Monitoring Forests with Hyperion and ALI

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***Abstract*- Hyperion, a hyperspectral sensor, and the Advanced Land Imager (ALI) are carried on NASA's EO-1 satellite. The Evaluation and Validation of EO-1 for Sustainable Development (EVEOSD) is our project supporting the EO-1 mission. With 10% of the world's forests and the second largest country by area in the world, Canada has a natural requirement for effective monitoring of its forests. Eight test sites have been selected for EVEOSD, with seven in Canada and one in the US. Extensive fieldwork has been conducted at four of these sites.**

A comparison is made of forest classification results from Hyperion, ALI, and the ETM+ of Landsat-7 for the Greater Victoria Watershed. The data have been radiometrically corrected and ortho-rectified. Feature selection and statistical transforms are used to reduce the Hyperion feature space from 220 channels to 12 features. Classes chosen for discrimination included Douglas Fir, Hemlock, Western Red Cedar, Lodgepole Pine and Red Alder. Overall classification accuracies obtained for each sensor were: Hyperion 92.9%, ALI 84.8%, and ETM+ 75.0%. Hyperspectral remote sensing provides significant advantages and greater accuracies over ETM+ for forest discrimination. The EO-1 sensors, Hyperion and ALI, provide data with excellent discrimination for Pacific Northwest forests in comparison to Landsat-7.

I. Introduction

In cooperation with NASA, we are conducting the Evaluation and Validation of EO-1 for Sustainable Development of forests (EVEOSD) project. NASA's EO-1 satellite was launched on November 21, 2000. EO-1 and Landsat-7 ETM+ data were collected over the Greater Victoria Watershed (GVWD) test site on Vancouver Island on September 10, 2001. At the same time, ground reflectance measurements were made of calibration sites. In preparation for airborne and spaceborne data collection and calibration, we collected in September 2000 foliar canopy and ground cover chemistry samples from 54 plots distributed across the GVWD test site. Chemical samples and mensurational data were taken of ten trees at each plot. These plots were sampled again in July 2001 with one tree per plot. The methodology and EVEOSD database are described in [1].

A major issue for the remote sensing community is the continuity of Landsat products as new sensors are introduced. The goal of this work was to evaluate the ability of Hyperion and ALI to classify forests and compare the results with classifications of Landsat-7 data for the same areas.

II. Remote sensing data preparation

Pre-processing of Hyperion, ALI and LANDSAT 7 ETM+ data is required before analysis. The Hyperion instrument is considered to have 6% absolute radiometric accuracy. The data used in the current analysis is Level 1a data [2] . The Hyperion data have been corrected for SWIR smearing effects, as well as SWIR echo residuals. Dark current removal is performed, followed by scaling by 40 for the VNIR and 80 for the SWIR. For the current work, we have used only 195 bands out of a total of 242 bands. These 195 bands cover a spectral regime of 438 nm to 2396 nm at an average full-width at half-maximum of 10 nm. We have scaled the VNIR bands by an additional factor of 1.08, and the SWIR bands by a factor of 1.18 to ensure radiometric fidelity [3]. The Hyperion data were corrected for abnormal pixels and striping [4]. Geocoding of the Hyperion data to UTM resulted in a root-mean-square (RMS) error of 5.82 meters for the VNIR and SWIR using 29 ground control points (GCPs). A subset of 11 check GCPs yielded a RMS error of 10.1 meters [5].

The GCPs for the ALI data were collected using the panchromatic channel, and tuned to each of the multi-spectral bands. For 40 GCPs in the panchromatic band of the ALI, the RMS error was 5.18 meters.

The pre-processing of the Landsat 7 ETM+ data is described in [6]. Compared with the Hyperion and the ALI, the geocoding was carried out for the entire image, resulting in a RMS error of less than 8.24 meters based on 21 GCPs. The ETM+ data were calibrated to top-of-atmosphere radiance and reflectance. Using the 6S model [7], the image was converted to ground reflectance.

III. Ground reference data

The Greater Victoria Watershed District maintains detailed forest cover GIS data. These data were queried and overlaid on one metre black and white ortho-photos during the delineation of the "truth" polygons used for training of the

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classification process. Also close inspection of the Landsat, ALI and Hyperion imagery revealed any obvious changes in the land cover that occurred after the GIS and orthophoto data were created.

The inspection of forest polygons that fit within the boundary of overlap of all sensors, revealed the type of classes we could expect to find in the image area. Classes were selected that showed dominants species of forest cover, as well as other non-forest classes that matched the definitions of NFI photo plots [8].

The forested cover in the common area consists predominantly of Douglas Fir (Pseudotsuga Menziesii) stands of varying age class and densities, as well as a few stands that are dominant in Lodgepole Pine (Pinus Contorta), Hemlock (Tsuga), Red Alder (Alnus Rubra) or Western Red Cedar (Thuja Plicata).

By querying the GIS data, polygons where selected and inspected. Areas within the polygons that appeared to be free of roads and other impurities were selected. Several unique training areas were aggregated after the classification to produce the final class. For example, the Douglas Fir dominant class training areas were created from five types of stands, dense 60 year old stands, dense 110 year old stands, open 40 year old stands, open 200 + year old stands and sparse 30 years old stands. There was a limited selection and size of stands predominant in the other species. The Lodgepole Pine stands were a mix of 90% and 60% pure Lodgepole Pine mixed with Douglas Fir. In order to get enough pixels for training these two types of stands were both included as one training polygon. The Hemlock stands were 60% mixed with Douglas Fir, and the Open and Dense stands were kept as separate training polygons, to be later aggregated to create the Hemlock dominant class. The Red Alder stands were mixed with Hemlock and Western Red Cedar. The Red Alder composes 50-70% of the stands. The Western Red Cedar dominant stands were 60% pure mixed with Douglas Fir.

The non-forest cover classes were selected from both the GIS data and from ground data. The exposed land class is an aggregate of two signatures, one is the combination of buildings and paved roads and the other is for clear-cuts that have occurred during the last six months. The water polygons were selected from two lakes in the imagery, Shawnigan Lake and the Sooke Reservoir. The water levels were quite low during the time of image acquisition; so water-training polygons were selected from the imagery. The Low Shrub class is a vegetated class where the forest cover is < 5% or older clear-cuts that have begun to grow back. The Herb graminoids class refers to a grass dominant land cover. The prime spectral calibration site is a farmer's field located just south of Shawnigan Lake. Swamp areas selected from the forest cover database were inspected on the one-meter ortho photo. Patches of trees obvious in the photos, but not excluded from the forest cover polygons, have been excluded from the training polygons.

TABLE 1
TRUTH FILE TRAINING AND CHECK POLYGONS (NUMBER OF 25M PIXELS)

Training Polygons	Check	Truth	Total	Ratio	Class
Building and Road Surfaces	10	24	34	0.29	Exposed Land
Recent Cuts < 6 mo.	37	80	117	0.32	Exposed Land
Shawnigan Lake Sooke Reservoir	210	414	624	0.34	Water
Shrub low (DF) <5%cc	27	54	81	0.33	Shrub Low
Old Clear Cuts	21	42	63	0.33	Shrub Low
Farmer's Field	23	46	69	0.33	Herb graminoids
Swamp	68	138	206	0.33	Wetlands
Red Alder 50-70% HW CW, DE	31	59	90	0.34	Red Alder Dominant
Hemlock 60% DE	37	67	104	0.36	Hemlock Dominant
Hemlock 60% OP	23	45	68	0.34	Hemlock Dominant
LodgePole Pine 60-90% DE	93	171	264	0.35	Lodgepole Pine Dominant
Western Red Cedar 60% DF40	0	12	12	0.00	Western Red Cedar Dominant
Douglas Fir DE 60 yr	52	95	147	0.35	Douglas Fir Dominant
Douglas Fir DE 110 yr	72	169	241	0.30	Douglas Fir Dominant
Douglas Fir Open 40 yr	36	72	108	0.33	Douglas Fir Dominant
Douglas Fir Open 200+ yr	122	244	366	0.33	Douglas Fir Dominant
Douglas Fir Sparse 30yr	144	288	432	0.33	Douglas Fir Dominant

The training polygons were converted into a 25-meter grid truth channel. Seventeen training classes were used to create the 10 aggregated classes. A random bitmap was used to move one third of all the pixels from the truth channel to a check channel. Due to the randomness and the relatively small number of pixels in some classes, some editing was required to ensure that each unique training class had one third of its pixels as check classes. The Western Red Cedar Dominant training class was very small after griding, so all the pixels were used for training only.

IV. Classification results

With all of the remote sensing orthorectified to a common map, we were able to proceed to classification. A variety of algorithms could be used and there is the issue of incorporating spatial information. ALI has a 10 m panchromatic band, compared to ETM+ with its 15 m panchromatic band. For this paper, we chose to reduce complexity in the sensor comparison and relied upon supervised maximum likelihood pixel classification. In subsequent work, we will investigate the stationarity of segmentation from each sensor, and proportion estimation of forest classes from Hyperion.

Fig. 1 shows the ETM+ image from September 10, 2001 corresponding to the region imaged by each sensor. Approximately 5109 hectares were available for classification comparison. Training areas were identified as described in the previous section. Test areas were also identified. Thus, if training plus test areas equals 100%, then 70% of the training area was used for classification, and 30% was used to test the classification.

Table 2 summarizes the classification results for the individual classes before aggregation. The highest accuracies were achieved with the Hyperion data at 88.2% correct on the training data and 84.2% on the test data. The ALI was second with accuracies of 79.5% on the training data and 74.8% on the test data. The Landsat-7 ETM+ had the lowest accuracies of 67.5% on the training data and 61.3% on the test data.

TABLE 2
DETAILED CLASSIFICATION COMPARISONS

	ETM+	**Hyperion**	**ALI**
Class Label	Accuracy %	Accuracy %	Accuracy %
Exposed land	100.0	100.0	100.0
Recent cuts <6 mo	100.0	100.0	98.8
Water	100.0	100.0	100.0
Shrub low	92.6	100.0	98.2
Old clear cuts	97.6	100.0	92.9
Herb graminoids	93.5	100.0	100.0
Swamp	92.0	95.7	98.6
Red Alder	62.7	89.8	79.7
Hemlock 60% Dense	56.7	76.1	46.3
Hemlock 60% Open	68.9	91.1	84.4
Lodgepole Pine	38.0	84.2	62.6
Western Red Cedar 60%	83.3	83.3	75.0
DF Dense 50 yr	77.9	81.1	73.7
DF Dense 110 yr	61.0	83.4	74.0
DF Open 200 yr	13.9	69.4	22.2
DF Open 30 yr	29.1	69.7	61.5
DF Sparse 30 yr	50.7	87.9	77.1
Overall Accuracy with 70% of the training data	67.5	88.2	79.5
Accuracy with 30% of the test data	61.3	84.2	74.8

ETM+ and ALI had the lowest accuracies on the open classes of forests. These classes were aggregated to produce a new set of classes as shown in Table 3. The order of sensors by classification accuracies on the test data were: Hyperion 92.9%, ALI 84.8%, and ETM+ at 75.0 %.

TABLE 3
AGGREGATED CLASSIFICATION ACCURACIES

	ETM+	**Hyperion**	**ALI**
Class Label	Accuracy %	Accuracy %	Accuracy %
Exposed land	100.0	100.0	100.0
Water	100.0	100.0	100.0
Shrub low	99.0	100.0	99.0
Herb graminoids	100.0	100.0	100.0
Swamp	98.6	95.7	98.6
Red Alder	79.7	89.8	79.7
Hemlock	63.4	76.1	63.4
Lodgepole Pine	62.6	84.2	62.6
Western Red Cedar	75.0	83.3	75.0
Douglas Fir	85.0	81.1	85.0
Overall Accuracy with 70% of the training data	77.5	95.1	87.5
Accuracy with 30% of the test data	75.0	92.9	84.8

The classification legend for the aggregated classes is shown in Fig. 2. The classification images are depicted in Fig. 3 (ETM+), Fig. 4 (Hyperion), and Fig. 5 (ALI). The GIS reference data covered only 45.03% of the area in common. In addition, Hyperion and ALI each missed a different portion of the corresponding ETM+ scene. Within the GIS reference data, we are confident of the classification results.

TABLE 4
AREA COMPARISON OF CLASSES WITHIN UNION OF IMAGE BOUNDARIES

	ETM+	**Hyperion**	**ALI**
Class Name	ha	ha	ha
Exposed Land	406	308	708
Water Body	178	191	156
Shrub Low	215	152	172
Herb Graminoids	20	18	19
Swamp Area	542	630	404
Red Alder Dominant	335	396	303
Hemlock Dominant	713	290	481
Lodgepole Pine Dominant	277	550	236
Western Red Cedar Dominant	242	1	12
Douglas Fir Dominant	2180	2573	2620

The class areas in Table 4 sum to 5109 ha for each sensor. The Hyperion classification is the most accurate of the three sensors.

V. Conclusions

Data from ETM+, Hyperion, and ALI were corrected and fused for a classification comparison. The classification results by sensor for the aggregated classes in the test areas were: Hyperion 92.9%, ALI 84.8%, and ETM+ 75%. The improved classification accuracies are due to the greater signal-to-noise ratios of ALI compared with ETM+ and the hyperspectral dimensionality of Hyperion compared to the 6 bands used for ETM+. Hyperion provided operational accuracies for forest classification. ALI classification results were much better (10%) than ETM+.

Future research will investigate the spatial properties of these sensors and the improvements in forest species recognition when spatial information is included.

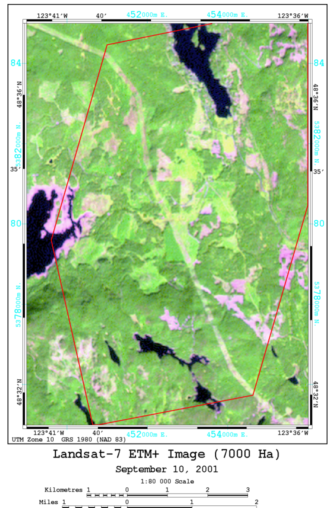

Fig. 1. GVWD Study Area

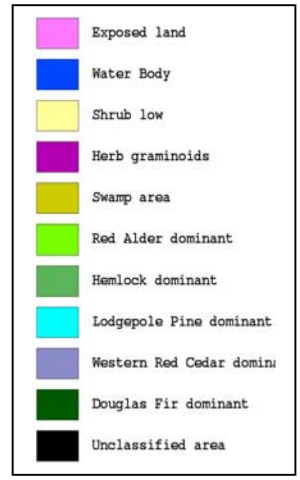

Fig. 2. Classification Legend

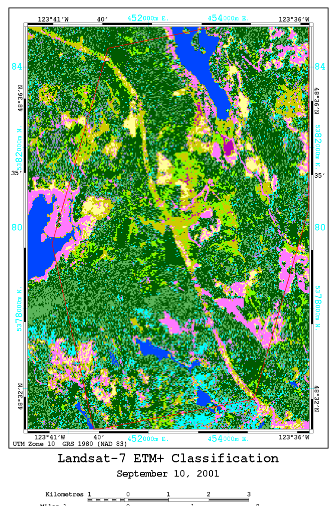

Fig. 3. ETM+ Classification

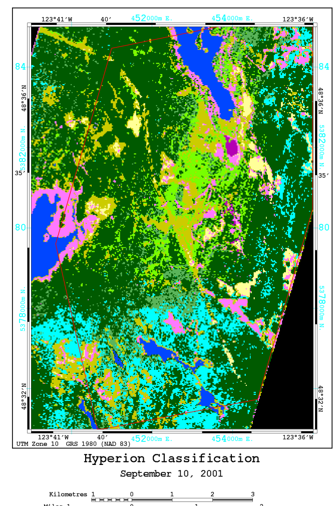

Fig. 4. Hyperion Classification

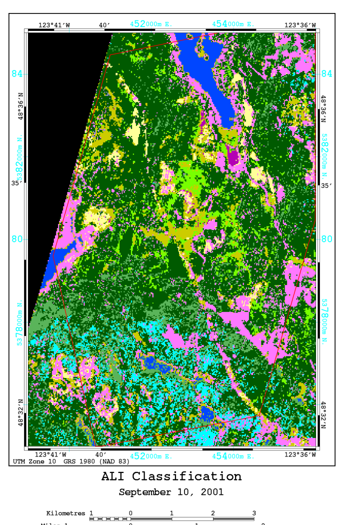

Fig. 5. ALI Classification

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