CORN BLIGHT WATCH EXPERIMENT

FINAL REPORT

VOLUME III

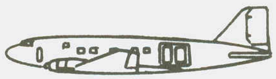
EXPERIMENT RESULTS

National Aeronautics and Space Administration

LYNDON B. JOHNSON SPACE CENTER

Houston, Texas

May 1974



1971 CORN BLIGHT WATCH EXPERIMENT FINAL REPORT

VOLUME III - EXPERIMENTAL RESULTS

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION
EARTH RESOURCES PROGRAM
LYNDON B. JOHNSON SPACE CENTER

The Corn Blight Watch Experiment Final Report, Volumes I, II, and III were cooperatively written and published by Purdue University, the Johnson Space Center, and the U. S. Department of Agriculture.

Table of Contents

GLOSSARY

Volume III

1. ACGS - Aerospace Cartographic and Geodetic Service (USAF)
2. A/D - analog to digital conversion system
3. AFB - Air Force Base
4. AOV - analysis of variance
5. ARC - Ames Research Center (Moffett Field, California--NASA)
6. ASCS - Agricultural Stabilization and Conservation Service (USDA)
7. CBR - Corn Blight Record
8. CBWE - Corn Blight Watch Experiment
9. CES - Cooperative Extension Service (USDA)
10. CIB - confidence interval-blight
11. CIS - confidence interval-stress
12. CRT - cathode-ray tube
13. DEW Line - Dixie Early Warning Line
14. DLSN - disease lesion(s)
15. DRC - Data Reduction Center
16. DSTK - dry stalk(s)
17. EOAPO - Earth Observations Aircraft Program Office (NASA-MSC)
18. EPIMAY - Epidemiology of *Helminthosporium maydis* (computer simulation program)
19. ERTS - Earth Resources Technology Satellite
20. FOPS - Film Output Specification Branch (NASA-MSC)
21. FSTK - fertile stalk(s)
22. GOS - Ground Observation Summary
23. GSTK - green stalk(s)
24. IR - infrared
25. ISA - intensive study area

26. kHz - kilohertz

27. LAI - Leaf Area Index

28. LARS - Laboratory for Applications of Remote Sensing (Purdue University)

29. LARSYS - LARS' pattern recognition-oriented data analysis software system

30. LARSYSAA - LARS' multispectral image data analysis program

31. MCBT - Master Corn Blight Tape

32. MSB - Mapping Sciences Branch (NASA-MSC)

33. MSC - Manned Spacecraft Center (NASA)

34. MSS - multispectral scanner

35. N-Cytoplasm - "normal" corn (blight resistant)

36. NASA - National Aeronautics and Space Administration

37. NCBT - incubating fungi

38. n.m. - nautical miles

39. NOAA - National Oceanic and Atmospheric Administration

40. non-ISA - non-intensive study area

41. NWS - National Weather Service (NOAA)

42. OMB - Office of Management and Budget

43. PDRC - Photo Data Reduction Center

44. PI - photointerpretation or photo-interpreter

45. PTD - Photographic Technology Division Laboratory (NASA-MSC)

46. SCLB - southern corn leaf blight

47. SPARC - Spectral Analysis and Recognition Computer

48. SPOR - spore(s)

49. SRS - Statistical Reporting Service (USDA)

50. SSO - State Statistical Office(s) (SRS)

51. Table 1.09, Figure 2.10 or Appendix II-A Code reference to Tables, Figures and Appendices in this Report. Table 1.09 is the ninth Table in Vol. I. Figure 2.10 is the tenth Figure in Vol. II. Appendix II-A is the first Appendix in Vol. II.

52. TMS - Texas male sterile (corn cytoplasm)

53. USAF - United States Air Force

54. USDA - United States Department of Agriculture

55. WCATCH - "wet catch"

56. WDPC - Washington Data Processing Center

57. WRL - Willow Run Laboratories (University of Michigan)

FIGURES

In-Depth Analysis of Segment 212

Economic Analyses

(no figures)

Related Projects

Summary and Conclusions

(no figures)

TABLES

Page

Section I.

Introduction

I. INTRODUCTION

Volume III of the Corn Blight Watch Experiment, Final Report describes the analysis performed on the data acquired during the 1971 Corn Blight Watch Experment and discusses the results obtained from these analyses. Remote sensing techniques and concepts are evaluated with reference to their use in (1) detecting the development and spread of SCLB across the Corn Belt Region; (2) assessing different levels of infection present in the Corn Belt; (3) amplifying information acquired by ground visits to better assess blight status and its probable impact on crop production; and (4) estimating the applicability of these techniques to similar situations in the future.

Sections II, III, and IV of this volume discuss the blight estimates arrived at by the three distinct techniques used - ground observation, photointerpretation and multispectral imagery analysis. Section V, Evaluation of Blight Classification Results, is important in that it describes both the accuracy achieved and the techniques utilized in evaluating the performance. Many of these same procedures can be utilized in the future to evaluate other remote sensing classifications.

Section VI describes the intensive analysis conducted on the results from one segment covered by the Experiment. Included are several significant investigations into reasons classification performances were what they were, the results of some basic research to quantify the spectral changes caused by blight, and discussion of extraneous factors affecting classifications. An attempt to quantify the variability among analysts is also included.

Section VII contains material and discussions which led to tentative conclusions about the economic efficiency of remote sensing. In other words, is the product worth the cost? Considerable information is presented both on what it cost to conduct the various remote sensing functions and on what it would have cost to obtain the same or equivalent information using conventional survey techniques. This section concludes with a discussion of ways available resources can be used to obtain the most information at the least cost.

Section VIII reports the results of a NOAA computer simulation of SCLB development and a NASA aerial SCLB spore-collection experiment. These projects were conducted separately but in cooperation with the CBWE, and their results show how other kinds of information gathering may someday support and complement remote sensing.

In the final section of the report, the Experiment results are summarized and measured against the objectives of monitoring the spread of SCLB, assessing the impact of SCLB on production, and estimating the applicability of remote sensing to other wide-scale surveys. A look to the future is provided by reviewing the insights gained from the CBWE into a remote sensing system designed to collect, analyze, interpret, and distribute information repeatedly and at short intervals. Finally, guidelines for future research and technology development are presented.

SECTION II.

FIELD OBSERVATION RESULTS

II. FIELD OBSERVATION RESULTS

Introduction

The ground-observed spatial and temporal development of blight in the CBWE test area was discussed in Volume II, as were the procedures for expanding the biweekly observations to estimates for the intensive and non-intensive study areas (ISA and non-ISA). Following a brief review of that blight spread, this section discusses the quantitative ground estimates of blight severity and the effect SCLB had on yield.

The development of SCLB during the 1971 growing season is summarized in Figure 3.01. Through July 30 the average blight severity over the entire area was only none to slight although in T-cytoplasm fields mild levels of infection were developing in Missouri, southern Illinois, and southern and west-central Indiana. Two weeks later, there had been a further increase in the prevalence and severity of blight infection with some areas of severe infection present in Illinois and Indiana.

By the last week of August, blight infection had become even more widespread with at least mild levels present in much of the eastern Corn Belt area. The severely infected areas in Illinois and Indiana were now being called "hotspots," a reflection of their isolated nature. By the end of the growing season, less than 20 percent of the acreage had moderate (level 3) or severe (level 4) infection levels, and only about 5 percent of the total crop was severely infected (Figure 3.02). Although there was some further increase in the severity of leaf infection in September, most of the crop was nearly mature and further infection had little or no effect on yield. In fact, it should be noted that the 1971 growing season produced the highest yields on record. Even though blight was only locally severe, it was an omnipresent influence; 55 percent of the acreage in the Corn Belt had slight (1) or mild (2) levels of infection. With warmer, more humid weather these acres would have developed to more severe levels.

A. Acreage Estimates

The results of the expansion of ground observation data (described in Vol. I and II) are shown in Tables 3.01 to 3.04 for the four mission periods extending from July 26 to September 19. These tables show the estimated number of acres, by cytoplasm, of each blight severity class present in the non-ISA, the ISA, and the total area.

The same results are summarized in Figures 3.03 and 3.04 where the average blight severity level of each flightline and of the intensive area is shown for mission periods 4, 5, 6, 7. (The maps of blight development shown in Section I of Vol. II are based on these data.)

As can be seen from the tables, the effect of cytoplasm on blight severity is quite evident. In general, as had been expected, very little SCLB developed in the normal cytoplasm fields, the TMS

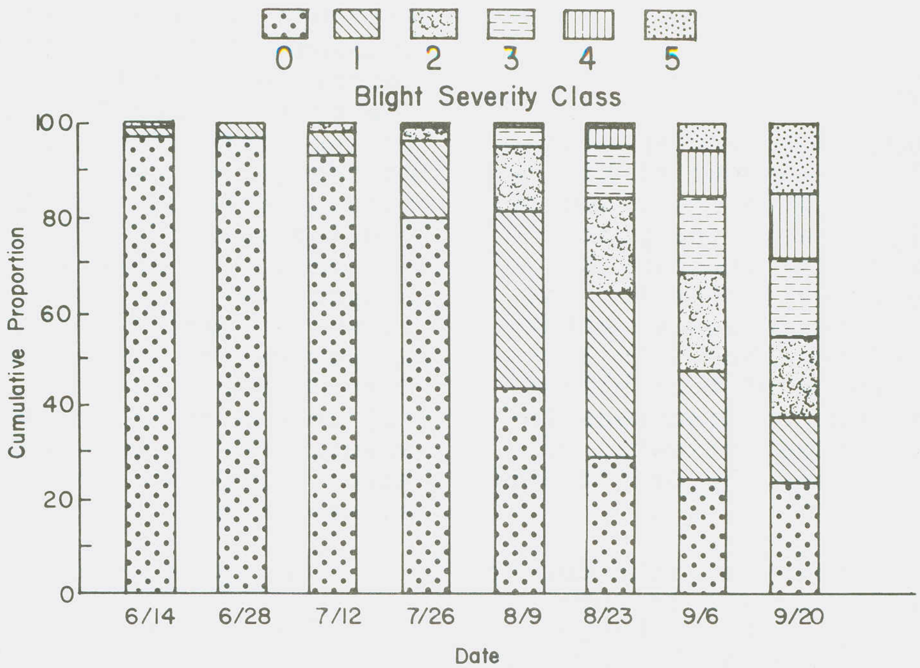


Figure 3.01. Development of SCLB during 1971 in the Corn Belt area.

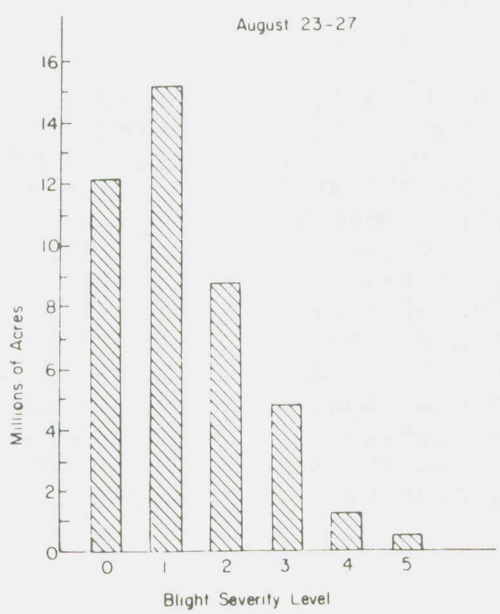


Figure 3.02. Number of acres in each blight severity class in the total test area.

Table 3.01 Estimates of blight extent based on field observations: July 26-30.

Location	Cytoplasm	Number of Acres per Blight Severity Level 0	1	2	3	4	5
Non-ISA*	N	8,609,068	1,361,750	24,753	47,779	6,080	0
	T	10,324,608	1,734,015	435,844	151,534	110,300	0
	B	9,514,831	2,196,331	390,009	99,889	26,945	0
	F-2	196,181	85,795	18,813	2,483	2,008	0
	O	4,671,744	639,089	123,897	37,475	10,270	0
	TOTAL	33,334,432	6,016,980	993,316	339,160	155,603	0
ISA	N	288,392	282,924	64,796	18,010	2,951	0
	T	67,400	86,365	50,647	36,716	13,670	0
	B	389,775	275,025	100,991	35,284	2,386	0
	F-2	45,483	13,150	2,777	8,159	0	0
	O	141,874	120,304	49,128	43,356	0	0
	TOTAL	932,924	777,768	268,339	141,525	19,007	0
Total Area	N	8,897,460	1,644,674	89,549	65,789	9,031	0
	T	10,410,008	1,820,380	486,491	188,250	123,970	0
	B	9,904,606	2,471,356	491,000	135,173	29,331	0
	F-2	241,664	98,945	21,590	10,642	2,008	0
	O	4,813,618	759,393	173,025	80,831	10,270	0
	TOTAL	34,267,356	6,794,748	1,261,655	480,685	174,610	0

*ISA: Intensive Study Area

Table 3.02 Estimates of blight extent based on field observations: August 9-13.

		Number of Acres per Blight Severity Level					
Location	Cytoplasm	0	1	2	3	4	5
Non-ISA	N	5,940,107	2,813,453	1,068,465	142,981	32,821	47,779
	T	4,943,764	5,430,412	1,626,847	421,372	257,817	93,149
	B	4,460,097	5,238,064	1,850,666	553,877	121,964	0
	F-2	143,369	56,321	91,659	6,566	4,244	2,008
	O	2,294,297	2,427,591	561,081	146,642	24,807	26,222
	TOTAL	17,781,634	15,965,841	5,198,718	1,271,438	441,653	169,158
ISA	N	224,117	119,132	208,580	67,313	34,633	0
	T	17,533	36,282	78,857	77,859	19,486	24,651
	B	104,073	203,893	318,121	134,105	43,139	0
	F-2	36,759	8,810	13,063	4,947	5,858	0
	O	75,689	138,142	64,448	49,779	694	25,996
	TOTAL	458,171	506,259	683,069	334,003	103,810	50,647
Total Area	N	6,164,224	2,932,585	1,277,045	210,294	67,454	47,779
	T	4,961,297	5,466,694	1,705,704	499,231	277,303	117,800
	B	4,564,170	5,441,957	2,168,787	687,982	165,103	0
	F-2	180,128	65,131	104,722	11,513	10,102	2,008
	O	2,369,986	2,565,733	625,529	196,421	25,501	52,218
	TOTAL	18,239,805	16,472,100	5,881,787	1,605,441	545,463	219,805

Table 3.03 Estimates of blight extent based on field observations: August 23-27.

Location	Cytoplasm	Number of Acres per Blight Severity Level 0	1	2	3	4	5
Non-ISA	N	4,360,348	3,276,784	1,463,551	599,799	298,360	44,863
	T	3,405,369	4,950,395	2,449,331	1,309,445	453,081	203,774
	B	2,619,626	4,580,106	2,919,477	1,590,094	467,467	48,103
	F-2	92,437	60,944	63,579	57,801	21,902	7,451
	O	1,289,768	1,971,269	1,331,531	623,721	154,159	88,235
	TOTAL	11,767,548	14,839,469	8,227,469	4,180,860	1,394,969	392,426
ISA	N	158,409	100,253	123,253	117,093	115,053	42,141
	T	10,893	21,005	44,441	74,864	66,705	36,803
	B	31,421	129,505	257,318	251,068	103,031	30,944
	F-2	34,633	8,028	5,251	8,028	7,508	5,987
	O	68,658	63,233	110,409	49,562	57,201	5,685
	TOTAL	304,014	322,024	541,412	500,615	349,498	121,562
Total Area	N	4,518,757	3,377,037	1,587,544	716,892	413,413	87,004
	T	3,416,262	4,971,400	2,493,772	1,384,309	519,786	204,577
	B	2,651,047	4,709,611	3,176,795	1,841,162	570,498	79,047
	F-2	127,070	68,972	68,830	65,829	29,410	13,440
	O	1,358,426	2,034,502	1,441,502	673,283	211,360	93,920
	TOTAL	12,071,562	15,161,522	8,768,881	4,681,475	1,744,467	513,988

Table 3.04 Estimates of blight extent based on field observations: September 6-10.

Location	Cytoplasm	Numbers of Acres per Blight Severity Level					
		0	1	2	3	4	5
Non-ISA	N	3,628,216	2,561,878	1,815,663	895,341	827,722	313,081
	T	3,283,804	3,223,270	2,924,099	1,618,347	1,070,301	650,624
	B	1,813,417	2,849,320	2,900,523	2,807,643	1,320,893	533,919
	F-2	72,035	13,748	67,856	62,607	64,270	23,425
	O	1,001,246	1,335,819	1,167,728	1,175,504	508,280	270,939
	TOTAL	9,798,718	9,984,035	8,875,869	6,559,442	3,791,466	1,791,988
ISA	N	145,042	66,749	69,049	109,845	97,780	168,218
	T	14,191	0	31,638	63,277	34,025	111,668
	B	29,555	52,253	111,060	195,516	209,491	205,542
	F-2	33,765	5,164	347	5,251	9,330	15,523
	O	30,553	18,531	86,886	86,713	75,646	56,333
	TOTAL	253,106	142,697	298,980	460,602	426,272	557,384
Total Area	N	3,773,258	2,628,627	1,884,712	1,005,186	925,502	481,299
	T	3,297,995	3,223,270	2,955,737	1,681,624	1,104,326	762,292
	B	1,842,972	2,901,573	3,011,583	3,003,159	1,530,384	739,461
	F-2	105,800	18,912	68,203	67,858	73,600	39,048
	O	1,031,799	1,354,350	1,254,614	1,262,217	583,926	327,272
	TOTAL	10,051,824	10,126,732	9,174,849	7,020,044	4,217,738	2,349,372

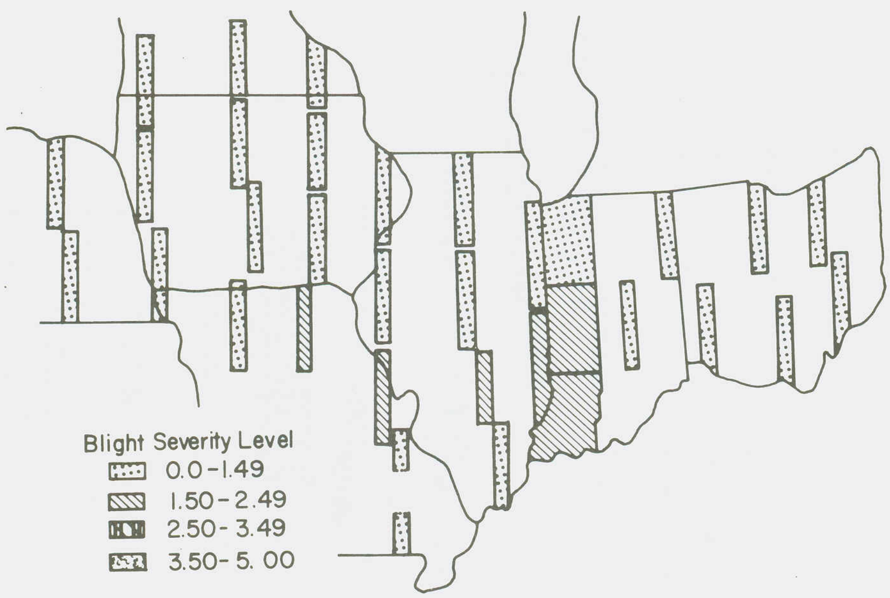


Figure 3.03. Average blight severity by flightline for July 26-30 (top) and August 9-13 (bottom).

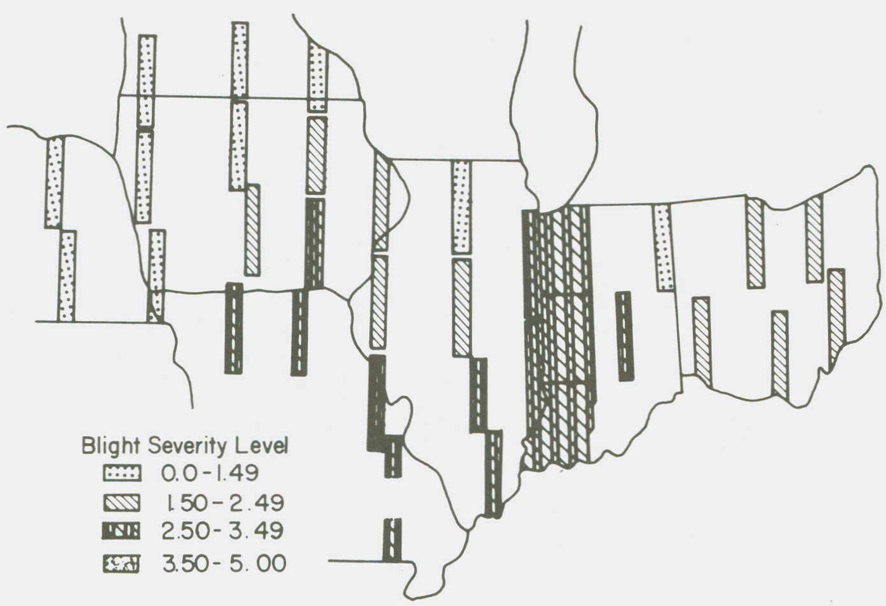


Figure 3.04. Average blight severity by flightline for August 23-27 (top) and September 6-10 (bottom).

cytoplasm fields had the largest percentage of moderate to severe blight infection, and the blend fields were affected to an intermediate extent. The data in the tables needs to be considered in the light of the unequal number of acres planted with each cytoplasm. Further evidence of the effect of cytoplasm on blight severity is shown in Table 3.05 which lists the weighted average blight severity of each cytoplasm for the entire study area.

B. Variance of Acreage Estimates

The variances, coefficients of variation (CV), and confidence intervals of the acreage estimates for mission periods 5 and 6 (Aug. 9-Sept. 5) are shown in Tables 3.06 to 3.08 for the non-ISA, the ISA, and the total area. These variances are measures of the variation of blight levels present at the place under consideration at a given time. Earlier in the summer, for instance, the variances were smaller, especially for the lower blight levels, since most fields tended to be either blight level 0, 1, or 2 (see Figure 3.01).

Since the magnitude of variance is a function of the number of acres in a blight class, variances between blight classes or areas cannot be compared directly. However, the coefficient of variation, which is a measure of relative variation, does permit such comparisons. These statistics (Table 3.07) indicate that the precision of the blight severity acreage estimates was similar for the ISA and non-ISA. This is a somewhat unexpected result since it had been anticipated that the total variances of each blight level estimate would be smaller (greater precision) in the ISA because segments were not restricted to flightlines. The explanation is that in much of the non-ISA, blight development was restricted to only one or two blight severity levels, thereby resulting in less variation within a blight class while in the ISA blight was spread over more severity classes.

The effect of the sampling model on the precision of the acreage estimates is illustrated in Table 3.06 which shows the individual sources of variation. Note that in the non-ISA, the variation due to flightlines is by far the largest factor (greater than 99 percent of the total variation). The next greatest source of variation is that due to segments. Though the variation among fields in a segment is 10 to 50 times that due to within-field variation, these two sources of variance are very small compared to the segment and flightline effects.

In the ISA the total variance is considerably smaller than that in the non-ISA. However, differences among the segments account for more than 99 percent of the total variation that does exist. Within- and between-field variances are similar in magnitude to those found in the non-ISA. The most significant conclusion that can be drawn from these results is that for a phenomenon such as SCLB, which varies considerably from location to location, a more random location of samples without the restrictions of flightlines (or even segments) would be beneficial.

Table 3.05 Weighted averages of blight severity for individual cytoplasms throughout the growing season.

Date	Non-ISA						ISA						Total Area					
	N	T	B	F-2	Other	Ave.	N	T	B	F-2	Other	Ave.	N	T	B	F-2	Other	Ave.
6/14- 6/27	0.30	0.03	0.05	0.01	0.01	0.04	0.11	0.06	0.10	0.27	0.06	0.09	0.04	0.04	0.06	0.06	0.02	0.04
6/28- 7/11	0.02	0.04	0.03	0.05	0.02	0.03	0.20	0.21	0.21	0.41	0.12	0.19	0.03	0.04	0.04	0.12	0.02	0.04
7/12- 7/25	0.03	0.10	0.08	0.21	0.07	0.07	0.30	0.62	0.28	0.42	0.25	0.33	0.05	0.11	0.09	0.25	0.08	0.09
7/26- 8/8	0.16	0.27	0.28	0.45	0.19	0.24	0.73	1.38	0.74	0.62	0.98	0.85	0.19	0.30	0.31	0.49	0.24	0.27
8/9 - 8/22	0.57	0.90	0.91	0.94	0.77	0.80	1.34	2.47	1.76	1.05	1.55	1.66	0.62	0.93	0.96	0.96	0.82	0.85
8/23- 9/5	0.94	1.30	1.42	1.60	1.39	1.26	2.09	3.08	2.45	1.48	1.94	2.30	1.01	1.34	1.48	1.58	1.42	1.31
9/6 - 9/19	1.37	1.68	2.05	2.34	1.94	1.75	2.69	3.72	3.39	1.97	2.92	3.09	1.45	1.72	2.13	2.27	2.00	1.82
9/20-10/3	1.84	2.13	2.56	2.94	2.57	2.25	2.90	4.13	3.85	1.97	3.33	3.45	1.90	2.16	2.64	2.76	2.62	2.31

Table 3.06 Sources of variation in the blight severity class acreage estimates based on field observations.

Date	Location	Source of Variation	Blight Severity Class 0	1	2	3	4	5
August 9-13	Non-ISA	Within Fields ($x10^6$)	.1358	.1873	.0991	.0300	.0092	.0016
		Among Fields ($x10^7$)	.5305	.4714	.3094	.0636	.0235	.0079
		Among Segments ($x10^{10}$)	.8858	.8959	.2213	.0326	.0104	.0060
		Among Flightlines ($x10^{13}$)	.3221	.2536	.0450	.0066	.0011	.0007
		Total ($x10^{13}$)	.3230	.2545	.0452	.0067	.0011	.0007
	ISA	Within Fields ($x10^5$)	.3937	.6973	.6425	.4290	.3080	.0855
		Among Fields ($x10^7$)	.1487	.1265	.1321	.0866	.0326	.0518
		Among Segments ($x10^{10}$)	.4962	.3795	.8997	.3358	.0616	.0995
		Total ($x10^{10}$)	.4964	.3797	.8998	.3359	.0616	.0995
August 23-27	NonISA	Within Fields ($x10^6$)	.1086	.2348	.2021	.0658	.0275	.0086
		Among Fields ($x10^7$)	.5127	.5743	.4211	.3266	.0659	.0139
		Among Segments ($x10^{10}$)	.5310	.8100	.3826	.1363	.0512	.0078
		Among Flightlines ($x10^{13}$)	.2224	.2677	.0782	.0325	.0063	.0010
		Total ($x10^{13}$)	.2230	.2685	.0785	.0326	.0063	.0010
	ISA	Within Fields ($x10^5$)	.3377	.3608	.6399	.5212	.4328	.1870
		Among Fields ($x10^7$)	.0989	.1013	.1161	.1261	.0951	.0383
		Among Segments ($x10^{10}$)	.3533	.3222	.5896	.4810	.3805	.1339
		Total ($x10^{10}$)	.3534	.3222	.5896	.4810	.3805	.1339

Table 3.07 Coefficients of variation for blight severity acreage estimates based on field observations.

Date	Location	Blight Severity Class 0	1	2	3	4	5
		Percent					
August 9-13	Non-ISA	10.1	9.9	12.9	20.3	23.9	49.0
	ISA	15.4	12.2	13.9	17.4	23.9	62.3
	Total Area	9.9	9.6	11.5	16.5	19.9	40.4
August 23-27	Non-ISA	12.7	11.0	10.8	13.7	18.1	26.1
	ISA	19.5	17.6	14.2	13.8	17.6	30.1
	Total Area	12.4	10.8	10.1	12.3	14.9	21.1

Table 3.08 Ninety-five percent confidence intervals for blight severity acreage estimates based on field observations.

Date	Location	Blight Severity Class 0	1	2	3	4	5
		(000 acres)					
August 9-13	Non-ISA	14,187- 21,376	12,775- 19,156	3,853- 6,543	754- 1,788	230- 653	3- 335
	ISA	317- 599	383- 629	493- 873	218- 450	54- 153	0- 113
	Total Area	14,642- 21,937	13,279 19,665	4,523- 7,239	1,075 2,135	327- 763	42- 397
August 23-27	Non-ISA	8,781- 14,754	11,562- 18,117	6,454- 10,000	3,038- 5,323	891- 1,899	188- 587
	ISA	185- 430	208- 436	388- 695	362- 639	226- 473	48- 194
	Total Area	9,082- 15,060	11,882- 18,441	6,989- 10,548	3,530- 5,832	1,222- 2,263	296- 731

C. Influence of Blight on Yields

Field observation data were used for a study of the influence of SCLB on yields. In most of the test area, blight did not seriously lower corn yields. In fact, state average yields were the highest ever recorded (see Section 1, Volume 2). Despite this, there were certain restricted areas where blight did significantly reduce yields.

Of the more than 1400 fields for which yield estimates were made, 91 T-cytoplasm fields had blight levels 3, 4, or 5 during the August 23-27 observation period when ear-filling was occurring. Twenty-four of the fields which had also had moderate to very severe blight levels on July 26-30 produced an average yield of only 71 bushels per acre. This contrasts with those TMS fields which had none to mild blight on July 26-30. There the average yield was 97 bushels per acre. The blend fields from the same segments had mild to moderate blight levels in late August and yielded an average 118 bushels per acre; the normal cytoplasm fields yielded 130 bushels per acre.

The effect of blight on corn yields over the entire test area was also investigated using the yield data collected for the eight to 10 fields in each segment for which ground observations were made during the summer (data available from a total of 2941 sample units). The results are weighted by the acreages of each cytoplasm type present in a segment. As was stated in Volume II, the cytoplasms were not uniformly distributed over the test area. Relatively more susceptible T-cytoplasm was planted in the western and northern Corn Belt -- an area in which blight did not develop. Corn yields, however, were not as high there as in eastern Iowa, Illinois, and Indiana where blight developed to a greater extent (Figure 3.05). These differences are associated with the natural productivity of the areas involved, rather than with blight.

The average yields associated with each blight level at four times during the growing season are summarized in Figure 3.06. Note that the estimates reported are somewhat higher than those reported by USDA for the major corn producing states since the figure portrays only an estimate of physiological yield and makes no allowance for harvest loss. While the estimates for any one field are not reliable because of the small size of the sample from each field, the overall estimates are considered to reflect the yield situation quite precisely except for the overestimation (about 10 percent) mentioned above. The coefficients of variation for the yield estimates for the individual blight classes vary from 3.8 to 5.4 percent for blight classes 0 to 4 and to 9.7 percent for blight class 5 during period 7.

Figure 3.06 shows the relationship of yield to the time that blight developed. These data are the weighted averages of all yield and blight data collected for the entire test area. As

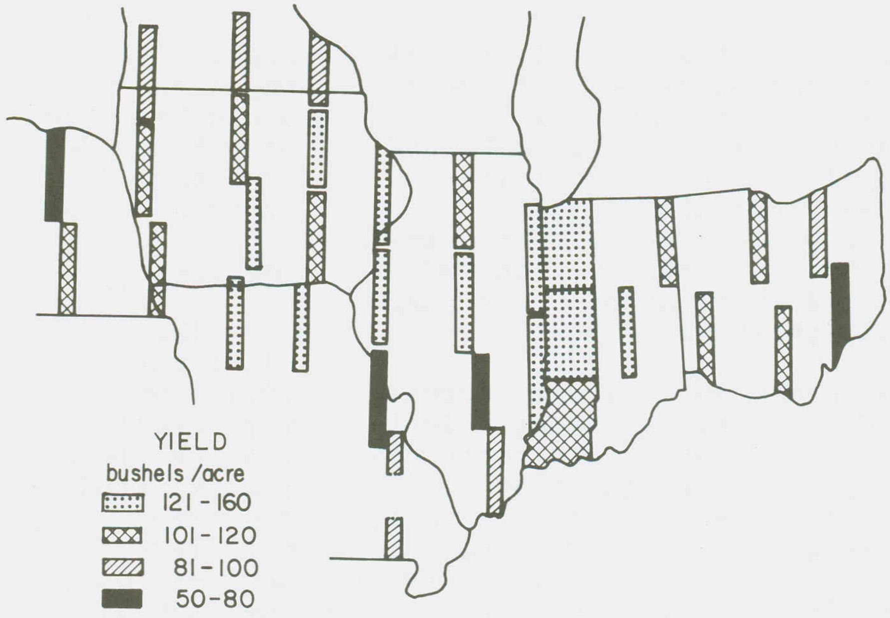


Figure 3.05. Effect of geographic location on average corn yield.

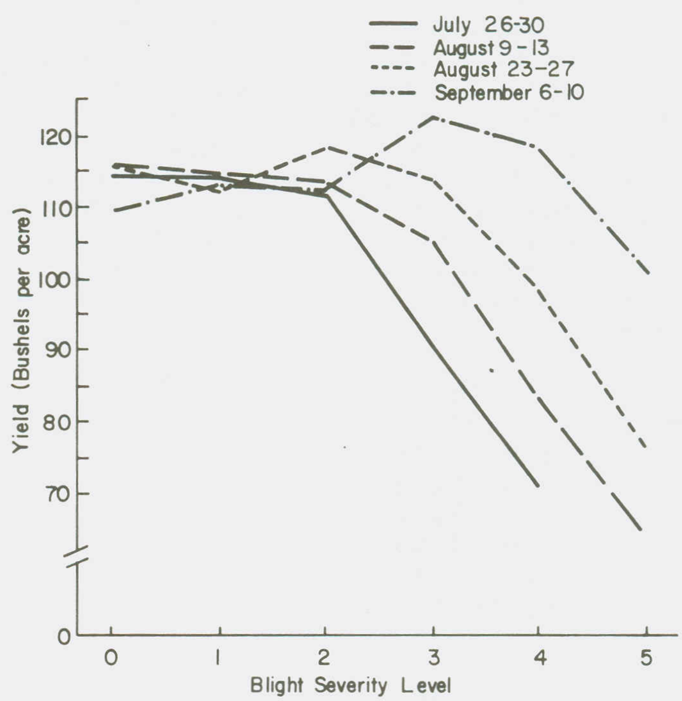


Figure 3.06. Effect of severity and time of blight infection on corn yield.

before, blight levels of 2 or less had no effect on yield, but there were substantial reductions in yield as severity increased beyond that point. Also, the earlier in the season moderate to severe blight occurred, the more the yields were reduced. Actually, however, only a small portion of the acreage fell into these categories.

There was an apparent increase in yield for fields showing blight levels 3 and 4 during the September 6-10 period. Since the crop is nearly mature at this time of year, blight would have had no direct effect on yield. The yield increase is more likely due to the predominance of the higher yielding TMS and blend cytoplasm fields in the eastern half of the test area (see Figure 3.05).

To obtain an estimate of the effect of SCLB on total corn production, the acres of each blight level (all cytoplasms included) were multiplied by the estimated yield per acre. For the August 23-27 mission, during the critical ear-filling period, the average yield of those acres having blight levels 0, 1, 2, or 3 was 114.9 bushels per acre. The 112-to 119-bushel-per-acre range in yield in these four severity levels was not a significant difference.

Of the 1290 acres of corn in the average segment, 1200 acres had blight level 3 or less. Of the remaining 90 acres, 68 had blight level 4 with an average yield of 98.5 bushels per acre and 22 had blight level 5 and produced an average yield of 76.4 bushels per acre.

The average yield for the segment then was 113.3 bushels per acre or 1.3 percent less than would have been expected if no blight had developed. This represents a loss of 1960 bushels in total production per segment.

Conclusions

There was a high incidence of blight in the Corn Belt in 1971, but the severity was not very great. Severe blight infection was restricted to only a few isolated areas until after the crop was mature. Slight to mild infection levels were present, however, over a large portion of the Corn Belt acreage. While the incidence of blight was quite high, its impact on yield was very small. The weather conditions which prevented the disease from developing to more severe levels were favorable for high yields. In fact, record breaking yields were produced. Only in those few areas where blight developed to severe levels early in the season was there a noticeable reduction in yield. It is significant, however, that the severe levels of blight which did affect yield were those most accurately detected by remote sensing techniques.

Section III.

Photointerpretation Results

III. PHOTOINTERPRETATION RESULTS

Introduction

Photointerpretation results from aerial color IR imagery acquired during 1970 indicated that blight-infected corn fields were detectable since their responses were lower than those of surrounding, healthy fields. It was on this premise that the photo-analysis portion of the 1971 Corn Blight Watch Experiment was based.

Three components of that premise were:

1. that changes in color infrared film response were a reliable measure of the degree of blight infection;
2. that interpreters possessing good color perception and working with predefined corn fields could identify different levels of response associated with different levels of blight infection; and
3. that film emulsion and processing variables could be held to a minimum so that variations in the observed response of corn fields definitely indicated a variation in the fields.

The results presented in this section, then, measure the validity of these assumptions, as well as the ability of photo-interpreters to identify blight infection from small-scale color infrared photography, and the success of photo-interpreters in distinguishing and identifying crops.

A. Blight Detection and Classification

Individual Blight Classes

--Acreage Estimates--

Tables 3.09 and 3.10 show the photointerpretation-based expanded estimates of acreages of each blight severity level for two missions (those beginning August 9 and 23). Similar tables based on field observation data are included in Section II of this Volume and are useful for comparative purposes.

The acreage of corn estimated by PI's to be present in each blight severity class is summarized in Figure 3.07 for all missions. During the first four mission periods (July 14 through August 8) approximately 99 percent of all corn fields were identified as blight level 0 by the photointerpreters. The ground observations (Figure 3.01), on the other hand, showed a gradually decreasing percentage of uninfected corn during periods 1 through 4 and a corresponding increase in blight level 1. The fact that this increase does not show in the PI-derived estimates indicates that slight SCLB infections caused no perceivable change in response on the color IR film.

The missions beginning August 9 and 26 are considered to be the most useful for evaluating the photointerpretation results since these are the only periods for which representative amounts of blight were present and data was

Table 3.09 Estimate of the blight severity and extent based on photointerpretation: August 9-22.

Location	Cytoplasm	Acres per Blight Severity Level					
		0	1	2	3	4	5
Non-ISA	N	8,054,790	835,628	485,438	248,438	109,447	3,272
	T	8,898,691	1,643,857	1,453,787	465,101	90,363	11,761
	B	8,443,601	1,566,053	1,221,577	316,083	118,648	561
	F-2	124,923	55,533	76,172	27,907	10,767	2,354
	O	3,471,422	779,403	801,197	269,708	44,625	1,760
	TOTAL	28,993,427	4,880,474	4,038,171	1,327,317	373,850	19,708
ISA	N	463,555	15,450	116,138	52,904	5,468	1,909
	T	67,313	14,452	108,803	42,792	11,544	8,419
	B	475,273	29,381	202,938	72,651	17,707	3,515
	F-2	43,964	3,298	19,269	5,945	347	0
	O	200,160	17,056	100,731	30,076	4,383	520
	TOTAL	1,250,265	79,637	547,879	204,368	39,449	14,363
Total Area	N	8,518,345	851,078	601,576	301,422	114,915	5,181
	T	8,966,004	1,658,309	1,562,590	507,893	101,907	20,180
	B	8,918,874	1,595,434	1,424,515	388,734	136,355	4,076
	F-2	168,887	58,831	95,441	33,852	11,114	2,354
	O	3,671,582	796,459	901,928	299,784	49,008	2,280
	TOTAL	30,243,692	4,960,111	4,586,050	1,531,685	413,299	34,071

Table 3.10 Estimate of blight severity and extent based on photointerpretation: August 23-September 5.

Location	Cytoplasm	Acres per Blight Severity Level					
		0	1	2	3	4	5
Non-ISA	N	5,509,662	956,296	1,745,690	1,305,115	314,009	29,105
	T	5,486,972	1,480,075	2,904,270	1,925,499	644,165	152,150
	B	5,752,522	1,470,517	2,592,205	1,758,952	453,513	69,951
	F-2	78,278	23,241	74,347	93,279	27,993	8,542
	O	1,923,544	824,720	1,352,494	958,985	286,340	72,565
	TOTAL	18,750,978	4,759,849	8,669,006	6,041,830	1,726,020	332,313
ISA	N	167,306	10,936	149,990	198,902	107,979	19,443
	T	18,227	5,641	40,318	103,986	53,512	31,855
	B	116,225	13,757	207,842	279,712	143,306	40,188
	F-2	3,558	911	11,066	20,007	36,933	433
	O	50,126	5,034	104,376	127,378	53,989	12,021
	TOTAL	355,442	36,279	513,592	729,985	395,719	103,940
Total Area	N	5,676,968	967,232	1,895,680	1,504,017	421,988	48,548
	T	5,505,199	1,490,716	2,944,588	2,029,485	697,677	184,005
	B	5,868,747	1,484,274	2,800,047	2,038,664	596,819	110,139
	F-2	81,836	24,152	85,413	113,286	64,926	8,975
	O	1,973,670	829,754	1,456,870	1,086,363	340,329	84,586
	TOTAL	19,106,420	4,796,128	9,182,598	6,771,815	2,121,739	436,253

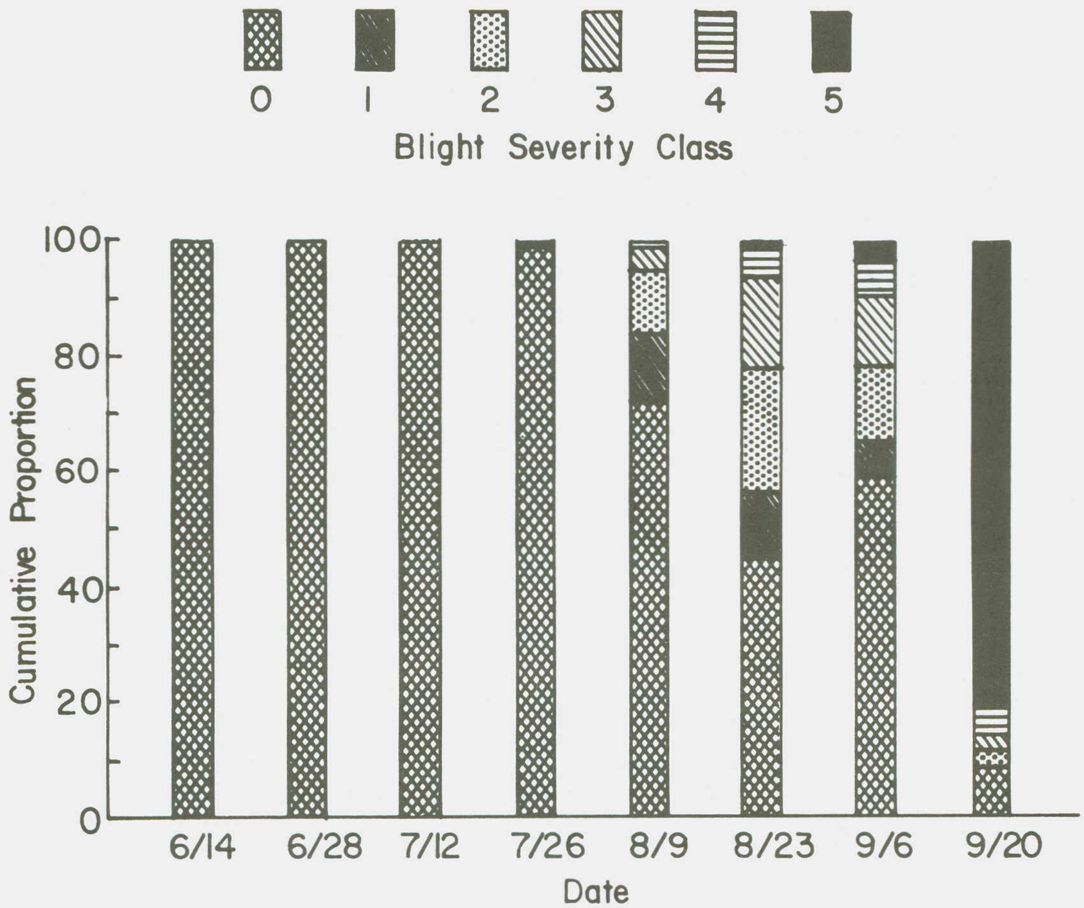


Figure 3.07. Development of SCLB throughout the summer as estimated by photointerpretation.

collected for the entire test area. In the preceding mission and following mission, weather conditions and aircraft mechanical problems limited coverage to only the western half of the test area. Data from the last mission is not considered reliable since by the start of that mission on September 20 most of the corn was undergoing natural senescence which caused considerable overestimation of blight severity.

In Figure 3.08 the estimates of the acreage of each blight severity class present in the total test area (for the August 23-September 5 mission period) is compared to the photointerpretation estimates. There is good agreement between PI and ground estimates except for blight levels 0 and 1. Relative to ground observations, blight level 0 was overestimated and blight level 1 underestimated.

The photointerpretive results are summarized in Figures 3.09 and 3.10 in the form of weighted average blight severity levels by flightline. These maps show the changing blight situation as seen by the photo-interpreters. Comparing these results to those previously shown for ground observations (Figures 3.03 and 3.04) reveals that during the July 26-August 8 period the estimated average blight severity by field observations was 1.50 for every flightline while by photointerpretation it was less than 1.50 for 13 of 14 available flightlines.

The reverse was true during the periods beginning August 9 and August 23 (Figures 3.09 and 3.10); the photo-interpreters tended to overestimate the average blight levels compared to ground observations. This was largely due to the difficulty of distinguishing blight stress from stresses caused by other factors (i.e., other diseases, drought, insect damage and nutrient deficiencies).

Unfavorable weather prevented collection of photography over the eastern half of the area during the period from September 6-19 (Figure 3.10). However, for those flightlines where comparisons could be made, there was good agreement between ground observations and photointerpretation results though relatively little blight was present in the area.

--Variances of Acreage Estimates--

The variances, coefficients of variation, and confidence intervals of the photointerpretive acreage estimates are shown in Table 3.11 to 3.13 for the non-ISA, the ISA, and the total test area (August 9 and 23 periods). Many of the comments already made about these statistics as they related to the ground observation estimates also apply to the photointerpretation estimates. Briefly, as was the case for the ground observations, variances may be characterized by the following sequence: variation among flightlines>among segments>among fields>within fields. Again, the greatest source of variation by far was the flightline component. Also, the magnitudes of the variances for each level of sampling were very similar to those of the ground observation estimates. However, because approximately 99 percent

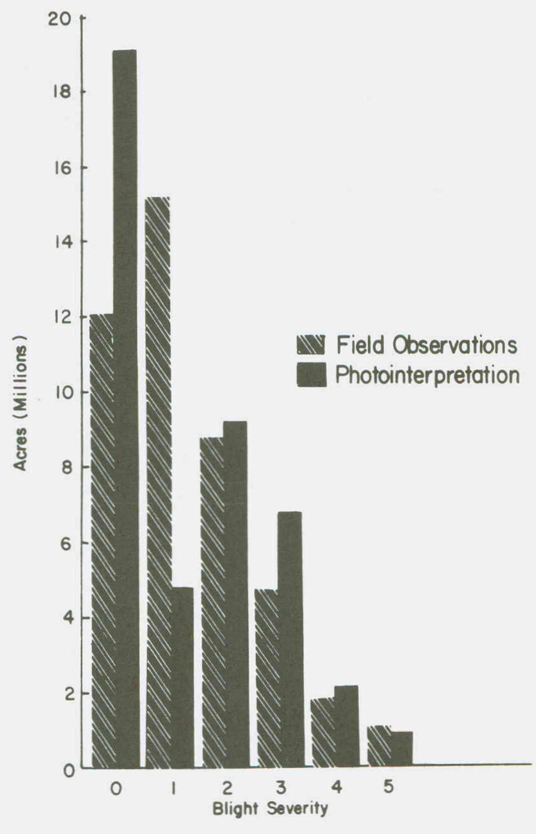
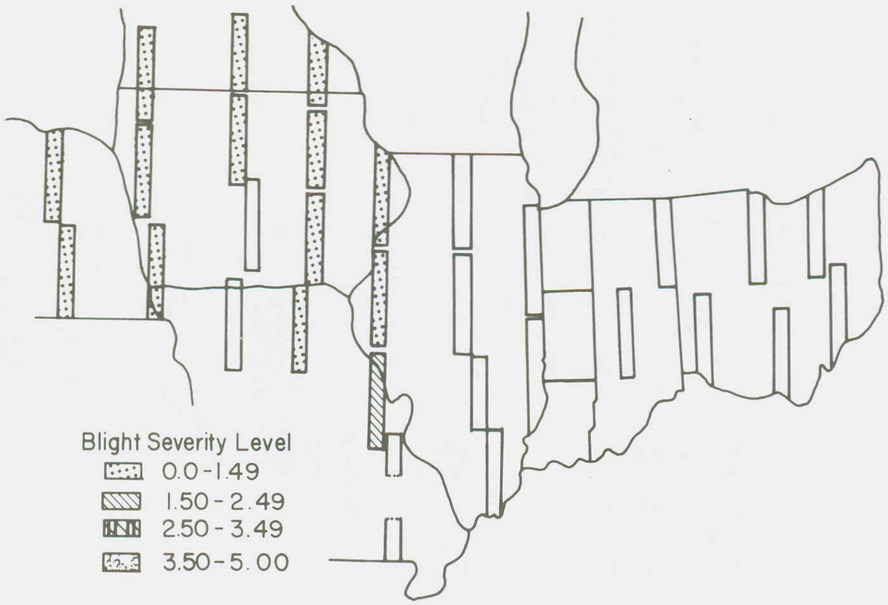


Figure 3.08. Comparison of ground observation and photointerpretation blight acreage estimates: August 23-September 5.



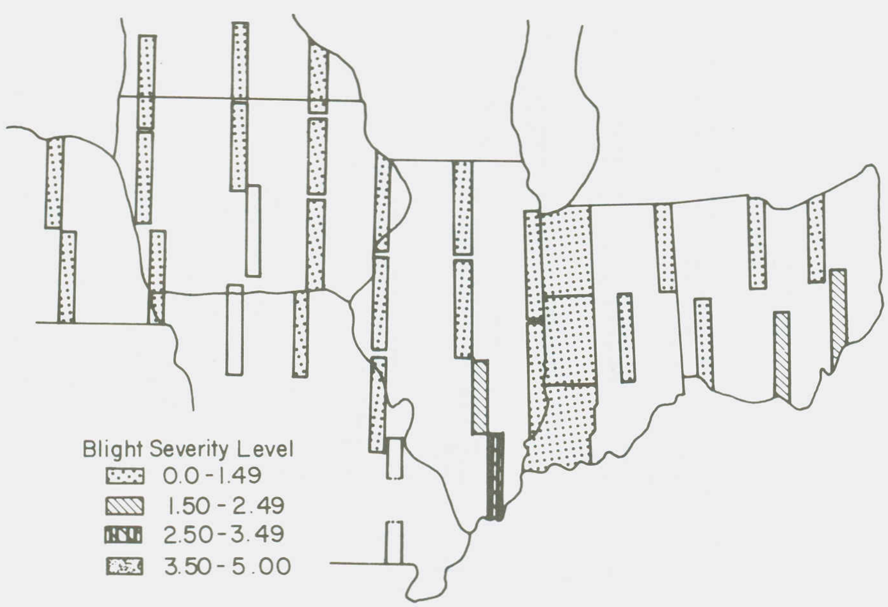


Figure 3.09. Average blight severity by flightline as estimated by photointerpretation: periods beginning July 26 (top) and August 9 (bottom).

Figure 3.10. Average blight severity by flightline as estimated by photointerpretation: periods beginning August 23 (top) and September 6 (bottom).

Table 3.11 Sources of variation in the photointerpretive estimates of blight class acreages.

Date	Location	Source of Variation	Blight Severity Class 0	1	2	3	4	5
August 9-22	Non-ISA	Within Fields (x 10^6)	.1310	.0658	.0477	.0109	.0023	.0005
		Among Fields (x 10^6)	.4774	.3737	.3445	.1187	.0311	.0016
		Among Segments (x 10^{10})	.8733	.1268	.0787	.0146	.0027	.00005
		Among Flightlines (x 10^{13})	.6825	.0339	.0162	.0032	.0014	.000006
		Total						
	ISA	Within Fields (x 10^6)	.1306	.0111	.0972	.0335	.0039	.0061
		Among Fields (x 10^6)	.1327	.0263	.1091	.0461	.0142	.0038
		Among Segments (x 10^{11})	.1121	.0031	.0281	.0102	.0019	.0006
		Total (x 10^{11})	.1121	.0031	.0281	.0102	.0019	.0006
August 23-September 5	Non-ISA	Within Fields (x 10^6)	.1725	.1100	.1565	.0933	.0215	.0028
		Among Fields (x 10^6)	.4899	.3223	.5196	.3878	.1235	.0311
		Among Segments (x 10^{10})	.5872	.0730	.1384	.1160	.0150	.0032
		Among Flightlines (x 10^{13})	.5390	.0277	.0711	.0299	.0042	.0006
		Total (x 10^{13})	.5395	.0278	.0713	.0300	.0042	.0006
	ISA	Within Fields (x 10^5)	.3826	.0616	.8513	.9102	.5972	.0722
		Among Fields (x 10^6)	.0977	.0165	.1125	.1363	.0965	.0369
		Among Segments (x 10^{10})	.4996	.0075	.2684	.5915	.0233	.0456
		Total (x 10^{10})	.4997	.0075	.2685	.5915	.2331	.0456

Table 3.12 Coefficients of variation for photointerpretive estimates of blight severity acreages.

Date	Location	Blight Severity Class 0	1	2	3	4	5
				Percent			
August 9-22	Non-ISA	9.0	11.9	10.0	13.5	31.3	39.5
	ISA	8.5	22.1	09.7	15.6	35.0	53.1
	Total Area	8.6	11.7	08.9	11.9	28.5	32.0
August 23-September 5	Non-ISA	12.4	11.1	9.8	9.1	11.9	22.7
	ISA	19.9	23.8	10.1	10.5	12.2	20.5
	Total Area	12.2	11.0	9.2	8.2	9.9	18.0

Table 3.13 **Ninety-five percent confidence intervals for photointerpretation blight class** acreages.

Date	Location	Blight Severity Class 0	1	2	3	4	5
				(000 acres)			
August 9-22	Non-ISA	23,745	3,712	3,227	968	140	4
		34,202	6,045	4,842	1,684	607	35
	ISA	1,038	44	441	140	11	0
		1,462	114	654	268	67	30
	Total Area	24,992	3,791	3,768	1,167	178	12
		35,458	6,126	5,397	1,894	649	56
August 23-September 5	Non-ISA	14,101	3,702	6,964	4,951	1,309	182
		23,392	5,810	10,341	7,143	2,129	483
	ISA	214	19	410	576	299	61
		497	54	617	884	492	147
	Total Area	14,454	3,738	7,474	5,671	1,694	280
		23,750	5,846	10,858	7,884	2,536	593

of the total variation was accounted for by sampling within flightlines, there was no reduction in total variance when sampling entire fields and all fields in the segment by photointerpretation as compared to observing only two small units (five corn plants in each unit) in each of eight to 10 fields in a segment. The small reduction in the variance among fields within segments was not sufficient to have any significant effect on the total variance of each acreage estimate. The significant conclusion that may be drawn from these results is that there was little advantage to analyzing the condition of each and every corn field in the segment as opposed to observing two sample units in a relatively small number of fields.

Grouped Blight Classes

By combining the estimates made for the individual blight levels into two classes, none (0) to mild (2) and moderate (3) to very severe (5), the precision of the acreage estimates was increased and agreement between ground observation and photointerpretive estimates was improved. These results are summarized in Table 3.14 for period 6, August 23-September 5, for the non-ISA, ISA, and total test area.

While grouping the six individual blight classes recognizable on the ground into two classes improves the performance, the ground and PI acreage estimates still differ considerably. Relative to the ground observations, the PI's underestimated the amount of corn in blight class 0-1-2 by 11 percent in both the non-ISA and the ISA. The 3-4-5 class was overestimated by a similar amount in each case.

The coefficients of variation which ranged from 8 to 35 percent for the individual blight class acreage estimates were reduced to 5 to 10 percent. The confidence intervals were also considerably reduced in size indicating an improvement in the precision of the acreage estimates. Similar results were found for other periods.

Conclusions

The above results show that blight-infected fields could be quite accurately classified by photointerpretation as being in one of two categories: none to mild SCLB infection or moderate to severe infection; individual blight classes could not be accurately identified.

Returning to the initial assumptions, it can be said that, if all other factors could be held constant, changes in response as recorded by color IR film would be a reliable measure of blight infection. However, such ideal situations are seldom, if ever, found in nature. In the CBWE a great many interacting variables, not all agricultural, were responsible for the recorded changes. These included changes or variation in the ground scene, in atmospheric effects, in film emulsion and processing, and finally, the variation that naturally arises in any system based on subjective human judgment. Most of these factors and others which

Table 3.14 Comparison of ground observation and photointerpretation estimates for two severity classes: August 23-September 5.

Area	Statistic	Ground Observations 0-1-2	Ground Observations 3-4-5	Photointerpretation 0-1-2	Photointerpretation 3-4-5
		Blight Severity Class			
Non-ISA	Acres (000)	34,834	5,968	32,155	11,090
	Variance ($x\ 10^{11}$)	57.013	4.002	6.385	3.480
	CV (percent)	6.850	10.600	7.680	5.320
	95% Confidence Interval	30,059-39,610	4,703-7,234	27,101-37,210	9,911-12,270
ISA	Acres (000)	1,167	972	905	1,230
	Variance ($x\ 10^{10}$)	1.265	0.995	0.776	0.870
	CV (percent)	9.630	10.260	9.720	7.580
	95% Confidence Interval	943-1,392	772-1,171	729 1,081	1,043-1,416
TOTAL AREA	Acres	36,002	6,940	33,085	9,330
	Variance ($x\ 10^{12}$)	5.714	0.410	6.403	0.356
	CV (percent)	6.630	9.220	7.640	6.390
	95% Confidence Interval	31,228-40,776	5,660-8,220	28,030-38,141	8,137-10,522

affected the results and to some extent limited the information which could be extracted by photo-interpretation, also affected crop identification. They are discussed more thoroughly in a later sub-section entitled "Factors Affecting Blight Detection and Crop Identification."

An important problem unique to blight detection was that individual blight classes are an artificial creation and one which nature is not required to follow. Blight in the field exists as a continuum and does not fall into easily distinguishable classes. As a result, there is bound to be confusion as to proper labels, particularly in border areas such as that between mild and moderate.

B. Crop Identification

The goal of identifying crops through the interpretation of CBWE photography was added to those of the total Experiment, as was discussed in Volume II, Section V. To review, specific objectives of this portion of the Watch were:

1. to train photo-analysts in identifying crops primarily through color tones;
2. to determine if crop identification from high-altitude photography was accurate enough to be termed feasible; and
3. to evaluate identification accuracies from photography acquired at various times during the growing season to determine an optimum identification period for each crop type.

Procedurally, a different tract designation was selected for each mission and just that tract was analyzed within each segment. In the event, however, that the designated tract for a segment happened to be uncropped (i.e., water or forest), no replacement was selected. Crop identification was accomplished before blight analysis in order that accuracies wouldn't be favorably biased by previous information. As with the corn blight analysis, PI's analyzed only segments within their assigned areas.

Results

Four-crop identification accuracies for one segment as analyzed by the same team throughout the growing season (eight missions from June through October) are graphed in Figure 3.11. These may be considered a fairly typical example of the results used to compile the more comprehensive Table 3.15, which averages six analysis teams' eight-cover-type results over 120 segments.

As may be seen from both the figure and the table, corn was consistently identified with high accuracy. The decrease in correct identification during the July 26-August 8 period may be attributed both to variations in crop canopy characteristics caused by tasseling and problems with imagery quality caused by cyan spotting (discussed later in this section and in Volume II, Section III).

Identification of soybeans was not as consistent and did not level off at a relatively high

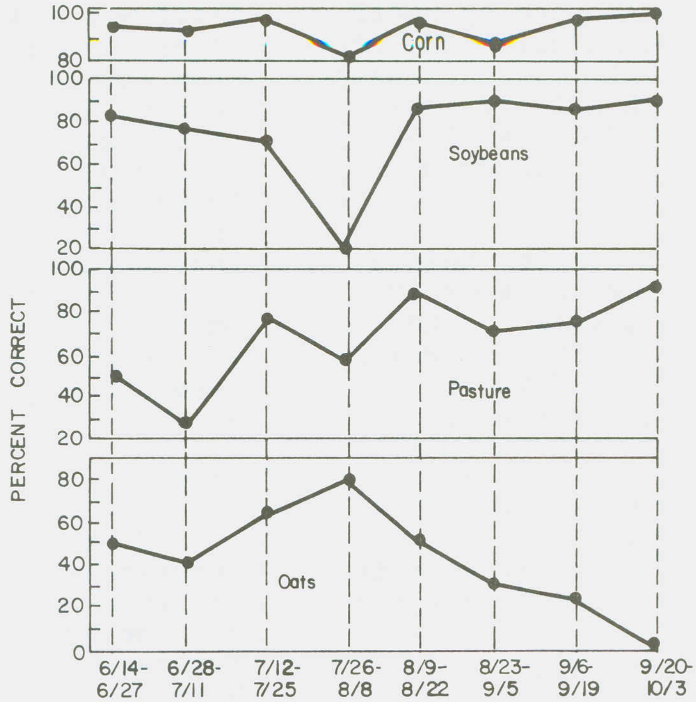


Figure 3.11. Accuracy of major crop cover identification by photointerpretation in Central Iowa (Segment 116) through the 1971 growing season.

Table 3.15 Photo-interpreter accuracies for eight Corn Belt cover types.*

Date / Cover Type	PERCENT CORRECT IDENTIFICATION 6/14 ↓ 6/27	6/28 ↓ 7/11	7/12 ↓ 7/25	7/26 ↓ 8/8	8/9 ↓ 8/22	8/23 ↓ 9/5	9/6 ↓ 9/19	9/20 ↓ 10/3
Wood lot	97.6	82.3	90.5	100.0	98.3	99.3	95.6	98.5
Corn	73.2	84.7	92.2	88.7	92.5	91.0	96.3	95.5
Soybeans	54.2	66.0	56.0	58.7	83.2	84.2	77.0	64.8
Pasture	61.0	47.1	64.0	47.6	77.0	68.0	67.6	72.1
Hay	53.8	37.8	43.1	21.3	37.2	35.0	37.6	50.5
Wheat	73.2	58.5	26.2	----	35.5	21.8	----	21.8
Oats	39.2	12.0	37.2	51.0	32.7	20.2	7.3	3.5
Diverted Acres	21.8	10.4	19.8	3.0	32.5	39.2	42.0	28.8

*Average results of six photo-interpreter teams over eight data-collection periods.

percentage (about 80 percent) until mid-August, the period of maximum ground cover for this crop. The corresponding low points in corn and soybean identification accuracy may be related to the "red-saturated" IR film. Such film response had a tendency to mask the naturally occurring variations between these two crops.

Further examination of the data in Table 3.15 shows that pasture recognition increased as the season progressed while identification of oats peaked when that crop reached maturity. Generally then, it can be seen that the accuracy of crop identification varied with the crop and the point in the growing season during which the imagery was acquired. More specific details on identification of cover types are discussed below.

Discussion

--Woodlots--

Accuracies in the identification of woodlots were the highest of any cover (nearly 100 percent for most of the data collection periods). This high accuracy may be attributed to the type's distinct color and textural characteristics. Misidentification was largely confined to confusion with pastures, combinations of woods and pasture, and various non-farm categories.

--Corn--

The consistently high accuracies in the identification of corn can be attributed largely to its omnipresence throughout the study area and to the greater experience of the analysis teams in working with that crop.

In general, Table 3.15 shows accuracy increased during mid-July and in September and early October. It is during these periods then that corn is apparently most distinct from surrounding crops. The first increase may be explained by the fact that in the early weeks of the Watch, corn was commonly misidentified as soybeans, which exhibited a markedly similar spectral response. However, upon tasseling (in general during July), the infrared reflectance of corn was significantly reduced, yielding a reddish-brown color instead of the former bright red, and distinction between the crops became much more apparent.

This phenomenon had been previously noted when it was established that tassels imaged as green on color infrared film, and corn leaves, when green and healthy, imaged as red. Thus, the reddish-brown imaged on the small-scale color infrared photos was a combination of the reflectance of leaves and the increased influence of the tassels. It follows that, as the tassels matured and became more "bushy," the reflectance of the leaves beneath would be further masked, yielding a browner image which would eventually turn green as the leaves themselves dried up and lost their high infrared reflectance. It is this latter change which partially accounts for the second accuracy increase in September-October. The other factor which may have contributed to the increased accuracies of corn identification in later missions is the fact that many of the crops which were earlier confused with corn had been harvested by August 23.

--Soybeans--

Identification accuracies of soybeans were highest during August and early September, whereas identification during the early and late portions of the growing season proved difficult.

During the early portion of the growing season, soybeans, corn and other crops have similar appearances, imaging first as light pinks then progressing to brighter, stronger reds. As the season progresses, many of these crops (corn, wheat, clover) undergo changes which reduce their spectral reflectances. Soybeans, however, retain their bright red image until late in the growing season. The optimum time for soybean identification then (particularly for distinction from corn) appears to be that middle portion of the growing season after corn has tasseled and before the leaves of the soybeans turn their characteristic late season yellow.

--Pasture--

On the imagery, pasture has a distinctive mottled color throughout the growing season. This is an aid to its identification particularly during the early part of the growing season when pasture may be confused with winter wheat or hay. Supplementary aids in pasture identification are proximity to farm buildings and bodies of water and/or a unique topographic location (e.g., a steep hillside).

Pasture was often misidentified as hay during the middle and later parts of the growing season. There is a good explanation for this in the mixed land use practices which may occur when, for instance, a third growth of hay is used as pasture rather than being cut. In this case, the interpreter may observe both the effects of grazing and the characteristic spectral color of hay within a field which leads to misidentification.

--Hay--

Accuracies for identification of hay from the photography analyzed barely rose above 50 percent. It is generally believed, though, that had the photography of mid-May been analyzed for crop identification, more accurate identification of hay would have been attained; the reason for this belief is that hay is one of the few crops to exhibit a bright red infrared image early in the growing season. Even though pasture and winter wheat also exhibit red images at this point, there are spectral differences that make them separable. However, as the season progresses, the identification accuracy decreases and by the time June imagery was analyzed, the correct identification percentage was down to 50 percent.

--Wheat--

As with all small grains, wheat was difficult to identify. There is, however, a point during its maturation at which wheat ripens and becomes significantly different and easy to identify. The tabular results indicate that this point occurred either during or immediately before the mid-June collection period since accuracies dropped off after this point.

--Oats--

Like other small grains, oats were difficult to identify. Also, as with wheat, the highest identification accuracy probably occurs at maturation. The 51 percent accuracy represents samples from the western segments during late July and early August.

--Diverted Acres--

"Diverted acres" is perhaps the most varied (and therefore difficult to identify) cover type. This category serves as a "catch-all" for all remaining cover types and, therefore, has great variability in spectral response within itself. Diverted acres may include such diverse covers as idle land, wheat, oats, red clover, rye, and "volunteer" vegetation such as weeds, the only general qualification being that the vegetation cover in these fields is not harvested. This span of variability naturally reduces the accuracy of identification for the category and, as may be seen from the table, results were erratic and accuracy low.

Conclusions

Overall, identifications of the categories corn, soybeans, and woodlot were the most successful. In the first case corn, after tasseling, showed a marked reduction in infrared reflectance due to the fact that the tassel, which has low reflectance, tends to block out the high reflectance of the leaves underneath. This caused tasseled corn to image as a rust or brownish-red color and, during this period, corn was easy to distinguish from soybeans, which had undergone no major change in spectral response and were still imaging as bright red.

Oat accuracy, although never high, peaked just prior to harvest when the crop apparently had a distinguishable and characteristic response. Pasture, on the other hand, reached several peaks, the highest of which was for the last observation period. This erratic response could be attributed to either response changes brought about by grazing practices or to confusion with hay and diverted acres which had similar appearance through various portions of the growing season.

Procedures were the root of some errors in cover type identification, particularly in the categories of woodlot, pasture and diverted acres. Ambiguity in definition of these categories led to problems, especially with such borderline types as a pasture containing scattered trees.

Further complications resulted from the too inclusive category of diverted acres which could be covered by a widely varying combination of weeds, volunteer corn, trees and other cover types. This same problem was, of course, as much a hindrance to the ground observation personnel who had to classify the land in the segment as it was to the photointerpretive teams and resulted in varying ground identifications of borderline areas that were, in fact, similar.

In addition to providing

experience, training, and a knowledge of factors affecting identification of cover types from infrared photography, this part of the CBWE demonstrated the feasibility of identifying major crop species such as corn, soybeans, and wheat from small-scale infrared photography.

C. Factors Affecting Blight Detection and Crop Identification

Agricultural

From these results, it can be seen that there is a large number of agricultural variables which can have an impact on the success of photointerpretive crop identification and blight detection. Generally, these can be grouped into crop maturity, cultural practices and crop stresses.

Crop maturity, of course, proved to be the primary factor in that crops varied within themselves as much as among each other throughout the growing season. Because of this, the date of the observations was critical. The highest identification accuracy was obtained when the crops, through their own inherent maturation processes, exhibited the most consistent response that was distinguishable from other species.

Cultural practices too, and their application as determined by prevailing weather parameters, could dramatically affect the response of a crop. Had the responses of various species under differing farming practices been better understood, the categories of hay (i.e., forage crops) and pasture might have been identified more successfully. An understanding of the effect of cultural factors on spectral response could have also helped in the identification of diverted acres since, though extremely variable, the composition of this type depends on previous land uses. Even more specific knowledge of these types of factors may be needed in the future since lack of weed control and the appearance of "volunteer" corn caused misidentification in a significant number of soybean fields.

Weediness was, of course, only one of several stress factors that affected identification by distorting the crops' typical spectral responses. In the case of the CBWE, these stress factors occasionally caused the appearance of one crop to closely approximate that of another crop. The effect of this variable was limited to severe stresses which significantly altered the crop's image; hence stress was not a large source of error. In future operational remote sensing surveys, however, it could be.

Some of the crop stress conditions consistently reported by CBWE photo-interpreters were:

+Weediness--highly reflective in near-infrared (identified in all missions)
+Flooding--identified initially as bare soil or standing water which later appeared as bare, unplanted areas
+Hail damage--when severe, damaged upper leaves, thus reducing infrared reflectance

+Infertile soils--usually resulted in reduced or stunted plant population and appeared similar to bare soil
+Drought--if over long period of time, resulted in loss of infrared reflectance.

Generally speaking, identifiable stresses were those that were recordable; i.e., those that affected the response to a degree noticeable by the PI.

Non-Agricultural

--PI Experience--

Though image quality, weather conditions and crop maturity status were all significant factors in the accuracy of blight and crop identification, the experience and training of the photo-interpreters were and remain the most important variables. An experienced PI can, in fact, ameliorate the worst effects of the other factors. Knowledge of crops and cultural practices can provide valuable insights into variations in crop reflectance and the resultant variation in image colors. A companion and equally important skill is, of course, training in photointerpretation. Although their influence is essentially unmeasurable, these variables did have an effect on crop identification and blight detection/classification during the CBWE since few of the PI's available were both experienced agriculturalists and trained photo-interpreters.

--Data Quality--

Another factor of consequence was data quality. (The term "data quality" as used here refers principally to the quality of the image color.) This quality is influenced by the relative proportions of colors reproduced on the film--proportions which varied considerably between CBWE missions and even somewhat between film rolls during a single mission. More specifically, this variation usually consisted of quantitative differences in the red color constituent (saturation) and qualitative variation between film emulsion batches. Since texture, topography, and field geometry tend to be of minimal importance at 1:120,000 scale, color provided the primary interpretive parameter in the Corn Blight Watch photography and this color inconsistency was of major significance.

Red color "saturation" problems centered on the color infrared film's cyan layer which is sensitive to energy reflected in the near-infrared portion of the spectrum (.7μm to .9μm). This layer was, in fact, more sensitive to exposure than the others and therefore responded more rapidly to energy impinging upon it. Because of this characteristic, there was a particular problem with recording living plants whose near-infrared reflectance tended to increase as crop cover increased. The result was that the more mature the crops became, the more saturated in red the imagery became. Since this saturation not only increased the response but also compressed the response in the other wavelengths, it was bound to subdue whatever natural basis for distinction between crops existed and therefore make interpretation difficult. Figure 3.12, which illustrates the overall quality of sequential imagery collected during the Corn Blight Watch Experiment, also illustrates the problem with red saturation, particularly in the variation between the June 14 and July 27 imagery.

The cyan spotting problem that was discussed in Volume II, Section III, also hindered crop identifications, but not to the extent that it affected blight interpretation. This was primarily due to the fact that the typical "spot" was smaller than field size and was more likely to be interpreted as a variation in blight severity than it was a variation in cropping within a field.

Another factor affecting the color IR imagery was a variation in response between batches of film. Figure 3.12 also shows differences in quality which may be attributed to differing film batches. The striking difference in color rendition of the May 10-June 1 imagery, for instance, is due to this factor, as is the variation in the August 23-September 5 period.

In addition to the straightforward problem posed by obliteration of ground features by clouds and cloud shadows, weather conditions were also capable of altering color quality. Haze, for example, although permeable to some extent by color infrared film, was responsible for the effect seen in the September 20-October 3 photography.

In addition to the factors already discussed, other non-agricultural variables can affect image quality. Such parameters as time of exposure, latitude and longitude of exposure, anti-solar point phenomena and a host of film processing variables may also have an impact which varies in significance. At any rate, the final result of all these potential variations is usually a variation in image color which, if not understood by the interpreter, results in confusion and incorrect identification.

D. Use of Small-Scale IR Photography by Field Personnel

As has been discussed in Volume II, Section III-B, small-scale (1:120,000) color IR photography of the CBWE segments was sent to ground observation teams throughout Phase 3 to aid them in their observations and to train them in photointerpretive techniques. Accompanying each packet of photos was a questionnaire designed to determine the relative success of such a training method (sample included in Appendix JJ to Volume II). This sub-section is intended to draw inferences from the responses to those questionnaires. Approximately 70 percent were completed and returned to the Photo Data Reduction Center (PDRC) at LARS.

Overall, both the handbook (An Introductory Handbook for the Interpretation of Color Infrared Photography--See Volume II) and segment information included in the questionnaire packages were favorably received and considered useful although 20 percent of the respondents indicated that late delivery hampered that utility. Although there was general satis-

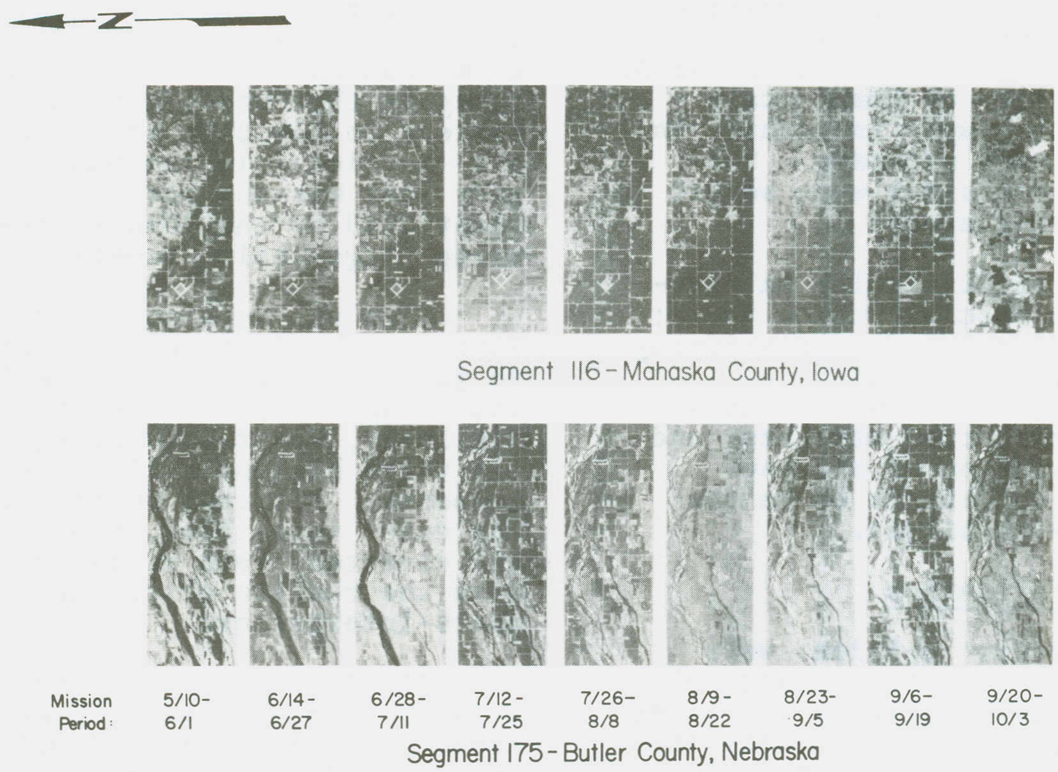


Figure 3.12. Color IR imagery of Segments 116 and 175 through the 1971 growing season.

faction with the quality of the training materials, some felt that the quantity should have been increased. Fifteen percent of the observers requested more printed information and nearly all were in favor of an early "live" training session to supplement the written materials.

Questions asked on the questionnaire for ground observation period B-8 were designed to elicit observers' overall opinions on the utility of small-scale aerial photography in identifying crops and crop stresses. Subjective impressions were sought in the following areas:

1) degree of difficulty in identifying specific cover types;
2) optimum period for identifying corn and soybeans;
3) ability to distinguish SCLB from other crop stresses; and
4) determination of stresses likely to obscure or be confused with blight.

Crop Identification

Observers' opinions were categorized into "difficulty of identification" classes for cover types which paralleled those used by the PI teams at the PDRC in their crop identification project using larger scale imagery (see sub-section B). Subjective classes used ranged from "difficult" through "moderate" and "easy" to "very easy." Though the results (as graphed in Figure 3.13) show that the conservatism of the field personnel tended to bunch the results in the middle two classes, trends similar to those of the more objectively based results of the PI teams do appear.

Very generally, on the basis of similar observer response, cover types tended to be grouped into three categories--row crops, small grains, and non-crop covers. These groupings (corn-soybeans, wheat-oats, and pasture-diverted-hay) probably indicated their similar appearance on small-scale photography. Corn and soybeans, for instance, although difficult to distinguish from each other, are relatively separable from wheat and oats. Note that the category that was considered the easiest to identify by the observers--woodlots--is the same category that was the most accurately identified by the PDRC PI teams using large-scale imagery.

Corn and soybeans paired rated as the next easiest category to identify, generally paralleling the objective results of the PI's. Similarly, wheat-oats received the third highest affirmative response. Opinions on the remaining cover types (hay, pasture, and diverted) were mixed, as were the results obtained by the photo-interpreters.

The final crop ID question asked of the CES and ASCS personnel concerned the optimum identification period for corn and soybeans. Here too, the observers' subjective impressions generally matched the results of the PI teams. Most observers, for instance, indicated that July was the most favorable for corn identification while August was the best month for identifying soybeans. This, in fact, corresponded roughly with the periods during which the PI teams had the most success distinguishing these crops.

Though it is intuitively

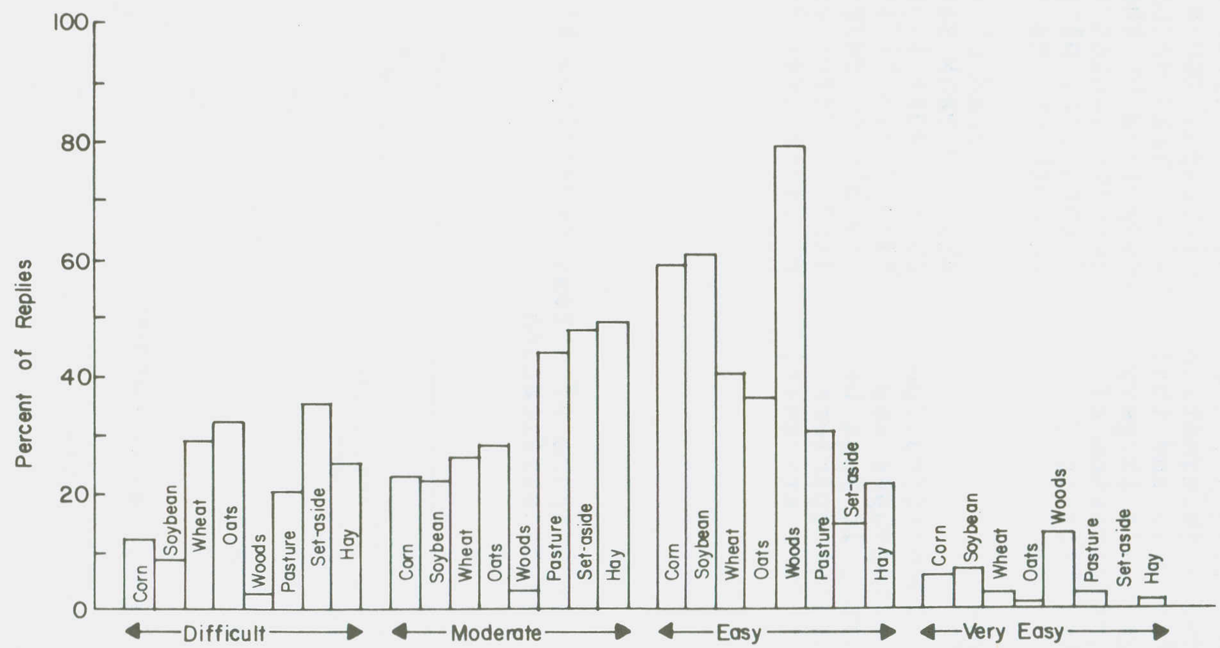


Figure 3.13. Difficulty reported by field personnel in identifying various crops and cover types. (Average for all periods.)

obvious that crop identification using small-scale imagery cannot be as accurate as that using imagery of a larger scale (and observers' opinions were mixed as to its degree of utility), the correspondence between information obtained from small-scale and that obtained from large-scale imagery indicates that identification of at least broad categories is feasible.

Stress Identification

Although crop identification from small-scale photography was moderately successful, it must be assumed from observers' opinions that recognition of crop stresses, including blight, was not successful. Over half of the observers felt that blight could not be distinguished from other stress conditions and nearly three-fourths didn't believe that slight levels of blight could be detected at all. This second opinion was supported by the PI teams, whose results indicated a problem with identifying blight levels 1 and 2 throughout the season.

Ground observers were, however, able to rank seven stress factors as to their impairment of correct blight identification; this order roughly corresponds with a similar list of stresses identified by PI teams (see Table 3.16).

Table 3.16 Importance of stress conditions to blight misclassification.

Stress Factor	Percent*
Maturity Effects (tassel color, natural senescence, etc.)	26
Drought	18
Nutrient Deficiency	15
Weediness	12
Weather Factors (lodging, flooding, hail)	8
Diseases (other than SCLB)	6
Insect Damage	4
Miscellaneous	12

*Percentage of CES and ASCS field personnel considering stress factor "most likely" to be confused with blight.

Section IV.

Multispectral Scanner Data Analysis Results

IV. MULTISPECTRAL SCANNER DATA ANALYSIS RESULTS

Introduction

Section IV of this final report provides an overview of the results obtained from analyses of the multispectral scanner data acquired by the WRL C-47 during the Corn Blight Watch Experiment. First, acreage estimates of blight infection and variances computed on a mission-by-mission basis are reported, both for individual blight classes and for logical groupings of blight classes. Next, attention is given to the accuracy with which the corn crop was discriminated, and finally, some observations are made concerning the apparent effectiveness of the available spectral bands in making the desired discriminations.

Because of the very different data processing technologies used by LARS and Willow Run Laboratories, it was deemed unworkable in many cases to try to evaluate the two sets of results using identical criteria. In these cases therefore, the results are discussed separately.

Further evaluation of the blight classification results is also the focus of two subsequent sections, Section V--Evaluation of Blight Classification Results and Section VI--In-Depth Analysis of Segment 212.

A. Acreage Estimates and Variances

Acreage

The estimates of the acreage in each blight severity level, based on the MSS data analysis results for the ISA, were derived in the same manner as the ground observation and photointerpretive estimates and may be compared directly to them. The information presented by the tables and figures needs little discussion. The MSS-derived "picture" of the temporal development of blight in the intensive area is summarized in Figure 3.14 which also shows the proportion of the area infected at each blight level at two week intervals throughout the summer.

The MSS-based acreage estimates for the ISA for each of four missions (beginning July 26 and ending September 13) are presented in Table 3.17. These estimates are also subdivided by cytoplasm and blight level for each mission. In order to facilitate comparison of the three types of acreage estimates, a bar graph showing the ground observations, PI results, and MSS results for the August 23-September 5 period is presented as Figure 3.15. Note, first, that the MSS results agree closely with the ground observations for all levels of blight severity and, second, that the MSS estimates agree much more closely with the ground estimates than do the PI estimates.

Variances

The variances of the MSS-based acreage estimates were of similar magnitude to those of the field observation and PI acreage estimates. Examples of these variances for the August 9-22 and August 23-September 5 missions are shown in Table 3.18. Notice that here too, the majority of variation was among segments rather than within segments. Again this

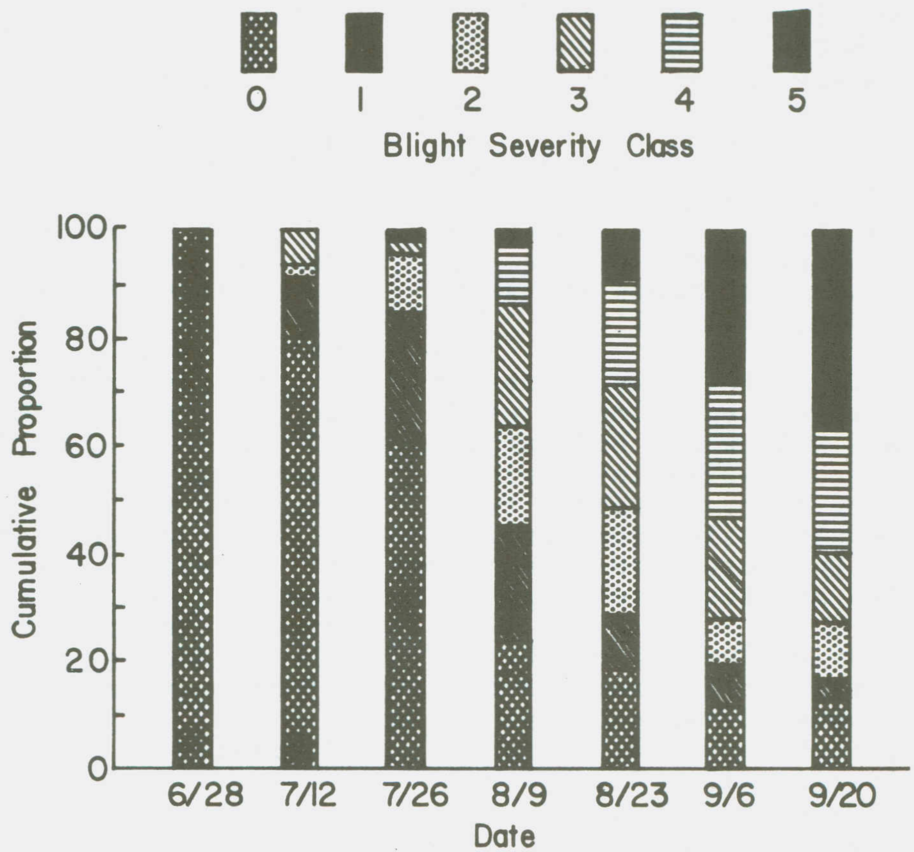


Figure 3.14. Development of SCLB throughout the summer as estimated from MSS classifications.

Table 3.17 Estimates of blight in the ISA based on MSS data.

Date	Cytoplasm	Acres per Blight Severity Level 0	1	2	3	4	5
July 26-Aug. 8	N	391,250	169,997	68,485	13,627	12,629	0
	T	146,474	59,674	32,940	8,940	5,902	0
	B	506,217	182,540	83,371	20,875	9,244	0
	F-2	47,870	12,889	8,072	3,775	303	0
	O	209,404	88,449	42,618	10,763	2,039	0
	TOTAL	1,301,215	513,549	235,486	57,980	30,117	0
Aug. 9-22	N	162,749	130,937	98,344	166,829	91,096	5,468
	T	50,821	53,772	54,770	41,967	35,978	16,361
	B	170,214	190,048	157,802	177,288	97,085	9,330
	F-2	36,238	9,070	7,204	15,754	4,643	0
	O	92,051	75,472	75,255	79,378	23,522	7,594
	TOTAL	512,073	459,299	393,375	481,216	252,324	38,753
Aug. 23-Sept. 5	N	134,105	68,354	104,854	155,979	137,881	54,032
	T	43,790	27,298	48,998	51,906	48,217	32,983
	B	116,745	72,651	180,196	198,207	167,871	65,620
	F-2	31,985	216	5,251	13,367	14,755	7,117
	O	70,481	46,828	90,445	71,089	52,123	22,133
	TOTAL	397,106	215,347	429,744	490,548	420,847	181,885
Sept. 6-19	N	87,667	58,025	51,906	117,657	143,957	196,254
	T	28,557	13,844	23,913	40,535	67,964	71,826
	B	61,193	57,591	67,617	164,746	216,739	233,839
	F-2	32,680	520	3,905	11,283	12,238	12,282
	O	41,663	34,285	32,072	72,347	95,740	77,121
	TOTAL	251,760	164,265	179,413	406,568	536,638	591,322

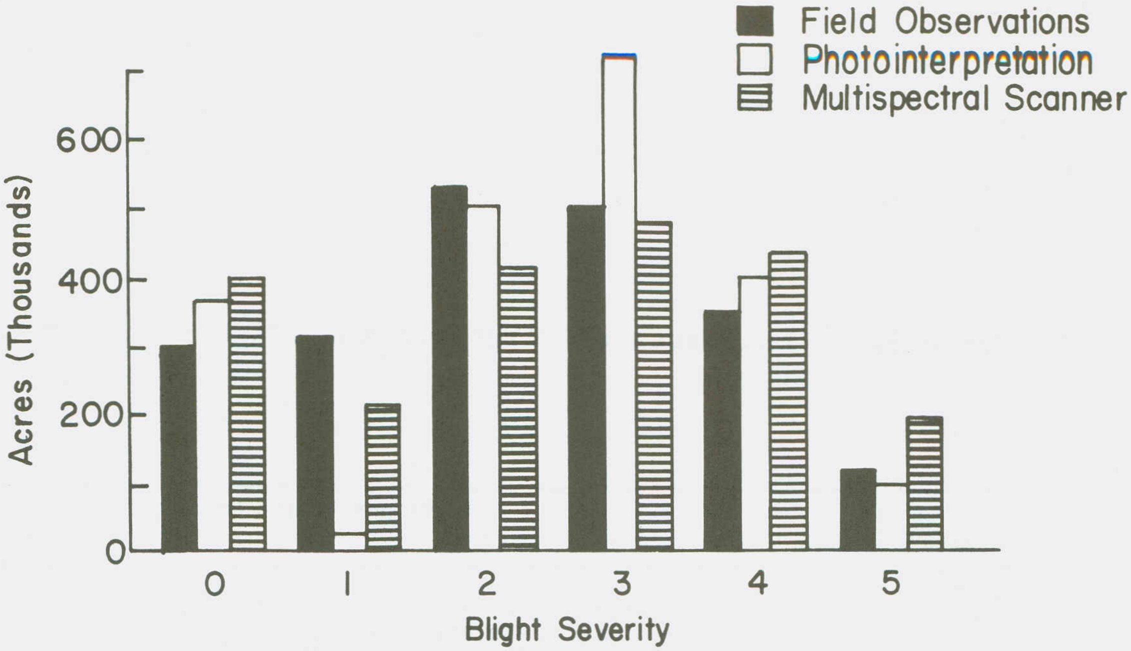


Figure 3.15. Comparison of blight severity estimates derived from field observation, photointerpretation, and MSS data analysis: August 23-September 5.

Table 3.18 Sources of variation in the MSS estimates of blight severity acreages.

Date	Source of Variation	Blight Severity Class 0	1	2	3	4	5
August 9-22	Within Fields (x 10^5)	.9050	.8696	.6741	.6789	.4961	.1019
	Among Fields (x 10^5)	.5450	.5663	.4120	.5637	.2078	.3476
	Among Segments (x 10^{10})	.5063	.5279	.3607	.5178	.4313	.0156
	Total (x 10^{10})	.5063	.5280	.3608	.5179	.4314	.0157
August 23-September 5	Within Fields (x 10^6)	.0818	.0674	.1053	.0771	.0983	.0567
	Among Fields (x 10^5)	.3950	.2805	.5071	.4057	.5039	.1727
	Among Segments (x 10^{10})	.3934	.1404	.3596	.3818	.3391	.1332
	Total (x 10^{10})	.3935	.1404	.3596	.3818	.3392	.1332

category of variation accounts for about 99 percent of the total.

It must be kept in mind, however, that with these variances, as well as those of the ground and PI estimates, even though a large number of fields was included in the sample (every corn field in the 30 1x8-mile segments in the intensive study area), the acreage estimates for the individual blight levels are still not very precise. For example, the coefficients of variation for the MSS-based acreage estimates for the August 23-September 5 mission range from 12 to 20 percent (Table 3.19). Once the confidence intervals are used to put the variation in terms of the acreage totals of individual blight levels, the variation becomes even more striking. For example, there are an estimated 490,548 acres of blight level 3 in the ISA for this time period. With the degree of variation present in the data and with the kind of sampling model used, there can be only 95 percent confidence even when making the rather general statement that the true or actual number of acres of blight level 3 in the area is between 366,968 and 614,128 acres (Table 3.20). This interval would, of course, be still larger if the confidence level were increased to 99 percent.

The conclusion is that even when the more intensive sampling model was used, there were not sufficient segments to ensure precise estimates. The relationships between the sampling model, precision of estimates, and costs are discussed in Section VII of this volume as well as in LARS Information Note 021072, "A Three-Stage Sampling Model for Remote Sensing Applications," by L. M. Eisgruber.

B. Crop Identification

Laboratory for Applications of Remote Sensing

In evaluating the crop classification performance achieved during the CBWE, it is of interest to use three different types of evaluation: (1) test field performance, (2) gross in-the-large performance and (3) error-corrected in-the-large performance. All of these evaluations may be performed on the results listed in Table 3.21.

--Test Field Performance--

The classical method for evaluating pattern recognition analysis results is the use of "test samples" (i.e., the performance of the classifier is checked on data for which the real classification is known but which were not used in the training process). This could be done extensively for crop species identification in this experiment because the crop species for virtually every field in each segment had been recorded during the Initial Interview Survey and subsequently verified during the growing season.

At LARS, a large percentage of both the corn and noncorn fields in every segment were used as test fields. The results appear in Table 3.21 in the columns labeled "Pct. Correct Class Corn," "Pct. Correct Class Other," and "Pct. Correct Class Test." The first column gives the accuracy with which corn was identified as corn, the second gives the accuracy with which "other" (noncorn) was classified as "other," and the third

Table 3.19 Coefficients of variation for MSS estimates of blight severity acreages.

Date	Blight Severity Class 0	1	2	3	4	5
			Percent			
August 9-22	13.9	15.8	15.3	14.9	26.0	32.3
August 23-September 5	15.8	17.4	14.0	12.6	13.8	20.1

Table 3.20 Ninety-five percent confidence intervals for estimates based on MSS data analysis.

Date	Blight Severity Class 0	1	2	3	4	5
			(000 acres)			
August 9-22	370	314	273	337	121	137
	654	604	514	625	384	638
August 23-September 5	272	140	310	367	304	109
	522	290	549	614	537	254

Table 3.21 Crop identification performance for fifteen segments analyzed by LARS.

40M: June 28-July 11

Segment	Pct. Correct Class[1] Corn	Pct. Correct Class[1] Other	Pct. Correct Class[1] Test	Pct. Segment Report[2] Corn	Pct. Segment Class[1] Corn	Pct. Segment Calculate[3] Corn
206 {4}	0.0	0.0	0.0	50.43	0.0	0.0
207	57.40	85.12	65.06	43.69	37.01	52.04
208	61.94	92.80	79.11	48.68	33.71	48.44
209	91.09	57.03	68.44	38.36	61.11	37.71
210	75.59	76.71	76.47	22.80	35.62	23.58
215	75.13	94.28	81.86	15.03	36.93	44.97
216	53.67	84.06	80.04	18.44	15.28	-1.75
217	78.77	63.30	70.33	21.89	49.54	30.51
218	48.12	83.41	80.19	4.53	17.10	1.60
219	52.93	81.10	77.45	16.75	27.60	25.57
221	79.98	84.86	82.16	40.48	33.97	29.05
223	83.94	80.82	81.15	14.73	35.13	24.63
225	75.84	94.98	81.14	29.21	40.17	49.63
228	86.24	98.86	90.87	25.85	35.28	40.12
230	63.37	72.67	67.73	15.74	33.50	17.14
Average	70.77{4}	81.66	78.85	27.20	35.16	30.50

41M: July 12-25

Segment	Pct. Correct Class Corn	Pct. Correct Class Other	Pct. Correct Class Test	Pct. Segment Report Corn	Pct. Segment Class Corn	Pct. Segment Calculate Corn
206	92.66	92.43	92.55	50.43	41.62	40.02
207	92.79	81.85	88.61	42.69	46.81	38.41
208	85.73	99.84	88.47	48.68	38.99	45.38
209	89.58	97.35	92.37	38.36	34.20	36.30
210	65.62	96.06	93.63	22.80	17.15	16.29
215	56.77	98.97	90.51	15.03	13.14	18.75
216	73.35	92.65	89.34	18.44	16.57	18.66
217	85.51	94.86	88.28	21.89	19.91	21.65
218	69.69	68.78	69.13	4.53	32.04	1.52
219	89.69	95.06	91.95	16.75	13.41	13.08
221	89.39	100.00	93.91	40.48	33.91	37.93
223	44.82	99.50	75.56	14.73	8.91	18.97
225	71.49	89.84	81.59	29.21	18.54	13.66
228	91.96	93.30	92.60	25.85	42.19	41.67
230	83.70	90.14	87.56	15.74	20.81	14.84
Average	81.87	91.86	89.14	27.20	26.46	24.84

(1) Class = Classified (from MSS data)
(2) Report = Reported (by ground observation)
(3) Calculate = calculated (see text)
(4) Mission 40M Segment 206 MSS data not collected; not included in column averages.

Table 3.21 (Continued)

42M: July 26-August 8

Segment	Pct. Correct Class Corn	Pct. Correct Class Other	Pct. Correct Class Test	Pct. Segment Report Corn	Pct. Segment Class Corn	Pct. Segment Calculate Corn
206	89.10	89.76	89.42	50.43	43.05	41.60
207	74.60	95.86	85.10	42.69	41.88	53.56
208	84.89	91.19	87.67	48.68	42.96	44.88
209	90.97	85.06	87.60	38.36	43.00	36.91
210	96.45	97.87	97.46	22.80	20.76	19.75
215	86.09	93.46	92.47	15.03	19.45	16.24
216	88.16	98.15	96.71	18.44	12.39	12.21
217	84.84	91.62	89.05	21.89	26.60	23.83
218	97.53	90.75	91.02	4.53	24.70	17.50
219	87.68	86.51	86.69	16.75	23.86	13.98
221	94.12	87.85	90.64	40.48	40.11	34.11
223	81.05	95.25	93.90	14.73	16.53	15.44
225	83.92	90.99	87.17	29.21	38.16	38.91
228	97.86	96.06	97.07	25.85	39.47	37.84
230	89.55	95.85	94.38	15.74	16.68	14.68
Average	86.75	92.54	90.96	27.20	30.03	28.47

43M: August 9-22

Segment	Pct. Correct Class Corn	Pct. Correct Class Other	Pct. Correct Class Test	Pct. Segment Report Corn	Pct. Segment Class Corn	Pct. Segment Calculate Corn
206	71.51	95.86	84.19	50.43	35.87	47.09
207	78.68	84.11	81.99	42.69	36.98	33.58
208	85.77	91.66	88.49	48.68	44.59	46.81
209	94.14	91.02	92.40	38.36	43.84	40.94
210	97.95	97.97	97.96	22.80	21.67	20.47
215	93.49	87.55	88.63	15.03	24.80	15.23
216	77.69	94.55	92.70	18.44	18.31	17.81
217	85.07	94.71	92.84	21.89	26.37	26.42
218	84.25	71.22	71.85	4.53	26.02	-4.96
219	61.76	94.65	85.98	16.75	14.81	16.78
221	91.46	95.83	94.64	40.48	35.64	36.05
223	85.23	93.54	91.84	14.73	20.64	18.00
225	79.08	95.64	87.71	29.21	27.42	30.87
228	99.49	56.13	66.98	25.85	60.44	29.78
230	93.94	93.83	93.85	15.74	21.23	17.16
Average	84.25	89.14	88.00	27.20	30.02	26.12

Table 3.21 (Concluded)

44M: August 23-September 5

Segment	Pct. Correct Class Corn	Pct. Correct Class Other	Pct. Correct Class Test	Pct. Segment Report Corn	Pct. Segment Class Corn	Pct. Segment Calculate Corn
206	94.44	95.19	94.83	50.43	45.90	45.85
207	92.59	80.30	85.70	42.69	47.69	38.40
208	87.25	96.07	91.39	48.68	44.05	48.16
209	85.40	88.28	86.97	38.36	42.24	41.42
210	97.90	92.29	93.17	22.80	31.97	26.90
215	94.10	94.46	94.40	15.03	18.03	14.09
216	92.99	90.41	90.68	18.44	25.18	18.70
217	93.48	76.46	77.96	21.89	45.06	30.77
218	71.80	80.56	80.22	4.53	21.68	4.28
219	66.53	88.61	84.42	16.75	23.10	21.24
221	76.56	78.75	78.22	40.48	41.07	35.82
223	92.05	87.07	87.52	14.73	24.42	14.52
225	85.48	80.20	82.21	29.21	34.32	22.11
228	72.91	62.87	65.37	25.85	42.17	14.10
230	90.03	84.85	85.65	15.74	26.77	15.52
Average	87.53	85.00	85.69	27.20	34.46	26.58

45M: September 6-19

Segment	Pct. Correct Class Corn	Pct. Correct Class Other	Pct. Correct Class Test	Pct. Segment Report Corn	Pct. Segment Class Corn	Pct. Segment Calculate Corn
206	86.29	96.84	91.32	50.43	41.86	46.55
207	93.03	69.98	79.19	42.69	53.66	37.52
208	87.89	96.01	91.64	48.68	44.94	48.81
209	92.06	96.09	94.31	38.36	39.65	40.54
210	94.58	96.47	95.92	22.80	26.34	25.05
215	63.60	98.16	93.15	15.03	11.47	15.58
216	76.59	97.01	94.60	18.44	14.72	15.93
217	83.30	82.71	82.88	21.89	31.54	21.59
218	82.41	93.18	92.82	4.53	11.62	6.35
219	85.38	94.57	92.94	16.75	22.29	21.09
221	81.16	80.20	80.46	40.48	37.98	29.62
223	83.47	94.22	92.18	14.73	19.78	18.03
225	68.71	90.67	80.95	29.21	29.28	33.60
228	98.66	43.68	60.32	25.85	55.51	-1.89
230	82.87	84.71	84.42	15.74	26.56	16.67
Average	85.08	88.70	87.72	27.20	30.87	25.87

column gives the overall accuracy (a weighted average of the first two).

A summary of these data, by mission, appears in Table 3.22.

Except for very early in the growing season when the agricultural fields were predominantly bare soil, the classification accuracy achieved for test fields was better than 85 percent. These results reflect the improvement of data analysis techniques over those of only a few years ago.

A disadvantage of evaluating the results in this manner arises from the fact that the present processing software at LARS requires that test fields be rectangular with field boundaries oriented either parallel or perpendicular to the direction of flight. The net result of this restriction is that the test field boundaries are generally taken well within the boundaries of the agricultural fields, and it is not known what sort of bias this may introduce into the estimates of classifier accuracy. The evaluation criteria described below represent attempts to overcome this problem.

--Gross In-The-Large Performance--

The "known" acreage of each segment (planimetered from aerial photography) and the "known" acreage planted to corn in each segment (from the initial interview survey) provide another means of evaluating the classification accuracy. The ratio of "known" corn acreage to "known" total acreage gives the fraction of the segment "known" to be planted to corn, which can be expressed in terms of the classification results as the ratio of the number of data points classified as corn to the total number of data points in the segment. Moreover, the latter ratio is independent of the accuracy with which individual field boundaries can be delineated.

Comparison of the two ratios, then, provides another measure of the accuracy with which corn was classified. The only qualification here has to do with the approximate status of "known"; "known" corn acreage, for example, depends on the accuracy of the estimates by farmers or surveyors during the initial interview survey, and the "known" total acreage depends on the measurement error associated with planimetering the segment photography. Though the latter error has been estimated at only a few percent, no estimate of the former potential source of error is available. However, at worst, this uncertainty introduces at least a constant bias into the evaluation of the results for a given segment, and even this can be accounted for in part by observing the consistency of the results over the course of several missions.

The pertinent gross in-the-large results appear in Table 3.21 in the columns labeled "Pct. Segment Report Corn" and "Pct. Segment Class Corn." The averages at the bottom of the columns are weighted averages, where the weights are determined from the number of acres in each segment. A summary of the results appears in Table 3.23. The standard deviation of 2.93 indicates the relative fluctuations in the crop identification accuracy which can be expected.

Table 3.22 Summary of crop ID results for test-field classification.

Mission	Pct. Report Corn	Pct. Class Corn
40M (6/28-7/11)	27.20	35.16
41M (7/12-7/25)	27.20	26.46
42M (7/26-8/8)	27.20	30.03
43M (8/9- 8/22)	27.20	30.02
44M (8/23-9/5)	27.20	34.46
45M (9/6-9/19)	27.20	30.87
Six-Mission Average	27.20	31.16
Standard Deviation		2.93

Table 2.23 Summary of crop ID results for gross in-the-large classification.

Mission	Pct. Correct Corn	Pct. Correct Other	Pct. Correct Overall
40M (6/28-7/11)	70.77	81.66	78.85
41M (7/12-7/25)	81.87	91.86	89.14
42M (7/26-8/8)	86.75	92.54	90.96
43M (8/9- 8/22)	84.25	89.41	88.00
44M (8/23-9/5)	87.53	85.00	85.69
45M (9/6-9/19)	85.08	88.70	87.72
Six-Mission Average	82.71	88.20	86.73

The first conclusion to be drawn from these results is that apparently either the acreage classified as corn from the MSS data tended to be biased high or else the acreage reported as corn was low. Subsequent results will indicate that the former is most likely the case.

--Error-Corrected In-The-Large Performance--

Another form of evaluation was used which combines the characteristics of the first two and tends to remove bias. The test field performance provides estimates of the type 1 and type 2 error rates; i.e., the rate at which corn was misclassified as "other" and the rate at which "other" was misclassified as corn. These estimated error rates can then be used to improve the acreage estimates for corn and "other."

In particular, it can be shown that the actual amount of corn in a segment can be expressed as:

$$C = \frac{E_{n/n}C_c - E_{c/n}C_n}{E_{c/c} - E_{c/n}}$$

where

C = total acres of corn actually in segment

C_c = total acres of segment classified as corn

C_n = total acres of segment classified as "other"

$E_{n/n}$ = fraction of actual "other" classified as "other"

$E_{c/n}$ = fraction of actual "other" classified as corn

$E_{c/c}$ = fraction of actual corn classified as corn

However, the test field performance does not give the exact values of $E_{n/n}$, $E_{c/n}$ and $E_{c/c}$ but provides estimates of these parameters which will be denoted $\hat{E}_{n/n}$, $\hat{E}_{c/n}$ and $\hat{E}_{c/c}$ respectively. Then an estimate of the amount of corn in a segment $\hat{C}$, which is better than the raw results obtained directly from the classification, is given by

$$C = \frac{\hat{E}_{n/n}C_c - \hat{E}_{c/n}C_n}{\hat{E}_{c/c} - \hat{E}_{c/n}}$$

(provided that sufficient test fields are available to represent the classes adequately). For this experiment, there were enough test fields for species identification but not for corn blight severity recognition.

The difference between this estimate and the "known" corn acreage (with the same qualifications applying to "known" as discussed earlier) is referred to as the error-corrected in-the-large performance.

The pertinent results appear in Table 3.21 in the columns labeled "Pct. Segment Report Corn" and "Pct. Segment Calculate Corn." The averages at the bottom of the columns are again weighted averages. These results are summarized by mission in Table 3.24.

Under this criterion for evaluating the results, the deviation from the mean recognition accuracy is somewhat less than for the gross in-the-large results. Again, as in both previous cases, large deviations

Table 3.24 Summary of crop ID for error-corrected in-the-large results.

Mission	Pct. Report Corn	Pct. Calculate Corn
40M (6/28-7/11)	27.20	30.50
41M (7/12-7/25)	27.20	24.84
42M (7/26-8/8)	27.20	28.47
43M (8/9- 8/22)	27.20	26.12
44M (8/23-9/5)	27.20	26.58
45M (9/6-9/19)	27.20	25.87
Six-Mission Average	27.20	27.06
Standard Deviation		1.88

occurred early in the growing season when the percentage of ground cover was small and it was hard to achieve a representative spectral characterization for most crops.

--Conclusions--

These results suggest that, given an operational system under which ground observations are available both for training and for testing classification accuracies, it is possible during much of the growing season to obtain from MSS data large area crop acreage estimates which are accurate to within a few percent. Though in the CBWE a large amount of ground observation data was used, this was merely in order to be as accurate as possible in the evaluation of the results. In practice, the training and test sets need be only large enough to be representative of the ground covers present - perhaps only a fraction of a percent of the area to be surveyed.

Willow Run Laboratories

At WRL, the accuracy of corn mapping was checked by performing two types of analyses on data from segments 201-205, 211-214, and 220, 222, 224, 226, 227 and 229 for missions 42M through 45M. First, histograms of the "number of fields" versus "percentage detection of the field" were prepared using all credible data from all four missions. Second, SPARC recognition maps from three segments (203, 204, and 212) were compared to the color IR photography collected by the C-47 in order to correlate missed detection by SPARC with anomalous field conditions, thereby eliciting a more realistic measure of SPARC performance in classifying corn. There will, however, always be anomalous field conditions present in corn fields which, at least part of the time, are not classified "correctly."

--Histograms--

All histograms (Figure 3.16) were characterized by a large number of fields which were well-recognized (greater than 80 percent correct detection), a relatively small number of fields with mediocre recognition (20-80 percent detection) and an increasing number of fields with poor recognition (0-20 percent detection). The slope of the histograms between 50 and 90 percent detection represents a normal situation. If SPARC classified a number of fields with slightly varying signatures after having been trained on a few fields, most of them would be recognized very well, but a few would be recognized poorly. The slope of the histograms from 0.50 percent represents the inability of the typical five training sets used for this analysis to classify some corn fields. There were apparently some fields which did not resemble the available training sets well enough to be well recognized. Additional training sets selected from these fields or more optimally selected training sets should improve the recognition of corn considerably.

The histograms also reflect the improved corn recognition performance determined from more detailed analysis. For missions 43M and 44M, the low percentage detection peak is smaller relative to the high detection peak than

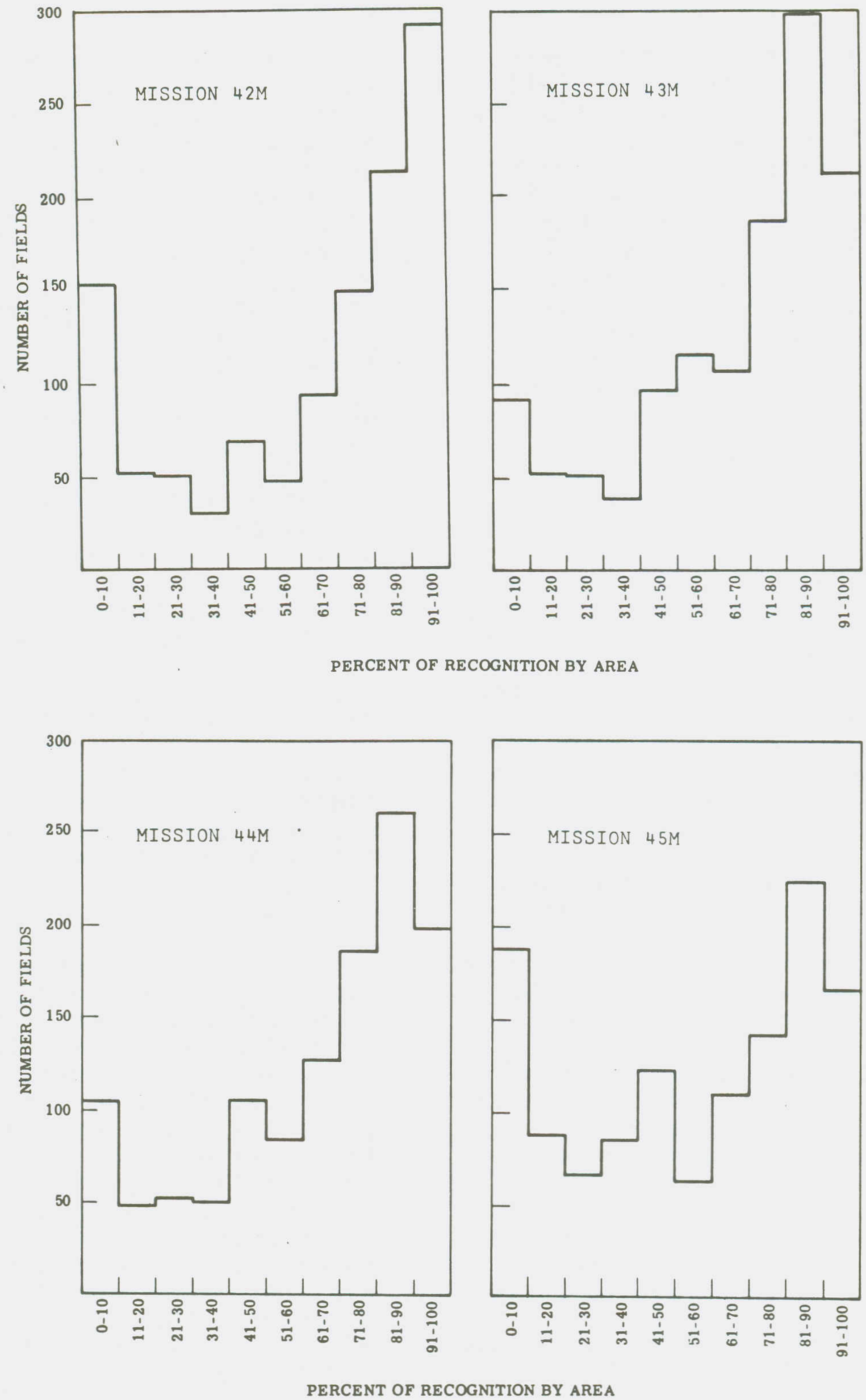


Figure 3.16. Frequency distribution of number of corn fields by percent of recognition by areas (WRL).

for missions 42M and 45M, indicating that relatively fewer fields were poorly classified. This was undoubtedly caused by the relatively uniform color and cover of corn during August (when missions 43M and 44M were flown). The histogram for 45M is much flatter--more mediocre percentage detections occurred. This was probably caused by the spectral variation of corn signatures caused by maturity differences. This variation was partially accounted for by the training sets, but apparently less completely than for previous missions.

Additionally, histograms show that a number of fields were poorly detected in all missions. This is believed to be caused by the limited number of training sets used for this analysis and is an indication that either five more optimal training sets or more than five training sets are desirable for more complete corn recognition.

Corn recognition accuracy of SPARC maps tended to be better for missions 43M and 44M than for 42M or 45M. The poorer performance on mission 42M, where fewer of the SPARC-missed detections could be correlated with obvious field conditions, was probably caused by percentage cover variations in corn in the two northern segments analyzed. In 45M data, where inferior performance was also noted, the cause was most likely due to maturity differences in the corn which caused variations in spectral signatures too large to be covered by the limited number of SPARC training sets used.

All conclusions regarding corn detection must be interpreted with caution for two very important reasons. First, it is known that the probability of detection of agricultural crops may be markedly affected by the choice of training sets. Though the use of models of the crop canopy, intervening atmospheric effects and illumination geometry, or empirical cluster analysis techniques applied to the data itself may assist in the selection of an optimum set of training sets for species mapping, there is no indication that selection of corn training sets portraying different blight severity levels yields an optimum set of training sets for corn acreage recognition.

Second, training sets were varied from mission to mission to accommodate the changes in blight level. Conclusions that data from one mission may be more useful than data from another for recognizing corn may simply reflect the fact that training sets more optimal for species recognition happened to be used.

--SPARC-Color IR Comparison--

As has been mentioned, after producing the histograms the accuracy of corn mapping was checked with a more intensive experiment. Data were selected from segments 203, 204 and 212 (missions 42M through 45M). The test sets used are summarized in Table 3.25. Ideally, it would have been desirable to send ground investigators to the sites with recognition maps in hand to explain missed detections. This procedure, though used for analysis of segment 212 data from mission 43M (see Section VI), was impossible because all corn had been harvested at the time of this

Table 3.25 Test sets for corn recognition accuracy measurements.

Segment		
203	204	212
Field		
BB5	A2	EE8
BBB5	A5	EE9
D7	AA7	EE11
D11	d5	EE15
DD4	DD4	F2
EE10	f5	II1
EE17	f8	L18
G3	HH2	N1
LL10	K5	N2
NN1	K11	NN2
O7	OO5	OOQ1
UU1	OO10	RR2
V4	Q3	RR3
V9	QQ18	RR4
WW5	S2	RR5
	S4	SSS1
		SSS2
		UU1
		UU4
		UU6
		UU7
		UU8
		UU10
		VV6
		WW2
		ZZ7

analysis. Instead, color IR photography collected from a 5000-foot altitude by the C-47 was analyzed in an attempt to correlate missed detection areas on the SPARC maps with obvious field conditions such as weeds, water damage, low percentage cover, etc.

Photo-interpreters concurrently analyzed the color IR photography and SPARC recognition maps and noted the percentage of the field they felt was not corn (from photo), the percentage of the field not classified as corn (from SPARC maps) and the correlation between the two. These measurements allowed computation of a revised probability of detection based on the number of acres of corn it was felt were actually in the field. Table 3.26, illustrating the importance of this restricted corn definition, shows the percentage of the test set estimated to contain corn.

The most common noncorn acres in corn fields were weedy patches, areas of poor sandy soil (especially in segment 203), or areas of obviously sparse (and probably non-productive) corn cover perhaps caused by water damage. The low percentage of corn in segments 203 and 204 test sets for mission 45M are attributable to premature harvest of several of the test set fields.

The revised probabilities of corn detection are shown in Table 3.27. This revised probability is defined as the fraction of the test set's actual corn area which was detected by SPARC. Areas which were mistakenly identified were, in general, peripheral to weedy patches or areas of generally low corn cover. These areas represent transitions between normal corn and obvious field problems areas. In some cases, weedy patches were erroneously detected as corn.

Detection probabilities for segments 203 and 212 were the largest for mission 44M. On the other hand, the detection probability for segment 204 was largest for mission 42M and declined slowly until mission 45M when it dropped off considerably. The difference in behavior of detection probabilities was felt to have been an artifact of the training set selection procedure based on blight levels (i.e., the training sets selected for segment 204, Mission 42M, seem to have been more suitable for corn recognition). Indeed, since there was very little blight observed in segments 203 and 204 for 42M, training sets could be selected to optimize corn detection. The poorer performance in segment 203 is attributable to the fact that 203 has generally sandy soil.

Detection probabilities for segment 212 were generally higher than for either of the two other segments, with the exception of mission 43M. This may have been because segment 212 was more representative of corn belt farming practices than 203 or 204 or may simply have been an artifact of the training sets used for classification. (See Section VI.)

--Conclusion--

In conclusion, the SPARC results showed about 65 percent of the corn field area detected as corn for all four missions.

Table 3.26 Corn acreage of test set (percentage based on photointerpretation).

	Segment		
Mission	203	204	212
42M	0.711	0.837	-
43M	-	0.789	0.860
44M	0.613	0.821	0.877
45M	0.565	0.680	0.798

Table 3.27 Modified corn detection probabilities (from analysis of test set data).

	Segment		
Mission	203	204	212
42M	0.623	0.980	-
43M	-	0.962	0.903
44M	0.828	0.903	1.000
45M	0.510	0.787	0.860

However, much of the missed detection could be accounted for by the presence of weedy patches, drowned spots, or areas of low crop cover which were interpretable on the color IR film. Once these areas were accounted for in this manner, close to 90 percent of the corn acreage was recognized using mission 43M and 44M data. Missed detection in the other missions was accounted for by drought (in the northern segments on mission 42M) and maturity differences (in all segments on 45M).

Overview: LARS and WRL

From the preceding discussions, it is possible to draw reasonably optimistic conclusions concerning the ability of remote sensing technology to perform crop identification. It is unfortunate that the approaches taken by LARS and WRL to both the classification and the evaluation of the results were so different as to be beyond any direct comparison. On the other hand, since a truly objective comparison by the participants in the CBWE would be difficult, it is probably best left to the reader to make a critical comparison and evaluation between the LARS and WRL data processing technologies.

C. Effectiveness of Spectral Bands

The feature selection algorithm was used for every segment analysis performed at LARS and an examination of these channel selections (see Figure 3.17) yields some interesting information about which bands and band combinations were most effective for the various classification tasks. However, interpretation of these results should be undertaken only after noting the following:

1) It is not known to what extent the selection of channels used for the cluster analysis may have biased the feature selection (the "standard" LARS procedure recommended use of channels 1, 3, 6, 9, 10, and 11 for the cluster analysis); and
2) The problems of discriminating corn from noncorn and discriminating among the blight levels were given equal weight in the analysis instructions. Since the instructions also specified that the criterion of minimum pairwise transformed divergence should be used for the selection, it is not clear whether species discrimination or blight level discrimination had a dominant influence.

The most striking aspect of the results is the apparent importance of the infrared channels. The two individual channels selected most frequently were channel 9 (1.0-1.4 μm, in the near-reflective infrared) and channel 12 (9.3-11.7 μm, in the thermal infrared portion of the spectrum). The four-channel combination selected typically included one channel each from the visible, near infrared, middle infrared, and thermal infrared portions of the spectrum. (Available near-infrared channels were .72-.92 and 1.0-1.4 μm, middle infrared were 1.5-1.8 and 2.0-2.6 μm, and the one available thermal channel spanned 9.3-11.7 μm.)

It would appear from these selections that the scanner contains

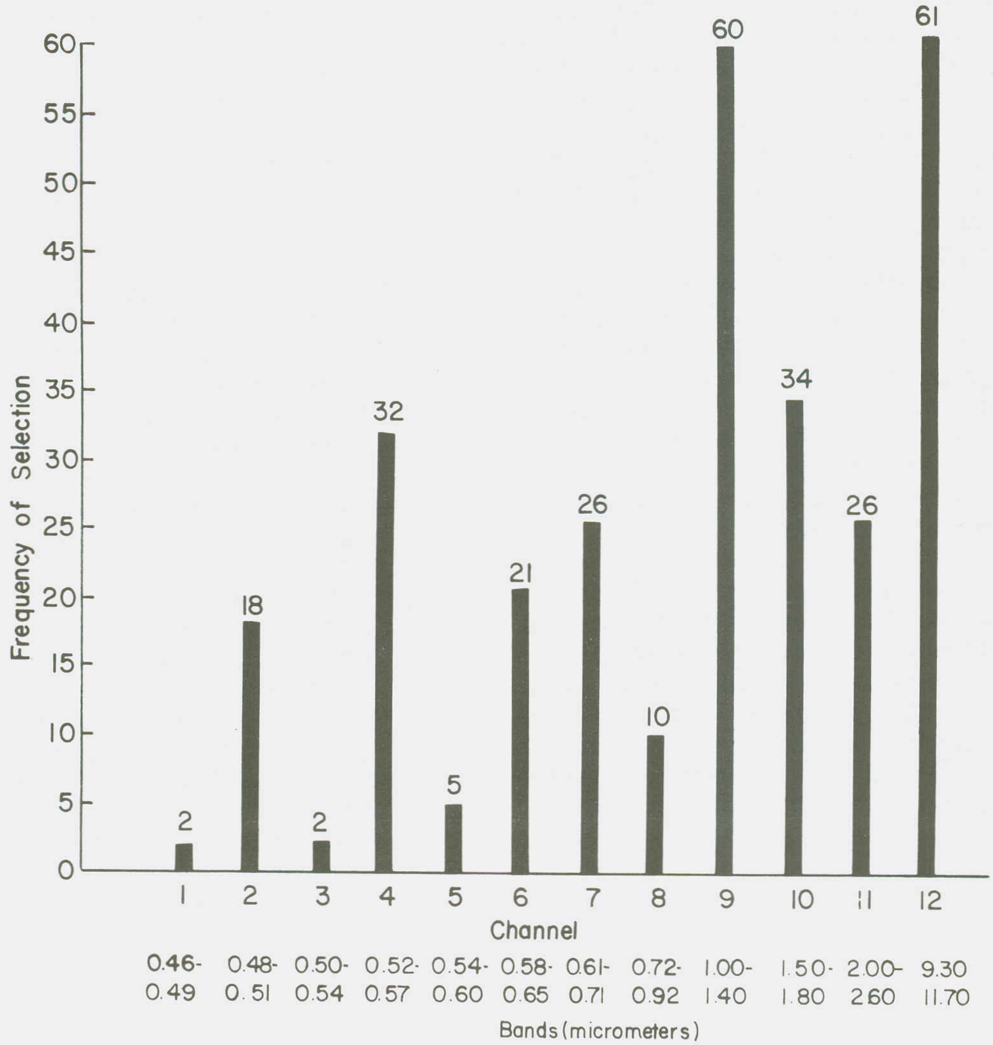


Figure 3.17. Histograms of LARS channel selection frequency for missions 41M through 45M.

many more channels in the visible portion of the spectrum than are necessary for most analysis purposes. Since the visible portions of the spectrum most frequently selected included the peak of the green reflectance (between the strong chlorophyll absorption bands in the blue and red) and a channel each in the blue, red and yellow portions of the spectrum, it might be possible, at least for vegetation mapping purposes, to eliminate the remaining three channels in the visible portion without a significant loss in informational content. However, for other purposes such a conclusion should be thoroughly checked on the basis of field spectrometer data and additional MSS data analysis.

Further analysis of the channel selection results indicates that the five most frequently used channels included two channels in the visible, one in the near-infrared, one in the middle infrared and the thermal channel. The most frequent six-channel combination was two visible, one near infrared, two middle infrared and the thermal channel. It is significant that in the near-IR a strong preference was shown for channel 9 (1.0-1.4 μm) over channel 8 (.72-.92 μm).

These results indicate that within the IR region the middle infrared portion of the spectrum is the most important and that overall the infrared (both reflective and thermal) are generally much more useful wavelengths than are the visible wavelengths. Previous work had indicated that the thermal infrared region was of particular importance in separating corn from pasture areas and also for detecting stress conditions in vegetation; such stresses affect the plant temperature and thus are detectable in the thermal region before they are in the reflective infrared or visible portions of the spectrum. The trends shown in this data set are consistent with hypotheses and predictions developed on the basis of laboratory and field spectrometer measurements.

Section V.

Evaluation of Blight Classification Results

V. EVALUATION OF BLIGHT CLASSIFICATION RESULTS

Introduction

An important part of any experiment is a rigorous evaluation of the results. In this section and the next, the blight classification results obtained by remote sensing techniques are evaluated. The standard of comparison is the ground observation data collected during the Experiment. The ground data cannot, however, be considered absolute since they are only a small sample from the population and since the blight severity ratings were made by people who sometimes disagreed in their perception of blight severity.

Evaluating remote sensing performance is always a difficult problem because of the lack of "ground truth," and, the larger the area covered by the remote sensing classification, the harder it is to obtain sufficient ground data for evaluating the results.

Two techniques have been used to measure the performance of the remote sensing classifications: correlation and test fields. The first is statistical and depends on a large number of observations; the second is empirical.

A. Correlation

Although ratings of blight severity were made in many fields across the Corn Belt, an average of only eight fields per segment were checked on the ground and most of these fields were used for training. To carry out the best test of classification accuracy, ratings would have been needed from many more fields so that field-by-field comparisons could have been made. Since only a limited number of fields were available for this kind of test, other kinds of statistical analyses were used to evaluate the classification results. One of the procedures used was correlation, a quantitative measure of the degree of agreement between two blight assessment methods, both of which are known to be subject to experimental error. Close agreement between field observations and results of photointerpretation or machine analysis of MSS data indicates that the two methods are estimating the same value for the parameter.

Graphs plotting field observation estimates versus photointerpretative estimates of average blight severity for two periods are presented in Figures 3.18 and 3.19. Segment means are shown in these Figures whereas flightline means were shown in the maps in Section III (Figures 3.09 and 3.10). Note that there is an increase in the correlation coefficient (r) for the later period when more levels of blight were present. The 1:1 line is shown as an aid in determining when there is good agreement between the two methods; it should not be confused with a regression line. Perfect agreement between the two methods would result in all points falling on the 1:1 line. A consistent bias (either over- or under-estimation) would still result in high correlation; for example, as compared with ground estimates, photointerpretive results tended to underestimate

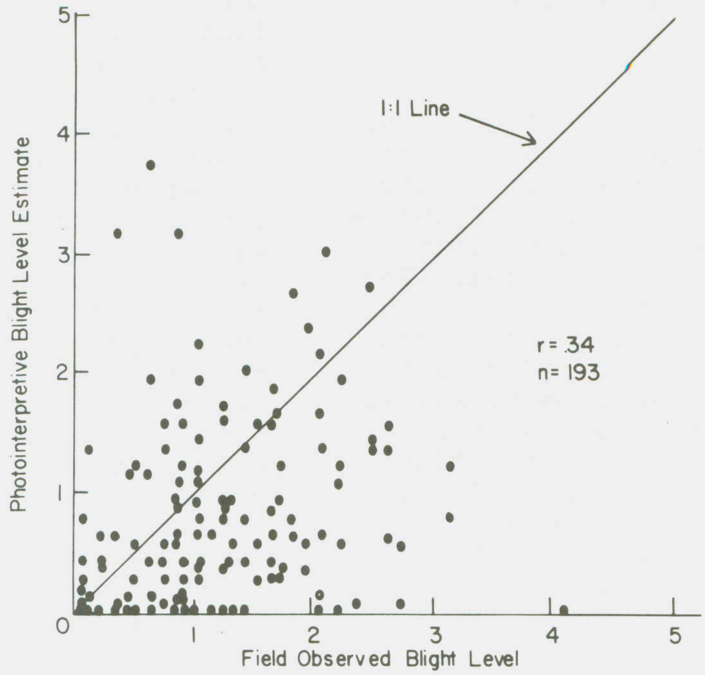


Figure 3.18. Correlation of field observation and photointerpretation estimates based on segment averages: period beginning August 9.

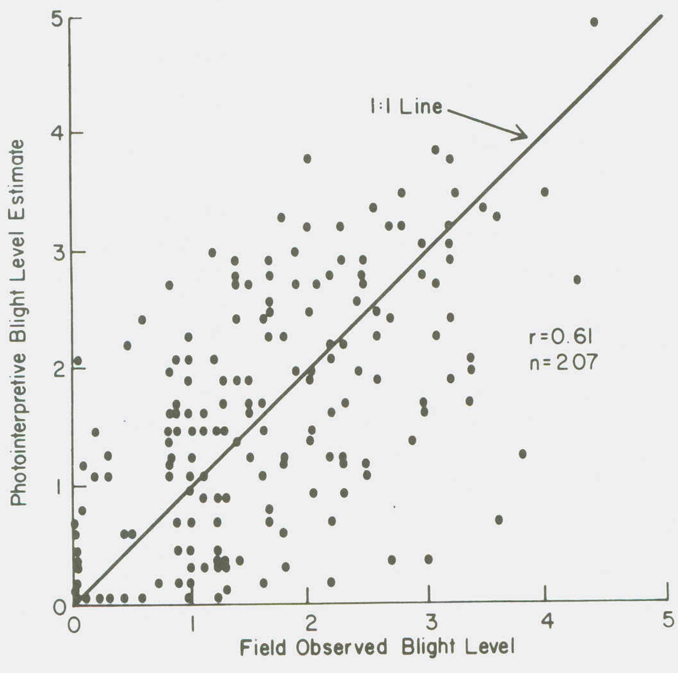


Figure 3.19. Correlation of field observation and photointerpretation estimates based on segment averages: period beginning August 23.

the acreages in the healthy corn class and to overestimate the acreages in the moderate-to-severe blight class. There are statistical methods available to remove the effects of biases.

A major objective of the CBWE was to determine if healthy corn could be distinguished from diseased corn by remote sensing methods. The graph of correlations for two classes of blight severity (0-1-2 and 3-4-5) indicates that photo-interpreters can accurately separate corn fields into the two classes, healthy to slightly blighted and moderately to severely blighted (Figure 3.20). (The data points represent acres of each blight severity class in a segment.) Correlation coefficients of .90 and .64 were obtained for the two classes, respectively. Attempts to differentiate the six individual blight classes which can be distinguished on the ground were unsuccessful. This is indicated by the lower correlation coefficients (r = .21 to .67), the "scatter" of the data points, and the large deviation from the 1:1 line (Figure 3.21). This was not surprising; differences between individual classes are subtle, and infection at the early stages is confined to the lower leaves and hidden from view of the sensor.

The correlations between blight-level estimates by field observations and by machine analysis of data for two periods are shown in Figures 3.22 and 3.23. The higher r values (.86 and .90) and the close fit to the 1:1 line indicate that machine-analysis results more closely paralleled ground observation estimates than did the photointerpretation results. Again, the early stages of blight infection were difficult to detect.

As was the case with photo-interpretation techniques, the correlation coefficients for MSS data analyses were lower for attempts to divide corn acreage into six blight levels (Figure 3.24). The separation of fields into two categories, healthy vs. blighted, is shown in Figure 3.25. In this case there is excellent agreement between the field observation and the estimates made from analysis of MSS data; correlation coefficients were .94 and .92 for the two classes, and the points lie close to the 1:1 line.

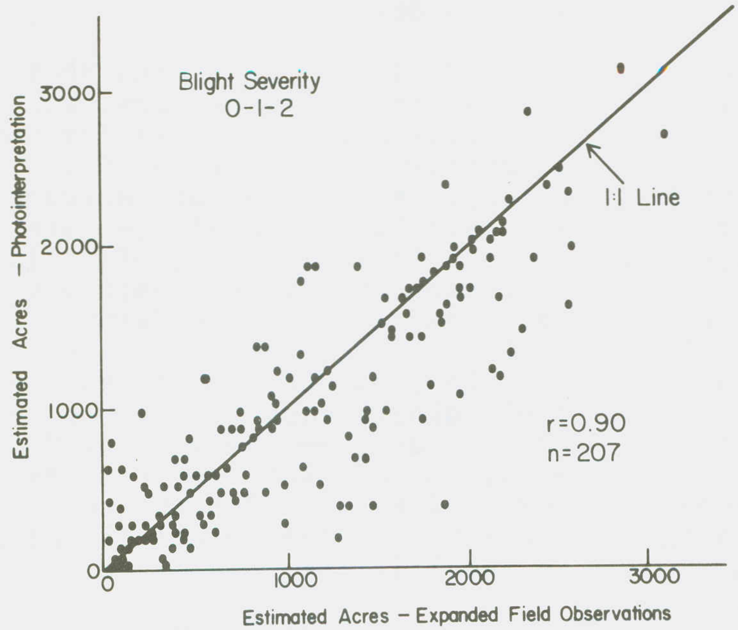
B. Test Fields

As described in Volume II, Section VI, test field classification was used to evaluate the blight level identification by both photo-interpreters and multispectral data analysts. The percent of acres classified into each blight level for each method was balanced against the ratings obtained from ground observation.

Photointerpretation

Initially, photointerpretive results were compared with expanded ground observations for the total test area during a single mission period (see Figure 3.08). There was close agreement between the two estimates for all blight levels except 0 and 1 probably because blight in its early stages is not detectable on color IR film.

A further comparison of ground ratings and PI estimates of blight severity was also made for



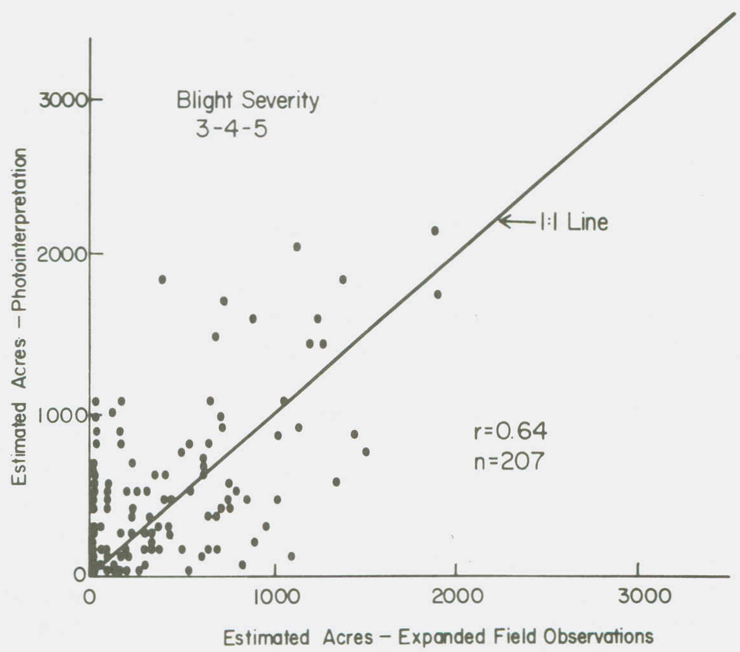


Figure 3.20. Correlation of field observation and photointerpretation estimates of segment acreages of healthy (blight level 0-1-2) and blighted (3-4-5) corn: August 23-September 5.

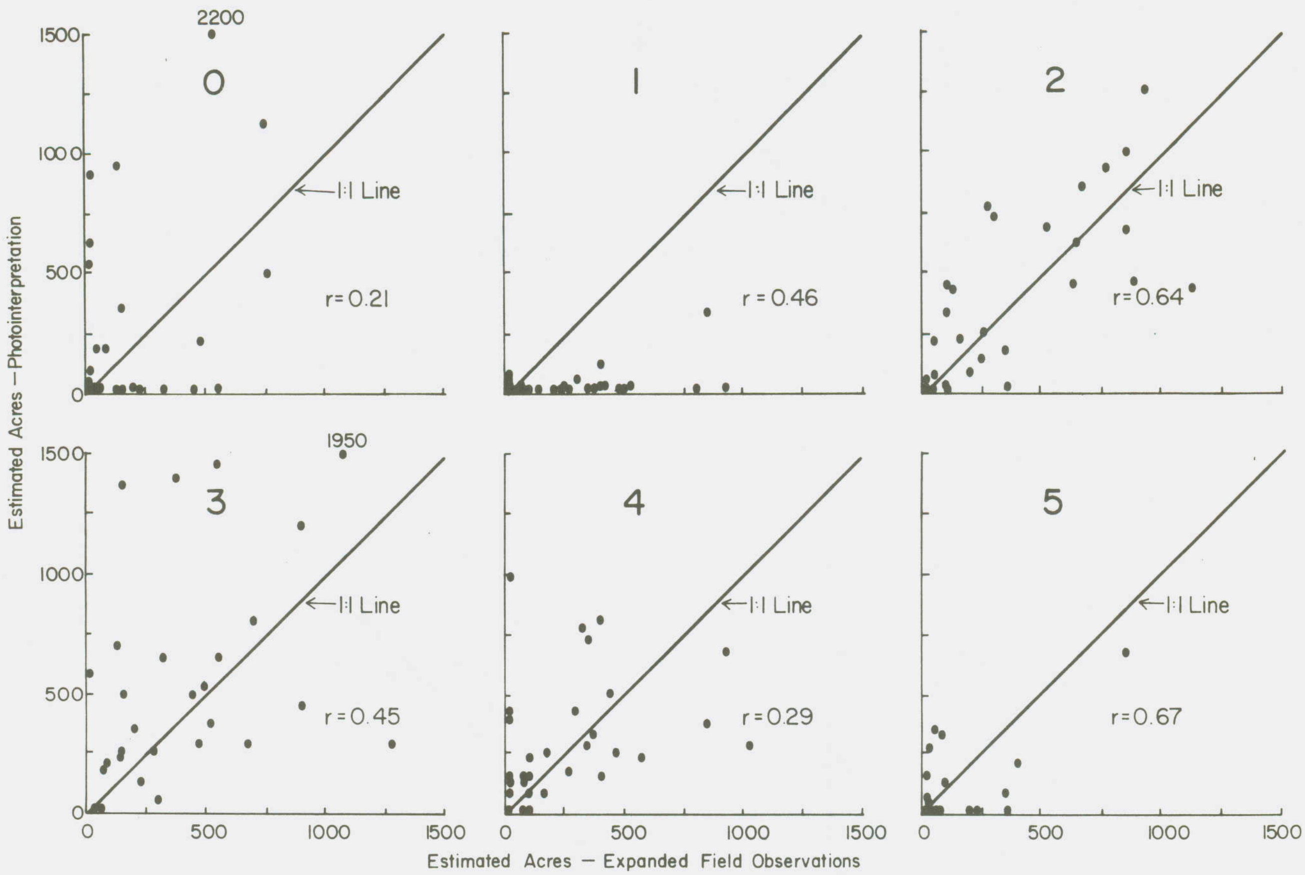


Figure 3.21. Correlation of field observation and photointerpretation estimates of individual blight classes in the intensive study area: period beginning August 23.

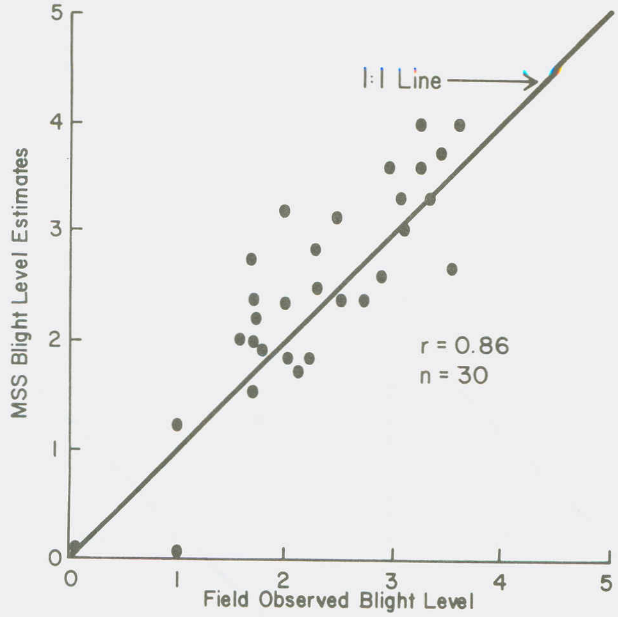


Figure 3.22. Correlation of field observation and MSS analysis estimates of segment average blight levels: August 23-September 5.

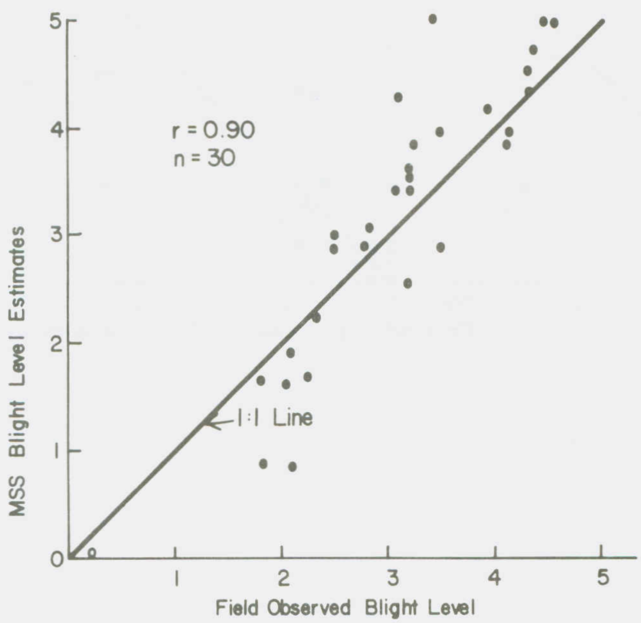


Figure 3.23. Correlation of field observation and MSS analysis estimates of segment average blight levels: September 6-20.

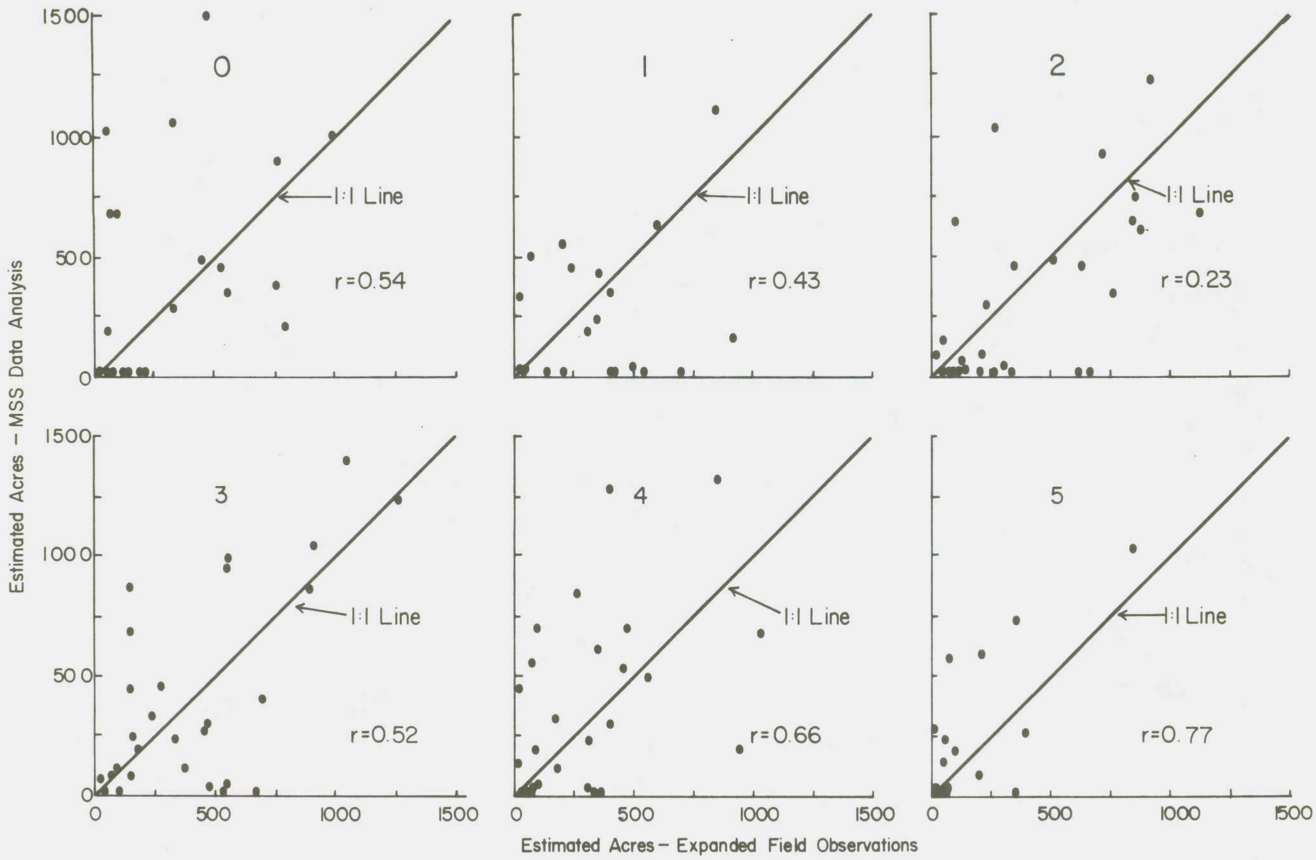


Figure 3.24. **Correlation of MSS analysis and field observation estimates of acreages of individual blight classes in the ISA: period beginning** August 23.

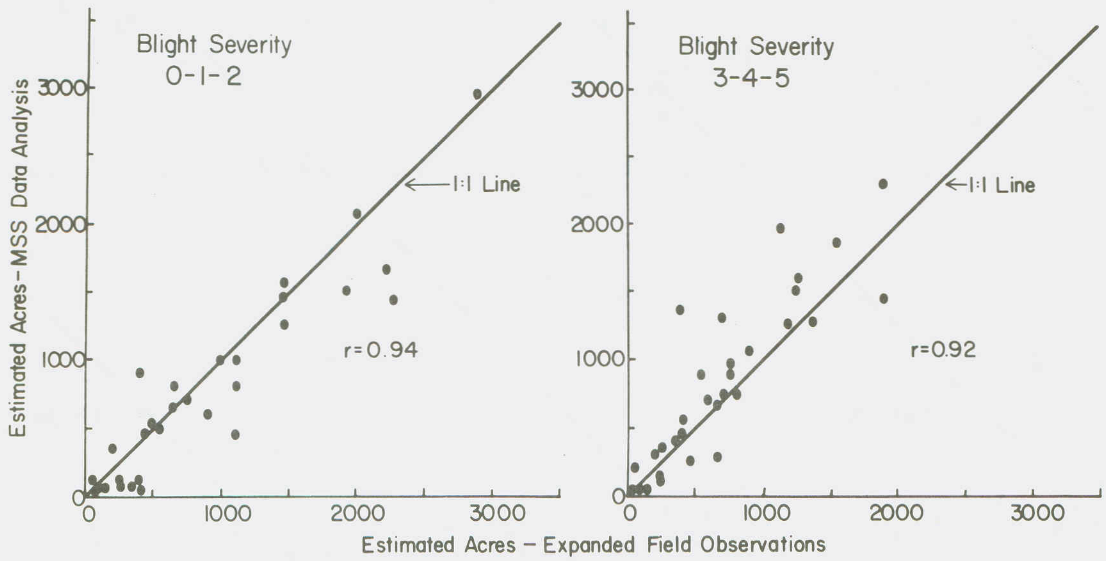


Figure 3.25. Correlation of MSS analysis and field observation estimates of acreages of healthy (blight level 0-1-2) and blighted (3-4-5) corn in the ISA: period beginning August 23.

two mission periods, August 9 and August 23, based on a different sample of fields from those used in the regular biweekly survey. SRS drew a stratified random sample from corn fields located in 24 segments across the test area (see Figure 3.26), and ASCS observers collected data in these approximately 100 fields in the same way that CES enumerators had. This information, however, was not available to interpreters during their analyses.

Once the PI teams had made their blight severity ratings, these ratings were compared to the ASCS ground observations. To make the comparison, it was necessary to assume that the blight levels estimated by the ground teams were accurate approximations of the actual distribution of blight in the fields.

Comparisons were based on the percentage of the field acreage classified in each blight severity level (Figure 3.27 and Figure 3.28). Results corresponded favorably for all levels except 0 and 1, and this may be explained by the similarity of their appearance on the color IR film. Confusion in the other levels was attributable to natural conditions, specifically various stresses and corn maturity stages. The latter is of particular interest since during the August 23 period corn was approaching natural senescence and this brought about a drop in the near-infrared response. The resultant tonal change on the film could easily have been interpreted as blight by PI's. Ground observers, on the other hand, would have been more able to distinguish this from blight.

Similar comparisons were not conducted for later mission periods; inadequate ground data were available for the September 6 period, and by September 20, natural senescence had interfered seriously with the detection of blight.

MSS Data Analysis

The performance of the MSS blight severity ratings also was evaluated using test fields. This was the most rigorous test which could be used since the majority of points in each field had to be correctly identified in order for the field to achieve a "passing grade." The tests comparing the number of acres in each blight class were less demanding.

There were, however, several limitations to the use of test fields. The more serious include the need for forcing blight conditions into discrete classes when they are actually continuous and the small number of test fields available. These problems are discussed more fully in Section VI.

Ground data for this comparison came from two sources: the county ASCS personnel's biweekly observations in 22 fields in four segments, and the LARS and WRL personnel's field-gathered blight information on approximately 100 more fields in 12 segments during period 6, August 23-September 5.

The results of this method of measuring classification performance are presented in Tables 3.28 and 3.29 for periods 5 and 6, respectively. Classification into the six individual blight classes

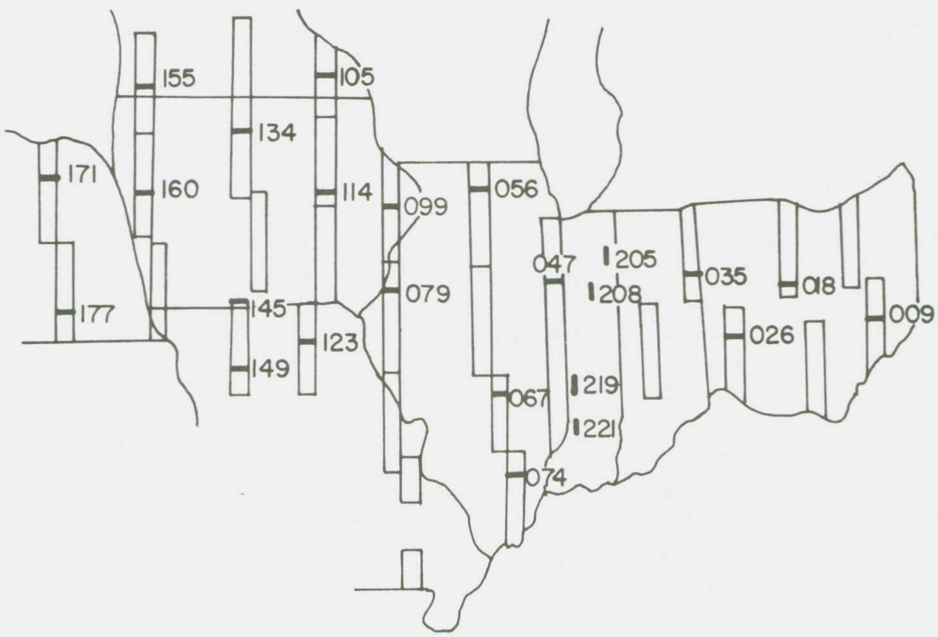


Figure 3.26. Test segments for photointerpretation.

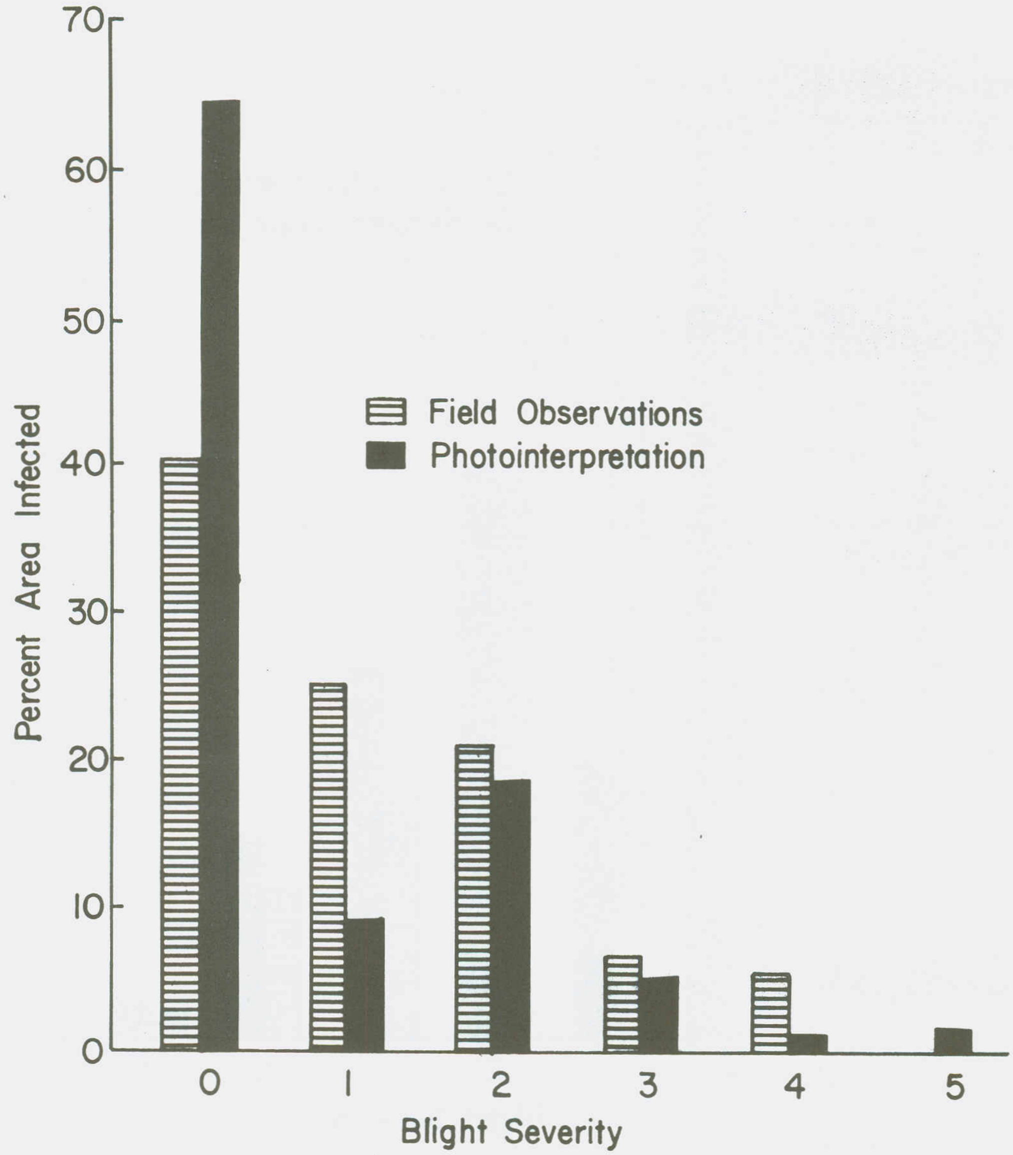


Figure 3.27. Comparison of ground observation and photointerpretation blight estimates for test fields: August 9-22.

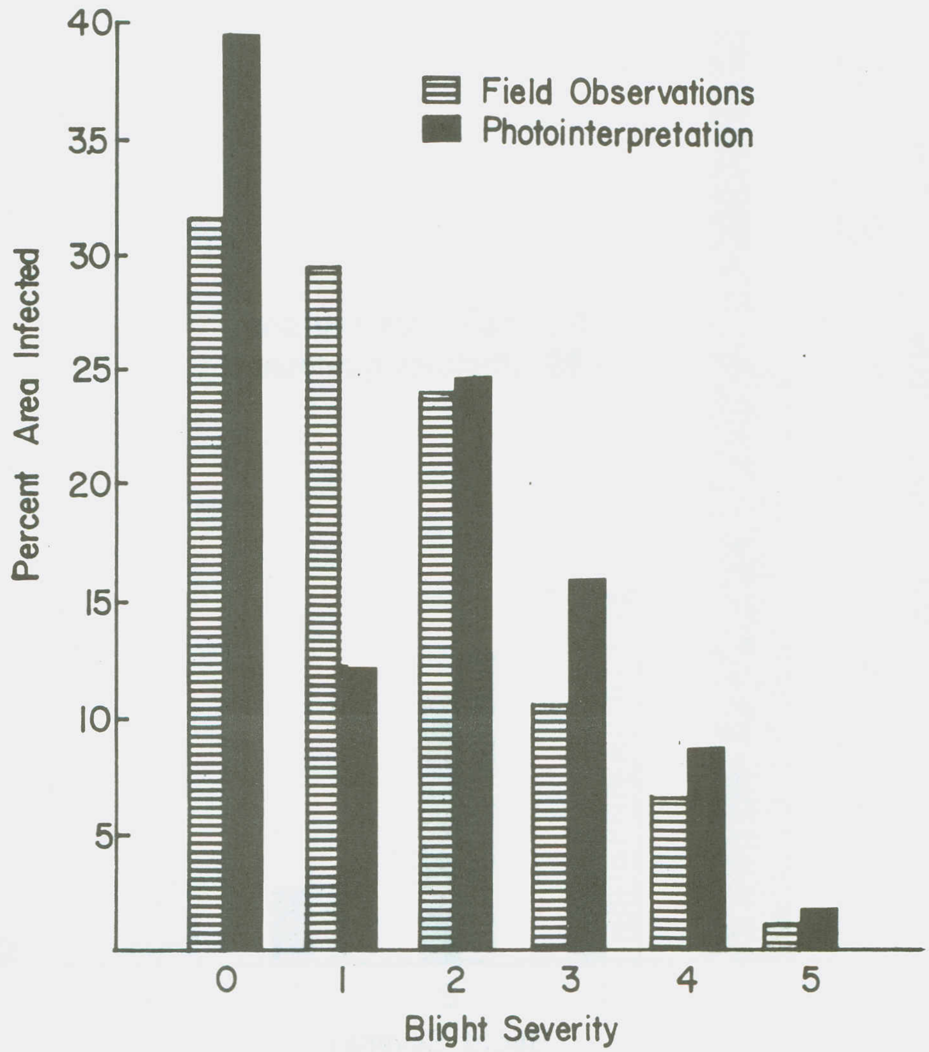


Figure 3.28. Comparison of ground observation and photointerpretation blight estimates for test fields: August 23-September 5.

Table 3.28 MSS classification performance of 22 test fields: August 5-22.

Field Observed Blight Level	No. Acres	No. Acres Classified as Blight Level 0	1	2	3	4	5	Percent Correct
0	0	0	0	0	0	0	0	--
1	79	24	28	4	1	22	0	35
2	153	69	52	32	0	0	0	21
3	78	10	24	25	19	0	0	24
4	56	0	18	0	36	2	0	5
5	0	0	0	0	0	0	0	--
Total	366	103	122	61	56	24	0	

Overall Performance $\frac{81}{366}$ = 22.1 percent

Table 3.29 MSS classification performance of 123 test fields: August 23-September 5.

Field Observed Blight Level	No. Acres	No. Acres Classified as Blight Level 0	1	2	3	4	5	Percent Correct
0	697	164	25	92	83	183	150	24
1	407	82	76	27	138	70	14	19
2	746	232	63	150	99	125	77	20
3	705	13	58	55	99	347	133	14
4	102	0	1	0	6	93	2	91
5	172	0	0	0	27	56	89	52
Total	2829	491	223	324	452	874	465	

Overall Performance $\frac{671}{2829}$ = 23.7 percent was not very accurate; only about 25 percent of the data points in the test fields were correctly classified. When individual classes were combined in two classes of 0-1-2 vs. 3-4-5, performance was markedly improved. For the two-class case, overall performance was 73 and 60 percent for periods 5 and 6, respectively.

Conclusions

While only a limited amount of information was available to measure the performance of the blight classifications, two kinds of tests were conducted. The first was a correlation of acreage estimates based on the expanded field observations and on the remote sensing classifications. The two estimates agreed well for two classes of blight severity: none to mild and moderate to very severe. The results showed that MSS classifications were more highly correlated with the ground estimates than were the PI classifications. The conclusion from these tests was that over a large area either MSS classifications or field observations of blight severity could have been used to assess the blight situation -- both were estimating the same parameter.

The results from the test fields are inconclusive. The ground observations for the limited number of test fields did not agree well with either PI or MSS blight classifications. This was attributed to two factors: errors in the ground level blight ratings and the fact that whole fields were not uniformly in the same blight severity class. A third factor affecting MSS analysis was the failure of the training statistics to be representative of the various blight severity classes. As pointed out earlier in this report, the spectral differences between individual blight classes are small and there are a number of factors other than blight that affect spectral response. Classifications into two blight classes, none to mild and moderate to very severe, were considerably more accurate than classifications into six individual classes. The discrimination of blight is discussed in more detail in Section VI.

Section VI.

In-Depth Analysis of Segment 212

VI. IN-DEPTH ANALYSIS OF SEGMENT 212

Introduction

During the CBWE, both LARS and WRL performed several special analyses on ground observation data, color infrared photography, and multispectral scanner data acquired during mid-August from ISA segment 212. These analyses were designed to answer questions which were difficult to answer adequately with routine procedures; specifically, to:

1. determine how reliably blight severity could be mapped using various sets of training fields;

2. make an objective comparison between results obtained from photographic data and those obtained from multispectral scanner data;

3. quantify the degree of variation in results due to the photo-interpreters or MSS data analysts;

4. evaluate non-routine analysis techniques which might give improved results; and

5. measure the effect of blight, soil background and percent ground cover on the relative spectral response of corn fields.

Segment 212, in Montgomery County, Indiana, (see Volume II, Figure 2.20) was selected because it contained a large number of corn fields with a good representation of the various blight severity levels. The northern half of the segment has level to gently rolling topography and contained fairly large fields planted primarily in corn and soybeans. The southern half of the segment had rougher terrain and smaller, less uniform fields planted in non-row crops.

Ground data for this analysis were collected on August 17 and 18 by six ground observation teams composed of the photo-interpreters and MSS analysts from WRL who visited nearly every corn field. Data collected included an overall blight severity rating, crop maturity, plant density, tassel color, stresses present, and identification of other irregularities in the field. Crops in all noncorn fields were also identified. Further assessment of the blight condition in selected corn fields was made from a helicopter (see Volume II, Figure 2.23).

Also available for analysis were color photography and color-infrared photography collected by the Purdue Beechcraft (see Volume II, Section III B) at altitudes of 2000 and 4000 feet. In addition to the data specially obtained for the segment 212 analysis, multispectral scanner data were routinely collected on August 17 at 11:19 a.m. under near-optimal weather conditions. The RB-57F had obtained small-scale photographic coverage of the area on August 12.

The test data set consisted of 100 corn fields, including 14, 45, and 41 fields of N, T, and B cytoplasms, respectively. The average blights were 0.82, 2.91, and 2.07 for N, T, and B cytoplasm, respectively.

The reader is cautioned that the results presented in this section are based on analyses of one segment for one time. It is not known to what extent the results can be generalized to other segments and times. Certainly there would be some risk in doing so. Similar analyses over more segments and dates would have greatly increased the reliability and value of the results, but resources were not available to conduct such further studies.

A. Photointerpretation

The six regular analysis teams plus two special teams composed of area coordinators used the standard biweekly procedure to determine the amount of blight in segment 212. These results were then compared against the ground-derived ratings in order to determine the ability of the teams to evaluate blight conditions. Table 3.30 shows the combined results of these analyses.

The number of fields classified into correct blight levels was low. There was, however, a tendency for the PI's to assign higher blight levels as the ground observed blight level increased, as shown in the last column of the table. For blight levels 2 or above, the PI's generally assigned lower blight levels than did the ground observers and higher blight levels for levels 0 and 1. These results are in agreement with those presented in Section III of this volume.

An analysis of variance (AOV) was performed on average per-field blight levels for cytoplasms N, T, and B and for all eight teams with the objective of determining if either the team analyzing the data or the cytoplasm of the corn had any statistically significant effect on assignment of blight levels. The data for this analysis and the accompanying AOV data are shown in Table 3.31. As the table indicates, there were significant effects due to both cytoplasms and interpretation teams.

Next, the Scheffé test for multiple comparisons (Ref. 1) was run to determine for which pairs of cytoplasms blight levels were perceived to be different. The results of this test show that the average assigned blight level for T-cytoplasm fields was significantly higher than the average assigned blight levels for N- and B-cytoplasm fields. However, no conclusion could be drawn from the comparison of average assigned blight levels in the N and B fields.

The conclusions which can be drawn from these results are that the accuracy of discrimination of individual blight levels by the photo-interpreter teams was low. Further, there was a considerable amount of variability in the blight severity assignments made by the various photo-interpreter teams.

B. MSS Data Analysis

Willow Run Laboratories Results

WRL's involvement in the analysis of data from segment 212 consisted of participation in the special ground survey, digital

Table 3.30 Corn blight severity class recognition by PI's.

Ground-Observed Level	PI-Assigned Level*						Average PI Blight Rating
	0	1	2	3	4	5	
0	38	13	26	10	7	1	1.34
1	52	30	43	16	7	0	1.30
2	74	54	101	42	11	0	1.51
3	34	34	53	50	8	8	1.80
4	5	1	6	7	12	0	3.13
5	0	0	0	0	0	0	----

*Results shown are the total number of fields classified into each blight level by all eight teams.

Table 3.31 Analysis of variance of average blight levels.

Teams	Cytoplasm Type		
	N	T	B
1	2.92	2.90	2.47
2	1.45	1.85	1.15
3	1.33	2.42	1.96
4	0.44	0.28	0.08
5	1.00	1.24	0.74
6	1.28	2.27	2.11
7	2.00	2.58	1.74
8	0.75	1.73	0.61

Analysis of Variance

Source	d.f.	s.s.	m.s.	F.
Cytoplasms (C)	2	1.52	.76	6.23*
Teams (T)	7	12.76	1.82	15.00*
Error (CxT)	14	1.70	.12	

*Significant (α) at .05 level

analysis of the MSS data and SPARC analysis based on the digital analysis results.

The digital analyses of the data were performed (1) to determine whether or not preprocessing was necessary and, if so, what type would be the most useful; (2) to select a subset of channels for use in the SPARC analysis; and (3) to make a preliminary determination of the ability to map blight severity levels. Preprocessing to compensate for changes in solar irradiance and variations in observed radiance across a scan line was generally found to enhance the value of digitized data; however, classifications based on the preprocessed data seldom distinguished between the lowest blight levels.

The SPARC analysis procedures for segment 212 varied somewhat from the normal procedures. The optimal set of channels and the necessary preprocessing corrections were determined by the preliminary digital analysis of the data, and training sets were chosen mainly from the areas visited by the enumerators and not from biweekly visited fields.

In this process, test fields comprising about 17 percent of the total corn acreage in the run and representing all blight levels were selected to check classification accuracy. Figures 3.29 and 3.30, respectively, show the classification map and ground observation data for a portion of segment 212. Table 3.32 lists the results of these test field classifications. Note that confusion between blight levels 0 through 3 (as indicated by the digital analyses) was common but that the more severe levels (4 and 5) were somewhat more distinguishable than lower levels. There was some tendency for lower blight levels to be classified as high blight levels, but the reverse situation did not occur. Table 3.33 shows the acreage classified into each blight level as computed from the percent of each field recognized and the known field acreages. Table 3.34 provides the same information for three grouped blight levels (0-3, 4, and 5). However, since there were very few fields with high blight level identified by the ground survey, the testing of classification accuracy for level 4 and level 5 fields was very limited.

Overall, it was concluded from analysis of SPARC results that two blight groups (level 0-3 and 4-5) could be mapped with reasonable reliability taking into consideration the tendency to misclassify low blight level fields as high blight level fields for this data set.

LARS Results

Seventeen MSS analysis teams at LARS performed analyses on data acquired over segment 212 during mission 43M, using three sets of training data and the standard analysis procedures. Several different measures of performance were used to determine how well blight infection was classified, and differences in analysis results due to the use of different training sets and to different analysts were evaluated.

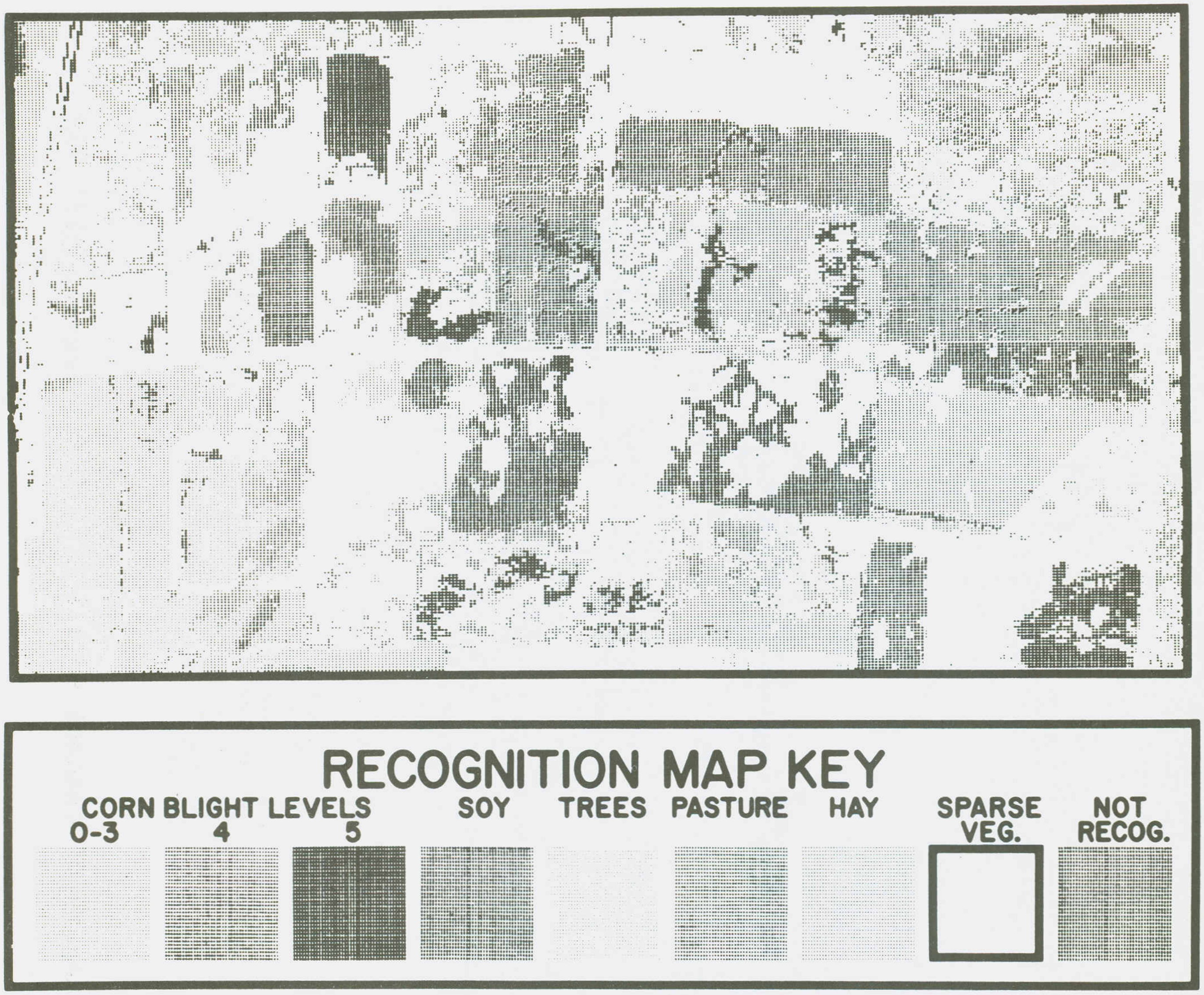


Figure 3.29. Digital recognition map of a portion of Segment 212 (43M).

Key: C_n = Corn with n the Designated Blight Level
S = Soybeans
WW = Winter Wheat
DA = Diverted Acres
P = Pasture
T = Trees
H = Hay
O = Oats

Figure 3.30. Scanner imagery of channel 9 (1.0-1.4μm) for Segment 212 (43M).

Table 3.32 Test field classification (WRL).

Field	Ground-Observed Blight Level	MSS-Derived Blight Levels					
		0	1	2	3	4	5
NN-2	0	20*	0	0	30	10	30
RR-4	0	0	10	0	70	0	5
RR-5	0	0	70	0	0	0	0
WW-2	0	0	50	0	25	0	5
SSS-1	0	0	0	0	0	10	85
SSS-2	0	50	15	5	0	20	0
L-18	0	0	0	70	0	0	0
II-1	1	25	0	0	0	60	0
RR-3	1	10	0	0	70	0	0
UU-7	1	70	0	0	20	0	0
UU-6	1	60	15	0	10	0	0
UU-8	1	60	0	0	20	5	5
UU-4	1	0	70	5	0	0	0
VV-6	1	10	5	0	5	60	5
EE-15	2	5	5	0	10	0	0
EE-9	2	0	30	5	45	0	0
ZZ-7	2	10	10	0	20	20	15
EE-8	3	10	10	0	60	0	0
EE-11	3	0	85	0	0	0	0
RR-2	3	0	40	0	35	5	5
UU-10	3	60	0	20	0	10	0
UU-1	3	Not on data					
F-2	3	30	0	0	0	30	30
N-1	3	0	0	0	0	0	95
QQQ-1	4	0	0	0	0	50	30
N-2	5	0	0	0	0	0	85

*The above figures are percentage detection of each blight level in each field from the second part of Form F (MSS Data Analysis Results).

Table 3.33 Acreage recognition of six blight levels (Segment 212)* (WRL).

Ground Rating	MSS-Derived Rating 0	1	2	3	4	5	Not Classified
0	9.90	26.05	0.75	33.20	5.20	8.50	19.70
1	42.85	17.20	0.95	24.30	14.40	2.20	19.10
2	1.80	9.30	1.25	14.85	3.00	2.25	13.55
3	15.80	23.15	3.80	19.45	4.25	11.85	12.70
4	0	0	0	0	6.0	3.6	2.4
5	0	0	0	0	0	14.45	2.55

*Acreages shown were computed from Part 2 of Form F. Field acreage figures were obtained from Form B (Field Observations).

Table 3.34 Recognition of three blight level groupings (Segment 212)* (WRL).

Ground Rating	MSS-Derived Rating 0-3	4	5	Not Classified
0-3	24.46	26.85	24.8	65.05
4	0	6.0	3.6	2.4
5	0	0	14.45	2.55

*Acreages shown were computed from Part 2 of Form F. Field acreages were obtained from Form B.

--Evaluation of MSS Blight Classifications for 100 Test Fields--

The ability of MSS analysts to classify fields into correct blight levels was tested by using as "ground truth" a set of one hundred observed fields for which ground observations were considered reliable. The fields were grouped into four blight levels (0-1, 2, 3, and 4-5) for the initial testing. Levels 0 and 1 were grouped because there were not significant differences in spectral characteristics to distinguish between them; levels 4 and 5 were grouped because only one level 5 field was found in the whole segment.

Table 3.35 lists the percent of test field points correctly identified by each analysis team in each of four blight levels using the point-by-point method of classification and differing training sets. Also shown are the average correct recognition percentages for each of the 17 teams and the average percent correctly classified into each blight level for each training set. Notice that although recognition accuracy of blight levels varied greatly, it tended to be low and, in fact, all of the team average correct recognition percentages were less than 40 percent.

Chi-square Test for Random Classification--Since individual MSS classifications of segment 212 showed poor recognition of blight severity levels, a Chi-square test for random classification (contingency table analysis - Ref. 1) was performed on each of the seventeen analyses to determine whether or not the MSS classifications could be considered statistically independent of the ground observations.

First, in order to determine what degrees of blight infection were detected, individual blight levels were grouped into various categories. The average percentages of test data points classified into each group-observed category are shown in Table 3.36 for blight groups 0-1-2-3 and 4-5 (Matrix I), 0-1-2 and 3-4-5 (Matrix II), and the original levels 0-1, 2, 3, and 4-5 (Matrix III). Note that even the discrimination of no or little blight vs. moderate to severe blight was at best moderately successful for this set of data and that detection of four blight levels was extremely difficult.

In interpreting the results of the Chi-square test (if MSS analysis techniques were indeed correctly classifying varying degrees of blight infection), it was expected that the results of the two methods of classification (ground and MSS) would not be independent. The hypothesis tested in this analysis was that ground observations and MSS classifications of blight levels were independent. The hypothesis was rejected at the .005 significance level. Thus, the two methods were not statistically independent despite the relatively poor MSS recognition. It was concluded that the MSS classifications were related to the blight conditions in the field.

Performance Index--Having proved that there was a statistical relationship between the MSS

Table 3.35 Percent correct MSS recognition* (LARS).

Training Set	Analysis Team	Blight Level 0-1	2	3	4-5	Avg % Correct Recognition
1	1	58.7	11.7	28.1	38.9	34.3
	2	55.5	10.8	28.1	50.2	36.2
	3	57.2	17.8	3.2	60.4	34.7
	4	66.6	0.0	13.2	60.7	35.1
	5	74.7	0.0	15.4	53.3	35.9
Average		62.5	8.1	17.6	52.7	
2	6	39.9	39.1	36.8	33.9	37.4
	7	22.8	16.1	43.8	33.1	29.0
	8	30.0	36.5	30.4	12.5	27.4
	9	46.0	44.0	37.5	21.1	37.1
	10	37.7	55.0	26.1	19.7	34.6
	11	47.9	24.5	24.0	15.3	27.9
	12	43.5	49.6	29.6	30.5	38.3
Average		38.3	37.8	32.6	23.7	
3	13	40.4	11.4	20.6	37.9	27.6
	14	31.1	21.7	25.1	48.5	31.6
	15	36.8	20.6	44.3	31.9	
	16	31.6	3.6	44.3	51.1	32.7
	17	28.9	20.9	33.6	47.0	32.6
Average		33.8	15.6	29.9	45.7	

Table 3.36 Average percent MSS classified into various blight categories* (LARS).

Training Set	Ground-Observed Blight Levels	MATRIX I 0-1	2	3	4-5	MATRIX II 0-1-2	3-4-5	MATRIX III 0-1-2-3	4-5
1	1	68.9	10.9	12.5	7.5	79.9	20.0	92.3	7.5
	2	71.9	8.7	12.0	7.2	80.6	19.2	92.6	7.2
	3	53.9	7.9	19.2	18.8	61.8	38.0	81.0	18.8
	4	20.3	4.7	18.2	56.6	25.0	74.8	43.2	56.6
2	1	42.5	31.5	22.6	3.2	73.0	25.8	96.6	3.2
	2	37.4	40.9	19.9	1.6	78.3	21.5	98.2	1.6
	3	29.3	29.0	36.0	5.5	58.3	41.5	94.3	5.5
	4	15.7	25.0	31.3	27.7	40.7	59.0	72.0	27.7
3	1	40.0	16.7	36.1	7.1	56.7	43.2	92.8	7.1
	2	36.8	17.8	40.6	4.6	54.6	45.2	95.2	4.6
	3	26.9	24.0	34.5	14.3	50.9	48.8	85.4	14.3
	4	13.5	18.0	16.7	51.7	31.5	68.4	48.2	51.7

*These percentages are based on only those data points known to be corn and classified as such. Failure of percentages to total to 100 is a results of rounding.

classifications and the ground observations, the next step was to determine how much better than random the MSS classifications were. The average correct percent recognition of the four blight levels was not considered to be the most appropriate measure of success since misclassification into an adjoining blight level was penalized as much as misclassification into a more distant blight level. Clearly the former error was much less severe than the latter. Therefore, a "performance index" was computed for each of the four blight levels for each MSS analysis to more appropriately determine the correctness of the classification. The performance index is a relative measure of how much the MSS blight level classification differed from the ground observation levels. Thus, the lower the index the more accurate the classification, and the higher the index the less accurate the classification. The performance index obtained was then compared to the performance index that would have been obtained for a random classification of the test fields (25 percent of the data points in each blight category).

To compute the performance index, results from the ground and MSS classifications of 100 test fields were arranged in a 4 x 4 matrix with the four ground-assigned blight level groupings as rows and the four MSS-derived levels as columns. Thus, each row indicated the classification of a 'known' (ground) level into four levels by MSS analysis. (A possible source of error was the fact that corn data points could be classified by MSS techniques as other vegetation. However, these points were deleted from the computations since it was assumed that corn points classified in this manner were so different from the remainder of the corn population that it was logical to call them "noncorn.")

The performance index for each blight level was defined as:

$$Pi = \frac{1}{RF}\left(\frac{\sum_{j=1}^{4} |i-j|\,[NPTS_j]}{NPTS_i}\right)$$

where:

i = blight level for which the performance index is being calculated

j = possible blight levels into which level i points can be classified

$NPTS_j$ = number of level i points classified as level j

$NPTS_i$ = total number of points in level i

RF = performance index of a random classification:

= 1.5 for i = 0-1 or 4-5
1.0 for i = 2 or 3

Table 3.37 shows the performance indices according to training set, analysis team and blight level. As with the percent correct classification (Table 3.36), the performance indices showed that the extreme blight levels (0-1 and 4-5) tended to be more accurately classified than the intermediate levels (2 and 3). Examination of the individual analyses shows that the results are not indentation; i.e., good classification of one level tends to degrade performance of other levels. There were also differences among the three training sets which will be discussed later in this chapter.

Test for Linear Trends--The concept of a Chi-square test for independence of classification and a graduated penalty for misclassification were combined in a regression analysis to further determine what trends were present in the MSS classifications. If the MSS classification of the 100 test fields had been effective, a linear regression model could be expected to be adequate; and in fact the hypothesis tested in this analysis was that the MSS classifications were a linear function of the ground observations (the alternative being that a higher order model was more appropriate).

For each of the seventeen MSS classifications a Chi-square statistic was computed in the same manner as had been done for the random classification study. This value was then decomposed into sums of squares due to linear regression and sums of squares due to deviations from linear regression, and an analysis of variance was run to test the hypothesis of linear trends (Ref. 2).

Different weights were assigned to the blight levels to reflect the severity of misclassification. In all, three groups of weights were studied. The first set of weights (the standard 1, 2, 3, and 4) defined misclassifications of consecutive blight levels as errors of equal magnitude no matter what the blight levels were. The second set of weights related to the percent of upper leaves of the corn plant infected with blight lesions. For this case, weights 1, 5, 20, and 50 were used to reflect the assumption that confusion of lower blight levels was less in error than was confusion of higher blight levels which should have been more easily detectable. The third set of weights was basically the same as the second set except that levels 0, 1, and 2 were combined into one level; i.e., no attempt was made to distinguish between level 0, 1, and 2 fields. In this case the weights were 3 (average weights for levels 0, 1, and 2), 20, and 50. Table 3.38 shows the results of the test for linear trends.

From the results, it is clear that in most cases MSS classifications were not linearly related to ground observations since the hypothesis of linear trends was rejected for most analyses. In fact, the second set of weights which was supposed to reflect the state of nature gave the poorest results since the hypothesis of linear trends was rejected for every case. The overall poor results may be a reflection of the fact that many analyses showed a tendency to overclassify data points into one or two blight levels.

Conclusions--Although the MSS classification and ground observations were not found to be statistically independent, test field results show that it was not possible to achieve a high degree of accuracy in classifying four degrees of blight infection (levels 0-1, 2, 3,

Table 3.37 Performance index results (LARS).

Training Set	Analysis Team	Blight Level Groupings 0-1	2	3	4-5	Weighted Avg Over All Levels
1	1	0.38	0.91	1.12	0.74	0.84
	2	0.49	0.97	1.16	0.56	0.89
	3	0.36	0.88	1.56	0.57	0.97
	4	0.40	1.10	1.44	0.50	1.00
	5	0.27	1.06	1.48	0.59	0.94
2	6	0.63	0.62	0.89	0.69	0.73
	7	0.81	0.84	0.71	0.57	0.77
	8	0.61	0.61	0.97	0.94	0.76
	9	0.55	0.56	0.85	0.94	0.73
	10	0.52	0.42	0.93	1.00	0.67
	11	0.40	0.73	1.25	0.99	0.86
	12	0.52	0.50	0.94	0.86	0.69
3	13	0.60	0.90	1.17	0.79	0.91
	14	0.67	0.77	0.89	0.51	0.77
	15	0.72	0.84	1.01	0.74	0.86
	16	0.90	1.04	0.77	0.50	0.87
	17	0.76	0.79	0.80	0.58	0.77

Table 3.38 Results of test for linear trends (LARS).

Training Set	Analysis Team	RATING SET #1 1, 2, 3, 4	RATING SET #2 1, 5, 20, 50	RATING SET #3 3, 20, 50
1	1	0.31	0.37	0.35
	2	0.30	0.38	0.39
	3	0.32	0.42	0.43
	4	0.31	0.39	0.40
	5	0.34	0.42	0.43
2	6	0.26*	0.34	0.36
	7	0.23*	0.34	0.34
	8	0.19*	0.29	0.29*
	9	0.26	0.27	0.26*
	10	0.25	0.29	0.28*
	11	0.20*	0.31	0.33
	12	0.29	0.35	0.35*
3	13	0.16*	0.27	0.26*
	14	0.31	0.39	0.38
	15	0.17*	0.26	0.25*
	16	0.20	0.30	0.31
	17	0.23	0.33	0.32

*Failure to reject hypothesis of linear trend at $\alpha=.05$ (i.e. failure to reject H_o: $Y=\alpha_0+\alpha_1 Z_1$)

4-5) using the usual biweekly procedures. Moreover, even distinction between "blight" and "no blight" conditions was at best moderately successful. Though some blight levels were classified with an acceptable degree of accuracy (as measured either by percent correct recognition or a performance index), good classification of one blight level generally tended to degrade classifications of other levels. Finally, linear regression analysis for MSS and ground classifications reaffirmed that there was poor agreement between these two estimates.

--Sensitivity of Training Set Selection--

Throughout the Experiment, variations in MSS blight severity classification success were a function not only of actual differences in the data being classified but also of differences in training sets used and in details of the techniques used by analysts performing the classifications. Through the use of three different sets of training data for the special analysis of segment 212, the variance due to training sets and that ascribable to analysts using the same training set was estimated. Variance due to analysts for segment 212 was assumed to approximate the variance in classifications due to analysts throughout the Experiment.

The first set of training data was composed of the standard biweekly training fields; the second set consisted of a random sample of ten N, T, B and "other" cytoplasm fields selected in the same manner from the 100 fields as the sample of biweekly fields (except that fields were larger); and the third set contained only large (10 acres or more), uniform N and T cytoplasm fields (Table 3.39). Analysis teams were assigned to the three different training sets in such a way that analysis experience was distributed as uniformly as possible over the three training sets.

Thus, differences among classifications of the three groups were assumed to be due only to training sets rather than to the assignment of particular analysts. Any variation within training sets (variation due to analysts) resulted from analysts' choice of training samples within the training fields and other details in the classification procedure.

Differences between classifications based on different training sets can be seen from Table 3.40-A. Classifications using Set 1 did not distinguish blight level 2, probably since the set contained only one small nonuniform level 2 field which two of the analysts did not use at all. Use of Sets 1 and 3 led to better overall discrimination of blight level 4 than did use of Set 2. This result again could probably be attributed to the number of samples available for training: Training Sets 1 and 3 contained two fields of level 4 severity while Set 2 contained only one.

A more quantitative examination of differences in classifications attributable to training sets was undertaken using the analyses of variance and multiple comparisons techniques (Ref. 1). The following four variables were analyzed with these procedures:

Table 3.39 Acreage and field assigned blight level of the corn fields in the three training sets used for Segment 212 analyses.

Training Set 1			Training Set 2			Training Set 3		
Field ID	Acre-age	Blight Level	Field ID	Acre-age	Blight Level	Field ID	Acre-age	Blight Level
C-8	26	0	L-25	11	0	L-9	12	0
OO-11	43	1	XX-1	6	0	WW-2	12	0
AA-2	4	1	R-9	31	1	F-8	20	1
AAA-5	50	1	UU-11	15	1	EE-8	26	2
L-8	6	2	B-6	16	2	UU-2	18	2
UU-1	10	3	C-5	25	2	EE-10	18	3
KKK-11	20	3	VVV-2	45	2	EE-12	20	3
N-2	17	5	UU-15	18	3	SS-6	10	3
QQQ-1	12	4	QQQ-2	44	3	W-3	12	4
			QQQ-1	12	4	QQQ-1	12	4

Table 3.40 Data Analyzed for AOV of training sets (LARS).

A. Average Percent Correct Recognition of Four Blight Classes

	Training Set 1	Training Set 2	Training Set 3
	30.5	37.3	23.4
	30.3	28.5	27.9
	22.5	30.1	27.6
	25.3	39.4	28.3
	27.5	35.1	28.9
		28.7	
		38.1	
Mean	27.3	33.9	27.3

$F_{2,14}=6.50$ $F_{2,14}(.05)=3.75$

B. Average Blight Level of Non-training Fields

	Training Set 1		Training Set 2		Training Set 3	
	Per-field	Per-acre	Per-field	Per-acre	Per-field	Per-acre
	1.83	1.81	2.15	2.08	1.95	1.85
	2.00	1.96	1.85	1.87	2.03	2.07
	1.72	1.57	2.04	1.96	2.20	2.18
	1.60	1.52	1.89	1.84	2.28	2.20
	1.55	1.45	1.92	1.92	2.56	2.51
			1.88	1.88		
			1.89	1.85		
Mean	1.74	1.66	1.95	1.91	2.20	2.16

Per-field $F_{2,14}=8.81$ Per-acre $F_{2,14}=9.62$ $F_{2,14}(.05)=3.75$

C. Average Performance Index for Four Blight Levels

	Training Set 1	Training Set 2	Training Set 3
	0.844	0.726	0.913
	0.890	0.766	0.768
	0.971	0.763	0.862
	1.000	0.731	0.868
	0.984	0.675	0.768
		0.859	
		0.691	
Mean	0.938	0.744	0.836

$F_{2,14}=13.750$ $F_{2,12}(.05)=3.75$

D. Correlation of MSS and Ground Observations on 100 Test Fields (using ratings 1,5,20 and 50)

	Training Set 1	Training Set 2	Training Set 3
	0.365	0.342	0.265
	0.383	0.336	0.385
	0.416	0.291	0.255
	0.390	0.269	0.303
	0.423	0.287	0.330
		0.311	
		0.349	
Mean	0.395	0.312	0.308

$F_{2,14}=9.348$ $F_{2,14}(.05)=3.75$

- percent correct recognition of blight levels,
- average per-field and per-acre blight level,
- performance index, and
- correlation of MSS and ground observation results for 100 test fields.

In each case, after the assumption of equal within-treatment variances was verified, a one-way analysis of variance was performed using training sets as treatments (the data used in each AOV is given in Table 3.37). Since significant differences in treatment means were found for all four variables, the Scheffé test for multiple comparisons (Ref. 1) was conducted to determine which pairs of means were significantly different. All tests were made at the $\alpha = .05$ significance level.

From the classifications of the 100 test fields, percent correct recognition was tabulated for four blight severity classes. The Scheffé test showed that classifications based on Training Set 2 led to a higher percent recognition than did classifications based on the other two training sets.

Additionally, average blight levels were computed on both a per-field and a per-acre basis for the test set corn fields in each individual analysis of segment 212. It was found that for both computations of average blight level, classifications based on Training Set 3 had a significantly higher average blight level than did classifications based on Training Set 1. Average blight levels from classifications using Training Set 2 were intermediate to those from Sets 1 and 2.

Analysis of the third variable (performance index for classification of 100 test fields) showed that Training Set 2 classifications had a significantly lower performance index (and were thus more accurate) than did Training Set 1 classifications; i.e., analysts using Training Set 1 tended to misclassify data more often and/or more severely than did analysts using Training Set 2. The average performance index for Training Set 3 was midway between those for Training Sets 1 and 2.

The correlation coefficient between MSS classifications and ground observations for 100 test fields was calculated using ratings 1, 5, 20, and 50 for the four blight levels and revealed that Training Set 1 had a significantly higher correlation with the ground observations than did Sets 2 and 3. This, however, was attributed to the lack of a good level 2 training field rather than a better classification.

From the analysis of variance table for each of the four variables studied, variance components (estimates of the population variances) were computed for training sets and for analysts. The ratios of the training set variance component to the analyst or error variance component ranged from about 1.0 to 2.2 which means that the amount of variation in classification results due to different training sets was at least as large (and sometimes over twice as large) as the amount of variation due to analysts.

Conclusions--Use of different training sets did indeed alter the classification results. The results emphasize the importance of having sufficient training fields to adequately represent the characteristic which is to be mapped, in this case SCLB. A sample of 10 fields selected from the segment did not provide sufficient information to characterize all of the blight conditions present in the segment. Another random sample of 10 large fields gave improved results. The major problem encountered in the analysis of segment 212, and undoubtedly in other segments as well, was the lack of even one training field for each blight class. Such a situation greatly reduces the accuracy of classifications. This study showed that variation due to the selection of the training sets was one to two times as great as that due to individual analysts. The ability to produce consistent results is important.

C. Comparison of PI and MSS Results

Since regular classifications of segment 212 were made by both MSS analysts and photo-interpreters, a comparison of the results generated by the two different methods was undertaken. (Like MSS analysts, PI teams made individual decisions about how to use the ground information for training purposes, which accounted at least partially for the variation in results.)

MSS and PI average per-field blight ratings were compared to determine how well the two methods detected blight in different cytoplasms. Table 3.41 lists these ratings. Since it was assumed that T cytoplasm fields would be more severely infected than B and N cytoplasm fields, and that B fields in turn would show more blight damage than N fields, the number of comparisons that showed the expected results could be tabulated. No attempt at indicating statistically significant results is made for these comparisons since the necessary AOV assumptions could not be met by all the data.

For 94 percent of the MSS analyses, the average blight level for T fields was greater than that for N and B fields; for PI analyses the number was 75 percent. The results for B and N fields were about the same for each method. Twenty-four percent of MSS analyses showed a higher average blight level in B fields than in N fields--for PI analyses, the figure was 25 percent.

The other variable studied was the variation in average blight level rating within cytoplasms due to analysts. In examining this, the average per-field blight level for each of the three cytoplasms was computed for each classification of the segment. Since the eight PI teams all used the same set of training data, the PI variation within cytoplasms was compared to the within-cytoplasm variation computed for individual MSS training sets. The result was that the computed PI within-cytoplasm variation was over 13 times as large as the largest MSS within-cytoplasm variation and 18 times

Table 3.41 **Average per-field blight levels for individual cytoplasms (LARS).**

A. PI Results

Team	Cytoplasm N	Cytoplasm T	Cytoplasm B
1	0.44	0.28	0.08
2	1.45	1.85	1.15
3	1.00	1.24	0.74
4	0.75	1.73	0.61
5	2.00	2.58	1.74
6	1.28	2.27	2.11
7	1.33	2.42	1.96
8	2.92	2.90	2.47

S^2=0.6329

B. MSS Results

Training Set	Analysis Team	Cytoplasm N	Cytoplasm T	Cytoplasm B
1	1	1.74	2.17	1.62
	2	1.77	2.43	1.66
	3	1.42	2.06	1.50
	4	1.47	1.89	1.34
	5	1.14	1.88	1.38
		S^2=0.0461		
2	6	2.06	2.24	2.10
	7	1.65	2.16	1.62
	8	2.13	2.12	1.92
	9	1.86	2.06	1.72
	10	1.83	2.09	1.78
	11	1.72	2.09	1.74
	12	1.87	2.13	1.65
		S^2=0.0203		
3	13	1.90	2.01	1.84
	14	2.06	2.26	1.83
	15	2.25	2.39	2.01
	16	2.26	2.51	2.09
	17	1.74	2.49	1.55
		S^2=0.0454		

as large as the average MSS within-cytoplasm variation. However, since the range in average blight ratings for a given cytoplasm was at least two blight levels for the PI classifications and about one-half of one blight level for MSS classifications, the large difference in variances is not surprising.

Conclusions

The comparison of MSS and PI classifications of segment 212 revealed that MSS analysts classified the severest blight in T fields more often than PI's did although this result is based only on a comparison of averages. Also, results among photo-interpreters were more variable than among MSS analysts; this may reflect the relatively greater objectivity of the machine-processing method as compared to photointerpretation.

D. Spectral Characteristics of Corn Fields

In order to obtain a more thorough understanding of how various factors affected the spectral characteristics of corn fields, the 100 selected fields in segment 212 were subjected to further analysis and evaluation. Factors investigated were blight severity level, general soil type, and amount of vegetative cover.

Effect of SCLB on Corn Field Spectral Response

As a first step in the study, the 100 fields were divided into four blight level groups: 0-1, 2, 3, and 4-5. Mean relative spectral response and standard deviations were computed for each grouping for each of twelve wavelength bands. In order to minimize the effects of sun-angle variability without introducing the incompletely-understood effects of available sun-angle preprocessing techniques, the flightline was halved longitudinally; i.e., in the direction of flight. Next, each field was assigned to either the east or west side of the flightline according to where the major part of that field was located. This resulted in 60 fields on the west side and 40 fields on the east side.

Figure 3.31 shows histograms in each of the 12 wavelength bands for the 40 fields on the eastern side of the flightline, divided into the four blight classes previously described. Corresponding means and standard deviations are given in Table 3.42. These histograms, and the conclusions which may be drawn from them, are similar to those resulting from limited observations in other segments and are considered to be reliable indicators of how spectral properties of corn are modified by the occurrence of SCLB.

Histograms for the western side of the flightline were not similar to those from the eastern side except for band 12. In fact, the fields of blight level 1 on the western side were distinctly bimodal in several visible wavelength bands. Additionally, each "western" blight class had a larger standard deviation. As a result of these differences, it was concluded that sun-angle/look-angle effects were being confounded with blight effects, and the data from the western side were

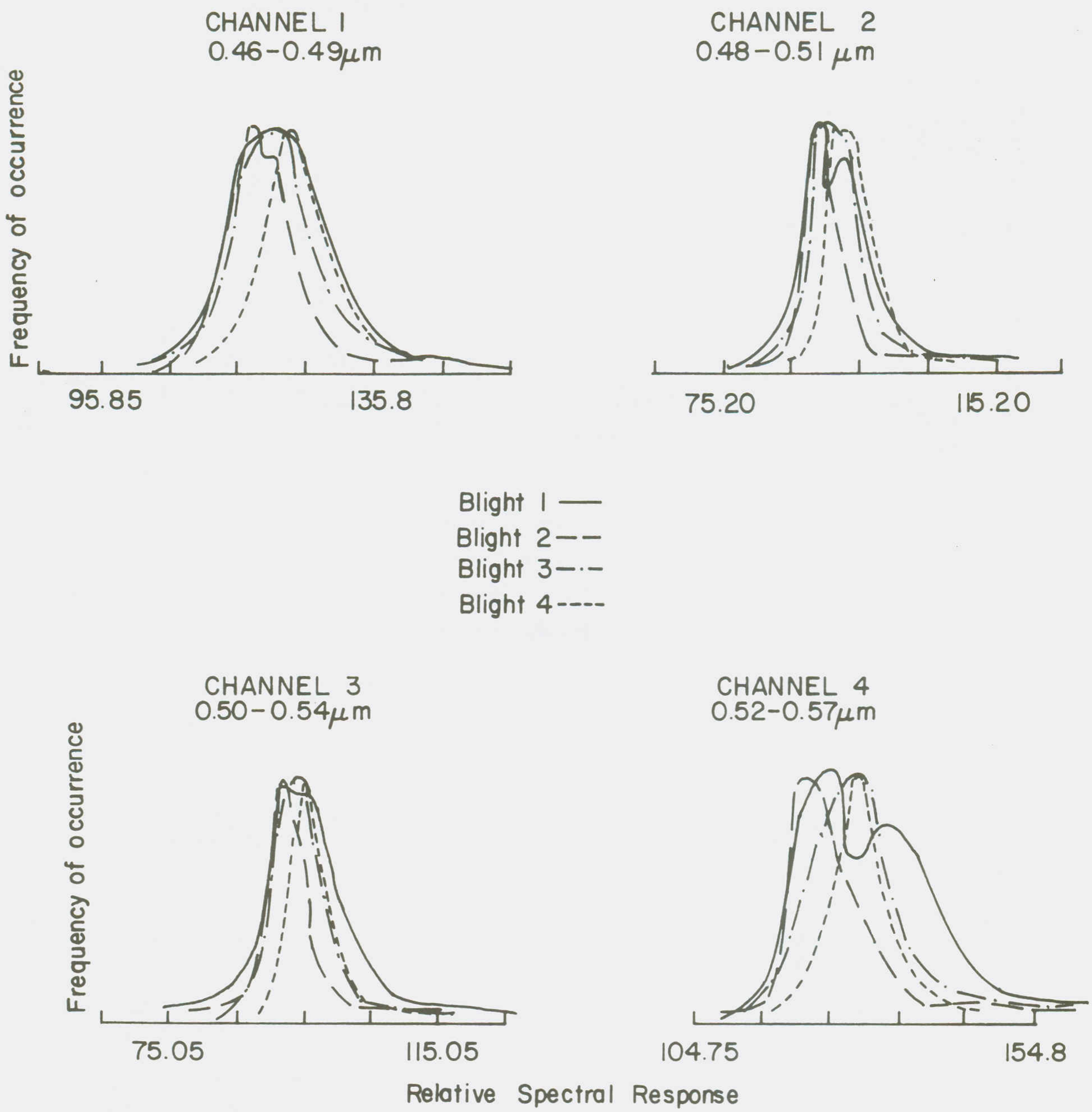


Figure **3.31.** Histograms of relative spectral response in 12 wavelength bands for four blight levels (40 corn fields, Segment 212, August 12). (continued)

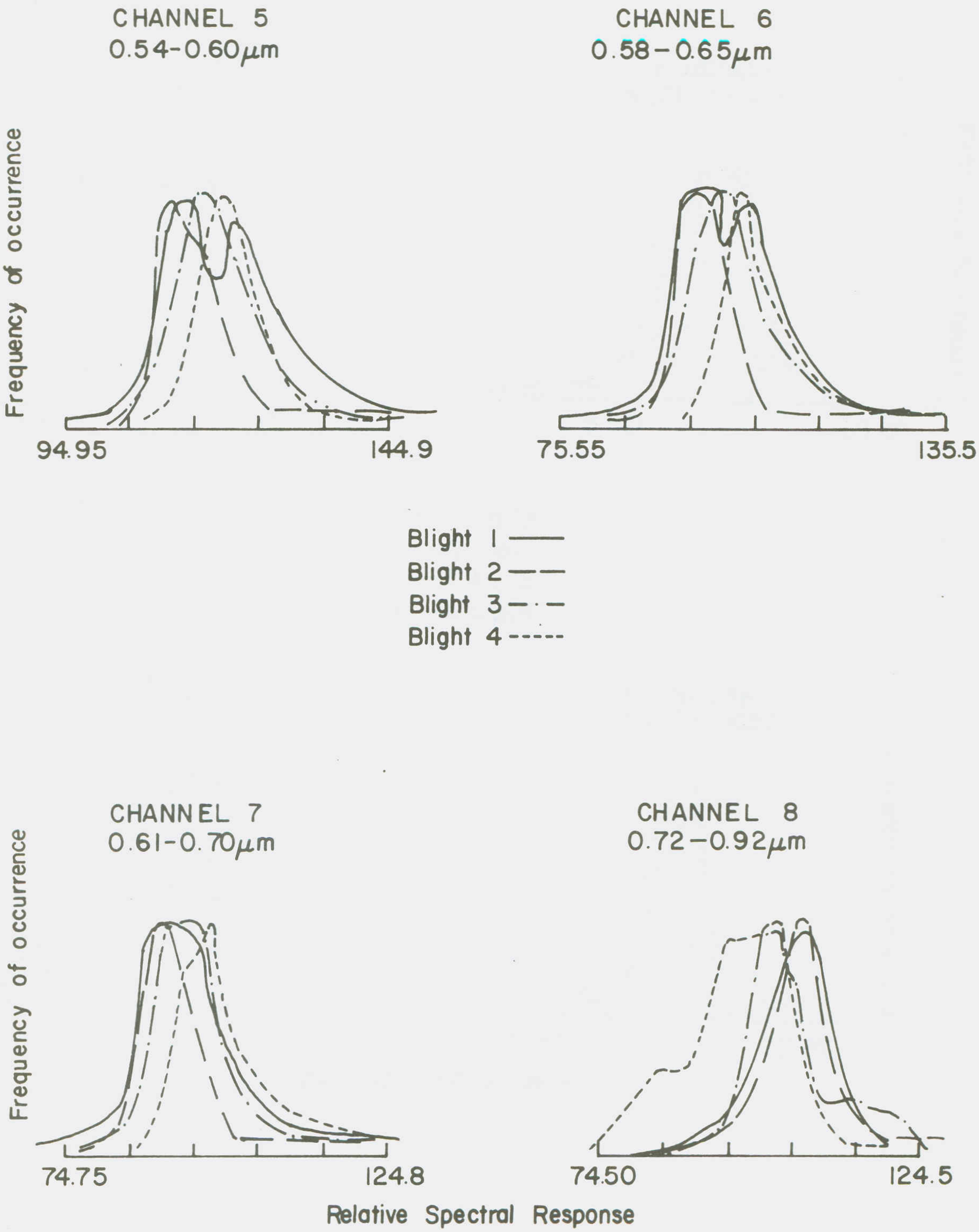


Figure 3.31. (continued)

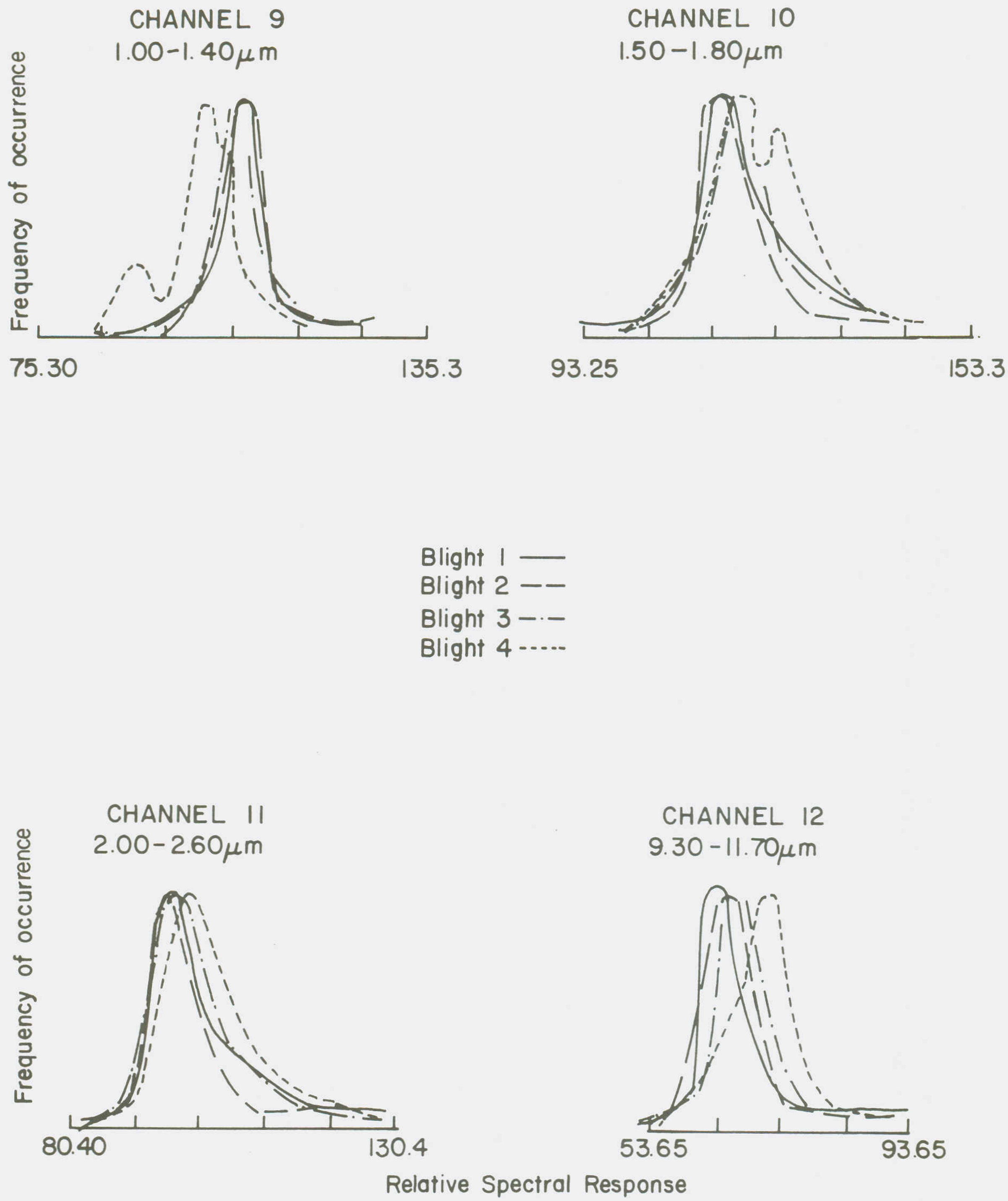


Figure 3.31. Concluded.

Table 3.42 **Mean spectral response and standard deviations for four blight severity classes in 12 wavelength bands*.**

Wavelength Bands	Mean Spectral Response				Standard Deviations			
	Blight 1	Blight 2	Blight 3	Blight 4	Blight 1	Blight 2	Blight 3	Blight 4
1 0.46-0.49μm	122.35	118.23	120.33	123.72	7.44	4.83	5.82	4.88
2 0.48-0.51μm	92.06	89.07	90.80	92.99	5.46	3.06	3.92	3.28
3 0.50-0.54μm	94.76	91.32	93.58	94.79	5.36	3.09	4.11	2.90
4 0.52-0.57μm	129.74	123.74	127.78	128.74	8.91	5.97	7.27	4.55
5 0.54-0.60μm	118.94	113.04	117.45	119.40	9.13	5.48	7.20	4.77
6 0.58-0.65μm	102.91	97.39	101.93	105.40	9.23	4.83	6.88	5.58
7 0.61-0.70μm	94.55	89.42	93.88	98.57	9.50	4.52	6.84	7.11
8 0.72-0.92μm	104.53	103.84	102.52	95.25	5.65	4.85	6.58	7.68
9 1.00-1.40μm	106.05	106.27	105.53	99.70	3.49	3.75	4.09	5.56
10 1.50-1.80μm	118.28	115.45	118.49	119.10	8.14	5.59	7.03	6.93
11 2.00-2.60μm	99.53	96.11	98.93	100.69	9.09	4.97	6.94	6.93
12 9.30-11.70μm	64.22	64.17	67.37	69.77	5.57	3.81	5.36	4.56

*from August 12, 1971 data acquired over 40 corn fields in Segment 212.

therefore considered unreliable for determining effects of blight on spectral response. Therefore, results discussed here are based on the "eastern" fields.

Despite the fact that Figure 3.31 shows that the blight level 1 fields had a larger variance than the others (and gave bimodal histograms in several of the visible wavelength bands), it is noted that, in general, in the visible wavelength bands (channels 1 through 7) an increase in blight severity caused an increase in spectral response. In the near-IR (channels 8 and 9) an increase in blight severity caused a decrease in spectral response. This effect appeared to be measurable (in spite of other factors which caused spectral variations within a blight severity class) when the blight severity reached level 3.

In wavelength bands 10 and 11 (1.0 to 1.8 μm and 2.0 to 2.6 μm) an increase in blight severity caused an increase in spectral response, though the magnitude of this increase relative to the spectral variation within blight severity classes was smaller than for some of the other wavelength bands (notably bands 7, 8, and 9). In band 12, the thermal band (9.2 to 11.8 μm), an increase in blight severity caused an increase in response. This relationship corresponds to a higher temperature in the more severely blighted corn; the relationship seems logical since plants damaged by SCLB might indeed have a decreased transpiration rate resulting in a higher temperature.

Effect of SCLB on Corn Leaf Spectral Response

In order to obtain information on the effect of SCLB on spectral reflectance when blight was the only variable, a laboratory study was initiated. Corn leaves representing four levels of blight were obtained from the Purdue University Agronomy Farm on September 4, 1971. Seven spectral reflectance curves were recorded for each blight-group of leaves with a Beckman DK2A spectrophotometer. Figure 3.32 shows average reflectance for each group. In all cases, areas of measurement were selected at random except in that the midrib was avoided.

The normal leaves were characterized by very small variations in reflectance among the leaves measured, intense absorption at 0.68 μm, about 45 percent reflectance in the near-IR, and prominent water absorption bands.

Since the leaves with slight infection had very few lesions, the lesions did not directly influence the reflectance measurements. These leaves were distinguished chiefly by greater variation in their reflectance curves than normal leaves. Though some of these curves were identical to those obtained for the normal leaves, there were also curves which showed appreciably less absorption in the chlorophyll absorption region. Overall, the mean reflectance in the near-IR was less for leaves with blight than for the normal leaves.

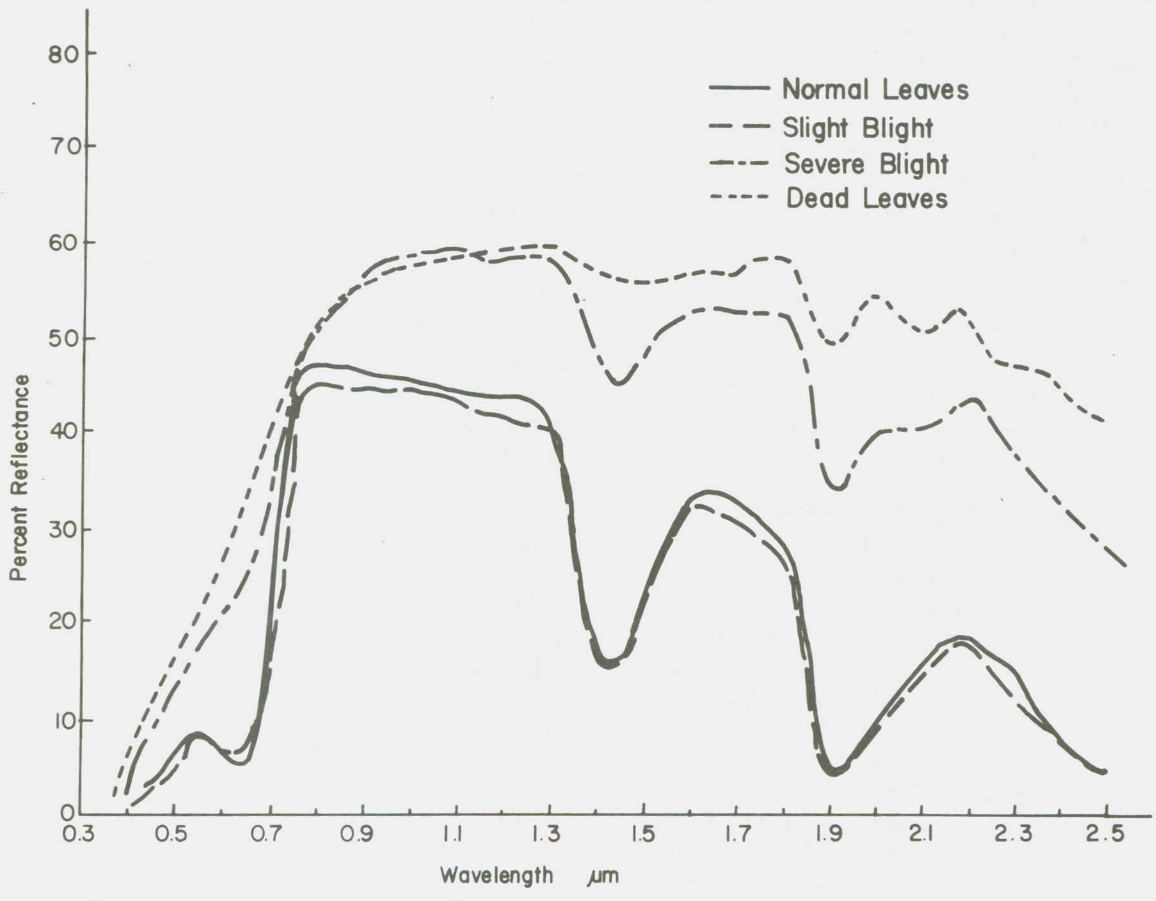


Figure 3.32. Spectral reflectance of corn leaves as determined by DK-2A measurements.

Leaves with moderately severe blight exhibited the most variation although the reflectance was higher at all wavelengths than for the normal leaves. Even though there were areas on these leaves that were green, none of the curves showed absorption approaching that of the normal leaves.

The very severely blighted (dead) leaves had nearly uniform reflectance characteristics. Chlorophyll absorption was almost completely absent, and the water absorption bands were extremely weak compared to the normal leaves.

Effects of Soil on Corn Field Spectral Response

Soils are thought to influence the spectral properties of corn fields in two ways, each of which could have been a factor in blight interpretation. First, the physical and chemical properties of the soils (including fertility and internal and surface drainage) influence the growth of corn throughout the season. The variations in soils over a flightline therefore result in variation in amount and vigor of vegetative cover, with corresponding variation in spectral reflectance of the corn fields. Second, under certain conditions of ground cover the color of the soil also affects the spectral response.

In studying these phenomena, a set of 100 corn fields was selected from segment 212 for detailed analyses. First, black and white photography (scale 1:20,000) collected in April 1971 at an altitude of 50,000 feet was used to examine soil patterns. Using the photography in conjunction with an existing soil survey map, each corn field was assigned to one of two predominant soil categories -- dark-colored soils (occurring in depressional or low lying areas) and light-colored soils (occurring away from depressional areas and having varying natural drainage which was, in general, better drained than the dark-colored soils). Over seventy percent of the 100 fields were categorized as having light-colored soils. Each of these two categories of fields was then further subdivided into blight classes, and the mean relative spectral responses were computed for all 12 wavelength bands.

Figure 3.33 plots relative spectral response in the 0.61-0.70 micrometer wavelength band (band 7) for the 100 corn fields by blight severity class and soil category. It can be seen that corn fields on dark-colored soils had a lower spectral response in this wavelength than those on light-colored soils, as long as the blight severity was level 3 or less. (This effect was not observed in corn fields with blight severity level 4.)

Soil type variations caused spectral variations within a blight severity class that would not have been encountered if soils had been more uniform. While the overall trend was for higher blight severity levels to be associated with higher spectral responses in the visible wavelengths, the opposite was true for some combinations of blight severity level and soil type. For example, turning again to Figure 3.33, note that the average

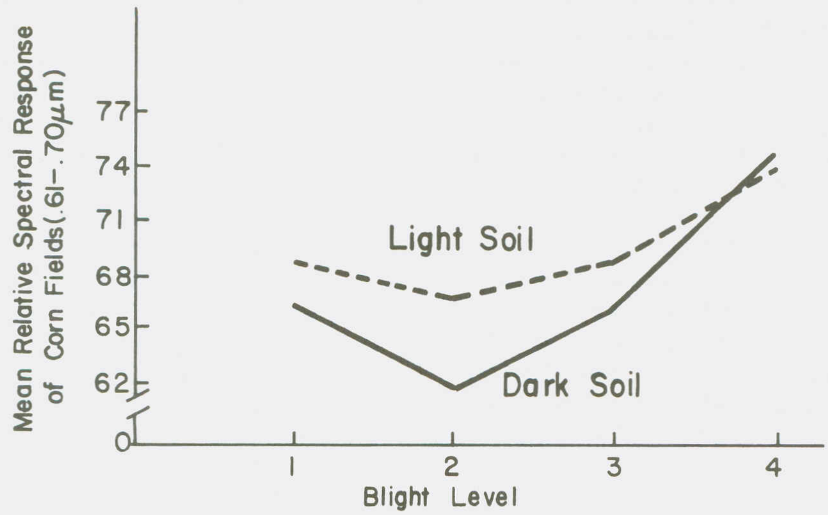


Figure 3.33. Influence of soil color on relative spectral response.

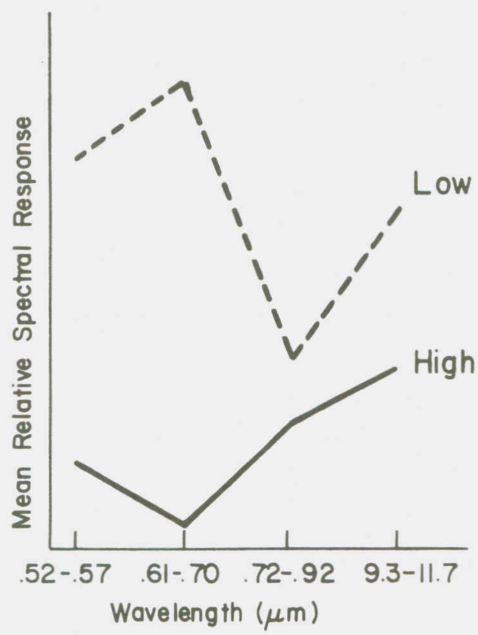


Figure 3.34. Spectral variation associated with amount of vegetative cover.

spectral response in wavelength band 7 for blight severity level 3 on dark-colored soils was lower than the average spectral response for blight severity level 2 fields on light-colored soils.

In the computer analysis and classification procedure, this phenomenon could result in a field with blight severity level 1 or 2 being classified as blight severity level 3 because it occurred on light-colored soil. This type of classification error was observed in field AAA-10, blight severity level 2, where areas of the field on dark-colored soils were classified as blight severity level 1 and areas of the field on light-colored soils were classified as blight severity level 3.

Effect of Amount of Vegetative Cover on Corn Field Spectral Response

In discussing this factor, it should be noted that overall there was some correlation between soil type and amount of vegetative cover. In general, it was observed that dark-colored soils had more vegetative cover than light-colored soils.

The effect of amount of vegetative cover on spectral response was evaluated on fields selected from the set of 100 fields to represent extremes of cover. In the example shown here (Figure 3.34) the dense vegetative cover was due to higher plant populations and application of greater amounts of fertilizer although the effect on spectral response is believed to be similar regardless of how the greater amount of vegetative cover is accomplished.

The previously-mentioned figure illustrates that greater vegetative cover resulted in lower spectral response in the visible and IR wavelengths at least for these extreme cases. It is noted, however, that the differences are greatest in channel 7 (0.61-0.70 μm) and least in channel 8 (0.72 to 0.92 μm). This indicates that for less extreme cases, the greater vegetative cover would have a higher response in channel 8. In the figure, the relatively high response in channel 8 for the low vegetative cover was believed to have resulted from the fact that a significant area of very light-colored soil was actually exposed to the sunlight and the scanner's field of view. This was verified by a ground check which revealed a relatively low plant population and small plants. If sufficient plant material had been present to shade most of the soil between the rows, this effect would have been less pronounced.

Conclusions

These results provide insight into why SCLB was difficult to classify accurately on a field-by-field basis. Examination of the spectral data showed that there was a great deal of overlap among the blight severity classes in their relative spectral response. Still, certain trends were apparent. The tendency, for instance, for an increase in the visible wavelengths and a decrease in the near infrared with greater amounts of infection undoubtedly accounts for why it was possible to make accurate assessments of the blight situation over large areas like the ISA where a large number of observations was available.

The results also give quantitative evidence of the fact that blight was only one of several factors influencing the spectral response. Others included soil background and amount of vegetative cover as well as such non-agronomic things as the scanner view angle. All other things being equal, blight severity would likely be quite easy to classify accurately using multispectral reflectance; however, as shown in this work, that is seldom the case in nature.

E. Conclusions

Intensive analysis of ground observations, MSS classifications, and photointerpretation results for segment 212 in mid-August revealed several important things which increase our understanding of results from the bulk of the Experiment. Among these are that differences in spectral reflectance due to blight are very small and that the blight class discrimination problem is further complicated by extraneous variables such as soil background, amount of vegetative cover, and look-angle. Nevertheless, there are certain trends in the spectral data which enable quite accurate classifications to be made over large geographic areas.

On an individual field basis, such as for these analyses of segment 212, the blight classification performance for identifying individual blight classes was not high. Although there were definite trends toward correct classification, there was considerable confusion among blight classes.

There was a large amount of variation in the results of the individual photo-interpreters compared to that of the MSS data classifications. The results provide strong evidence that machine processing methods provide more consistent and unbiased results than human interpreters of photography.

Adequate data for training the classifier was found to be extremely important. Different training sets could produce strikingly different classification results. Poor results for segments and dates may very well have been due simply to a lack of sufficient training samples for each class of interest. In the future, steps need to be taken to insure that proper and adequate samples for training are available. When this is done, it may be possible to classify (using one training set) areas much larger than those routinely classified in this experiment. In doing this, the training area could be only a small fraction of the total area to be classified.

F. References for Section VI

1. Ostle, B. Statistics in Research. 2nd Edition. The Iowa State University Press (1963).
2. Yates, F. "The Analysis of Contingency Tables with Groupings Based on Quantitative Characters," Biometrika, 35 (1948), 176-181.

Section VII.

Economic Analyses

VII. ECONOMIC ANALYSES

Previous sections of this Report have detailed the procedures which made up the 1971 Corn Blight Watch Experiment. The primary purpose of this section is to quantify and analyze the costs inherent in planning, implementing and drawing results from those procedures. Keys to that analysis are not only a discussion of the overall $1.9 million Experiment cost, but also a comparison of the relative costs of the aerial photographic and multispectral methods of data gathering and an analysis of the ways in which sample selection affects costs.

A. Experiment Costs

An Experiment total cost of $1.9 million was arrived at by estimating a value for all the labor, computer time, aircraft flying time, film, processing, etc., used in the Experiment. The breakdown of this total, itemized by research function, is shown in Table 3.43.

It was difficult to place a value on many of the variables, intangibles, and factors for which no standard accounting was recorded. What rate, for instance, was to be charged for the internal use of a computer? What charge would be made for those salaried personnel who worked many overtime hours throughout the summer? Would overhead charges be included? In order to answer these and other questions and to establish consistant and reasonably accurate cost-accounting procedures, the following decisions were applied:

1. All contract work, the RB-57F and C-47 flights plus part of the keypunching of computer cards, was valued at the face value of the contract. No estimates, therefore, were made of the man-months of professional and support labor included in these contracts.

2. An internal hourly rate for computer time was used. This internal rate usually covered the variable costs (computer rental, operators, supplies) but did not include overhead (building rental, administration, environmental control, etc.).

3. All labor services were valued at normal salary and did not include employer-paid benefits or overhead (in this case, building space and maintenance services).

4. No charge was made for depreciation of aircraft and other equipment or for capital purchases.

5. Preparation and publication costs for Experiment research reports, such as this Final Report, were not included.

It can then be seen that, because of these decision rules, the $1.9 million cost figure is an estimate of variable costs rather than an estimate of total costs. This refinement was necessary in order to allow comparisons of differing research functions and to standardize the varying cost reporting of the several participating agencies. For example,

	Man-Months# *Support	Professional	Total*# value
I. PREPARATION			
A. Experimental design and segment selection	26.6	3.9	$ 19,994
B. Photo acquisition for segment identification			
1. Phase I (Mission 171) flight film and processing	--	--	$ 59,298
2. ASCS photo acquisition	--	2.6	$ 11,468
SUBTOTAL			$ 70,766
C. Supplemental flights and photography			10,764
D. Equipment handling and shipping charges			3,589
TOTAL - PREPARATION			$105,113
II. PLANNING, GUIDANCE AND ADMINISTRATION			
A. LARS	4.7	58.2	$ 72,753
B. NASA and WRL	--	27.9	49,470
C. AES and CES	7.8	16.8	32,520
D. USDA agencies	--	16.8	40,423
TOTAL - PLANNING			$195,166
III. GROUND DATA COLLECTION			
A. Initial interview survey			
1. Survey personal training	11.0	25.5	$ 53,585
2. Field enumeration	22.2	47.2	55,350
3. Information editing and processing	3.9	7.6	18,371
SUBTOTAL			$127,306
B. Selection and delineation of sample fields	17.5	0.6	$ 9,920
C. Biweekly field surveys			
1. Survey personnel training	--	27.6	$ 47,522
2. Field enumeration	20.0	89.2	119,854
3. Information edition and processing	15.6	21.4	47,633
SUBTOTAL			$215,009
D. Field ID and boundary verification	14.6	21.3	$ 32,541
E. Laboratory flight verification	--	3.7	7,738
TOTAL - GROUND INFORMATION			$392,514
IV. COLOR IR PHOTOGRAPHY AND ANALYSIS			
A. Training			
1. Phase 2 (Mission 166) flight, film and processing	--	--	$ 56,066
2. Photo-interpreter training	--	--	21,605
SUBTOTAL			$ 77,671
B. Phase 3			
1. Missions 173-180	--	--	$264,345
2. Film and processing	--	--	163,568
3. Photointerpretation and summarization	4.0	66.1	81,568
SUBTOTAL			$509,790
TOTAL - PHOTOGRAPHIC INFORMATION			$587,461
V. MSS COLLECTION AND ANALYSIS			
A. Training (Phase 2)			
1. Mission 38M	--	--	$ 27,585
2. Analysis and summarization	11.0	15.6	47,960
SUBTOTAL			$ 75,545
B. Phase 3			
1. Missions 40M - 46M	--	--	$243,055
2. Analysis and summarization	11.0	56.2	287,766
SUBTOTAL			$530,821
TOTAL - MSS INFORMATION			$606,366
GRAND TOTAL			$1,886,620

"Support" (*) refers to typists, clerks, keypunchers and lab technicians. Man-months of labor (#) is not listed for some items. This may be for either of two reasons: (1) the work was done under a contract and the labor employed is not known, or (2) the labor input was not obtained in the reporting process as, in most cases, the quantities were relatively small.

"Total value" (*#), figures include the wages of support and professional personnel plus all other costs incurred.

Table 3.43 Summary of CBWE inputs and costs (by research function).

while SRS and ASCS set up separate categories in their internal accounting systems to identify Corn Blight Watch expenditures and labor use, the Cooperative Extension Services and Agricultural Experiment Stations used a combination of methods to estimate their expenditures and labor.

B. Itemized Explanation of Inputs and Costs: Table 3.43

Preparation

This research function consisted of three parts--experimental design and segment selection, the acquisition of photography over sample areas, and supplemental flights to gather additional information about selected segments. The segment selection and location (A) was accomplished primarily by SRS's statisticians. The agency's clerical staff then transferred segment boundaries to county transportation maps and, later, to black and white photographic prints.

These prints (B) came from two sources: NASA and ASCS. The NASA cost includes the flight charge for mission 171 and attendant charges for black and white film and processing. The ASCS cost includes the cost of materials and labor to provide black and white photography.

The "supplemental flights" cost (C) includes $2,000 for the use of a helicopter to make detailed observations of segment 212 in Indiana, and $3,764 for use of the Purdue Beechcraft to collect supplemental low altitude photographic coverage. An additional $5,000 was spent in purchasing and processing the resultant photographs.

Equipment charges (D) include locating Variscan viewers and other equipment plus shipment to LARS.

Planning, Guidance, and Administration

This research function consisted primarily of the time and travel expenses of the Executive Committee, CES and AES coordinators and the technical coordinators at LARS.

Ground Data Collection

Included in this category are all activities associated with the collecting, editing, and processing of data obtained from initial interviews and field observations.

The initial interview (A) was conducted from May 6 to May 22. Interview expenses are divided into (1) training, (2) enumeration, and (3) editing and processing of information.

Training consisted of seven one-day training schools (one in each participating state). The training expense includes the labor and travel expenses of two four-man training teams and of the 475 ASCS enumerators, substitutes, and supervisors who attended the schools. Also included are expenses for the preparation of interview training manuals distributed at the schools.

ASCS enumerators visited over 8,000 farms and collected information on 56,000 fields. Average interview time per farm was about one hour, including time from the enumerator's home or office. The professional man-months figure includes both enumeration time and office time. The 22.2 support man-months accounts for the work of clerks who helped with the survey in the county ASCS offices.

Editing and some processing of the initial interview survey were done by SRS with the remainder of the processing accomplished at LARS. The questionnaires were initially sent to SRS in Washington, D.C., where they were edited; then the data were punched on cards (60,450 of them) and processed at the Washington Data Processing Center, USDA. The resulting data tapes were sent to LARS for further processing so that they could easily be used by photo-interpreter and multispectral analysis teams. Costs include $5,743 for 7.6 man-months of staff time, $7,716 for computing and programmer costs, $1,629 for keypunching, and $3,283 for other expenses.

Selection and delineation of biweekly samples (B) were performed by a team of SRS clerks. The total cost of $9,920 includes $8,980 for clerical work and $940 for professional supervision.

The biweekly field surveys (C) were conducted from June 15 to September 21 by county Cooperative Extension agents. In 24 of the segments, additional biweekly visits were made by county ASCS personnel. Training schools were held from June 1-10 for the nearly 300 people who were involved in this phase of the Experiment. Costs consist of wages and travel costs of the training team and trainees, additional time spent by trainees preparing for the survey, and materials used for training.

Enumerators made approximately eight visits to selected plots in corn fields in each segment during the Phase 3 survey. The first visit (location and identification of sample plots) took an average of 1 and 3/4 days per segment. On later visits, enumerators were generally able to check all plots within a segment in about one full day. At the end of the Experiment the enumerators harvested corn samples from the plots in order to estimate yields. Some enumerators harvested the corn on their eighth visit, others made a ninth trip to harvest the corn. Accountable enumeration costs include professional and support man-months of labor (professional time charges at $6.50 per hour and support time at $2.00 per hour), mileage at 10 cents per mile, and a small charge for postage and telephone calls (see Table 3.44 for breakdown of enumerator time and mileage). Returning to Table 3.43, the last item listed under biweekly field surveys, "information editing and processing," includes $15,135 for computing by LARS and SRS; $7,716 for clerical support for editing, typing, and keypunching; $18,873 for professional time and $5,909 for other expenses.

Field identification and boundary verification (D) were performed by ASCS county personnel between July 2 and July 25. Expenditures include $20,432 for professional time, $8,427 for part-time employees and $3,682 for postage, telephone calls, some travel and other expenses.

Laboratory blight verification (E) was performed by seven plant pathologists. The $7,738 expense listed covers the time of the pathologists plus some allowance for lab expenses.

Table 3.44 **Time and mileage of enumerators (for each biweekly check of the corn field sample plots).**

Biweekly visit no.*	Enumerator hours#		Mileage travelled	
	Per segment	Total*#	Per segment	*#Total
1	14.0	2,800	97	19,400
2	8.3	1,660	77	15,400
3	8.9	1,691	80	15,200
4	9.1	1,638	75	13,500
5	7.7	1,386	72	12,960
6	7.3	1,314	75	13,500
7	6.9	1,173	73	12,410
8 and 9	11.2	2,016	110	19,800
TOTAL	73.4	13.678	659	122,170

Note: The field visits (*) were made to the segments every two weeks. Some fields were visited but no report made of time spent or mileage driven and a few fields were not visited. For example, during the first biweekly period, time and mileage logs were received for 91 percent of the 210 segments. By the seventh period, the reporting rate had declined to 72 percent. For those segments where no report was received, the average time and mileage for all reported segments was assumed.

Hours (#) start when the enumerator left his office or home and end upon his return.

Totals (*#) do not include time and mileage of ASCS personnel who visited additional fields in 24 segments.

Color IR Photography and Analysis

This research category includes RB-57F data collection, film processing, photointerpretation, and summarization of results. Distinction is made between stages as they occurred during training and during the actual operations of Phase 3.

Training (A) includes the cost of mission 166 by the RB-57F ($31,627), the film and processing ($24,439), and training the photo-interpreters ($21,605). The latter expense includes the salary of the photo-interpreters during the training period ($14,263), travel and per diem expenses ($5,442), expenses of the two-man training team from the Forestry Remote Sensing Laboratory ($1,200), and other expenses ($700).

Phase 3 (B) includes collection, analysis, and summarization of data from missions 173-180. A total of 25 people (nine from state universities, six from USCS, four from NASA/MSC, five from LARS and one from ARS) were involved in interpreting color IR photography during the Experiment. They contributed 54.1 Phase 3 man-months at a total salary cost of $46,876. Expenditures for photointerpretation and summarization include this $46,876 plus $17,755 for transportation and living expenses of the photo-interpreter teams, $6,960 for salary of the data management personnel, $7,486 for 38 hours of computer time, and $2,800 for other expenses.

MSS Collection and Analysis

This function includes C-47 flight expenses, plus the costs of analyzing and summarizing the data at LARS and WRL.

Training costs (A) cover mission 38M ($27,585) and the expenses of the MSS teams prior to Phase 3 ($18,193 of salary for 15.6 man-months of MSS training, $27,211 for computing, and $2,556 for other expenses). Computing ($27,211) includes 25 hours of analog to digital conversion (A/D time), 88 hours on the IBM 360/67 (LARS), 120 hours on the SPARC processor (WRL), 45 hours on the IBM 1604 (WRL), and 10 hours on the IBM 1401 (WRL).

Phase 3 (B) includes the cost of data collection of missions 40M-46M ($243,055). In addition, the two teams of MSS analysts (LARS and WRL) spent 37.7 man-months analyzing the Phase 3 data. Their salary amounts to $46,368.

Supplementary expenses include other LARS staff involved in preparing the data for analysis and summarizing the results (18.5 man-months or $15,350), Willow Run Labs' $9,456 for clerical support, materials and travel, and $8,855 for photo lab expenses. Miscellaneous expenses at LARS were established at $2,800.

Finally, computing was a major expense. LARS used 177 hours of A/D time and 706 hours on the IBM 360/67. WRL used 1300 hours on their SPARC. Using internal charge rates of $115 per hour for A/D, $197 per hour for the IBM 360/67 and $35 per hour for the SPARC, the total computing bill was $204,937 out of a grand total of $287,766 for analysis and summary of MSS-Phase 3.

C. Cost Comparisons

Photointerpretive vs. Multispectral

One of the major opportunities presented by the Corn Blight Watch Experiment was the chance to compare not only the performance of color infrared photographic and multispectral techniques but also the relative costs of the two methods. Although such cost comparisons should be viewed with caution since the two technologies were not used under the same set of conditions (different sampling techniques, different types of aircraft, and different data products), the Corn Blight Watch did offer the first real opportunity to examine the cost of the two remote sensing technologies under at least similar conditions.

Some comparison difficulty is encountered at the onset since much of the total cost of the Experiment cannot be separated into distinct photointerpretive and multispectral functions. For instance, the first three research functions listed in Table 3.43 (preparation, administration, and ground data) are crucial components of both color IR analysis and MSS data analysis. These three functions alone account for over one-third (37 percent) of the total cost of the Experiment (about $3,360 per segment).

There are, however, other expenses that can be differentiated as being directly attributable to either analysis of color IR photography or to MSS data. These break down to a cost of $2,797 for each of the 210 segments covered by color IR and $20,212 for each of 30 MSS segments. This, obviously, is a major difference in technique costs, but further background information is needed in order to put it into the proper context.

A further breakdown of the relative costs of the two technologies (Table 3.45) aids in constructing that context. Note that Table 3.45 compares only LARS costs for PI and MSS. The reasons for this are that: (a) PI analysis was performed only at LARS; (b) since both MSS analysis and photointerpretive analysis were done at LARS, there is no cost difference due simply to different methods of cost accounting at different institutions; (c) since basically different MSS analysis methods were used by LARS and WRL, a cost comparison with photointerpretive techniques could be based on either LARS' costs or Willow Run's costs, but not on a mixture of the two; and (d) the final step of MSS data summary for all 30 segments was performed at LARS.

As can be seen in Table 3.45, the cost per segment per mission was $304 for color IR photography versus $3,085 for MSS analysis. The cost difference of $2,781 per segment per mission can be attributed to (a) a difference of $1,000 in aircraft flying costs, (b) a difference of $220 in the cost of preparing the data for interpretation--film and developing costs on the one hand, preprocessing of data tapes on the other--and (c) a difference of $1,561 in the cost of analysis and summary.

Theoretically the inherent cost of data collection by aircraft need not differ significantly for

Table 3.45 **Total cost, cost per mission, and cost per segment per mission (Phase 3, color IR photography and multispectral sensing).**

NOTE

- LARS analyzed half the MSS data so only half of the total aircraft flight costs are included.
- Cost per mission are for eight photographic and seven MSS missions.
- Cost per segment per mission are for 210 photographically-covered segments; and for the 15 LARS-analyzed MSS segments.

	Total cost	Cost per mission	Cost/ segment/ mission
A. Phase 2 color IR photography, analysis and summary			
1. Aircraft flight costs	$ 264,345	$ 33,043	$ 157
2. Film and processing	163,568	20,446	98
3. Photo interpretation and summary	81,877	10,235	49
TOTAL	$ 509,790	$ 63,724	$ 304

	Total cost	Cost per mission	Cost/ segment/ mission
B. Phase 3 multispectral sensing; LARS expense only			
1. Aircraft flight cost	$ 121,528	$ 17,361	$ 1,157
2. Preprocessing (including A/D conversion)	33,385	4,769	318
3. Analysis and summary	169,020	24,146	1,610
TOTAL	$ 323,933	$ 46,276	$ 3,085

the two kinds of remote sensing technologies. The $1,000 difference in cost in the Corn Blight Watch Experiment was due to a number of factors including (a) the low cost per hour of flying time for the RB-57F, (b) the efficiency gained by photographing entire flightlines rather than locating and photographing individual segments as was necessary in the ISA, and (c) the attendant efficiency per segment obtained by photographing 210 segments instead of just 30.

Thus, the real cost gap between the two at the time of the Corn Blight Watch Experiment was the non-aircraft difference of $1,781 per segment. There are reasons to believe that this cost gap, too, will be cut greatly in the near future. First, since photointerpretation is a more mature technology, it is a more financially efficient technology. Additionally, the Corn Blight Watch Experiment was basically designed around this technology and not around MSS data analysis, thus contributing to further PI efficiencies. Because of these combined factors, the cost per segment for the photointerpretive approach is probably as low as could be reached with the current state of the technology.

Multispectral data analysis, on the other hand, is an infant technology. A "first generation" scanner was used in the aircraft, and the computer software was likewise in the early stages of development. Projected technological advances and their concomitant efficiencies will lower future MSS expenditures. Predicted breakthroughs in computer data analysis--by far the most expensive facet of MSS analysis--could easily cut computer costs in half. Finally, another key to per-segment/per-mission cost reduction is the implementation of sampling procedures specifically designed for multispectral techniques.

Costs Per Acre Surveyed

A second method used to evaluate the cost of information obtained by the Corn Blight Watch is to examine the cost-per-acre-surveyed for the initial interview survey, the biweekly field observations, and the color IR analysis in the seven-state test area. The same comparison can be made for the intensive study area and the MSS analysis.

The 210 segments in the test area consisted of 278,666 corn acres. Although the initial interview survey obtained crop identification information for other fields, detailed information was collected only on these 278,666 acres. Biweekly field observations were then made on a subsample of the corn acres in each segment. Finally, photo-interpreters used this information in analyzing the entire 278,666 acres of corn, field by field.

The initial interview survey plus training, editing, and verification of field boundaries cost $159,847 or $0.57 per acre of corn in the sample. The cost per farm (8,216 farms visited) was $19.45.

The biweekly field observations, including training and editing expenses, cost $215,009. On the basis of 7.4 visits to 1,747 fields, the average cost of one visit to one field was $16.63. The cost of obtaining this biweekly information, when spread over the total 278,666 corn acres was $0.77 per acre for the 7.4 visits, or $0.10 per acre for one visit.

Total photointerpretation costs, including training, were $587,461 or $2.11 per acre of corn in the sample for all eight missions. Omitting training costs, the cost was $0.23 per acre of corn in the sample per mission.

The combined cost per acre of corn, therefore, for the initial interview survey ($0.57), the biweekly field observations ($0.77), and the photointerpretation ($2.11), was $3.45 for all eight missions. This figure does not include preparation or planning costs (items I and II in Table 3.43).

The cost of MSS analysis, including training, was $364,469 for LARS' share of the analysis--the $323,933 from Table 3.45 plus $40,536 for LARS' share of training. There were 25,727 acres of corn in the 15 segments analyzed by LARS; thus the cost per corn acre was $14.17 for all seven MSS missions. Omitting training costs, the cost was $1.80 per acre of corn in the sample per mission.

The combined ground observation costs ($0.57 + $0.77) per acre of corn in the sample (which do not differ significantly from the per acre cost in the intensive study area alone) plus MSS costs ($14.17) give a per acre total of $15.51--substantially higher than the $3.45 per acre figure for the photo analysis phase of the Experiment. But on the other hand, all the land in the 15 MSS segments was analyzed, not just the corn acres. One could argue, therefore, that the cost per MSS acre should be figured as $364,469 divided by 94,596 acres, the total acreage in the 15 segments. This would give a per acre cost of $3.85 for all seven missions. This lower cost, however, would be valid only if the remote sensing results for all crops were actually wanted and used.

Costs Compared with Conventional Survey Techniques

In order to compare remote sensing costs with the cost of obtaining crop information using conventional survey techniques, objective yield survey cost figures were obtained from SRS. Essentially this comparison is useful as a general indication and is not specifically valid because of the immeasurability of increased remote sensing data value. In the conventional yield survey, sample plots in corn and soybean fields are visited by enumerators an average of four times during the growing season. Data obtained from the sample plots are expanded to give overall yield estimates for the two crops.

The cost-of-survey figures for the 1970 objective yield survey were obtained for only the seven states included in the Corn Blight Watch Experiment. In these states, 2250 sample corn plots were observed and the total cost of the survey, including wages, mileage, per diem, and other expenses for training, enumerating, editing and processing, was approximately $250,000. The coefficient of variation of estimated corn production in the seven-state area was three percent.

In the Corn Blight Watch, the costs and research functions that would be most comparable to the objective yield survey would be the combined costs of the biweekly field observations and the photointerpretive analysis. Although only data from the ground observations were needed to make estimates of blight infection, the data from the photo analysis must be added as a measure of the expanded utility of remote sensing surveys. The total cost of these two functions, taken from Table 3.43, is about $802,000. This cost, however, covers eight data collection periods while the objective yield survey covers only four periods. Adjusting the $802,000 costs back to four periods but still including all training costs reduces them to $459,000. Thus, the combined cost of the photointerpretive analysis and biweekly field observations is about 1.8 times more than the objective yield survey when both are put on a similar basis.

As previously mentioned, this cost comparison is useful only to give a rough estimate of the relative cost of obtaining data using remote sensing techniques vs. the cost of using conventional techniques. One major factor ignored by this analysis is the product obtained from the ground survey and that obtained from the remote sensing survey. In the latter case, the survey yields not only the numerical estimates of the parameter under question but also the photography. The photograph acts as (a) a storage of information about the parameter being measured (corn acreage, for instance) and (b) a store of information about any other feature that is within the geographical area covered by the photography. Either of these two characteristics of remote sensing could justify the additional cost over a ground survey.

D. Optimum Resource Allocation

Given the type of information elicited from the previous cost breakdown, it now becomes possible to determine the relationship of per-segment and flightline costs to sample variances. This must be done keeping in mind that almost all sample size decisions in the 1971 Corn Blight Watch Experiment were made because of resource limitations. Thus, the maximum number of flightlines which could be covered was about 30, the maximum number of segments about 200, and the maximum number of fields which could be visited in one day was from 10 to 12. Therefore, survey designers could not approach the decisions from either a minimization of variance or cost standpoint.

In examining 1971 cost and variance results in terms of optimum allocation of flightlines and segments, one may begin with a general case as follows:

(i) $\bar{x}$ = average acres of a given cytoplasm of corn per segment
σ_1^2 = between-flightline variance component (1st stage)
σ_2^2 = between-segment, within-flightline variance component (2nd stage)

(ii) Variance of $\bar{x}$ is given by:

$$\sigma^2_{\bar{x}} = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_1 n_2}$$

where:

n_1 = number of flightlines sampled (1st stage)
n_2 = number of segments sampled (2nd stage)

and

(iii) Total variable cost is represented by:

$$C = n_1 c_1 + n_1 n_2 c_2$$

where:

c_1 = cost of adding a single flightline
c_2 = cost of adding a single segment

It follows logically that minimum variance and minimum cost occur when the product of variance times cost is minimized. This minimization process indicates that the optimum sample size for n_2 segments is:

$$n_2 = \frac{\sigma_2^2 \; c_1}{\sigma_1^2 \; c_2}$$

The value for n_1 (flightlines) is then derived from a given variance limitation or a given cost restriction.

Table 3.46 shows the variance components of the average corn acres per segment in the seven-state area.

Table 3.47 shows the total variable costs incurred for the 1971 CBWE (note that figures are not in exact correspondence with earlier figures since slightly different combinations of costs were used for this analysis).

In order to perform optimum allocation, c_1 (costs directly associated with adding a flightline) and c_2 (costs directly associated with adding a segment) must be calculated. Photointerpretation might be assigned to either cost depending on the type of survey hypothesized. For instance, if photointerpretation is to involve only those segments for which current ground data is available, the quantity of photointerpretation will vary with the number of suitable segments. If, on the other hand, a given amount of photointerpretation will be necessary for every flightline regardless of the amount of ground data, photointerpretation becomes a flightline cost.

A summary of costs under four different assumptions of this type is shown in Table 3.48. Note that the various assumptions differ both in assignment of photointerpretation costs and inclusion of other costs (sample preparation, etc.).

In the event that other costs are excluded, an operational or repetitive survey in which most of the preparation costs have been already incurred is assumed.

Table 3.49 gives the computed optimum value of n_2 (by corn cytoplasm) under the various assumptions. Note that estimates of σ_1^2 and σ_2^2, S_1^2 and S_2^2 have been used for these calculations.

The results for normal Texas male sterile and blend strata illustrate the basic assumption of sampling by flightlines. The largest contribution of variance:

Table 3.46 **Corn acres and variance components by cytoplasms.**

Type Cytoplasm	Average acres per segment	Between-flightline variance component	Between-segment variance component
Normal.............	314.306	49,848.533	54,965.064
Texas male sterile.	403.145	100,778.716	43,300.834
Blend..............	377.173	66,667.366	89,296.963
F-2................	10.061	84.171	650.323
Other..............	169.789	3,370.627	38,656.443
TOTAL..............	1,274.473	-----------	----------

Table 3.47 **CBWE variable costs.**

Item	Cost
Ground Information	
Training, enumeration, field verification and lab verification..........	$ 1,730/segment
Air Information	
Flights and color IR photography......	$13,827/flightline
Photointerpretation	
Training and interpretation..........	$ 569/segment
Other Costs	
Sample preparation and selection, administration......................	$ 1,470/segment

Table 3.48 **Flightline and segment costs (based on various assumptions).**

ASSUMPTION 1, Amount of photointerpretation variable		
c_{11}	Flight costs/flightline	
	Air Information	$13,827
	Total	$13,827
c_{21}	Ground costs/segment	
	Ground Information	$ 1,730
	Photointerpretation	$ 569
	Other Costs	$ 1,470
	Total	$ 3,769
ASSUMPTION 2, Amount of photointerpretation fixed		
c_{12}	Flight costs/flightline	
	Air Information	$13,827
	Photointerpretation $569/segment x segments/ flightline	$ 3,414
	Total	$17,241
c_{22}	Ground costs/segment	
	Ground Information	$ 1,730
	Other Costs	1,470
	Total	$ 3,200
ASSUMPTION 3, Variable photointerpretation with other costs ignored		
c_{13}	Flight costs/flightline	
	Air Information	$13,827
	Total	$13,827
c_{23}	Ground costs/segment	
	GI	$ 1,730
	PI	$ 569
	Total	$ 2,299
ASSUMPTION 4, Fixed photointerpretation with other costs ignored		
c_{14}	Flight costs/flightline	
	Air Information	$13,827
	PI	$ 3,414
	Total	$17,241
c_{24}	Ground costs/segment	
	GI	$ 1,730
	Total	$ 1,730

Table 3.49 **Optimum values of segments per flightline by cytoplasm.**

Corn Cytoplasm	Value of $\sqrt{S_2^2 \div S_1^2}$	Assumption number and $\sqrt{c_1 \div c_2}$ ratio			
		A_1=1.915	A_2=2.321	A_3=2.452	A_4=3.157
Normal	1.050	2.011	2.437	2.575	3.315
Texas male sterile	0.655	1.254	1.520	1.606	2.068
Blend	1.157	2.216	2.685	2.837	3.653
F-2	2.782	5.328	6.457	6.822	8.783
Other	3.386	6.484	7.859	8.303	10.690

$$\frac{\sigma^2}{\chi} = \left(\frac{\sigma_1^2}{n_1}\right)\left(\frac{\sigma_2^2}{n_1 n_2}\right)$$

comes from the between-flightline portion. Therefore, as many flightlines as possible should be selected with fewer segments per flightline.

The data in Table 3.49 could also be used to indicate the optimum allocation results of four different types of cropping patterns. The normal and blend strata, for example, are representative of crops planted uniformly both across an area and within flightlines. Second, Texas male sterile results should be indicative of crops that are scattered throughout the area but primarily concentrated in only a few portions. Third, F-2 stratum results could represent specialty crops which might be planted in only a few flightlines and in only a few sample segments within those flightlines. Finally, the "other" category represents crops which though they occur in most flightlines, vary widely in acreage per segment.

In order to calculate the number of flightlines (n_1) to sample for a given cost assumption and the number of segments to sample (n_2), a cost or variance restriction must be given. For example, if a test cost assumption for a survey of $1,275,443 (preliminary total for 1971 CBWE) is made, the optimum number of flightlines is:

$$n_1 = \frac{\$\ 1,275,433}{c_1 + n_2\ c_2}$$

Table 3.50 shows optimum n_1 values under the four previous cost assumptions for N cytoplasm corn. Note that a corollary assumption, that six flightlines can be covered per day, is made and that the table reads in flight days (fd).

Table 3.49 indicated an optimum number of segments per flightline that varied from 2.011 for A_1 to 3.315 for A_4. Thus, if three segments per flightline were selected, the number of flightlines to sample would be about 48 to 60, depending, of course, on the cost assumption.

If instead of a cost limitation, a variance limitation were imposed, the effect of finite correction factors would need to be considered. Because each flightline contained about 100 segments, only a small portion of the segments within a flightline would be sampled and the correction factor could eventually be ignored. However, the first stage finite correction factor (n_1/N) would be large since only 324 flightlines were possible.

For example, if a severe percent coefficient of variation were desired for acres of all cytoplasms of corn (the same as in 1971), the value of n_1 (flightlines) could be calculated as follows:

$$S_1^2 = \sum_{m=1}^{5} S_{1m}^2$$

$$= 49,849 + 100,779 + \dots + 3,371$$

$$= 220,748$$

Table 3.50 **Number of flight days required to cover test area (under various cost assumptions).***

Number of segments per flightline	Cost assumption number (From Table 3.49)			
	A_1	A_2	A_3	A_4
1	12 fd	10 fd	13 fd	11 fd
2	10 fd	9 fd	12 fd	10 fd
3	8 fd	8 fd	10 fd	9 fd
4	7 fd	7 fd	9 fd	9 fd
5	7 fd	6 fd	8 fd	8 fd
6	6 fd	6 fd	8 fd	8 fd

*Number of flight days is number of flightlines needed divided by 6.

$$S_2^2 = \sum_{m=1}^{5} S_{2m}^2$$

$$= 54{,}965 + 43{,}301 + \ldots + 38{,}656$$

$$= 226{,}867$$

$$CV = .07 = \frac{S\bar{x}}{\bar{x}}$$

$$S\bar{x} = .07\,(\bar{x}) = 89.18$$

$$S_{\bar{x}}^2 = (1-f_1)\,\frac{S_1^2}{n_1} + \frac{S_2^2}{n_1 n_2}$$

$$= \left(1-\frac{n_1}{N}\right)\frac{S_1^2}{n_1} + \frac{S_2^2}{n_1 n_2}$$

$$\text{optimum } n_2 = \frac{S_2^2\, c_1}{S_1^2\, c_2}$$

$$= \frac{226{,}867}{220{,}748}\ \frac{13{,}827}{2{,}299}$$

$$= 2.5 \text{ (under cost assumption 3)}$$

$$\text{optimum } n_1 = \frac{S_1^2 + S_2^2/n_2}{S_{\bar{x}} + S_1^2/N}$$

$$= \frac{220{,}748+226{,}867/2.5}{(89.18)^2 + 220{,}748/324}$$

$$= 36.08$$

Thus, the optimum values are n_1=36 flightlines and n_2=2.5 segments per flightline in order to give the desired seven percent coefficient of variation with a minimum cost. Results could be calculated similarly for other cost assumptions.

Since it is very unlikely that the exact CBWE sampling procedure would be used in future surveys, additional calculations or cost assumptions would be of little use. What is important is the realization that any similar remote sensing study should be set up with as many flightlines as possible (or with stratification of the test area before selecting flightlines) in order to reduce both costs and variances.

Section VIII.

Related Projects

VIII. RELATED PROJECTS

Introduction

As discussed in Vol. II, Section VIII, the cooperation of the EPIMAY computer simulation project of the National Oceanic and Atmospheric Administration (NOAA) and the Spore Collection project of the National Aeronautics and Space Administration were sought because information elicited by those projects could provide statistical and pathological indicators of blight spread.

Although the results obtained by these projects had no direct impact on the Corn Blight Watch Experiment and its tracking of SCLB, two important goals were achieved. First, as with the CBWE, a solid base of information and cooperating personnel was established, one on which future operations could be built. Second, in a full-scale remote sensing operation, rather than an experiment such as the CBWE, the collection of ancillary input such as the simulations of EPIMAY and the clues provided by the presence of spores in the air above infected areas could be vital in allocating resources, specifically in delineating areas in which remote sensing efforts should be concentrated. Although such direct feedback between these associated projects and the CBWE was not possible, it would be desirable in future operations.

A. EPIMAY

Background

EPIMAY is discussed thoroughly in Vol. II, Section VIII; briefly, it is an attempt to use laboratory observations and weather data to simulate real-world events in the computer. Since SCLB spore and stalk production move through their cycles according to known parameters of moisture, light and temperature, since the spreading of spores by wind and rain follows established rules (Ref. 1 and 6), and since germination and penetration occur under conditions of temperature and moisture determined in the laboratory, the progress of the disease becomes predictable. In addition, once the fungus has incubated, the enlargement of the lesions proceeds according to the temperature conditions.

Other than the initial pathological data regarding the H. maydis organism, only meteorological information is needed to operate the simulation. Under the EPIMAY program, such information consists of temperature, leaf wetness (dew or precipitation), light (vs. darkness), wind speed and rainfall intensity data collected eight times a day at three-hour intervals. The inventories of SCLB growth stages are then updated for each data collection period.

During the 1971 summer, such information was received from 23 stations (see Vol. II, Section VIII) across the Corn Belt. This number could and should have been larger, but was limited by the number of stations that were equipped to measure dew.

The dew and precipitation data that were available were summarized once a week (each Friday morning) and telephoned to the Central

Regional Office of the National Weather Service (NWS) in Kansas City. The other data (temperature, wind, and light) were collected at nearby NWS aviation stations and reported several times daily. All of this information came from within 50 miles of the dew sensor stations. Throughout the summer, there were occasions when all data were not available. In this event, values were estimated since missing data could not be adjusted for in the EPIMAY program.

Procedures

The primary purpose of the EPIMAY calculations was to obtain the relative rate of blight increase in various areas of the Corn Belt on a week-by-week basis, but not to estimate the severity of infection in each area. While a particular area may have had a high rate of increase in number of lesions during the week, it may still have had a small total number of lesions because of conditions in previous weeks. Maps presenting the rate of increase in number of lesions per hectare were prepared each week for eight weeks and printed in the Weekly Weather and Crop Bulletin, a joint publication of NOAA and SRS (see Figure 3.35).

Primary consideration is given here to a discussion of EPIMAY results for the ISA, where six dew sensors were available and thus more detailed input was obtained.

In order to arrive at measurable results, the response of EPIMAY was compared to the ground observer blight ratings during the four-week period from mid-July to mid-August. Specifically, the blight ratings, on a unit scale of 0 to 5, were associated with the EPIMAY output for the nearest dew sensor, with exceptions as described below. For example, Wanatah data appeared to be representative of northwestern Indiana and were used for Segments 201 through 207. On the other hand, West Lafayette data (Purdue University's Agronomy Farm) were used for Segments 208 through 216 even though the station at Hedrick was closer to some of these segments; analysis had indicated that the Hedrick station's data was not as representative for these segments as was that of West Lafayette. Similarly, using Terre Haute data, EPIMAY indicated increases in lesion multiplication for nearby segments several times greater than was expected. Subsequent examination showed that, though Terre Haute was closer, Segment 214 was better represented by data from the West Lafayette station and that conditions in Segments 217-219 correlated more closely with data from the station to the south, Vincennes.

In order to obtain the appropriate increase in ground observer blight ratings during this period, the ratings from only the biweekly T-cytoplasm fields were averaged for each segment. Since there were no "T" fields in the southernmost segments, these were not included in this study.

First, the difference between the average on the third visit (approximately July 12) and the fifth visit (approximately August 10) was plotted against the

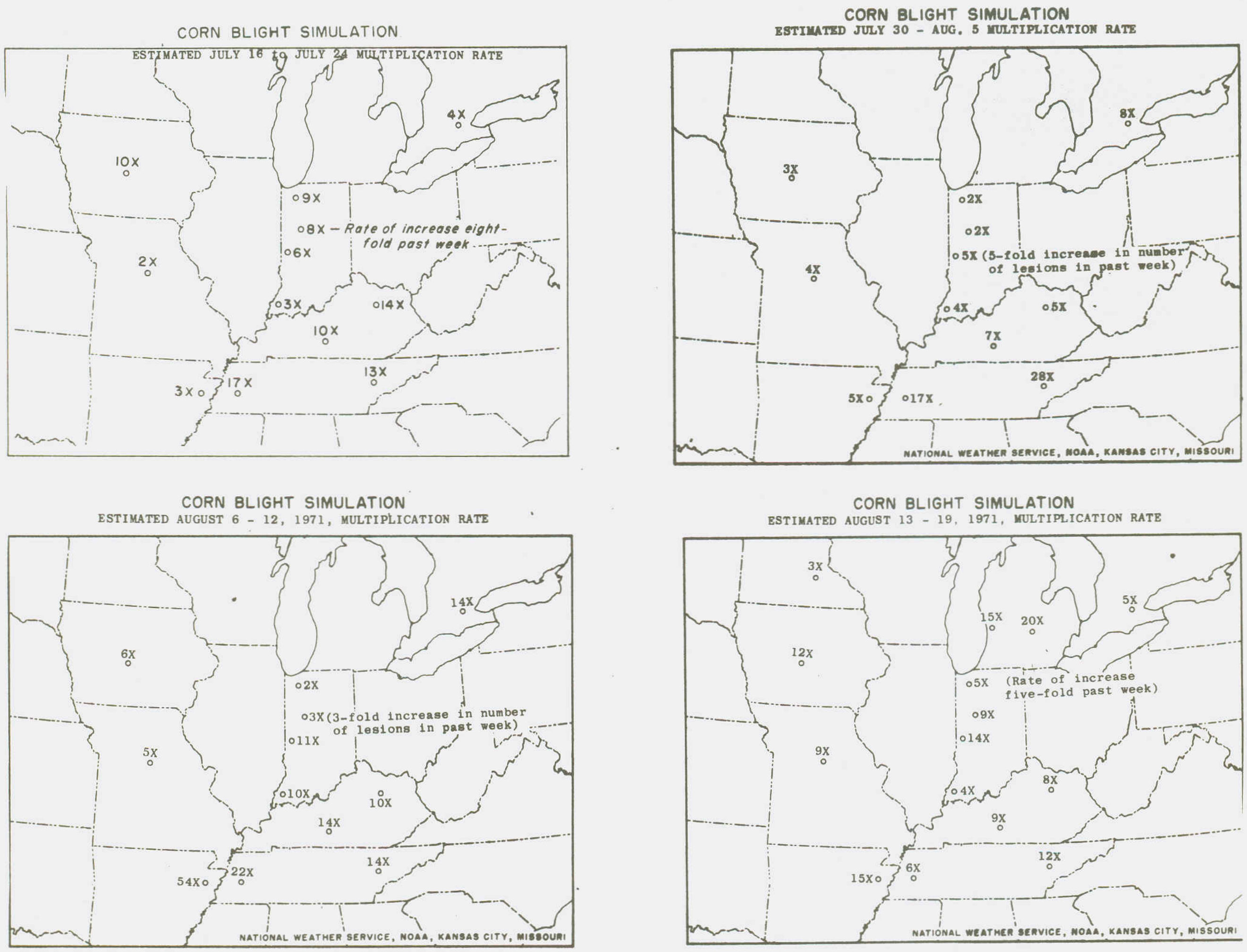


Figure 3.35. EPIMAY-based maps of blight development.

EPIMAY-indicated multiplication in number of lesions during the corresponding period. Then, (since the number of lesions on the beginning dates had varied from location to location) the increase was "normalized" by dividing the number of lesions present on the last day of the period by the number present on the first day. This gave a lesion multiplication factor (the number of times the original number of lesions increased during the four-week period). It must be noted, however, that the data generated in this manner must be interpreted with some degree of caution since in many of the segments observations were made in only one or two T-cytoplasm fields and the maximum number for any segment was five.

Results

Figure 3.36 shows that there is, in fact, a general relationship between the EPIMAY-derived increase in number of lesions and the actual increase in blight according to ground observers. Furthermore, simple correlation analysis (Ref. 4) gives a correlation coefficient of r=0.64, which is significant at the 0.01 level of confidence. However, because of the relative nature of these values, it is not possible to perform regression analyses in order to use the data for prediction purposes.

Even so, considering the limited number of samples that were used and the many possible sources of variation in the data itself, the results of the simple correlation analysis are encouraging.

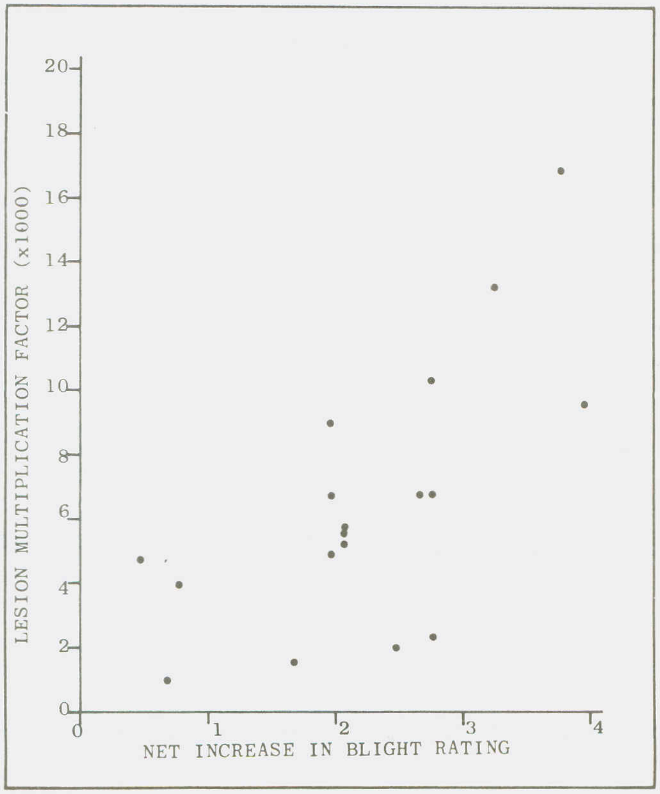


Figure 3.36. Ground truth vs. EPIMAY-derived blight increase.

B. Aerial Spore Collection

Background

As with the EPIMAY project of the National Oceanic and Atmospheric Administration, the Spore Collection project, carried out by NASA's Ames Research Center (ARC) as part of a larger atmospheric study, is described thoroughly in Vol. II, Section VIII of this Report. Briefly, epidemiological evidence collected during the 1970 incursion of Southern Corn Leaf Blight strongly suggested that, in combination with other factors, aerial transport of the causal fungus *Helminthosporium maydis* was a major factor in the spread of the disease. Since ARC was interested in the overall relationship between the airborne state of microbes and disease transmission in plant communities, and the CBWE was interested in a more specific facet of that relationship, the relationship of aerial spore concentration to SCLB severity, a cooperative effort was set up whereby ARC sampled spores over CBWE flightlines to determine vertical and horizontal distributions of *Helminthosporium maydis*. This aerial sampling was to be supplemented by ground-level monitoring of spore concentrations at 17 locations in the Corn Belt.

Aerial sampling was carried out by means of two impaction-type spore collectors, one mounted on the WRL C-47 during its scheduled multispectral scanner missions and the other installed in an Aerocommander which flew only spore collection missions (details of aircraft, spore collectors and procedures included in Vol. II).

Sampling Procedures

--Acquisition--

More than 5000 miles of Corn Belt were covered by the Aerocommander during five weeks of sampling (July 1 to September 15). The Willow Run Laboratories' C-47 flew 385 flightline miles between July 24 and October 6 while equipped with the Spore Collector. See Tables 3.51 and 3.52 for detailed collection schedules.

Coverage by the C-47 was limited by several factors including the weather, inability to reload the trap filters during flight, and the secondary nature of spore collection relative to the primary mission of the aircraft (MSS coverage from a constant altitude of 5000 feet). This third factor had been foreseen, however, and was alleviated by the addition of the more flexibly scheduled Aerocommander. Despite these limitations, the C-47 did obtain good coverage over the central and southern parts of the state, those most affected by SCLB.

As was expected, the schedule flexibility of the Aerocommander resulted in much more extensive coverage. For example, 2-1/2 to three days were normally required for horizontal sampling along all nine selected flightlines in Indiana, Illinois, and Iowa (see Vol. II, Figure 2.37). This schedule allowed an additional day or two during each work week for vertical sampling (profile flights) over selected areas. This was accomplished by sampling at an altitude of 500 to 1000 feet AGL over a ten-mile flightline that was also ten miles wide (five miles on either side of the area of

Table 3.51 **C-47 Sampling schedule.**

Line No.	Area	Week I	Week II	Week III	Week IV	Week V	Week VI
210		7-12-71		-	8-5-71		
205		7-12-71		7-31-71	-		
201	Northwestern Indiana	7-12-71		-	8-5-71		
204		7-12-71		-	8-5-71		
206		7-12-71		7-31-71	-		
208		7-12-71		7-31-71	-		
220		7-16-71		7-27-71		8-12-71	10-6-71
224		7-16-71		7-27-71		8-12-71	10-6-71
227	Southern Indiana	7-16-71		7-27-71		8-12-71	10-6-71
229		7-16-71		7-27-71		8-12-71	10-6-71
228		7-16-71		7-27-71		8-12-71	10-6-71
223		7-16-71		7-27-71		8-12-71	10-6-71
217			7-21-71	7-29-71			
219	Central Indiana		7-21-71	7-29-71			
216			7-21-71	-			
215			7-21-71	7-29-71	8-11-71		
213			-	7-29-71	8-11-71		
211			-	7-29-71	8-11-71		

Table 3.52 **Aerocommander sampling schedule.**

Line No.	Area	Week I	Week II	Week III	Week IV	Week V
6	Northeastern Indiana	-	8-4-71	8-17-71	8-31-71	9-14-71
8	Northwestern Indiana	7-2-71	8-5-71	8-16-71	8-30-71	9-13-71
8B	Central western Indiana	7-2-71	8-5-71	8-16-71	8-30-71	9-13-71
9	Southwestern Indiana to Northern Kentucky	7-2-71	8-6-71	8-16-71	8-30-71	9-13-71
11	Central Illinois	7-3-71	8-5-71	8-16-71	8-30-71	9-13-71
12	South Central Illinois	7-3-71	8-5-71	8-16-71	8-30-71	9-13-71
13	South Central Illinois to Northern Kentucky	7-3-71	8-6-71	8-16-71	8-30-71	9-13-71
19	Southeastern Iowa	7-3-71	8-2-71	8-15-71	8-29-71	9-12-71
23	South Central Iowa	7-3-71	8-2-71	8-15-71	8-29-71	9-12-71
Profile flights 1,000 to 10,000	Rockville, Indiana	-	8-3-71	8-17-71 8-18-71	8-31-71	9-14-71
Bi-hourly Sampling over a single site	Rockville, Indiana	-	-	8-19-71	9- 2-71	-

interest), then reversing directions, climbing 1000 feet and repeating the operation. In this manner, a column of air extending to an altitude of 10,000 feet was sampled in 1000-foot increments. Most of this work was conducted on an east-to-west flightline over Rockville, Indiana (see Table 3.52), an area in which SCLB infection was reported to be moderate to severe. Six profile flights were made over this region during the summer months. Two similar flights were made in September over Indiana and Illinois fields in which harvesting and shelling operations were in progress.

The Rockville, Indiana, area also served as the test site for bihourly sampling at 1000 feet between the hours of 8 a.m. and 6 p.m. to determine the times at which airborne spore concentrations reached their maximum.

--Examination--

Aerocommander samples - A typical microscopic field of airborne particulates collected by the Aerocommander is shown in Figure 3.37. This sample, which represents the particulate concentration in approximately 0.25 cubic feet (6.8 liters) of air (STP), was collected at 1000 feet over southern Illinois on September 13.

Fungal spores comprised most of the catch with general Alternaria, Chladosporium, Fusarium, Ustilago, Helminthosporium and Aspergillus nearly always present. Collectively, these common inhabitants of the corn canopy accounted for nearly 30-40 percent of the catch. Another 10 to 15 unidentified, but distinctive, spore types occurred with regularity. Approximately 15 percent of the total catch appeared, because of uniformity of color and texture, to be of biological origin. This material, composed of particulates ranging in size from 1-10μ, could be categorized as neither spores nor pollen. In fact, few of the common plant pollens were encountered and, additionally, all samples appeared to be relatively free of dust except when flightlines intersected industrial areas.

Hydration - Typical Helminthosporium maydis spores, suspended in distilled water, are illustrated in Figure 3.38. Spores are long and slender, ranging in length from 40 to 80 microns, and in width from 10 to 50 microns. The spore is characterized by rounded ends, a curving profile, and thick cross-walls that define 6-10 segments throughout its length. The northern variety is similar in appearance but smaller and thicker, containing fewer segments.

It must be noted that spores collected in the air often exhibit a morphology quite different from that exhibited by spores collected from infected corn leaves. This difference can be accounted for by the hydration state of the spores. Those collected from leaves are usually hydrated while those in airborne catches are often dehydrated. SCLB spores in the dehydrated state are illustrated in Figure 3.39. These spores are thick and wrinkled, rather than long and slender. They appear to contain highly refractile

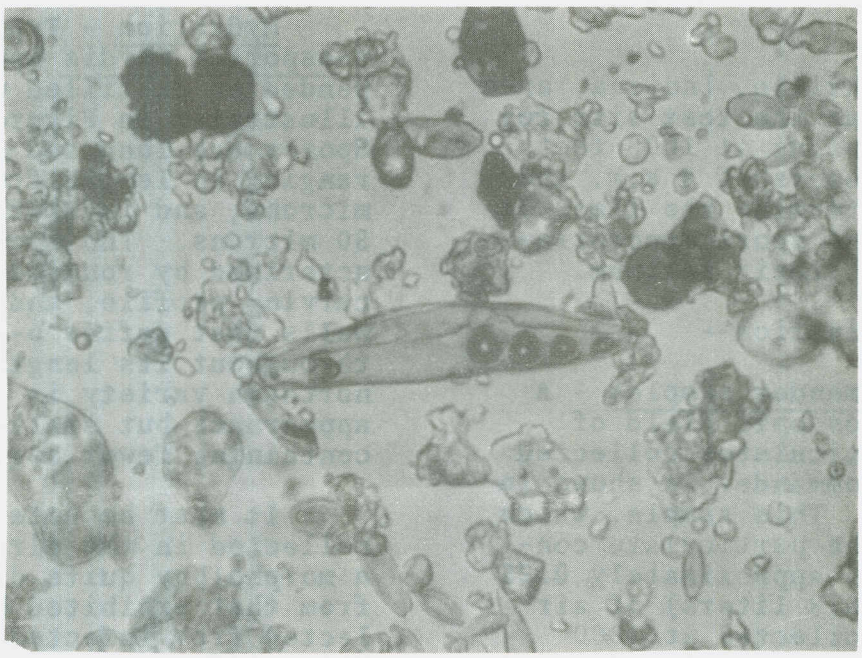


Figure 3.37. Representative field from Kramer-Collins trap slide illustrating H. *maydis* spore (center) and diverse particulates. (Magnification: X900).

Figure 3.38. H. maydis spores in hydrated state. (Magnification: X530)

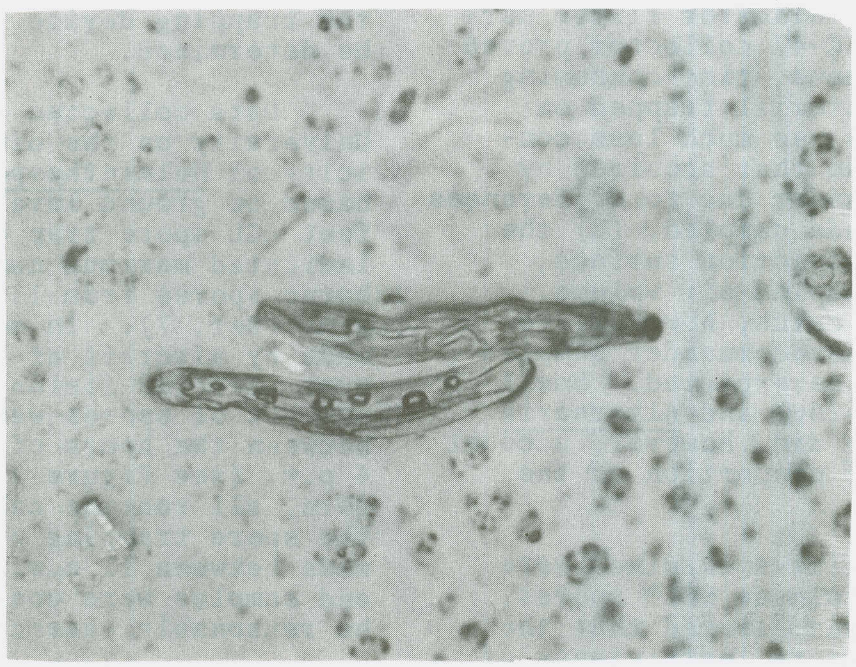


Figure 3.39. H. maydis spores in dehydrated state. (Magnification: X710)

substances or "granules" in the cytoplasm. Cross-walls are indistinguishable, and spores are more often straight than curved.

During the handling of the airborne catch, in which several drops of water are placed on the slide and covered by a cover-slip, some H. maydis spores change from the dehydrated state to the hydrated. Rapidly imbibing water, they assume the typical hydrated morphology within five to ten minutes. First a smooth contour develops, then curving becomes more pronounced. As "granules" disappear, segmentation becomes apparent. Rehydration rate varies among different spores in the same field of view, and, more often than not, both dehydrated spores and those in various stages of rehydration were observed in routine examinations.

C-47 samples - Examination of the four-inch-diameter filter surfaces of the C-47 collector proved to be an arduous, time-consuming task. The material trapped on these filters was much less concentrated than that acquired by the Aerocommander due to differences in (1) altitude sampled, (2) the area of the impaction surface, and/or (3) sampled air volume. The airborne catch, however, resembled the Aerocommander sampler at 5000 feet as expected. Small particles (1-20μ) and Alternaria conidiospores did, however, account for a greater proportion of the total.

Those filters examined were found to contain no SCLB spores. At first it was assumed that the result was due to inefficiency of the sampler since the air mass actually passing through the instrument under flight conditions was unknown. Later, however, spore counts on samples collected at various altitudes over heavily infected Indiana fields by the Aerocommander revealed that the occurrance of SCLB spores at 5000 feet was indeed a rarity.

Results

Due to the more extensive data obtained from the Aerocommander, the results presented here are based entirely upon a sampling of that program. Analysis is still partially incomplete. Several months were required to complete spore counts on the many samples collected; it is anticipated that many months more will be required to fully analyze the data in terms of weather effects and degree of infection in many of the areas sampled. Also, collection efficiency of the trapping device is still to be determined.

Data collected at Iowa State University on the diurnal periodicity of Helminthosporium spores, based on ground level and 50-60 feet AGL spore trap catches, indicated maximum numbers of airborne spores from 11 a.m. to 1 p.m. (Ref. 7). In measurements made by aircraft at 1000 feet over infected fields, maximum numbers of spores were trapped between the hours of 11 a.m. and 4 p.m. (see Figure 3.40). Therefore, all routine collections in the spore trapping program were made between 11 a.m. and 5 p.m., and samples were considered to be reasonably characteristic.

It was noted that weather

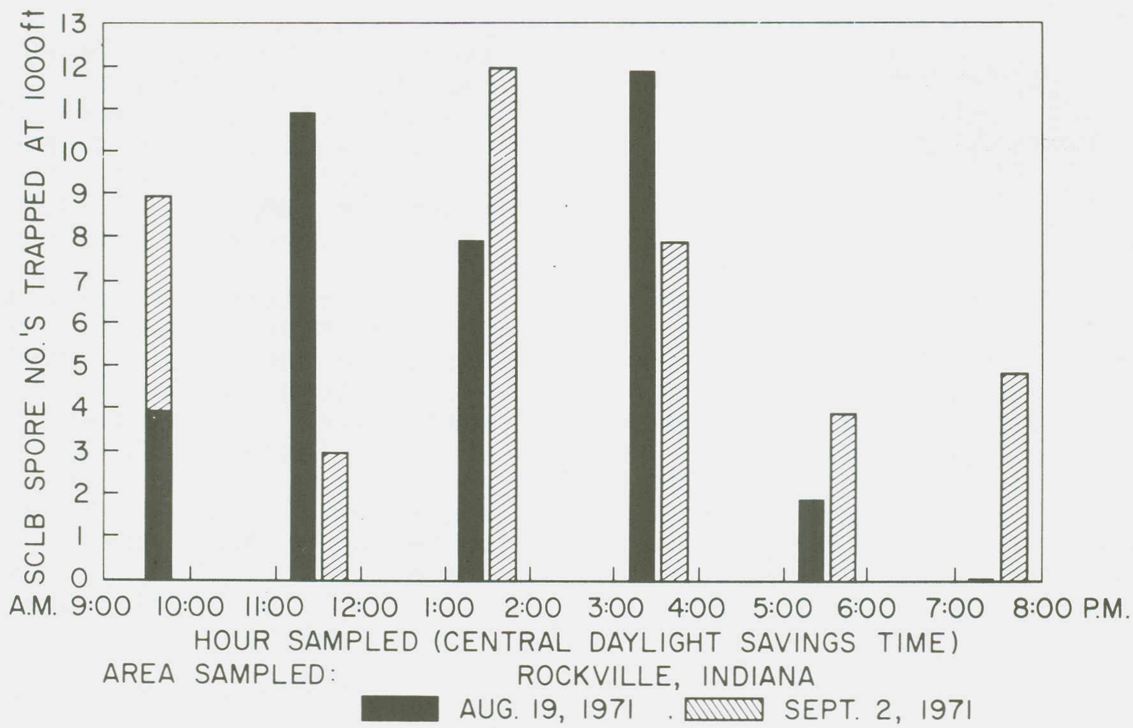


Figure 3.40. Diurnal periodicity of SCLB spores.

conditions influenced the numbers of spores encountered. September 2, for example, was characterized by very stable air beneath an extensive cloud cover; this resulted in smaller bihourly fluctuation in spore numbers than did the weather on August 19, a warm, cloudless day. Generally, particulates tend to remain suspended in stable air, and the results of the September 2 sampling most likely included both spores very recently released into the atmosphere and those released at an earlier hour.

The vertical and horizontal distribution of SCLB spores across the Midwest was more extensive than expected, but overall numbers were low. Wallin (Ref. 7) reported similar findings in spore trapping experiments conducted at ground level in Iowa corn fields. In view of the low numbers of SCLB spores encountered in the aircraft sampling program, counts of conidiospores of _Alternaria_, a common co-habitant of the corn canopy, were made for comparison.

--Vertical Distribution--

Data on concentrations of SCLB and _Alternaria_ spores over a blight infected field are given in Tables 3.53 and 3.54. Note that though only small numbers of _H. maydis_ spores were found relative to _Alternaria_ at all of the altitudes sampled, SCLB spores were, as had been expected, most abundant at the lower levels of the atmosphere (1000 - 2000 feet).

It appears that meteorological conditions exerted strong influences upon the heights that blight spores attained. For instance, the abrupt disappearance of SCLB spores in the air column between 2000 and 5000 feet on five out of eight sampling dates was accounted for by inversion layers which very effectively limited upward diffusion. Visible precipitation, such as clouds, fog and rain, were observed on August 3 and September 1 just above the 2000 foot level and had an even greater effect, confining spores to the lowest levels observed. Note that the single instance of blight spore collection at 10,000 feet was probably due to sampling error, as subsequent extensive sampling at 10,000 feet was conducted without success.

By September 15 harvesting operations under clear, sunny skies had increased _H. maydis_ spore concentrations in the atmosphere. It is known that half of those found at 500 feet did not reach the 1000 foot level, but, since sampling had to be discontinued above 3000 feet, the maximum heights reached by spores released by harvesting operations remains unknown.

Airborne _Alternaria_ spores, which are approximately half the length and one quarter the density of _H. maydis_ conidiospores, exhibited similar behavior. Heavier concentrations of spores were found below 5000 feet and layering effects due to the concentration of particulates just below inversions were evident. However, unlike _H. maydis_ spores, _Alternaria_ frequently occurred above 6000 feet and it was not unusual to find them in small numbers even at 10,000 feet. In fact, though moisture reduced numbers of _Alternaria_ throughout

Table 3.53 **Vertical distribution of SCLB spores over Rockville, Indiana (#'s per cu meter of air sampled).**

	ALTITUDE (thousands of feet)										
	.5		2	3	4	5	6	7	8	9	10
July 2	-	4	13	0	13	0	-	-	-	-	-
Aug. 3	-	3	2	0	0	0	0	0	0	0	0
Aug. 17	-	20	2	1	4	0	0	0	0	0	0
Aug. 18	-	11	1	3	1	2	0	0	0	0	0
Aug. 31	-	9	6	8	0	0	0	0	0	0	0
Sept. 1	-	6	9	0	0	0	0	0	0	0	1
Sept. 14	-	15	6	11	1	0	0	0	0	0	0
Sept. 15 (harvest)	35	18	6	22	-	-	-	-	-	-	-

Table 3.54 **Vertical distribution of Alternaria Spores over Rockville (#'s per cu meter of air sampled).**

	ALTITUDE (thousands of feet)										
	.5	1	2	3	4	5	6	7	8	9	10
July 2	-	381	225	221	155	73	-	-	-	-	-
Aug. 3	-	91	66	59	53	21	18	7	7	18	3
Aug. 17	-	211	128	138	114	13	3	0	0	0	1
Aug. 18	-	233	192	123	84	40	6	4	4	0	0
Aug. 31	-	95	68	33	52	4	63	4	2	0	2
Sept. 1	-	77	36	26	0	2	0	0	2	0	2
Sept. 14	-	249	239	268	54	12	11	0	0	0	0
Sept. 15 (harvest)	722	283	497	597	-	-	-	-	-	-	-

the air column, spores still persisted in and above cloud layers. Spores of Alternaria were recovered at 6000 and 7000 feet on August 3 in spite of a drizzle at these levels. It is possible that differences in size and moisture-absorption characteristics may well account for the difference in airborne behavior noted between Alternaria and Helminthosporium spores. Further examination of the effect of hydration on H. maydis could provide a much more thorough knowledge of its aerial dispersion.

--Horizontal Distribution--

Plots of spore numbers trapped biweekly in each of nine major sampling areas from June 29 to September 16 are shown in Figure 3.41. Each point on the map represents a single spore trapped. The results of these horizontal aircraft collections, made at a constant altitude of 1000 feet, indicate that the atmosphere was responsible for widespread distribution of SCLB spores throughout the corn growing season.

In the first week of sampling (June 29 through July 3), a light scattering of airborne spores was distributed rather evenly throughout those areas sampled. A single exception occurred in central Iowa (flightline 23) where aggregates of spores were suddenly encountered. This was thought to be due to corn shelling operations in the area.

When these samples were collected, disease severity was very low in most areas but, as sampling indicated, disease incidence was widespread; H. maydis spores were usually distributed randomly throughout the bands of deposited material on all collection surfaces.

Few spores were trapped during the second week (August 2-5), a week characterized by rain and low temperatures in many areas. Increasing numbers of airborne spores were encountered in Indiana and Illinois during the third week and the early part of the fourth week when the weather, although remaining cool, was drier.

The largest numbers of spores were encountered during the fifth week (September 13-16). During this time, a pattern of spore distribution became discernible, and spore concentrations began varying more greatly from area to area within the air corridor being sampled. Alternative causes for this phenomenon are (a) strong, localized convective currents rising from infected fields covered by the line of flight, and (b) clouds of spores carried from distant ground sources. Evidence thus far favors cause (a) since the vertical distribution studies over a single infected Indiana field showed a relatively constant number of airborne spores at 1000 feet throughout the sampling period. Moreover, the clustering of points in the central portions of flightlines 8 and 11 corresponded to areas of increased disease severity as reported by the USDA.

Evaluation

Overall, the Aerocommander

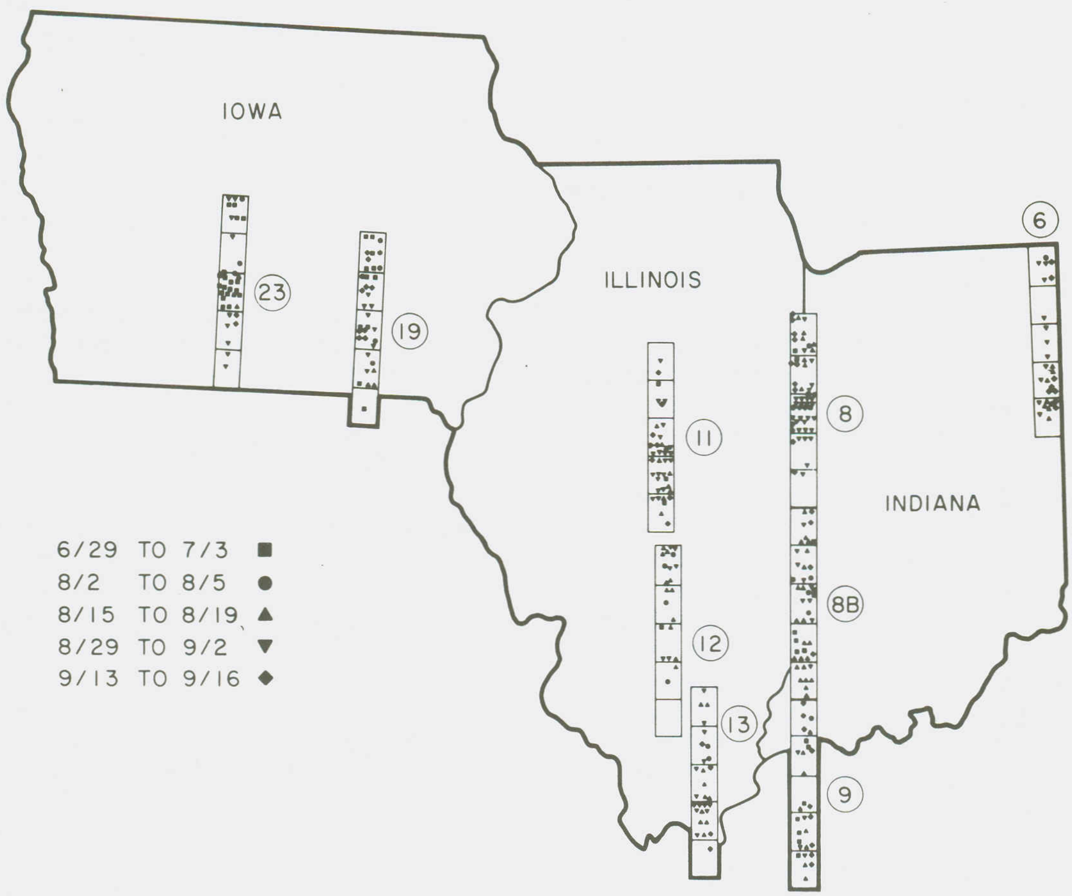


Figure 3.41. Frequency map of SCLB spore collection. (Each point = one spore trapped at 1000 feet.)

portion of ARC's Spore Collection project was successful. It was determined that in all but a few cases, maximum numbers of spores occurred at 1000 feet and below, and that above that level concentration began to fluctuate due to atmospheric inversion layers and visible precipitation.

While very few SCLB spores were trapped above 4000 feet, even their occurrence at 1000 to 3000 feet provided the opportunity for rather extensive dissemination of the pathogen via the atmosphere. Because of this, weather patterns, particularly frontal movement accompanied by high winds, may very well play a significant role in extensive disease spread. Such conditions, however, were not encountered during the sampling program.

The flight data, collected under relatively stable weather conditions, indicated that convection was important in the vertical movement of spores, and that spores tended to be held in suspension within inversion layers beneath the cloud cover. Thus, spores occurring at the 1000-foot level probably originated from local sources.

Observations made at ground level by the USDA showed that the 1971 epidemic of SCLB followed a pattern different from that of the previous year. Infection was lightly spread throughout the Corn Belt; moderately severe infection were spotty, and there appeared to be little south-to-north spread of the disease. Measurements of airborne spores made along sampling flightlines throughout the Corn Belt appeared to reflect these trends.

C. References

1. Waggoner, P. and G. Horsfall. 1969. "EPIDEM." Connecticut Agricultural Experiment Station Bulletin.

2. Steel, R.G.D. and J.H. Torrie. 1960. Principles and Procedures of Statistics. McGraw Hill Book Co., New York.

3. Davis. D.R. and J.E. Hughes. 1970. "A New Approach to Recording the Wetting Parameter by the use of Electrical Resistance Sensors." Plant Disease Reporter 54(6): 474-479.

4. Felch, R.E. and G.L. Barger. 1971. "EPIMAY and Southern Corn Leaf Blight." Weekly Weather and Crop Bulletin 58(43): 13-17.

5. Joos, L.A. 1971. "EPIMAY 1971--Waggoner Corn Blight Simulation Program: Operations and Results." Mimeo Report, NWS, Kansas City, Missouri.

6. Waggoner, P. 1971. "EPIMAY." Mimeo Report. 48p.

7. Wallin, Dr. Jack, USDA, Iowa State University. Personal communication.

Section IX.

Summary and Conclusions

IX. SUMMARY AND CONCLUSIONS

A. Results

The significant results of the 1971 Corn Blight Watch Experiment can perhaps be best expressed by summarizing the achievements related to the application objectives and by discussing the performance of the technology relative to those achievements.

The application objectives required (1) the detection of outbreak, identification of temporal increases in severity levels and the tracking of SCLB spread over the total study region; (2) an assessment of the impact of SCLB on production; and (3) an estimate of the applicability of remote sensing to other situations which would require surveys on a large scale.

Objective 1

With reference to the first objective, it can be concluded that neither the manual interpretation of small-scale photography nor the machine-aided analysis of multispectral measurements provided adequate detection of SCLB during early stages of infection. Analysis of these data did, however, permit the detection of outbreaks of moderate to severe infection levels and mapping of the spread of those levels over the study regions with relatively high accuracy.

Additionally, analysis of data showed that although flightlines were efficient in a data acquisition sense, they were not statistically optimal and actually contributed to increased variance in blight acreage estimates. This leads to the conclusion that a more accurate assessment of conditions due to SCLB could have been realized with a smaller set of data samples better distributed over the total study area.

Objective 2

In attempting to assess the impact of SCLB on production, investigators were able to associate significant yield reductions with moderate to severe infection levels occurring in August and still greater reductions associated with moderate to severe infection levels occurring in July. The results of the Experiment indicate that acreages infected at these levels were identified in the late July and August periods with relatively high confidence.

Results also led to a conclusion that machine-assisted analysis of multispectral scanner data was more effective both in detecting and tracking the spread and in assessing the impact of SCLB than was the analysis of the small-scale photography. This conclusion had been anticipated since the small changes correlating to blight infection levels are more easily measured quantitatively; i.e., by multispectral sensors, than qualitatively; i.e., by photo-interpreters.

Objective 3

Results clearly indicate that the technology is capable of both identifying and measuring the extent of agricultural crops and land use categories. Major crops were accurately identified throughout the season by both photointerpretive and machine-assisted analysis techniques even though this aspect of the Experiment received relatively little emphasis compared to the more difficult blight detection problem.

It can further be concluded that the technology is suitable for large-scale detection of crop stress in those instances where changes in the radiation characteristics of the crop accompany the stress. These stresses, which affect crop production, included low plant population, drought damage, hail damage, and extreme weediness. There were instances, however, when these factors could not be differentiated from the effects of blight.

B. Accomplishments

In addition to the specific fulfillment of objectives, the CBWE provided an excellent opportunity to evaluate all aspects of a system designed to collect, analyze, interpret, and distribute information repeatedly and at short intervals throughout a growing season.

First, much was learned about how to manage the volume of data involved in acquiring information over a large geographic region. The use of a statistically sound sampling model was found to be a key element in accomplishing this.

Second, a file of photography, multispectral measurements, and field observations collected at biweekly intervals over an entire Corn Belt growing season is now available. It will prove extremely valuable in further studies.

Third, knowledge was gained about the costs of a large-scale information system using remote sensing. Information on the cost in both dollars and time for each part of the Experiment will be useful in the planning of future experiments or operational systems. These data on labor, computer costs, aircraft, film, processing, etc., expended in the Experiment are being used to investigate the relationship between subsampling ratios, costs, and precision of estimates.

Fourth, the Corn Blight Watch Experiment also demonstrated the value of pooling the resources of a number of cooperating groups. At this time no single organization has the expertise or resources to conduct such an experiment alone; the CBWE provided valuable data related to resource requirements for this type of program as well as insight into the practices which are most effective in the design and operation of such cooperative systems.

Fifth, because of the CBWE many agriculturists had an opportunity to work with remote sensing data. The majority of field personnel responded favorably to the aerial color infrared photography sent to them and reported that it could be used to good advantage in their work. As a corollary to that, the Experiment also demonstrated the need for more agriculturalists with training in remote sensing. It is hoped that more schools of agriculture will provide and encourage their students to take course work in this field. If remote sensing is to be utilized in agricultural situations, it is imperative that people are trained to work with this data.

Further, since the data-acquisition elements performed well, the Experiment provided evidence that a fully-committed, high-flying aircraft can effectively acquire data at biweekly intervals for a region as large as the Corn Belt, even under the less-than-optimum Corn Belt weather conditions. The University of Michigan C-47 was similarly able to collect multispectral measurements over a 13,000 square-mile area in western Indiana. A helicopter proved to be a valuable aid in acquiring field observation data. Such a system can often permit a more accurate assessment of more fields in shorter periods of time than can conventional ground methods.

Finally the Experiment resulted in significant improvements in aerial infrared film. The condition causing the "cyan spots," which hampered the analysis because of their similarity to blight, has since been corrected. This deficiency in the film was discovered by the photo-analysts of the Experiment.

C. Guidelines for Future Research and Technology Development

The Corn Blight Watch Experiment demonstrated that a statistical sampling model is a fundamental element of a remote sensing survey system. A general conclusion is that additional effort needs to be expended to develop sampling concepts suited to remote sensing data acquisition systems and automatic data analysis procedures. As a part of the Experiment, investigators did gain valuable experience developing a capability for setting up survey prediction models utilizing remotely sensed measurements.

Results also indicate that much would be gained from techniques which would insure consistent photographic exposure from mission to mission. Similarly, improved preprocessing techniques would provide more useful multispectral scanner data over a wider range of conditions (i.e., atmospheric and sun angle).

Results of the CBWE indicate that while crops can be reliably identified by either photointerpretation of small-scale infrared photography or through computer processing of multispectral measurements, if acreage measurements are to be obtained from scanner data, additional techniques need to be developed. Such efforts need to be undertaken in the near future. It is possible, for instance, that a capability to register different data sets required for temporal analysis would also solve the area determination problem. Multispectral data sets would be registered to a photogrammetrically corrected data base. Area measurements could then be made from the geometrically corrected multispectral data classification output.

The results further indicate that if either remote sensing approach is to offer a decided advantage over ground-acquired data, ways must be found which require less ground observation for the initial selection of training samples, and techniques must be developed which permit the use of training statistics with data collected under a wider range of conditions and over larger geographic distances. In many instances, especially in those cases involving clearly visible phenomena, selected high-resolution photography could probably remove the need for much ground-acquired data.

There is a need for further work establishing the statistics of the spectral patterns of natural scenes to better determine the causes of variations (including sun angle, observation angle, and atmospheric effects) described by those statistics. It is believed that variations in response not caused by variations in the ground scene led to the relatively low accuracies which were achieved over small areas (10's of square miles). The variances were sufficiently large to require samples over relatively large areas before accurate estimates were realized.

Again, results indicate that there could have been considerable improvement in performance had analysts been capable of making multitemporal data sets coincident; more can be gained from eight channels of data collected at three different times than from 24 channels collected at one time. Data registration is the key to this type of analysis.

An examination of the physical characteristics of SCLB (uniform infection, within a field) indicates that improved results could have been obtained by using sample classifiers instead of the point classifiers currently being used. Before sample classifiers can be employed, however, techniques need to be developed to automatically identify the boundaries of data fields.

D. Conclusions

The 1971 Corn Blight Watch Experiment provided a prototype remote sensing system in which techniques of data gathering, storage, retrieval, processing and analysis and information dissemination were successfully used in one integrated system operated in a quasi-cperational environment. The experiment effectively focused the efforts of many disciplines and agencies on a common problem and resulted in many people becoming acquainted with remote sensing techniques.

In conclusion, accurate identification of agricultural crops and land use over large geographic areas using remote sensing techniques was clearly demonstrated as was the potential utility of these techniques to assess crop stress over large geographic regions. The 1971 Corn Blight Watch Experiment provided the most quantitative information available on the extent and severity of blight.

But most important, the Experiment was a major milestone in the development of earth resources survey by remote sensing. Existing remote sensing techniques were refined and many new ones implemented as remote sensing moved a step further into the real world.

Finally, the Experiment provided valuable direction for future research and development of remote sensing technology and guidelines for the design of operational information systems utilizing remote sensing.

Appendix III-A

Bibliography of CBWE Related Publications

APPENDIX III-A

LARS publications related to the Corn Blight Watch Experiment:

Information Note 051371 by M. E. Bauer, P. E. Anuta, P. H. Swain, R. B. MacDonald and R. P. Mroczynski. Detection of Southern Corn Leaf Blight. 20p.

Information Note 020172 by L. M. Eisgruber. The Effect of Subsampling Ratios on Precision of Estimates from Remote Sensing. 27p.

Information Note 100272 by R. B. MacDonald, M. E. Bauer, R. D. Allen, J. W. Clifton, and J. D. Erickson. Results of the 1971 Corn Blight Watch Experiment. 33p.

Information Note 080172 by P. E. Anuta, T. L. Phillips, and D. A. Landgrebe. Data Handling and Analysis for the 1971 Corn Blight Watch Experiment. 16p.

Information Note 110173 by J. A. Sharples. The Corn Blight Watch Experiment: Economic Implications for Use of Remote Sensing for Collecting Data on Major Crops.