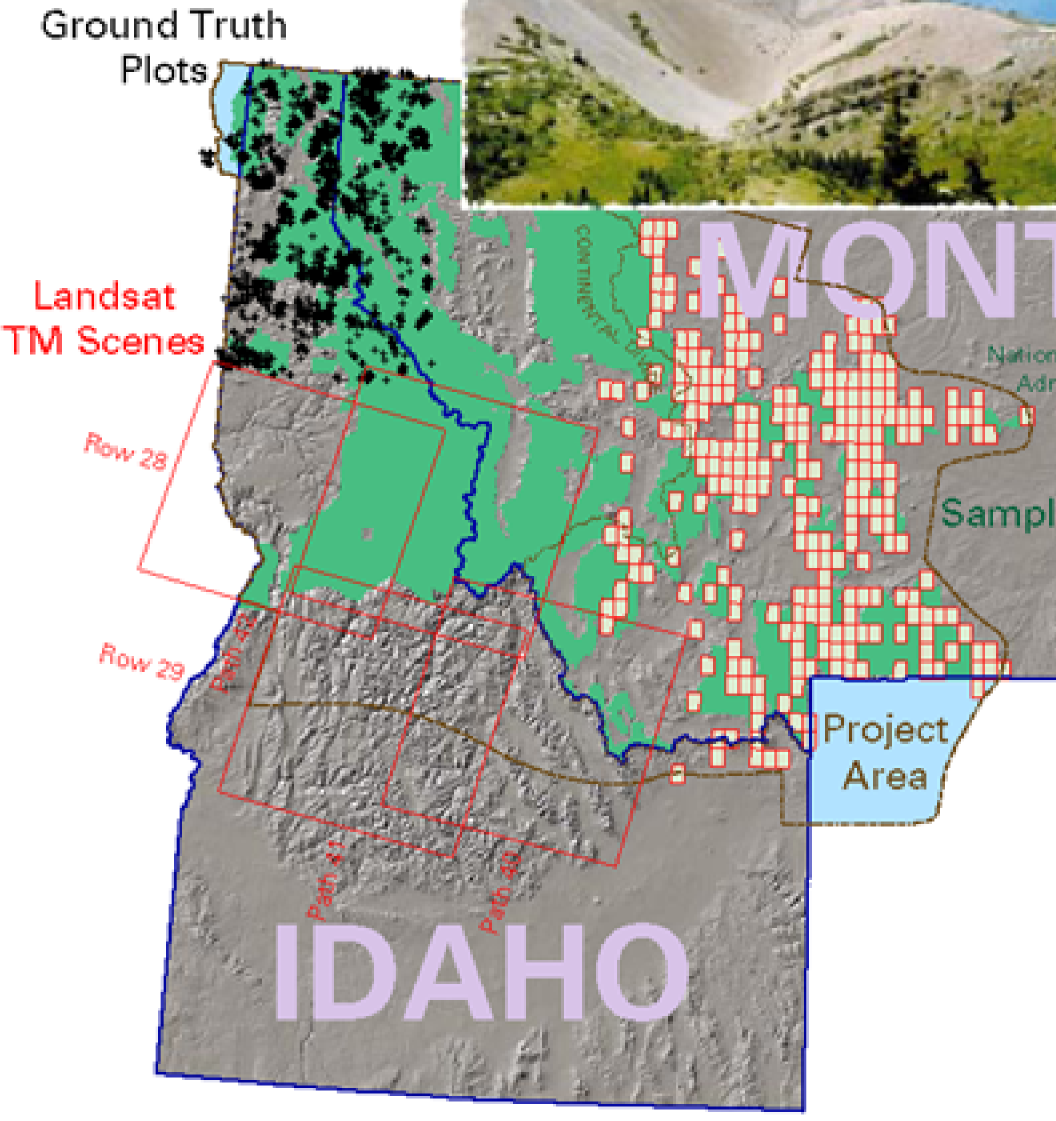
Mapping Existing Vegetation and Land Cover Across Western Montana and Northern Idaho

Executive Summary



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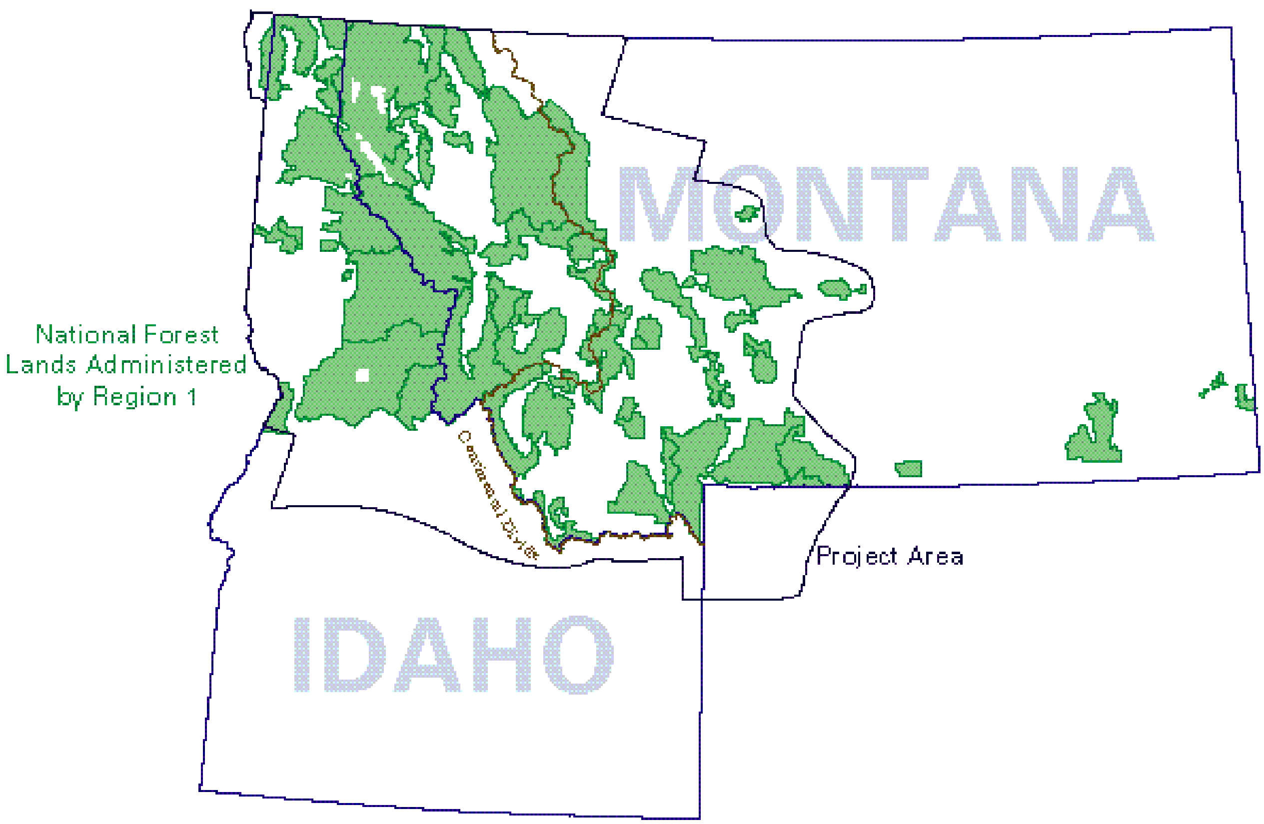


Figure 1. Project Area.

Mapping Existing Vegetation and Land Cover Across Western Montana and Northern Idaho

This Executive Summary describes the assembly and contents of several digital databases that were produced to map existing vegetation and land cover in a standardized, consistent manner across all of western Montana and northern Idaho (Fig. 1). The databases are ideally suited for analyses at the regional, subregional, and landscape levels, as well as for support of nearly all management disciplines, including timber, wildlife, fisheries, and recreation. Brief descriptions of the delivered products, general methods, results and conclusions are provided below; additional details about the methods and how to interpret the accuracy assessments follow in two appendices. Complete documentation may be found in the contract Final Report.

Description of Products

The main product is a set of geographic information system (GIS) databases that characterize existing vegetation and land cover across 26.2 million hectares (64.8 million acres) and all land ownerships in northern Idaho and western Montana (Fig. 1). Cover type, size class, and canopy closure information are stored in raster GIS databases (ARC/INFO grids) created for 18 Landsat TM scenes covering the project area. Each of the 18 land cover databases is roughly 50 megabytes in size and is comprised of about 300,000 raster polygons or regions that are 2 ha (5 ac) or larger in size. Each region is analogous to a stand; it has a unique identifier and more than 30 attributes describing such features as lifeform, cover type, size class, and canopy closure (see Table 1). Accompanying the databases is a detailed Final Report that includes accuracy tables for each TM scene; these will allow users to evaluate the classification accuracies for individual cover types on a scene-by-scene basis.

A separate GIS layer was created to map riparian cover types in each TM scene at a 0.09 ha (0.2 ac) minimum mapping unit (MMU) that corresponds to individual 30 m^2 pixels. File sizes for these riparian databases are smaller because they contain fewer attributes; but they contain nearly as many regions because of their considerably smaller MMU. Attributes for both the land cover and riparian databases can be accessed, updated, and manipulated through the INFO (or ORACLE) database, or through the GRID module of ARC/INFO. Intermediate data products were provided to enable users to track steps in the classification process and to make their own modifications. Elevation and hydrographic source data for the project area were also delivered as digital files corresponding to standard USGS 1:100,000 scale quadrangles (122 quads for elevation and 107 for hydrography). The elevation data were 7.5 minute digital elevation models (DEMs) from the USGS and the Forest Service (Geometronics Service Center); hydrography data came from USGS Digital Line Graphs (1:100,000 scale).

In addition to the detailed Final Report, three other reports were completed as part of this contract. The first two were comparisons between classification methods and results for portions of the Boise and Colville National Forests (Tady et al. 1995a, b), and the third was a feasibility study of using Landsat data to measure and monitor vegetative change between the 1970's and the 1990's for two areas in western Montana — the Swan Valley and the Elkhorn Mountains (Winne 1996).

Methods

Although the classification process involves many steps (Fig. 2), two major stages are addressed here. The first is the unsupervised classification that groups 30 m^2 pixels into classes with similar light reflectance properties, as measured by the Landsat TM sensor (see Fig. 3a, b). After the unsupervised classification, pixels are merged into polygons at least 2 ha (5 ac) in size based on spectral similarities between neighboring areas (Fig. 3c). The resulting

Table 1. Description of the 37 attributes for each raster polygon (or region) in the 18 land cover databases.

ATTRIBUTE	DESCRIPTION
VALUE	Unique identification number for each region by TM scene
COUNT	Number of 30 m^2 pixels in the region
LIFEFORM	Dominant lifeform of region
COVERTYPE	Land cover type assigned to region
CANOPYCODE	Canopy closure class based on sliced MNDVI histogram
SIZECLASS	Size class for tree and shrub cover types
ELE	Mean elevation of region
SLP	Mean slope of region
ASP	Majority aspect of region (recoded to 8 classes)
SPECTRAL_CLASS	Spectral class code assigned to region by unsupervised classification
COV_CODE_1	Most likely cover type assigned to region by supervised classification
COV_PROB_1	Euclidean distance that led to cover type assignment
COV_CODE_2	2nd most likely cover type assigned to region by supervised classification
COV_CODE_3	3rd most likely cover type assigned to region by supervised classification
TREE_SIZE	Forest size class assigned to region by supervised classification
TREE_SIZE_P	Euclidean distance that led to forest size class assignment
SHRUB_SIZE	Shrub size class assigned to region by supervised classification
SHRUB_SIZE_P	Euclidean distance that led to shrub size class assignment
MNDVI	Modified normalized difference vegetation index (from Nemani et al. 1993)
TM1	Mean spectral value of region for TM channel 1
TM2	Mean spectral value of region for TM channel 2
TM3	Mean spectral value of region for TM channel 3
TM4	Mean spectral value of region for TM channel 4
TM5	Mean spectral value of region for TM channel 5
TM6	Mean spectral value of region for TM channel 6
TM7	Mean spectral value of region for TM channel 7
AREA	Area of region
PERIMETER	Perimeter of region
X-COORD	X coordinate of region center in meters (based on Albers projection)
Y-COORD	Y coordinate of region center in meters (based on Albers projection)
SCENEPOLY_ID	Unique identifier for region within entire project area
DOM	Indicator of dominance relationships with all adjacent scenes
DOM_N	Indicator of dominance relationship with adjacent scene to north
DOM_W	Indicator of dominance relationship with adjacent scene to west
DOM_S	Indicator of dominance relationship with adjacent scene to south
DOM_E	Indicator of dominance relationship with adjacent scene to east
KEEP	Indicator of whether the region will be kept after edgematching

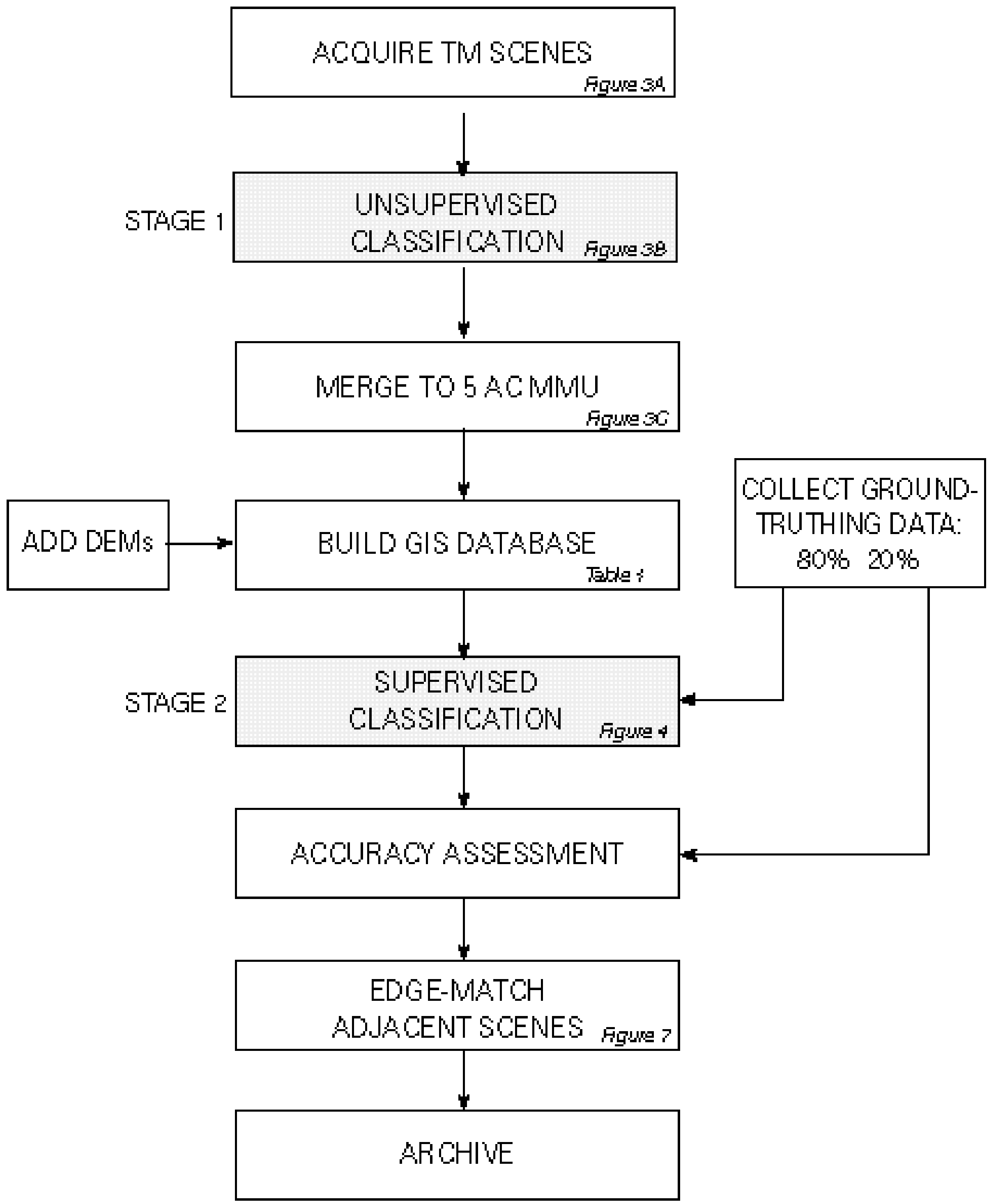
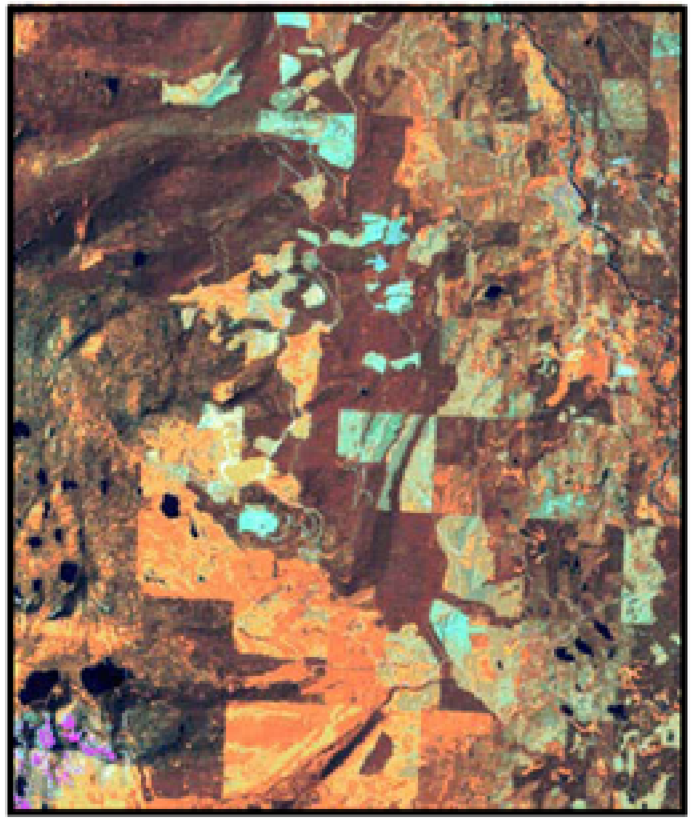
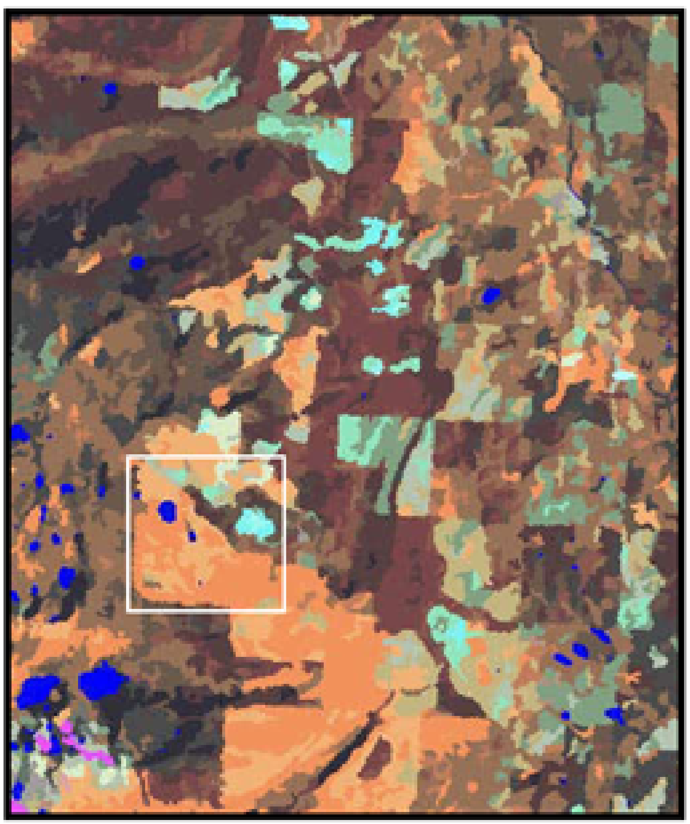


Figure 2. Major steps in constructing the digital databases of existing vegetation and land cover.

(a) Color composite of TM channels 4,5,3 (R G B).



(b) Unsupervised classification of TM channels 3,4,5.



(c) Classification regrouped and merged to 2 ha minimum mapping unit, with area of enlargement *(d)* outlined.

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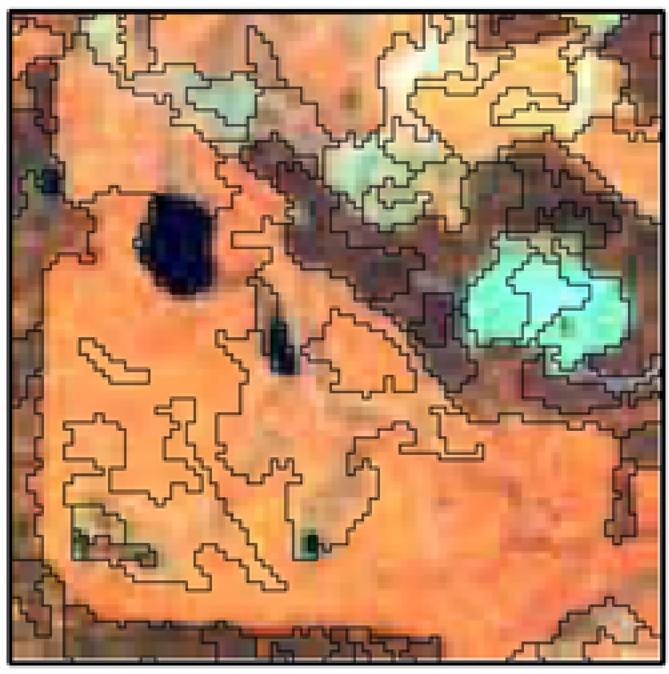

(d) Enlargement showing polygons derived from *(c)*, overlaid on *(a)*.

Figure 3. Steps in the unsupervised classification process, illustrated for the central Swan Valley, Montana.

polygons (shown in Fig. 3d) serve as the base units in the GIS database. The second stage, a supervised classification, uses field data to classify all polygons according to their cover type, size class, and canopy closure (Fig. 4).

Landsat TM imagery, DEMs, digital hydrography, and ground-truth plots were the primary data layers incorporated in the mapping process. Eighteen full TM scenes were individually processed. A total of 17,854 plots were compiled for the classifications; of these, 80% were used to “train” the computer to assign land cover attributes to unsampled regions, and 20% were held aside to assess the accuracy of the assigned cover type, size class, and canopy cover attributes. Once all the scene classifications were complete, an edge-matching technique was applied so that seamless outputs could be generated across the entire project area.

Results

In all, 58 cover types were classified and mapped in the project area (Table 2). By lifeform, 57% of the area was classified as forested, 19% as grasslands, 11% as shrublands, 7% as agriculture, and the remaining 6% as non-vegetated. The seven riparian cover types comprised only 3.2% of the project area. Accuracy assessments were quite variable for the 18 TM scenes. Cover type accuracies ranged from 87% for TM scene P39/R27 (Highwood Mountains/Benton Lake, MT) to 53% for P42/R28 (Dworshak Reservoir/Kooskia, ID). Similarly, canopy closure and size class accuracies ranged from 78% for canopy closure on P40/R28 (Anaconda Pintlar/Georgetown Lake, MT) to 23% for size class on P41/R26 (Glacier National Park, MT).

Discussion & Conclusions

Many factors can influence the accuracy of classifications derived from Landsat TM data (see Lachowski et al. 1995). These range from limitations associated with input data, including TM imagery or ground-truth data, to errors introduced in the classification process. In general, better results were obtained when larger numbers of high quality ground-truth data were available. Nevertheless, all stated accuracies represent conservative estimates, and users should find the GIS databases to be more accurate than these figures might otherwise indicate. The nature of the databases makes modifications relatively simple and straightforward; hence, additional field data can be easily incorporated to improve the results. The full scene units were maintained so that the databases can be more easily updated when new TM imagery is acquired. Finally, by supplementing these data with others designed for both broader applications (e.g., Forest Inventory and Analysis), as well as for more site-specific ones (e.g., Timber Stand Management Record System), the utility, efficiency, and effectiveness of all can be enhanced.

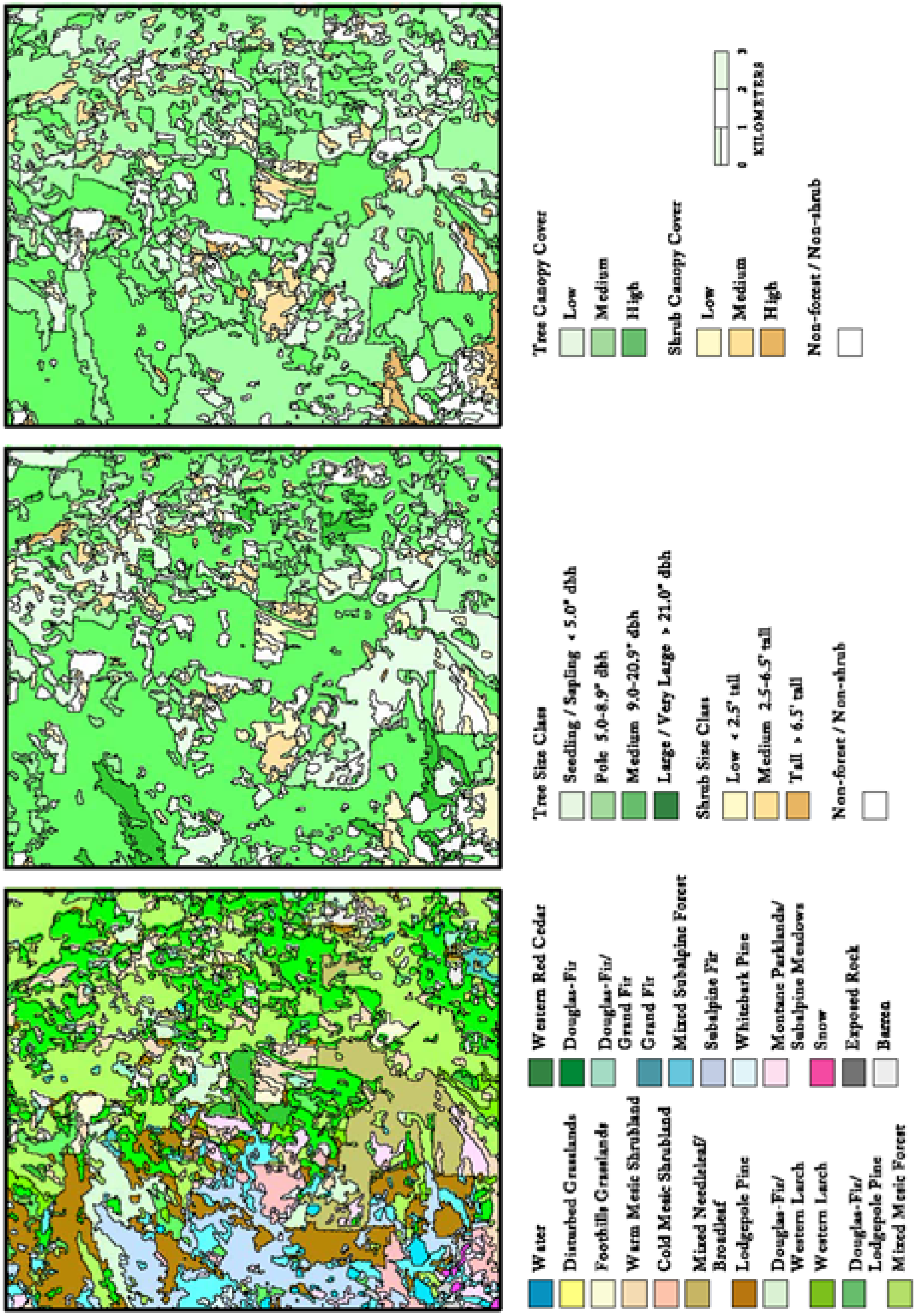

Figure 4. Classification of land cover type, size class, and canopy cove illustrated for the central Swan Valley, Montana.

Table 2. Codes and descriptions of the 58 cover types mapped across northern Idaho and western Montana.

Code	Description	Code	Description
1000	Urban	4220	Mixed Subalpine Forest
2000	Agriculture	4221	Mixed Mesic Forest
3101	Foothills Grassland	4222	Mixed Xeric Forest
3102	Disturbed Grassland	4223	Douglas-fir/Lodgepole Pine
3104	Subalpine Meadow	4224	Burnt Timber Stands
3201	Mesic Upland Shrubland	4225	Douglas-fir/Grand Fir
3202	Warm Mesic Shrubland	4226	Western Red Cedar/Grand Fir
3203	Cold Mesic Shrubland	4227	Western Red Cedar/Western Hemlock
3301	Curlleaf Mountain Mahogany		
3303	Skunkbrush Sumac	4228	Western Larch/Lodgepole Pine
3304	Bitterbrush	4229	Western Larch/Douglas-fir
3305	Mountain Big Sagebrush	4301	Mixed Needleleaf/Broadleaf Forest
3306	Wyoming Big Sagebrush		
3307	Basin Big Sage Shrubland	5000	Water
3308	Black Sagebrush Steppe	6101	Needleleaf Dominated Riparian
3312	Rabbitbrush	6102	Broadleaf Dominated Riparian
3313	Creeping Juniper	6103	Needleleaf/Broadleaf Riparian
4101	Aspen	6104	Mixed Riparian
4102	Broadleaf Forest	6201	Grass-forb Riparian
4201	Engelmann Spruce	6202	Shrub Riparian
4203	Lodgepole Pine	6203	Mixed Non-forest Riparian
4205	Limber Pine	7300	Exposed Rock
4206	Ponderosa Pine	7400	Barren Tundra
4207	Grand Fir	7500	Mine/Quarry/Gravel Pit
4208	Subalpine Fir	7800	Mixed Barren Land
4210	Western Red Cedar	7900	Shoreline/Gravel Bars
4211	Western Hemlock	8100	Alpine Meadow
4212	Douglas-fir	9100	Snow
4214	Rocky Mountain Juniper	9800	Cloud
4215	Western Larch	9900	Cloud Shadow
4219	Mixed Alpine Forest		

By providing an integrated GIS database, users can query and process information contained in many layers in a cost-efficient manner and at a controlled level of accuracy. Because these full scene databases are relatively small, they can be retrieved quickly and processed efficiently; they also can be edge-matched seamlessly to examine larger areas at once. Thus, many problems associated with conventional methods of mapping large areas have been solved by the methodology developed for this project. Finally, the results provide a powerful tool for the Forest Service and other land management agencies to examine vegetation patterns across large areas of mixed ownerships and to conduct the following types of analyses and applications:

- broadscale assessment and planning efforts, such as the Columbia River Basin project;
- revision of National Forest Plans (Analysis of the Management Situation, cumulative effects and trade-off analyses, existing condition, alternative development);
- identification of land management projects that will achieve the ultimate goals of producing goods and services for people within the sustainable capacity of ecosystems; and
- monitoring trends in existing vegetation and evaluating whether land management activities have had desired effects.

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Appendix 1
Methods

The entire methodological process is summarized in Fig. 5. Two stages were involved in the classification process. In the first stage, land cover patterns were derived from a color composite of Landsat TM bands 4, 5, and 3, using an unsupervised classification algorithm, and pixels were grouped into regions (analogous to raster polygons) that were at least 2 ha (5 ac) in size. The second stage incorporated a supervised classification algorithm within ARC/INFO GIS software to label all regions according to existing vegetation and land cover type. Both stages of the classification hinge on Euclidean distance calculations. In the first stage, each pixel is assigned to a spectral class by determining the shortest distance (i.e., the best match) between the RGB (red-green-blue) color values for that pixel and those for any available spectral class. In the second stage, each region is assigned to a cover type by measuring the shortest distance between the mean TM and elevation attributes for that region, and the attributes for any of the ground-truthed regions.

Data Inputs

Landsat TM imagery, digital elevation models (DEMs), digital hydrography, and groundtruth plots were the primary data layers incorporated in the mapping process. Eighteen full TM scenes were classified; all were collected during the growing season (mid-June to late September) in 1991-1993, and most are cloud-free. Elevation, slope, and aspect information were derived from digital elevation data. U.S. Geological Survey (USGS) 7.5' DEMs were used wherever possible. Some quadrangles, however, particularly on the periphery of the project area, were not available in digital form. These quads were patched with three arc-second data (from the Defense Mapping Agency, source scale 1:250,000), resampled to 30 m^2 pixels and co-registered to the TM scenes. In all, 7.5' DEMs were acquired for 3,203 quadrangles, and used in compiling 102 DEM tiles. Hydrography data came from USGS 1:100,000 digital line graphs (DLGs). Ground-truth data were acquired from the U.S. Forest Service, Northern Region. ASCII files containing plot information were converted to ARC/INFO point coverages, then sorted and stored in separate coverages for each TM scene. To maximize the training data available for use in supervised classification, plots that fell in multiple scenes (see Edge-Matching section, p. 20) were maintained in multiple coverages. Additional training data were collected from USFS personnel during reviews of preliminary classifications, and were compiled from other sources where available (e.g., aerial photos or forest stand maps).

Unsupervised Classification of Pixels

The color composite of raw TM data (Fig. 3a) and the unsupervised classification output (Fig. 3b) are illustrated for a portion of the central Swan Valley in northwestern

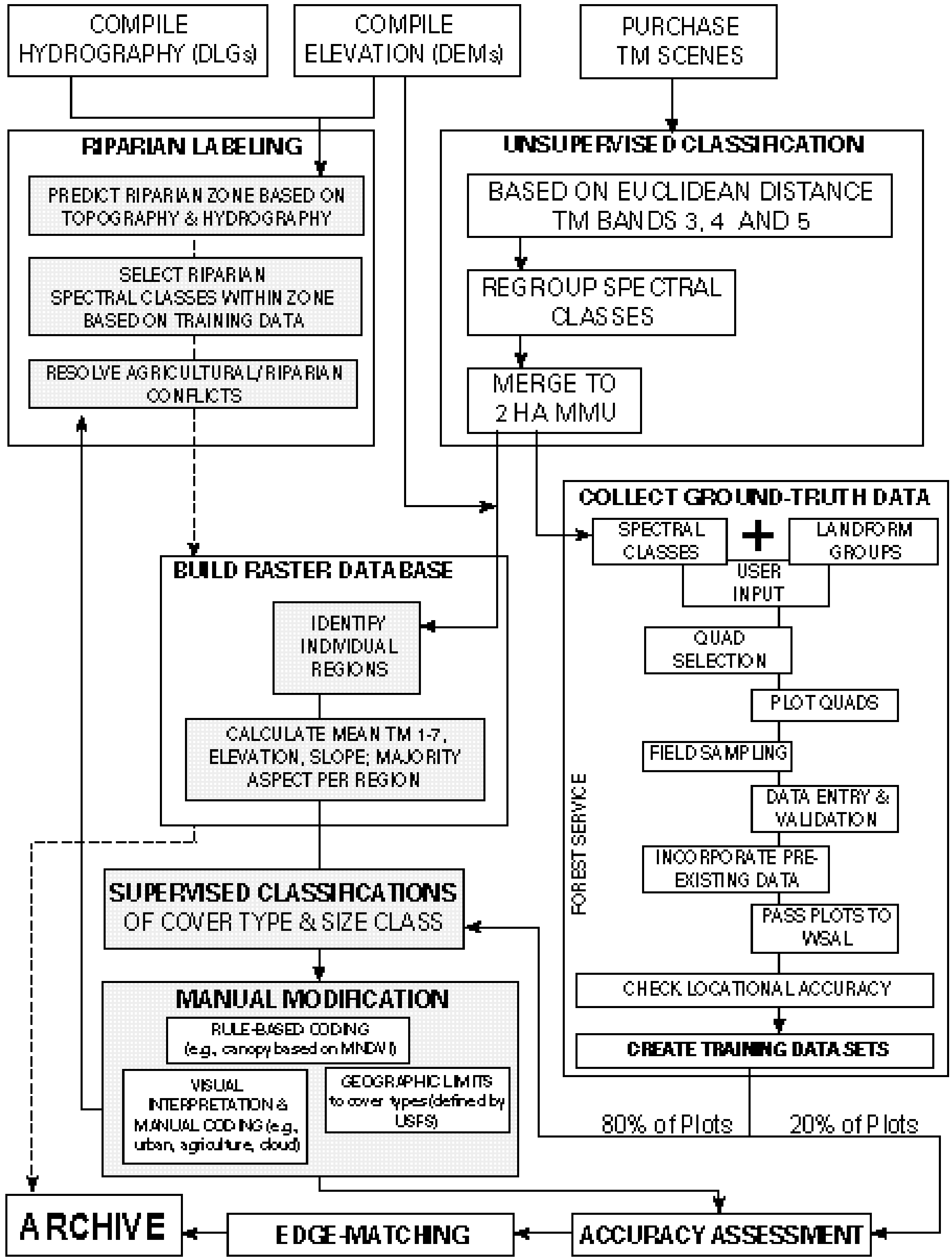

Figure 5. Major steps in constructing digital databases of existing vegetation and land cover, elevation, and hydrography for northern Idaho and western Montana. Processing path for riparian classification indicated by dashed line.

Montana. Spectral classes were next regrouped to reach a more manageable number of classes, and to better reflect some land cover patterns (Fig. 3c). Typically, the number of classes was reduced from approximately 60-80 to 30-40. After regrouping and filtering, each contiguous area of pixels assigned to the same spectral class is referred to as a region (again, analogous to a polygon, but in raster format). Regions less than the selected MMU of 2 ha, or 23 pixels (30 m * 30 m * 22 = 19,800 m^2 = 1.98 ha), were eliminated in a customized merging process. The 2 ha MMU was enforced for all spectral classes except those corresponding to water; to aid in future riparian evaluations (e.g., wildlife habitat assessments), an early decision was made to maintain individual 30 m^2 pixels that might represent water. The merging process centered around construction of a similarity matrix used to control the incorporation of small regions into larger neighbors. This matrix was built based on the TM channel values for the input spectral groups. The merging process first identified regions smaller than the MMU, listed neighboring regions, then examined similarities between small regions and their neighbors. Small regions were then merged with larger neighbors having the most similar spectral values. Once the merging process was finished, region shapes and sizes were established permanently (Fig. 3d). These regions serve as the base units in the raster database. At this point, all steps in the unsupervised classification were complete. To assign labels to these base regions through the supervised classification process, collection of ground-truth data was necessary.

Ground-truth Data Processing Pipeline

A total of 17,854 unique plots were compiled in the ground-truth database; all were subjected to a series of logical and positional checks. ARC/INFO point coverages were then created and manipulated to obtain training datasets for each TM scene. Because of the extensive overlap between scenes, plots falling in overlap areas could be stored in more than one training set coverage. Consequently, a total of 31,369 plots were available for classifying all 18 scenes. Training data were readily available for cover type and canopy cover class, but size class underwent a *post hoc* assignment because many forested plots contained multiple size class groups which did not fit readily into a single size class.

Setting up the Raster Database

The supervised classification, where regions are assigned labels based on ground-truth data, requires a raster database containing multiple TM and ancillary attributes. Logically, then, classifications could not take place until such databases had been constructed for each TM scene. Once a classified and merged image was created through the unsupervised classification process, the resultant file was converted from ERDAS GIS to ARC/INFO GRID format, thus maintaining its raster file structure. Next, for each scene database, a value attribute table (VAT) was built to contain statistics by region for spectral (TM) and biophysical (DEM) data. In addition to the mean values for TM channels 1-7, mean elevation and slope values for each region were calculated and stored within the attribute table. Because mean values were unlikely to offer representative measures for aspect (e.g., when averaged, northeast and northwest slopes would be recorded as south), aspect was classified into eight groups and stored as majority values for each region. A modified normalized difference vegetation index (MNDVI) was calculated after Nemani et al. (1993).

Training Data Analysis

The supervised classifications would not be possible without the input of high-quality data to 'train' the computer to assign the proper cover type, size class, and canopy class labels to each region. After preliminary inspection, plots expected to cause problems were identified and eliminated from the training set, if questions could not be resolved. Examples include multiple plots with different vegetation types in a single polygon, and plots with low or unknown locational accuracy. Generally, plots were set aside if they had cover type codes that would be manually rather than digitally labeled; these included urban, agricultural, and water cover types, but the specific set of excluded types varied by TM scene. Riparian plots also were set aside for use in a separate classification of riparian vegetation (see below). In addition, plots were eliminated if they represented cover types that were determined by USFS personnel to be minor components of a scene, and thus not important for mapping purposes.

From the remaining set of plots, 20% were randomly selected for each cover type and set aside for assessing classification accuracy. The other 80% comprised the potential training set for cover type classification. These plots were subjected to further spectral examination. Outliers were identified for each cover type by examining plots in relation to TM and ancillary data for the regions in which they fell. Plots were inspected both visually and in relation to statistical measures like Euclidean distance and standard deviation. Outlier or otherwise questionable plots were eliminated from the training set. Separate test and training sets for tree and shrub size classes were created using this process as well.

Supervised Classification of Regions

Once the raster database and training data sets were complete for a given TM scene, supervised classifications were conducted to assign cover type and size class labels to each region. This proved to be an iterative process. Multiple classifications may have been conducted for a single attribute, with intermediate modifications to training data, until satisfactory results were obtained. Furthermore, 'classifications within classifications' may have been conducted. For example, west of the Continental Divide, rough elevation breaks and simple decision rules were defined to separate Cold and Warm Mesic Shrub types from a more general Mesic Upland Shrub class. To complete the process, however, additional classifications were conducted to separate the two types within an intermediate elevation zone.

The first step in each supervised classification was to overlay training plots with regions in the raster database and extract the necessary attributes from each region for use in the classification. For each training plot, an attribute was added to identify the exact region in which it fell. Attribute tables were then related for the training plot and raster files, and the attribute values desired for each classification were exported into a training data file (ASCII format), sorted by group (cover type or size class). Mean values for TM channels 1-7 plus elevation were used to classify cover types, whereas only the mean TM values were used to classify forest and shrub size classes. Presumably, elevation should not influence size class as it could cover type. In addition to creating ASCII files for training data, similar files were created by exporting a matching set of attributes for every region in the raster database. Attribute values thus played the primary role in determining which labels should be assigned to each region.

Manual Modifications

Once supervised classifications had been conducted, manual modifications proved simple within the raster database structure. Three basic types of manual modifications were used: attribute recoding based on decision rules, geographic limits (defined by the Forest Service for some cover types), or visual interpretation of Landsat TM imagery. As an example of a rule-based modification, MNDVI was used in conjunction with training data to classify canopy cover for forest and shrub types. MNDVI offered an objective alternative to separate supervised classifications because its derivation emphasizes variation in middle infrared wavelengths which are known to be associated with canopy closure (Butera 1986). Separate histograms showing frequency distributions for MNDVI were plotted and examined for forest, mesic shrub, and xeric shrub training regions. Breakpoints for low, medium, and high canopy cover were determined based on the distribution modes. A decision rule was then used to assign canopy classes to regions with tree and shrub cover types based on those breakpoints. Other decision rules were used to subdivide or recode cover types based on elevation or other attributes; mesic shrub types, water, snow, and rock were commonly manipulated in this manner.

Geographic limits were also applied to cover type distributions as per instructions provided by the Forest Service (in the form of small-scale, hardcopy maps). If a region was labeled Ponderosa Pine (COV_CODE_1 = 4206), but fell outside the limits of this type, as defined by the Forest Service, the value from COV_CODE_2 was transferred to COVERTYPE. Visual interpretation was used to distinguish urban and agricultural lands, as well as clouds and cloud shadows, and these classes were labeled manually.

Accuracy Assessment

Because the land cover classification scheme is complex (see Table 2), and many cover types overlap to varying degrees, map accuracy was evaluated using fuzzy sets (Gopal and Woodcock 1994). A fuzzy matrix, derived from two-way tabulation of cover types, was constructed to evaluate misclassification errors. Acceptability was ranked through scores assigned to each possible combination of cover types. For example, confusion between Douglas-fir and Douglas-fir/Lodgepole Pine was determined to be less serious than confusion between Douglas-fir and Foothills Grassland. Acceptability was rated on a scale from 1 to 5: 1) absolutely wrong; 2) understandable, but wrong; 3) acceptable; 4) good; 5) perfect match. By rating acceptability in this manner, accuracy assessments could be conducted at both the acceptable and ideal levels, thereby offering more information about the utility of the classification than traditional accuracy tests.

Separate assessments of accuracy were conducted for cover type, size class, and canopy cover class. Plots from the test data sets were overlayed with the raster database; plot attributes were compared with classification results, and scores of 1-5 were drawn from the fuzzy matrix. Final accuracy figures were weighted based on the mapped extent of each cover type or class within the TM scene.

Accuracy was not assessed for all the types that were mapped. Specifically, cover types like urban, agriculture, and water were omitted from the accuracy assessment, in part because the available test data were not representative of common occurrences of these types. Nevertheless, because urban, agriculture, and water types can be readily identified through visual interpretation, their actual accuracy should exceed 80%. Riparian classes also were omitted because they were mapped separately, and at such a fine resolution (30 m pixels) that the correspondence between test plot and individual pixel could not be guaranteed.

Riparian Labeling

Because riparian vegetation often occurs in small patches associated with wet conditions, much information about its distribution was lost in the process of merging 30 m pixels to 2 ha MMUs. To rectify this situation, riparian cover types were classified separately for each TM scene, using unregrouped spectral values for individual pixels, and a variable-width buffer around water features to estimate where these types were likely to occur. First, using hydrographic features and digital elevation data, riparian zones were predicted for each Landsat TM scene. Next, within the predicted riparian zone, spectral classes were selected by examining field data and spectral class characteristics, and then assigned to one of seven riparian classes (Table 2; Fig. 8).

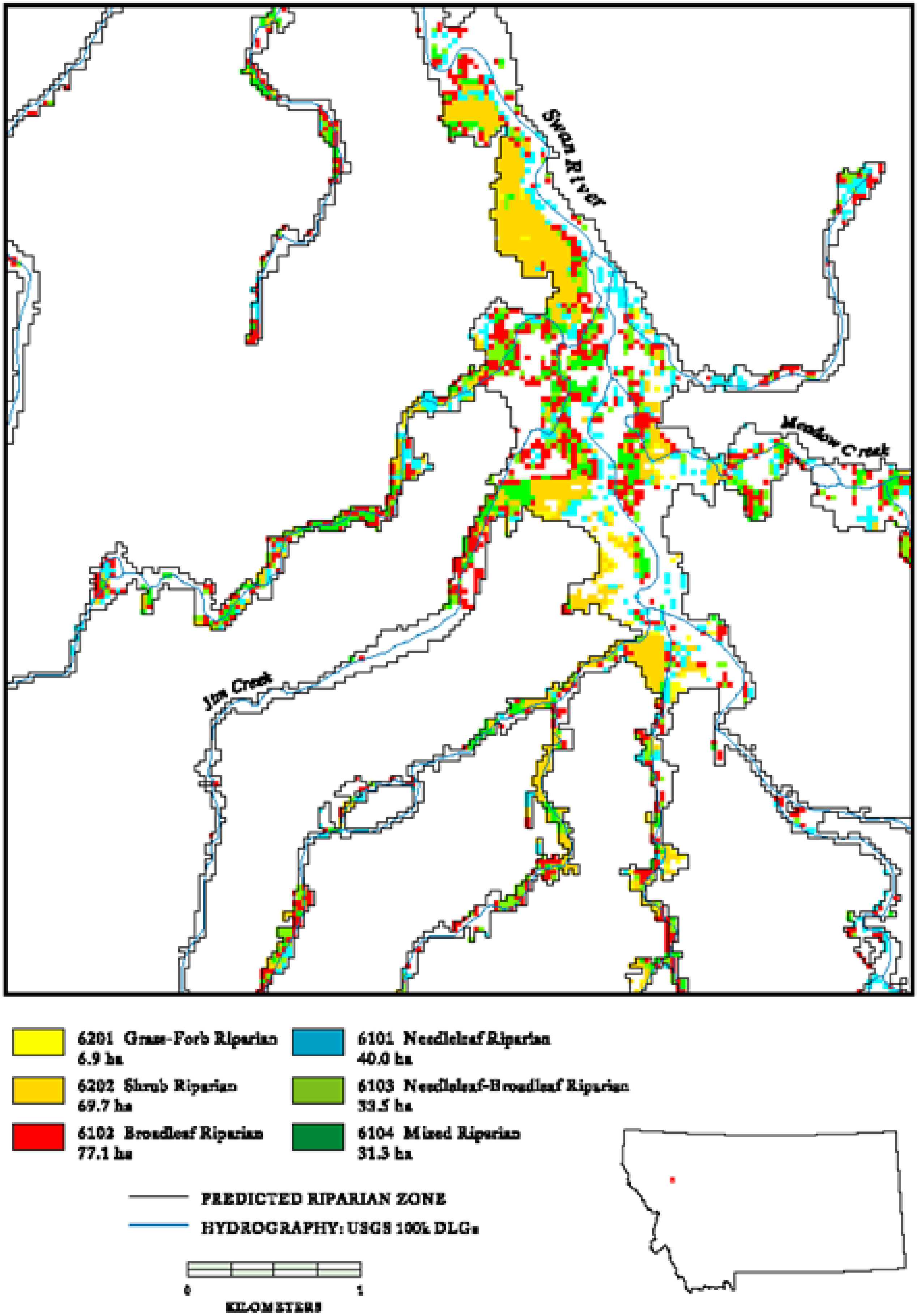

Figure 8. Classification of riparian vegetation cover types within predicted riparian zone for a portion of of the central Swan Valley, Montana.

Edge-matching

A simple process was devised to seamlessly edge-match adjacent scenes (Figs. 6 & 7). This ‘cookie cutter’ method was designed to preserve the integrity of individual scene classifications, and to minimize the perception of an “edge” between adjacent overlapping scenes. The method allows each image to be processed independently using all available spectral information, then edge-matched to its neighbors based on natural boundaries observed from land cover patterns. Through this method, adjacent scenes are “virtually” edge-matched. Rather than physically deleting regions, they are simply flagged to indicate whether or not they should be used. As a result, the original data can always be retrieved, and new edge-matching schemes can be devised and implemented at any time.

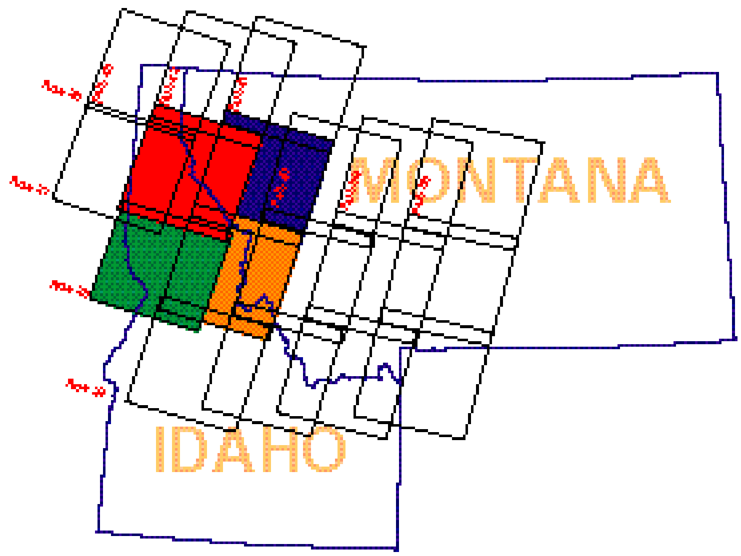

Figure 6. Landsat TM Scenes: Overlap among the 18 Landsat TM scenes covering the project area (~40% by row and 20% by path); dominance relationships among four scenes indicated in color.

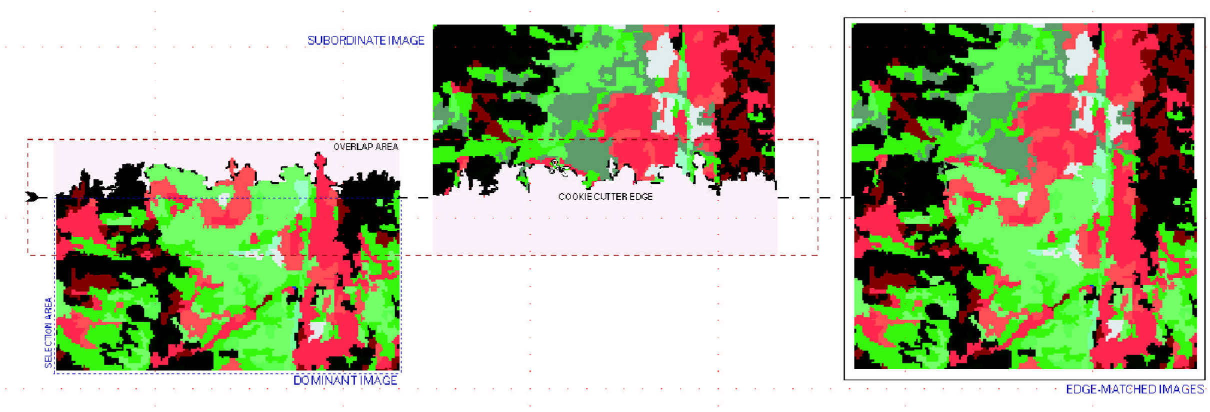

Figure 7. Details of the Cookie Cutter Method. The dominant image is merged with the subordinate one. In the process, the dominant image acts as a “cookie cutter”, replacing the underlying portion of the subordinate image.

Appendix 2
Interpreting Error & Accuracy Assessments

Error matrices, also referred to as “confusion matrices” or “difference matrices,” were used in two ways for assessing accuracy or agreement between a set of reference data (“true” data) and a classified map. First, error matrices were generated from USFS plot data to assess the ability of plots to correctly classify themselves, and thereby to evaluate spectral variation among cover type classes. Error matrices were also used to assess the final accuracy of mapped cover types in relation to test plots. An understanding of error matrices and how they specifically apply to the land cover database is important to make the best use of this product; basic information on interpreting error matrices is provided toward this end.

To determine how well a set of ground-truth data or training plots correspond to consistent patterns of spectral reflectance, an assessment can be made using an error matrix. The error matrix shows confusion between plots, and also cover type misrepresentation by certain plots in the data set. It further provides a sense of the general variation in spectral patterns represented by the ground-truth set overall. To assess confusion, a “bootstrap” technique was used — a single plot was extracted from the full data set (the population) and then classified to cover type (size class, canopy cover class, etc.) using the spectral information provided by the remaining plots in the data set. The Nearest Member of Group classifier was used to identify the plot in the remaining set that had the smallest Euclidean distance from the extracted plot (based on the seven TM channels, as well as elevation for cover type). The extracted plot then received a cover type label corresponding to the label for the plot identified as the best match. This process was repeated for all of the points in the ground-truth set. The output of the bootstrapper program, the error matrix, provides an abundance of useful information if interpreted correctly. To illustrate this, the error matrix generated for cover type codes from the ground-truth data set for scene P43/R27 (Table 3) is interpreted below.

The matrix provides information for all of the cover type codes represented by the ground-truth plot set. The codes along the top of the matrix represent the output classified data set generated from the bootstrapper program (classified Cover Types), and those along the left column represent the input ground-truth data set (Plot Cover Types) which are assumed to be 100% accurate. The major diagonal, top left to bottom right shows how many points classified by the ground-truth training set were actually given the same code as their original designation. These “correct hits” are referred to as “diagonal elements.” For example, if a ground-truth plot labeled as 3101 was extracted from the ground-truth training set and then classified as 3101 in the bootstrapping process, the plot would be counted on the diagonal as an exact match or as having no error. Table 3 shows that 61 out of 87 plots coded as 3101 were actually classified as 3101.

The matrix is read across each row to assess commission error, or errors of inclusion, located off of the major diagonal. For example, Table 3 shows that 12 out of 87 plots coded as 3101 (Foothills Grassland) were incorrectly classified as 3201 (Disturbed Grassland). The matrix is read down the columns to assess omission error, or mistakes due to exclusion. In

Table 3. Confusion matrix calculated for cover type classes from training data for P43/R27. Diagonal elements = 213; Total data points = 462; Percentage agreement = 46.1%; TAU w/equal probability = 0.43.

	CLASSIFIED COVER TYPES																	
PLOT COVER TYPES	3101	3201	4102	4203	4206	4207	4208	4210	4212	4215	4220	4221	4222	4223	4301	7301	7800	TOTAL
3101	61	12	1	1	4	0	0	0	0	0	0	1	1	0	1	2	3	87
3201	8	2	8	1	1	2	0	0	0	1	0	0	2	0	0	0	0	53
4102	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4203	1	0	0	2	0	0	0	1	2	2	1	7	0	2	0	0	0	18
4206	5	4	1	0	7	0	0	0	3	1	0	2	2	0	0	0	0	25
4207	0	0	0	0	0	0	1	2	0	0	0	8	2	0	0	0	0	13
4208	0	0	0	0	0	1	3	0	0	2	1	4	0	0	0	0	0	11
4210	0	0	0	1	0	2	0	7	0	0	0	1	0	1	1	0	0	13
4212	0	1	0	3	2	4	1	0	12	1	1	3	3	2	2	0	0	35
4215	0	0	0	1	1	0	1	1	1	2	1	2	1	1	0	0	0	12
4220	0	0	0	0	0	0	1	0	1	0	10	1	0	0	0	0	0	13
4221	0	2	0	7	2	7	3	1	9	2	1	64	3	5	4	0	1	111
4222	0	2	0	0	7	2	0	0	2	1	0	2	5	0	0	0	0	21
4223	0	0	0	2	0	0	0	1	1	2	0	6	0	0	1	1	0	14
4301	1	0	0	0	1	1	0	1	1	0	0	5	1	1	1	0	0	13
7301	3	1	0	0	0	0	0	0	0	0	0	0	0	1	0	4	1	10
7800	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	7	12
TOTAL	92	51	3	18	26	17	10	14	33	13	15	109	18	13	10	8	12	462

the case mentioned above, 12 plots that should have been classified as 3201 were omitted from that class and instead classified as 3101. Errors of commission and omission are simply inverse concepts that convey different information about a map's utility for various purposes, or in the case of Table 3, what kind of problems are likely to be associated with the training plots. The following accuracy measurements were made for each classification:

User's Accuracy

This measurement relates to commission error and represents the probability that a classified plot actually represents that class on the ground, or in the ground-truth set in the case of Table 3. User's accuracy is calculated by dividing the total number of correct classifications for a class (diagonal elements) by the total number of classified data plots for that class, found in the bottom row of each column.

User's Accuracy for 3101 = 61/92 = 66%

Producer's Accuracy

This measurement relates to omission error and represents the probability of a plot being correctly classified. Producer's accuracy is calculated by dividing the total number of correct classifications for a class (diagonal elements) by the total number of reference plots for that class, found in the far right column for each row.

Producer's Accuracy for 3101 = 61/87 = 70%

Overall Accuracy

This measurement is calculated by dividing the total number of correct classifications (diagonal elements) by the total number of ground-truth data plots. It is equal to percentage agreement (Table 3).

Overall Accuracy = 213/462 = 46%

Tau with Equal Probability

Because percentage agreement does not take into account agreement between data sets due to chance alone, it tends to overestimate classification accuracy. The Tau coefficient is one way to adjust for chance agreement (Ma and Redmond, 1995); it is calculated as:

$$T = \frac{\%\ \text{Agree} - P_r}{1 - P_r} = \frac{0.43 - \frac{1}{17}}{1 - \frac{1}{17}} = 0.43$$

where

$$P_r = \frac{1}{\text{n groups}}, \text{ with equal probability}$$

The bootstrapper error matrix is used to help image analysts decide which ground-truth plots are inadequate for use as training data for the supervised classification process. The overall accuracy figure for the error matrix also gives a fairly reliable indication of the actual supervised classification accuracy. Ground-truth plots that do not represent their assigned cover type will result in poor supervised classification; hence they must be set aside at the earliest possible step. Examples include plots that fall in the wrong geographic location, and plots that are atypical of the assigned cover type (e.g., a forested plot that just meets the 15% cover breakpoint for assignment to a forest type, where spectral reflectance is dominated by shrub species). The influence of one incorrect training plot can potentially spread throughout an entire map. The use of an error matrix to assess potential training plot confusion is a simple and effective method that, when employed at an early stage, may increase the accuracy of a land cover classification based on satellite imagery. Nonetheless, an exact match between plots does not necessarily mean that the plot is a good representative of a cover type, but only that it is similar to other plots with the same cover type in the ground-truth set.

For the final accuracy assessments of cover type, size class, and canopy cover class, both user's and producer's accuracies were calculated by fuzzy set score (see Appendix 1) and summarized in match and accumulation matrices for each classified TM scene. With this information, users can compare different class accuracies at the perfect level (score 5) versus the acceptable level (score 3) and thereby see which classes were consistently confused as opposed to being classified correctly.