Forest Mapping at Lassen Volcanic National Park, California, Using Landsat TM Data and a Geographical Information System

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Abstract

Knowledge of forest species composition is an integral part of designing and implementing resource manangement policies in a national park. Managers must rely on cost-effective methods of vegetation mapping, namely, use of remotely sensed data coupled with digital geographic data, to help them meet their management goals. In this study, we demonstrate that genus-level maps can be generated from unsupervised classifications of Landsat TM data at an accuracy level of 73 percent. Species-level maps can be created to an accuracy level of 58 percent by post-stratification of the spectral classification with topographic data in a geographic information system (GIS). This modification method is a rule-based system whereby spectral forest classes are sorted based on elevation and soil-moisture gradients established for each species through ecological research. Our observations illustrate that spectral classification is optimized by using all six reflective TM bands and that classification accuracy is affected by canopy cover and understory vegetation. Modifying spectral classifications by environmental data in a GIS is a useful way of defining species composition of forests in an area where access to forests is limited but need for map information is great.

Introduction

Reduction of forest and woodland habitats in North America has stimulated development of resource management tools to assist future forest conservation. Preservation of these forests is vital because of their role in global carbon cycling and species diversity (Bormann, 1985). Anthropogenic disturbance such as air pollution, acid rain, and global climate change could affect the functioning, distribution, and survival of plant and animal species in their present ranges. National parks, national forest wilderness areas, and private reserves such as those held by the Nature Conservancy provide refuges for these species and their habitats. Automated phytocartography from remotely sensed data coupled with geographic databases can play an important role in documenting present plant species distribution in these protected areas.

Computer-aided classification of remote sensing information has become a standard tool for mapping vegetation across large areas (Iverson *et al.*, 1989). Data from Landsat and airborne radiometers have been used to identify the species composition of various deciduous and coniferous forest ecosystems (Likens *et al.*, 1982; Khorram and Katibah, 1984; Benson and DeGloria, 1985; Hughes *et al.*, 1986; Skidmore, 1989). Mayer and Fox (1981) discriminated lodgepole pine, ponderosa pine, and fir at a rate of 91 percent using Multispectral Scanner (MSS) data at the McCloud Ranger District near Mt. Shasta, California. Walsh (1980) mapped forests composed of lodgepole pine, ponderosa pine, white fir, shasta red fir, and mountain hemlock at Crater Lake National Park using classification of MSS data with an overall accuracy level of 88.8 percent. Moore and Bauer (1990) reported accuracies of 63 to 67 percent mapping various Minnesota conifer species such as red pine, jack pine, black spruce, white pine, and tamarack using the Landsat Thematic Mapper (TM). Shen *et al.*, (1985) mapped the same species using TM simulator at 68 percent. The higher mapping performance of the studies using MSS over TM sensors is notable considering the refined spectral and spatial resolution of the TM sensors; however, this may be function of both the environmental conditions and spectral characteristics of those particular forest species.

Typically, previous mapping projects have utilized supervised classification techniques. Supervised classification can be costly in terms of time and money spent selecting and sampling training sites to represent the range of morphological and topographical variation of a particular mapping category (Walsh, 1980; Mayer and Fox, 1981). Unsupervised classification of spectral data may be preferable when mapping large areas with a rugged terrain (Fleming *et al.*, 1975). Terrain effects, expressed as topographic data, may be used to modify remote sensing classifications to map forested areas in which species are not easily distinguished spectrally (Skidmore, 1989; Richards *et al.*, 1982; Cibula and Nyquist,

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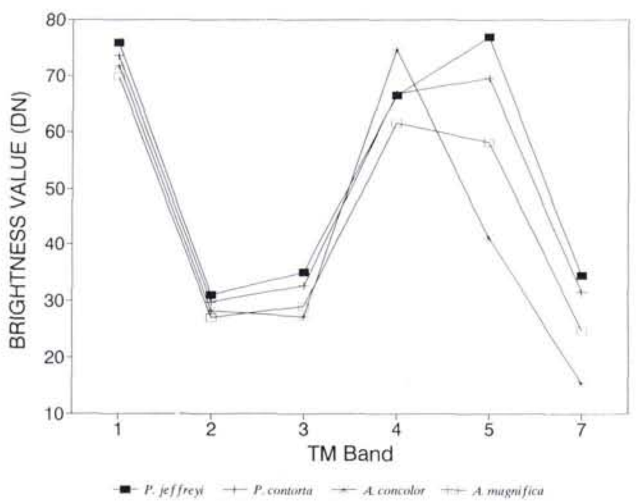

Figure 1. Spectral response of four dominant tree species of Lassen Volcanic National Park across the reflective TM bands.

1987). Bolstad and Lillesand (1992) mapped forest species between 73 and 89 percent by coupling TM data with soil and topographic data.

The purpose of this study is to demonstrate that (1) genus-level mapping of mixed conifer forests can be accomplished using simple, unsupervised clustering of Landsat TM data and (2) forest species can be identified by modifying spectral classification with topographic information through a geographic information system (GIS). The importance of this study is to show that valid forest composition maps can be produced using readily available spectral and image processing/GIS software. Use of this technology by resource managers in other protected areas will increase our knowledge about forests at present and can ultimately be used to monitor the change in forest composition over time (Vande Castle, 1991). Also, compilation and integration of vegetation maps into a geographic database from many public and private reserves would expand our understanding of forest species distributions from local to regional scales.

Methods

The Earth Resource Data Analysis System (ERDAS) software was used to perform an unsupervised classification of Landsat TM data covering the forests of Lassen Volcanic National Park. Two techniques were tested for their usefulness in identifying conifer tree species. In addition, a GIS model based on topographic data was developed to differentiate species that could not be differentiated using only spectral data. The format of the mapping process consisted of (1) classification of the spectral data, (2) interpretation, (3) modification of the spectral classification using habitat variables in the GIS environment, and (4) accuracy assessment.

Site Description

Lassen Volcanic National Park covers approximately 500 km^2 of the southernmost peaks of the Cascade Mountain range. Elevation in the park varies from 1616 m at Warner Valley to 3187 m on Lassen Peak. Most of the park below 2400 m is forested, with the distribution of forest species being affected by altitude (Gillette *et al.*, 1961). *Abies magnifica* (red fir) and *Pinus contorta* var. *murrayana* (lodgepole pine) dominate upper elevations (2100 to 2400 m), whereas *A. concolor* (white fir) and *P. jeffreyi* (Jeffrey pine) are most abundant at lower elevations (<2100 m). Limited stands of *Tsuga mertensiana* (mountain hemlock) occur along the treeline >2400 m.

Other vegetation communities occurring in the park include (1) montane chaparral dominated by *Arctostaphylos patula*, *Castanopsis sempervirens*, and *Ceanothus velutinus;* and (2) seasonally wet habitats located in valley meadows and along streams and lake margins. *Alnus tenuifolia* and *Carex* spp. are common constituents of these saturated areas (Bailey, 1963).

Data Processing

TM data were acquired for 12 June 1987 at approximately 9:30 AM with cloud-free conditions. This date was selected to optimize the photosynthetic potential of the tree vegetation (as well as possible spectral characteristics) while minimizing snow cover at higher elevations. A subset of 935 by 658 pixels containing Lassen Park was extracted from the original Landsat data for classification. This subset was linearly georectified using forty ground control points selected from USGS 1:24,000-scale quadrangle maps to a root-mean-square error (RMSE) of one pixel in the horizontal plane.

Errors related to reflectance path and random sensor malfunction result in radiometric noise in the data (Jensen, 1986; Conese *et al.*, 1988). To reduce the confounding effects of this noise, a 3- by 3-pixel low pass filter was applied to the data.

Satellite Data Classification and Interpretation

The TM data were classified using a clustering algorithm offered in the ERDAS software. Bands 1, 2, 3, 4, 5, and 7 were classified into 20 clusters using the CLUSTR program. CLUSTR is a sequential classifier in which cluster means are calculated from the data just as it occurs in the data file, beginning with data in row one, column one and continuing to a user defined limit. Classes, therefore, may be affected by the spectral information contained within the first few rows of data.

Interpretation of the 20 classes was based on expert knowledge of the forested areas supplemented with aerial photography interpretation. Classes were placed into *Pinus*, *Abies*, non-forest, and non-vegetation categories. Non-forest classes consisted of shrub and meadow domintated areas and non-vegetation classes were bare ground, lava, water, and snow. In cases where classes could not be resolved by this method, a normalized difference vegetation index (NDVI) was calculated based on the mean cluster values for bands 3 and 4 for each class. Classes with low NDVI values were assigned as non-vegetation, medium values as forest, and high values as non-forest vegetation. The range of NDVIs was established from NDVIs of known classes.

Average DN values for ten homogeneous species stands were collected for the six reflective bands to test the spectral definition of each species. These data were plotted (Figure 1) and Student's t test values were calculated to determine significant differences in spectral values between species and genera. Spectral classes were only interpretable at the genus level based on this analysis.

Table 1. Separation of Spectral Based Tree Classes by Elevation.

Elevation (m)	Spectral Class *Pinus*	*Abies*
< 1830	*P. jeffreyi*	*A. concolor*
1830 to 1920	pine (non-specific)	*A. concolor*
1980 to 2180	pine (non-specific)	fir (non-specific)
2220 to 2350	pine (non-specific)	*A. magnifica*
> 2350	*P. contorta*	*A. magnifica*
> 2560	*T. mertensiana**	*T. mertensiana**
> 2620	*P. albicaulis**	*P. albicaulis**

*Identified but no accuracy assessed.

Table 2. Separation of Tree Spectral/Elevation Classes by Potential Topographic Moisture Gradients (Generalized from Ten Topographic Moisture Classes to Three).

Tree/Elev. (m) Classes	mesic		xeric
pine/1830 to 1920	*P. contorta*	*P. jeffreyi*	*P. jeffreyi*
pine/1980 to 2180	*P. contorta*	*P. contorta*	*P. jeffreyi*
pine/2220 to 2350	*P. contorta*	*P. contorta*	*P. jeffreyi*
fir/1980 to 2180	*A. concolor*	*A. magnifica*	*A. magnifica*

Classification Modification Using a GIS Model

A GIS model based on elevation, slope, aspect, and proximity to a water source was used to subdivide the *Pinus* and *Abies* classes from the spectral classifications to the species level. Elevation and soil moisture value ranges which defined the habitats of tree species were obtained from the literature (Gillette *et al.*, 1961; Vankat, 1982; Holland, 1986; Rundel *et al.*, 1988).

Elevation for the GIS model was derived from 1:24,000-scale elevation data (DEM) obtained from the U.S. Geological Survey. These contained errors of horizontal striping and empty areas caused by scanning procedures used in their generation (USGS, 1987). To reduce the effects of theses errors, a 3 by 3 row-wise filter,

$$\begin{matrix} 0 & -1 & 0 \\ 0 & -1 & 0 \\ 0 & -1 & 0 \end{matrix}$$

was applied to the DEM to reduce striping. Missing data points were then identified in the data and replaced with the averages of the surrounding elevation values (Stitt, 1990). Elevations were grouped into 30 classes smoothed with a 5- by 5-pixel median value filter to remove errors persisting after filtering the DEM data.

Potential soil moisture was evaluated using a topographic moisture gradient (TMG) model suggested by Vankat (1982). Though other models exist for evaluating soil moisture (Beven and Wood, 1983; O'Loughlin, 1986), the TMG model was chosen because of the (a) specificity of the model to the Lassen forest species and (b) simplicity in construction-based topographic analysis. In this model, potential soil moisture is expressed as a range of values from 1 (wettest) to 10 (driest) and is a function of slope, aspect, and position on slopes. Stream valleys are considered wettest and ridgetops driest. The intermediate range is created as a combination of aspect and slope. Slopes and aspects were computed using the topographic module in ERDAS. Ridgetop and valley positions were derived by applying a filter to the DEM data which returned the average height of the peripheral pixels to the center,

$$\begin{matrix} 0.125 & 0.125 & 0.125 \\ 0.125 & 0 & 0.125 \\ 0.125 & 0.125 & 0.125 \end{matrix}$$

termed D_a. Values of D_a were subtracted from the original DEM data (D_s) and scaled to a mid-range of 100 to obtain a topographic position value D_t ($D_t = D_s - D_a + 100$). For $D_t < 100$, the position is a lower slope or valley depending on the difference from 100, $D_t = 100$, positions are midslopes, and for $D_t > 100$, positions are upper slopes and topographic ridges. The file was recoded so that the resultant GIS file had three classes: valley, midslope, and ridge. Stream channels were established by correlating low sloping areas with digitized perennial and intermittent streams from the 7.5-minute topographic maps. Streams flowing through valleys with shallow slopes would tend to greatly affect soil moisture beyond the confines of the stream channel (Gregory *et al.*, 1991).

A species composition map was created from a post-stratification of the spectral classified images using the elevation data and the TMG map. In a decision tree process, *Pinus* and *Abies* categories of the spectral based classifications were partially separated into species based on elevation ranges. As species could not be distinguished solely by elevation due to broad overlap of ranges at mid-elevational levels (Gilette *et al.*, 1961; Holland, 1986) (Table 1), the TMG variable was used to differentiate species at elevations where separation was incomplete (Table 2).

Accuracy Assessment

Map accuracy was assessed for genus-level, spectral classification and the species-level, GIS-stratified map. Accuracy was checked against 30 field samples ranging in size from 240 by 240 m to 150 to 150 m for a total of 1580 pixels sampled. Samples were subdivided into 30- by 30-m plots for plot-to-pixel comparison. The variation in sample size was a function of sampling technique used. Generally, size had no relation to variation in map accuracy at this scale. Species and estimated coverage for three vegetation layers in the forest canopy and other site variables including slope, aspect, and general site moisture conditions were assesed for each pixel within sampled areas. Forest types were determined by coverage in the upper canopy in each 30- by 30-m plot for each genus and/or species. Most forests sampled were dominated by one forest type by at least 50 percent cover and were designated as single species type forests.

Sample locations were chosen based on geographically identifiable trail, stream, or road crossings, and aerial photographs. Remote sampled areas which could not be identified on 7.5-minute topographic maps were located using the Global Positioning System (GPS). Though a random sampling regime is preferred to reduce the incidence of spatial autocorrelation associated with TM data, the steep, volcanic terrain of Lassen coupled with dense forests and underbrush necessitated location of sampling areas in accessible areas.

Number maps were produced from the genus- and species-level maps for correlation with the field data. Pixel by pixel counts were made to assess map to field agreement and disagreement and were collected in a contingency table format for each map (Tables 3 and 4). Percent correct, com-

TABLE 3. ACCURACY ASSESSMENT OF THE SPECTRAL CLASSIFICATION.

TM Spectral Classification	Field Classes			
Landsat Classes	*Pinus*	*Abies*	NF	NV
Pinus	632	104	12	2
Abies	196	361	8	4
Non-forest (NF)	52	18	95	5
Non-vegetation (NV)	15	7	3	66
Percent Correct (%)	71	74	81	86
Commission Error (%)	29	26	19	14

Map Statistics
n = 1580
Percent Correct = 73%
Commission Error = 27%
Confidence Interval (95% Confidence Level) = 0.71 to 0.75
K = 0.5850
σ^2_K = 0.0017

mission error, standard deviation, confidence interval (95 percent confidence level)(Thomas and Allcock, 1984), and the Kappa statistic (κ) and variance (σ^2_κ) (Congalton *et al.*, 1983) were calculated for each table.

Results and Discussion

An analysis of the average spectral response of some of the most heavily forested and species-homogeneous sample areas demonstrates that marginal differences exist between forest species (Figure 1). For bands 1, 2, and 3, the brightness values among species were nearly identical. The maximum differences among species occurred for bands 5 and 7 where the pine species had greater brightness values than the fir species. There was little interspecific difference between reflectance patterns between *P. jeffreyi* and *P. contorta*, but greater differences between the fir species, especially for bands 5 and 7, though not statistically significant. The higher reflection in band 5 of pines over firs may be indicative of the lower projected leaf area (LAI) of pines (Kaufmann *et al.*, 1982). The Lassen forest species could not be classified to the species-level based on spectral clustering alone due to the small spectral variation among species. However, genus-level classification was possible based on the slight spectral characteristic differences at this higher taxonomic level.

Spectral information alone was suitable for discriminating between forest genera. The spectral classification predicted *Pinus* and *Abies* forest classes by 71 percent and 74 percent, respectively (Table 3). The classification accuracy for the map on the whole was 73 percent, including non-forested and non-vegetated areas. The Kappa value for this map was lower at 0.59. The commission errors, or errors of inclusion, differed between *Pinus* and *Abies* classes from 29 percent to 26 percent. Of these errors, 7 percent of the *Pinus* class were contributed from non-forest and non-vegetated classes versus 5 percent in the *Abies* class. This slight difference may be explained by prominence of understory vegetation in the pine forests. Analysis of understory vegetation shows that understory cover is significantly greater ($P<0.05$) in *Pinus* forests than *Abies* forests.

The ability to discriminate forest species is positively correlated with canopy closure (Franklin, 1986) and negatively correlated with understory vegetation prominence (Spanner *et al.*, 1990) and reflection from soil (Ezra *et al.*, 1984). Sub-pixel heterogeneity, or variation in the land cover at a scale less than sensor detection, may also be important. Mean sample canopy and variance in understory cover are plotted along an axis of decreasing classification accuracy (percent) for forest genera from 20 selected samples based on confidence in the cover values (Figure 2). This plot illustrates two major trends in the classified data: (1) forest classification accuracy decreases with canopy cover and (2) variance in understory increases with decreasing canopy cover and decreasing forest classification accuracy. One major exception to this is the NOBLES-01 site which had high canopy cover, low understory variance, and low classification accuracy. This site was dominated by a dense, moderately aged, *P. contorta* forest intermingled with small riparian shrubs. The health and general vigor of the stand was poor, probably a result of the high density of trees. Low canopy foliage coupled with dense, exposed stemwood presumably resulted in a confusing spectral signature. The variance in the understory may increase on a sample basis due to gaps in the canopy which provide growing space for forest floor vegetation. On the whole, understory cover may vary greatly as the size and spatial distribution of the gaps vary across a sample area. From a mapping standpoint, these gap communities are smaller than the sensor resolution and may be ommitted in a field survey; however, their presence on a sub-pixel basis may greatly confound the spectral response of a forest type.

The species mapping accuracies were less than those for forest genera. Mapping accuracies were 55 percent for *P. jeffreyi*, 44 percent for *P. contorta*, 84 percent for *A. concolor*, and 50 percent for *A. magnifica* (Table 4). The overall map accuracy was 58 percent, commission error of 42 percent, and Kappa value of 0.48. Clearly, some species were better defined by the stratification process than others, especially *A. concolor*. The elevational gradient for the fir forests is fairly restricted as opposed to the broad elevational intergrading of the pine forests. In addition, the moisture tolerances of the fir species are better defined in the literature. The lower accuracy of the *A. magnifica* class may be a function of the sparser canopy and greater understory prominence in *A. magnifica* forests. The misclassification of the *A. magnifica* forests may, therefore, be due to classfication error in the spectral clustering. The low accuracy for the pines is mostly a function of the broad environmental limits of these forests. *T. mertensiana* could not be delineated in the spec-

TABLE 4. ACCURACY ASSESSMENT OF THE GIS-STRATIFIED MAP.

	Field Classes					
GIS Classes	*Pj*	*Pc*	*Ac*	*Am*	NF	NV
P. jeffreyi (Pj)	167	170	13	41	1	2
P. contorta (Pc)	35	260	11	39	11	0
A. concolor (Ac)	43	94	208	20	4	4
A. magnifica (Am)	26	33	11	122	4	0
Non-forest (NF)	23	29	4	14	95	5
Non-vegetation (NV)	9	6	0	7	3	66
Percent Accuracy (%)	55	44	84	50	81	86
Commission Error (%)	45	56	16	50	19	14

Map Statistics
n = 1580
Percent Correct = 58%
Commission Error = 42%
Confidence Interval (95% Confidence Level) = 0.56 to 0.60
K = 0.4769
σ^2_K = 0.0009

tral classifications due to low tree densities and high snow cover. However, *T. mertensiana* was identified preliminarily in the GIS model by designating any non-forest vegetation above 2560 m as *T. mertensiana*. Non-forest vegetation comprises shrub, pasture, and areas of scattered trees. However, at altitudes > 2560 m shrubs and pastures do not occur and only scattered trees are present. These groves of trees are primarily *T. mertensiana* or rarely *P. albicaulis*. Accuracy values were not calculated except in the agreement with personal experience or field notes.

Although more advanced spectral classifications employing maximum-likelihood classifiers with signature analysis are available, they are unlikely to improve the species classification unless they are able to differentiate species on spectral properties alone. The simple genus classifications employed here were >70 percent accurate, whereas the species classifications were as low as 44 percent. Because GIS modifications were used to refine the relatively higher accurate genera classes to less accurate species classes, the inaccuracies occur in the GIS process. More involved spectral analyses that only result in marginal increases in genera classifications cannot markedly improve the species accuracies.

This study demonstrates that conifer species in wildland habitats can be accurately identified to the genus level solely using Landsat data, but that identification of species using only spectral data may be difficult. Species maps can be produced using ancillary data in a GIS model to modify spectrally based information.

The success of the GIS modification technique is related to definition of species habitat, quality of ancillary data, and software capabilities. Results of the GIS modified maps indicate that forest species identification is possible using a combination of spectral and ancillary data. Use of terrain data to augment the mapping process allows modification of land-cover classes in cases where spectral data are insufficient (Richards *et al.*, 1982; Likens *et al.*, 1982). Accuracy may be enhanced by (1) accurately defining the environmental habitat of each species, (2) improving the quality of ancillary data input into the GIS, and (3) changing the method in which data layers are integrated in the GIS software.

Ultimately, the accuracy is limited by the degree of environmental heterogeneity in an area and the ability to describe the habitats of the species. The accuracy for GIS modified maps is based on the available habitat data reported in the literature on these species. Most of the data reported on topographically-induced zonation of these species are from the Sierra Nevada (Vankat, 1982; Holland, 1986; Rundel *et al.*, 1988). As some disparities exist between the forest zonation in the Cascades and the Sierra Nevada (Parker, 1991), it is difficult to extrapolate the optimum habitats for the Lassen Volcanic National Park forest species from the Sierra Nevada zonation models. Descriptions of vegetation distribution at Lassen (Gillette *et al.*, 1962; Heath, 1967; Cooke, 1962; Griffin, 1967; Taylor, 1990; Parker, 1991) are generally too limited in scope and emphasize the floristic rather than the quantitative viewpoint required by this study.

At present, digital elevation models are the primary source for topographic data at the 1:24,000 scale. Information extracted from the DEMs such as slope, aspect, elevation, and potential soil moisture are affected by errors associated with these data (Walsh *et al.*, 1987) which can cause spurious results in the GIS modification process and reduced mapping accuracy of forest species. These errors include horizontal striping and missing data. Local errors such as missing data or pits may be corrected by interpolation with surrounding data. Striping affects entire datasets, making error amelioration especially difficult. In this study, we used mutliple filters to vertically interpolate across striped areas and to smooth the resultant image. This may have reduced the overall accuracy of the topographic information; however, products from our topographic analysis were affected significantly by the presence of these errors.

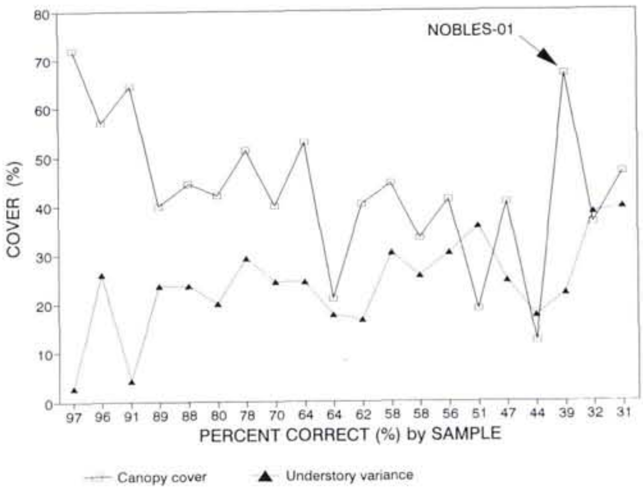

Figure 2. Analysis of canopy and understory cover variance across a gradient of decreasing sample accuracy for spectral classification.

Mapping could be improved by altering how ancillary and spectral information are correlated in the GIS context. Skidmore (1989) reported that class modification by environmental data is enhanced using Bayesian probabilities in an expert system. This method assumes that species are distributed across a continuum of environmental gradients rather than distinct, exhaustive habitats. Translation of this approach into popular GIS softwares will ultimately increase mapping ability.

Finally, usage of the image processing techniques and GIS integration described in this study beyond the Lassen Park ecosystem should be done with discretion. The methods and results presented here represent our best effort to use the spectral and environmental data to describe the Lassen landscape. A review of the literature on forest mapping using remote sensor sources demonstrates some site-specificity as to which spectral wavelengths are most informative or which classification procedure is most effective. The variablity from one site to another is great given the spectral response to heterogeneity at the sub- and super-pixel level. Equivalent mapping performance in other forest systems using the procedures outlined in this study would be a function of similarity in forest species composition, structure, age, vigor, and other stand variables, as well as the response of the forest species to topographic zonation as defined here.

Conclusions

Forest species could not be separated using only spectral data, whereas genus level mapping is possible at a level of 73 percent accuracy using an unsupervised classification of Landsat TM data. Forest structure, especially canopy coverage and understory vegetation, seems to affect classification performance. This study also demonstrated that spectral based, genus level maps can be modified with terrain data in a GIS to produce forest species maps at an accuracy level of 58 percent. Maps may be improved by refining the information through a majority analysis to accentuate specific map characteristics over others, based on usage and need. GIS map accuracies are a function of confinement of forest species to modeled habitats and reliable definition of these habitats, data quality, and GIS software capability.

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