N86-11641

Application Of AIS Technology To Forest Mapping

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ABSTRACT

Concerns about environmental effects of large-scale deforestation have prompted efforts to map forests over large areas using various remote sensing data and image processing techniques. Basic research on the spectral characteristics of forest vegetation are required to form a basis for development of new techniques, and for image interpretation. Examination of Landsat data and image processing algorithms over a portion of boreal forest have demonstrated the complexity of relations between the various expressions of forest canopies, environmental variability, and the relative capacities of different image processing algorithms to achieve high classification accuracies under these conditions. AIS data may in part provide the means to interpret the responses of standard data and techniques to the vegetation based on its relatively high spectral resolution.

INTRODUCTION and OVERVIEW

Available forest maps are of insufficient accuracy, currency and scale to evaluate the effect massive forest cutting is having on global carbon balance (Houghton and Woodwell, 1981). Scientists are concerned that an imbalance in the global carbon cycle will promote a "greenhouse effect" by the middle of the next century (Sagan et al., 1979). To help evaluate this concern, they have advocated the use of space-based remote sensing to produce accurate maps of the world's forests (Botkin et al., 1984; Woodwell et al., 1983). The accuracies of such maps, particularly in areas of high spatial complexity, may depend upon both the environmental characteristics of the area, and the data processing algorithms used to generate these maps.

This paper summarizes our work on the relative performance of image processing algorithms, and discusses our preliminary findings on the potential of data from the Airborne Imaging Spectrometer (AIS) to supplement existing remote sensing technology for distinguishing forest type classes. We describe our study area in the forests of northern Minnesota, and summarize results of performance tests of standard processing algorithms developed to reduce undesirable variations in spectral reflectance data. This is followed by description of the AIS data from the study site, and a discussion of the potential of these data to complement the vegetation classification process.

Surface spectral variations are needed to classify forest types. Undesirable spectral variations related to the angles of the sun and sensor, the state of the atmosphere, and the type of background soil, however, typically have an adverse effect on classification accuracy. Algorithms have been developed to reduce these undesirable spectral variations and enhance features in agricultural and rangeland vegetation (Kriegler et al., 1969; Carneggie et al., 1974; Richardson and Wiegand, 1977; Tucker, 1979; Holben and Justice, 1980). We have tested whether such algorithms offer advantages over unprocessed data when large and complex forested areas are classified.

SUMMARY OF CURRENT WORK

Landsat MSS data from a complex forested area in northern Minnesota were used to analyze the relative performances of waveband ratios, statistical filters, and principal components for classification of natural vegetation in the forests of Northern Minnesota. We analyzed performances of spectral variables produced using standard image processing algorithms (Table 1), grouping categories of ground cover into 9 classes (Table 2).

Table 1.
Spectral Variables of Landsat Data, Minnesota Study Area.

Score (%)	Type	Description	A	B	C	D	E	F	G	H	I
48	14 O	MSS7,MSS5	*	*	*	**	**	**	**	.	***
47	17 RT	(7/5),MTex	*	**	***	**	*	.	**	.	***
46	15 O	MSS6,MSS5	*	*	*	**	**	**	**	.	***
45	7 R	VI6	*	*	**	**	**	.	**	.	***
45	10 R	TVI7	*	*	**	**	*	.	**	.	***
44	5 R	MSS7/MSS5	*	*	**	**	*	.	*	.	***
44	8 R	VI7	*	**	**	**	*	.	**	.	***
44	9 R	TVI6	*	**	*	*	*	*	**	.	***
43	6 R	MSS6/MSS5	*	*	**	**	*	.	**	.	***
42	3 O	MSS6	*	**	.	.	**	**	**	.	***
42	4 O	MSS7	.	**	.	.	**	**	**	.	***
42	18 C	(7/5)/PC2	*	.	***	**	*	*	.	.	***
38	11 T	MSS5,MTex	.	.	*	**	*	**	.	*	***
37	1 O	MSS4	.	*	*	*	*	**	*	.	***
36	2 O	MSS5	.	.	**	**	*	**	.	*	***
28	16 RT	(7/5)SDTex	*	.	.	**	*	.	.	.	**
28	19 C	((7/5),SDTex)/PC2	*	.	.	***	*	.	**	.	.
26	21 RT	(7/5)/(7/5),SDTex	**	.	.	.	.	.	.	.	***
22	20 RT	7,SDTex/5,SDTex	.	.	***	*	.	.	.	**	.
22	13 T	MSS7,SDTex	.	.	.	.	*	*	.	*	***
20	12 T	MSS5,SDTex	.	.	*	.	.	.	.	.	**
10	22 C	PC1	.	.	**	.	.	.	.	.	.
9	23 C	PC2	.	.	**	.	.	.	.	.	.

Table 2.
Groundcover Classes

Class A	= Evergreen needle-leaved woodland with round crowns, ENLWRC (Pinus banksiana/Jack pine; Pinus resinosa/Red pine; Pinus strobus/White pine)
Class B	= Evergreen needle-leaved forest with round crowns, ENLFRC (Pinus banksiana/Jack pine; Pinus resinosa/Red pine; Pinus strobus/White pine)
Class C	= Grass
Class D	= Dwarf Shrub/Bog (Picea mariana/Black spruce <5m and >10% cover; Sphagnum, Typhus)
Class E	= Evergreen needle-leaved woodland with conical crowns, ENLWCC (Picea mariana/Black spruce; Picea glauca/White spruce; Abies balsamea/Balsam fir)
Class F	= Evergreen needle-leaved forest with conical crowns, ENLFCC (Picea mariana/Black spruce; Picea glauca/White spruce; Abies balsamea/Balsam fir)
Class G	= Deciduous broad-leaved forest, DBLF (Populus spp./Aspen; Betula papyrifera/Paper birch; Acer rubrum/Red maple)
Class H	= Mixed evergreen needle-leaved and deciduous broad-leaved forest, MF (Classes B, F, and G)
Class I	= Water

Differences in performances of the spectral variables apparently result in part from the relative capacities of data processing algorithms to reduce undesirable variations in background reflectance and surface illumination, and to enhance the spectral reflectance of different classes.

Performance differences between two-dimensional ORIGINAL variables and the RATIO variables were insignificant overall. RATIO or "vegetation index" variables appear to be functionally equivalent, and do not perform significantly better than the individual ORIGINAL Landsat variables. Overall classification accuracy for any given RATIO variable is <50%. ORIGINAL MSS6 is the best unprocessed one-dimensional spectral variable overall, while a local-mean filter of MSS7/MSS5 performed best of both processed and unprocessed one-dimensional spectral variables. RATEX and COMPLEX variables performed poorest overall, but RATEX variables 20 and 21 performed best on Classes A and H, respectively.

These results of these tests suggest the complexity of relations between the physical expression of natural vegetation, environmental variability, and data processing techniques that is likely to exist when large geographic areas are surveyed by satellite-borne sensors. Based on these results, the processing of the original Landsat MSS bands does not result in significant increases in performance for the majority of classes. We believe in the excellent performances of certain variables on certain classes. However, further examination into the spectral characteristics of vegetation is required to enable future development of image processing algorithms.

THE POTENTIAL OF AIS TECHNOLOGY

The AIS was flown over the Northern Minnesota Study Area on August 6, 1983. The time of the overflight was roughly local noon. The instrument was flown at 24,000 feet above the ground, which suggests a 14.8 m pixel size (based on the stated FOV = 3.7°) at nadir. The data appear blurred, so a precise identification of the ground characteristics is not possible.

Based on our knowledge of ground conditions below the AIS flight path, however, several trends are noticeable.

* There are clear gradations in brightness, which show changes in the amount of vegetation along the scan track. The contrast ratios appear to be significantly higher in the 1.4μm than the 1.2μm region.

* The dark areas are water bodies. The imagery picks up detail in the water, which probably includes surface and partially-submerged vegetation.

* Differences in gray tone patterning and intensity probably relate to the different mixtures of broadleaf and coniferous vegetation typical of this area.

* A lake and island are imaged at the bottom of Figure 2. The relative intensity is higher on the island due to the greater amount of bulk vegetation compared with non-island vegetation, which is often patchy due to logging or fire disturbances.

SUMMARY AND CONCLUSIONS

Previous research completed in the forests of Northern Minnesota demonstrated the complexity of relations between natural vegetation, remotely-sensed data from Landsat, and the algorithms used to process these data. Though the current spectral resolution of AIS is not comparable to Landsat MSS, the Airborne Imaging Spectrometer appears to be a powerful tool for studying the spectral behavior of natural vegetation. AIS data may clarify the results from processing and classification of natural vegetation.

We examined AIS data collected along a corridor within our Minnesota study area. Our data cannot be interpreted precisely, but we are convinced that very subtle changes in the land complex in this area can be detected with the aid of the AIS. The spectral responses to changes in vegetation are particularly apparent in several bandpasses. This information could be useful in the interpretation of data from the Thematic Mapper and SPOT.

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