

Landcover Classification of the City of Rocks National Reserve Using ASTER Satellite Imagery

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Acronyms:

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CIRO	City of Rocks National Reserve
ESRI	Environmental Systems Research Institute
ENVI	Environmental Vision Software
NPS	National Park Service
UCBN	Upper Columbia Basin Network
VNIR	Visible Near Infrared

ABSTRACT:	<u>4</u>
INTRODUCTION:	<u>4</u>
METHODS:	<u>5</u>
<i>STUDY AREA</i>	5
<i>IMAGERY AND DATA</i>	5
<i>FIELD DATA COLLECTION</i>	7
<i>HYBRID CLASSIFICATION</i>	8
<i>UNSUPERVISED CLASSIFICATION</i>	9
<i>SEPARABILITY TESTS</i>	9
<i>MAXIMUM-LIKELIHOOD CLASSIFICATION</i>	10
<i>REFINEMENT OF FINAL PRODUCT</i>	11
<i>ACCURACY ASSESSMENT</i>	11
RESULTS	<u>11</u>
DISCUSSION	<u>14</u>
LITERATURE CITED:	<u>18</u>

Abstract:

The Landscape Dynamics Lab (LDL) at the University of Idaho worked with the Upper Columbia Basin Network (UCBN) of the National Park Service to accomplish a landcover classification for the area described as the City of Rocks National Reserve. LDL has completed efforts to acquire, process, and analyze satellite data to provide a more accurate and updated landcover classification for use by specialists and managers. These maps of landcover were derived from analysis of ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), using a combination of various classification techniques to generate the data. The final landcover classification achieved an overall accuracy of 89% at a cost of approximately \$0.60/acre. These results demonstrate the ability to develop high quality landcover classifications in a cost and time effective manner.

Introduction:

Land cover is a critical biophysical parameter that determines the functioning of terrestrial ecosystems in biogeochemical cycling, hydrological processes, and the interaction between the surface and the atmosphere. It is therefore of strong interest in scientific studies aimed at improved understanding of the dynamics of terrestrial processes, at all scales from local to regional to global. Land cover and land-use change data are also key inputs into land use and management decisions. Thus, the extraction of landcover from satellite remote sensing data has been the focus of many studies using a variety of data sources and methods (Cihlar et al. 2000).

Vegetation mapping was done for City of Rocks National Reserve (CIRO), in the late 1980's. Since that time, there have been fires, insect infestations, grazing, and increased recreational use in the area. The need for current and updated information in a timely and costly manner is important to monitor the unique areas within and surrounding the park.

The Upper Columbia Basin Network (UCBN) Inventory and Monitoring program identified the following goals for landcover classifications:

1. Determine the current spatial distribution and size of landcover types within and surrounding UCBN parks at a thematic resolution most appropriate for long-term monitoring and management.
2. Identify, map, and monitor changes in landcover pattern within and adjacent to UCBN parks.
3. Enable Network staff and resource managers to assess landuse impacts and make better-informed resource management decisions.
4. Provide base-level support for various vital sign monitoring (e.g., sampling design, watershed analysis, focal species occurrences).
5. Provide a cost-effective and timely product with resolution and accuracy standards similar to the NPS Vegetation Mapping Program (0.5 ha minimum mapping unit, >80% accuracy/class).

Coinciding with the objectives of the UCBN, objectives of this project were to determine current spatial distribution and size of landcover types within CIRO and the surrounding areas (2mi) at a thematic resolution most appropriate for monitoring and mapping. This classification provides resolution and accuracy standards close to the NPS Vegetation Mapping Program (80% accuracy/class at the 90% confidence level, 0.5 hectare minimum mapping unit).

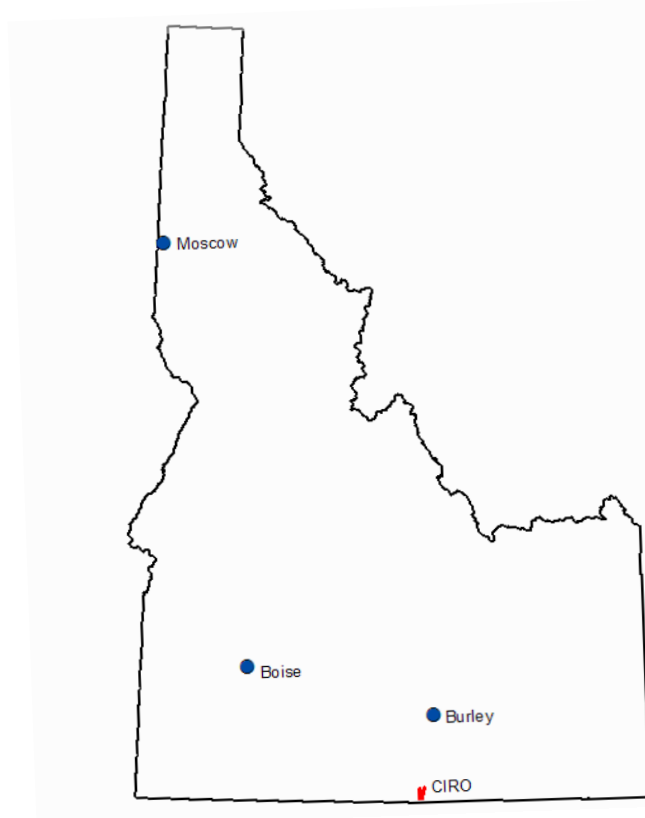


Figure 1. Proximity of City of Rocks National Reserve

Methods:

Study Area

CIRO (Figure 1) is located 45 miles south of Burley, Idaho in the southcentral portion of the state. The reserve encompasses approximately 14,665 acres. The range of elevations within the compact area of the reserve combines with other factors to create a varied pattern of vegetation and wildlife habitat. At high elevations the forests contain lodgepole pine, limber pine, and Douglas fir. The mid-elevation forests contain quaking aspen, mountain mahogany, and cottonwood. Sagebrush, pinyon pines, and juniper dominate lower elevations. The reserve has Idaho's tallest, and only, pinyon pines.

Imagery and Data

Data used for the classification process includes ASTER (Advanced Spaceborne Thermal Emission and Reflection radiometer) satellite imagery, field data collected by LDL, and a vegetation map created in the late 1980's from aerial photos.

The ASTER sensor obtains data across 14 spectral channels with a swath width of 60 km (Rowan and Mars 2003) and a temporal resolution of 16 days (Abrams 2000). The sensor is comprised of three radiometers (Table 1), each responsible for measuring different portions of the electromagnetic spectrum (Abrams 2000). The visible and near infrared (VNIR) radiometer collects data in three spectral channels between 0.52 – 0.86 μm . The VNIR instrument is also equipped with a separate backward looking channel in the near infrared portion of the electromagnetic spectrum (channel 3B), inclined 27.60 from nadir, which provides stereo viewing capability (Abrams 2000). The thermal infrared (TIR) radiometer obtains data in four spectral channels between 8.125 – 11.65 μm with a spatial resolution of 90 m, and the short wavelength infrared (SWIR)

radiometer obtains data across six spectral channels between 1.60 – 2.430 μm with a spatial resolution of 30 m (Figure 2).

Table 1. ASTER instrument characteristics

Subsystem	Band No.	Spectral Range (μm)	Spatial Resolution, m	Quantization Levels
VNIR	1	0.52-0.60	15	8 bits
	2	0.63-0.69		
	3N	0.78-0.86		
	3B	0.78-0.86		
SWIR	4	1.60-1.70	30	8 bits
	5	2.145-2.185		
	6	2.185-2.225		
	7	2.235-2.285		
	8	2.295-2.365		
	9	2.360-2.430		
TIR	10	8.125-8.475	90	12 bits
	11	8.475-8.825		
	12	8.925-9.275		
	13	10.25-10.95		
	14	10.95-11.65		

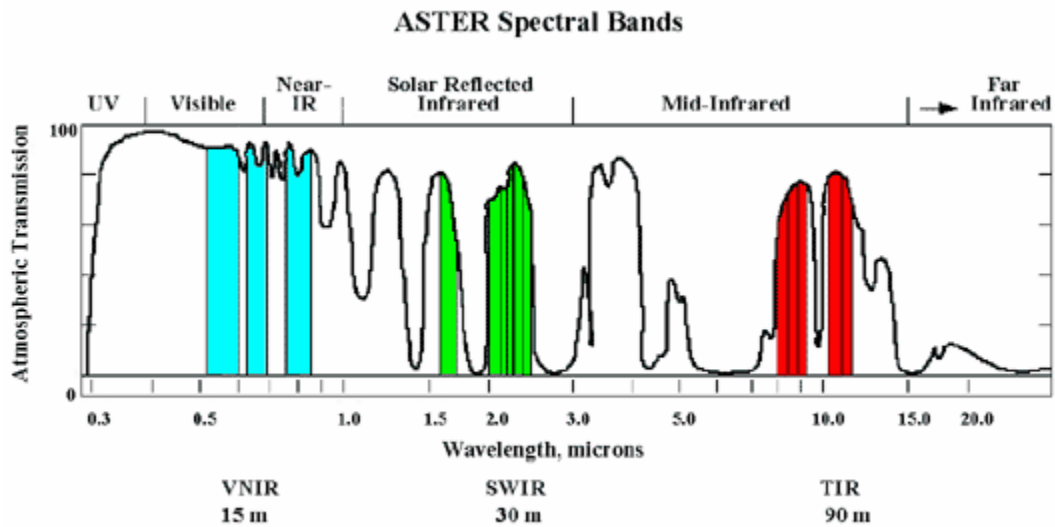


Figure 2. ASTER Spectral bands

One ASTER scene in the visible/near infra-red (VNIR) dated May 29, 2001 was acquired from the Land Processes Digital Active Archive Center, EROS Data Center, USGS over the CIRO study area. The image was geometrically registered to UTM Zone 12, WGS 84 using a nearest neighbor resampling method. The image was co-registered pixel to pixel to an absolute accuracy of 15 meters.

Using ENVI 4.1 software from RSI Inc. Boulder, Colorado the image was converted to exo-atmospheric reflectance. By converting the images from raw digital numbers to surface reflectance, the image can be directly comparable to other images. This allows a user to broaden a study's spatial extent by image mosaics. It also allows for direct comparisons of two similar but geographically distant sites. Reflectance is as much scientific measure as temperature or weight. Converting to reflectance allows some degree of inter-scene comparison to be performed because the reflectance values are computed taking into account the actual amount of radiation that reaches the earth's surface and determining what percentage of that radiation is reflected back to the satellite.

The image date of late spring/early summer image, provided near perfect conditions. Thus, no atmospheric correction was done on the scene.

Field Data Collection

Data was collected using ArcPad (ESRI, 2002) on handheld Windows CE based PC's with GPS receivers. Custom data entry forms were created within ArcPad for on-the-fly GIS data collection. Data was automatically usable within any ESRI GIS program (Figure 3).

FID	Shape	SITE_NUM	DATE	PARK	OBSERVER	PICT_NAME	PICT_DIR	WEED_NAME	WEED_AREA	WEED_COVER	VEG_NAME	VEG_AREA	COMMENT
0	Point	1	6/11/2004	CIRO	lks				0		Grassland*	10	wet meadow
1	Point	2	6/11/2004	CIRO	lks				0		Riparian /	30	plus
2	Point	3	6/11/2004	CIRO	lks				0		Basin big	30	plus
3	Point	4	6/11/2004	CIRO	lks				0		Roads	0	at a Y
4	Point	5	6/11/2004	CIRO	lks				0		Singleleaf	30	plus
5	Point	6	6/11/2004	CIRO	js			Chicory	3	5-25%		0	NO WEED
6	Point	7	6/11/2004	CIRO	lks	roll1.fr8	S	Wavyleaf T	0		Rock / Bar	30	ch weed
7	Point	8	6/11/2004	CIRO	lks			Wavyleaf T	0		Rock / Bar	10	
8	Point	9	6/11/2004	CIRO	JLS				0		Basin big	30	LARGE AREA
9	Point	10	6/11/2004	CIRO	JLS				0		Singleleaf	30	PLUS
10	Point	11	6/11/2004	CIRO	lks				0		Mtn snowbe	15	
11	Point	12	6/11/2004	CIRO	lks				0		Quaking as	20	sparse
12	Point	13	6/11/2004	CIRO	lks				0		Riparian /	0	
13	Point	13	6/11/2004	CIRO	lks				0		Quaking as	0	nice
14	Point	14	6/11/2004	CIRO	lks				0		Utah junip	0	sageinters
15	Point	15	6/11/2004	CIRO	lks				0		Utah junip	0	sageinters
16	Point	16	6/11/2004	CIRO	lks				0		Riparian /	0	
17	Point	17	6/11/2004	CIRO	lks				0		Quaking as	30	
18	Point	18	6/11/2004	CIRO	lks	dig5	N	Grassland*	0		ambitterbr	0	
19	Point	19	6/11/2004	CIRO	lks			Bitterbrus	30		ampinyon	0	
20	Point	20	6/11/2004	CIRO	lks			Bitterbrus	0		am-lowusage	0	
21	Point	21	6/11/2004	CIRO	lks			Grassland*	0		cheat	0	
22	Point	22	6/11/2004	CIRO	lks			Low sagebr	0			0	
23	Point	23	6/11/2004	CIRO	lks			Bitterbrus	0		am-lowusage	0	
24	Point	24	6/11/2004	CIRO	lks			Rock / Bar	0		sattick	0	
25	Point	24	6/11/2004	CIRO	lks			Basin big	30		plus	0	
26	Point	16	6/11/2004	CIRO	lks			Rabbitbrus	30			0	
27	Point	17	6/11/2004	CIRO	js			Grassland*	30		cheatgrass	0	
28	Point	25	6/11/2004	CIRO	lks			Riparian /	0			0	
29	Point	27	6/11/2004	CIRO	lks			Utah junip	0		ripar	0	
30	Point	27	6/11/2004	CIRO	lks			Utah junip	0		ripar	0	
31	Point	28	6/11/2004	CIRO	lks			Basin big	30		plus	0	
32	Point	29	6/11/2004	CIRO	js			Low sagebr	90		spars veg	0	
33	Point	30	6/11/2004	CIRO	js			Bitterbrus	30		hwsg/bttrb	0	
34	Point	1	6/12/2004	CIRO	JLS	1	SW	Riparian /	0		STREAM	0	
35	Point	2	6/12/2004	CIRO	JLS	2	N		0		10% DIRT	0	
36	Point	5	6/12/2004	CIRO	JLS			Mtn mahoga	60		SMLLP TCH	0	
37	Point	6	6/12/2004	CIRO	JLS			Mtn big sa	30		PLUS	0	
38	Point	7	6/12/2004	CIRO	JLS			Mtn mahoga	30		PLUS	0	
39	Point	8	6/12/2004	CIRO	JLS			Quaking as	30		S PTCH	0	
40	Point	9	6/12/2004	CIRO	JLS			Mtn big sa	1200		L AREA	0	
41	Point	11	6/12/2004	CIRO	JLS			Quaking as	60		PLUS	0	
42	Point	12	6/12/2004	CIRO	JLS	133		Grassland*	30		plus	0	
43	Point	13	6/12/2004	CIRO	lks			Mtn bin sa	100		on flat	0	

Figure 3. GIS database

A total of 156 plots (Figure 4) were randomly sampled within the mapping area for training data. Plots were located arbitrarily in order to incorporate a broad variety of

landcover types. Locations were found by driving through accessible portions within CIRO and observing areas of uniform vegetation at least 30m² in size. Other samples sites were taken along existing trails in the study area. Accessibility within CIRO was limited due to the limited motorized travel routes and private inholdings.

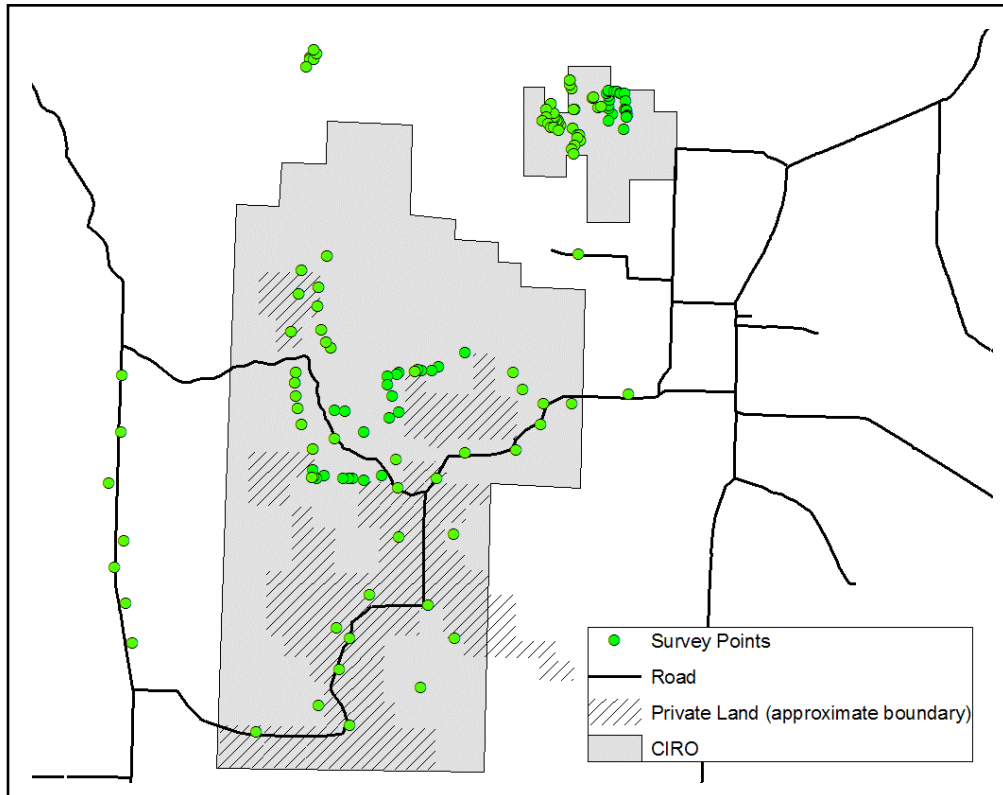


Figure 4. Plot locations

Hybrid Classification

A hybrid supervised/unsupervised classification methodology was used. In a supervised classification, the image analyst is responsible for defining "training areas," which represent all of the cover types he or she wishes to extract from an image. However, it is often difficult to account for all the cover types in an image as well as variability within cover types.

Fleming et al. (1975) outlined a hybrid approach for image classification that makes use of the benefits of both supervised and unsupervised approaches. This approach requires the following four steps:

1. Use clustering algorithms to determine the spectral classes into which the image can be divided.
2. Use ground truth data to assign information classes to the statistical clusters.
3. Use statistical distance measures to evaluate the initial clusters and delete or merge clusters as necessary.

4. Using a maximum-likelihood algorithm, classify the entire image into the set of spectral classes.

Unsupervised Classification

Unsupervised classification differs from supervised classification in that the computer develops the signatures that will be used to classify the scene. The classification process results in a number of spectral classes, which the analyst must then assign to information classes of interest. This requires knowledge of the terrain present in the scene as well as its spectral characteristics.

Following Smith et al. (1995), the K-Means process began by determining the 50 arbitrary cluster means (Figure 5) that were requested. On the first iteration of the K-Means algorithm, the means of the 50 clusters were arbitrarily determined. After each iteration, a new mean for each cluster was calculated, based on the actual spectral locations of the pixels in the cluster, instead of the initial arbitrary calculation. These new means were then used for defining clusters in the next iteration. The process continued until there was little change between iterations. The convergence threshold was set to 95 percent, the maximum percentage of pixels whose class values were allowed to be unchanged between iterations. After each iteration, the normalized percentage of pixels whose assignments were unchanged since the last iteration was displayed, and when the percentage of unchanged pixels reached 95 percent, the classification was complete.

Separability tests

Statistical separability tools were used to determine if clusters from K-Means were to be used as a class in the final classification, combined with another class generating a new land cover type, or discarded. Signature separability is a statistical measure of distance between two signatures. Separability can be calculated for any combination of bands that will be used in the classification generated by the K-means clustering algorithm. Bands 3 (near-infrared) and 2 (red) were used to calculate the separability of the class signatures.

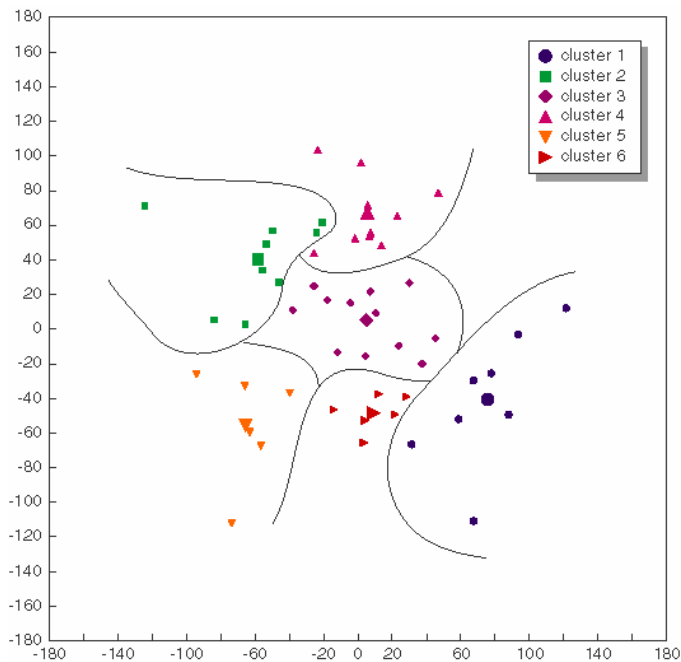


Figure 5. Concept of mean class clusters

Transformed divergence (TD) is a measure of separability (Figure 6) that was used to determine whether the signatures were separable. TD values have an upper (2) and a lower bound (0). If the calculated divergence is equal to the upper bound, then the

signatures can be said to be totally separable in the bands being analyzed. A calculated divergence of zero means that the signatures are inseparable. For this study, any class combination with a TD above 1.5 was considered separable. Any class combination with a TD below 1.5 was combined or one of the classes was disregarded. The next step was to select the class combination with the lowest TD. Each class was analyzed individually to identify the class type through the use of ground truth data. After the class types were determined, the TD separability values were used to decide which class types should be deleted or combined. An analysis of the number of pixels in each class and the distribution of pixels in the classified images was accomplished before generating the final classification.

After analyzing class combinations with a TD of less than 1.5, the final number of separable classes was 28.

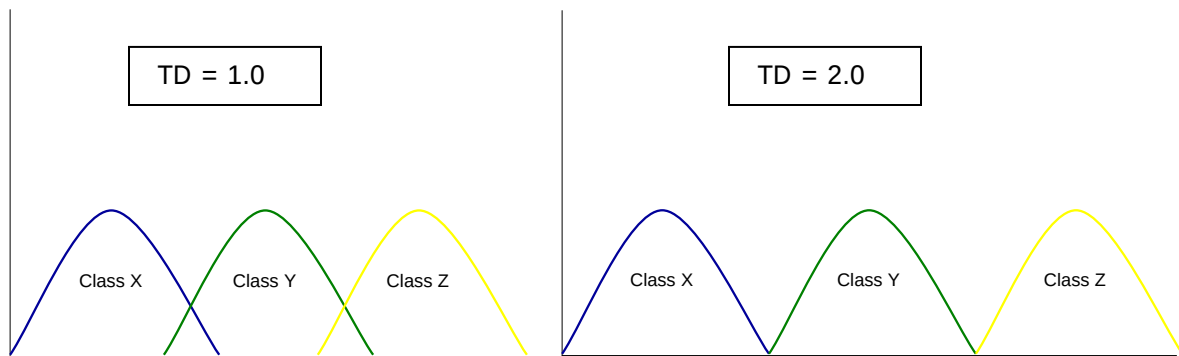


Figure 6. Schematic of separability

Maximum-Likelihood Classification

The next stage of the classification process involved using a maximum-likelihood algorithm. The 28 class signatures developed using K-Means were input to the maximum-likelihood algorithm. The maximum-likelihood classification makes use of the statistical parameters developed through the K-Means process and, in addition, uses estimates of probability distributions to determine the relative likelihood that a pixel belongs to a certain class (Figure 7).

Even though these classes had been identified once using K-Means, each class was checked with the DOQ's and existing vegetation coverage to make sure classes were mapped correctly.

Refinement of Final Product

Once the maximum-likelihood classification was complete, there were many isolated, very small (one to nine pixels in size) classes present. A filtering approach using a 3x3 low-pass filter eliminated the small areas that occurred through the classified image. The first application of the filter removed any small areas in the classified image. The second application eliminated any small areas generated by using the filter the first time.

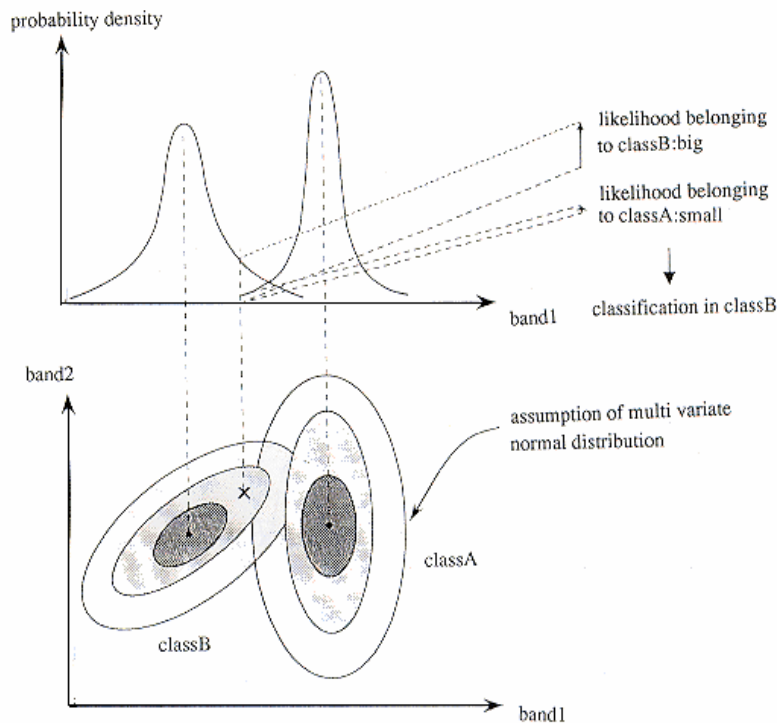


Figure 7. Maximum-likelihood

Accuracy Assessment

As with all land cover maps produced using this process, the result of the classification represents only a generalization of the real landscape types. Therefore, it was necessary to check the accuracy of the land cover classification with ground truth data (Ahmad et al. 1992). Ground truth data and the classification results were compared, statistically analyzed, and contingency tables or error matrices were produced. An error matrix analysis provides a natural framework for the convenient display of

results that can also be used for analysis. This is an effective tool that presents the overall accuracy of the classification as well as the producer and user accuracy of each category (Congalton et al. 1983). User's accuracy is the probability that a pixel classified on the map actually represents that category on the ground. The overall accuracy of the classification map is determined by dividing the total correct pixels by the total number of pixels in the error matrix. Computing the accuracy of individual categories is done by the total number of correct pixels in a category divided by the total number of pixels of that category as derived from the reference data (Jensen 2005). The Kappa Coefficient measures the agreement or accuracy between the remote sensing derived classification map and the reference data (Rosenfield et al. 1986).

Results

During the classification process, 50 training classes were initially generated from the ASTER image. Classes with spectral similarities were then aggregated to derive a land cover type map with 28 classes. The 28 classes were then further combined to form a final land cover map with 16 unique classes. Separability measures averaged 1.82. For example, *Artemisia tridentata*/*Agropyron spicatum* and *Artemisia tridentata*/*Agropyron*

cristatum classes the separability measured 1.667 and the Jefferies-Matusita, another type of separability test that is standard within ENVI was measured at 1.778.

Final classification results for the entire CIRO and the surrounding area are summarized in Table 2. The land cover classification is displayed in Figure 8.

Table 2. Classification acreage/hectares

Scientific Name	Common Name	Acres	Hectares
<i>Artemisia nova</i>	Black sagebrush	1277	517
<i>Artemisia tridentata</i> / <i>Agropyron cristatum</i>	Big sagebrush/Crested wheatgrass	4932	1996
<i>Artemisia tridentata</i> / <i>Agropyron spicatum</i>	Big sagebrush/Bluebunch wheatgrass	1852	749
Burned <i>Poa spp.</i> (Fire 2000)	Burned grasses	20	8
Burned <i>Pinus monophylla</i> / <i>Juniperous osteosperma</i> (Fire 2000)	Burned Single leaf pinyon and Juniper	768	310
<i>Cercocarpus ledifolius</i>	Mountain mahogany	885	358
<i>Artemisia arbuscula</i>	Low sagebrush	75	30
<i>Pinus monophylla</i>	Single leaf pinyon	368	148
<i>Juniperus osteosperma</i> / <i>Pinus monophylla</i> / <i>Cercocarpus ledifolius</i>	Juniper/Single leaf pinyon/Mountain mahogany	555	224
<i>Juniperus osteosperma</i> / <i>Pinus monophylla</i>	Juniper/Single leaf pinyon	878	355
<i>Juniperus osteosperma</i>	Juniper	805	325
Mixed Conifers - <i>Pinus flexis</i> , <i>Psuedotsuga menziesii</i> , <i>Abies lasiocarpa</i>	Limber pine, Douglas-fir, Subalpine fir	130	53
<i>Pinus monophylla</i> / <i>Juniperus osteosperma</i>	Single leaf pinyon/Juniper	157	64
<i>Pinus monophylla</i> / <i>Juniperus osteosperma</i> / <i>Cercocarpus ledifolius</i>	Single leaf pinyon/Juniper/Mountain Mahogany	928	375
<i>Populus trembuloides</i> / <i>Poa spp.</i> /Meadow/ <i>Salix spp.</i>	Aspen, Grasses, Meadows, Willows	1865	755
Rock/road		820	332

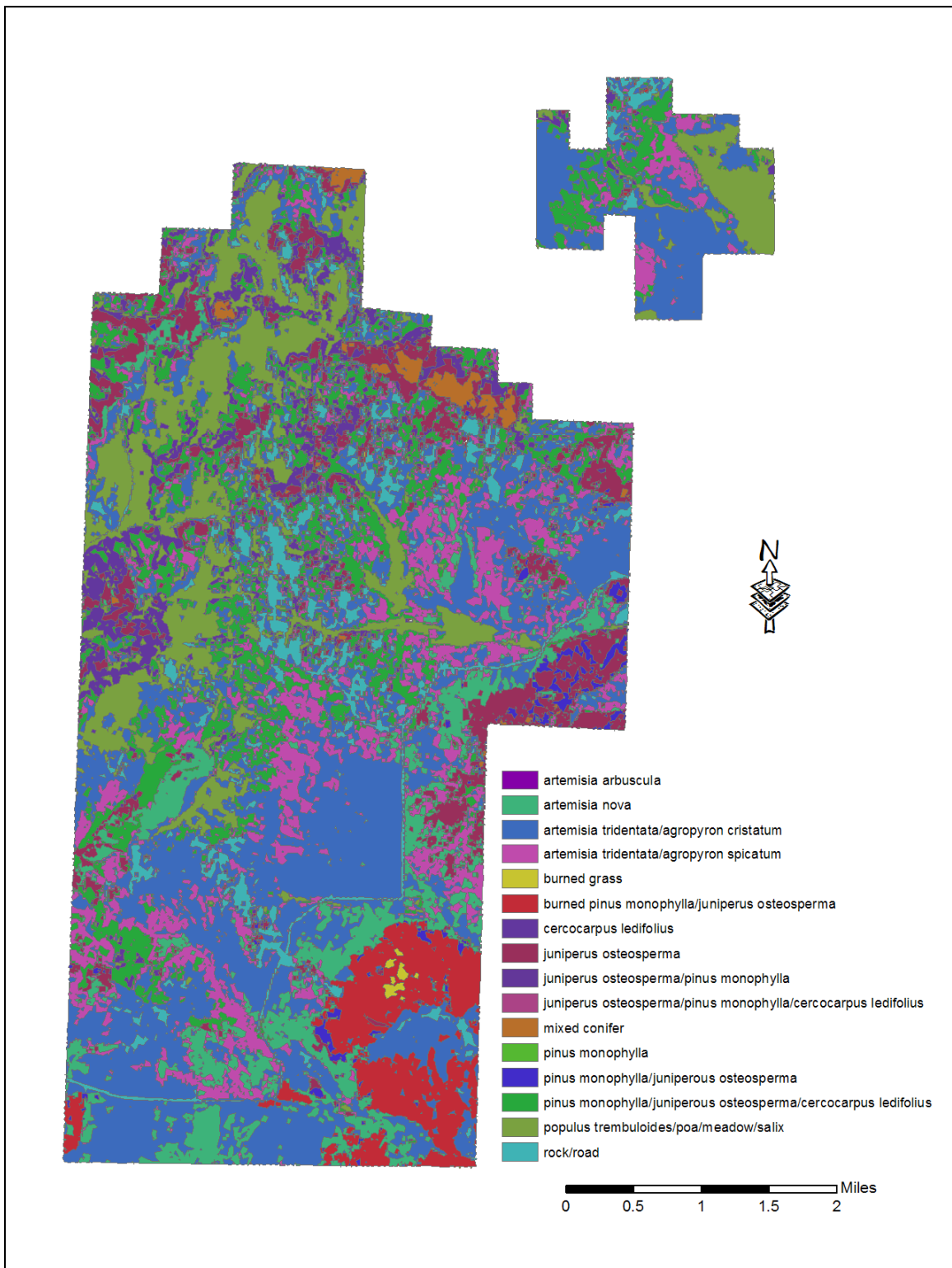


Figure 8. Final classification

The level of agreement or disagreement between the ASTER classification and the reference data is shown in Table 3. The overall accuracy of the classification was 89.27 percent. The rock/road and the *Populus tremuloides/poa* classes displayed the highest level of agreement with the reference data, with user accuracies of 99 and 98 percent, respectively. The lowest level of agreement occurred with the *Artemisia arbuscula* class at 70.53%.

This could be attributed to the low number of ground survey points (5 points) that were taken within this vegetation type. Accuracy for all other classes was above 80% accuracy.

Table 3. Accuracy Assessment

Overall Accuracy = (439659/492531) = 89.27%				
Kappa Coefficient = 0.86				
Class	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
	(Percent)	(Percent)	(Pixels)	(Pixels)
Burned grass (fire 2000)	81.82	83.55	2443/2986	2443/2924
Burned pimo/juos (fire 2000)	93.35	83.68	5936/6359	5936/7094
<i>Juniperus osteosperma</i>	99.41	85.57	789/865	789/922
Mixed conifer – pifl,psme,abla	98.88	82.69	1343/1556	1343/1710
<i>Pinus monophylla</i>	80.51	80.08	1974/2452	1974/2465
<i>Juniperus osteosperma/Pinus monophylla</i>	82.38	79.91	3295/4000	3295/4123
<i>Cercocarpus ledifolius</i>	91.25	81.6	7723/8464	7723/9464
<i>Juniperus ostersperma/Pinus monophylla/cercocarpus ledifolius</i>	88.07	82.69	8532/9688	8532/10318
<i>Artemisia arbuscula</i>	71.73	70.53	335/467	335/475
<i>Artemisia nova</i>	92.45	84.69	14212/15372	14212/16781
<i>Pinus monophylla/Juniperus osteosperma</i>	83.84	81.21	20389/24318	20389/25107
<i>Artemisia tridentata/Agropyron spicatum</i>	81.06	80.22	25834/31871	25834/32204
<i>Pinus monophylla/Juniperus osteosperma/Cercocarpus ledifolius</i>	85.32	90.78	34602/40554	34602/38116
<i>Artemisia tridentata/Agropyron cristatum</i>	82.03	90.65	55618/67805	55618/61355
<i>Populus tremuloides/salix spp./poa</i>	88.15	98.28	37621/42677	37621/38279
Rock/Road	77.73	99.96	19046/24503	19046/19054

Discussion

The results from this project demonstrate the ability to reach the UCBN goals maintaining a high standard of accuracy while sustaining cost and time efficiency.

The timing of imagery, however, can have a great effect on the classification output and not all association levels will be able to be determined consistently. For example,

because of the late spring/early summer timing of the scene used in this project, aspen, grasses, and riparian classes were difficult to separate due to their “greenness” being similar spectrally that time of year. Ancillary data, additional ground truth data and other methods such as textural analysis could be incorporated to help achieve greater separation. Further research is needed in this area.

Previous landcover classifications completed for the study area have been primarily based on aerial photography. While aerial photography can have higher spatial resolution and provides very detailed information, it is costly and time consuming to interpret. Human based interpretation methods are more subjective to individual error, inconsistent, and have low spectral resolution (information). For example, in comparing the 1980's aerial photo interpretation (left) to the ASTER classification (right) of the same area, there is a significant difference in information. The aerial photo classification is more generalized than the ASTER based (Figure 9).

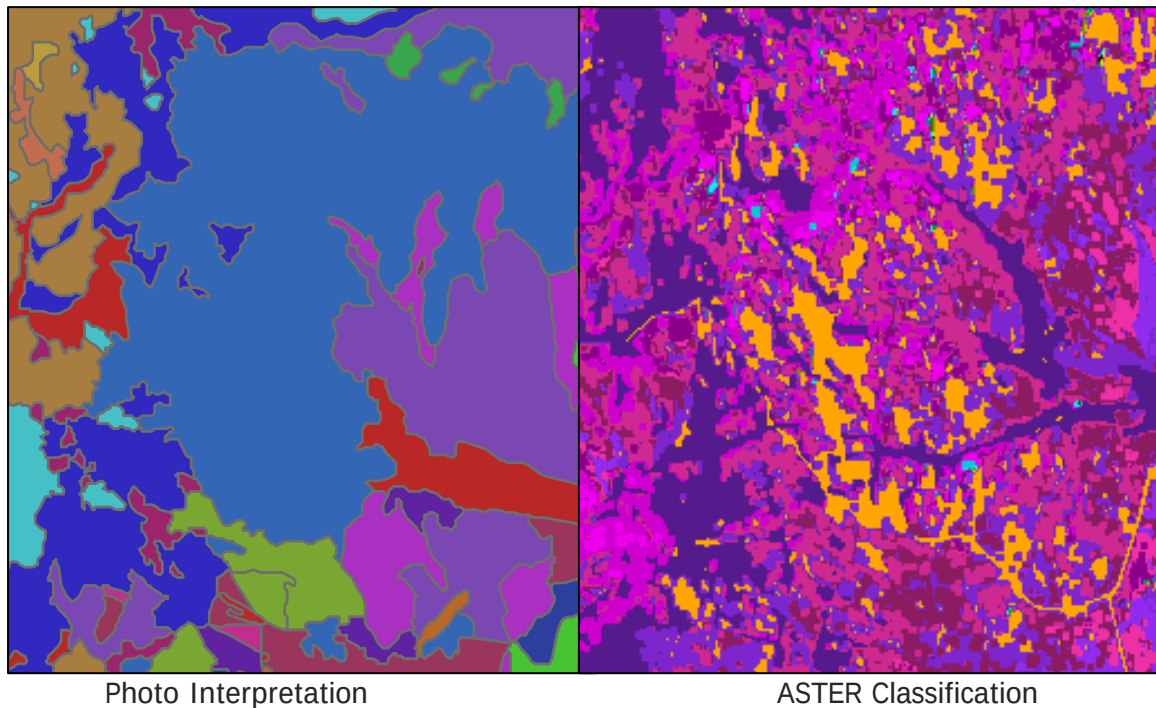


Figure 9. Classification comparison

Aerial photography can also be insensitive to structural and subcanopy properties, has limited application for quantitative estimates of biophysical properties or their change over time, and is not considered cost effective for a regional scale inventory and monitoring (Dobson et al. 1995, Wilen and Bates 1995, Stow et al. 1996).

Conversely satellite images portray continuous data across the landscape. Another advantage of mapping from satellite imagery is the reduction or elimination of interpreter bias by using automated classification algorithms. By avoiding visual interpretation, the products have greater consistency and reliability between different areas or dates. Increased reliability also results from the high positional accuracy of image data compared to aerial survey data (Wulder et al. 2004).

Other advantages of digital imagery are that it can be geocorrected (two dimensions) or orthorectified (three dimensions); these corrections facilitate integration of the remotely sensed imagery with other spatial datasets. These corrections also make it possible to compare images collected over multiple years, thereby providing an important monitoring tool. Additional strengths supporting the use of digital data are that objective, repeatable analysis of the data is carried out with equal effort across the landscape, and that digital techniques are applied in a systematic, consistent, and transparent manner. These features help reduce inconsistencies that can result from visual interpretation (Wulder et al. 2004).

Due to uncertainties associated with the continuation of the Landsat mission, ASTER satellite imagery may become more widely used as a substitute for land cover applications. ASTER imagery has the following enhanced characteristics over typical 30m satellite imagery (e.g. Landsat) or aerial photography traditionally used in landcover classification for various agencies including NPS:

- A wider spectral range and a higher spectral resolution
- 15m (visible and near infrared spectral region), 30m (shortwave infrared spectral region), and 90m (thermal infrared spectral region) spatial resolutions
- Both the nadir-looking telescope and a backward-looking telescope are used to produce stereoscopic images acquired on a single orbit.
- Inexpensive (\$60/scene)
- Resolution appropriate for most ecological studies
- Statistically generated analysis
- Effective measurement and monitoring tool
- Improved vegetation discrimination
- Soil/regolith mapping
- Water-based applications
- Multi-temporal analysis
- Change detection

Costs are the driving force of acquisition of current data information that is needed to map, monitor and make scientific decisions on a local, regional and global scale. Resolution of data is the catalyst for the costs with finer spectral resolution imagery having a much higher cost than imagery with medium resolution.

Costs for the project included field data collection, travel costs, image purchase, image processing, report generation, and hardcopy maps which amounted to approximately \$.60/acre for this particular study area. The timeline from beginning of project to completion was a mere 5 months (May – September 2004).

Once established, a remote sensing interpretation needs minimal field assistance, although occasional field site visitations are recommended to check the accuracy of the mapping processes and to update any changes. The first time mapping of a project area will be the most expensive. The second generation of the map will be an approximate reduction in cost of approximately 30%. Generations of mapping following the second generation should see a reduction in cost of another 30% (Figure 10).

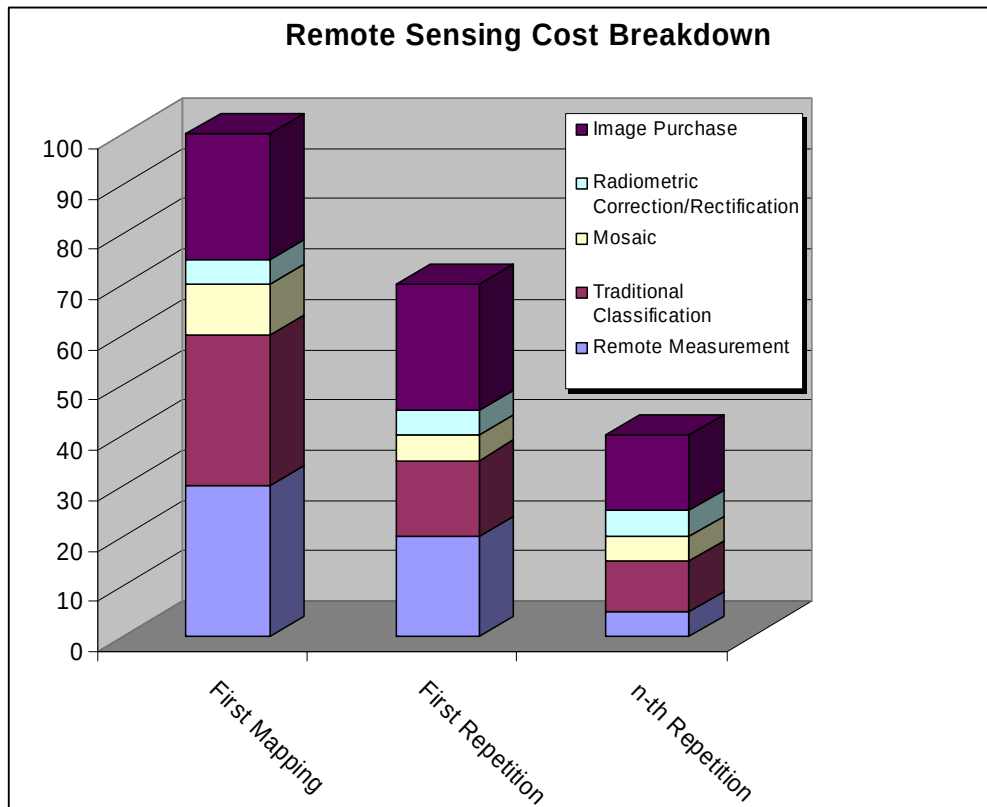


Figure 10. Remote sensing cost breakdown (CSIRO Land and Water, Canberra Technical Report 28/03, Apr. 2003)

Monitoring long-term changes in landcover composition, configuration, and connectivity will help establish a broader context for parks, and can help natural resource managers determine patterns in land use change which may threaten future ecological integrity within parks. By developing and implementing a protocol to efficiently and cost effectively monitor landcover change within and around UCBN parks at multiple spatial scales, the current knowledge of park ecosystem dynamics will be further advanced, allowing for better management practices and decision making in the future.

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