ABSTRACT: The Brazilian Amazon forest and cerrado savanna encompasses a region of enormous ecological, climatic, and land-use variation. Satellite remote sensing is the only tractable means to measure the biophysical attributes of vegetation throughout this region, but coarse-resolution sensors cannot resolve the details of forest structure and land-cover change deemed critical to many land-use, ecological, and conservation-oriented studies. The Carnegie Landsat Analysis System (CLAS) was developed for studies of forest and savanna structural attributes using widely available Landsat Enhanced Thematic Mapper Plus (ETM+) satellite data and advanced methods in automated spectral mixture analysis. The methodology of the CLAS approach is presented along with a study of its sensitivity to atmospheric correction errors.
CLAS is then applied to a mosaic of Landsat images spanning the years 1999–2001 as a proof of concept and capability for large-scale, very high resolution mapping of the Amazon and bordering cerrado savanna. A total of 197 images were analyzed for fractional photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and bare substrate covers using a probabilistic spectral mixture model. Results from areas without significant land use, clouds, cloud shadows, and water bodies were compiled by the Brazilian state and vegetation class to understand the baseline structural typology of forests and savannas using this new system. Conversion of the satellite-derived PV data to woody canopy gap fraction was made to highlight major differences by vegetation and ecosystem classes. The results indicate important differences in fractional photosynthetic cover and canopy gap fraction that can now be accounted for in future studies of land-cover change, ecological variability, and biogeochemical processes across the Amazon and bordering cerrado regions of Brazil.

**KEYWORDS:** Amazon; Cerrado; Forest structure; Gap fraction; Spectral mixture analysis; Tropical forest

1. **Introduction**

The Brazilian Amazon forest and cerrado savanna regions cover more than $7 \times 10^6 \text{ km}^2$ of South America. They are highly diverse in terms of species composition, ecosystem physiognomy, disturbance regimes, and human activities. The spatial coverage, inaccessibility, and structural variation of these biomes impede measurement and monitoring studies pertinent to ecological research, conservation studies, and land management.

Remote sensing is the best possible method for large-scale studies of Amazon forest and cerrado savanna structure and function, but limitations in sensor capabilities and methodologies have prevented detailed studies of ecosystem properties using space-based instruments. Systems that can cover the entire region on a daily or weekly basis, such as the National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS), provide vegetation metrics like the normalized difference vegetation index (NDVI) at spatial resolutions of 250–1000 m. The NDVI is often suitable for monitoring changes in greenness (e.g., Ferreira et al. 2003), but at low to moderate spatial resolutions ($\geq 250$ m), it is not sufficient for studies of many forest disturbances (e.g., Asner et al. 2003b). Even at high spatial resolution such as 30-m Landsat Enhanced Thematic Mapper Plus (ETM+) data, the NDVI can only provide an empirical metric of canopy greenness. It is not suitable for studies of ecosystem structure.

Many groups have undertaken the challenge of mapping Amazon forests and cerrado savanna using high spatial resolution Landsat data. At the scale of an individual satellite image or subscene ($\sim 185 \text{ km} \times 185 \text{ km}$ or less), techniques have ranged from band analysis to vegetation indices to spectral mixture analysis (e.g., Adams et al. 1990; Steininger 1996; Stone and Lefebvre 1998; Cochrane et al. 1999; Souza et al. 2003). Such studies often provide information on forest canopy cover, disturbance, and regrowth; however, the highly manual nature of these efforts prevents them from being used over millions of square kilometers of Brazil.

Very large-scale, labor-intensive efforts to compile Landsat data have mainly focused on estimating gross rates of forest clearing or deforestation (e.g., Skole
These studies utilize individual bands of Landsat data and manual/visual interpretation to identify cattle pastures and agricultural fields, compiling all of the results into an annual estimate of deforestation. These products are thematic; that is, they indicate whether there is forest present in an area. They do not provide a biophysical measure of forest structure, and thus they are difficult to use in studies of forest dynamics, ecology, biogeochemistry, and conservation planning. Studies of ecosystem structural attributes throughout the Amazon and cerrado biomes are a high priority in the Large-Scale Biosphere–Atmosphere (LBA) Experiment in the Amazônia program (Keller et al. 2004), as well as in many other conservation and policy development arenas. Currently available technologies for large-scale, high spatial resolution studies include synthetic aperture radar (Saatchi et al. 2000) and Landsat optical remote sensing (Asner 2001). Laser detection and ranging (lidar) is temporarily available from space via IceSat, but is limited by spatial sampling rather than contiguous coverage. Very high spatial resolution optical data, such as from the IKONOS satellite with resolution of 1–4 m, are available only for very small geographic areas (Hurtt et al. 2003), and thus they are not suitable for large-area, high-resolution ecological assessments. More generally, higher spatial resolution observations are data rich and therefore require automated analytical methods that isolate aspects of the structural properties of Amazon forests and cerrado savannas over large geographic extents.

We present an overview of a new automated system for very high spatial resolution analyses of ecosystems in Amazonía and the cerrado of Brazil. The system utilizes Landsat ETM+ data with advances in automated spectral mixture analysis to estimate one of the most important determinants of forest and savanna structure: the fractional cover of biological materials and bare surfaces. Fractional cover of photosynthetic vegetation (PV), nonphotosynthetic vegetation (NPV), and bare substrate are principal determinants of ecosystem composition, physiology, structure, biomass, and biogeochemical stocks. These quantities also capture the biophysical impacts of many types of disturbance caused by both natural (e.g., meteorological, fire, etc.) and human (e.g., logging, clearing, etc.) drivers. This paper is designed to (i) provide a detailed overview of the methodology of large-scale, high-resolution automated satellite data analysis of surface fractional cover using Landsat data; (ii) demonstrate our ability to carry out the analysis on a large area of the Brazilian Amazon and bordering cerrado; and (iii) develop a pre-land-use typology of the many ecosystem types found throughout the Amazon. The last goal is largely driven by the need to define the structural attributes of these systems without the major forms of land use (e.g., cattle ranching, agriculture, logging, etc.) so that subsequent studies of forest and savanna disturbance can be compared to a uniform baseline. This paper provides that baseline in the context of fractional cover analysis with Landsat ETM+ satellite data.

2. Methods

2.1. Per-pixel mixture analysis

Our methodology is centered on an effort to break individual satellite pixels into constituent cover fractions of surface materials. To do so, we employ a general,
probabilistic spectral mixture model for decomposing satellite spectral reflectance measurements into subpixel estimates of PV, NPV, and bare substrate covers (Figure 1). This model is based on an algorithm developed for forest, savanna, woodland, and shrubland ecosystems (Asner and Lobell 2000; Asner and Heidebrecht 2002; Asner et al. 2004a). It is fully automated and uses a Monte Carlo Unmixing (MCU) approach to derive uncertainty estimates of the subpixel cover fraction values. The Carnegie AutoMCU uses three spectral end-member “bundles” derived from field measurements and satellite imagery to decompose each image pixel using the following linear equation:

\[ \rho(\lambda)_{\text{pixel}} = \Sigma[C_e \rho(\lambda)_e] + \epsilon = [C_{pv} \rho(\lambda)_{pv} + C_{bare} \rho(\lambda)_{bare} + C_{npv} \rho(\lambda)_{npv}] + \epsilon, \quad (1) \]

where \( \rho(\lambda)_e \) is the reflectance of each land-cover end-member (\( e \)) at wavelength \( \lambda \), and \( \epsilon \) is an error term. Solving for the subpixel cover fractions \( C_e \) requires that the observations \( \rho(\lambda)_{\text{pixel}} \) in this case, Landsat ETM+ reflectance] contain enough information to solve a set of linear equations, each of the form in Equation (1) but at a different wavelength (\( \lambda \)).

Until recently, there were a limited number of spectral signatures of green and

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**Figure 1.** Schematic of the Carnegie AutoMCU algorithm. Spectral end-member databases developed for Amazon and cerrado regions are used to decompose multispectral observations from Landsat ETM+ into constituent surface fractional covers using Equation (1) and end members shown in Figure 2. Output includes mean PV, NPV, and bare substrate fractions; standard deviations from the Monte Carlo algorithm; and an rms error of fit between the measured and modeled spectrum.
senescent vegetation and bare substrates for areas in the Amazon and cerrado. Our mixture modeling technique requires spectral reflectance bundles $[\rho_{pv}(\lambda), \rho_{npv}(\lambda), \rho_{bare}(\lambda)]$ that encompass the common variation in canopy and soil properties. Asner (Asner 1998) and Asner et al. (Asner et al. 2003a; Asner et al. 2004a) collected these spectral data using full optical range field spectroradiometers (Analytical Spectral Devices, Inc., Boulder, Colorado) during field campaigns conducted from 1996 to 2000 (Figure 2). The spectral end-member database encompasses the common variation in materials found throughout Brazilian cerrado and Amazon ecosystems, with statistical variability well defined and deemed viable for end-member bundling (Asner et al. 2004a). The bare substrate spectra have been collected across a diverse range of soil types, surface organic matter levels, and moisture conditions. Spectral collections for NPV have included surface litter, senescent grasslands, deforestation residues (slash), and other dry-carbon constituents from a wide range of species and decomposition stages.

In contrast to the NPV and bare substrate spectra, which can be collected via ground-based spectroscopic measurements, the PV spectra of forest and savanna woody plant species require overhead viewing conditions. This is very difficult to achieve in woody canopies with heights ranging from 5 to 55 m. Spectral measurements of individual leaves, stacks of foliage, or partial canopies (e.g., branches) introduce major errors in spectral mixture models and cannot be used (Asner 1998). Therefore, we collected canopy spectra using the Earth Observing-1 (EO-1) Hyperion sensor. Hyperion is the first spaceborne imaging spectrometer for environmental applications (Ungar et al. 2003). We used Hyperion data from forest and woodland control sites established in 1999. The data were derived from more than 40 000 spectral observations made at 30-m spatial resolution (G. P. Asner 2005, unpublished manuscript), atmospherically corrected to apparent top-of-canopy reflectance using the Atmospheric Correction Now (ACORN) algorithm for hyperspectral data (ImSpec, Inc., Pasadena, California), and convolved to six Landsat ETM+ optical channels. These green vegetation spectra thus inherently included the variable effects of intra- and intercrown shadowing, which are prevalent in tropical forests (Gastellu-Etchegorry et al. 1999).

In Amazonia, shade fractions average 25% cover in humid tropical forests, but the variance is high with standard deviations of 12% or more (Asner and Warner 2003). In cerrado savannas, mean shade fractions range from 0% to 16%, with standard deviations up to 5% (Asner and Warner 2003). It is thus critically important to note that our PV results include shade, which varies substantially with forest structure. Using a separate shade end member is attractive (e.g., Souza and Barreto 2000), but doing so with multispectral Landsat data and such high shadow fraction variability often results in an underdetermined spectral and mathematical problem in linear mixture models. Imaging spectroscopy (hyperspectral) data are needed to solve this problem (Roberts et al. 1993). For now, we averted this issue by accepting the limitations of incorporating variable shade directly into our PV bundle derived from the EO-1 Hyperion sampling of woody plant canopies in Brazil. In the end, the total number of spectra retained in the end-member bundles for the AutoMCU mixture model was 252, 611, and 434 for PV, NPV, and bare substrate, respectively (Figure 2). These spectra represent the mean of more than 230 000 field and spaceborne spectrometer observations collected over a 5-yr period of study.
Figure 2. Spectral end-member bundles developed for Amazon and cerrado vegetation and employed in the Carnegie AutoMCU algorithm (Figure 1): (a) PV, (b) NPV, and (C) bare substrate.
2.2. The Carnegie Landsat Analysis System

The AutoMCU algorithm has been successfully employed on subsets of Landsat imagery for studies of deforestation, pasture condition, and selective logging (Asner et al. 2003a; Asner et al. 2004a). The automated features of the approach make it conducive to larger-scale application, but to do so requires many additional methodological advances. We sought to achieve nearly complete automation of the AutoMCU approach by embedding it in a processing system designed to ingest large amounts of Landsat data, to convert the data to radiance and top-of-canopy reflectance via atmospheric correction, to mask water bodies and atmospheric perturbations such as clouds and haze, and to avoid areas containing cloud shadows. In going to a very large operational scale, such as for the entire Brazilian Legal Amazon and bordering cerrado regions, the system must also allow for normalization of images via rescaling and for image edge detection and mosaicking. These criteria resulted in the Carnegie Landsat Analysis System (CLAS) presented in Figure 3.

Raw Landsat ETM+ data are geocorrected, then sensor gains and offsets are used to convert from a digital number (DN) to exoatmospheric radiance. The radiance data are passed to a fully automated version of the 6S atmospheric radiative transfer model (Vermote et al. 1997). The 6S program is integrated into the CLAS processing stream and uses average monthly aerosol optical thickness (AOT) and water vapor (WV) values from the NASA MODIS sensor. Time

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Figure 3. Processing steps of CLAS.
stamping of MODIS AOT and WV with Landsat data is done on an automated
basis (Figure 3).

A series of masks are designed to exclude clouds, water bodies, cloud shadows,
and nonimage areas from the analysis. These masks are derived directly from the
raw and calibrated Landsat imagery as well as from the AutoMCU submodel
output of CLAS. Clouds are masked using the thermal channel (band 6) from the
raw Landsat images (Figure 3). Following a series of tests, a thermal band thresh-
old DN value of 125 was found to conservatively detect cloudy pixels over Amaz-
nia. Water bodies are masked by finding pixels in the calibrated Landsat reflect-
tance data in which bands 1–4 (blue to near infrared) displayed a negative slope.
Only water displays such a negative spectral slope with increasing wavelength.
Nonimage areas containing zero values are masked. Cloud shadows are masked
using an empirically derived combination of the Landsat ETM+ reflectance values
and the AutoMCU root-mean-square (rms) error calculations (from Figure 1).

Following the mask computation for each image, the AutoMCU submodel
described above is run using the formulation and spectral end-member bundles
shown in Figures 1–2. This code spectrally decomposes each image pixel into
fractional cover estimates (0%–100% cover). Final steps include image rescaling
and mosaicking. Rescaling of the data is necessary to equalize very small (< 5%)
differences in fractional cover results that occur due to image calibration errors,
residual atmospheric constituents (e.g., cirrus clouds and light smoke), and other
random artifacts in the processing. This step produces a contiguous dataset that
could then be readily mosaicked together for large-scale production, visualization,
and study.

2.3. Proof of concept and capability

We tested CLAS on 197 Landsat ETM+ images compiled by the EarthSat Cor-
poration and provided via the NASA Data Buy to the University of Maryland.
These images were provided in orthorectified format as raw digital numbers at
28.5-m spatial resolution. The multiyear compositing of this mosaic results in a
limited applicability to most basinwide studies of gross deforestation, selective
logging, or agricultural expansion that require annual observations. However, this
mosaic did provide an avenue to test our automated system and to study the
structural typologies of Amazon and cerrado ecosystems, as discussed later.

The Landsat image dataset contained $10.87 \times 10^9$ pixels, spanning the years
1999–2001 as shown in Figure 4. CLAS was used to process this enormous dataset
on a Linux computer cluster utilizing distributed computational techniques on
multiple processing nodes. Each image is linearly divided into smaller datasets,
which are passed to each processing node along with the spectral unmixing code.
Following computation on each node, the data are sent back to a central processing
unit to reconstruct the final results in image format.

2.4. Sensitivity to atmospheric correction

A critical aspect of any large-scale, optical remote sensing study of vegetation lies
in the assessment of potential sources of error. Atmospheric correction of optical
satellite data has been a major issue in many studies of the humid Tropics, owing
to the often high water vapor and aerosol (from biomass burning) concentrations found over these regions (Kaufman et al. 1998). To determine the effects of aerosols and water vapor on the fraction images produced by CLAS, the 6S atmospheric radiative transfer model was iteratively run with a range of AOT and water vapor values on a “reference image” (from Asner et al. 2004a), with all other atmospheric parameters remaining fixed. The reference image was corrected with the 6S code using a “true” AOT and water vapor values of 0.086 and 2.15 cm, respectively. Noise was then introduced using value ranges observed throughout the MODIS AOT and water vapor products from 2000 to 2002 over Amazônia. By running these artificially noisy scenes through the AutoMCU submodel and comparing the resulting PV, NPV, and bare substrate fraction images, the effects of variable amounts of aerosols and water vapor were compared to the reference image output.

2.5. Analysis of ecosystem typologies

A valuable use of the multiyear mosaic lies in defining the structural typology—as quantified via fractional cover in Landsat imagery—of the many ecosystem types

Figure 4. States of the Brazilian Amazon included in this proof of concept and capability study. A total of 197 Landsat ETM+ footprints are shown with acquisition year indicated.
found throughout Amazônia and in bordering areas of the cerrado. To our knowledge, such an effort has never been attempted using any high-resolution satellite imagery. Fractional canopy cover analysis provides a means to define an aspect of ecosystem structure that bears on studies of forest growth, degradation, land use, carbon cycling, and a wide range of ecological processes from flora to faunal dynamics and food web structure. Basic statistics and intercomparisons of the major vegetation types and ecosystems found throughout the region provide a biophysically based starting point against which to monitor changes in the future.

We used the vegetation-ecosystem map developed by the Brazilian mapping and statistics agency [(Instituto Brasileiro de Geografia e Estatística) IBGE 1993] to partition the fractional cover observations into recognizable classes (Figure 5). We compared the fractional material cover of PV (usually green, woody plant canopies), NPV (usually herbaceous and surface litter), and bare substrate (usually soils) between IBGE classes, by Brazilian state, and for the entire coverage area (see Figure 4). To develop the baseline ecosystem typologies without significant imprints of land use, we only compiled data with PV values greater than 70%. This threshold was experimentally derived based on analyses of images throughout the region and from Asner et al. (Asner et al. 2004a). Areas of deforestation, including pasture systems, agriculture, suburban, and urban land covers were thus largely removed by this analysis.

Figure 5. Vegetation classification map of northern Brazil, including the Legal Amazon (IBGE 1993).
2.6. Case studies and forest gap fraction

To provide a more detailed understanding of the CLAS product, we focused on two LBA research areas where studies of forest structure, ecology, and biogeochemistry have taken place. One area is located on the Fazenda Cauaxi, in the Paragominas municipality in eastern Para State (Pereira et al. 2002). This area is a site of extensive selective logging, but it also contains several control forest areas useful for evaluation of the CLAS product. The second area is located in the Tapajos National Forest; it is an LBA core site with extensive measurements of forest structure and function (summarized by Keller et al. 2004). Tapajos contains a reduced-impact logging experiment and a large area of intact, mature forest. Together, these sites provided a means to examine details of the spectral mixture results, and to identify errors and limitations of the data.

Asner et al. (Asner et al. 2004a) developed a set of equations relating PV cover fraction derived via the AutoMCU algorithm to field-based measurements of forest canopy gap fraction. We extended these relationships to create regional mosaics of woody canopy gap fraction from the multiyear mosaic (Figure 4). We then calculated area-integrated canopy gap statistics for all IBGE vegetation classes (listed in Table 2).

3. Results and discussion

3.1. Sensitivity to atmospheric aerosol and water vapor

The sensitivity of the CLAS process to atmospheric correction errors resulting from inaccurate estimates of aerosol and water vapor are shown in Figure 6. Errors in PV estimates reached a maximum of only 2.5% over dark forest vegetation when both water vapor and aerosol were very high (Figure 6a). NPV and soil estimates had maximum errors of 5% and 6.5%, respectively, over dark forest vegetation. All errors were smaller for pixels over bright clearings such as cattle pastures (Figure 6b). We would expect similarly low errors caused by poor atmospheric correction in brighter savanna vegetation types.

At typical values of atmospheric column water vapor (1.0–2.5) and aerosol optical thickness (0.1–0.3), as determined from MODIS satellite observations over Amazônia (data not shown), we expect our uncertainty in PV, NPV, and bare substrate to average less than 5% in most cases. Because the AutoMCU approach uses spectral end-member bundles (Figure 2) to propagate uncertainty in spectral signatures via Monte Carlo analysis [right side of Equation (1)], the resultant uncertainties in derived cover fractions tend to range from 1% to 8% (Asner et al. 2003a; Asner et al. 2004a). This level of uncertainty meets or exceeds that which is caused by insufficient atmospheric corrections (Figure 5). That is, the uncertainty in spectral end members on the right side of Equation (1) matches the uncertainty in pixel reflectance following atmospheric correction [left side of Equation (1)].

3.2. Regional case studies

Two regional focus areas were extracted from the multiyear mosaic results to facilitate detailed analysis of the spatial complexity of the CLAS product. The 142
Figure 6. Sensitivity of CLAS to differing levels of atmospheric AOT and WV levels (cm) for (a) dark dense forests and (b) bright pasture clearings.


km² Cauaxi region contains a variety of forest conditions, from intact mature forest (area 1) to conventionally logged forest (area 2) to cattle pasture (area 3) and forest in preparation for selective logging (area 4). The latter area is distinguished by newly developed logging roads and decks (Figure 7). A 2000 km² portion of the Tapajos National Forest is shown in Figure 8. This image contains a reduced-impact logging experiment (Keller et al. 2004) and vast areas of mature, intact forest on two major soil types: clay and sandy (as described by Silver et al. 2000).

The Cauaxi and Tapajos scenes provide a reference to better understand the spatial variance of fractional cover values among differing land-cover and soil types, presented here as a means to discover how the data express small but significant variations in forest structure. This understanding is critical to studies of basin-scale variations, as presented in subsequent sections of this paper. We also provide the separated PV, NPV, and bare substrate images for Cauaxi (in Figure 9), along with the standard deviation images generated by the AutoMCU submodel (Figure 1). The latter images express the uncertainty in fractional cover estimates.

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Figure 7. Zoom image of CLAS results for the Fazenda Cauaxi region in eastern Para state (indicated by red dot in upper map). Areas of interest include (area 1) mature, intact forest; (area 2) forest with prelogging treatment of road and deck construction; (area 3) heavy damage following conventional, selective logging; and (area 4) deforested land for cattle pasture. Green, blue, and red tones quantitatively indicate variations in PV, NPV, and bare substrate fractional cover, respectively.
Figure 8. Zoom image of CLAS results for the Tapajos National Forest region in central Para state (indicated by red dot in upper map). Areas of interest include (area 1) forest on lowland, sandy soils, and (area 2) forest on upland, clay soils. Green, blue, and red tones quantitatively indicate variations in PV, NPV, and bare substrate fractional cover, respectively.
on a per-pixel basis. It is notable that uncertainty in PV fractions is extremely low in most forested pixels (0%–3%), owing to the spectral separability of PV from either NPV or bare substrates. Per-pixel standard deviations increase to as much as 10% for NPV and bare covers (Figure 9), which reflects the much greater level of uncertainty involved in studies of NPV soil fractions using spectrally limited data from Landsat and similar sensors (see Asner and Heidebrecht 2002).

Analysis of 4 km² areas around each point in Figures 7 and 8 demonstrated the sensitivity of the fractional PV, NPV, and bare substrate cover to four common land-cover and edaphic scenarios found throughout Amazônia (Figure 10). In the Cauaxi image, mature tropical forest (area 1, Figure 7) had PV values of 92.0% ± 2.7% (standard deviation), NPV of 7.4% ± 6.4%, and bare substrate levels of 1.6% ± 4.3%. On an area-average basis, forest prepared for selective logging (area 2, Figure 7) had statistically similar values to that of intact forest (t tests by cover type; p > 0.20): PV = 92.1% ± 2.5%; NPV = 6.6% ± 6.1%, bare = 2.4% ± 4.3% (Figure 10). However, within the individual logging decks found in area 2, PV was 68.3% ± 11.8%, NPV was 24.3% ± 9.5%, and bare substrate was 7.9% ± 9.1%. All of these were statistically different from that of the intact forest area 1 (t tests; p < 0.01).

Following conventional logging in area 3, fractional surface cover of PV and NPV changed significantly from that of the intact forest area (t tests; p < 0.01;
Area-integrated PV cover decreased to 86.4% ± 4.2% and NPV was elevated to 14.7% ± 8.3%, but bare substrate extent did not change (1.5% ± 4.8%). Individual pixels containing logging damage had much lower PV and higher NPV (surface debris and slash), as depicted in blue tones in area 3 of Figure 7. The fractional cover of materials substantially changed following deforestation for cattle pasture (area 4; Figure 7). In this large system of pastures, PV was 43.7% ± 3.4%, NPV was 24.4% ± 4.2%, and bare ground was 20.5% ± 2.6% (Figure 10).

As mentioned, the Tapajos image contains large areas dominated by sandy soils in low-lying zones and clay soils on uplands (Silver et al. 2000). These areas are visually distinct in Figure 8, with uplands having higher PV cover (92.2% ± 1.9%) than found on lowland terrain (89.3% ± 2.4%; t test; p < 0.05). Lowland, sandy soils areas of forest had slightly lower bare soil exposure and higher NPV, although these differences with the upland, clayey forest areas were not significant (t tests; p > 0.10).

Thus, the fractional cover of PV, NPV, and bare substrate highlighted the biophysical changes that occur with the land-use transitions from intact forest to selective logging to cattle pasture. In addition, differences in canopy opening (PV fraction) related to topo-edaphic conditions were evident. It is notable that small differences in these biophysical covers are clearly visible in the AutoMCU results. Our experience with the data indicates that the precision is very high, and that...
3.3. State-level and basinwide statistics

The IBGE vegetation map (Figure 5) provided a spatially explicit guide for developing topologies of fractional cover throughout the Amazon Basin and bordering cerrado regions. Thirty IBGE vegetation categories were identified for analysis (as shown in Table 2). The CLAS process identified $3.25 \times 10^9$ pixels or $2.9 \times 10^6$ km$^2$ of vegetation that was not masked for clouds, cloud shadow, and water bodies. Three IBGE classes—dense lowland tropical forest, dense submontane tropical forest, and open submontane tropical forest—accounted for more than 60% of the total area, or 1 768 000 km$^2$. However, tens to hundreds of thousands of square kilometers are covered by other vegetation types. In particular, the transition or contact areas between major vegetation classes accounts for more than 500 000 km$^2$ of Amazônia. IBGE vegetation classes vary by Brazilian state. Dense lowland tropical forests dominate the state of Amazonas, whereas open lowland (mostly bamboo) forest cover much of Acre. Submontane forests are most common in Roraima, Rondonia, Para, and Amapá, while transitional (contact) vegetation classes (e.g., dense tropical to seasonal deciduous forest) dominate in northern Mato Grosso (Table 2).

The mean fractional PV, NPV, and bare substrate covers differed significantly by vegetation class and, at times, by Brazilian state. Lowland and submontane tropical forests always had significantly higher PV cover than other vegetation types ($t$ tests; $p < 0.001$). Fractional PV values were lowest in savanna regions of Roraima and Mato Grosso (Table 1). The most densely foliated ecosystems are found in Amapá and Para, with moderate NPV exposure and extremely low bare substrate fractions (Table 1). Bare substrate exposure was highest in alluvial tropical forests areas of Amapá and in open tropical forests with secondary vegetation found in Acre. The highest NPV fractions were always found in savanna systems. Seemingly small differences in fractional cover were often highly significant, even between tropical forest classes. For example, 1%–3% differences in PV fraction, which includes intercanopy shadowing, are readily observable in the CLAS results (e.g., Figures 7–8) and equate to forest gap fraction variations of 10%–25% (Asner and Warner 2003; Asner et al. 2004b). This issue is highlighted in the next section.

A close inspection of the results within each state indicated spatial gradients of surface fractional cover, both within and between forested and nonforested regions (Figures 11–17 show these state-by-state results). Areas masked by the cloud, cloud shadow, and water body detection steps by the CLAS processing are shown in white throughout these figures. In Acre, forests to the southwest along the Brazil–Peru border had higher levels of NPV and decreased PV values (Figure 11). These bamboo-dominated forests are known to have a more open crown structure with exposed woody stems and other nonphotosynthetic material. Western Amapá (Figure 12) contains some of the most densely vegetated forests in all of Amazônia, but to the east, the state transitions to open forest, dense savanna, and flooded forests with lower PV fractions (Table 1). These eastern vegetation types
in Amapá have significantly higher NPV and bare substrate fractions leading toward the Atlantic Ocean.

Amazonas contains enormous areas of lowland tropical forest (Figure 13). Of the $1.7 \times 10^6$ km$^2$ of land in this state, nearly one-third is dense lowland forest and an additional 10% is a more open lowland forest type according to IBGE.

<table>
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<tr>
<th>State and IBGE vegetation</th>
<th>Area (km$^2$)</th>
<th>PV</th>
<th>NPV</th>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open lowland tropical forest</td>
<td>82 275</td>
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<td>89.9*</td>
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<td>Dense tropical forest with secondary vegetation</td>
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</tr>
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<td>9.2*</td>
<td>2.1*</td>
</tr>
<tr>
<td>Open lowland tropical forest</td>
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<td>90.6*</td>
<td>9.4</td>
<td>1.8</td>
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<tr>
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<td>87.0</td>
<td>7.5</td>
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<tr>
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<td>58 464</td>
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<td>2.6</td>
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<tr>
<td>Savanna, grassy-woody</td>
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<td>83.8</td>
<td>11.5</td>
<td>5.7</td>
</tr>
<tr>
<td>Campinarana, forested</td>
<td>10 109</td>
<td>88.1</td>
<td>13.3</td>
<td>0.9</td>
</tr>
<tr>
<td>Savanna steppe</td>
<td>81 77</td>
<td>82.3</td>
<td>14.7</td>
<td>5.2</td>
</tr>
</tbody>
</table>
Our method was unable to detect statistically different PV, NPV, or bare substrate fractions between these two classes (Table 1). This lack of sensitivity results from our PV spectral end-member bundle including variations in shade, which alone accounts for variations in canopy openness among these densely foliated ecosystems. Imaging spectrometer (hyperspectral) observations are needed for more detailed determination of forest structure. Both forest types are densely foliated from the perspective of nadir-viewing satellite observations.

In contrast to Amazonas, the northern portion of Mato Grosso is dominated by lower stature forest, seasonal woodlands, and transitions to cerrado savanna vegetation (Figure 14). Much of the blue tone shown in Figure 14 indicates forest clearings, but a larger fraction of the land has high NPV levels due to herbaceous vegetation (Table 1). The Landsat ETM+ scenes were acquired primarily in the dry season (July–November) when cloud cover is low and herbaceous cover is senescent. Variability in NPV among pixels of the woodland and savanna vegetation classes in Mato Grosso was relatively high (7%–12%) in comparison to that of forested areas (3%–5%). This likely results from variations in regional climate, soils, and other factors controlling the availability of water for herbaceous veg-

Figure 11. CLAS results for the state of Acre. Areas in white were those without data due to cloud, cloud shadow, and water masking.
etation growth, but also from greater uncertainty in measuring NPV and bare soil using multispectral observations.

In the state of Para, savanna and open woodland forests in the southeast transition into dense tropical forest in the central and northern regions (Figure 15). Extensive land use is found within this transition zone and along the TransAmazon Highway in the central portion of the state. Areas more heavily impacted by land use contain higher bare substrate fractions (red tones in Figure 15) than those with higher NPV cover (blue tones). Moreover, areas along the main stem of the Amazon River appear dominated by NPV and bare substrate fractions; these areas are alluvial plains with significant amounts of sedimentation (red tones) and herbaceous vegetation (NPV; blue tones).

The most obvious examples of the biophysical impacts of land-cover change are found in Rondonia (Figure 16). Areas once dominated by open lowland and submontane tropical forest (Figure 5) have been converted to pastoral and agricultural land uses. Very high NPV and bare substrate values are found in these clearings, with values typically ranging from 40% to 90%. Note the apparent differences in NPV and bare substrate conditions when crossing the boundary between Landsat images, such as shown in Figures 16a,b. These interscene dif-
ferences highlight the challenges to large-scale automated processing of multispectral imagery from Landsat and similar sensors.

The state of Roraima contains a very wide range of fractional cover. Dense submontane forests to the west have PV, NPV, and bare substrate values averaging 90.7%, 9.2%, and 2.8%, respectively. Large areas of savanna bordering with Venezuela averaged PV, NPV, and bare substrate covers of 82.3%, 14.7%, and 5.2%, respectively. Considering the area that is averaged among these vegetation classes (Table 2), these are enormous gradients of materials with very different phenologies, biogeochemical cycles, and disturbance regimes. After masking deforested lands used to tabulate Table 1, we found Roraima to contain the largest variation in pre-land-use surface cover among all states of the Brazilian Amazon.

Integrating all results to the basin level, and masking deforestation (see section 2), we summarize the ecosystem typologies of the major vegetation types found throughout Amazônia and the bordering cerrado (Figure 18). Evergreen and deciduous tropical forests had the highest PV fractions, ranging from 84% to 89%. Bare substrate and NPV fractional cover ranged from 2% to 7% and 7% to 10%, respectively. The less common campinarana systems found throughout ~100 000

Figure 13. Same as in Figure 11 but for the state of Amazonas.
km$^2$ of our study region develop around lowland depressions of nutrient-poor soils embedded in a matrix of tropical forest. The PV values in campinarana regions were very consistent at about 86%, but NPV varied substantially from $\sim$9% to 17% (Figure 18). Both the traditional forests and campinarana classes were typologically distinct from the transitional forest–savanna and wooded savanna lands bordering Amazônia. These systems had PV fractional cover values ranging from 74% to 85% depending on degree of woody cover, with concomitant differences in NPV and bare substrate (Figure 18).

Altogether these results suggest that the fractional PV, NPV, and bare substrate covers for different vegetation types varies sufficiently to warrant their separate treatment in future studies. Although the state-to-state differences in PV within most vegetation classes were often statistically different, the variation between IBGE classes was even more pronounced. These results provide an important baseline of ecosystem structural typologies for these regions and vegetation types against which future studies of forest and savanna disturbance should be compared using the same or similar method.

3.4. Woody canopy gap fraction

We estimated regional variations in woody canopy gap fraction using the CLAS results presented in Figures 11–17 along with PV gap equations derived from...
Asner et al. (Asner et al. 2004a). These equations were modified from their original formulation for terra firme forests to encompass a wider range of physiognomic conditions. The modifications included rescaling the equations and normalizing to values of fractional woody canopy cover reported for cerrado physiognomies (Sano and Pedrosa de Almeida 1998) and Amazon forest (Duivenvoorden 1996; Asner et al. 2004b). The equations are

\[
\text{if } PV_{\text{CLAS}} < 0.85, \quad GAP = (PV_{\text{CLAS}} - 90.0)/(-0.4) \\
\text{if } PV_{\text{CLAS}} \geq 0.85, \quad GAP = (PV_{\text{CLAS}} - 90.0)/(-0.8).
\]

The different denominators in Equation (2) arise from several factors. First, PV fraction is a planar metric, whereas canopy gap fraction is hemispherical in nature (Asner et al. 2004a; Asner et al. 2004b). Moreover, strong adjacency effects between satellite pixels result in a nonlinear component to vegetation mixture modeling with multispectral data (Richards 1994). This effect is maximum at forest gap values greater than \(~85\). Finally, the variable effects of intra- and intercrown shadow are not accounted for in this initial estimate. Shadow has a maximum impact on multispectral signatures of tropical forest when cover fractions are above \(~75\%\) and on cerrado savanna observations when woody canopy...
cover ranges from 35% to 65% (Asner and Warner 2003). Nonetheless, these equations are a first approximation for converting our PV fractions from CLAS to estimates of woody canopy gap fraction. This effort was intended to provide an initial typology of woody canopy gap fraction for use in carbon, disturbance, and biogeochemical modeling studies (Keller et al. 2004).

Conversions of satellite-derived PV to woody canopy gap fraction highlighted the wide range of values found throughout Amazônia. The spatial variability and quality of the results are shown for Rondonia and Mato Grosso (in Figures 19a,b). Throughout the entire region, lowland tropical forests had the smallest gap fractions of 6.5% ± 1.9% (Figure 20), followed by different types of “dense forest” vegetation as classified by the IBGE (Figure 5). These dense forests had mean gap fractions ranging from 7.3% to 9.6%. Campinarana forests and woodlands (L classes; Figure 20) had more open canopies with gap fractions of approximately 14% and standard deviations averaging 4%. Although the gap fractions were not statistically unique within dense forest and campinarana classes, these two major groupings were significantly different (t tests; p < 0.001). Seasonal woodlands...
(F classes; Figure 20) had yet larger gap fractions of up to 21.9% ± 3.8%, and cerrado savanna classes had an enormous range of values, from 17.5% to 40.5% over thousands of square kilometers of area.

Our field measurements in five IBGE classes were near in value to those derived from these satellite estimates of woody canopy gap fraction (Figure 20). Only the field measurements from site 3 at the Tapajos National Forest (From Figure 8) were statistically different by a small margin [one-way analysis of variance (ANOVA) on ranks; \( p = 0.061 \)]. Overall, the field data were well represented by this first-order model of canopy gap fraction throughout the Amazon and bordering cerrado region. Further studies in the field are needed to test and refine a canopy gap product for scientific use; however, the conceptual approach appears reasonable for this novel high-resolution mapping of a forest structural variable throughout Amazônia.

4. Conclusions

We developed the Carnegie Landsat Analysis System (CLAS) for studies of forest and savanna structural attributes using Landsat ETM+ satellite data and probab-
listic spectral mixture analysis. Details of the methodology were presented along with a study of its sensitivity to atmospheric correction errors. We then applied CLAS to a mosaic of Landsat ETM+ images spanning the years 1999–2001 as a proof of concept and capability for large-scale, high-resolution mapping of the Amazon and bordering cerrado savanna. A provisional estimate of woody canopy gap fraction was also developed to extend the spectral mixture results to a forest structural metric commonly employed in ecological studies. Our efforts provide the following conclusions and considerations.

- CLAS allows for high-volume processing of large, high spatial resolution datasets such as the ~200 image archive presented for Amazônia and the bordering cerrado savanna region.
- The automated Monte Carlo spectral unmixing approach with CLAS provides detailed spatial information the fractional cover of photosynthetic vegetation and, to a lesser extent, nonphotosynthetic vegetation and bare

Table 2. IBGE vegetation types observed in the 197 image Landsat mosaic (Figure 4), showing the percentage cover of the study area, total area per class, and number of pixels per class. The total area studied (without cloud and smoke interference) was 2,926,442 km² or 3.25 x 10⁹ observations.

<table>
<thead>
<tr>
<th>IBGE vegetation class</th>
<th>Percentage of total</th>
<th>Area (km²)</th>
<th>No. of pixels</th>
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</thead>
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<td>Dense submontane tropical forest</td>
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substrates that indicate fundamental structural differences in vegetation types in Amazônia and bordering cerrado savanna regions.

- CLAS maintains a reasonable level of sensitivity to uncertainties in atmospheric correction arising from aerosols and water vapor. This uncertainty is less than or equal to that which arises from spectral end-member variability.

- Small apparent differences in fractional photosynthetic vegetation cover highlight significant differences in forest, woodland, and savanna structure; these differences are most apparent following the analytical conversion of photosynthetic vegetation estimates to woody canopy gap fraction.

- A limitation of the method rests in the incorporation of inter- and intra-canopy shade within the photosynthetic vegetation end member, decreasing the sensitivity of the algorithm to finer differences in forest lateral structure. This trade-off was deemed necessary to allow for large-scale production of CLAS products and derivatives such as gap fraction.

- Preliminary analysis of the derived woody canopy gap fraction from the CLAS process shows that forest gap fractions vary within a relatively narrow range of values for most Amazon regions, whereas woodlands

![Figure 18. Basin-integrated ecosystem typologies of fractional material cover. IBGE vegetation codes are provided in Figure 5.](image-url)
Figure 19. (a) Forest canopy gap fraction for the state of Rondonia, derived from the CLAS modeling output (Figure 16) and the satellite PV–field gap relationships developed by Asner et al. (Asner et al. 2004a) (b) Forest canopy gap fraction for the state of Mato Grosso, derived from the CLAS modeling output (Figure 14) and the satellite PV–field gap relationships developed by Asner et al. (Asner et al. 2004a).
found on acidic soils (campinarana) and savannas have much higher levels of gap variation throughout the region.

Overall, this study demonstrates a new capability for very high spatial resolution analysis of enormous regions of the humid Tropics and subtropics. The data were collected at 28.5-m spatial resolution and decomposed into fractional covers of surface constituents within each image pixel. This study is the first in an effort to quantify the structural variation of inaccessible Amazon and cerrado ecosystems, and to provide a pre-land-use baseline of ecosystem typologies for future studies of land-cover change. The biophysical determinants of key functional processes in these ecosystems, including biogeochemical cycles, biological diversity, and disturbance, can be analyzed with this new system. Future studies will present changes in fractional cover and gap fraction over time, and at high spatial and temporal resolutions needed for a deeper process-oriented understanding of the biophysics and ecology of the Amazon.
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References


