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IDENTIFYING VEGETATIVE LAND USE CLASSES DURING EACH OF THE FOUR SEASONS ON AERIAL PHOTOGRAPHS AND LANDSAT IMAGERY IN COASTAL SOUTH CAROLINA

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I. ABSTRACT

Landsat MSS data were utilized to delineate vegetative types in Coastal South Carolina during the four seasons at Land Use Classification Levels I, II, and III. The information in the Landsat scenes was compared to data derived from ground samples and to low altitude color infrared aerial photographs. The identification of forest types with MSS data at Level I was 91 to 93% correct, but the non-forest types were only 46 to 68% correct, depending upon the season. At Levels II and III, the overall identification was submarginal, especially in the mixed and disturbed forest categories. In view of these poor results, it is apparent that there is a need for a photo interpreter to evaluate land use conditions that cannot be identified properly by MSS imagery and computer processing. Such conditions are frequently caused by forest management activities commonly found on forest vegetative sites.

II. INTRODUCTION

Landsat imagery has been examined intensively since its basic inception in 1972, especially with regard to biological fields like forestry. Further evaluation of certain aspects of Landsat imagery may enable it to be utilized more fully by foresters in their normal forest management activities. Several authors, including Dillman (1978), Heller et al. (1975), Joyce (1973), Kalensky and Sherk (1975), Kan and Dillman (1975), and Richardson et al. (1972), have discussed the potential for utilizing Landsat imagery during two or more seasons to achieve better interpretation of vegetative data on Landsat scenes. Dillman (1978) concluded that slight improvements in classification accuracy that occurred when imagery taken in Spring and Winter were combined would not justify the cost of additional processing time compared to the use of imagery taken in the Spring alone. There is still a question, however, concerning which season will provide the maximum amount of information for typing the vegetation in a large area.

Seasonal coverage has been emphasized in this study for two reasons. First, most studies have used one or, at most, two seasons in evaluating Landsat vegetative data. Secondly, the Forestry Department at Clemson University has the capability of taking its own aerial photographs during each of the four seasons for comparison to similar Landsat imagery, providing a convenient evaluation of seasonal effects.

III. METHODS

The 519,680 acres in Georgetown County are located in the lower Coastal Plain of South Carolina adjacent to the Atlantic Ocean. Landsat MSS data covered the entire county, aerial photographs were systematically located in five east-west flight strips, and ground samples were allocated systematically to coincide with the photographic coverage.

Color infrared aerial photographs at a nominal scale of 1:12,000 with 30 percent endlap were taken during the four seasons--Winter, Spring, Fall color, and Summer--from the Fall, 1979 to the Summer, 1980 by the Department of Forestry. The analysis of the photographs included (1) numbering and dating, (2) determining representative photo scales, (3) preparing transparent overlays of the sample area on each photograph, and (4) delineating and labeling the vegetative types on the overlays. The resulting vegetative typing covered approximately 12 percent of the county area. The area in each major cover type was estimated from the overlays using the dot grid method.

A multiphase sampling procedure was utilized with ground samples located on aerial photographs and the same areas subsequently identified on the Landsat imagery. Care was taken to insure that as few as possible of the ground samples were located in transition zones between the different vegetative types. Fifty-seven clusters of samples, each containing five basal area factor 10 (BAF 10) prism sampling points were located systematically throughout the area in forested types in the general vicinity of the principal points on the aerial photographs.

A total of four scenes were utilized in this study corresponding to the aerial photographs taken during the four seasons. Dates of Landsat imagery were January 5, 1979 (Winter), November 16, 1979 (Fall color), March 25, 1981 (Spring), and June 23, 1981 (Summer).

While the bulk of the computer work was done at Clemson University, the majority of the computer processing of the MSS data was done at the Engineering Experiment Station of The Georgia Institute of Technology in Atlanta, with the cooperation of the U.S. Forest Service. Other computer processing was accomplished at the Computer Graphics Division of the University of South Carolina in Columbia.

Landsat MSS data were processed using the supervised maximum likelihood classification method which involves taking and identifying training samples from the raw MSS data. Uniform areas of known vegetative types were located on aerial photographs and subsequently superimposed over a display of the same area of MSS data on the Ramtec monitor at the Georgia Tech. Lab. All training samples were at least four hectares (10 acres) in size and located on the Landsat imagery by comparing recognizable prominent features such as rivers, lakes, or roads that were present on both sets of imagery. Several training samples were taken for each cover category. In each of the scenes representing the four seasons, an attempt was made to locate the training samples in the same area.

The classification process used to assign each of the pixels to one of the training sample classes was based on the Gaussian Maximum Likelihood Algorithm. When classifying an unknown pixel, the classifier quantitatively evaluated both the variance and the correlations of the central spectral patterns and the probability of the pixel belonging to each of the training sample classes. After evaluating the probability for each class, the pixel was assigned to the most likely class.

IV. RESULTS

A. SEASONAL DIFFERENCES

The single cell method of accuracy provides for the comparison of known cover classes from aerial photographs to the unknown classes of Landsat imagery. Information regarding accuracy of identifying the samples were compared by the Land Use Classification System modified from the U.S. Geological System (Anderson et al. 1972) (Table 1).

Level I Classification. Classification accuracy at Level I (forest and non-forest types) ranged from 91 to 93 percent for correctly classified forest samples while non-forest ranged in accuracy from 46 to 68 percent. These accuracy levels for identifying forest types are reasonably high, which is especially noticeable because there will normally be a few errors in identifying forest types even from aerial photographs.

The accuracy levels of 46 to 68 percent for non-forest are somewhat disappointing. It would appear that such non-forest areas as urban, agriculture, barren, non-forest wetland, and water would be identified easily when combined into one category. This was not true in this study nor in other similar studies at Clemson University (Helms 1982, Gering 1982). When identifying land use categories from Landsat imagery, a purely computer analysis of non-forest types does not provide adequate evaluation of some vegetative sites. There is a need for a human interpreter to examine the site either on the ground or on aerial photographs and interpret some facets of information before a final identification can be made for some vegetative sites.

Level II Classification. Classification accuracy at Level II (non-forest, disturbed forest, pine, mixed-pine-hardwood, and hardwood forests) decreased substantially from Level I (Table 2). In many cases, the accuracy levels were erratic and inconsistent during the four seasons. This was especially true in the mixed pine-hardwood and disturbed forest classes where the accuracy levels were very low (12-39 percent).

Table 1. Classification Accuracy of Landsat Data at Level I for the Four Seasons in Georgetown County, South Carolina.

Aerial Photo	Types	Winter Landsat 1	2	Total	Percent Agreement
Forest	1	765	55	820	93
Non-forest	2	30	65	95	68
Total		795	120	915	

Aerial Photo	Types	Fall Landsat 1	2	Total	Percent Agreement
Forest	1	750	70	820	91
Non-forest	2	45	50	95	53
Total		795	120	915	

Aerial Photo	Types	Spring Landsat 1	2	Total	Percent Agreement
Forest	1	761	59	820	93
Non-forest	2	36	59	95	62
Total		797	118	915	

Aerial Photo	Types	Summer Landsat 1	2	Total	Percent Agreement
Forest	1	752	68	820	92
Non-forest	2	51	44	95	46
Total		803	112	915	

Table 2. Classification Accuracy of Landsat Data at Level II for the Four Seasons in Georgetown County, South Carolina.

Aerial Photo		Winter Landsat						
	Types	1	2	3	4	5	Total	Percent Agreement
Pine	1	160	99	29	3	9	300	53
Mixed	2	73	86	48	3	10	220	39
Hardwood	3	31	59	90	7	13	200	45
Disturbed	4	36	17	12	12	23	100	12
Non-forest	5	10	0	9	11	65	95	68
Total		310	261	188	36	120	915	

Aerial Photo		Fall Landsat						
	Types	1	2	3	4	5	Total	Percent Agreement
Pine	1	176	77	24	7	16	300	59
Mixed	2	107	65	22	10	16	220	30
Hardwood	3	66	59	48	2	25	200	24
Disturbed	4	46	13	6	22	13	100	22
Non-forest	5	11	4	9	21	50	95	53
Total		406	218	109	62	120	915	

Aerial Photo		Spring Landsat						
	Types	1	2	3	4	5	Total	Percent Agreement
Pine	1	163	23	93	7	14	300	54
Mixed	2	87	37	72	8	16	220	17
Hardwood	3	42	33	102	3	20	200	51
Disturbed	4	42	3	24	22	9	100	22
Non-forest	5	15	1	9	11	59	95	62
Total		349	97	300	51	118	915	

Aerial Photo		Summer Landsat						
	Types	1	2	3	4	5	Total	Percent Agreement
Pine	1	166	37	49	15	33	300	55
Mixed	2	60	63	61	20	16	220	29
Hardwood	3	45	68	69	10	8	200	34
Disturbed	4	21	28	26	14	11	100	14
Non-forest	5	14	5	15	17	44	95	46
Total		306	201	220	76	112	915	

The mixed category forest has generally proven to be relatively easy to delineate accurately from low altitude color infrared aerial photographs. On the Landsat scenes, however, the classification accuracy for mixed forest ranged from a low of 16 percent to a high of 39 percent, very disappointing when compared to accuracy levels expected when interpreting similar areas of mixed forest on aerial photographs. Another author, Dillman (1978), reported that Landsat classification accuracy decreased when a mixed forest type was included in the classification scheme.

Landsat classification of the disturbed forest category was also disappointing because the highest classification accuracy level was only 22 percent (Table 2). The interpretation of the same areas on aerial photographs is relatively simple and very accurate because disturbed forest is associated with such identification features as logging trails, windrows of logging residues left after site preparation, and the pattern of recent planting activities. These and other typical forestry activities enable the photo-interpreter to identify disturbed forests with almost complete accuracy. When these same areas of disturbed forest are classified by Landsat techniques, the predominant patterns of forestry activities are not recognized with any regularity. Only the reflective vegetative appearance is recorded by Landsat imagery and the subsequent classification schemes predict very little acreages in disturbed forest.

Summarization, Level II. The highest accuracy for Level II vegetative types was pine in the Fall, hardwood in the Spring, mixed forest in the Winter, and non-forest in the Winter. The lowest accuracy levels were mixed forest in the Spring, hardwood in the Fall, and non-forest in the Summer. Identification of disturbed forest was poor during all four seasons. Even though pine type identification was best in the Fall, all four seasons produced reasonably good results with this forest cover type.

Any classification accuracy that is less than 25 percent at Level II is considered to be very poor. Some of the possible reasons for this low accuracy include the following:

1. The selection of the supervised samples upon which to base the comparison may not represent the proper vegetative types.

2. It may not be possible to identify some vegetative types by simply identifying the vegetation growing on the land. This is probably true for mixed forest which includes a heterogeneous mixture of two or more homogeneous types, and for disturbed forest where a human interpreter must sometimes examine both the vegetation on the site as well as related activities and patterns of human involvement.

3. It is possible that the classification of some vegetative types such as mixed forest and disturbed forest using current Landsat imagery is beyond the capabilities of methods used in this study.

Level III Classification. Within the Level III classification system, the pine type was divided into three density classes--low, medium, and high; hardwood was divided into swamp hardwood and upland hardwood; and mixed forest was divided into predominately mixed pine and mixed hardwood. Other categories included non-forest and disturbed forest (Table 3). This classification system is similar to that normally utilized when using low altitude color infrared aerial photographs in general forest management activities. This may have been a mistake because current Landsat imagery does not have the capability of sensing the details of vegetative types with the resolution of good aerial photographs. This fact was emphasized when the ability to recognize many vegetative types decreased steadily from Level II to Level III (Tables 2 and 3). Some factors apparent when examining these tables are as follows:

1. Non-forest identification accuracy was similar in Level II and Level III because the criteria for identifying this type did not change as the Level changed.

2. The relatively low classification accuracy levels for disturbed forests in Level III was very similar to that in Level II because the criteria for identifying this type remained unchanged. Even so, most misclassifications in disturbed forest were actually low density pine and non-forest types.

3. Accuracy at Level III for mixed pine and mixed hardwood was uniformly low, ranging from 0 to 22 percent for mixed pine and from 4 to 18 percent for mixed hardwood. While all seasons resulted in poor identification of mixed forests, the Winter season produced the best classification of these types.

Table 3. Classification Accuracy of Landsat Data at Level III for the Four Seasons in Georgetown County, South Carolina.

Aerial Photo	Types	Winter Landsat 1	2	3	4	5	6	7	8	9	10	Total	Percent Agreement
Non-forest	1	55	12	13	0	0	1	10	0	9	0	100	55
Disturbed Forest	2	20	12	3	8	7	4	29	3	13	1	100	12
Water	3	0	0	0	0	0	0	0	0	0	0	0	0
Mixed Pine	4	3	1	1	22	14	4	18	11	15	11	100	22
Mixed Hardwood	5	1	2	1	16	14	1	23	11	18	13	100	14
Pine-Hi Density	6	2	0	0	19	15	8	14	32	6	4	100	8
Pine-Lo Density	7	4	1	0	18	10	4	42	10	6	5	100	42
Pine-Med Density	8	3	2	0	19	11	9	6	35	12	3	100	35
Swamp Hardwood	9	11	5	2	13	12	0	8	8	51	15	125	41
Upland Hardwood	10	4	2	0	10	16	1	19	3	21	24	100	24
Total		103	37	20	125	99	32	169	113	151	76	925	

Aerial Photo	Types	Fall Landsat 1	2	3	4	5	6	7	8	9	10	Total	Percent Agreement
Non-forest	1	45	21	6	2	0	1	14	0	11	0	100	45
Disturbed Forest	2	13	22	0	5	3	1	43	2	9	2	100	22
Water	3	0	0	0	0	0	0	0	0	0	0	0	0
Mixed Pine	4	8	3	0	16	7	9	27	9	12	9	100	16
Mixed Hardwood	5	6	5	1	10	4	6	38	5	17	8	100	4
Pine-Hi Density	6	10	0	0	8	7	22	23	18	10	2	100	22
Pine-Lo Density	7	3	6	0	6	4	11	46	5	11	8	100	46
Pine-Med Density	8	3	1	0	8	14	16	20	15	15	8	100	15
Swamp Hardwood	9	17	4	0	9	7	7	27	5	45	4	125	36
Upland Hardwood	10	9	1	0	10	7	13	24	5	21	10	100	10
Total		114	63	7	74	53	86	262	64	151	51	925	

Aerial Photo	Types	Spring Landsat 1	2	3	4	5	6	7	8	9	10	Total	Percent Agreement
Non-forest	1	54	12	7	0	2	1	14	0	8	2	100	54
Disturbed Forest	2	9	22	0	1	1	0	40	2	10	15	100	22
Water	3	0	0	0	0	0	0	0	0	0	0	0	0
Mixed Pine	4	5	5	0	0	10	1	20	12	22	25	100	0
Mixed Hardwood	5	9	3	1	2	18	5	28	5	15	14	100	18
Pine-Hi Density	6	0	3	0	1	3	32	9	26	12	14	100	32
Pine-Lo Density	7	2	2	1	7	7	6	22	9	14	30	100	22
Pine-Med Density	8	7	2	4	1	1	20	12	27	11	15	100	27
Swamp Hardwood	9	16	4	1	2	8	8	12	7	50	17	125	40
Upland Hardwood	10	3	0	1	0	13	1	29	3	23	28	100	28
Total		105	53	15	14	63	74	186	90	165	160	925	

Table 3. (continued)

Aerial Photo	Types	Summer Landsat 1	2	3	4	5	6	7	8	9	10	Total	Percent Agreement
Non-forest	1	47	18	1	0	0	0	12	2	15	5	100	47
Disturbed Forest	2	11	14	0	6	2	1	18	2	32	14	100	14
Water	3	0	0	0	0	0	0	0	0	0	0	0	0
Mixed Pine	4	9	7	0	5	16	14	9	9	10	21	100	5
Mixed Hardwood	5	5	9	0	8	14	12	6	3	17	26	100	14
Pine-Hi Density	6	5	3	0	0	4	38	4	29	4	13	100	38
Pine-Lo Density	7	16	4	0	3	7	11	17	15	7	20	100	17
Pine-Med Density	8	12	8	0	0	8	28	7	17	7	13	100	17
Swamp Hardwood	9	9	9	0	12	16	5	17	6	20	31	125	16
Upland Hardwood	10	2	5	0	14	6	7	13	5	21	27	100	27
Total		116	77	1	48	73	116	103	88	133	170	925	

4. Pine types had some of the best classification accuracies in Level III. Fall appeared to be the best season for identifying all categories of pine on Landsat imagery.

5. From these data, Spring was the optimum season for identifying hardwoods on both Landsat and on aerial photographs.

6. Swamp hardwood was identified more accurately during the Spring and Winter. During these two seasons, many samples from all categories of vegetative types appeared to accumulate in the swamp hardwood type, probably due to the common occurrence of water on the floor of the forest during these seasons.

V. SUMMARY AND CONCLUSIONS

A multiphase sampling procedure utilized a combination of ground samples, low altitude, color infrared aerial photographs, and Landsat MSS data to help identify vegetative types in Coastal South Carolina. Both aerial photographs and Landsat scenes were compared during each of the four seasons to determine which season provided the best means for identifying vegetative types.

Landsat MSS data were processed using the supervised method of analysis. From both the Landsat scenes and the aerial photographs, the vegetation was delineated at Level I, Level II, and Level III.

1. At Level I, forests were classified effectively (91 to 93% correct), but the non-forest types were only 46 to 68% correct depending upon the season.

2. At Level II, the best classification accuracy was for pine in the Fall and for hardwood in the Spring. Both mixed forest and disturbed forest were identified inaccurately in all seasons.

3. Level III classification accuracy levels was very low, especially in the mixed and disturbed categories. This led to the conclusion that current Landsat imagery does not provide a suitable medium for identifying many forest types. Too often, there is a need for the human interpreter to analyze types that include heterogeneous mixtures of vegetation and the activities and patterns of forestry operations.

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