMSE = RRMSE (%)	26.8	69.8	20.6	54.3
Standard Deviation = SD (C^{o}) or (mm)*	0.79	22.33	1.08	15.28
Relative Standard Deviation = RSD (%)	15.7	96.9	15.6	64.6
Percent of YR_MONTHS Absolute Difference > (1^{o}C or 10 mm)	36.9	63.0	29.8	36.2
Largest Negative Difference (C^{o} or mm)	-0.7	-73.3	-1.1	-59.4
Largest Positive Difference (C^{o} or mm)	3.9	12.3	6.1	11.1
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB value agrees with the actual (NCDC) values (%)	98	63	96	80
Pearson correlation coefficient between CAB and NCDC values	1.00	0.76	1.00	0.88

*Differences in standard deviation between Tables 3 and 4 are due to the use of an unbiased estimator of sample variance in Table 3 and the Maximum Likelihood estimator of sample variance in Table 4.

There was a significant difference among CRDs ($P < 0.0001$) for both temperature and precipitation values in the amount of difference between CAB and NCDC values. Table 5 shows the average differences for the forty-four year/months with complete data for all CRDs. The values are presented in descending order and one can see that the ordering of CRDs was not similar for temperature and precipitation differences nor were consistent patterns of N-S, E-W gradients seen, nor was there division by biotic region (Stewart 1975).

Next, an investigation was made of whether the differences might be related to a consistent bias. Plots of temperature differences indicated that the technique employed by CAB generally overestimated the NCDC value, and that this overestimation was fairly consistent throughout the year (Fig. 2). A simple transformation was made to remove the bias in CAB estimates by subtracting the mean difference (from Table 3) from each CAB temperature value for a particular CRD. This transformed data set was then tested against the NCDC values with the nonparametric ANOVA described above. Significant differences between CAB and NCDC values were found in only 2 CRDs (CRD 20 and CRD 90, see Appendix C). The nonparametric ANOVA alone was run because the transformation (subtraction of mean differences) rendered any parametric test for differences in means useless. Thus, it seems that the CAB process for estimating temperature values is biased in a consistent and simple manner, varying primarily with geographic location (CRD).

Plots of precipitation differences indicated that the CAB process generally underestimated the NCDC values, but that this underestimation was not of a consistent magnitude throughout the year (Fig. 2). The magnitude with which CAB precipitation values underestimated the true value appears to be the greatest during the warm season months, May through September. The influence of these months on CAB estimate bias may be due to greater spatial variability and amounts of rainfall during the summer. Plots of raw precipitation values (Fig. 1) show that high amounts of precipitation occurred during the summer months. Precipitation patterns during this period tend to be discontinuous and patchy (Huff and Shipp 1969). Since the average distance between stations used by CAB is much greater than the average distance between stations in the denser network used by NCDC, the probability of recording patchy precipitation may be lower with the stations used by CAB. It is also possible that the particular (non-randomly chosen) stations used by CAB generally have less rainfall than the surrounding areas. However, since storm system patterns tend to vary from year to year, it is doubtful whether this underrepresentation by itself could explain the underestimation of rainfall over the four summers. The bias in CAB precipitation estimates appears to vary not only geographically, but temporally and in proportion to the true amount of precipitation also. This conclusion is supported by the effect of different data transformations on the testing procedure outlined earlier. A simple additive adjustment to remove the bias was made to CAB precipitation estimates by subtracting the mean differences by CRD from Table 3) from each value, just as was done for temperature estimates. The transformed CAB data were then tested against the NCDC data using the nonparametric statistic. The simple, additive, transformation produced precipitation values significantly different than the NCDC values in all but two CRDs (Appendix C).

Table 5. Average monthly value differences (CAB values-NCDC values) for each CRD, in descending order (n=44)

A. Temperature differences (MSE for 344 d.f. = 0.5779)

CRD	Mean
10	1.025
20	0.941
30	0.796
70	0.673
90	0.671
40	0.586
50	0.434
60	0.402
80	0.121

B. Precipitation differences (MSE for 344 d.f. = 232.6970)

CRD	Mean
10	-5.445
80	-7.198
90	-8.318
60	-10.320
70	-10.843
40	-11.368
50	-17.414
30	-19.177
20	-20.120

A second transformation of CAB precipitation estimates was then made as follows:

(i) A simple linear regression of CAB values on NCDC values was conducted for each CRD. The NCDC values were used as the independent variable in this regression because they were assumed to be the "true" precipitation values. Regression coefficients are given in Appendix E.

(ii) The equations obtained in (i) were then solved to give prediction equations for NCDC values of the form

$$NCDC = \frac{CAB - b_0}{b_1},$$

where b_0 and b_1 are the estimated regression coefficients of intercept and slope, respectively, from the regressions conducted in (i).

(iii) CAB precipitation estimates were then plugged into these prediction equations and a set of transformed precipitation values obtained. Negative estimates were set equal to zero. This process is commonly referred to as calibration or inverse regression (Krutchhoff 1967, Halperin 1970, Martinelle 1970). The transformation made in this manner was basically a proportional transformation, having a greater effect on CAB values when actual precipitation was high. This second set of precipitation estimates was also tested against NCDC values with the nonparametric ANOVA. The proportional transformation produced precipitation values that were not significantly different from NCDC values in any CRD (Appendix C).

The preceding analysis of differences in CAB and NCDC weather values is subject to the same criticism as the original testing procedure; that is, it gives information about the central tendency of the distribution of differences but provides little insight to the reliability of CAB in producing values that are close to NCDC values. For example, it seems that the error in CAB temperature estimates does not depend on the magnitude of the temperature value. As a result, the average deviation of CAB from NCDC values in any given CRD may be explained by a simple additive effect, as shown by testing the transformed CAB data against the NCDC values. To determine if the bias of CAB temperature estimates was consistent across all years and months, reliability measures were calculated from the set of differences between transformed CAB and NCDC data (Table 6). Because the transformation removed the bias in CAB estimates, the root mean square error and standard deviation for these difference values are equal. Comparing the reliability measures in Table 6 to those calculated for untransformed CAB temperature data (Table 4), it can be seen that the reliability of transformed CAB temperature estimates was somewhat better than untransformed CAB estimates. The RMSE was smaller for transformed values, and the percent of observations which were greater than 1° C decreased by about 15% when averaged over CRDs.

Measures of reliability for proportionally transformed CAB precipitation estimates are presented in Table 7. The bias of these transformed values was shifted from large negative values (see Table 4) to small positive values or zero. The bias associated with transformed values was not taken to zero in all

Table 6. Measures of reliability for transformed CAB temperature estimates

Reliability Measure	CRD								
	10	20	30	40	50	60	70	80	90
Bias (C°)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Root MSE (C°)	0.78	0.68	0.79	1.10	0.78	0.96	1.08	1.14	1.11
Relative RMSE (%)	17.2	15.6	18.7	19.7	16.1	20.0	17.3	19.3	19.2
Percent of YR_MONTHS Absolute Difference > 1°C	19.1	15.6	15.2	34.8	19.1	17.0	17.0	25.5	22.7
Largest Positive Difference (C°)	1.6	1.5	3.1	3.0	3.3	4.2	5.4	4.3	4.1
Largest Negative Difference (C°)	-2.2	-1.3	-1.5	-2.8	-1.2	-2.0	-1.8	-1.6	-1.8
Pearson correlation coefficient between transformed CAB and NCDC values	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 7. Measures of reliability for transformed CAB precipitation estimates

Reliability Measure	CRD								
	10	20	30	40	50	60	70	80	90
Bias (mm)	0.45	0.23	0.00	1.40	1.07	0.00	0.00	0.00	0.63
Root MSE (mm)	20.98	35.71	29.24	20.84	26.29	19.21	17.33	9.75	19.02
Relative RMSE (%)	67.0	87.8	70.1	57.2	65.8	47.0	51.0	27.3	48.3
Percent of YR_MONTHS Absolute Difference $\geq$ 10 mm	34.0	64.4	65.2	45.6	46.8	55.3	34.0	21.3	52.3
Largest Positive Difference (mm)	62.0	98.3	84.2	48.8	74.7	56.4	56.5	26.2	44.0
Largest Negative Difference (mm)	-91.7	-82.0	-64.2	-59.0	-74.4	-48.4	-46.3	-23.8	-44.3
Pearson correlation coefficient between transformed CAB and NCDC values	0.75	0.69	0.76	0.83	0.79	0.88	0.88	0.96	0.86

CRDs because when the transformation yielded a negative estimate of precipitation, that estimate was set equal to zero for the sake of logic. Thus, although not strictly equal for CRDs with positive bias, the RMSE and RRMSE were extremely close in value to the standard deviation and relative standard deviation (these later quantities not reported). In contrast to the situation for the additive temperature transformation, the RMSE of differences between NCDC and proportionally transformed CAB precipitation values (Table 7) showed an increase over the RMSE of differences calculated from untransformed CAB values (Table 4). Increases were also seen in relative RMSE, and the percent of observations for which the absolute difference was greater than 10 mm. These increases indicate that although the proportional transformation decreased the average difference between CAB and NCDC precipitation estimates, it provided little information about consistent patterns in the CAB process for estimating precipitation; the transformed CAB values are closer to NCDC values "on the average," but the reliability of such values is <u>even worse</u> than that of untransformed values.

Adjusting CAB Estimates

Although it might be possible to use the transformations made to CAB weather estimates as adjustments to improve the original values, such adjustment is not wholly appropriate. The transformations were made to investigate the way in which CAB values differed from NCDC values and thus utilized the entire data set available. Adjustments made in this manner cannot be independently tested and may not be applicable in the future. Also, the proportional transformation made to CAB precipitation estimates is clearly undesirable as an adjustment, since it failed to improve the reliability as compared to untransformed CAB values; such an adjustment might even yield worse precipitation estimates than the original values. Any adjustments made to improve CAB weather values should be adjustments to the CAB process itself, not to the set of data that results from that process. Finally, it should be noted that the ability to make an appropriate adjustment depends in part on a well-defined and consistent method for converting point source data to CD level values. The process used by CAB to derive CD weather values is largely subjective, thus adjustments made to a set of CAB values may be inappropriate for further use if that subjective process changes in any way.

EFFECT OF ESTIMATED WEATHER VALUES ON CROP YIELD MODEL PREDICTIONS

The focus of this study was the direct comparison of a real-time weather value source to the standard NCDC source commonly used in the development of crop-yield prediction models. In the case investigated, statistically significant differences were found to exist between the real-time and NCDC data. An obvious question is whether differences between data sources have a substantial effect on the performance of predictive models. If not, evaluation of real-time data may become a moot point.

To determine if prediction models are sensitive to statistical differences in weather input data, barley yield prediction models for North Dakota were run with both NCDC and CAB weather values as input data. Two models were run, one developed by NOAA, Center for Environmental Assessment Services (CEAS), now AISC (Motha 1980), which has been slightly revised by USDA, Yield Evaluation Section

(YES) and a different, more recent model developed by YES. The CEAS model contains 2 trend terms and 4 weather-derived variables, while the YES model contains the same two trend terms and four different weather-derived variables (Table 8). The CEAS model has been evaluated by several authors (Barnett 1981, LeDuc 1982) and has been found to perform better in years with high yields than in years with poor yields (LeDuc 1982, p. 42). The YES model has been recently developed and not been fully evaluated. Using a bootstrap procedure, both models were run at the state level for the years 1979-1982, and the predicted yields compared to actual yields for each year (Table 9). Both models proved sensitive to differences in input weather data and performed better when NCDC values were used. In only one instance, the CEAS model in 1980, was a better estimate of actual yield obtained when CAB data were used. This is, perhaps, not surprising when one considers the circumstances. Barley yield in North Dakota was extremely low in 1980, and the CEAS model is insensitive to bad years. Thus, provided accurate weather input, one would expect the CEAS model to overestimate yield in this bad year, and such is the result when NCDC data are used. But CAB values generally are gross underestimates of precipitation for the months included in the CEAS model (Table 8), and this tends to pull yield estimates down; CEAS yield estimates using CAB values were much lower than the actual yield in 1979, 1981 and 1982. Thus, in 1980, the insensitivity of the CEAS model to poor years was countered by the underestimation of precipitation by CAB. Consequently, the two inaccuracies produced a more nearly correct estimate. The YES model appears to be sensitive to poor years as it produced an extremely low estimate of barley yield in 1980 when CAB data were used. In addition, the YES model provided a closer estimate to the observed yield than the CEAS model in all years when NCDC values were used (Table 9). Thus, it is important to consider the characteristics of a model used in a study of real-time data sources. Despite the interesting results for 1980 and the higher accuracy of the YES model, statistical differences between CAB and NCDC weather values were reflected in the yield predictions of both models, and both performed better when given NCDC values as input. This conclusion is further strengthened by measures of yield reliability (Table 10). Bias and Root Mean Square Error were both substantially greater for models using CAB data than for models using NCDC data. Although calculated using only four years of data, these measures indicate that the reliability of yield estimates was greater when NCDC values were used in the models.

CONCLUSIONS OF CAB EVALUATION

The CAB procedure of deriving CD level temperature and precipitation estimates uses point-source data that are available on a real-time basis. The time frame in which the estimates from CAB are sent to AISC is currently poorly defined and erratic but could be improved to provide CAB estimates in a time frame compatible with operational use of crop-yield prediction models. CAB weather estimates are not equivalent to NCDC values. The differences between CAB and NCDC values can be explained, in part, by systematic bias in the CAB procedure, particularly for temperature estimates. Thus modification of the CAB process may be possible for temperature estimation, but it would be more difficult for precipitation estimation. Because CAB weather values, as they are now derived, are not equivalent to NCDC values and because differences between CAB and NCDC

Table 8. Description of variables included in state level CEAS and YES barley models for North Dakota

Model	Variable	Description
CEAS	Trend 1 Trend 2	Trend terms are linear or quadratic functions used as surrogate variables for technological advances.
	Cumulative Precip.	Total precipitation from September through May.
	Precip. SDFN	Departure, squared, of June precipitation from long-term normal.
	Precip./PET	June precipitation divided by potential evapotranspiration for June.
	Temp. DFN	Departure of July temperature from long-term normal.
YES	Trend 1 Trend 2	See above.
	PPSQ_DEV	Preseason precipitation from September to planting, deviation from average, squared.
	AWT_DEV	Average winter temperature over December, January, and February, deviation from average.
	TAHD_DEV	Temperature around heading (1 week before and 2 after), deviation from average
	MSTR_DEV	Moisture stress, deviation from average.

Table 9. Comparison of CEAS and YES estimated barley yields with actual yields, 1979-1982 (bushels/acre)

Year	Actual	CEAS NCDC	CEAS CAB	YES NCDC	YES CAB
1979	46.0	40.0	32.9	45.0	42.3
1980	32.0	39.2	26.2	32.5	9.9
1981	48.0	45.4	35.2	47.2	28.1
1982	53.0	46.9	43.3	51.8	46.4

Table 10. Measures of yield reliability for CEAS and YES barley models using NCDC and CAB weather values over 4 years

Measure of Reliability	CEAS NCDC	CEAS CAB	YES NCDC	YES CAB
Bias (Bu/acre)	-1.88	-10.35	-0.63	-13.08
MSE $(\text{Bu/acre})^2$	32.95	115.78	0.83	235.32
RMSE (Bu/acre)	5.74	10.76	0.91	15.34
Largest $\lvert RD \rvert$ (%)	23	-28	±2	-69
Pearson r	0.82	0.94	1.00	0.90

precipitation values are complex and inconsistent, it would be desirable to find a more objective method to obtain CD level weather values from real-time point-source data.

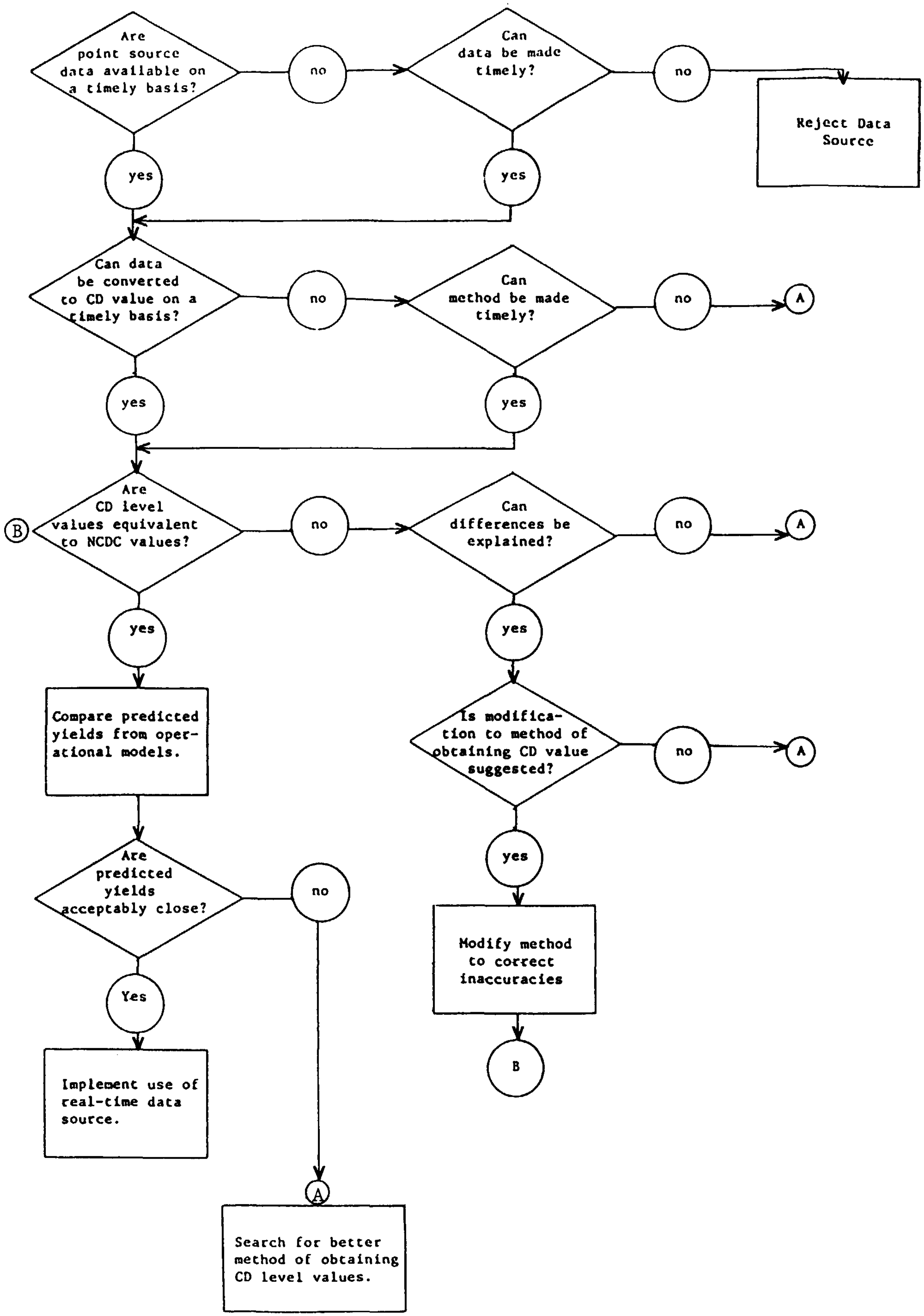
DISCUSSION OF EVALUATION PROCEDURE

A number of complicating factors influence the objective evaluation of real-time weather data. The characteristics of the model or models in which the data will be used may mask effects of different data sources. The spatial scale on which data are evaluated may dictate the types of models for which the evaluation is pertinent (Strand 1981). Because of these factors, it is desirable to evaluate real-time data sources directly against a standard set of values before an attempt is made to use them in crop-yield models. An evaluation of predicted yields obtained from using real-time data as input variables is primarily an evaluation of the prediction model, not the data source. More work is needed on the effects of errors in input weather variables on the reliability and accuracy of yield predictions. Understanding the way in which different sources of error influence the final product of a prediction equation would help eliminate the need for re-evaluation of data sources as new models are developed and brought into operational use.

Direct comparison of real-time data with standard values has been incorporated into a generalized procedure for evaluation of real-time data sources (Fig. 3). This procedure considers the three evaluation criteria listed in this document and is designed to provide a concrete conclusion without unnecessarily constraining statistical methodology. The authors hope it will prove useful to other investigators evaluating real-time weather data for use in crop-yield prediction models.

In the direct comparison of real-time data to a set of standard values, statistical procedures which test for differences in average values or central tendency are not sufficient to infer equivalence. Real-time weather values should be good estimates of true values on the average and distributed in the same way as true values, but they must also be consistent estimates at all points in time. Indicators of reliability can be used to measure this consistency. A set of measures of reliability is necessary because no one measure alone adequately describes the behavior of real-time estimates. The correlation coefficient, in particular, is not a sensitive indicator of reliability. A set of real-time data may show a strong linear relationship with true values, yet have a high percentage of values for which the relative difference is greater than a critical limit (see Table 7) or have a high bias (see Table 4). These types of differences can affect the prediction of crop yield models, particularly models which are sensitive to changes in weather values.

Figure 3. Flow chart for suggested paradigm in evaluation of real-time data sources.



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APPENDIX A. REAL-TIME WEATHER DATA SOURCES IN NORTH DAKOTA

Potential sources of weather values for North Dakota were identified through contact with personnel from the U. S. Department of Agriculture (USDA) Yield Evaluation Section (YES), the U. S. National Oceanic and Atmospheric Administration (NOAA) Assessment and Information Services Center (AISC) and National Weather Service (NWS), and the North Dakota Crop and Livestock Reporting Service.

Daily weather data for the U. S. (which may be processed to provide monthly values) are available from several types of systems, including (1) cooperative surface networks, (2) synoptic surface networks, and (3) satellite observations. The distinction between cooperative and synoptic networks may appear vague because some weather stations provide information to both systems. However, the division indicates different approaches to the collection and compilation of weather station data. Cooperative networks are characterized by the collection of basic weather data from as many weather stations as possible in a given area and make use of many varieties of weather stations. Synoptic networks attempt to provide an efficient summary of large scale weather patterns from stations deemed to provide reliable and timely data. Synoptic networks are generally sparse, making use of principal weather stations, and rely on automated reporting techniques.

Types of Collection Systems

Four sources of real-time weather data were identified from the three types of collection systems listed above (Table A1):

1. Cooperative Networks

Cooperative weather observers in North Dakota record temperature and precipitation values daily on forms provided by the NWS office in Bismarck, N.D. Although the number of stations reporting varies, records received by YES indicate that about 100 cooperative stations report in any given month. The NWS forms are designed to contain one month of data and are generally received in Bismarck between the 4th and 10th days of the following month (Car· e personal communication). Data are collated in Bismarck and sent to NCDC in Asheville, North Carolina. In addition, seven "major" stations send monthl' summaries directly to Asheville. These data are the basis for the monthly averages published by NCDC. The strong point of this system is that data are available from a large number of stations throughout the state. However, because all data are not available until the 10th day of the following month, current procedures are not sufficient for real-time models.

Another cooperative program in North Dakota provides weather values on a weekly basis. From April to October a subset of the NWS cooperators report weekly temperature and precipitation values to the NWS office in Bismarck by telephone each Monday morning. These data are then transmitted to the offices of the North Dakota Crop and Livestock Reporting Service in Fargo, N. D., also by telephone, where they are compiled and published in the weekly Crop-Weather Report. This program involves about 30 reporting stations, and the Crop-Weather Report is released on the first work day of each week.

Table A1. Potential real-time weather data sources for North Dakota

Type of Reporting System	Source	Type of Data
1. Cooperative Network	NWS monthly forms	Point Source, 100 stations
	N.D. Crop-Weather Weekly Report	Point Source, 30 stations
2. Synoptic Network	WMO DMONTH	Point Source, 13 stations
3. Satellite Data	USAF Agromet	Estimated Point Source on grid

NWS: National Weather Service
WMO: World Meteorological Organization
USAF: United States Air Force

2. Synoptic Network

The Global Telecommunications System (GTS), administered by the WMO, is a large scale network that reports values from first order and automated weather stations throughout the world. These values are processed weekly by the Climate Analysis Center (CAC) of the NWS, and a summary produced weekly in the form of a computer printout known as DMONDAY. A monthly summary known as DMONTH is also produced by CAC and contains the following weather data for each reporting station: number of days precipitation readings taken; percent of observations for which precipitation was recorded; total precipitation; normal precipitation; departure of recorded precipitation from normal; percent of normal precipitation recorded; number of years used to calculate normal precipitation; number of days temperature readings taken; mean temperature; normal mean temperature; departure of recorded mean temperature from normal; number of years used to calculate normal mean temperature; highest daily maximum temperature for month; date when highest daily maximum occurred; number of days maximum temperature recorded; lowest daily minimum temperature for month; date when lowest daily minimum occurred; and number of days minimum temperature recorded. Precipitation values are reported in millimeters and temperature values in degrees Celsius. The DMONTH summary currently reports values for thirteen stations in North Dakota; 3 National Weather Service (NWS) stations, 4 Federal Aviation Administration (FAA) stations, 2 stations from the Continental U. S. Meteorological Data System (COMEDS), U. S. Air Force, 3 Automatic or Remote Automatic Meteorological Observing Stations (AMOS/RAMOS), and 1 municipal airport station (Table A2). The DMONTH summary is available from CAC within several days of the end of a month of recorded data, making it a timely source of data for real-time models. Because the GTS is a large scale network, however, the number of stations reported for North Dakota is small, and some type of data manipulation is necessary to derive values suitable for us with models requiring weather values on a CD or CRD scale.

3. Satellite Data

The U. S. Air Force has developed a procedure known as Agromet to estimate meteorological values from data provided by polar orbiting satellites and the WMO network. The variables used by Agromet are reflectance, radiance, and temperature from satellites, and temperature and precipitation from surface reports. Agromet produces point estimates of maximum and minimum temperatures, precipitation, solar radiation, and evaporation with an Air Force 25-NM grid point spacing at 60° N. Agromet is run every three hours at Global Weather Central (GWC), Offutt Air Force Base in Nebraska. Daily summaries are prepared and compiled as weekly data sets each Monday. Weekly data sets are currently flown to the USDA, Foreign Agricultural Service (FAS), Foreign Crop Condition Assessment Division (FCAD) in Houston, Texas where they are p.ocessed and made available for use within 60 hours (Perry and Rogers, 1982). A complete description of Agromet is provided in USAF ETAC/TN-81-001 (Cochrane, Jr., 1981). If Agromet data prove appropriate for use with real-time models, data collection costs could be reduced (Perry and Rogers, 1982). Unfortunately, Agromet data for the U. S. have been available only since June of 1981.

Table A2. North Dakota Stations Reported on DMONTH Program

Station No.	Call No.	Latitude	Longitude	CD/CRD	Location	Type
72764	BIS	46.8	100.8	80	Bismarck	NWS
72753	FAR	46.9	96.8	60	Fargo	NWS
72768	ISN	48.2	103.6	10	Williston	NWS
	MOT	48.3	101.3	20	Minot	FAA
	GFK	47.9	97.2	30	Grand Forks	FAA
	DIK	46.8	102.8	70	Dickinson	FAA
	JMS	46.9	98.7	50	Jamestown	FAA
	MIB	48.4	101.3	20	Minot	COMEDS
	RDR	47.9	97.4	30	Grand Forks	COMEDS
72758	DVL	48.1	98.9	30	Devil's Lake	MUNI ARPT
72757	P11	48.1	98.9	30	Devil's Lake	AMOS/RAMOS
	P24	47.8	101.8	40	Roseglen	AMOS/RAMOS
	P67	46.1	97.1	90	Lidgerwood	AMOS/RAMOS

Conversion of Point Source Data to CD Level Values

Since crop-yield models use weather variables calculated at the CD level, point source data must be manipulated in some manner. Three methods currently show potential for converting raw data to CD level estimates (Table A3):

1. Simple Averages.

Monthly weather values are simply averaged across all reporting stations for a CD by NCDC. Thus taking simple averages of real-time station data is an obvious candidate when searching for operational methods of obtaining timely CD level values. The potential of this method lies in the possibility that a sample of cooperative network stations could (1) provide sufficient information for accurate estimates and (2) be obtained on a real-time basis.

2. Subjective Estimation.

Two sources of real-time weather data make use of subjective estimation procedures to derive temperature and precipitation values for CDs. These sources are (1) the USDA World Agricultural Outlook Board (WAOB) and (2) NOAA, Climatic Impact Assessment Division, Climate Assessment Branch (CAB), both located in Washington, D.C. Both receive station data from the WMO GTS (DMONTH program run in Suitland, Maryland), plot temperature and precipitation values on weather maps, draw isotherms and isohyets (lines connecting points of equal temperature and precipitation, respectively), and make subjective estimates of average temperature and local precipitation for each CD. Because these are the same weather variables reported by NCDC, and data are available on a CD level, little manipulation of the data would be needed to use these estimates in formulae for deriving model weather variables. In addition, the cost of obtaining weather data from these sources is low since the estimates are derived for purposes other than USDA crop yield modeling. Weather estimates from CAB have been obtained by YES since January 1979 through NOAA, Assessment and Information Services Center (AISC) personnel. Estimates from WAOB have been received since February 1982. CAB and WAOB data were received by AISC an average of 26 and 7 days, respectively, past the end of the month for which data were pertinent (see Table A4). The procedure for transfer of values from CAB and WAOB to AISC has been poorly defined on both ends. The most rapid turn around time (5 days) indicates that figures could be reported in a time frame consistent with monthly use of crop yield models, but the reporting method is currently too erratic for such use.

3. Objective Analysis or Spatial Interpolation

A number of techniques have been developed in the past 15 years to estimate meteorological values for an area, given a minimum of input data. Often a surface is fitted to a small number of points, and estimates of weather variables produced for many locations over the same geographic area. An appealing quality of these techniques is that they remove the subjective bias inherent in WAOB and CAB procedures, and may be useful with data provided by the DMONTH or Agromet programs. Whether objective methods can provide more accurate information than subjective procedures or data obtained from a sample of cooperative stations, however, remains open to question.

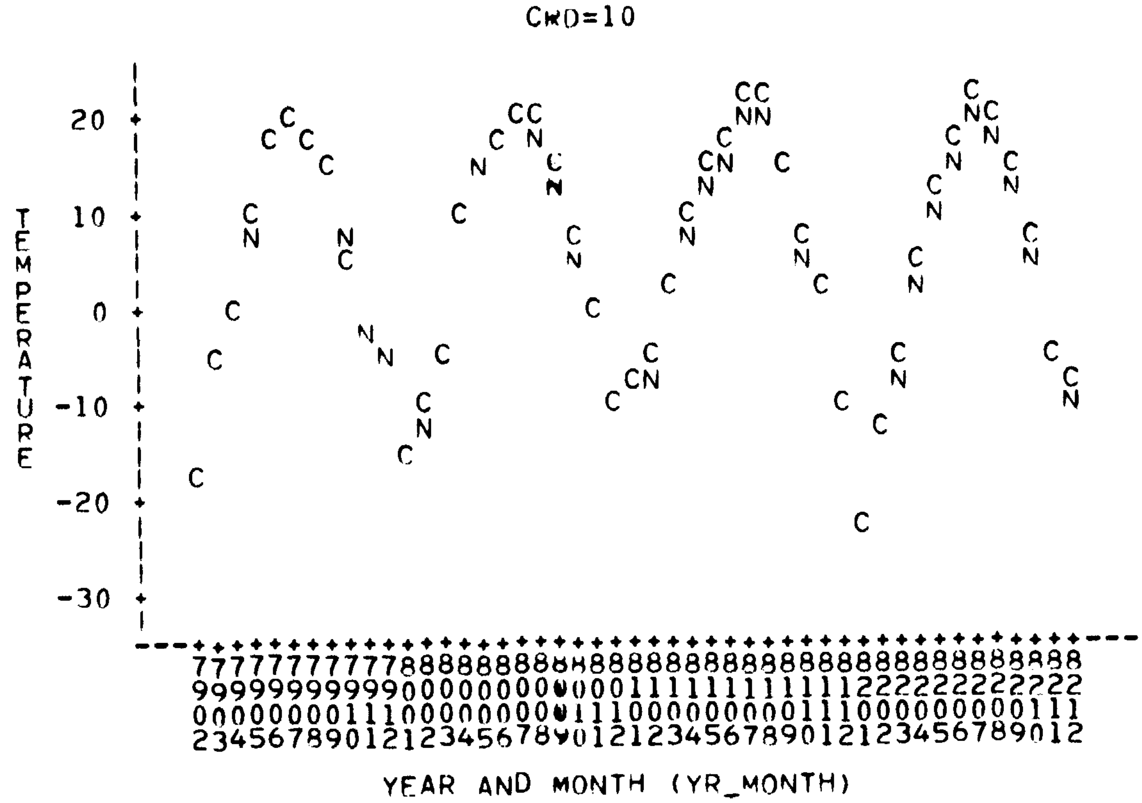
Table A3. Potential methods for conversion of real-time station data to CD level values

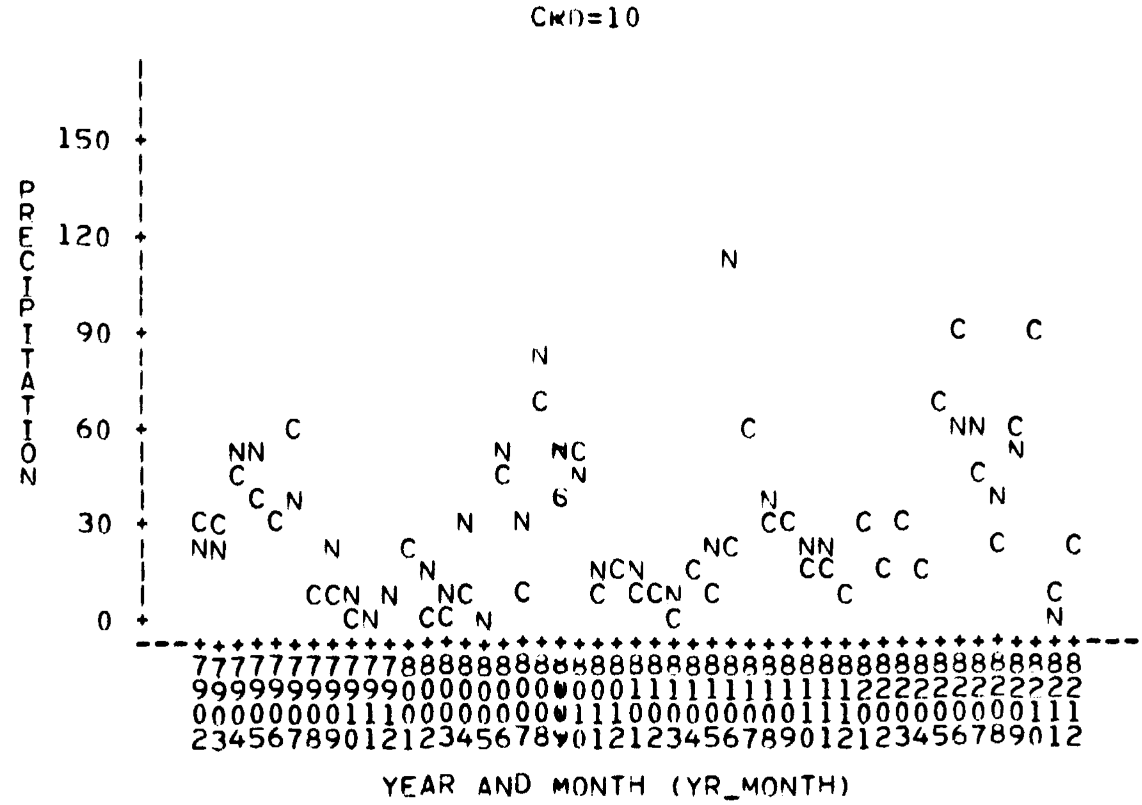
Type of Method	Source	Data Form
1. Simple average	Sample of coop. network stations	CD level avg.
2. Subjective estimation	USDA WAOB	CD level avg.
	NOAA CAB	CD level avg.
3. Spatial interpolation	Any of a variety of techniques	Yields estimated point source data which may be averaged, some methods give area avg. directly

Table A4. Dates CAB and WAOB weather value estimates were received at YES, 1981-1982

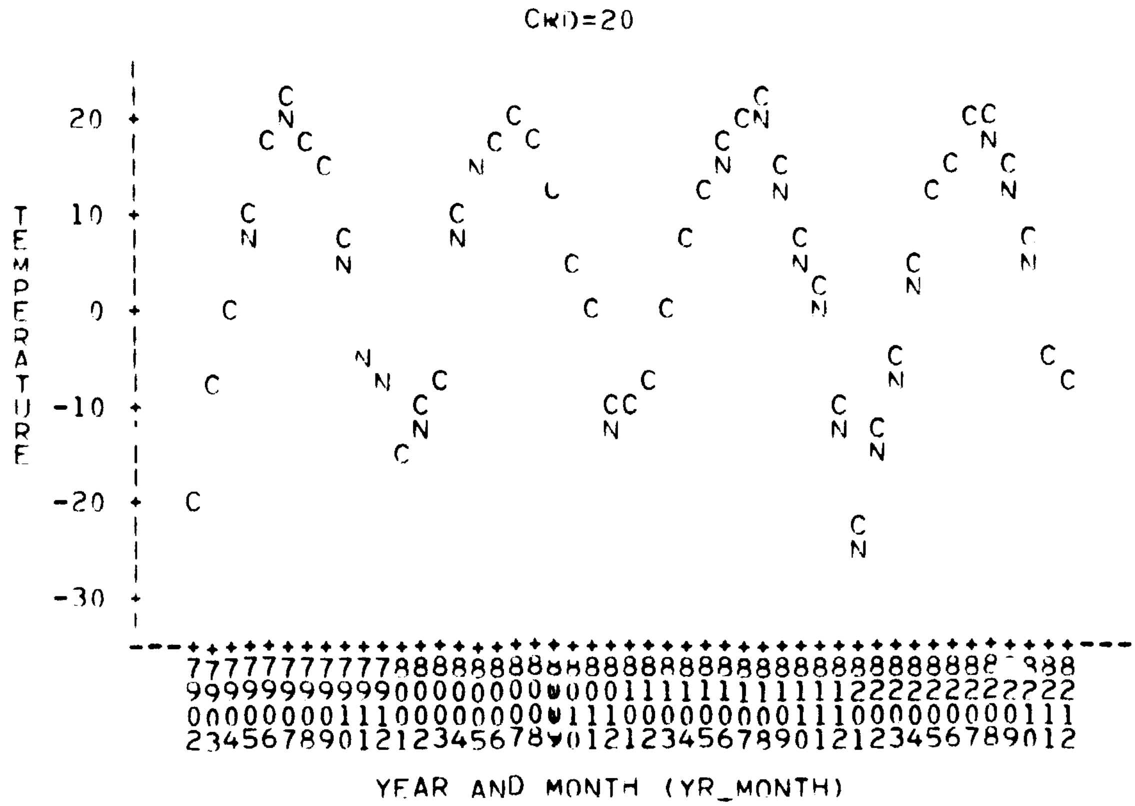
Source of Estimate	Year and month of data	Date received at YES	No. days between last day of month and date received
CAB	June 1981	6 August 1981	37
CAB	July 1981	14 August 1981	14
CAB	August 1981	26 September 1981	26
CAB	September 1981	missing record	-
CAB	October 1981	missing record	-
CAB	November 1981	missing record	-
CAB	December 1981	5 March 1982	63
CAB	January 1982	missing record	-
CAB	February 1982	24 March 1982	24
CAB	March 1982	28 April 1982	28
CAB	April 1982	6 May 1982	6
CAB	May 1982	16 June 1982	16
CAB	June 1982	27 July 1982	27
CAB	July 1982	25 August 1982	25
CAB	August 1982	21 September 1982	21
CAB	September 1982	3 November 1982	34
CAB	October 1982	22 November 1982	22
CAB	November 1982	3 January 1983	34
CAB	December 1982	26 January 1983	26
WAOB	February 1982	5 March 1982	5
WAOB	March 1982	6 April 1982	6
WAOB	April 1982	6 May 1982	6
WAOB	May 1982	9 June 1982	9
WAOB	June 1982	6 July 1982	6
WAOB	July 1982	5 August 1982	5
WAOB	August 1982	9 September 1982	9
WAOB	September 1982	6 October 1982	

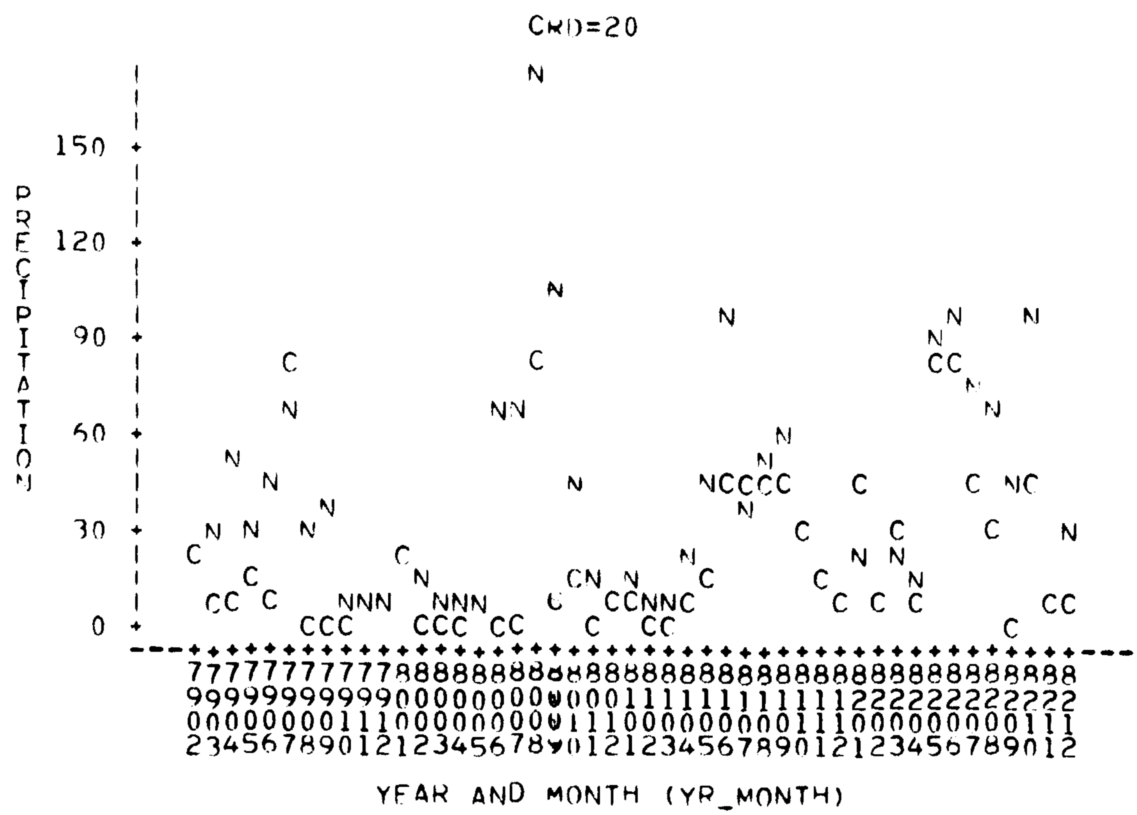
APPENDIX B, Part 1: Corresponds to Figure 1 in text.

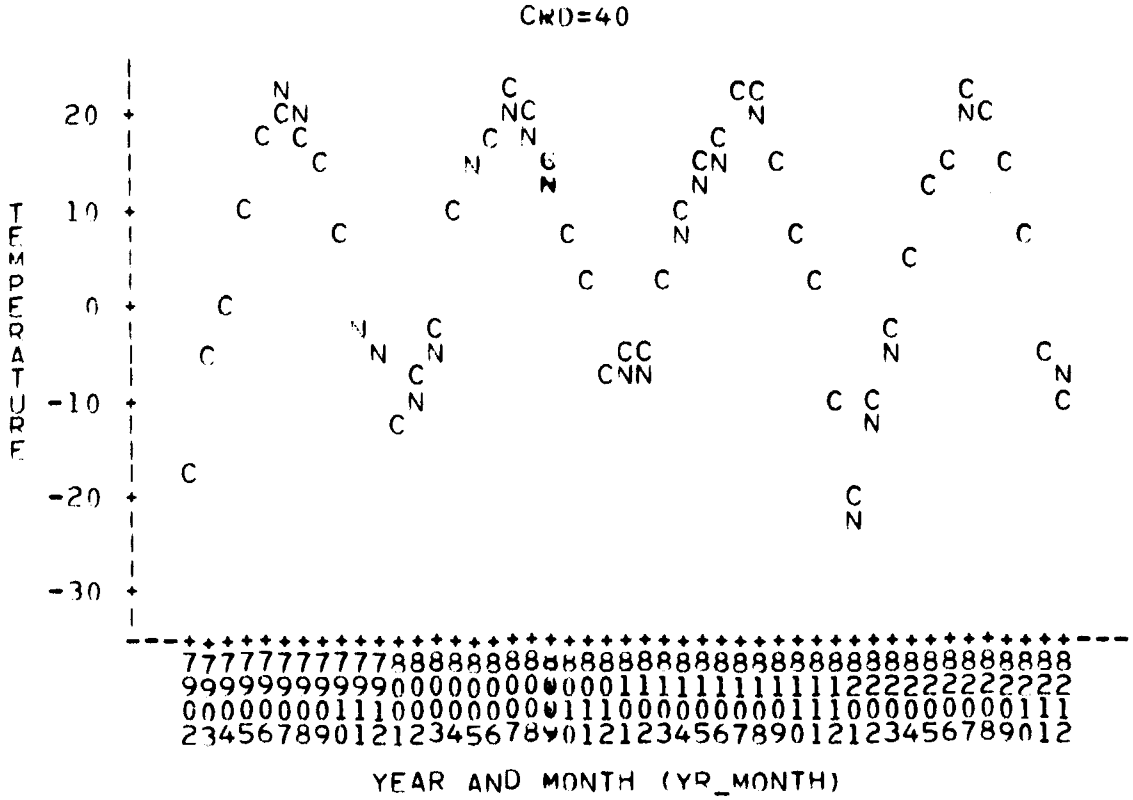




Appendix B, Part 1. Continued



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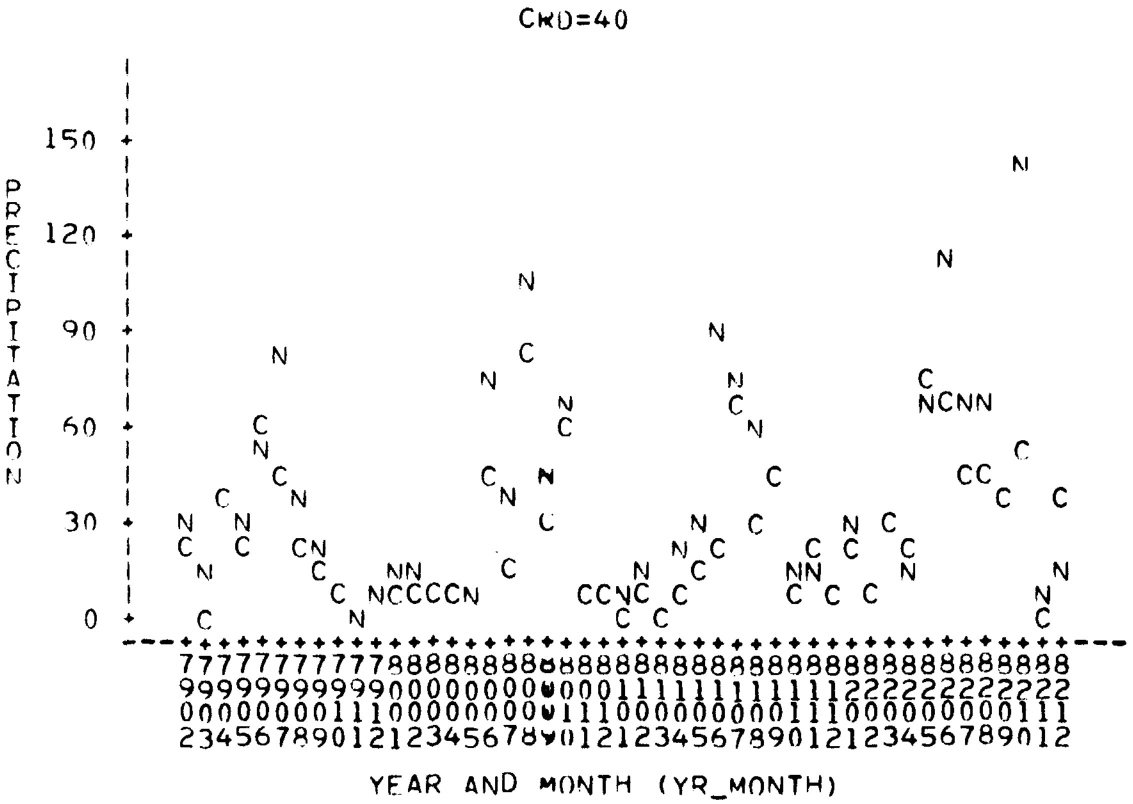
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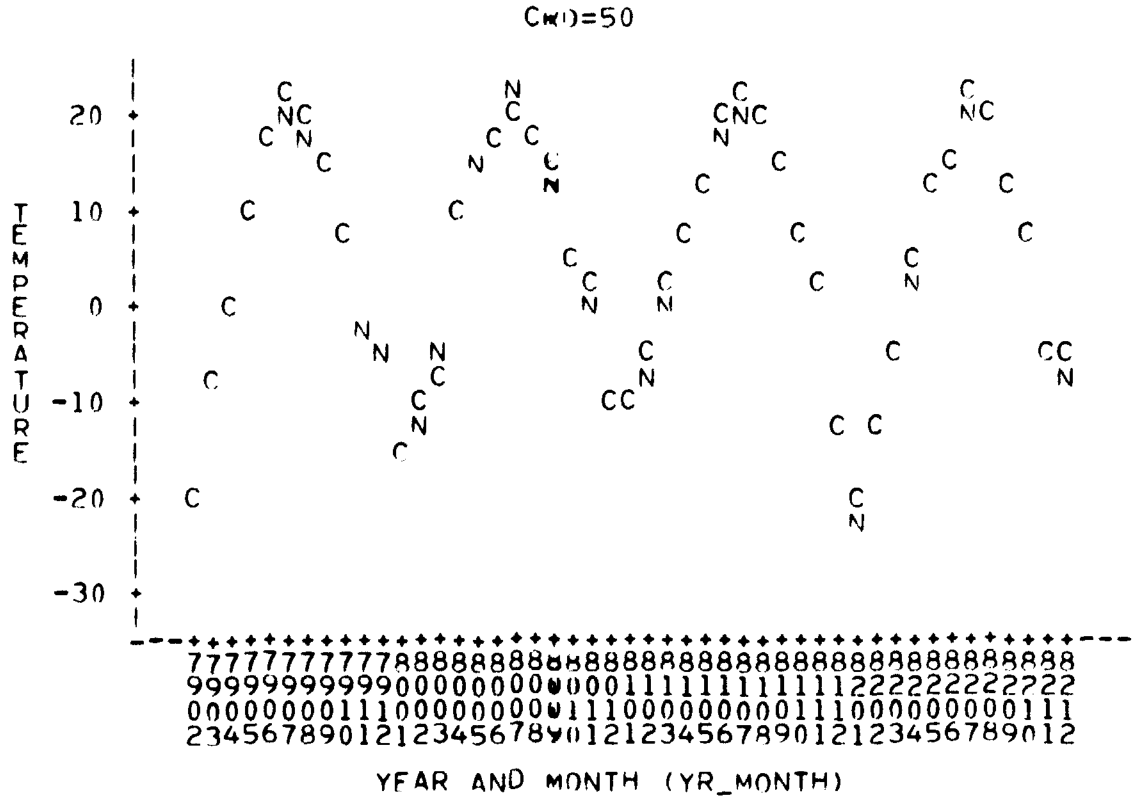
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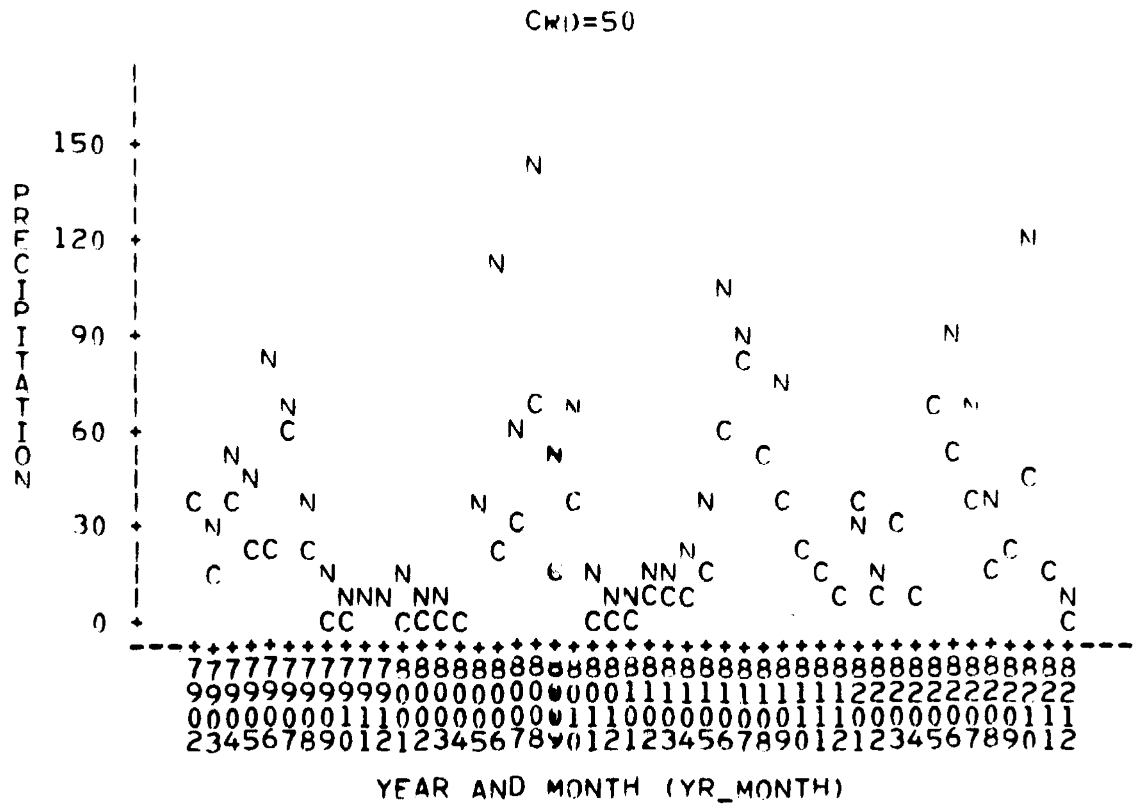
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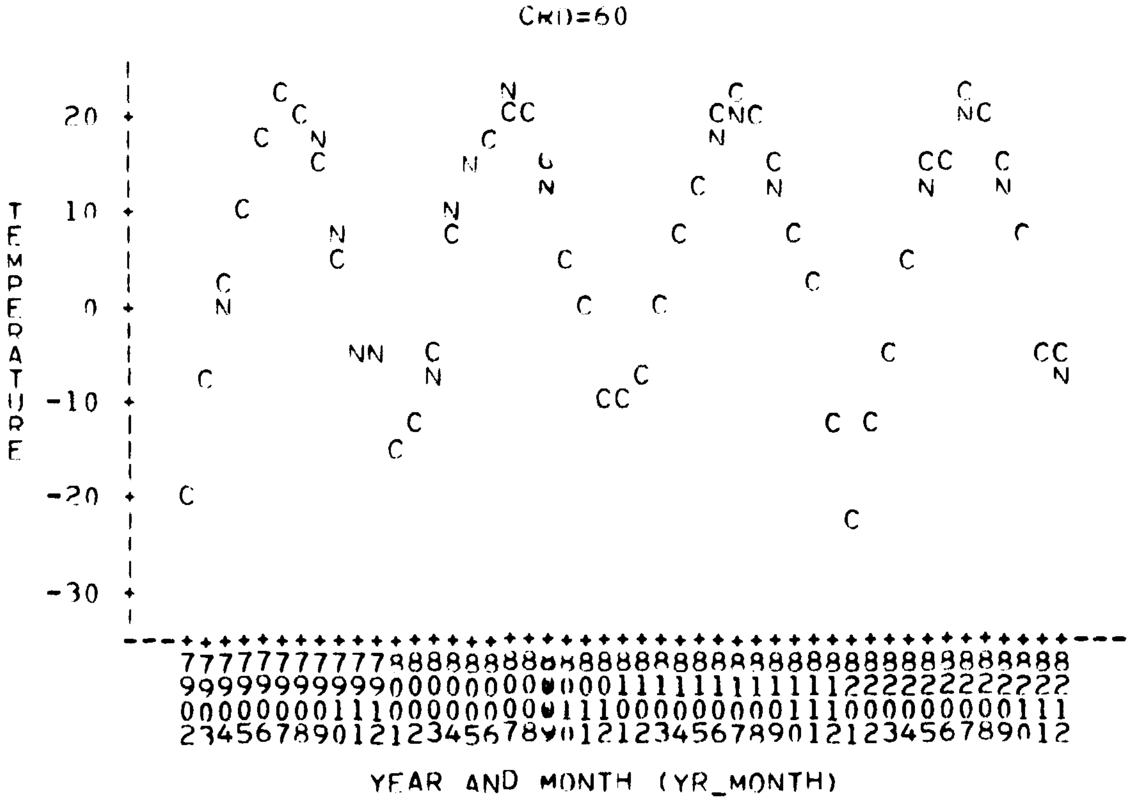
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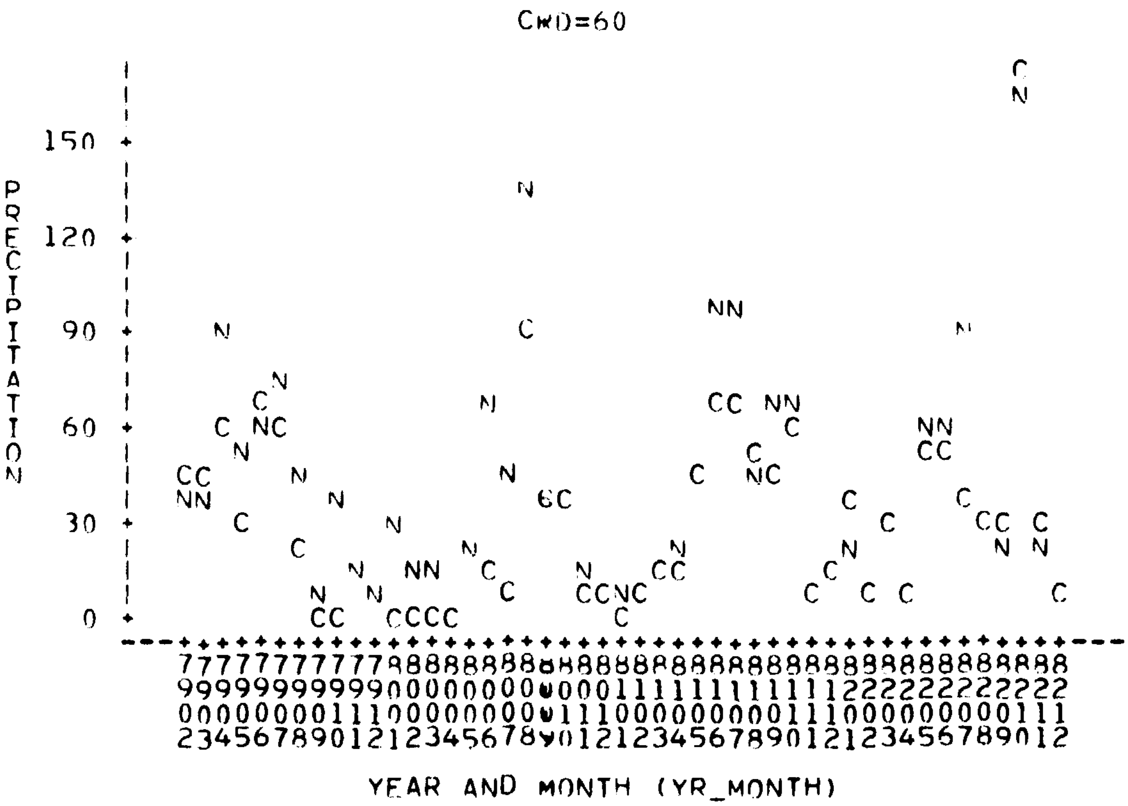
TEMPERATURE
20
10
0
-10
-20
-30
YEAR AND MONTH (YR_MONTH)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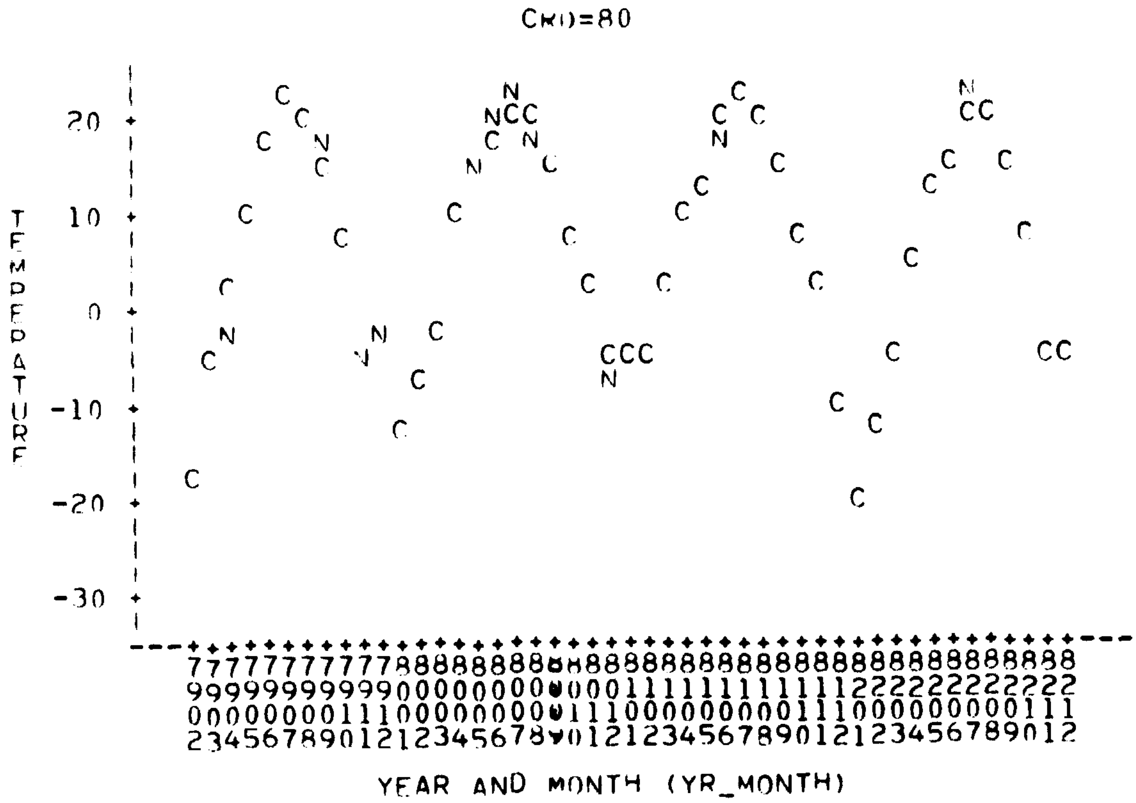
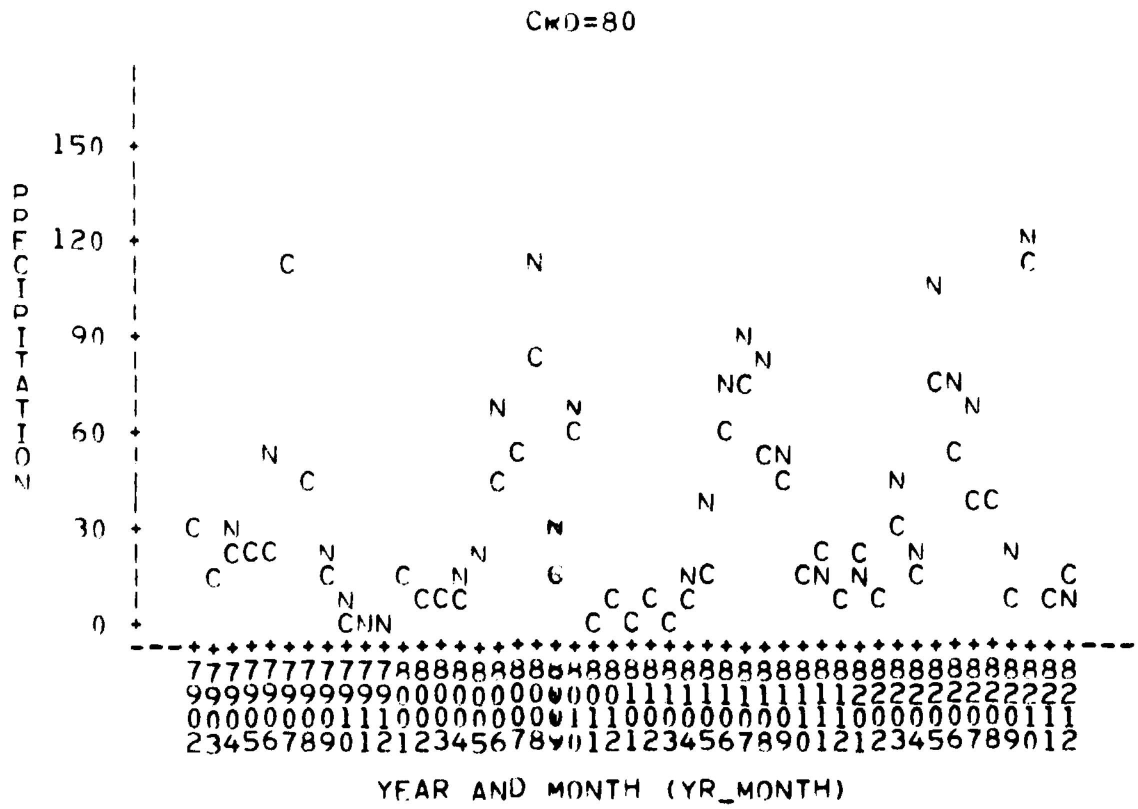
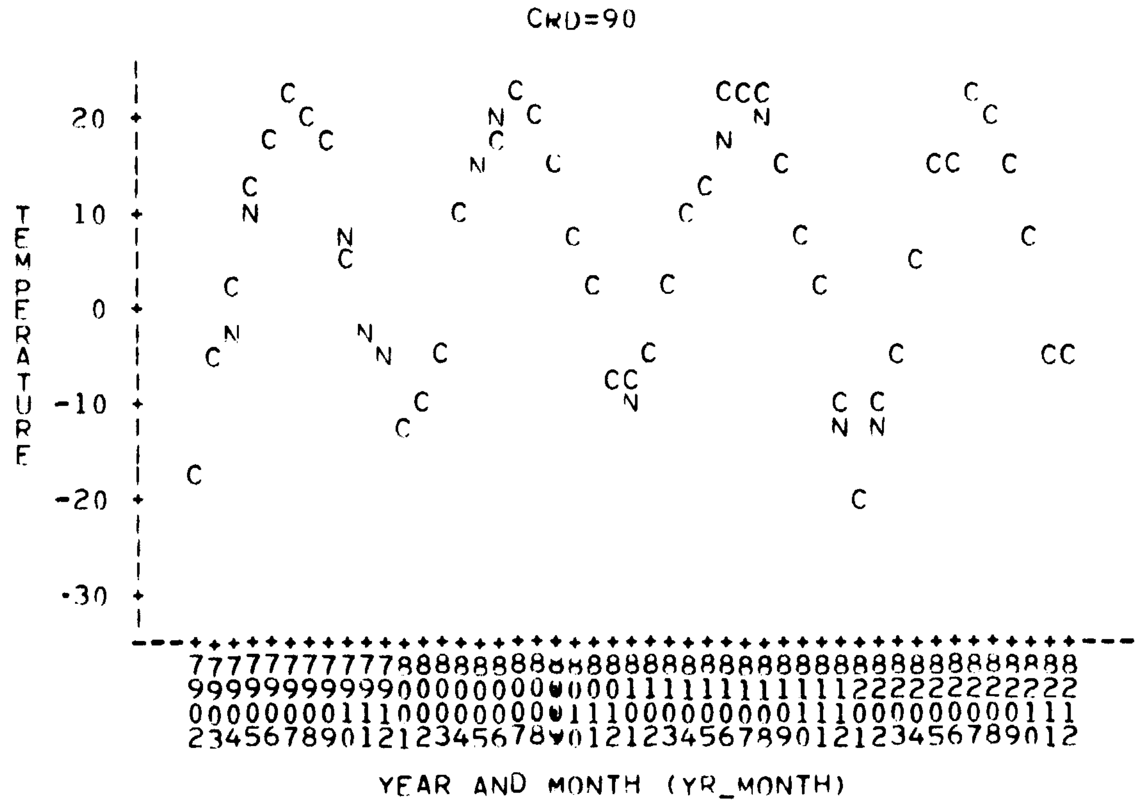
PRECIPITATION
150
120
90
60
30
0
YEAR AND MONTH (YR_MONTH)

Appendix B, Part 1. Continued



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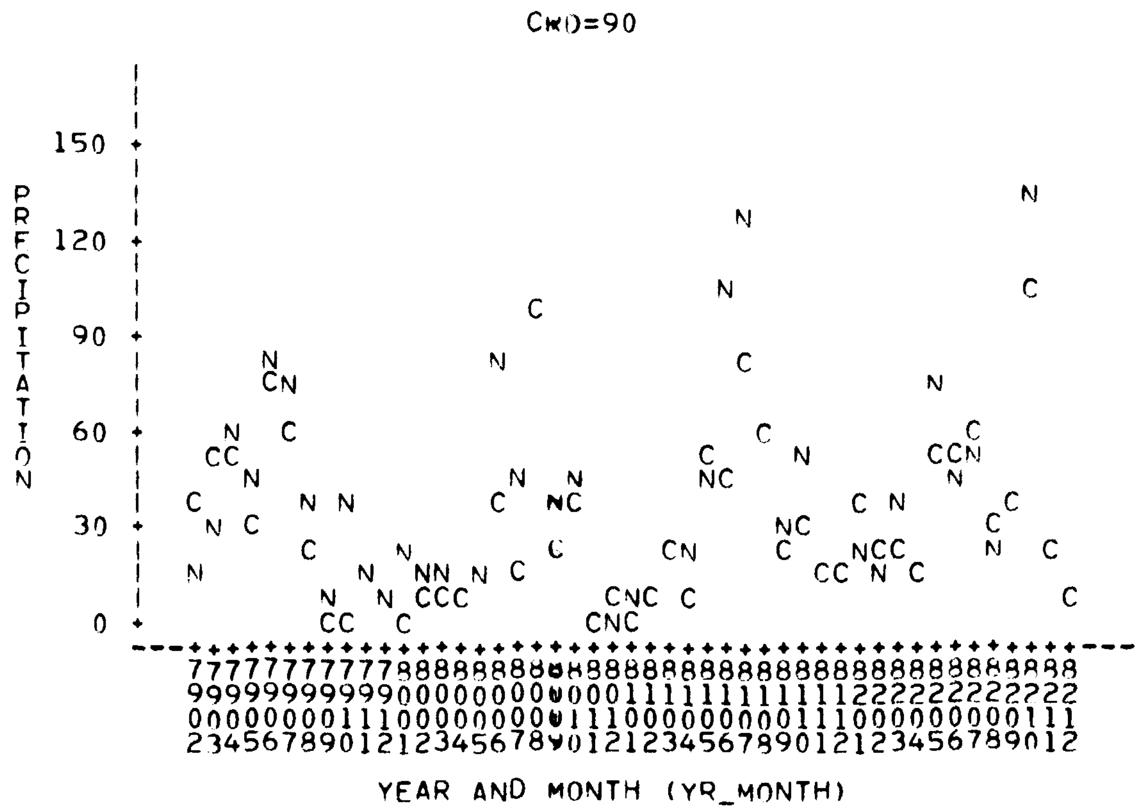
TEMPERATURE
YEAR AND MONTH (YR_MONTH)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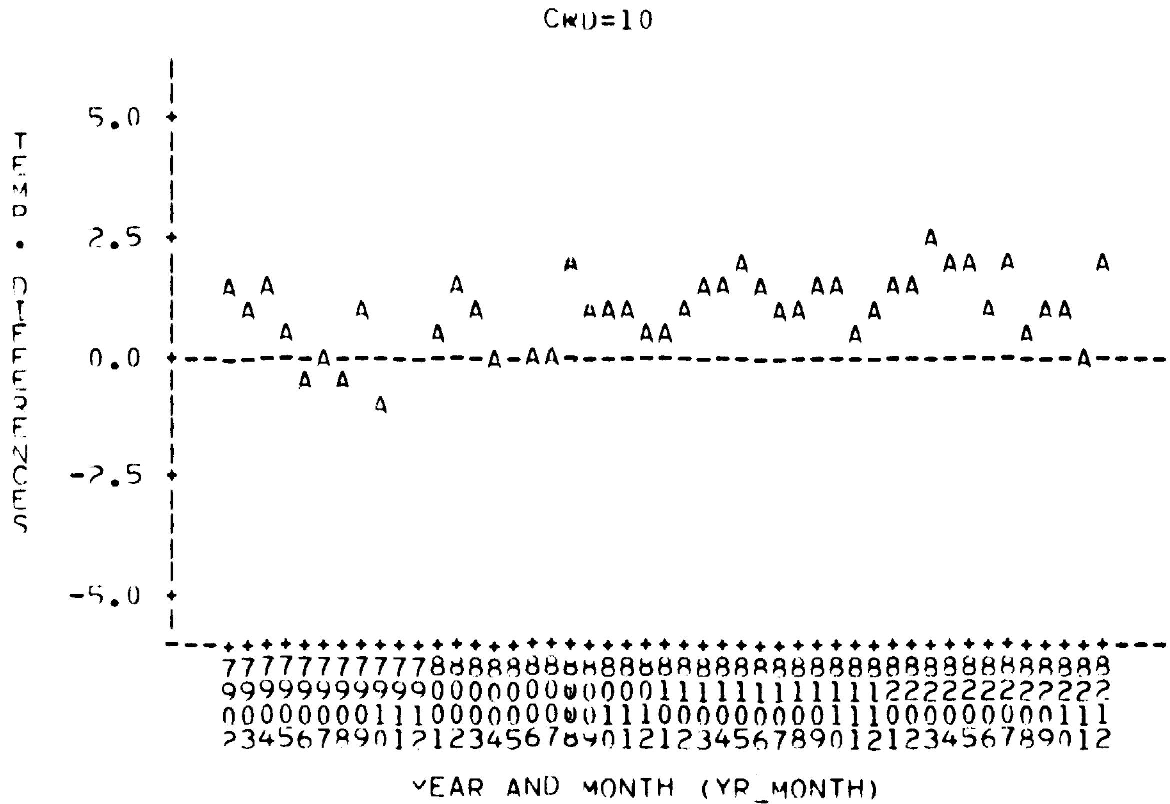
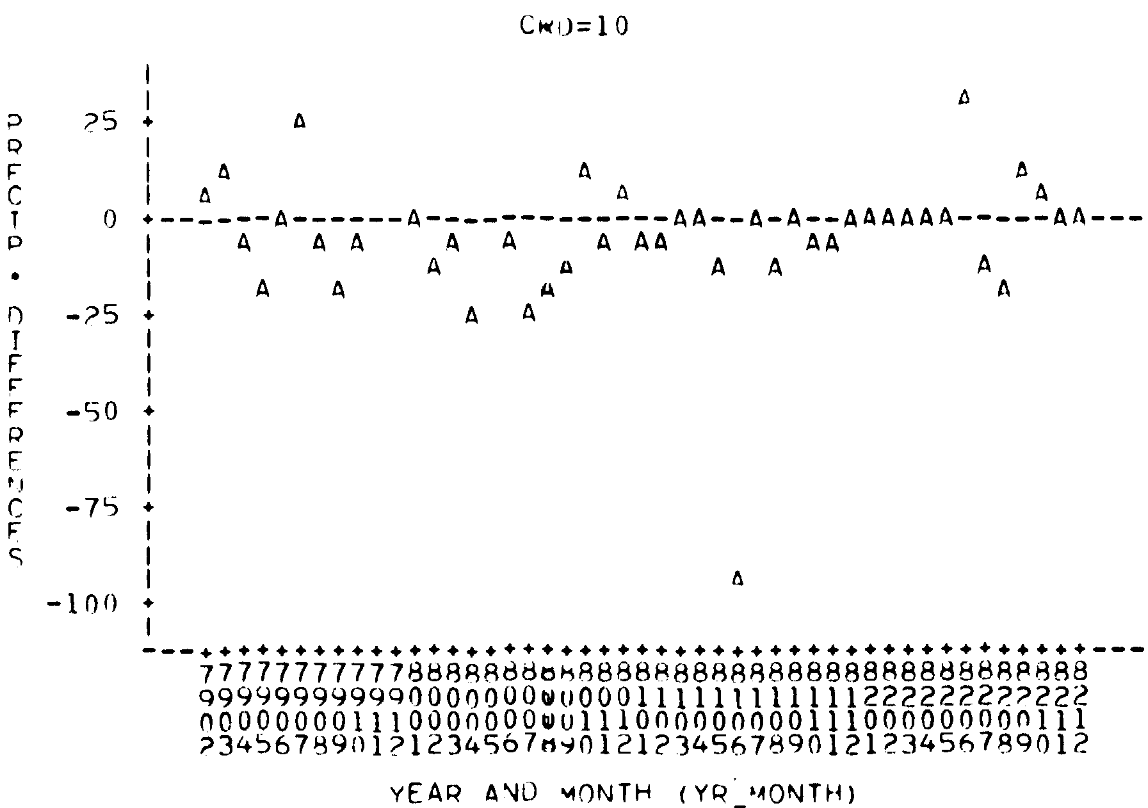
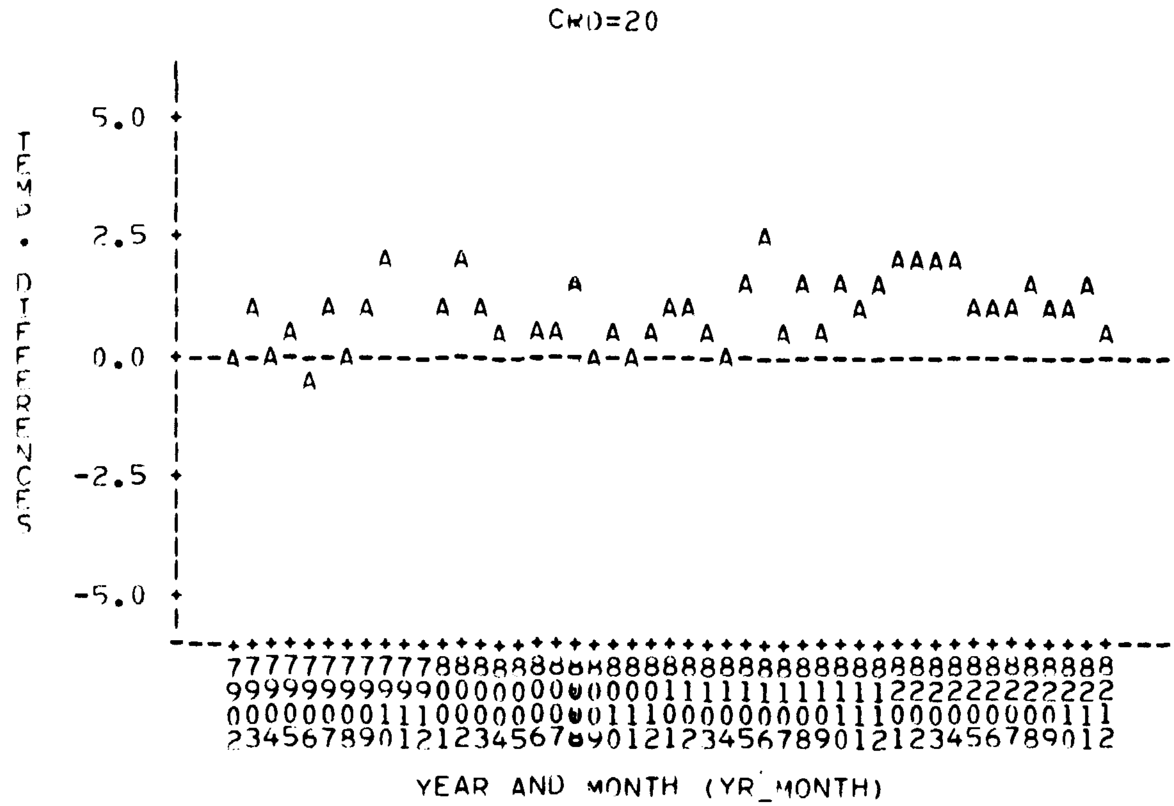
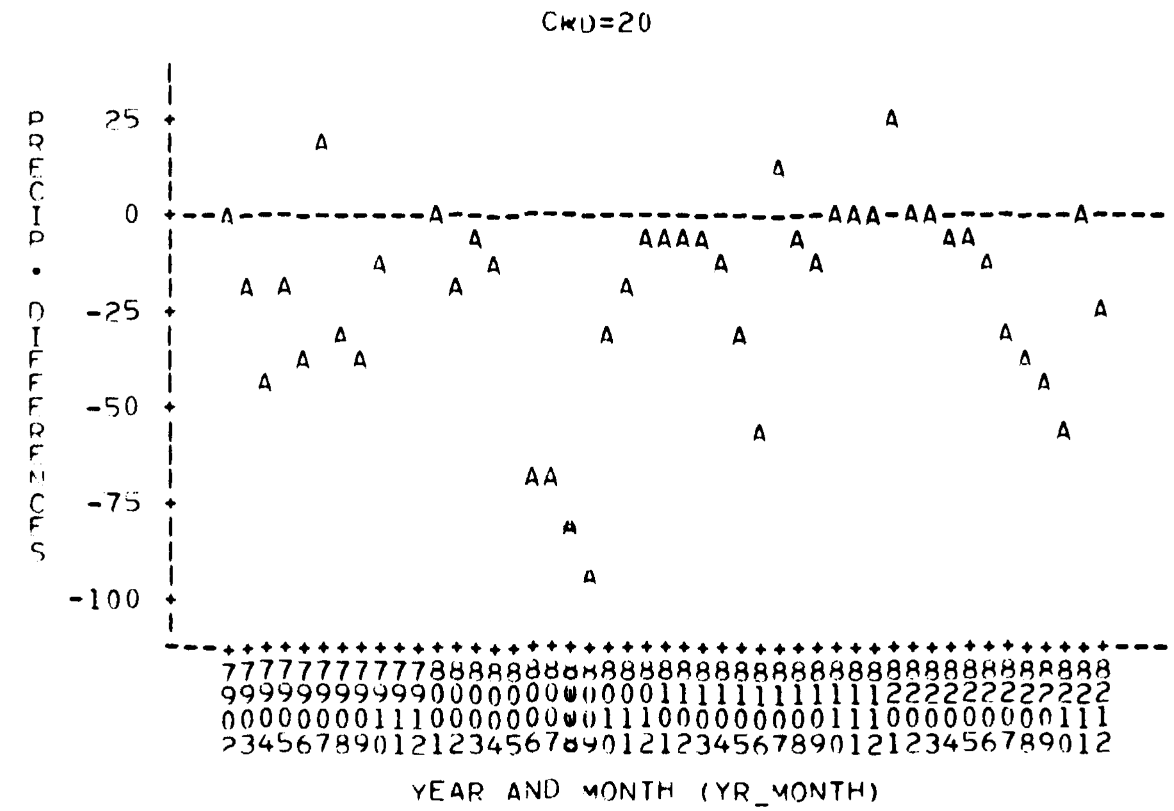
PRECIPITATION
YEAR AND MONTH (YR_MONTH)

APPENDIX B, Part 2: Corresponds to Figure 2 in text.

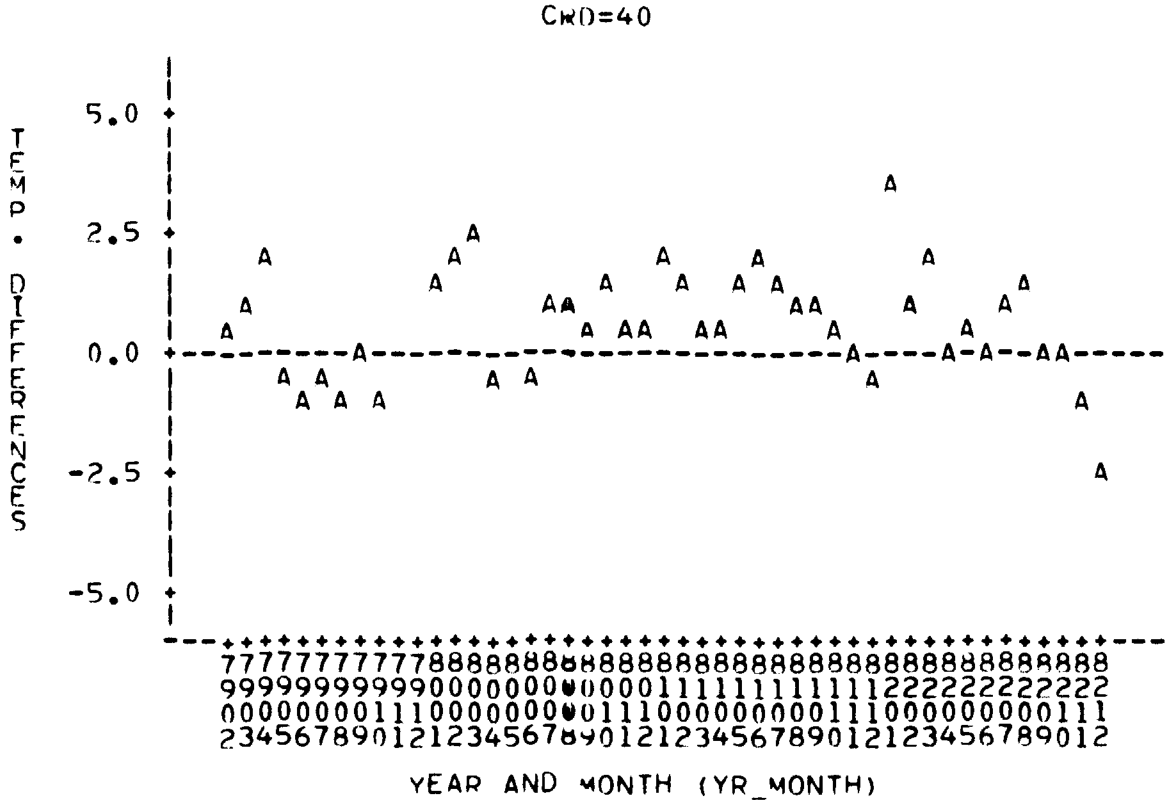


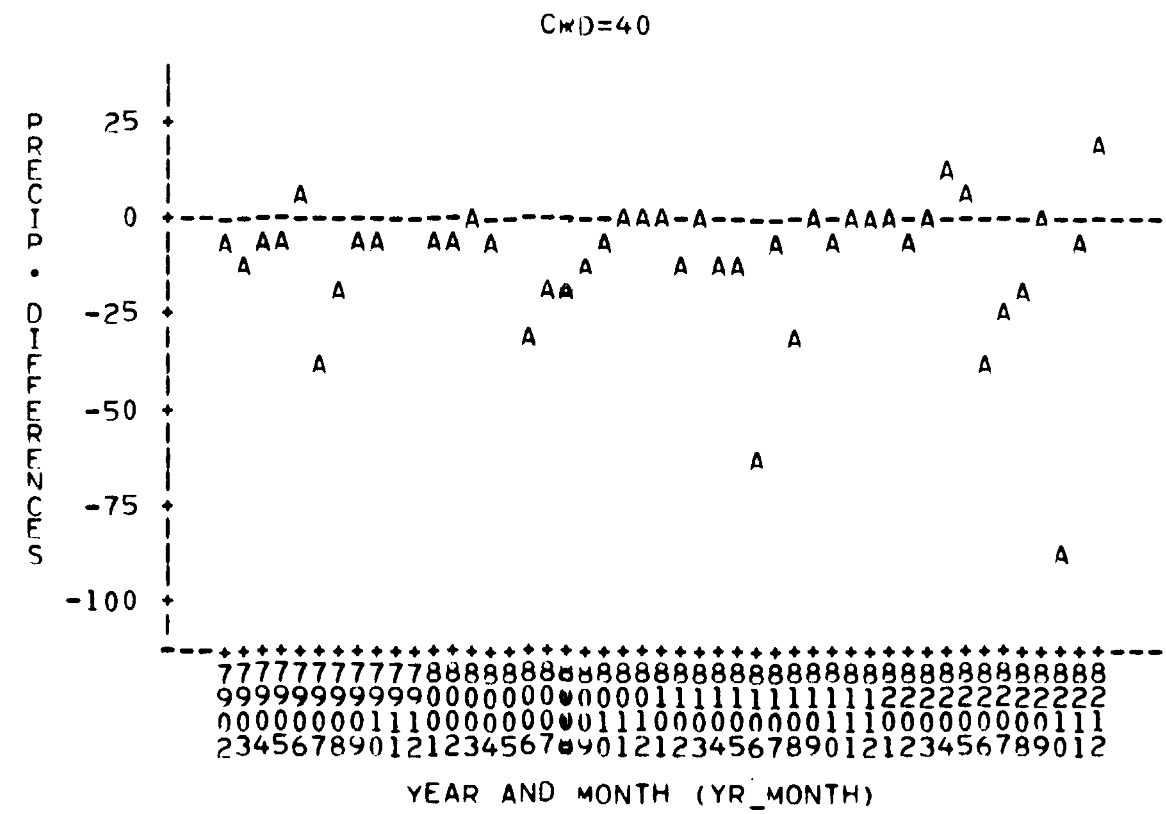


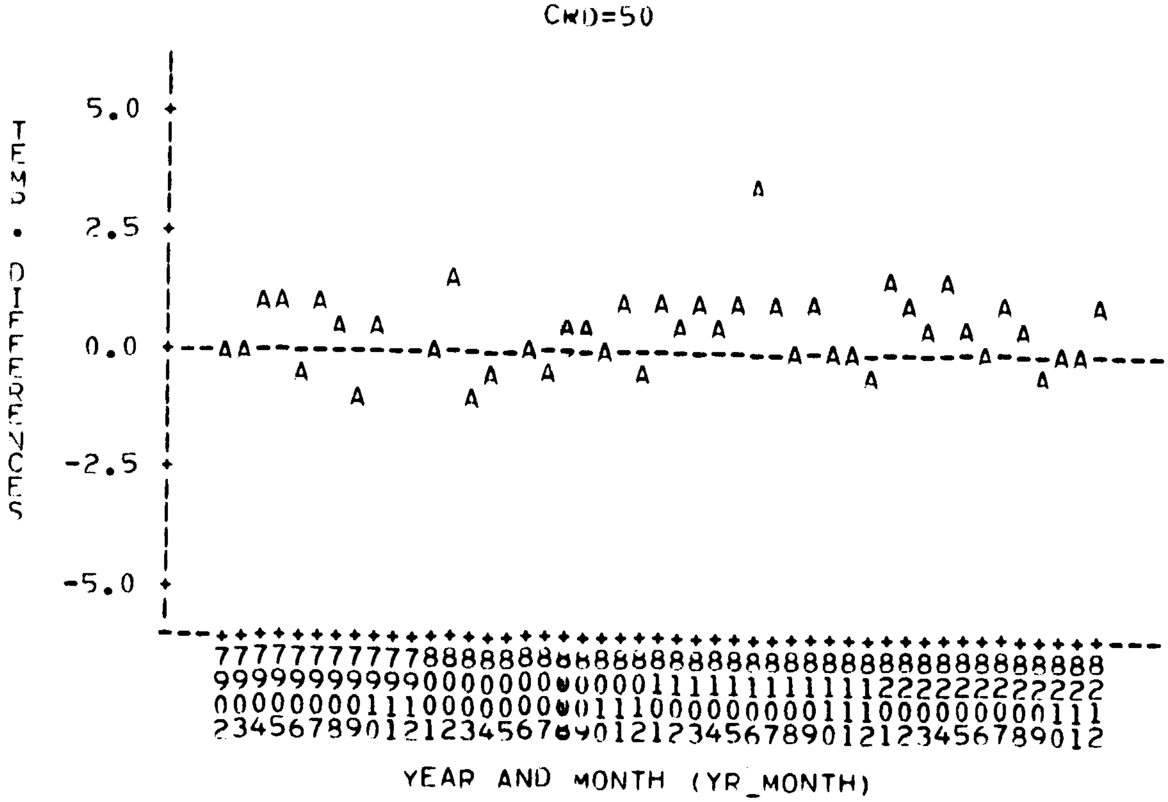

CRD=20
TEMP. DIFFERENCES
5.0
2.5
0.0
-2.5
-5.0
YEAR AND MONTH (YR_MONTH)

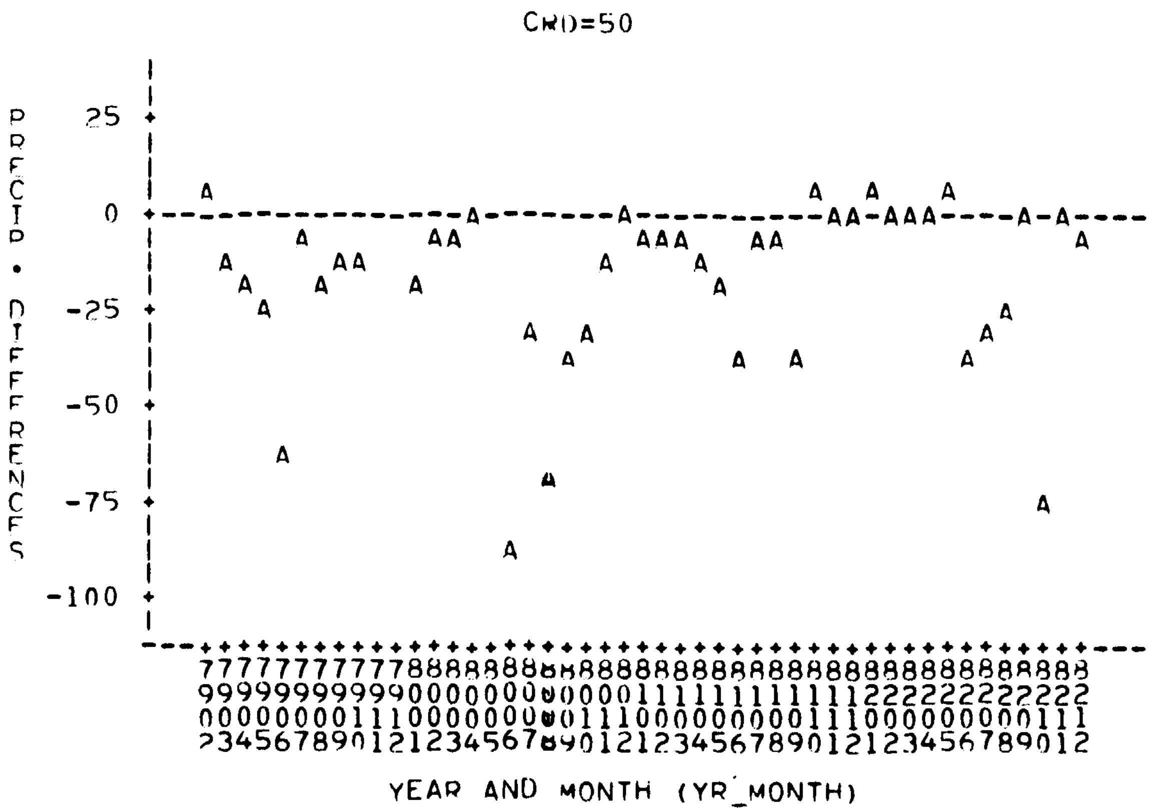

CRD=20
PRECIP. DIFFERENCES
25
0
-25
-50
-75
-100
YEAR AND MONTH (YR_MONTH)

Appendix B, Part 2. Continued



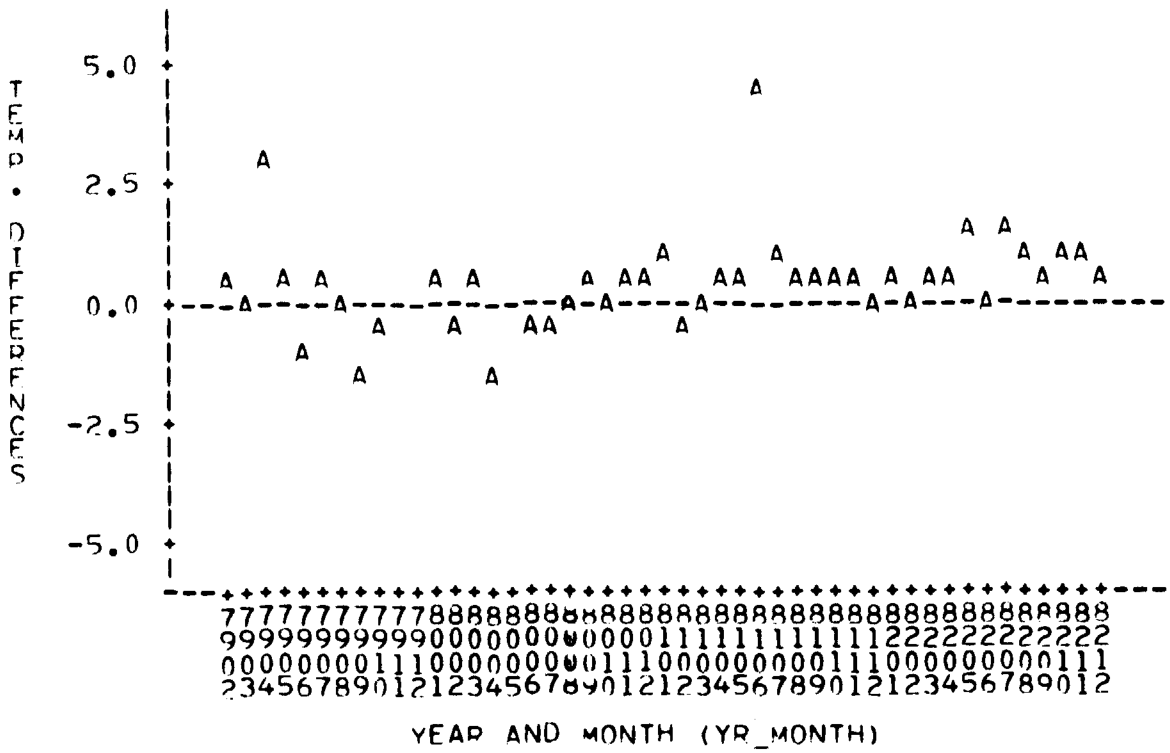



CWD=50
5.0
2.5
0.0
-2.5
-5.0
TEMP. DIFFERENCES
YEAR AND MONTH (YR_MONTH)


CWD=50
25
0
-25
-50
-75
-100
PRECIP. DIFFERENCES
YEAR AND MONTH (YR_MONTH)

Appendix B, Part 2. Continued

CWD=60



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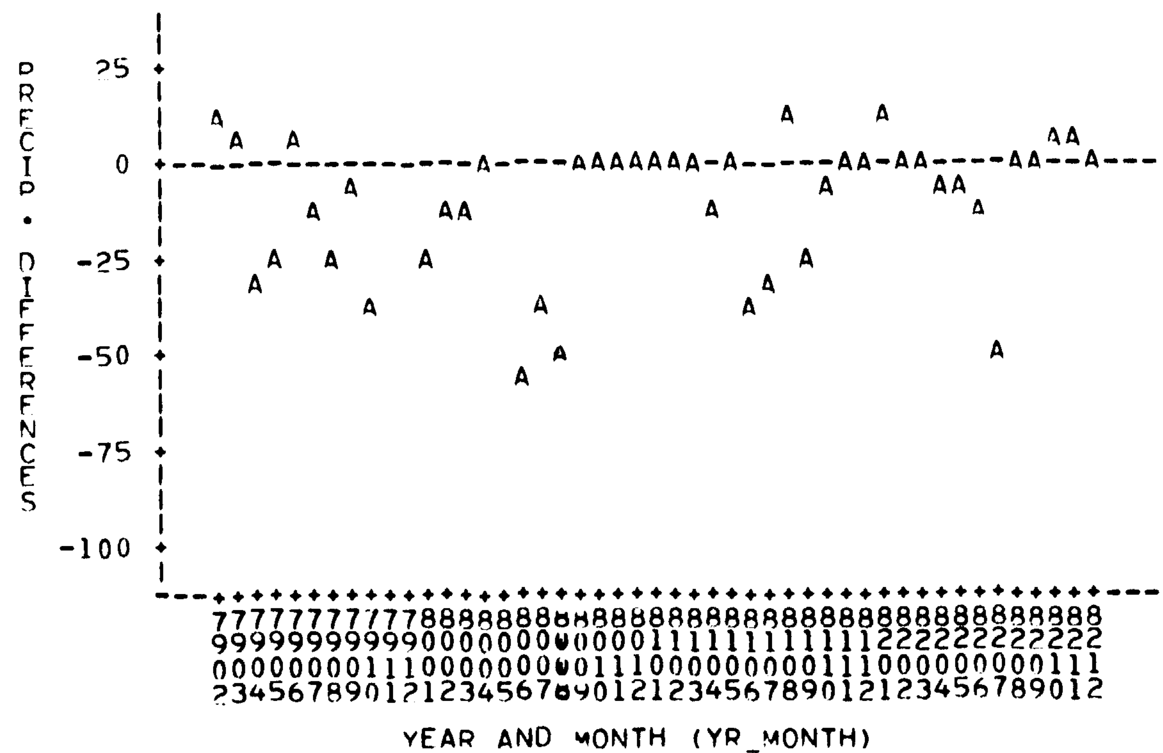
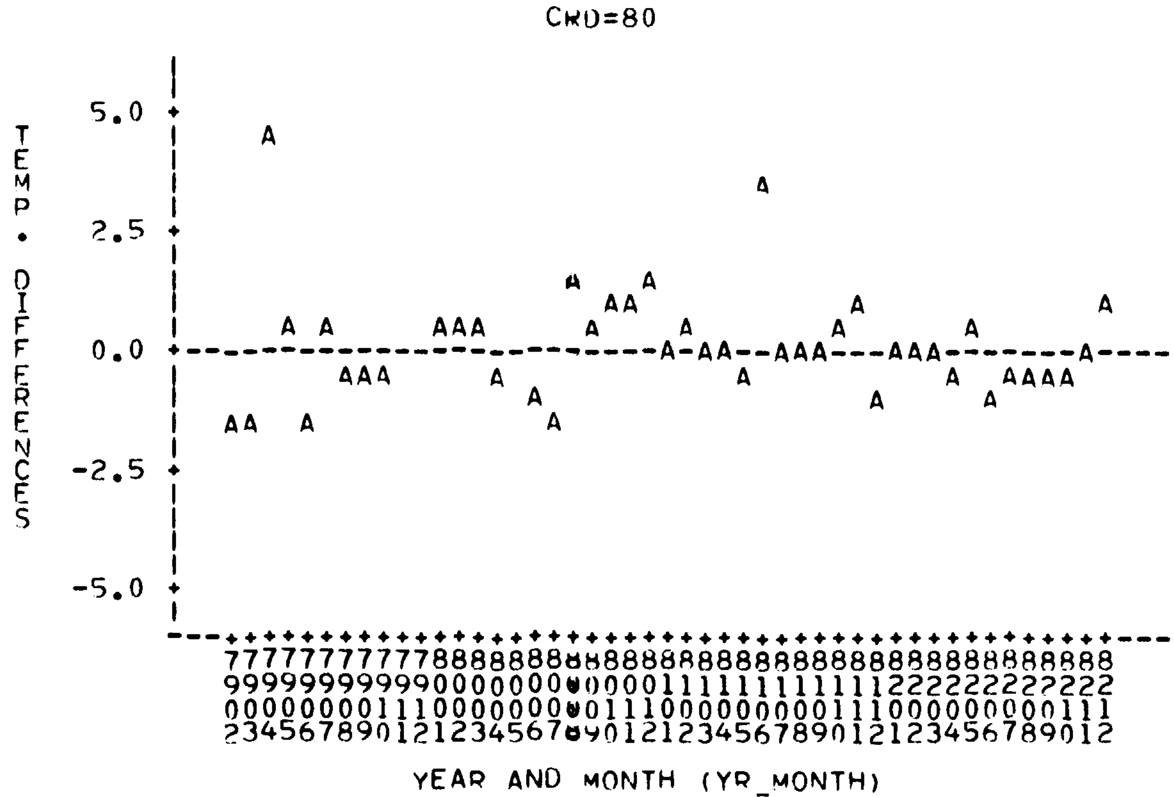
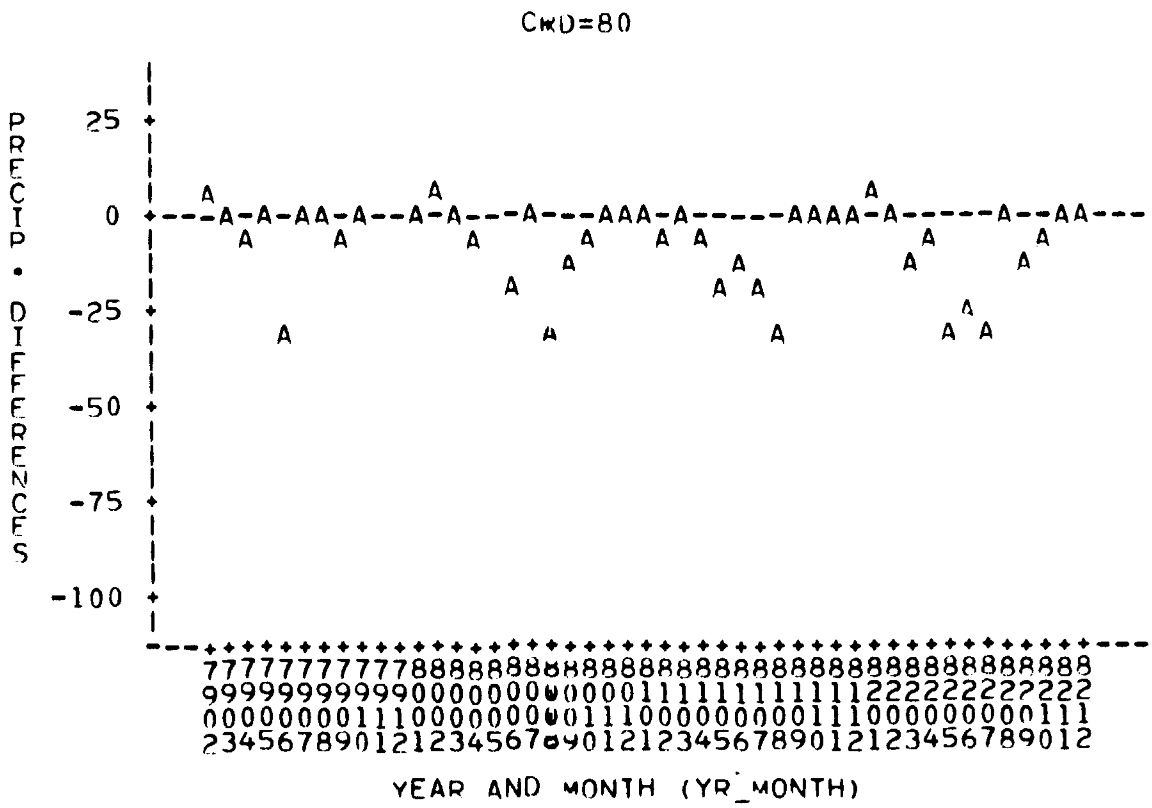
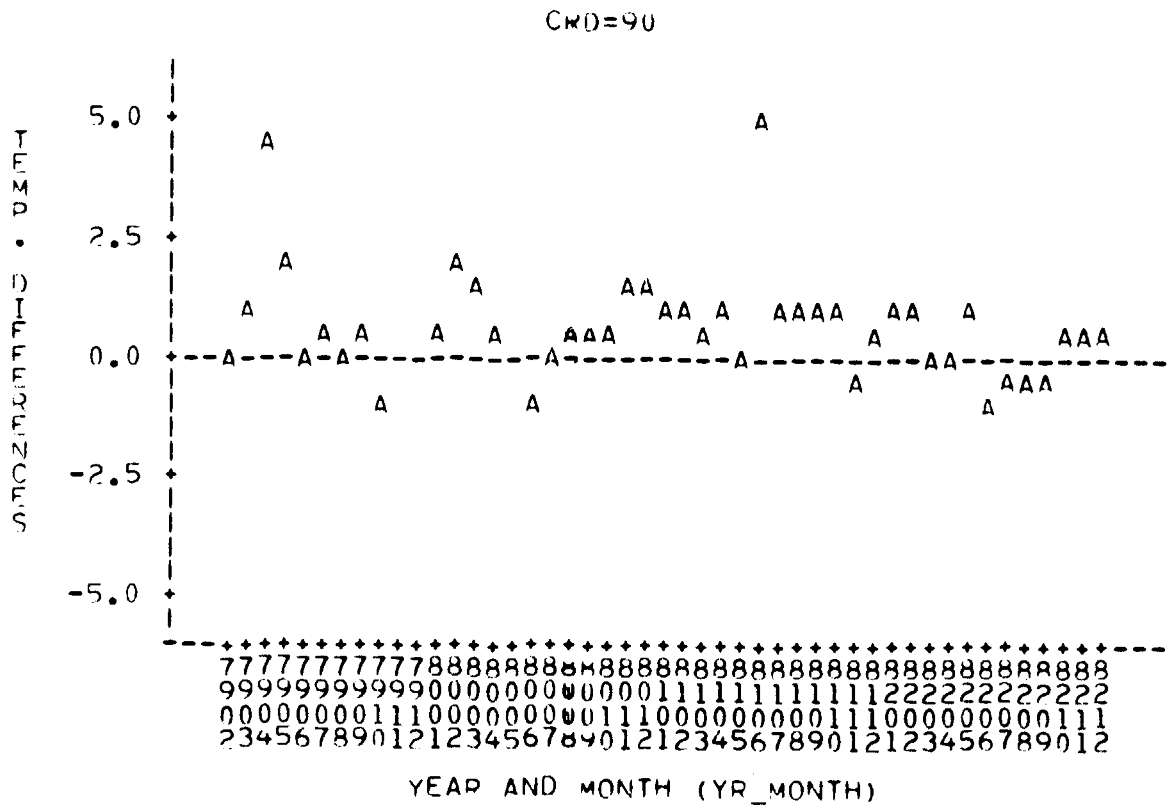
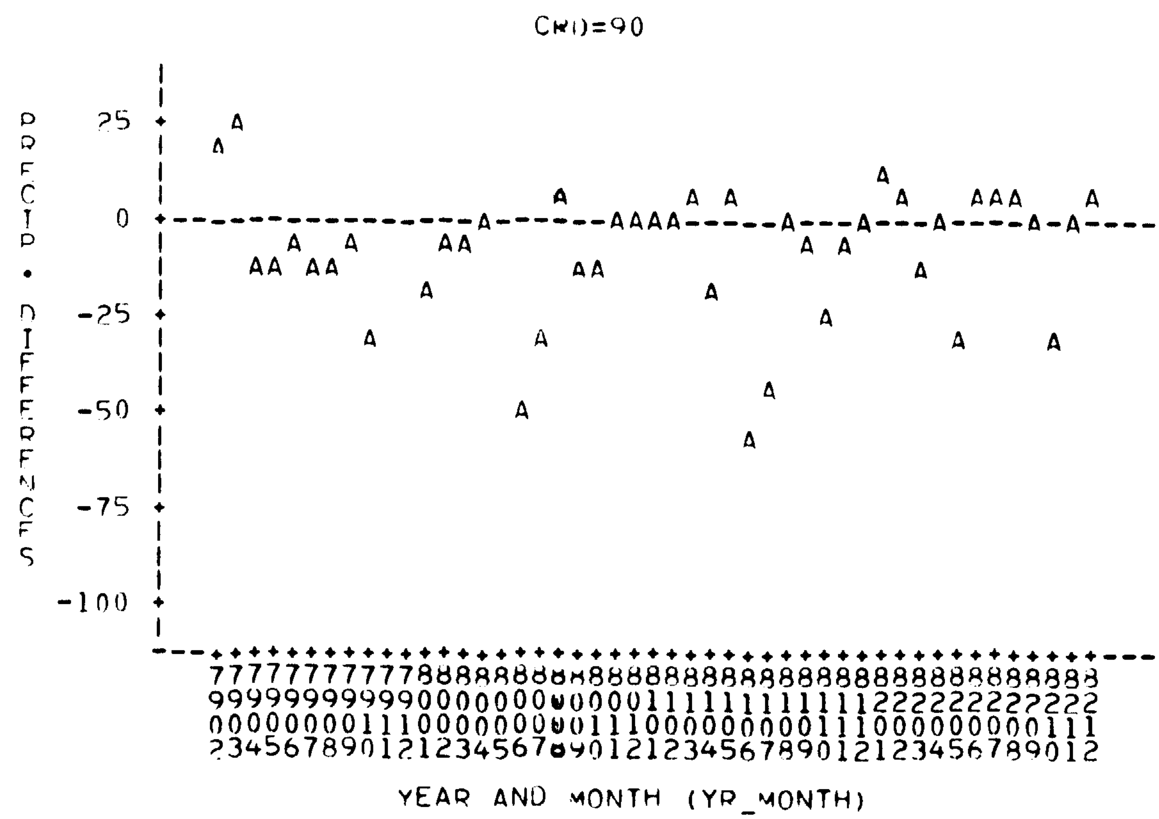


Appendix B, Part 2. Continued






CWD=90
TEMP. DIFFERENCES
5.0
2.5
0.0
-2.5
-5.0
YEAR AND MONTH (YR_MONTH)


CWD=90
PRECIP. DIFFERENCES
25
0
-25
-50
-75
-100
YEAR AND MONTH (YR_MONTH)

APPENDIX B, Part 3: Corresponds to Table 4 in text.

CRD 10

	Temperature	Precipitation
Bias = B (C^{o}) or (mm)	0.99	-5.27
Relative Bias = RB (%)	21.8	-16.8
Root Mean Square Error = RMSE (C^{o}) or (mm)	1.26	17.69
Relative Root Mean Square Error = RRMSE (%)	27.7	56.5
Standard Deviation = SD (C^{o}) or (mm)	14.1	64.9
Relative Standard Deviation = RSD (%)	49	81
Percent of YR_MONTHS Absolute Difference > (1^{o}C or 10 mm)	59.6	29.8
Largest Negative Difference (C^{o}) or (mm)	-1.2	-94.8
Largest Positive Difference (C^{o}) or (mm)	2.6	22.7
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	98	76
Pearson correlation coefficient between CAB and NCDC values	1.00	0.76

Appendix B, Part 3. Continued

CRD 20

	Temperature	Precipitation
Bias = B (C^o) or (mm)	0.93	-19.89
Relative Bias = RB (%)	21.3	-48.9
Root Mean Square Error = RMSE (C^o) or (mm)	1.15	31.82
Relative Root Mean Square Error = RRMSE (%)	26.4	78.2
Standard Deviation = SD (C^o) or (mm)	0.68	24.84
Relative Standard Deviation = RSD (%)	12.9	119.5
Percent of YR_MONTHS Absolute Difference > (1^oC or 10 mm)	51.1	57.8
Largest Negative Difference (C^o) or (mm)	-0.4	-91.9
Largest Positive Difference (C^o) or (mm)	2.4	23.6
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	100	75
Pearson correlation coefficient between CAB and NCDC values	1.00	0.69

Appendix B, Part 3. Continued

CRD 40

	Temperature	Precipitation
Bias = B (C^o) or (mm)	0.56	-10.90
Relative Bias = RB (%)	10.0	-29.9
Root Mean Square Error = RMSE (C^o) or (mm)	1.24	21.48
Relative Root Mean Square Error = RRMSE (%)	22.1	59.0
Standard Deviation = SD (C^o) or (mm)	1.10	18.51
Relative Standard Deviation = RSD (%)	17.9	72.5
Percent of YR_MONTHS Absolute Difference $\geq$ (1^oC or 10 mm)	47.8	39.1
Largest Negative Difference (C^o) or (mm)	-2.3	-89.7
Largest Positive Difference (C^o) or (mm)	3.6	20.8
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	98	83
Pearson correlation coefficient between CAB and NCDC values	1.00	0.83

Appendix B, Part 3. Continued

CRD 50

	Temperature	Precipitation
Bias = B (C^o) or (mm)	0.43	-17.32
Relative Bias = RB (%)	8.9	-43.3
Root Mean Square Error = RMSE (C^o) or (mm)	0.89	27.87
Relative Root Mean Square Error = RRMSE (%)	18.4	69.7
Standard Deviation = SD (C^o) or (mm)	0.78	21.84
Relative Standard Deviation = RSD (%)	14.8	96.4
Percent of YR_MONTHS Absolute Difference $\geq$ (1^oC or 10 mm)	17.0	46.8
Largest Negative Difference (C^o) or (mm)	-0.8	-89.0
Largest Positive Difference (C^o) or (mm)	3.7	8.3
Percent of YRMONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	98	89
Pearson correlation coefficient between CAB and NCDC values	1.00	0.79

Appendix B, Part 3. Continued

CRD 60

	Temperature	Precipitation
Bias = B (C^{o}) or (mm)	0.36	-10.44
Relative Bias = RB (%)	7.6	-25.6
Root Mean Square Error = RMSE (C^{o}) or (mm)	1.02	19.87
Relative Root Mean Square Error = RRMSE (%)	21.4	48.6
Standard Deviation = SD (C^{o}) or (mm)	0.96	16.90
Relative Standard Deviation = RSD (%)	18.6	55.5
Percent of YR_MONTHS Absolute Difference > (1^{o}C or 10 mm)	17.0	46.8
Largest Negative Difference (C^{o}) or (mm)	-1.6	-54.3
Largest Positive Difference (C^{o}) or (mm)	4.6	11.9
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	96	65
Pearson correlation coefficient between CAB and NCDC values	1.00	0.88

CRD 80

	Temperature	Precipitation
Bias = B (C^o) or (mm)	0.12	-6.93
Relative Bias = RB (%)	2.0	-19.4
Root Mean Square Error = RMSE (C^o) or (mm)	1.14	12.38
Relative Root Mean Square Error = RRMSE (%)	19.4	34.7
Standard Deviation = SD (C^o) or (mm)	1.14	10.26
Relative Standard Deviation = RSD (%)	18.9	35.7
Percent of YR_MONTHS Absolute Difference > (1^oC or 10 mm)	25.5	27.7
Largest Negative Difference (C^o) or (mm)	-1.5	-31.3
Largest Positive Difference (C^o) or (mm)	4.4	3.7
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	96	89
Pearson correlation coefficient between CAB and NCDC values	1.00	0.96

CRD 90

	Temperature	Precipitation
Bias = B (C^{o}) or (mm)	0.67	-8.26
Relative Bias = RB (%)	11.5	-21.0
Root Mean Square Error = RMSE (C^{o}) or (mm)	1.30	18.67
Relative Root Mean Square Error = RRMSE (%)	22.4	47.4
Standard Deviation = SD (C^{o}) or (mm)	1.11	16.74
Relative Standard Deviation = RSD (%)	17.2	53.8
Percent of YR_MONTHS Absolute Difference > (1^{o}C or 10 mm)	34.1	43.2
Largest Negative Difference (C^{o}) or (mm)	-1.1	-58.4
Largest Positive Difference (C^{o}) or (mm)	4.8	22.6
Percent of YR_MONTHS direction of change from the previous YR_MONTH in the CAB values agrees with the actual (NCDC) values (%)	98	77
Pearson correlation coefficient between CAB and NCDC values	1.00	0.86

Appendix C. Observed Significance Levels for Statistical Tests Referred to in Text

	CRD									Referred to on page no.
	10	20	30	40	50	60	70	80	90	
1. Shapiro-Wilk tests of normality on temperature differences	0.849	<0.01	< 0.01	0.209	<0.01	<0.01	<0.01	<0.01	<0.01	3
2. Shapiro-Wilk tests of normality on precipitation differences	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.015	3
3. Nonparametric ANOVA on temperature values after additive transformation	0.3822	0.2424	0.0204	0.5611	0.5611	0.2424	0.5611	0.1421	0.0236	14
4. Nonparametric ANOVA on precipitation values after additive transformation	0.0166	0.0765	0.0375	0.0375	0.1421	0.0375	0.0166	0.0375	0.1421	14
5. Nonparametric ANOVA on precipitation values after proportional transformation	0.3822	0.1421	0.7717	0.3822	0.2424	0.2424	0.7717	0.5611	0.2424	16

APPENDIX D

Formulae for measures of reliability for real-time weather value estimates

Y_i = Weather value as reported by NCDC for YR_MONTH i ("true" value)

$\hat{Y}_i$ = Weather value as estimated by CAB for YR_MONTH i

$d_i = \hat{Y}_i - Y_i$ = difference between CAB and NCDC values for YR-MONTH i

$RD_i = 100\ d_i/Y_i$ = relative difference for YR_MONTH i

i = 1,...,n = number of YR_MONTHs and $\Sigma = \sum_{i=1}^{n}$ = summation over the YR_MONTHs

$\overline{Y} = \frac{1}{n} \Sigma Y_i$

Bias = B = $1/n\ \Sigma d_i = \overline{d}$

Relative Bias = RB = $100\ B/\overline{Y}$

Mean Square Error = MSE = $1/n\ \Sigma d_i^2$

Root Mean Square Error = RMSE = $(MSE)^{\frac{1}{2}}$

Relative RMSE = RRMSE = $100\ RMSE/\overline{Y}$

Variance = Var = $1/n\ \Sigma (d_i - \overline{d})^2$

Standard Deviation = SD = $(Var)^{\frac{1}{2}}$

Relative SD = RSD = $100\ SD/(\overline{Y} + \overline{d})$

MSE = Var + B^2

Pearson r between $\hat{Y}_i$ and Y_i:
$$r = \frac{\left[\Sigma \hat{Y}_i Y_i - \frac{(\Sigma \hat{Y}_i)(\Sigma Y_i)}{n}\right]}{\left[\Sigma \hat{Y}_i^2 - \frac{(\Sigma \hat{Y}_i)^2}{n}\right]\left[\Sigma \hat{Y}_i^2 - \frac{(\Sigma Y_i)^2}{n}\right]^{\frac{1}{2}}}$$

APPENDIX E

Estimates of equation parameters for regressions of CAB precipitation estimates on NCDC precipitation values for 47 months in North Dakota

CRD	b_0	b_1
10	2.8863	0.7395
20	0.6486	0.4950
30	-1.0837	0.5782
40	4.6596	0.5728
50	2.7011	0.4992
60	-1.6531	0.7849
70	-2.0513	0.7557
80	0.2572	0.7985
90	4.0424	0.6876

*U.S. GOVERNMENT PRINTING OFFICE : 1984 O-420-931/SRS-727