Forest Biometrics From Space

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ABSTRACT

Geographic Resource Solutions (GRS) recently completed mapping the Applegate River watershed in southern Oregon for existing vegetation. This was a cooperative effort between the USDA Forest Service, and Bureau of Land Management. GRS used Landsat TM satellite imagery, Digital Elevation Models, measured field data, GIS, and GPS. The final database estimated polygon attributes using continuous variables including canopy closure, average tree size, species composition, trees per acre, and variance for tree size and canopy closure. This paper describes the various methodologies used in the project, that include: field data collection, image processing techniques for removing the effects of topography, hybrid supervised and unsupervised image classification techniques, ecological rule-based pixel aggregation, and quantitative accuracy assessment.

INTRODUCTION

Biodiversity, Watershed Management, and Ecosystem Management are a few of the terms being bandied about the natural resources community. These "buzz" words and phrases exemplify the changing values society places on the forest ecosystem. As resource professionals, we must address these changing values in our decision making processes. In addition to these values, management decisions must also be based on the most current and accurate information available. A Geographic Information System (GIS) is a useful tool which may provide this type of information to decision makers. Organizations, both public and private, use GIS to help resolve complex current and future natural resource management issues. Remotely sensed data have become increasingly popular for providing information for GIS analysis. Digital imagery may be used to produce information describing the characteristics of a forest ecosystem that is both current and accurate. However, satellite image processing can only produce consistent, accurate, and hence reliable maps when used with methodologies that account for the tremendous variability found in forested environments. Several recent attempts at mapping forested ecosystems have met with limited success. These attempts have used methodologies which separate a forested ecosystem into separate components (i.e., canopy closure, species type, or tree size) and then attempt to recombine the components during final polygon formation. These popular methodologies ignore the interrelatedness of these characteristics within an ecosystem. These methods further inhibit the potential of image processing for vegetation inventory by describing the separate components as a series of classes or groups. While useful for generalizing the data, these artificial classes rarely occur in nature (Congalton, 1991.) The characteristics of any ecosystem are an interrelated gradient. This fact must be accounted for when using satellite image processing techniques to produce reliable and accurate vegetation inventories.

The Applegate River watershed was distinguished as an Adaptive Management Area (AMA) in President Clinton's Forest Plan. This watershed, located in southern Oregon and northern California (Figure 1.), is managed by the Bureau of Land Management (BLM), USDA Forest Service (FS) and private land owners, each managing roughly one third of the watershed. Resource professionals identified existing vegetation as the single most important GIS layer needed to complete their analysis. The existing GIS vegetation layers varied in quality and extent, lacked consistency in stand typing, and included no information on private lands. This paper describes a project Geographic Resource Solutions (GRS) recently completed that was a cooperative effort between the BLM and FS to map the Applegate River watershed. The goal of the project was to create a GIS theme of vegetation which was flexible and accurate. The information would be suitable for use by all resource managers (i.e., timber, silviculture, wildlife, watershed, fire, and others). The project incorporated techniques and methodologies developed by GRS during previous remote sensing projects.

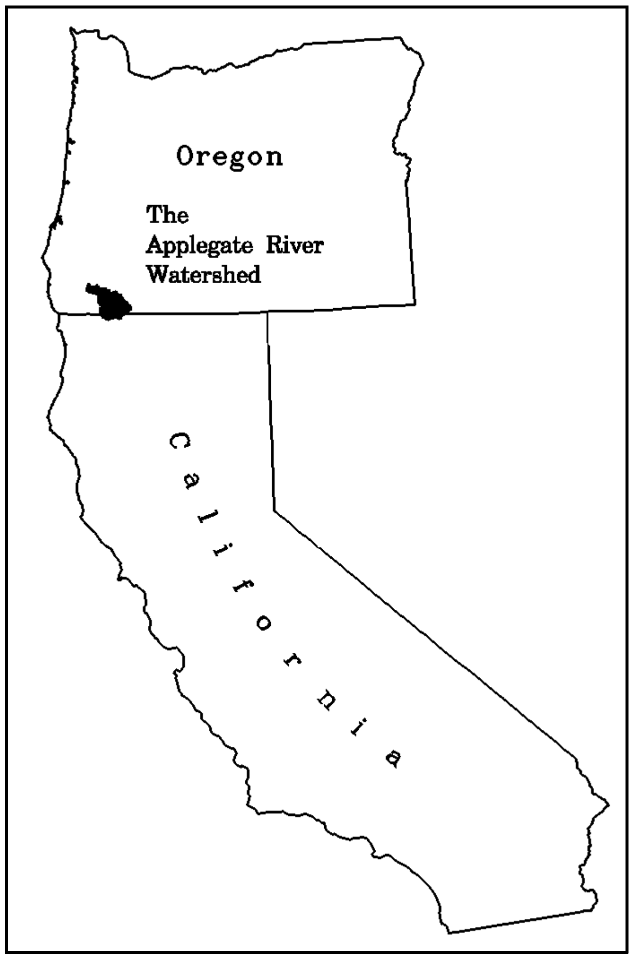

Figure 1. The Applegate River watershed.

METHODS

In October of 1994 GRS began work on mapping the Applegate River watershed. Landsat TM data, acquired August 29, 1993, was obtained from the BLM office in Portland, Oregon. Existing GIS layers for the watershed were incorporated into the project GIS. These layers consisted of: Public Land Survey (PLS), ownership, hydrography, and transportation. A digital elevation model (DEM) of the project area was also incorporated into the project's GIS database.

Classification Scheme

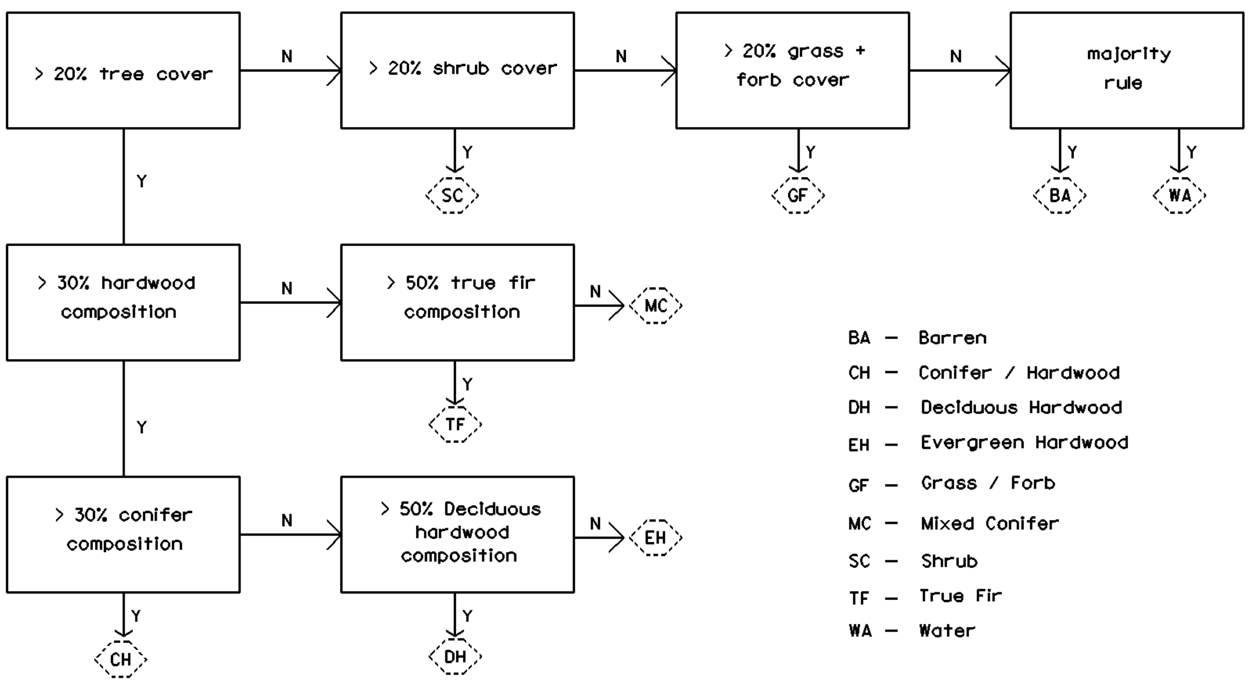

Figure 2. Cover typing scheme flow chart.

FS and BLM cooperators choose to use plant community descriptions from the "Management of Wildlife and Fish Habitats in Forests of Western Oregon and Washington" (Anonymous, 1985) for cover type attributes. GRS described canopy closure, average tree size, trees per acre, and percent hardwood, conifer, shrub, and grass as continuous estimates rather than the traditional approach which utilized categorical classes or groupings. Continuous estimates of vegetation characteristics were used because the data could be later adapted to any series of classes depending on the needs of the user. This project also included variance estimates for canopy closure, and average tree size estimates. GRS summarized the discrete estimates of average tree size and canopy closure using nine size classes and eight canopy closure classes at the request of the BLM and FS officials. Figure 2 describes the cover typing scheme and decision process.

Field data collection

Vegetation mapping projects that rely on digital image classification require a mechanism for identifying vegetation characteristics on the ground (i.e., "ground truth"). Popular methods utilize photo interpretation (PI) as a source of "ground truth." PI is well suited for general land cover classification schemes. However its application in a detailed classification scheme (one which uses canopy closure, average tree size, and species groupings) will produce maps of questionable reliability. Research has found photo interpretation to be highly subjective. This research also concluded "photo interpretation may not be as accurate as many people have believed." (Biging, etal., 1991). The main reason why PI has been frequently used for "ground truth" is the cost of acquiring actual ground data is too expensive (Congalton and Green, 1993.) Field data collection costs can be the most expensive portion of a mapping project. However, even greater costs can be incurred if the maps produced are inaccurate and unusable.

Decisions based on the information contained in an inaccurate map can result in costs not limited to money including habitat loss and job loss. If a mapping project is started with errors in the "ground truth" these errors are compounded through the various stages of the mapping process. The goal of the Applegate project was a detailed vegetation inventory. With this goal in mind, GRS started the project using the most reliable and accurate ground truth available: measured field data.

Total Cover Summary:

Size Class: Species:	0-4"	5-8"	9-12"	13-16"	17-20"	21-25"	26-31"	32-47"	48"+	Tree Cover	Non-Tree Cover	Total Cover
Douglas-fir	1.0%	2.5%	1.0%	2.0%	6.0%	8.0%	12.0%	25.0%		57.5%		57.5%
sugar pine									3.0%	3.0%		3.0%
white fir	2.0%	4.0%	2.0%	3.0%						11.0%		11.0%
hardwood			1.0%							1.0%		1.0%
madrone		8.5%	7.0%	3.0%						18.5%		18.5%
misc shrub											1.0%	1.0%
forb/herbac											3.0%	3.0%
duff/debris											5.0%	5.0%
Total Cover	3.0%	15.0%	11.0%	8.0%	6.0%	8.0%	12.0%	25.0%	3.0%	91.0%	9.0%	100.0%

Tree Cover Summary:

Size Class: Species:	0-4"	5- 8"	9-12"	13-16"	17-20"	21-25"	26-31"	32-47"	48"+	All Sizes
Douglas-fir	1.1%	2.7%	1.1%	2.2%	6.6%	8.8%	13.2%	27.5%		63.2%
sugar pine									3.3%	3.3%
white fir	2.2%	4.4%	2.2%	3.3%						12.1%
hardwood			1.1%							1.1%
madrone		9.3%	7.7%	3.3%						20.3%
Total Tree Cover	3.3%	16.5%	12.1%	8.8%	6.6%	8.8%	13.2%	27.5%	3.3%	100.0%

Quadratic Mean DBH (by Cover) Summary:

Size Class: Species:	0-4"	5- 8"	9-12"	13-16"	17-20"	21-25"	26-31"	32-47"	48"+	All Sizes
Douglas-fir	4.1"	6.5"	12.0"	15.5"	18.4"	23.8"	29.3"	37.6"		30.3"
sugar pine									48.0"	48.0"
white fir	3.6"	7.5"	9.0"	15.0"						9.9"
hardwood			12.0"							12.0"
madrone		7.3"	10.7"	13.3"						9.8"
QMean DBH	3.7"	7.2"	10.6"	14.5"	18.4"	23.8"	29.3"	37.6"	48.0"	26.3"
QMean DBH - Con	3.7"	7.1"	10.1"	15.2"	18.4"	23.8"	29.3"	37.6"	48.0"	29.2"
QMean DBH - Hwd		7.3"	10.8"	13.3"						9.9"

Trees Per Acre Summary:

Size Class: Species:	0-4"	5- 8"	9-12"	13-16"	17-20"	21-25"	26-31"	32-47"	48"+	All Sizes
Douglas-fir	5.5	10.6	1.0	1.0	4.4	3.6	3.6	7.0		36.8
sugar pine									0.6	0.6
white fir	18.2	9.6	4.3	1.0						33.2
hardwood			1.0							1.0
madrone		35.3	18.9	6.6						60.8
All Trees	23.7	55.5	25.1	8.6	4.4	3.6	3.6	7.0	0.6	132.2
All Trees - Con	23.7	20.3	5.3	2.0	4.4	3.6	3.6	7.0	0.6	70.5
All Trees - Hwd		35.3	19.8	6.6						61.7

Quadratic Mean Crown Size Summary:

Size Class: Species:	0-4"	5- 8"	9-12"	13-16"	17-20"	21-25"	26-31"	32-47"	48"+	All Sizes
Douglas-fir	10.0ft	11.9ft	24.0ft	35.4ft	29.1ft	36.9ft	43.7ft	51.2ft		43.3ft
sugar pine									55.0ft	55.0ft
white fir	8.1ft	15.3ft	16.0ft	40.0ft						24.1ft
hardwood			24.0ft							24.0ft
madrone		12.6ft	15.8ft	17.7ft						14.8ft
QMean CD	8.8ft	13.3ft	17.6ft	32.1ft	29.1ft	36.9ft	43.7ft	51.2ft	55.0ft	37.5ft
QMean CD - Con	8.8ft	14.1ft	19.0ft	38.2ft	29.1ft	36.9ft	43.7ft	51.2ft	55.0ft	41.5ft
QMean CD - Hwd		12.6ft	17.0ft	17.7ft						15.4ft

Table 1. An example of summarized transect data used for field data collection.

information require measured field data. GRS' vegetation sampling technique used a line-point transect method. For this project, transects were 1188 feet in length, with points spaced 12 feet apart. A total of 100 points were sampled along the transect. At each point along a transect a vertical sighting was taken using the GRS_densitometer (vertical sighting device). This device projected a vertical line of sight, with cross hairs to identify the vertical point. If the vertical point intercepted a tree crown, field personnel recorded the following information: species, canopy position, diameter at breast height (DBH) to the nearest inch, crown diameter to the nearest foot, shrub cover, herbaceous cover, and non-vegetative cover. Table 1 illustrates a summary of the information collected by the line-point transect method. Transects were oriented like a triangle for training data. This type of orientation enabled field personnel to install transects in small stands. Transects were elongated for accuracy assessment to facilitate sampling as much of a polygon as possible. Each transect was assigned a unique sequential number representing its order of placement. Field data were recorded using software loaded on a hand held computer. GPS data were collected as reference points (RP) for each transect's location. Distance and azimuth from the RP to the start of the transect were measured and stored in the header of the transect data files. Upon completing a transect, the field crew described the sampled stand. Forest Service personnel differentially corrected the GPS data. The transect data, stand descriptions, and GPS RP locations were incorporated into the project GIS. The field crew used the GIS layers displayed on the satellite imagery, RP locations, and distance and azimuth measurements to place the transect locations in the GIS. The transect data were summarized and loaded as attributes for each transect. In addition to field data collected for this project, additional field data were used from a previous GRS project with the California Department of Forestry and Fire Protection. These transects were collected during 1992 and were immediately adjacent to the Applegate River watershed.

<u>Image Processing</u>

The Applegate River watershed contains rugged terrain typical of western Oregon. These steep slope angles and orientation combine with the solar angle and azimuth to cause a tremendous amount of reflectance variation in satellite imagery. Differential illumination can be a significant source of classification error in areas of high relief. Upon receiving the satellite data from the BLM, the imagery was topographically normalized using the Backwards Radiance Correction Transformation (BRCT) based on a non-Lambertian assumption and a Minnaert constant (Colby, 1991). This technique uses estimates of slope and aspect from the DEM, and sun angle and azimuth parameters during image acquisition to correct for differential illumination caused by terrain.

The project area was initially divided into three eco-regions. These regions were developed to help resolve confusion between vegetation types that were spectrally similar but had different vegetation properties. FS personnel familiar with the project area assisted in developing the eco-regions. After the initial data sets were reviewed by BLM, FS, and GRS representatives, four eco-regions were redefined as follows: below 3500 foot elevation, low elevation; 3500- 5500 on west to south east aspects and 3500-6200 foot elevation on south to south west aspects, mid elevation; above the mid-elevation, high elevation; and serpentine and peridotite soils. Each eco-region was treated as a separate classification. Supervised training sets were

CONFUSION SUMMARY FOR TRANSECT#:			10					
	MC	Douglas-fir	91.0%	26.3	3448	NE	C	
TRANSECT#	VEG_TYPE	PR_SPECIES	DENSITY	QM_DBH	ELEVATION	ASPECT	SLOPE_CLASS	JM_DISTANCE
552	MC	Douglas-fir	77.0%	30.7	4005	E	S	1.12050
31	MC	Douglas-fir	99.0%	30.3	3776	SE	S	1.14560
572	MC	Douglas-fir	85.0%	51.7	4639	NE	M	1.27500
16	MC	Douglas-fir	80.0%	25.1	5101	N	S	1.29330

Table 2. An example of J-M divergence analysis with respect to the class' vegetation characteristics.

developed for each eco-region. Transect locations from the GIS were used as seed points for generating supervised spectral statistics. Spectral statistics were loaded into a database table and associated with each respective transect. Variability and normality were analyzed for each supervised training area. Training area boundaries were modified as needed. Results from Jeffries-Matusita (J-M) divergence analysis were also loaded into a database table to facilitate analyzing vegetation and spectral differences between transects. Table 2 shows the results of J-M analysis with respect to vegetation. This process was iterative, depending on the results from each analysis.

Once "clean" supervised training sets were completed for each eco-region, final classifications and unsupervised techniques were utilized. All the following methodologies were implemented using batch processing within each eco-region. An initial maximum likelihood (ML) classification was performed with a 90% probability threshold. The resultant unclassified areas in the class map were then used as a mask for developing unsupervised clusters. An ISODATA algorithm was used to develop 60-100 spectral classes from an initial 255 clusters. Two ML classifications were then run at a probability threshold of 95%: one using the supervised statistics, and one using the unsupervised statistics. A spatial overlay was performed between the supervised and unsupervised class maps. The unsupervised classes were used to augment the unclassified areas in the supervised class map. Three products were produced from this overlay process. The first was the merged class map. The second was a report of the overlay indicating the supervised classes corresponding to each unsupervised class (which pixels share the same spatial location). This report was later used in unsupervised class labeling. The third product was a mask of areas which remain unclassified in the merged class map. These areas, generally “edge types” or some anomaly, typically represented less than two percent of the area. Another ML classification was run on these unclassified areas with a probability threshold of 100%, and the resultant class map was merged creating a final merged class map. After this hybrid supervised/unsupervised classification was completed, there were no unclassified pixels in the class map.

Unsupervised Class Labeling

The unsupervised class labeling algorithm (Fox and Brown, 1992.) used was similar to stratified sampling for forest inventory. Weighted vegetation characteristics were calculated for each unsupervised class based upon the supervised classes which share the same spatial location. Each unsupervised class'

Unsupervised Class	Supervised Class	Pixel Count
2104	0	1670
2104	3	655
2104	30	3866
2104	35	372
2104	48	140
2104	518	437
2104	531	980

Table 3. An example of the results for an unsupervised class from the GIS overlay between supervised and unsupervised class maps.

vegetation characteristics were then checked for integrity. This process was also used to validate the supervised classes. Table 3 is an example of the report produced from the GIS overlay process. Upon completion of the unsupervised labeling procedure, all eco-regions were merged to form a final pixel map of the entire project area. In this map, every grid cell contained an estimate of the vegetation characteristics similar to those illustrated in Table 1.

Aggregation

A major obstacle in many mapping projects that rely on image classification is how to develop a vector database where all stands - polygons - meet or exceed the minimum mapping unit (mmu). The solutions to the problem of how to build an accurate and reliable database with an mmu far above that represented by a single pixel are not well publicized. Conventional methods for eliminating heterogeneous pixel data utilize various pixel smoothing algorithms. Such techniques as modal, mean and/or majority filtering are abundant in commercial image processing software packages. However, these techniques are mathematical solutions. In the case of vegetation mapping, a mathematical solution applied to an ecological problem will result in a poor quality map.

This mapping project had a mmu of 5 acres. There were 445 unique classes represented in the final classified pixel map. When these 445 classes were displayed there was a "salt and pepper" effect. This heterogeneity is typical of most results of image classification. GRS used a ecological rules-based polygon formation routine (Stumpf, 1993) to produce polygons of similar vegetation characteristics. This process compared the vegetation characteristics of a subject pixel (or group of pixels) to all adjacent pixels (or groups of pixels). Pixels, or groups, were merged with their most similar neighbor. Similarity was estimated by evaluating vegetation characteristics such as: percent canopy closure, average tree diameter, species composition, percent hardwood composition, percent conifer composition, and stems per acre. Table 4 illustrates the aggregation process and similarity calculations. There were nine iterations in the aggregation process each with progressively larger mmu's and different similarity thresholds up to the desired mmu of 5 acres. Final polygon attributes were summarized from all the original pixel data within the polygon boundaries. Each polygon had a vegetation summary similar to Table 1. A sample database record is shown in Table 5. Aggregating the pixel map for the

Stand ID #	Veg Type	Predominant Species	Tree Cover	Percent Conifer	Ave. QMD	Trees Per/Acre		Similarity Index
5534	MC	Douglas-fir	75%	70%	24"	187		
5533	MC	Douglas-fir	95%	80%	16"	250		
diff =	0	0	5.0	1.5	4.0	0.6	=	11.1
5534	MC	Douglas-fir	75%	70%	24"	187		
5532	CH	Madrone	89%	35%	14"	232		
diff =	10	12	3.5	3.5	5.0	0.5	=	34.5
5534	MC	Douglas-fir	75%	70%	24"	187		
5545	GF	Annual Grass	0%	0%	0"	0		
diff =	25	25	18.8	10.5	12	1.9	=	93.2
5534	MC	Douglas-fir	75%	70%	24"	187		
5541	DH	White Oak	35%	0%	10"	104		
diff =	14	15	10.0	10.5	7.0	0.8	=	57.3

Similarity was based on the combined difference in vegetation characteristics.
In this example, the subject stand 5534 was merged with stand 5533.

MC = Mixed Conifer
CH = Conifer Hardwood
GF = Grass/Forb
DH = Deciduous Hardwood

Table 4. An example of the determination of the most similar adjacent stand based on many vegetation characteristics.

project and producing an attributed vector GIS database was accomplished in 26 hours of processing. Errors in preliminary data sets were identified by FS and BLM officials. Since there was no human intervention in the pixel aggregation process, these errors were usually systematic and easy to track down. Since GRS methodologies were highly automated, GRS analysts were able to validate and correct the errors rapidly.

Accuracy Assessment

Accuracy assessment is the process of comparing map data to some assumed 100% correct reference data. Though this appears to be a straight forward task, many methodologies for this vital step in the mapping process are severely flawed. The reason is that assumed correct reference data have traditionally consisted of existing maps, PI, and/or ocular estimates. These types of reference data test for agreement between the map and reference data, not map accuracy. Existing maps may or may not have estimates of reliability. PI and/or ocular estimates, while useful for general land cover information, are subjective and have questionable reliability when estimating percent canopy closure, average tree diameter, species composition, percent hardwood composition, percent conifer composition, and stems per acre. GRS used both measured field data for forest characteristics and ocular estimates only for non-forest cover types (i.e., shrub, grass, barren, and water). In addition, FS personnel used PI to check only cover types in the non-forest sampled polygons.

COLUMN	VALUE
pri_key	36506
veg_type	MC
closure_class	8
pct_closure	80.3
pct_conifer	77.3
pct_hdwood	22.7
size_class	5
qmdbh	17.6
qmdbhcon	19.2
qmdbhhwd	10.6
pix_ct	497
grid_val	29232
class_status	10
acreage	76.7
pr_species	Douglas-fir
pred_sp_pct	44.2
cv1	7.7
cv2	13.2
cv3	14.8
cv4	13.8
cv5	12.0
cv6	10.6
cv7	3.9
cv8	3.3
cv9	0.9
cv_shr	5.8
cv_hrb	3.0
cv_bar	10.9
cv_oth	0.0
tpa_tot	297.5
tpa_con	186.7
tpa_hwd	110.8
tpa1	171.9
tpa2	49.2
tpa3	29.9
tpa4	21.8
tpa5	10.7
tpa6	10.1
tpa7	1.9
tpa8	1.2
tpa9	0.9
tpa_class	3

Table 5. An example database record.

GRS utilized a stratified random sampling (SRS) scheme with replacement. This scheme provides information on all map categories regardless of the amount of area consumed by any one stratum. Research has shown SRS to be well suited for accuracy assessment of maps derived from remotely sensed data (Congalton, 1991). The first step in the accuracy assessment was generating a GIS theme of sample points. Random UTM coordinate pairs were generated throughout the project area. These coordinate pairs were used as sample points. Each sample point was assigned a unique sequential number representing its order of placement. A spatial overlay in the GIS associated the map strata with each sample point. Polygons were selected for sampling based on their sample number, within each stratum. Since cost was the primary factor in determining sample size, GRS and FS agreed that 20 samples per stratum would suffice and a collapsed series of classes would have to be used. GRS used the following classes for canopy closure estimates: 0-19%,20-39%,40-59%,60-79%, and >=80%; and non-forest, 0-4", 5-12", 13-20", 21-32", and >32" for average tree size estimates.

GRS collected field data for accuracy assessment using the same technique as was used during training data phase of the project. Transect data were recorded on hand held computers with the same software as was used during training data collection. Transect summaries were processed using the same program that summarized training data and final polygon attributes. These steps insured consistent reference data. Field personnel were supplied with maps which had the sample point, polygon boundaries (without labels), transportation, hydrography, and PLS. Transects, installed within sampled polygon boundaries, were orientated to facilitate sampling as much of the polygon as possible. GPS positions were used to check the actual transect placement relative to the desired location. Transect summaries were loaded as attributes for their respective samples. The summaries served as reference data for generating error matrices. Correspondence between map and reference data will be determined by confidence intervals established for the discrete estimates of canopy closure and average DBH. Unfortunately, at press time these procedures were not yet finalized. However, they will be presented during the symposium. GRS used a more conservative estimate of correspondence between map and reference data by using a sliding class width (Hill, 1993). GRS used this technique to account for those cases in which class estimates between the map and reference data did not correspond, but the discrete estimates were within a specified range. GRS used a range of five inches for average DBH estimates, and ten percent cover for canopy closure estimates. The ranges corresponded with the original classes used at the start of the project. Class width match determination for cover type was based on the dominant cover. This addressed the differences found in mixed types such as Mixed Conifer and Conifer Hardwood and cover types such as True Fir and Evergreen Hardwood respectively. Table 6 illustrates the situation described above.

	stand ID	VEG TYPE	Dominant Species	Closure Class	Closure	Size Class	Average DBH
reference	271	MC	white fir	2	59%	4	20.6"
map	12254	TF	white fir	3	61%	5	22.4"

Table 6. An example of two estimates of a polygon's vegetation characteristics. The two estimates have very similar characteristics, but the do not have the same class values.

RESULTS

Error matrices were developed for each major forest characteristic: canopy closure, average DBH, and cover type. Each error matrix contained both "producer's" and "user's" accuracy measures by class stratum, an overall percent correct figure, an overall percent correct figure weighted by the area consumed by individual stratum, and a Kappa coefficient. The canopy closure error matrix is presented in Table 7. The overall percent correct was 86%, percent correct weight by area was 74%, and a Kappa of .46. While the overall figures are good, some individual stratum have poor results (i.e. 20% correct for the SPARSE class). Table 8 presents the error matrix for average DBH. The overall percent correct was 92%, percent correct weight by area was 88%, and a Kappa of .51. The results for average tree size were excellent. Table 9 shows the error matrix for cover type. The overall percent correct was 88%, percent correct weight by area was 85%, and a Kappa of 0.86. The cost of the Applegate River watershed mapping project are shown in Table 10.

		REFERENCE DATA								
		NON-TREE 0-20%	SPARSE 20-40%	OPEN 40-60%	MODERATE 60-80%	DENSE 80% +	TOTAL	PERCENT CORRECT	ACRES	CORRECT ACRES
MAP DATA	NON-TREE	20					20	100.0%	67,677	67,677
	SPARSE		1	1	3		5	20.0%	77,290	15,458
	OPEN			3	2		5	60.0%	100,610	60,366
	MODERATE			1	11	2	14	78.6%	156,790	123,192
	DENSE					21	21	100.0%	192,845	192,845
	TOTAL	20	1	5	14	25	65		595,212	459,538
	PERCENT CORRECT	100.0%	100.0%	60.0%	78.6%	84.0%		86.2%	527,535	391,861
					TOTAL PERCENT CORRECT ACRES			74.3%		
							Kappa	0.4574		
							Var(Kappa)	0.0032		

Table 7. Canopy Closure Error Matrix.

MAP DATA	REFERENCE DATA 0 non-forest	1 0-5"	2 5-13"	3 13-21"	4 21-32"	5 +32"	TOTAL	PERCENT CORRECT	ACRES	CORRECT ACRES
0	20						20	100.0%	67,677	67,677
1		1					1	100.0%	299	299
2			13	1			14	92.9%	163,788	152,089
3	1		1	13			15	86.7%	263,881	228,697
4				1	5	1	7	71.4%	92,047	65,748
5						2	2	100.0%	7,470	7,470
TOTALS	21	1	14	14	6	3	59		595,162	521,979
PERCENT	95.2%	100.0%	92.9%	92.9%	83.3%	66.7%		91.5%		
				TOTAL PERCENT CORRECT ACRES				87.7%		
							Kappa	0.5126		
							Var(Kappa)	0.0023		

Table 8. Average Tree Size Error Matrix.

MAP DATA	REFERENCE DATA BA	CH	DH	EH	GF	MC	SC	TF	WA	TOTAL	PERCENT CORRECT	ACRES	CORRECT ACRES
BA	2									2	100%	3,871	3,871
CH		5		1						6	83%	230,481	192,068
DH		2	4				1			7	57%	32,331	18,475
EH		3		2						5	40%	33,410	13,364
GF					20					20	100%	41,035	41,035
MC						14		1		15	93%	193,733	180,818
SC					1		16			17	94%	21,429	20,169
TF							1	14		15	93%	21,429	20,001
WA	1								4	5	80%	1,391	1,113
TOTAL	3	10	4	3	21	14	18	15	4	92		579,111	490,913
PERCENT	67%	50%	100%	67%	95%	100%	89%	93%	100%		88%		
						TOTAL PERCENT CORRECT ACRES					85%		
										Kappa	0.8589		
										Var(Kappa)	0.0015		

Table 9. Cover Type Error Matrix.

Applegate Cost Summary		
ITEM		COST
Project Administration		$4,254
Field Data - Training Phase		$24,067
Field Data - Accuracy Phase		$24,875
Image Training		$10,505
Image Processing		$3,396
Image Classification		$5,285
Pixel Aggregation		$21,073
Data Conversion		$2,566
	Total	$96,020
	Cost Per Acre	$0.16
	Cost Per Hectare	$0.40

Table 10. The Applegate River watershed project costs by task.

DISCUSSION AND CONCLUSION

Although the accuracy information presented indicate high levels of accuracy compared to similar projects, the results should be viewed with some skepticism because the sample sizes in most stratum are extremely low. The reason for the small sample sizes was the lack of funds available for such field data collection. However, given the high quality reference data, the results indicate that the goal of the project was met - producing an accurate, flexible, “wall to wall” vegetation inventory for the Applegate River watershed. More samples are needed in each map stratum to facilitate an adequate accuracy assessment and remove any skepticism. This is essential in any remote sensing project. The cost information presented in this paper are from GRS invoices for the project. There were additional costs incurred by FS and BLM personnel involved with the project. Over half of the money spent was used to collect measured field data. While field data collection was a significant component of the project cost, it provided the opportunity to develop very specific estimates of cover, tree size, and species composition. User needs will dictate the necessity of developing specific or generalized categorical estimates. GRS has developed and applied a successful methodology for developing a detailed vegetation inventory by utilizing image processing techniques with measured field data.

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