# Using Thematic Mapper Imagery to Examine Forest Understory

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ABSTRACT: Most recent research in remote sensing has focused on the canopy vegetation characteristics with little attention given to the associated understory. The objective of this study was to examine the feasibility of detecting the presence or absence of vegetated understory for varying canopy closures within the Sierran mixed conifer zone using the high spectral and spatial resolution of Landsat Thematic Mapper (TM) data. Canopy and understory density and composition were measured in the field for 60 plots within a USGS 7.5 minute quadrangle map. The TM image was classified using an unsupervised classification approach. The TM band combinations evaluated include (A) 2,3,4; (B) 2,3,4,7; (C) 1,3,4,5; (D) 2,3,4,5,7; (E) 2,4,5; and (G) 4,5,7. The forested areas were stratified into three categories of canopy closure: sparse (<30percent), moderate (30 to 70 percent) and dense (>70percent). In each of the canopy classes, presence or absence of vegetated understory was then determined using spectral response pattern analysis. All of the ground data were then used to assess the accuracy of the classification for each of the seven band combinations. Any TM band combination including band 5 produced equally accurate canopy and understory classification results. Overall, the accuracy of understory presence or absence ranged from 55 to 69 percent.

## INTRODUCTION

RESOURCE MANAGERS are required to identify, map, assess, and manage vegetation communities so that multiple-use objectives, as defined in the Multiple Use and Sustained Yield Act (1960), are achieved. Maps derived from satellite imagery have been used to quantify natural resources over large areas for the purpose of identifying and evaluating timber resources (Fox *et al.*, 1983; Franklin *et al.*, 1986) wildlife habitats (Lyon, 1983: Stenback *et al.*, 1987); watershed resources (Smith and Blackwell, 1980; Khorram and Katibah; 1984), and fire potential (Sadar *et al.*, 1982; Burgan and Shasby, 1984). However, the focus on overstory conditions in these satellite-derived maps has limited their applicability to the resource manager (De-Steiguer, 1978; Mayer 1984). In addition, previous studies have not made actual measurements of understory properties.

From a resource management perspective, the understory represents a critical component of a forest ecosystem. Knowledge of herbage and browse production, as well as composition, enables the wildlife manager to identify areas of suitable habitat. Erosion potential, evapotranspiration rates, and water quality are also influenced by understory conditions. Understory conditions also affect seedling survival, as well as the prescription for any burning activity.

If a methodology using TM data can be developed to characterize the understory, an additional component of the spectral response from a particular area can be explained. In the past, the understory has been treated as"noise," as it confused the expected spectral response from the forest overstory. Improvements in spectral and spatial resoultion in the TM sensor suggest that the understory component can now be examined, particularly because the first five bands of the TM sensor were designed specifically to sense the biophysical properties of vegetation (Lillesand and Kieffer, 1979). Therefore, the purpose of this paper is to investigate the utility of Landsat TM data for detecting the presence of vegetated understory within the Sierran mixed conifer zone.

## LITERATURE REVIEW

Few remote sensing studies of coniferous forests have investigated the spectral characteristics of both understory and overstory (i.e., the canopy) in terms of the contributions of each to the recorded pixel value. When the canopy is open, the resultant spectral signal is a combination of the response from the canopy and whatever occupies the area under the canopy (Curran, 1980: McCloy, 1980). Several agricultural studies have investigated the effect of soil background, shadowing and plant spacing to the response signal of a crop (Kauth and Thomas, 1976; Richardson and Wiegand, 1977; Westin and Lemme, 1978). However, the agricultural techniques were applied to environmental conditions that rarely exist in the forest ecosystem (flat terrain, uniform soils, homogeneous crops, etc.).

Cover type and stand structure of the forest overstory have been investigated using remotely sensed data, where structural properties include crown closure, basal area, leaf area index, and tree size (Fox *et al.*, 1983; Sjpanner *et al.*, 1984; Franklin *et al.*, 1986; Peterson *et al.*, 1986). In these studies, the effect of the understory was acknowledged, but it was not related quantitatively to the reflectance response. Using the lower spatial and spectral resolution MSS data, Mayer and Fox (1981) describe the effect that a brush understory has on the spectral curve for poorly stocked mixed conifer and ponderosa pine stands. Their lowest classification accuracy was for poorly stocked mixed conifer stands (56 percent). This forest class often had a high peak in MSS band 6 (700 to 800 nm) which they attributed to the highly IR-reflective brush understory. Because their objective was to identify conifer species groupings, they used this information to rule out that spectral curve (with a higher peak in MSS band 6) as a representative spectral signature, rather than as a separate class associated with an understory. Their findings do support the idea that the understory's contribution to the pixel value can be quantified, particularly when plotted as a function of canopy density (percent stocking) for each of the MSS spectral bands.

Sadowski and Malila (1978), using reflectance modeling, demonstrated that canopy reflectances for increasing vegetation densities differed dramatically depending on spectral band, base material, and vegetation type. However, they conclude that "only the sparse overstory situations produced sufficient variation in reflectance as a function of understory condition to offer hope of direct Landsat sensing of understory conditions." Their empirical results were also based on MSS data. With the higher spectral and spatial resolution of the TM sensor, understory detection is more feasible. TM signals are averaged over 0.22 acres, instead of the one acre MSS resolution. Depending upon the spatial orientation of the stand, the TM sensor offers a better opportunity to look between tree canopies.

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It has been suggested that remotely sensed data of finer spatial resolution has an increased level of "scene noise" (or variance which may degrade classifier performance (Sadowski and Malila, 1978; Wierson and Landgrebe, 1979). The conclusions from a forested region investigated in northern Idaho with Thematic Mapper Simulator (TMS) data indicate that the variance within their scene was primarily due to the structural characteristics of the forest canopy (Spanner *et al.*, 1984). They recommended that future work should further define the contribution of specific forest canopy structural properties to scene variance. As a follow up to the Idaho experiment, an analysis of forest structure in Sequoia National Park using TMS data was reported by Peterson *et al.* (1986). The results from this study suggest a strong spectral contribution to the total reflectance from smaller trees that are present in forest gaps. It is this type of sensitivity to forest structure which suggests the utility of TM data for detecting the presence of vegetated understory. Peterson *et al.* (1986) also discovered a saturation effect in the response from the clustering of older trees; it is expected that the contributing response from an associated understory may be obscured in this situation.

## METHODS

### Study Area

The study area for this investigation was the USGS 7.5-minute Meadow Valley quadrangle within Plumas County in northern California (Figure 1). This area is part of the Sierra Nevada mixed conifer forest cover type (Society of American Foresters, 1980). Forest structure in this cover type is typically multi-layered. Dominant overstory species include white and red fir (*Abies concolor* and *A. magnifica*), ponderosa, Jeffrey, and sugar pines (*Pinus ponderosa, P. jeffreyi,* and *P. lambertiana*), Douglas fir (*Pseudotsuga menziesii*), and incense cedar (*Calocedrus decurrens*). When openings occur in the overstory, vegetated understory is more prevalent (Kosco, 1980). The understory is predominated by brush; conifer and hardwood seedlings; and many species of grass and forbs. Specific brush species include deerbrush (*Ceanothus* sp.), manzanita (*Arctostaphylos* sp.), chinquapin (*Castanopsis* sp.), tanoak (*Quercus* sp.), bitter cherry (*Prunus* sp.), and gooseberry (*Ribes* sp.). Granitic outcroppings, exposed ultramafic soils, and mine tailings are also common throughout the area.

### Reference Data

For the vegetation analysis, 60 plots were selected randomly from the Meadow Valley quadrangle using a stratified systematic unaligned sampling scheme (Ayeni, 1982). These plots were previously established from an earlier study by DeGloria (1986). These plots were useful for this study because of the earlier data collected on associated soil types and terrain conditions. DeGloria (1986) also had identified each plot on 1:24,000-scale aerial photography. Canopy closure was assessed using U.S. Forest Service tree crown desity scales, where each plot was categorized as having a canopy closure class of sparse (<30 percent), moderate (30 to 70 percent), or dense (>70 percent).

Understory conditions were measured in August 1986. The method for collecting the understory information (species composition and density) was the line-intercept method (Deusar

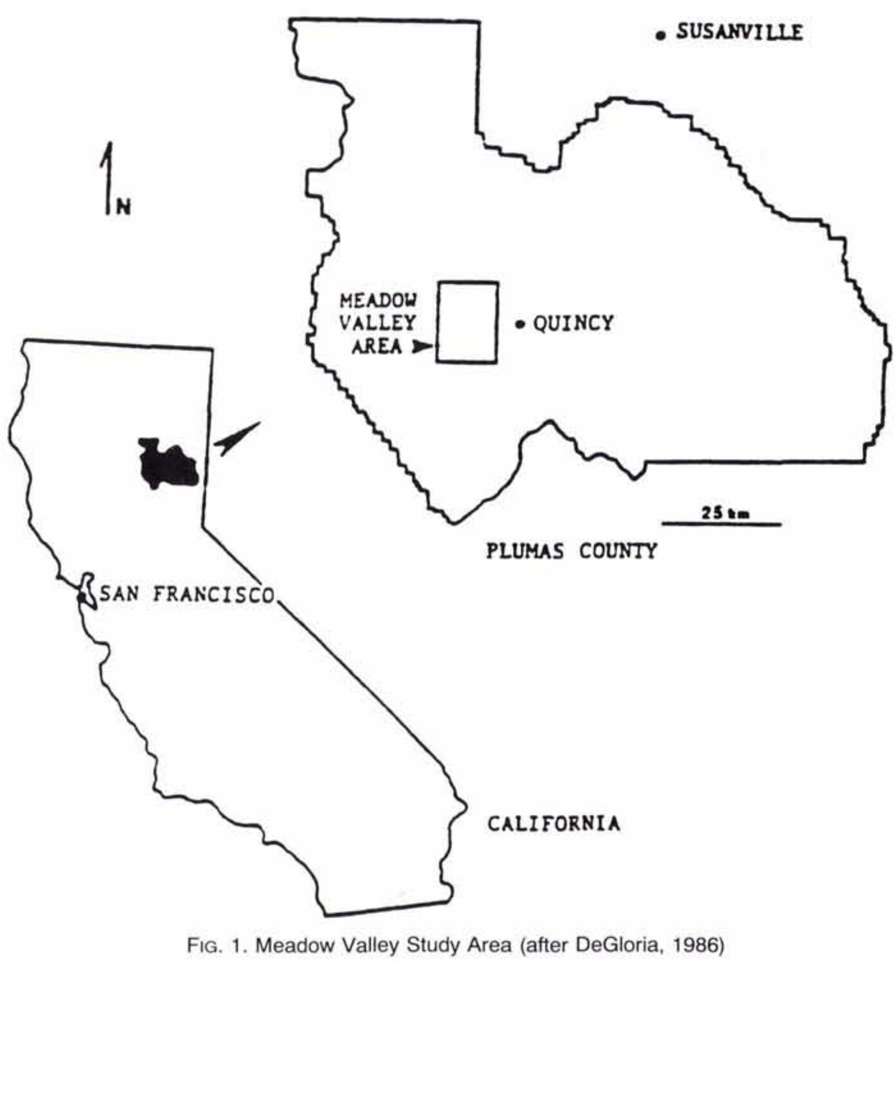


FIG. 1. Meadow Valley Study Area (after DeGloria, 1986)

and Shugart, 1978). Understory vegetation (brush, seedlings, saplings, and pole trees) and exposed base materials (rock, bare soil, and litter) were recorded to the nearest cm as they intercepted two 50-metre transects positioned perpendicular to each other at the plot center. Orientation was dependent on slope: one transect ran parallel to the slope, the other perpendicular. This orientation accounts for vegetation variability as it relates to local topographic conditions. In the event of multiple layers of understory, the species that overtopped the others was recorded. The assumption was made that the overtopped vegetation has a greater effect on the understory's radiance contribution because it is that which is "seen" by a nadir-looking sensor. For purposes of this initial investigation, each plot was summarized in terms of the presence or absence of vegetated understory, where "presence" was defined as greater than 50 percent vegetated cover. It is recognized that transect sampling may over-sample the center of an area. However, it is a very convenient method for sampling on slopes.

### Image Processing

Landsat Thematic Mapper (TM) digital imagery was acquired 28 July 1986. A subscene of the study area was extracted. All image processing was performed on the University of California, Berkeley—Remote Sensing Research Program's SUN microcomputer using ELAS digital image processing software. Using an unsupervised approach with a maximum likelihood classifier, seven classifications were generated utilizing the following TM band combinations:

(A) Bands 2,3,4
(B) Bands 2,3,4,7
(C) Bands 1,3,4,5
(D) Bands 2,3,4,5,7
(E) Bands 2,4,5
(F) Bands 3,4,5
(G) Bands 4,5,7

Selection of the seven band combinations was based on recommendations published in the literature and from past experience. For example, the first combination was selected for comparison with MSS results (Mayer and Fox, 1981). TM band combinations that provided the greatest spectral separation for forested areas were then selected. Band combination (C) provided the best overall separability for a forested area in a study by Latty and Hoffer (1980). This study also found that using more than four bands did not improve classification accuracy substantially. Thus, band combinations (A), (B), and (D) were selected for comparing the effects of an increased number of bands on classification accuracy. In addition, the last three band combinations (E, F, and G) were evaluated to see what effect reducing the quantity of TM data had on the classification accuracies. In addition, band combinations representing continous portions of the electromagnetic spectrum were emphasized because the slopes between bands were known to be key features in the labeling process (Mayer and Fox, 1981). Thermal band 6 was not investigated because of its low spatial resolution.

No registration and therefore no resampling was performed on the data to insure that all of the spectral variability within the study site was preserved (Verdin, 1983). The unsupervised classification approach was selected for this initial examination. This approach was considered the most appropriate because it characterizes the full range of spectral variability in the data and is not dependent on training areas.

### Image Classification

Labeling each cluster within each of the seven band combinations was accomplished in two steps. The first step involved labeling the cluster by canopy closure class. Using the display device, each cluster was isolated and categorized into one of the three canopy closure classes (i.,e., sparse, moderate, or dense) or identified as "non-forest." Spatial and spectral patterns of each cluster were examined in conjuction with the corresponding orthophoto to aid in the labeling process. Familiarity with the Meadow Valley quadrangle faciliated the canopy density labeling.

The second step involved labeling each cluster by presence or absence of vegetated understory. Each cluster's spectral response curve was graphed and grouped according to the canopy cover class it was assigned to in step one. Distinct patterns existed in the graphs corresponding to the sparse and moderate canopy cover classes. It was hypothesized that the variation in the graphs associated with these two canopy cover classes was indicative of variations in understory conditions.

The spectral response patterns were used for identifying key features indicative of each understory class. Key features include (1) the slopes between successive bands, particularly between TM bands 2 and 3, and TM bands 4 and 5; and (2) the range of spectral values in each band. Because the image processing software, ELAS, does not save the rescaling constants, the actual DN (digital numbers) are not represented. Radiance values would have been useful to compute for comparison with past results (Peterson *et al.*, 1986), but these values also could not be determined from the rescaled values reported by ELAS. However, comparisons can be made with the shape of the spectral response curve, particularly with the study by Mayer and Fox (1981).

Examples of the spectral response patterns associated with each of the four classes are shown in Figures 2 and 3. These patterns were created by taking the mean cluster value in each band for each class, in each of the seven classification combinations (Table 1). Mean standard deviations (STD) were also computed by taking the means of each sample STD in each band for each class, in each of the seven classifications.

Examples of key features are more evident in the mean spectral response patterns corresponding to the sparse canopy conditions (Figure 2). For example, presence of vegetated understory was characterized by a negative slope between bands 2 and 3 whereas a positive slope indicated an absence of understory. When the slopes were the same, slopes between bands 4 and 5 could be evaluated. Peaks in band 4 were representative of a vegetated understory condition, and peaks in band 5 and 7 were associated with the absence of vegetated understory. However, the larger standard deviations corresponding to TM band 5 also indicate greater classification confusion.

In analyzing the range of spectral values corresponding to

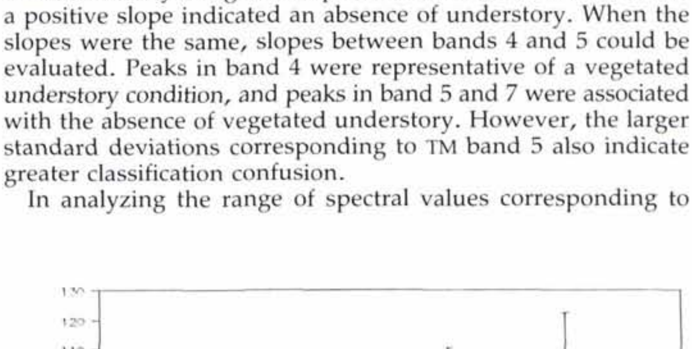


FIG. 2. Mean Spectral response patterns for sparse canopy with understory present and absent.

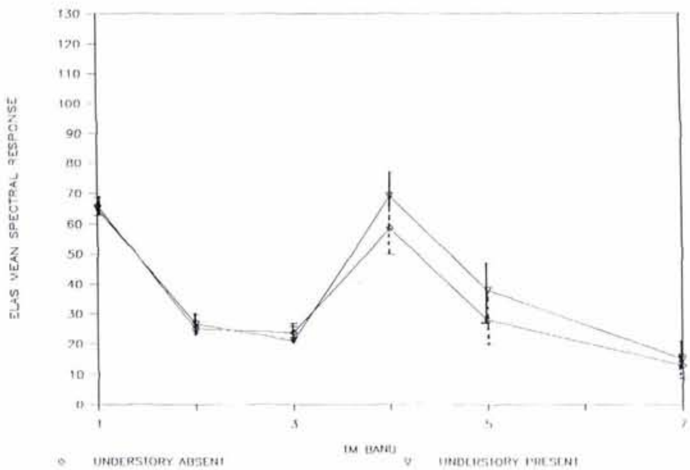


FIG. 3. Mean spectral response patterns for moderate canopy with understory present and absent.

each band, different spectral thresholds were set depending upon the canopy cover class under investigation. Every attempt was made to remain consistent in the labeling decisions between each of the seven classifications. In general, the emphasis was on the slopes between bands rather than the actual ELAS spectral response value.

### CLASSIFICATION ACCURACY

Fifty-one of the 60 field plots were used as the reference data for testing the classification accuracy (note: the other nine plots were either under cloud cover or in the dense canopy cover class). Each canopy-understory class had 14 plots, with the exception of the sparse canopy-understory absent class which had nine plots. Each field plot was registered to the raw image so that the corresponding cluster value could be extracted. A 3 by 3 window was centered on each plot and the most frequently occuring cluster value was selected as representative of that plot. This procedure was used so as to minimize misclassification of plots due to registration errors. In the case of a tie, the value of the centered cluster was extracted.

An error matrix was generated for each of the seven band combinations for the overstory classification (density) and for the understory classification (presence or absence). A measure of overall performance accuracy (percent correct) was computed for each matrix. In addition, another measure of agreement, Kappa, was computed for each matrix. The Kappa statistic incorporates the off-diagonal elements (i.e., error) of the error matrix into the accuracy measure. It also allows one to perform a statistical test between error matrices to determine which are significantly different (Congalton *et al.*, 1983). This technique was used to statistically determine which band combinations were best for detecting forest understory.

## RESULTS

Table 2 presents the results for the overall performance accuracies and Khat values (i.e., computed Kappa statistic) for the overstory classification. Table 3 presents the results for the understory classification. TM band combination 2,3,4,5,7 resulted in the highest overall accuracy for both overstory and understory classifications (86 percent and 69 percent, respectively). However, TM band combinations 1, 3, 4, 5 and 4, 5, 7 also tied for highest overstory and understory classifications, respectively. In contrast, the lowest accuracies were associated with band combinations 2,3,4,7 (71 percent and 55 percent respectively).

TABLE 1. MEAN SPECTRAL RESPONSES FOR EACH CLASS

| Thematic Mapper Band: | 1 | 2 | 3 | 4 | 5 | 7 |
|---|---|---|---|---|---|---|
| Sparse Canopy-Understory Absent: | | | | | | |
| Mean: | 82 | 37 | 46 | 69 | 95 | 41 |
| Mean STD: | 8 | 5 | 9 | 6 | 28 | 12 |
| Sparse Canopy-Understory Present: | | | | | | |
| Mean : | 70 | 29 | 28 | 93 | 58 | 17 |
| Mean STD: | 7 | 2 | 3 | 18 | 10 | 4 |
| Moderate Canopy-Understory Absent: | | | | | | |
| Mean: | 66 | 25 | 24 | 58 | 28 | 13 |
| Mean STD: | 3 | 1 | 3 | 8 | 8 | 4 |
| Moderate Canopy-Understory Present: | | | | | | |
| Mean: | 65 | 27 | 21 | 69 | 38 | 15 |
| Mean STD: | 1 | 3 | 5 | 8 | 9 | 6 |

TABLE 2. OVERSTORY CLASSIFICATION ACCURACIES (IN PERCENT)

| Band Combination | Overall Classification Accuracy | KHAT |
|---|---|---|
| TM 2,3,4,5,7 | 86.0 | 72.8 |
| TM 1,3,4,5 | 86.0 | 72.8 |
| TM 2,4,5 | 84.3 | 69.3 |
| TM 4,5,7 | 84.3 | 69.0 |
| TM 3,4,5 | 84.3 | 68.7 |
| TM 2,3,4 | 84.3 | 68.7 |
| TM 2,3,4 | 74.5 | 48.3 |
| TM 2,3,4,7 | 70.6 | 38.5 |

TABLE 3. UNDERSTORY CLASSIFICATION ACCURACIES (IN PERCENT)

| Band Combination | Overall Classification Accuracy | KHAT |
|---|---|---|
| TM 2,3,4,5,7 | 68.6 | 37.9 |
| TM 4,5,7 | 68.6 | 37.3 |
| TM 1,3,4,5 | 66.7 | 33.6 |
| TM 3,4,5 | 66.7 | 29.5 |
| TM 2,4,5 | 64.7 | 29.5 |
| TM 2,3,4 | 60.8 | 22.0 |
| TM 2,3,4,7 | 54.9 | 7.9 |

Kappa analysis resulted in lower accuracies; however, the rankings agreed with those achieved with the traditional accuracy assessment approach. The Kappa test also indicated that, for measures of overstory, only band combination 2,3,4,7 was significantly different than the rest of the combinations. Applied to compare understory classifications, the Kappa test concluded that none of the seven band combinations were significantly different. It might appear surprising that the Khat values for the band combinatin 2,3,4,7 is not significantly different (8 percent for understory). This may be attributed to the small sample size ($n = 51$) and to the small 2 by 2 matrices (where overstory was either classified as sparse or moderate,and understory was either present or absent), resulting in a loss of statistical power. The two band combinations that ranked last in classification accuracy for both overstory and understory did not include band 5; this suggests the importance of this particular band for forest canopy-understory classification. Unfortunately, the range of accuracies associated with understory classification (55 to 69 percent) are not encouraging. However, presence of vegetated understory was more accurately classified in sparse canopy conditions, confirming the results of past studies cited earlier in this paper.

Although the results of the Kappa analysis show no significant differences between understory classifications, there are significant differences in individual spectral bands. The mean spectral response patterns for each canopy-understory class (Figures 2 and 3) reveal the significant differences between understory presence and absence for the individual TM bands 3,4,5, and 7 in the sparse canopy graph (Figure 2). This information is useful in selecting the optimum bands for classifying understory presence and absence.

## DISCUSSION

The acquisition date of the TM image is considered to be the critical factor controlling the level of classification obtainable. The August image date selected may not reflect the vegetated understory's "peak" contribution to the pixel value. For further investigations, this analysis could be repeated using different acquisition date, selected on the basis of the dominant canopy and understory phenology. However, the August date was consistent with the date selected for the McCloud study by Mayer and Fox (1981), a geographically similar area.

Misclassification could also be attributed to registration errors. Each classification was performed on the raw unregistered TM image; thus, finding the corresponding field plot location was difficult at times. This task was accomplished by registering a 1983 UTM-registered TM scene for the same area along with the digitized field plot locations to the raw 1986 image. The 3 by 3 window was used to extract the corresponding cluster values which minimized misregistration errors.

Another consideration for future investigations is the selection of threshold values. Presence of vegetated understory was identified in the reference data—set as those plots exhibiting greater than 50 percent vegetated understory. Higher densities may need to be present (i.e.,>70 percent) before detection is feasible.

Vegetation composition, both in the overstory and understory, should also be evaluated. Because there were not any pure stands of a particular overstory species, a mixed spectral response was expected, characteristic of the Sierran mixed coniferous forest. Some stands were dominated by particular species, and this could have influenced the spectral response observed. Similarly, areas were encountered where there was a dominance of a particular understory vegetation (i.e., manzanita and fir seedings). However, stratifying the area in terms of these dominant vegetation cover types would have resulted in even smaller samples sizes per class. Instead, the reference data were collapsed into the most general classes: sparse or moderate overstory associated with the presence or absence of vegetated understory. For future studies, it is recommended that this analysis be performed using pure stands with homogeneous understory vegetation (such as in platations where brush control is practiced versus areas where it is not). Spectral influences from the atmosphere, slope, and aspect should also be investigated. However, the spectral values did not appear to be influenced by shadowing effect, particularly within the sparse and moderate canopy cover classes, since low values in the infra-red bands were not encountered.

The seven band combinations selected also may not be optimum for understory detection. In addition to the specific TM band combinations selected, the number of bands should be more thoroughly investigated. Accuracies associated with the three-band combinations did not rank the highest. Thus, the added spectral information provided by additional bands may be needed for increased classification accuracy. The inclusion of more bands (greater than three) is useful from a labeling standpoint because it allows for greater interpretation of the spectral response patterns, especially when bands are continuous (i.e., TM bands 2,3,4,5,7). The tradeoff is the resultant increase in processing time. The analysis of change in spectral values from band to band (i.e., slopes) was more helpful than separate examination of means alone.

The importance of TM band 5 is apparent in the reported classification accuracies. The spectral region of this band (1.55 to 1.75 μm) is known to be responsive to leaf moisture content (Lillesand and Kiefer, 1979). Although leaf moisture content was not a measured variable, we can speculate that TM band 5 is responding to the combined canopy and understory moisture contents, when the understory is present. In retrospect, a band combination excluding TM band 4 also should have been examined. TM band 4(0.76 to 0.90 μm) is an indicator of vegetation biomass (Lillesand and Kiefer, 1979). Thus, classification accuracies could have been significantly reduced without the inclusion of this band as well.

## CONCLUSION

With the tremendous developments in satellite technology, particularly the spatial and spectral improvements of the TM sensor, it is essential that the potential of the high resolution imagery be evaluated. A methodology has been presented here using an unsupervised classification approach in conjunction with spectral response pattern analysis for evaluating the spectral contribution from vegetated understories. In this initial investigation, TM band combinatin 2,3,4,5,7 ranked the highest for classification of overstory and understory, and TM band combination 2,3,4,7 ranked the lowest. The added spectral information provided by TM band 5 appears to be the key ingredient. Overall, the classification accuracies for understory were low (55 to 69 percent). A detailed classification using TM imagery needs to be performed in an area of more uniform canopy-understory condition to fully assess the potential of this technology. This future work should concentrate on studying individual spectral band responses to various biophysical phenomena as well as band combinations.

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