



Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery

E. H. HELMER^{††}, S. BROWN[§] and W. B. COHEN^{¶¶}

[†]Department of Forest Science, Oregon State University, Corvallis, OR 97330, USA

[§]Winrock International, 1611 N. Kent Street, Suite 600, Arlington, VA 22209, USA

^{¶¶}U.S. Forest Service, Pacific Northwest Research Station, 3200 S.W. Jefferson Way, Corvallis, OR 97331, USA

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Abstract. When mapping land cover with satellite imagery in montane tropical regions, varying illumination angles and ecological zones can obscure the differences between spectral responses of old-growth forest, secondary forest and agricultural lands. We used multi-date, Landsat Thematic Mapper (TM) imagery to map secondary forests, agricultural lands and old-growth forests in the Talamanca Mountain Range in southern Costa Rica. With stratification by illumination and ecological zone, the overall accuracy for this classification was 87% with a Kappa coefficient of 0.83. We also examined spectral responses to forest successional stage, ecological zone and aspect illumination for the TM Tasseled Cap indices, TM (2 × 6)/7, TM 4/5 and TM difference bands, and whether using digital data from multiple decades improved classification accuracy. Digital maps of ecological zones should be useful for large-scale mapping of land use and forest successional stage in complex montane regions such as those in Central America.

1. Introduction

Changes in forest land use and land cover impact biodiversity, watershed processes, and biogeochemical cycles such as forest carbon budgets (Salati and Vose 1984, Franklin and Forman 1987, Detwiler and Hall 1988, Brown and Lugo 1990, Bierregaard *et al.* 1992, Houghton 1995, Helmer and Brown 1999). In tropical regions, such changes include logging, clearing and burning for conversion to pasture or cropland, and secondary vegetation regrowth during fallow periods or after abandonment. In such changing landscapes, ecosystem degradation can slow or prevent recovery from such disturbances (Uhl *et al.* 1988). In addition, mistaking secondary forests for old-growth forests (1) underestimates the role of tropical forests as a carbon sink because old-growth forests are assumed to be in carbon balance, whereas secondary forests sequester carbon and may be partly responsible for the 'missing sink' in global carbon budgets (Brown and Lugo 1990) and (2) overestimates

[†]Corresponding author's current address: U.S. Forest Service, International Institute of Tropical Forestry, P.O. Box 25000, Río Piedras, PR 00928-5000, USA; email: chelmer@iitf@fs.fed.us

the carbon pool of tropical forests, because secondary forests contain less biomass, and most likely less soil carbon, than do old-growth forests. Any differences in the rates at which carbon accumulates on abandoned lands are important to include in landscape analyses of forest carbon dynamics. If sustainable development of these landscapes includes maintaining ecosystem functions, then ecosystem components that enable forest recovery, such as remnants of old-growth forest, must be maintained (Perry 1995, Turner and Corlett 1996). To understand how human disturbances interact with forest recovery, we need to be able to monitor the extent and condition of tropical secondary forests, a topic that is currently receiving much attention in remote sensing (e.g. Moran *et al.* 1994, Foody *et al.* 1996, Steininger 1996).

Most previous land-cover and forest successional stage mapping with satellite imagery in tropical regions has been at lower elevations with relatively gentle topography. Mapping disturbed versus undisturbed vegetation over large regions within Central America and other parts of the world will need to account for changes in vegetation zones that occur with changes in altitude. Yet to our knowledge little research has explicitly addressed the impact of topography on mapping land use and forest successional stage in mountainous tropical regions that are complex because they extend across several ecological zones. Spectral signatures of areas with similar cover type are also more variable in montane forests because of variable topographic illumination (Sader *et al.* 1989). Although digital elevation models (DEMs), of scale 1:250 000 or less, can assist with normalizing digital image data for topographic effects (Smith *et al.* 1980), DEMs at this scale have not been widely available for most tropical regions. An additional complication in mountainous regions is that vegetation zones usually change with altitude.

Although researchers have successfully used satellite imagery to measure forest conversion in the humid tropics (e.g. Sader and Joyce 1988, Skole and Tucker 1993), detecting the fate of cleared lands has presented some difficulties. Determining forest successional stage involves detecting more subtle vegetation differences than does mapping deforestation. As a result, mapping these elements with satellite imagery currently requires more detailed reference data. Obtaining finer-scale aerial photos and access to field sites for many tropical regions can be costly (Sader 1995). Furthermore, tropical secondary forest older than 12–20 years is difficult to distinguish from old-growth forest with Landsat Thematic Mapper (TM) imagery (Sader *et al.* 1989, Moran *et al.* 1994, Steininger 1996). Distinction of different disturbed land cover classes, both forest and non-forest, can also be inaccurate (Sader *et al.* 1991, Foody *et al.* 1996, Steininger 1996).

The overall objective of our study was to determine the feasibility of using Landsat imagery from multiple dates to map land use and forest successional stage at a single date in a mountainous tropical region for which limited reference data were available. To attain our overall objective, we used the following approaches. First, we examined various spectral indices for distinguishing land-cover classes, including spectral differences between image dates. Multi-date imagery also allowed us to estimate secondary forest age. Secondly, we sought to determine whether adding the dimension of temporal changes in spectral response would improve classification accuracy. Previous work with multi-date imagery (e.g. Tucker *et al.* 1985, Lambin and Strahler 1994) merged imagery from multiple seasons to use in classifying land cover. We tested the usefulness of merging spectral data from multiple decades for detecting land use and land cover, including successional forest. Because atmospheric differences between image dates can become important with many

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change detection applications (Coppin and Bauer 1996), we also incorporated radiometric normalization of image dates. Thirdly, we applied these techniques to create a land-use/land-cover (LULC) map of a mountainous region of Costa Rica.

2. Methods

2.1. Study region

The 42 300 ha study region is located in southern Costa Rica, in the south-western part of the Talamanca Mountain Range (figure 1). It includes private lands and portions of two forest reserves, both of which are situated on either side of the Inter-American Highway: the Rio Los Santos on the Pacific slope, created in 1975, and the Rio Macho on the Atlantic slope, created during the 1960s. Both reserves provide buffer zones to the UNESCO La Amistad Biosphere Reserve and World Heritage Site (Kappelle and Juarez 1994), which will soon include what is now the Rio Macho reserve.

Elevation within the study area ranges from about 1500 to 3500 m. Forest ecosystems include lower montane moist forest, lower montane wet forest, montane rain forest and subalpine rain páramo (*sensu* Holdridge *et al.* 1971), with a dry

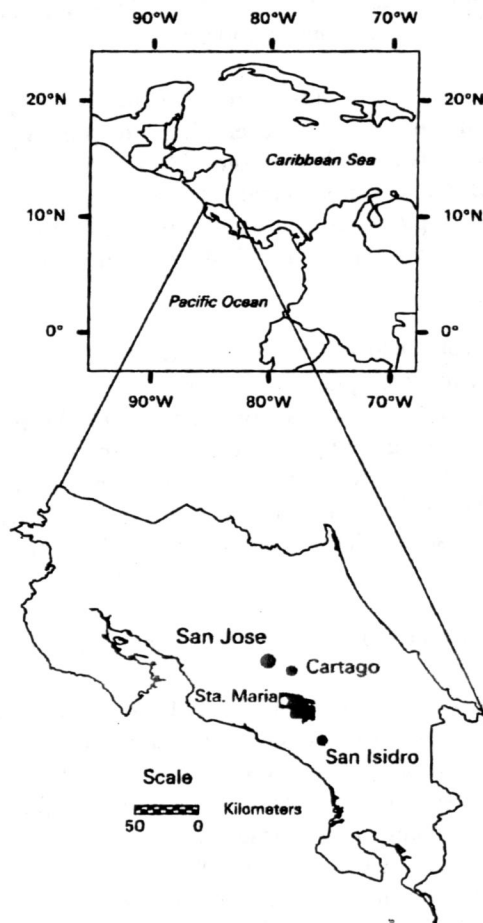


Figure 1. Location of study area (black shaded area) within Costa Rica.

season from December through April. The lower montane wet and montane rain forests are tropical evergreen and consist of communities dominated by one to three species of *Quercus*. Between about 2200 and 2900 m elevation, the average canopy heights of these communities range from 25 to 40 m, depending on community type and elevation (Kappelle *et al.* 1989). Taller forest transitions to subalpine forest (*sensu* Kappelle 1991, and Soto and Diego Gomez 1993), with canopies as short as 12–20 m, between about 2700 and 3000 m. Between 2900 and 3100 m, upper montane and subalpine forest grades to subalpine rain páramo, where Ericaceous species or grasses of the bamboo genus *Chusquea* dominate (Kappelle *et al.* 1989, Kappelle 1991). The elevations of these transitions depend on the maximum elevation of a given massif (Kappelle *et al.* 1989) and its aspect relative to the trade winds, and they are at lower elevation on windward (north-east-facing) aspects.

Clearing of montane forests for pasture or crops began with the construction of the Inter-American Highway in the 1940s. However, most deforestation in the study region occurred between 1950 and the early 1970s, when small settlements became villages after construction of the highway. On the Pacific slope, coffee (*Coffea* sp.) is cultivated below about 1800 m elevation, and fruit orchards occur between about 1800 m and 2400 m. Cattle grazing and blackberry cultivation (*Rubus* sp.) occur on both slopes between about 1800 and 2950 m. Charcoal and fence posts, mainly from native oak trees and often from dead wood in previously cleared areas, are produced from about 2650 to 2950 m. Other crops include potatoes and vegetables (Kappelle and Juarez 1995).

The landscape now consists of a mosaic of old-growth forest, pasture, orchards and secondary shrublands and forests developing on previously cleared lands. Secondary forests are easily distinguishable from old-growth forest because of differences in species composition and canopy height. For example, Kappelle *et al.* (1996) reported that maximum canopy height was about 10 m in 8–20 year-old forest, and 15 m in 25–32 year-old forest, compared with 20–40 m attainable in old-growth forest.

2.2. Approach

Using reference data from field observations and aerial photos, we used multi-date, Landsat TM imagery to develop a classification scheme that mapped secondary forests, agricultural lands and old-growth forests in 1992. Mapping LULC with satellite imagery consisted of image pre-processing, collecting reference data, categorizing land cover into thematic classes which would both meet study objectives yet still be distinguished reliably, and selecting a classification model through comparing the accuracies achieved by using different combinations of spectral indices.

2.3. Image pre-processing

Image pre-processing converts original satellite images into more readily interpretable data that feed directly into classification modelling. It included co-registering and merging multiple image dates (1) to observe patterns of spectral responses for the same locations over time, (2) to estimate age classes of secondary vegetation, and (3) to test whether including spectral indices from multiple image dates would improve classification accuracy. It also included examining spectral indices that correlated with forest development in other research, such as the TM Tasseled Cap (Crist *et al.* 1986), wetness index (e.g. Cohen *et al.* 1995) and radiometrically normalizing spectral data in multi-date images. Finally, image pre-processing included masking clouds and cloud shadows and stratifying the imagery by ecological zone.

We co-registered two Landsat TM images dated 6 February 1986 and 3 April 1992 to UTM coordinates using a nearest neighbour resampling to a 25 m cell size. The quadratic transform, based on 65 points, had a root mean square error (RMSE) of less than ± 0.5 pixels. Cloud-free, digital Landsat Multi-Spectral Scanner (MSS) data were not available for this region from the 1970s. However, we created a grey scale MSS image by scanning a 9 × 9 inch black-and-white positive of MSS band 5, dated 12 February 1975. We co-registered this image to the other dates using a nearest neighbour resampling to a 25 m cell size. The RMSE of the quadratic transform, based on 37 points, was about ± 1.9 pixels. We did not use digital data from the scanned image in classification, but we used it for visual interpretation of secondary forest age.

A second image pre-processing step normalized imagery for radiometric differences between dates. Its goal was to minimize between-date spectral changes caused by changes in such things as earth-sun distance, detector calibration, sun angle, atmospheric condition and sun-target-sensor geometry (Jensen *et al.* 1995). The radiometric normalization method of Hall *et al.* (1991) calibrates each TM band in an image to the corresponding band in a reference date. The calibration is done by developing regression lines between the two dates, one line for each band, from bright and dark targets. Bright targets usually correspond to rock outcrops or human-made structures such as metal buildings, while dark targets may correspond to deep water. Such targets are assumed to exhibit changes resulting only from radiometric differences between images.

We modified the method of Hall *et al.* (1991) to radiometrically normalize raw TM bands before transforming them to the TM Tasseled Cap (Crist *et al.* 1986) or other indices. We used co-locatable image elements for our bright and dark targets, instead of choosing targets from spectral space as in Hall *et al.* (1991). For dark target pixels, we sampled a relatively large number of pixels (about 200) from ocean water far offshore to minimize variability resulting from sediment-laden run-off, sun glint or waves. Normally preferable bright targets, such as human-made structures and rock outcrops, were too small to balance the large number of dark target pixels. As a result, we chose bright targets from the centres of large, bright pastures without trees. Rainfall timing, seasonality and pasture age can make pasture a relatively unstable target. However, we found that spectral differences between the two image dates were the same whether bright targets were from pasture or human-made structures ($p < 0.05$).

We transformed the TM images to the TM Tasseled Cap (TC) indices of brightness, greenness and wetness, using fixed TC coefficients from a guided principal components analysis (Crist *et al.* 1986). The TC transform condenses TM bands 1 through 5 and 7 into three indices that have ecologically meaningful interpretations and can be viewed in three-dimensional colour space, which enhances visual interpretation of imagery (Cohen *et al.* 1995). In addition, wetness showed promise for distinguishing secondary forest from old-growth because it can distinguish differences in forest structure (Cohen and Spies 1992, Fiorella and Ripple 1993, Cohen *et al.* 1995, Collins and Woodcock 1996). In the Pacific Northwest of the USA it is useful for distinguishing old-growth from mature secondary forest, and differences in aspect illumination do not greatly impact its values in closed canopy forests (Fiorella and Ripple 1993, Cohen *et al.* 1995).

We also examined the usefulness of two additional TM band indices for distinguishing old-growth from secondary forest, including the TM band index $(2 \times 6)/7$

(visible green \times thermal/mid-infrared) (Boyd *et al.* 1996). Although the original resolution of the TM thermal band 6 is 120 m, we resampled it to a 25 m cell size for calculating this index. We also calculated the TM band 4/5 ratio (near-infrared/mid-infrared), because Fiorella and Ripple (1994) and Kushla and Ripple (1998), found that it distinguished forest structure in the Pacific Northwest of the USA. Finally, we calculated three difference bands by subtracting each TC index in 1986 from the corresponding TC index in 1992 (i.e. brightness in 1992 minus brightness in 1986 for pasture, etc.). We compared class-by-class differences with the average difference band values of all LULC classes.

To avoid confusing clouds, cloud shadows and urban areas with land covers of major interest, we masked these image elements using the unsupervised classification algorithm ISODATA (ERDAS 1997). Beginning with 100 classes, we iteratively reclassified confused spectral classes until we isolated clouds, cloud shadows and urban areas from other scene components. Using the ERDAS (1997) program SIEVE, we excluded scattered pixels of topographic shadow from the cloud shadow mask.

To ensure that we could reliably identify secondary forest, we stratified the Landsat scenes by ecological zone using a 1:250 000-scale digital map of life zones (*sensu* Holdridge *et al.* 1971) developed by Bolanos and Watson (1993). Preliminary observations of spectral data had indicated that secondary forest in the oak-dominated montane rain and lower montane wet forest zones was confused with old-growth forest in adjacent premontane and lower montane rain forest.

Potential confusion between montane secondary forest and shorter upper montane and subalpine forest and shrublands had also become evident. Because humans do not intensively exploit the vegetation at these elevations, we isolated the upper montane and subalpine vegetation by digitizing four simple polygons around them. We classified the area within these polygons separately from the remaining image.

2.4. Reference data for classification training and testing

Reference data consisted of 356 polygons which averaged about 3 ha in size (range 0.75–9 ha). We categorized reference patches into the LULC types listed in table 1. In tables 1 and 2, old-growth forest refers to forest apparently undisturbed at least in the last century or more. About 80% of the reference patches were from direct field observations made by travelling on roads in the area in 1996 and 1997. The remaining observations were from interpretation of black-and-white stereo pairs of aerial photos, scale 1:60 000, dated the same season and year of the most recent TM screen image (dry season, 1992). There were few discrepancies between field observations in 1996–1997 and land cover in 1992, except that a few of the pastures had become overgrown with shrubs during the intervening 5 years.

For field-derived polygons we noted the presence of remnant old-growth trees on disturbed lands and any evidence that pasture was still in use. We also visually estimated the relative percent cover of bare soil, grasses, shrubs and trees for a subset of 96 of the polygons. We used the percent cover information to define secondary shrub/forest as apparently abandoned lands with 30% or more shrub cover that co-dominated with trees rather than pasture grasses. These shrub-dominated lands were not reliably distinct from cultivated blackberries (*Rubus* sp.) in our aerial photos. Although the uncertainty mainly occurred on shadowed slopes, we limited our reference data for this cover type to field-derived patches only, resulting in 28 secondary shrub/forest patches ≥ 6 years (19 sunlit and 9 shadowed) and 12 patches of cultivated blackberries or blackberries with pasture.

Table 1. Categories of land use and land cover for interpreting the 1992 TM image of the study area. Multi-pixel reference patches were grouped into the categories of land use and forest successional stage shown. The symbols listed are those used for figures 2–5. Table 2 lists symbols for shadowed slopes.

Category	Land use/land cover	Symbol on sunlit slopes
Agricultural lands	pasture lands, including:	PA
	pasture	
	pasture with shrubs	
	pasture with trees	CF/R
	pasture with trees/shrubs	
	pasture with remnant trees	
	fruit orchard	CF/R
	tree/shrub crops, including	
	coffee	
Transitional lands	blackberries, blackberries with pasture	SFSH <6
	secondary shrub/forest, <6 years old	
Abandoned/		
Successional lands†	secondary shrub/forest ≥6 years	SFSH ≥6
	secondary forest 6–16 years	SF 6–16
	secondary forest ≥17 years	SF ≥17
Undisturbed lands	old growth	OG
	subalpine old-growth forest and shrub	SubalpOG‡
	old-growth forest on ridges above 2400 m elevation	Other OG‡
	páramo	páramo‡

†All Abandoned/Successional lands may contain remnant old growth trees.

‡Lands not categorized by illumination class.

Table 2. Grouping of land-use and land-cover types on shadowed slopes for classifying the study area. Symbols shown are those used in figures 2–5.

Category	Land use/land cover	Symbol on shadowed slopes
Agricultural lands and	all pasture lands and fruit orchards	PA/AG
	Transitional lands	
	tree/shrub crops (coffee, blackberries)	
	secondary shrub/forest <6 years	PA/AG
Abandoned/		
Successional lands†	secondary shrub/forest ≥6 years,	SFSH/SF ≥6
	secondary forest ≥6 years	
Undisturbed lands	old growth	OG

†All Abandoned/Successional lands may contain remnant old growth trees.

We assigned each reference polygon an aspect/illumination category of either *shadowed* or *sunlit* based on visual interpretation of imagery. We also visually interpreted images from 1975 and 1986 to assign sunlit secondary forest patches to one of three secondary forest age classes: <6 years, 6–16 years and ≥17 years (Lucas *et al.* 1993). For example, if secondary forest in 1992 also appeared to be secondary vegetation in 1986, we assumed it was greater than or equal to 6 years old (≥6 years); if it appeared to be pasture, we assumed it was less than 6 years old (<6 years). Interpreting land cover on shadowed slopes in the 1975 image was less

3. Results

3.1. Spectral responses to land cover

On both sunlit and shadowed slopes in 1992, the TC index of brightness decreased and that of wetness generally increased from agricultural lands to secondary forest to old growth (figure 2). Greenness was lowest in pasture, generally increased towards a peak in secondary forest aged 6–16 years, and decreased toward secondary forest

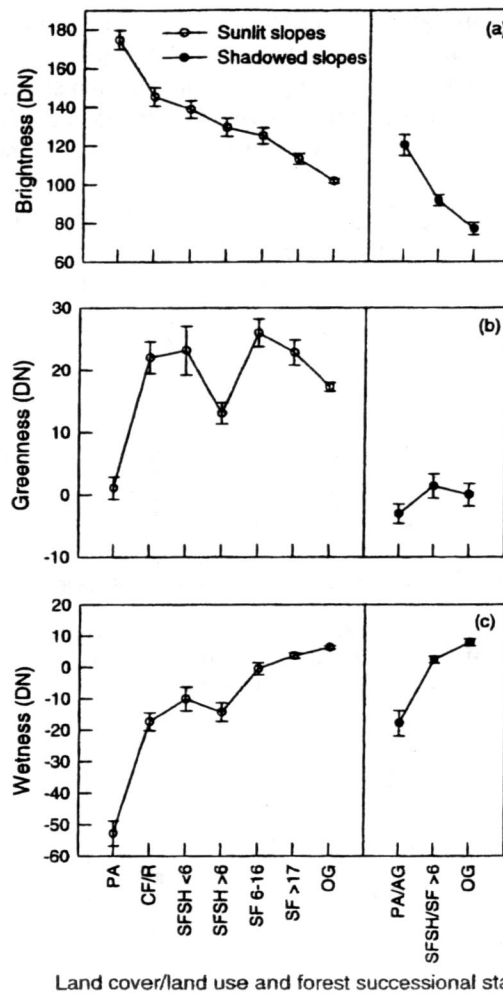


Figure 2. Patch level mean band value (DN, digital number) and 95% confidence interval of the Tasseled Cap indices (a) brightness, (b) greenness and (c) wetness for various land-use/land-cover cover classes in 1992. On sunlit slopes, PA, pasture or pasture with trees and/or shrubs; CF/R, coffee or blackberry cultivation; SFSH ≥ 6 , secondary vegetation dominated by shrubs or co-dominated by shrubs and trees ≥ 6 years old, which may include trees or remnant old-growth trees; SF 6–16, secondary forest 6–16 years old; SF ≥ 17 , secondary forest ≥ 17 years old; SFold, secondary forest 25–35 years old; and OG, old-growth forest. On shadowed slopes, PA/AG, agricultural lands used for pasture (with and without trees or shrubs), coffee or blackberry cultivation and secondary vegetation < 6 years old; SFSH/SF ≥ 6 , all secondary vegetation ≥ 6 years old; and OG = old-growth forest.

≥ 17 years and old growth (figure 2(b)). Sunlit secondary forest lands co-dominated by both tree and shrub species (SFSH ≥ 6 years) showed lower greenness and wetness than both secondary forest 6–16 years and secondary shrub/forest <6 years. We attribute the lower greenness and wetness of these patches to the denser cover of senescent shrub vegetation that we observed during field studies.

Both brightness and greenness values were significantly lower on shadowed than on sunlit slopes for any given LULC class (figure 2). In comparison, values of the wetness index were similar for shadowed versus sunlit secondary forest and shadowed versus sunlit old growth (figure 2(c)), implying that the index is less sensitive to aspect induced variations than are brightness or greenness. The highest wetness values were obtained from old-growth forest, regardless of illumination class.

Similar to wetness, the band indices $(2 \times 6)/7$ and $4/5$ generally increased from agricultural lands to secondary forest to old growth but showed slightly lower values for secondary shrub/forest ≥ 6 years (figures 3 and 4). The 95% confidence intervals of sunlit secondary forest ≥ 17 years overlapped with those of both sunlit and

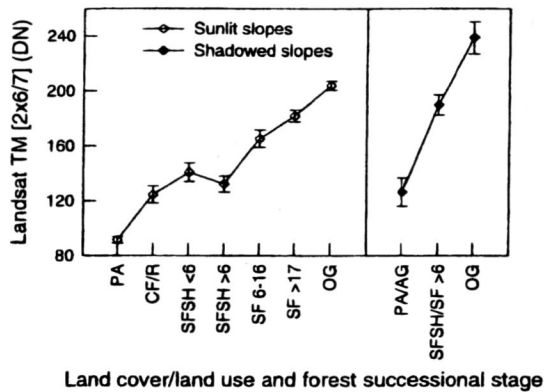


Figure 3. Patch level mean values (DN, digital number) and 95% confidence interval of the band index Landsat TM $(2 \times 6)/7$ for land-use/land-cover classes in 1992. Land use and forest successional stage symbols are as in figure 2.

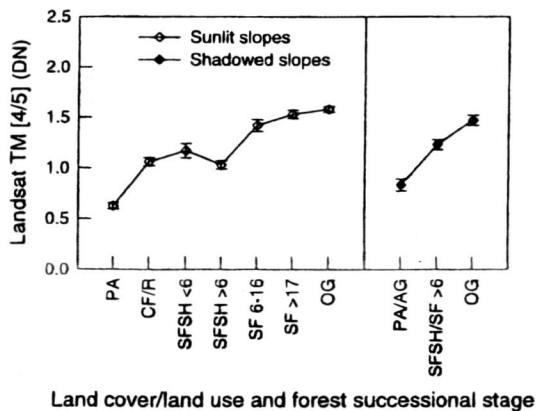


Figure 4. Patch level mean band value (DN, digital number) and 95% confidence interval of the band ratio Landsat TM $4/5$ for various land-use/land-cover classes in 1992. Land use and forest successional stage symbols are as in figure 2.

shadowed old growth in the band 4/5 ratio. The index $(2 \times 6)/7$ showed significantly higher values for old growth than for secondary forest. However, old growth on shadowed and sunlit slopes had very different values, implying that illumination significantly influences this index. Topography had less influence on the band 4/5 ratio in that all forest classes on sunlit and shadowed slopes fell within a similar range.

Subalpine zone vegetation signatures were more similar to shadowed secondary montane forest than to those of old-growth montane forest (figure 5). For example, páramo and shadowed pasture showed similar greenness and wetness, though they showed lower brightness. The spectral similarity between secondary montane forest and undisturbed subalpine forest required us to isolate subalpine vegetation from the other montane vegetation in our analyses.

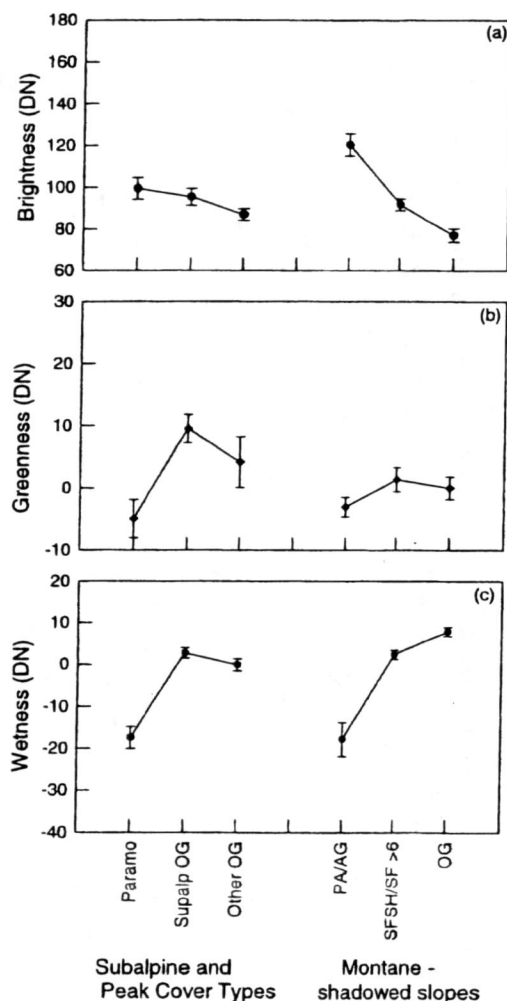


Figure 5. Patch-level mean band values (DN, digital number) and 95% confidence interval for the Tasseled Cap indices (a) brightness, (b) greenness and (c) wetness of subalpine forest and other ridge-top vegetation and páramo, as compared with shadowed land-use/land-cover types at lower elevations. Symbols for classes on shadowed slopes are as in figure 2.

3.2. Temporal changes in tasselled cap indices

The mean difference bands over all LULC classes between 1986 and 1992, shown as dashed lines in figure 6, represent baseline spectral changes between image dates caused largely by radiometric differences. Points above or below these means likely represent soil moisture or vegetation changes that increased or decreased spectral responses from 1986 to 1992. These between-date spectral differences were generally smaller and less variable in old-growth forest and secondary forest ≥ 6 years than in agricultural lands and secondary shrub/forest. At the 95% confidence level, these temporal differences were not reliably distinct between secondary forest aged 6–16 years and ≥ 17 years; nor were those difference bands for secondary forest distinct from old growth. In contrast, differences from 1986–1992 were consistently large for sunlit secondary shrub/forest < 6 years. These changes were negative for brightness

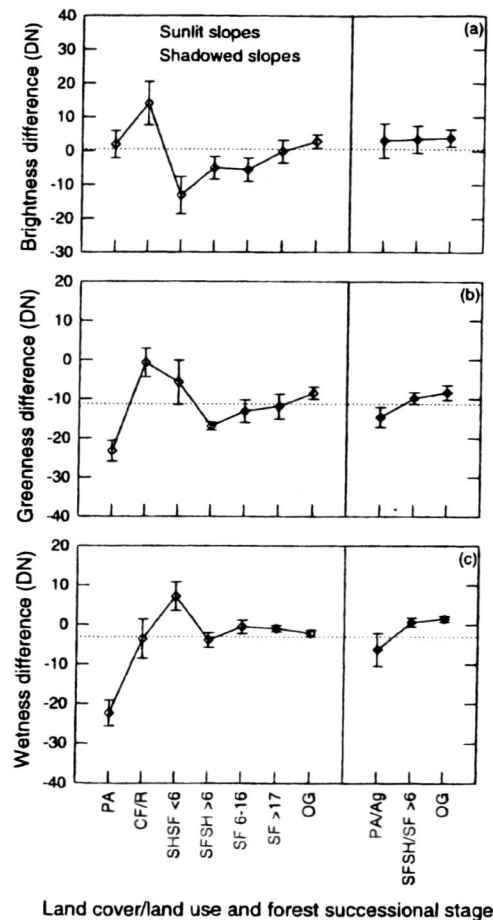


Figure 6. Difference bands by land use/land cover and forest successional stage. Data are differences in patch level mean Tasselled Cap band values (1992–1986, DN, digital number) for (a) brightness, (b) greenness and (c) wetness. Values for 1986 were not radiometrically adjusted. Error bars indicate 95% confidence intervals of the difference. The dashed line indicates the mean change over all classes. Land-cover/land-use and forest successional stage symbols are as in figure 2.

and positive for greenness and wetness. The mean difference band for all pasture classes, including pasture with trees or shrubs, generally increased in brightness and decreased in greenness and wetness. Brightness and greenness differences were large and positive for tree/shrub crops, but wetness differences varied relatively widely from positive to negative. All shadowed classes increased slightly in brightness, probably because the sun was closer to zenith in 1992.

3.3. Classification accuracy

The highest Kappa coefficients for combinations of spectral indices occurred for classifications which included either all three TC indices from one or two image dates (0.83), brightness and greenness from two image dates (0.81), or brightness, greenness and the band 4/5 ratio from one image date (0.81) (table 3). If brightness and greenness from only one image date were used in classification, Kappa was lower at 0.76. The highest Kappa coefficient also included stratification of classes by illumination. In the models with spectral index combinations that included multiple dates, classification accuracy did not improve with radiometric normalization of the TC bands from 1986. Kappa coefficients were below 0.80 for models that used any of the other spectral index combinations. However, these coefficients do not differ significantly at the 95% confidence level.

An error matrix from using all three TC indices from both image dates for classification (table 4) indicates that errors of both commission and omission were highest for secondary forest/shrub ≥ 6 years, which was mapped with 63% accuracy. This class was mainly confused with tree/shrub crops and secondary forest, and this result concurs with earlier studies (Sader *et al.* 1991, Foody *et al.* 1996). Although some confusion occurred between secondary and old-growth forest, 80% of secondary forest and 87% of old-growth forest patches were correctly classified.

Table 3. Kappa coefficient and 95% confidence intervals. Data are for the set of classes shown in table 3 for various index combinations.

Indices used in classification	Stratified by illumination		Not stratified by illumination Not radiometrically normalized
	Not radiometrically normalized	Radiometrically normalized	
Brightness 1992 (B92)			
Greenness 1992 (G92)	0.76 \pm 0.10	—	0.72 \pm 0.11
B92			
Wetness 1992 (W92)	0.72 \pm 0.11	—	0.71 \pm 0.11
G92, W92	0.75 \pm 0.10	—	0.72 \pm 0.11
B92, G92, W92	0.83 \pm 0.09	—	0.73 \pm 0.11
B92, G92, (2 \times 6)/7	0.78 \pm 0.10	—	0.72 \pm 0.11
B92, G92, 4/5	0.81 \pm 0.09	—	0.74 \pm 0.11
B92, G92,			
Brightness 1986 (B86)			
Greenness 1986 (G86)	0.81 \pm 0.09	0.82 \pm 0.09	0.74 \pm 0.10
B92, G92, W92,			
86, G86, W86	0.83 \pm 0.09	0.79 \pm 0.10	0.76 \pm 0.10

Table 4. Error matrix for the map of land use and forest successional stage. See tables 1 and 2 for description of classes. Shadowed and sunlit classes which were stratified for the classification were combined for this error estimation. The Kappa coefficient of agreement was 0.83 ± 0.09 .

Reference class	Classified to					Per cent correct†
	Pasture/ Agriculture	Tree/shrub crops and secondary shrub/forest < 6 years	Sunlit secondary shrub/forest ≥ 6 years	Sunlit + shadowed secondary forest ≥ 6 years	Old growth	
Pasture/Agriculture	27	1				96
Tree/shrub crops and secondary shrub/ forest < 6 years		14				100
Sunlit secondary shrub/forest ≥ 6 years		3	5			63
Secondary forest ≥ 6 years	2		2	32	4	80
Old-growth forest			1	3	26	87
Per cent correct‡	93	78	63	91	87	87

†Omission error.

‡Comission error.

3.4. Land cover and forest successional stage in the study area

Of the 23 130 ha of disturbed lands in the study area, about 46% are still used for pasture, orchards and tree/shrub crops (coffee and blackberries) or are overgrown pasture (secondary shrub/forest <6 years) (figure 7 and table 5). About 54% of disturbed lands have not been used intensively for 6 years or more. Of these lands, secondary forest covers about 9000 ha (39% of disturbed lands), and secondary shrub/forest ≥ 6 years occupies about 15% of the disturbed lands, or 3510 ha. About 34% (15 260 ha) of the study area still contains old-growth montane forest. About

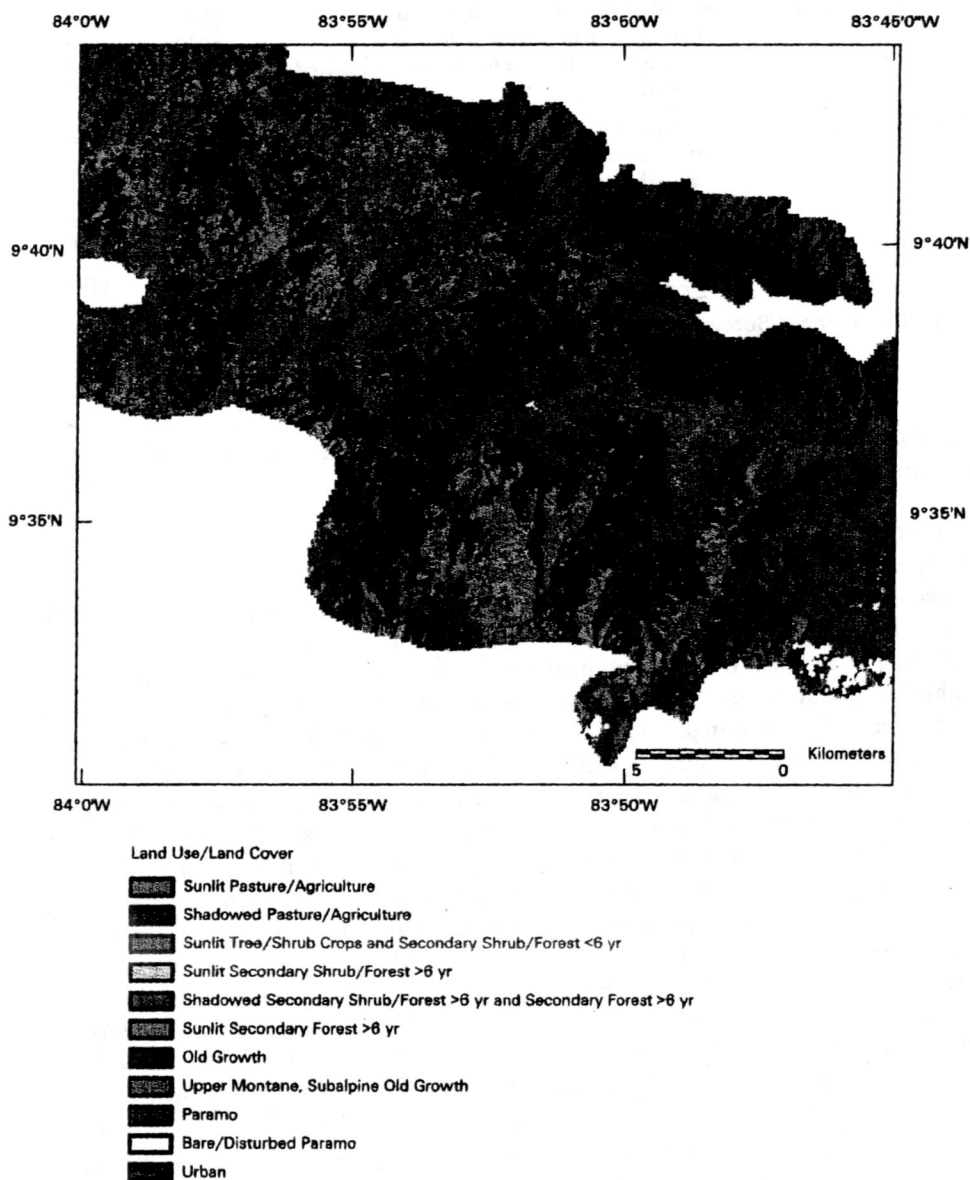


Figure 7. Map of land cover/land use and forest successional stage in the study area.

Table 5. Areas of land cover/land use and forest successional stage. See text and tables 1–2 for description of classes.

Land-use category	Symbol	Area (ha)	Per cent of area
Agricultural lands + Transitional lands	pasture—sunlit	3420	8.7
	pasture and agriculture—shadowed	4390	11.2
	tree/shrub crops and secondary shrub/forest < 6 years—sunlit	2710	6.9
	subtotal	10 520	26.8
Abandoned/ Successional lands†	secondary shrub/forest ≥ 6 years—sunlit	3510	8.9
	secondary forest ≥ 6 years—sunlit	5020	12.8
	secondary shrub/forest ≥ 6 years and secondary forest ≥ 6 years—shadowed	4090	10.4
	subtotal	12 610	32.1
Undisturbed lands	old growth forest	11 530	29.4
	subalpine/upper montane old-growth forest and shrublands	3730	5.5
	páramo	855	2.1
	subtotal	16 115	41.1
	total	39 245	100%

†All Abandoned/Successional lands may contain remnant old-growth trees.

2% of the entire area is subalpine páramo, and about 9% contains upper montane and subalpine forest and shrublands.

4. Discussion

4.1. Spectral responses of tropical forest successional stages

Secondary forest ≥ 17 years remained brighter, greener and less wet than old growth in the montane region of our study. Except for that finding, the trends in vegetation reflectance that we obtained agreed with other studies. The responses in brightness and greenness were similar to those from humid tropical forest in Brazil (Steininger 1996). Steininger (1996), however, concluded that for secondary forest, brightness decreased and greenness increased toward 'mature' forest by age 13 years, and secondary forest was indistinguishable from mature forest in these indices by age 19 years. Secondary forest ≥ 17 years may be distinguishable from old-growth forest in this study region because forests grow more slowly in its cooler, montane climate (Kappelle *et al.* 1996). Slower growth permits a longer time frame during which secondary forest is spectrally distinct from old-growth forest. In addition, the canopies of *Quercus* spp. that dominate old growth may have spectral response patterns that differ from the non-*Quercus* species that dominate secondary forest for at least 20 years and up to 30–35 years in some stands (Kappelle *et al.* 1996). In addition, secondary forest structure differs significantly from old growth for at least 30–35 years. Basal area is much lower at about 9.8 m² ha⁻¹ in 8–20 year old forest, and 17.4 m² ha⁻¹ at 25–32 years, compared with 60.7 m² ha⁻¹ in old growth. Secondary forest is also much shorter: maximum canopy height reaches about 10 m in 8–20 years, and 15 m after 25–32 years, compared with 36 m in old growth (Kappelle *et al.* 1996).

Because the greenness index contrasts the visible TM bands with near-infrared band 4 (NIR), it can be low in pasture through greater reflection in the visible bands from senescent vegetation or soil and moderate NIR reflectance. Greenness peaks in secondary forest, where vegetation dominates the spectral response with high NIR reflectance, resulting in maximum contrast between the visible and NIR bands. In older forest, vegetation reflectance remains dominant but NIR reflectance decreases, so greenness is lower (Moran *et al.* 1994, Steininger 1996, this study).

Mature humid tropical forest has lower values than secondary forest in the visible TM bands 1 to 3, the NIR band 4, the thermal band 6, and the mid-infrared (MIR) bands 5 and 7 (Moran *et al.* 1994, Nichol 1995, Boyd *et al.* 1996, Steininger 1996). As a result, brightness is low in old-growth forest because its coefficients for TM bands 1 through 5 and 7 are positive. Wetness and the band indices $(2 \times 6)/7$ and $4/5$ contrast one or more visible, NIR or thermal bands with the MIR bands 5 or 7. The numerators and denominators of the band indices $(2 \times 6)/7$ and $4/5$ are both higher in secondary forest than in old growth. However, the denominators have smaller absolute values and become smaller proportions of the numerators, so these indices increase in old growth. The lower reflectance from old growth in the MIR bands may be due to increased shadowing in forests with more structure (Moran *et al.* 1994). In shadows, visible and NIR reflectance are relatively greater than for the MIR bands (Crist *et al.* 1986). The TC wetness index increases in canopy shadow because its coefficients for the MIR bands are negative.

Although the band $4/5$ ratio was not greatly affected by topography, the 95% confidence interval of sunlit secondary forest ≥ 17 years overlapped with sunlit and shadowed old growth. Our results do indicate that the band index $(2 \times 6)/7$ may be useful for distinguishing age classes of tropical forest in flatter terrain in that the three sunlit forest age classes of secondary forest 6–16 years, secondary forest ≥ 17 years and old-growth forest were significantly different. In montane regions, however, values of this index increase markedly with topographic shadowing.

Differences in aspect illumination do not greatly impact TC wetness values, and the wetness index is significantly lower in secondary montane tropical forest ≥ 17 years than in old-growth forest. Because of these two attributes, wetness may be a useful indicator of old-growth forest in mountainous tropical regions where DEMs are not readily available. These spectral response patterns of forest successional stages have not been previously shown in a montane tropical region.

Wetness and the band $4/5$ ratio also decreased topographic shadowing in closed canopy conifer forests of the Pacific Northwestern USA and were useful for distinguishing old-growth from mature forest (Fiorella and Ripple 1993, Cohen *et al.* 1995). In those forests wetness increases from younger hardwood/conifer mixed stands toward closed conifer forest < 80 years, and then it decreases with age toward old growth. Wetness may be lower in conifer old-growth forest than in mature forest because dead wood and lichens become an important component of old growth canopies in Pacific Northwestern USA forests, and these components would have lower wetness.

4.2. Classification of tropical forest successional stage

Reports on the accuracy of identifying secondary forest age vary. We were unable to reliably distinguish secondary shrub/forest < 6 years from tree/shrub crops. However, on sunlit slopes the band indices of TC brightness, TC wetness and TM band $2 \times 6/7$ showed promise for distinguishing among the age classes of secondary

forest 6–17 years, secondary forest ≥ 17 years and old-growth forest. Brondizio *et al.* (1996) reported distinction accuracies greater than 85% for identifying three ages of secondary growth near Altamira, Brazil (<6, 6–10 and 10–15 years). Because of wide variation in spectral signatures of secondary growth, Steininger (1996) could reliably distinguish only two age groups of secondary forest: <13 years and 13–19 years. Those findings agree with those of Foody *et al.* (1996), who reported confusion between secondary forest classes aged 2–14 years but accurately distinguished secondary forest >14 years.

The secondary shrub/forest ≥ 6 years in our study area may, at least in part, represent lands where closed canopy forest is developing more slowly than in the secondary forest cover types. Verification of that conclusion would require more detailed analysis of vegetation cover and, possibly, a longer and higher-resolution temporal record. In Brazil, species composition and rate of succession differ after abandonment of cleared lands (Uhl *et al.* 1988, Mausel *et al.* 1993, Foody *et al.* 1996). While this variability complicates identifying secondary forest age and land-use status, both Foody *et al.* (1996) and Mausel *et al.* (1993) reported they were able to identify different successional rates or pathways with remote sensing data.

The high overall accuracy of distinguishing secondary forest from old-growth forest in our study, as well as those of Sader *et al.* (1991), Mausel *et al.* (1993) and Foody *et al.* (1996), could have occurred because little secondary forest within the study regions was old enough to reach spectral similarity to old growth. If the numbers of reference observations for older secondary forest were proportional to small relative extents in these study areas, confusion of older secondary forest would not greatly impact estimates of overall accuracy.

4.3. Classification accuracy estimation

As previously mentioned, the Kappa coefficients listed in table 3 did not differ significantly at the 95% confidence level. In fact, few reports include Kappa confidence intervals (Marsh *et al.* 1994 is an exception). The Kappa confidence intervals probably overlap because off-diagonal observations were too numerous relative to correct observations in the main diagonal cells of error matrices. If additional observations yielded higher Kappa coefficients, using more than the 120 observations that we used for accuracy assessment could have led to smaller confidence intervals. On the other hand, these results may support the concept that Landsat digital imagery has limited spectral dimensionality, and that many classification paths have similar outcomes.

Some researchers have concluded that accuracy estimations should have at least 50 observations per class (Hay 1979, Congalton 1991). This number of observations is possible for pixel-level accuracy assessments, which may have relatively few ground- or aerial photo level reference observations. However, resources may limit the number of reference observations at the patch level to fewer than 50 (e.g. Sader *et al.* 1991), especially when a portion is reserved for classification (as in our study).

4. Conclusions

In montane tropical regions, the relative differences between spectral responses of old-growth forest, secondary forest and agricultural lands vary over landscapes. Complex topography causes varying spectral responses of land covers through influencing sun illumination angles and through changes in ecological zones. For

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example, stand and canopy structures vary with ecological zone. Shorter, undisturbed upper montane and subalpine forest and shrublands can have spectral responses similar to secondary forest developed at lower elevations on abandoned agricultural lands. In addition, these montane secondary forest lands had spectral responses similar to lower montane rain forest, probably because *Quercus* spp. dominate old growth in montane zones, but a variety of species dominate both secondary forest in montane zones and mature forest in premontane and lower montane rain forest zones. Stratification by ecological zone or incorporation of other ancillary data appears necessary for mapping forest successional stage in mountainous tropical regions using satellite imagery.

Rates of forest regrowth also differ between ecological zones. At the higher elevations of our study region, slower secondary forest growth under cooler temperatures probably was partially responsible for our ability to distinguish secondary forest ≥ 17 years, from old-growth forest. Other research (e.g. Moran *et al.* 1994, Steininger 1996) using Landsat TM imagery has indicated that secondary forest older than 12–19 years is not spectrally distinct from old growth. Finally, we found that when DEMs are not available, stratifying each land cover class into two illumination classes alleviates confusion caused by aspect differences. These factors are important to consider when mapping forest successional stage. Large-scale mapping projects that do not pay close attention to these factors in montane tropical regions may easily over- or underestimate relative extents of old-growth and secondary forest.

Incorporating digital data into classification models from images only 6 years apart did not significantly improve classification accuracy in this montane region. However, our method of radiometric normalization may be sensitive to the particular set of bright and dark targets used for developing the calibration, and might have affected the classifications that used spectral bands from two image dates. Yet multi-date imagery allowed us to age secondary forest lands. In addition, temporal differences in spectral indices in agricultural lands and very young secondary growth were larger and more variable than changes in secondary and old-growth forest. This contrast in magnitude of spectral change may be useful for distinguishing secondary forest from agricultural lands in some applications.

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