POST-HARVEST RECOVERY OF FOREST STRUCTURE AND SPECTRAL PROPERTIES AFTER SELECTIVE LOGGING IN LOWLAND BOLIVIA

By

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Major Department: School of Forest Resources and Conservation

Our study combined extensive field measurements of the spatial and temporal dynamics of felling gaps and skid trails < 1-19 months post-harvest in a forest in lowland Bolivia with remote sensing measurements through simultaneous ASTER satellite overflights during the summer of 2003. An advanced probabilistic spectral mixture model (referred to as AutoMCU©) was used to derive per-pixel fractional cover estimates of photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and soil. These results were compared with the normalized difference in vegetation index (NDVI) and field-derived GIS maps of felling gaps and skid trails.

We found that NDVI, PV, NPV, and soil fractions were useful for identifying felling gaps > 400 m^2 for up to 6 months after logging, and for identifying felling gaps < 400 m^2 for up to 3 months after logging; but they were not useful for identifying skid trails. The PV fraction was most sensitive to felling gaps. The NPV and soil fractions were both highly correlated with topographic shade and were thus less useful for

monitoring forest disturbances, especially in areas with more pronounced relief. These results identify important spatial and temporal thresholds relevant to monitoring selective logging with remote sensing; and may be used in the development of automated programs for identifying selectively logged forests in the region.

CHAPTER 1
INTRODUCTION AND LITERATURE REVIEW

We examined post-harvest recovery of forest structure and spectral characteristics in felling gaps and skid trails after selective logging in a forest concession located in the Department of Santa Cruz, Bolivia. Here, is a brief overview of the forest sector in Bolivia; followed by a description of the ecological impacts of selective logging and recent approaches for monitoring selective logging in the tropics using analysis of remotely sensed imagery.

1.1 Deforestation, Forest Degradation, and Logging in Bolivia

There are about 40 million ha of Amazonian lowland tropical forest in Bolivia (Steininger et al., 2001a) and over 53 million hectares (nearly 48% of the national territory) of forest cover in the country as a whole (Rodriguez, 2001). Recently, Bolivian lowland forests were placed among the top global conservation priorities (Myers et al., 2000; Steininger et al., 2001b) because of their high diversity of flora (Gentry, 1995) and fauna (Armonia., 1995; Stotz et al., 1996), and their abundance of habitat types (Prado and Gibbs, 1993; Killeen et al., 1998). Over 316 species of mammals, including 16 species of primates (Ergueta and Sarmiento, 1992); 1274 species of birds (Armonia., 1995); and over 20,000 species of flowering plants, including more than 2000 species of trees and shrubs (Malleux, 2000), have been discovered so far in Bolivian forests.

Historically, deforestation rates in the Bolivian lowlands were low, with only 2.4 million ha (or 5.6%) of the original forested area cleared by 1990 (CUMAT, 1992). Recently, deforestation has accelerated from ~ 80,000 ha (or 0.2% of the forested area) per year in the late-1980s, to more than 270,000 ha per year through the mid-1990s (MDSMA, 1995; Rodriguez, 2001; Pacheco, 2002). Deforestation in the Amazon portion of the Department of Santa Cruz alone (which covers approximately 61% of the entire department) has increased dramatically from 38,000 ha per year cleared annually between 1986 to 1990 (CUMAT, 1992) to more than 200,000 ha per year in the mid-1990s (Camacho et al., 2001; Kaimowitz et al., 2002; Pacheco, 2002), partly as a result of increased colonization and expansion of cattle ranching (Pacheco, 2002) and soybean production (Kaimowitz, Thiele, and Pacheco, 1999; Kaimowitz and Smith, 2001). Analysis of the spatial patterns of deforestation in the Department of Santa Cruz, Bolivia, shows that areas near roads and population centers are most likely to become deforested (Kaimowitz et al., 2002).

Selective logging, defined as the extraction of timber species (Verissimo et al., 1995) having the greatest economic value (Uhl, Barreto, and Verissimo, 1997), is also an important factor in degradation in Bolivia. Previous timber extraction in Bolivia depleted forests of mahogany (*Swietenia macrophylla*), oak (*Amburana cearensis*), cedar (*Cedrela sp*.), morado (*Macherium sp*.), tarara (*Centrolobium sp*.), and tajibo (*Tabebuia sp.*) (CORDECRUZ, 1994).

In 2001, there were 40 million ha of forest designated for permanent forestry production (Rodriguez, 2001); equal to approximately 77% of the total national forest cover. Of this area only 8.5 million ha (or approximately 16 % of the total forested area) have active logging rights (Forestal, 2002). Illegal logging in Bolivia comprises much of the total selectively logged area. Cordero (2003) reports that of 133 inspections of logging operations by the Bolivian Superintendencia Forestal, 39% were found to be illegal with a further 19% legal, but not in compliance with regulations. In addition to causing extensive forest degradation, illegal logging makes legal operations less financially competitive; and illegally logged areas are often subsequently converted to pasture or agriculture, or burn in wildfires.

1.2 Ecological Impacts of Selective Logging

Forest damage resulting from selective logging operations can be divided into the general categories of: (1) ground area disturbances; (2) residual stand damages; and, (3) canopy cover reductions (Uhl and Viera, 1989; White, 1994; Johns, Barreto, and Uhl, 1996; Jackson, Fredericksen, and Malcolm, 2002). Ground-area disturbance results from the construction and use of skid trails, logging roads, and log landings (Nicholson, 1958; Fox, 1968; Gillman et al., 1985; Jackson, Fredericksen, and Malcolm, 2002; Pereira et al., 2002), which may result in soil compaction and damage hydrological functions (Reisinger, Simmons, and Pope, 1988; Jackson, Sturm, and Ward, 2001). Residual stand damage results from harvesting of trees; which can damage or kill surrounding trees and vegetation and disturb regeneration. Stand-level disturbances can be inferred from changes in composition of forest regeneration after logging (Weaks and Creekmore, 1981; King and Chapman, 1983; Uhl and Viera, 1989; Panfil and Gullison, 1998; Fredericksen and Licona, 2000a; Fredericksen and Licona, 2000b; Fredericksen and Mostacedo, 2000; Jackson, Fredericksen, and Malcolm, 2002); from residual stand damage (Nicholson, 1958; Whitman, Brokaw, and Hagan, 1997); or simply from the overall reduction in basal area (Webb, 1997). Canopy-cover reduction results from felling of trees, which then causes further damage as they fall and remove other neighbor trees' canopies through direct impact or liana intercanopy connections. Canopy disturbances, such as increases in canopy openness (Horne and Gwalter, 1982; Crome, Moore, and

Richards, 1992; Pereira et al., 2002) due to selective logging have been insufficiently studied (Pereira et al., 2002). Though often difficult to distinguish disturbance category boundaries, they still serve as a simple foundation for comparisons between varying harvest intensities and silvicultural treatments.

Reduced impact logging (RIL) techniques can significantly minimize forest damage as compared with conventional logging (CL). The main components of RIL logging (Putz and Pinard, 1993; Pinard and Putz, 1996; Bertault and Sist, 1997; Uhl, Barreto, and Verissimo, 1997; Pinard, Putz, and Tay, 2000; Sist, 2000; Pereira et al., 2002) are

- Inventory and mapping to reduce waste during logging
- Planning of roads, log decks, and skid trails
- Vine cutting prior to harvest
- Planning of extraction, and
- Directional felling and bucking of trunks.

Many of these RIL components were mandated in 1996 when the Bolivian government implemented Forestry Law #1700, which instituted new legal and regulatory frameworks for control and monitoring of forestry operations (Griffith, 1999; Alvira, Putz, and Fredericksen, 2004).

The forest damage resulting from CL and RIL techniques varies widely, and depends on factors such as basal area removed, minimum cutting diameters, and forest type (Gullison and Hardner, 1993; Pinard and Putz, 1996; Panfil and Gullison, 1998). Conventional logging has been shown to damage 10-40% of the living forest biomass (Uhl et al., 1991); may disrupt ecological processes (Uhl and Viera, 1989), including the regeneration of commercially valuable species (Fredericksen and Licona, 2000a; Fredericksen and Mostacedo, 2000); may alter species composition (Johns, 1992;

Fredericksen et al., 1999; Lewis, 2001; Sekercioglu, 2002; Fredericksen and Fredericksen, 2002); and may affect forest biogeochemical processes (Asner, Keller, and Silvas, 2004).

1.2.1 Ground Area Disturbances

Ground area disturbances (GAD) commonly result from the construction and use of log landings, logging roads, skid trails, or impacts from tree felling. Effects of GAD include increased levels of soil compaction (Whitman, Brokaw, and Hagan, 1997; Jackson, Fredericksen, and Malcolm, 2002), and altered site hydrology (Asdak et al., 1998; Fletcher and Muda, 1999; Tague and Band, 2001).

Relationships between harvest intensity and GAD are difficult to establish due to the large variety of harvesting practices (Gullison and Hardner, 1993). Figure 1-1 illustrates the relationship for data obtained from 25 published articles, of which 14 were classified as having planned and 11 unplanned logging operations. Ground area disturbances were less common after reduced-impact logging (RIL) compared to conventional logging (CL) in Paragominas, Brazil (Johns, Barreto, and Uhl, 1996; Pereira et al., 2002). Panfil & Gullison (1998) found a strong relationship between increasing harvest intensities and increasing GAD within the Chimanes Forest, Bolivia, at even the relatively low harvest intensities of 1 to 6 trees/ha.

Asner et al. (2004) found that between 4.8 and 11.2 % of the ground area was disturbed after RIL and CL, respectively, logging in an Amazonian forest. Harvest intensities for the RIL and CL logging in their study were 3 and 6.4 trees/ha, respectively. Skid trails comprised 2.9 to 8.8% of the parcel following harvest. Jackson et al. (2002) found that selective logging at 4.35 trees/ha in a tropical forest in Bolivia damaged approximately 50% of the total area studied.

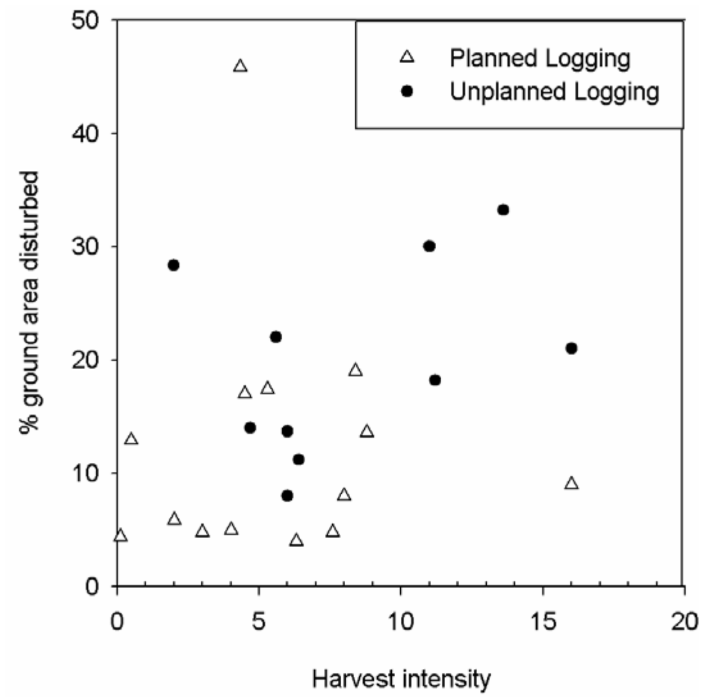

Figure 1-1. Ground area disturbed for varying levels of harvest intensity in planned and unplanned logging. Data from sources cited in Appendix A.

Of the disturbed area half was in the form of skid trails, roads, and log landings, and half was in the form of felling gaps (Jackson, Fredericksen, and Malcolm, 2002). Pereira et al. (2002) studied differences in disturbed area and canopy openness for RIL and CL techniques between 100 ha plots that were harvested at similar intensities (~3 individuals/ha). The total ground area disturbed was twice as great for CL (8.9 to 11.2% vs. 4.6 to 4.8% for CL and RIL, respectively) as it was for RIL (Pereira et al., 2002).

1.2.2 Residual Stand Damage

Aspects of residual stand damage, such as tree mortality (Johns, Barreto, and Uhl, 1996; Bertault and Sist, 1997; Webb, 1997; Panfil and Gullison, 1998; Sist et al., 1998; Sist and Nguyen-The, 2002), alterations in subsequent species composition (Panfil and Gullison, 1998), and regeneration (Fredericksen and Mostacedo, 2000) have been widely studied in the tropics. A significant linear relationship ($P < 0.05$, $R^2 = 0.96$) was found between increasing percentages of residual stand damage and increasing harvest intensity for unplanned logging operations for the literature reviewed in Appendix A, although the sample size (n = 4) was limited.

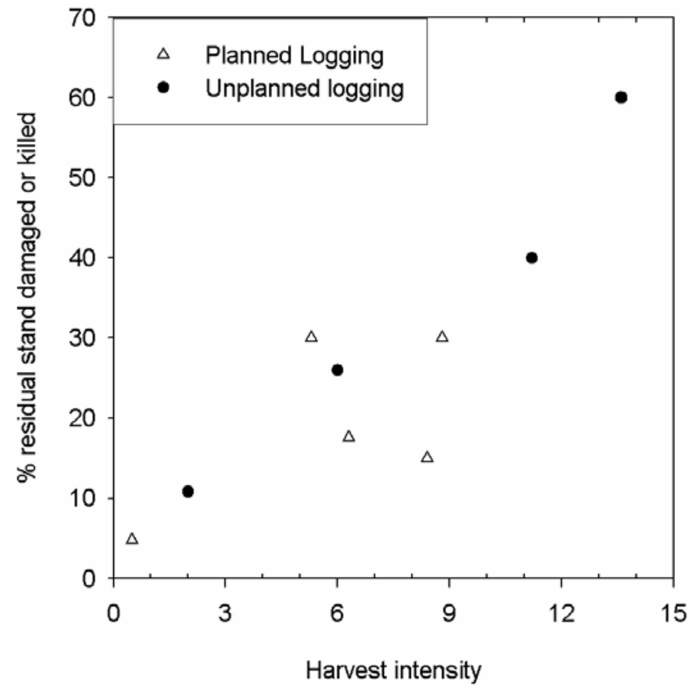

Figure 1-2. Residual stand damage for various levels and harvest intensity in planned and unplanned logging. Data from sources cited in Appendix A.

1.2.3 Forest Canopy Damage

Reductions in forest canopy cover are strongly related to silvicultural treatments, such as pre-harvest liana cutting (Putz, 1992; Vidal et al., 1997; Pinard, Putz, and Licona, 1999), as well as to increased harvesting intensity (Gullison and Hardner, 1993; Bertault and Sist, 1997). Silvicultural interventions can increase or decrease canopy coverage. For example, tree girdling or poisoning, and the cutting of unmarketable species, can lead to larger canopy reductions. Other techniques, such as vine cutting to minimize inter-canopy connections, can reduce the canopy damage per tree harvested for some forest types (Appanah and Putz, 1984; Vidal et al., 1997).

Panfil & Gullison (1998) found a correlation between increasing harvest intensities and increased canopy damage, which reached an asymptote at greater harvesting intensities due to the re-use of previously constructed skid trails and logging roads. Pereira et al (2002), found canopy openness of 16.5% and 21.9% for two CL blocks as compared with 4.9% and 10.9% for two blocks harvested with a RIL approach that included extensive pre-planning of roads, log decks and skid trails, as well as planned directional felling and vine cutting prior to harvest (Uhl, Barreto, and Verissimo, 1997). Other studies (Hendrison, 1990; Johns, Barreto, and Uhl, 1996), have found similar results.

Temporal patterns of recovery following logging operations have been studied extensively at the residual stand level (Dickinson, Whigham, and Hermann, 2000; Fredericksen and Pariona, 2002), including alterations in timber regeneration (Fredericksen and Mostacedo, 2000) and residual stand mortality rates (Sist and Nguyen-The, 2002). Canopy level damage, however, and its subsequent recovery (i.e. canopy closure), have been little studied (Pereira et al., 2002). Cannon et al. (1994) assessed canopy damage and closure for blocks in West Kalimantan, Indonesia. Three sites were selected that had undergone similar harvest intensities and had been harvested 0.5, 1 and 8 years prior to their study. The overall canopy openness for the sites decreased from 63% to 49% to 21% with increasing time since harvesting.

An analysis of planned and unplanned logging in Appendix A showed a significant linear relationship ($P < 0.05$, $R^2 = 0.72$, $n = 7$) between increasing harvest intensity and increasing levels of canopy loss (Figure 1-3). No relationship was found for unplanned logging, though it was obvious that much greater levels of canopy loss occurred at low harvest intensities. The utility of the relationship between increasing harvest intensity and increasing canopy loss for remotely monitoring logging operations is discussed in the following section. Forest canopy damage is markedly reduced in RIL relative to CL harvests (Howard, Rice, and Gullison, 1996; Johns, Barreto, and Uhl, 1996; Pereira et al., 2002).

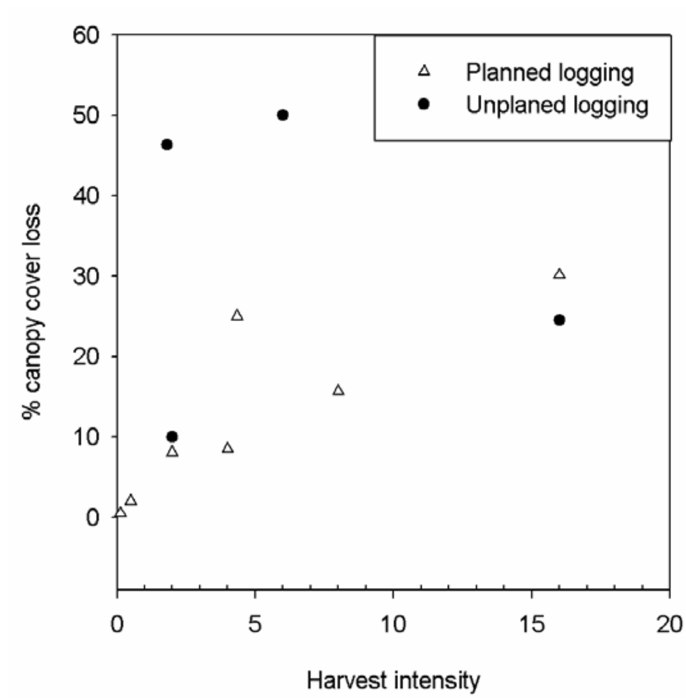

Figure 1-3. Significant relationship between increasing % canopy cover loss and increasing harvest intensity for planned logging. Data from sources cited in Appendix A.

1.3 Remote Sensing of Selective Logging

Improving the ability to estimate the extent, and intensity, of selective logging from remote sensors is essential for accurate modeling of carbon sequestration and release (Schroeder and Winjom, 1995; Schroeder and Winjum, 1995; Potter, 1999), developing effective wild-fire control policies (Holdsworth and Uhl, 1997; Nepstad et al., 1999; Cochrane and Laurance, 2002; Cochrane, 2003), conservation of fauna and flora, and monitoring logging activities (Keller et al., 2002). Currently, estimates of deforestation rates in the tropics are based primarily on remote sensing analyses discriminating between forested and non-forested regions (Skole, 1993; Steininger et al., 2001a; Achard et al., 2002). Landsat-based measurements of total forest conversion, normally to agriculture or pasture, are convenient as rapid and cost efficient deforestation estimators (Skole, 1993; Skole and Tucker, 1993) but are incapable of detecting forest areas degraded due to selective logging or fire (Stone and Lefebvre, 1998; Nepstad et al., 1999).

Acquiring accurate estimates of selective logging rates within the tropics has proven difficult (Stone and Lefebvre, 1998; Asner et al., 2002) because selective logging damage occurs on a fine spatial grain (Souza and Barreto, 2000; Pereira et al., 2002) compared with the spatial resolution of commonly available satellite imagery. Furthermore, the rapid regeneration of pioneer species in logged areas (Dickinson, Whigham, and Hermann, 2000; Fredericksen and Licona, 2000b; Fredericksen and Mostacedo, 2000) reduces indicators visible through optical remote sensing within 3 to 5 years (Stone and Lefebvre, 1998). Souza and Barreto (2000) were able to detect only 60% of field-verified logging patios (where logs are brought before being loaded on trucks for transport to a sawmill), and none that were > 3 years old due to rapid regeneration of vegetation.

Prevalent remote sensing image analysis techniques used for monitoring of forest disturbances are active radar (Siegert and Hoffmann, 2000; Siegert et al., 2001), texture analysis (Stone and Lefebvre, 1998; Asner et al., 2002), and basic relationships between single radiometric bands and logging disturbances (Asner et al., 2002). Vegetation indices, such as NDVI, have had limited utility (Jasinski, 1990; Carlson and Ripley, 1997; Stone and Lefebvre, 1998). Among the more successful methods for identifying logging disturbances are deriving per-pixel % vegetation cover (Todd and Hoffer, 1998) from linear spectral mixture models (Hall, Shimabukuro, and Huemmrich, 1995; Garcia-Haro, Gilabert, and Melia, 1996; Cochrane and Souza, 1998; Shimabukuro et al., 1998; Souza and Barreto, 2000), or probabilistic Monte Carlo versions of linear spectral mixture models, such as AutoSWIR or AutoMCU (Asner and Lobell, 2000b; Lobell et al., 2001).

1.3.1 Textural and Single Band Analysis

Textural analysis uses multi-pixel comparisons to enhance or diminish existing spatial variation (Asner et al., 2002; Debeir et al., 2002). Single band analysis compares the digital number, radiance, or reflectance from a single sensor band. Vegetation stress, or lack of typical vegetation spectral response, and the ability to discriminate vegetation from exposed soil and non-photosynthetic vegetation (residual logging slash) following selective logging may enhance the ability of remote sensors to identify these areas and will therefore be discussed in the following sections.

Individual Landsat Thematic Mapper (T.M) band reflectances can correlate with logging disturbances. Landsat TM bands 1, 2, and 3 (covering the visible spectrum between 0.45 and 0.69 um) have been helpful in delineating areas of exposed soil following selective logging (Asner et al., 2002), possibly due to decreases in moisture content to which these bands are sensitive (Ripple, 1986; Bowman, 1989). Bands 1 and 2 are often avoided in such analyses because they are susceptible to atmospheric aerosol contamination (Krueger and Fischer, 1994; Asner et al., 2002).

Landsat TM band 3 (red; centered at 0.67 nm) shows vegetation as very dark due to radiation absorption by foliar chlorophyll (Gaussman, 1977). TM band 4 (near-IR; centered at 0.83 nm) shows vegetation with high reflectance due to non-linear scattering of light by foliage, with soils and litter (NPV) having lower reflectance levels (Asner, 1998). These bands has been shown to correlate both positively (Thomas et al., 1971) and negatively (Penuelas et al., 1993) with vegetation drought stress according to a complex suite of leaf physiological factors, including variations in leaf area index (LAI) and greater shadowing from leaves wilting or curling up when exposed to increasing levels of drought stress (Jackson and Ezra, 1985).

The short wave infrared (SWIR) region of the spectrum, measured by Landsat TM bands 5 and 7, is a water absorption peak and thus decreasing SWIR reflectance has been found to correlate with increasing foliar water content (Tucker, 1980; Ripple, 1986; Bowman, 1989). Drought stress measurements using Landsat TM band 6 (thermal; centered at 11.45 nm) have focused on the increases in temperature (the thermal response) of plant foliage suffering water stress compared to the temperature of the surrounding air (Chuvieco et al., 1999).

Asner et al. (2002) combined field measurements of canopy gap fraction along a time series with textural and band-by-band analysis of Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data. Textural analysis was used to enhance post-logging variations between canopy and gap reflectance. These techniques, textural and single band analysis, were found sensitive only to high levels of canopy damage (>50% increase in canopy openness) and temporally limited to within 0.5 years post-harvest. These techniques may have some potential for broad delineation of very recently logged forests but are not useful for more detailed analyses of ecological or biogeochemical forest processes (Asner et al., 2002).

1.3.2 Band Indices

Band combinations, ratios, and indices provide a powerful image analysis tool for the assessment of moisture content, vegetation stress, and related logging damages

(Cibula, Zetka, and Rickman, 1992; Adegoke and Carleton, 2002; Aparicio et al., 2002). In the early 1980s it was found that leaf water content and photo-synthetically active biomass could be monitored through linear combinations of red and IR radiance changes (Tucker, 1979) and spectrum wavelengths between 1.55 and 1.75 um. Using these relationships Hunt et el. (1987 & 1989) developed a leaf water content index incorporating the wavelengths between .76-.90 um and 1.55-1.75 um.

Band indices have been developed to measure vegetation stress and moisture content (Gilabert et al., 2002). They have been used to estimate chlorophyll content (Tucker, 1979) and photosynthesis rates (Choudhury, 1987), primary productivity (Curren, 1980), susceptibility to wild fire (Chuvieco et al., 1999; Chuvieco et al., 2002) and leaf aging, drop and stress (Bohlman, Adams, and Peterson, 1998) in the Amazon. Indices, such as the soil and atmosphere resistant vegetation index (SARVI) (Huete et al., 1997), water deficit index (WDI) (Moran et al., 1994) or equivalent water thickness (EWI) (Ceccato et al., 2001; Ceccato, Flasse, and Gregoire, 2002; Ceccato et al., 2002), have been developed to estimate vegetation stress and water content with good accuracy.

The ratio of TM bands 4 to 5 has been found to be strongly indicative of changes in leaf water content (Hunt, Rock, and Nobel, 1987; Hunt and Rock, 1989). This is because decreases in leaf water content increase reflectance in the middle infrared spectrum while having little effect on reflectance in the near infrared spectra (TM band 5 and 4, respectively) (Knipling, 1970; Carter, 1991; Aldakheel and Danson, 1997).

Rock et al. (1994) found that, for an area with 100% vegetation cover, TM band 5 reflectance increased with increasing water stress with no change in the reflectance of TM band 4. Bohlman and Adams (1998) used the TM band 4 to 5 ratio to determine leaf aging, leaf drop and water stress during the transition from wet season to dry season for forests in Maraba, Brazil.

Several studies have noted the utility of the short wave infrared (SWIR 2 region, 2080–2280 nm) for remote measurement of leaf moisture content and discrimination of vegetation from soil and non-photosynthetic vegetation (i.e. slash or litter) (Asner, 1998; Asner and Lobell, 2000a, b; Lobell et al., 2001) due to the dominance of water absorption by green plant spectra (Elvidge, 1990; Drake, Mackin, and Settle, 1999).

1.3.3 Linear Spectral Mixture Model (LSMM) Analysis

Linear spectral un-mixing (Heinz, Chang, and Althouse, 1999; Heinz, 2001) or AutoSWIR (Asner and Lobell, 2000b) techniques decompose pixels to associated fractions of multiple selected materials of interest (MOI), termed endmembers. These materials of interest are chosen according to the ecological properties of the field location (as general as vegetation and soil or as specific as individual species if spectral seperability is adequate) and the desired resultant data product (Adams et al., 1995; Garcia-Haro, Gilabert, and Melia, 1999; Bateson, Asner, and Wessman, 2000).

For successful linear un-mixing of pixel reflectance materials of interest must be chosen that exhibit purity or extremity within the dataset and are known to contribute to pixel reflectance over the entire landscape of study (Schanzer, 1993; Bateson, Asner, and Wessman, 1998; Bateson, Asner, and Wessman, 2000; Heinz, 2001). Sub-pixel fractions, with appropriate endmembers, will sum to 100% pixel reflectance (Asner, Hicke, and Lobell, 2002). The number of endmembers that can be unmixed from any given pixel is dependent on the dimensionality (a function of the number of bands and amount of random noise in the data) of the satellite imagery (Asner and Lobell, 2000b; Asner, Hicke, and Lobell, 2002).

A least-squares based linear mixing model (constrained to 1) can be simplified to the following formula (Shimabukuro and Smith, 1991; Asner, Hicke, and Lobell, 2002):

$r_1 = \sum (a_{ij} \cdot x_j) + e_1$, where $\sum x_j = 1$ and,
r_i = spectral reflectance at the ith spectral band of the pixel;
a_{ij} = spectral reflectance known to the j^{th} component at the i^{th} spectral band;
x_j = value to be estimated from the proportion of the j^{th} component within the pixel;
e_1 = estimation error for the i^{th} spectral band;
i = number of spectral bands considered;
j = number of components.

The root mean square error fraction can serve as an indicator of how good the chosen endmembers are for the particular pixel.

A classic study of forested ecosystem reflectance using hyper-spectral AVIRIS found that 98% of spectral variation was explained by linear mixtures of three endmembers: photosynthetic vegetation (PV), shade, and soil (Roberts, Smith, and Adams, 1993), with non-photosynthetic vegetation (NPV) not able to be directly distinguished from the soil endmember. NPV differences, however, discriminated through analysis of residual spectra were helpful in distinguishing distinct communities of green vegetation.

The characteristic spectra of photosynthetic vegetation, dominated by foliar water absorbance across the spectrum (Elvidge, 1990) and C-H and O-H bonds in the SWIR region (Curran, 1989), as well as the presence of chlorophyll. NPV, lacking the water content of PV, and having distinct spectral features resulting from organic carbon bonds interacting with solar radiation (Curran, 1989), can be distinguished from the more similar spectra of soil partly through differences in the SWIR response attributable to the effects of cellulose and lignin in the vegetation (Roberts, Smith, and Adams, 1993) on the SWIR spectrum. Soil spectral properties vary according to mineralogy, clay content

(Drake, Mackin, and Settle, 1999), and moisture content (Weidong et al., 2002) and roughness (Pinty, Verstraete, and Gobron, 1998).

Shade spectra have been developed through both inversion of standard linear mixing models (Roberts, Smith, and Adams, 1993), and sampling of shaded areas in satellite imagery (Shimabukuro et al., 1998; Souza and Barreto, 2000), among other methods. Integration of a shade endmember can be helpful to compensate for the effect of topography, which is caused by differential illumination of the Earth's surface and generally results in darker slopes facing away from the sun (Civco, 1989), and inter- and intra-canopy shadowing (Asner and Warner, 2003) which are both prevalent in satellite imagery. Shade can also be incorporated directly into the endmember bundles (Asner et al., 2004). Other methods for topographic correction are based on the Lambertian assumption that measured reflectance does not vary with view angle (Holben and Justice, 1980), which provide poor normalizations and often over-corrects for topography (Jensen, 1996), or on complicated non-Lambertian models that require development and validation of image based coefficients (Hodgson and Shelley, 1994).

Linear spectral mixture analysis (SMA) has been used with success to locate areas of recent fire (Wessman, 1997; Cochrane and Souza, 1998), exposed soil from recent logging (Souza and Barreto, 2000), differentiate forested from non-forested areas through differences in shade fractions (Shimabukuro et al., 1998), estimate Amazonian transition forest biomass (Santos et al., 1999), and assess general land-cover change in tropical Amazonian forests (Adams et al., 1995). Souza and Barreto (2000) (Souza and Barreto, 2000) used LSMA to detect selectively logged Amazonian forest based upon sub pixel soil fractions. The study sites had 5 to 7 trees harvested per ha (Johns, Barreto, and Uhl,

1996) for planned and unplanned selective logging. Souza and Barreto (2000) chose pixels having 20% or greater soil fraction as indicators of patios used for selective logging. This technique was temporally limited due to rapid regeneration of pioneer vegetation over exposed soil areas and was unable to locate sites five years post-logging.

Adams et al. (1995) divided an Amazonian landscape into seven general categories based upon their LSMA endmember fractions. Primary forest areas visibly differed from those with large quantities of slash (i.e., areas recently selectively logged) due to higher fractions of NPV and soil, and reductions in the shade fraction. The temporal variations in the abundance of each endmember were used to assess landscape cover change.

Asner et al. (2004) estimated per-pixel fractional cover of photosynthetic (PV), and non-photosynthetic (NPV) vegetation, and soil in Amazonian forests near Paragominas Brazil using an automated un-mixing model, termed AutoMCU©, incorporating endmember bundles. Endmember bundles are field derived reflectances (measured with a field spectroradiometer) of materials that encompass the full naturally occurring variability within the endmember class (for example, a specific soil at different moisture levels) (Bateson et al., 1998). Pixel un-mixing using endmember bundles allows for higher accuracy levels of sub-pixel fractional compositions and confidence interval estimates for those fractions (Asner and Lobell, 2000b). Asner et al. (2004) found significant differences between conventional (CL) and reduced-impact logging (RIL) PV, NPV, and soil endmember fractions that varied strongly with time since harvesting due to gap regeneration and canopy closure.

Asner et al. (2002), employing the AutoMCU© unmixing technique and endmember bundles was able to discriminate selectively logged areas in the eastern

Amazonia for up to 3.5 years post logging. Canopy openness was found to be greater following conventional logging than reduced-impact logging immediately. Subsequent satellite and field-based measurements of canopy gap fraction were highly and inversely correlated. The 50% decrease in canopy openness derived from the unmixing process agreed well with ground based measurements. This technique seems the most promising but has yet to be studied for the gradient of harvest intensities and variety of forest types necessary for broader application in Amazon forests.

In November 2003 a special issue of Remote Sensing of the Environment was published dedicated to remote sensing analyses of land use and land cover change, including selective logging, in the Brazilian Amazon. Five of the 13 papers in this issue featured linear spectral mixture model methodology. Numata et al. (2003) assessed sub-pixel fractional cover of green vegetation, shade, soil, and non-photosynthetic vegetation within pastures and found that they were dominated by NPV, whose dominance increased with increasing pasture age. Dengsheng, Lu et al. (2003) found that a LSMM approach was a promising method for distinguishing successional and mature forests, and that sub-pixel percentages of green vegetation and shade were the most sensitive to changes in forest structure. A study by Souza et al (2003) analyzing sub-pixel fractions PV, NPV, soil, and shade found that NPV was positively correlated with aboveground biomass and improved the ability to map selectively logged forests. A decision tree approach (dichotomous categorization) of the sub-pixel fractions was used to then successfully delineate between intact, logged, and regenerating forests (Souza et al., 2003). Asner et al. (2003) used the AutoMCU© approach (Monte Carlo approach incorporating endmember bundles) to unmix Landsat Thematic Mapper pixels in areas bordering the

Tapajos National Forest in the Central Amazon and found that PV and NPV fractions were useful for quantifying biophysical variability within and between pixels .

1.3.4 Influences of Topography and Seasonality on Spectral Response

The topographic effect is caused by differential solar illumination of the Earth's surface, which generally results in darker slopes facing away from the sun and brighter slopes facing the sun (Civco, 1989). The topographic effect is a combination of

- Incident illumination defined as the orientation of the land surface to the sun's rays
- Exitance reflectance defined as the energy reflected as a result of the slope, and
- Land topography and shadowing (ERDAS, 1999).

Together these factors can cause identical land cover to be represented by different intensity values depending on the degree of shadowing. An ideal topographic normalization removes all intensity variation resulting from differential illumination, creating a pseudo flat reflectance surface.

It is possible to correct for the topographic effect using either Lambertian or non-Lambertian reflectance models or through the use of mixture model techniques employing shade endmembers (Souza and Barreto, 2000). The Lambertian model normalizes imagery according to the cosine of the sun illumination angle (zenith) at the time of image acquisition and the slope/aspect information from the digital elevation model (DEM) of the area (Smith, Lin, and Ranson, 1980). The Lambertian assumption, that the measured reflectance does not vary with view angle (Holben and Justice, 1980), provides poor normalizations and often over-corrects images, with sun-facing slopes appearing darker than those facing away from the sun (Civco, 1989). This results from not including non-Lambertian scattered reflectance, such as diffuse skylight or light reflected from surrounding mountainsides (Jensen, 1996).

Minneart and Sceicz (1961) proposed that all surfaces do not reflect incident radiation uniformly. The non-Lambertian reflectance model compensates for this by using image based correction factors within the algorithm (Hodgson and Shelley, 1994) and has been shown to have higher accuracy than Lambertian models (Smith, Lin, and Ranson, 1980) and fewer problems with over-correction (Civco, 1989). However, the development of a non-Lambertian model is time consuming and often requires field truthed data (ERDAS, 1999).

Few studies have closely examined the abilities of a shade fraction or endmember bundle to remove the effect of topography. However, in general, topography is thought to have a minimal effect on the response of band indices, such as NDVI, as shade is largely photometric and results in a general decrease in spectral response which is independent of the bandwidth. A band ratio (such as NDVI) could therefore compensate for topographic differences and return topographically independent results.

The effect of seasonality on the response of NDVI has been investigated in north-west Mexico (Salinas-Zavala, Douglas, and Diaz, 2002), where strong correlations were found between pluviometric data and atmospheric circulation and changes in NDVI. Other studies have found correlations between seasonality, including forest phenology, and the landscape's spectral response (Roberts et al., 1998; Asner and Lobell, 2000b; Ferreira et al., 2003; Siqueira, Chapman, and McGarragh, 2003).

CHAPTER 2
POST-HARVEST RECOVERY OF FOREST STRUCTURE AND SPECTRAL PROPERTIES AFTER SELECTIVE LOGGING IN LOWLAND BOLIVIA

2.1 Introduction

Timber production within the Amazon basin has been estimated at 30 million cubic meters per year, based on regional sawmill production, but estimates of the areal extent and intensity of the selective logging practices that supply that timber are very poorly constrained (Nepstad et al., 1999; Lentini, Verissimo, and Sobral, 2003; Nepstad et al., 2004). Much of the selective logging in the region is clandestine, and in many cases, even legally registered forest management plans are extremely imprecise. Improving the ability to estimate the extent, and intensity, of selective logging is essential for monitoring of logging activities (Keller et al. 2002), and for accurate modeling of carbon sequestration and release (Schroeder and Winjom, 1995; Schroeder and Winjum, 1995; Potter, 1999), and developing effective wild-fire control policies (Holdsworth and Uhl, 1997; Nepstad et al., 1999; Cochrane and Laurance, 2002; Cochrane, 2003).

Remote sensing technology may offer an objective means of determining the location, extent, and intensity of selective logging, but its use for those purposes is challenging because selective logging damage often occurs on a finer spatial grain than the spatial resolution of commonly available satellite imagery (Stone and Lefebvre, 1998; Souza and Barreto, 2000; Asner et al., 2002; Pereira et al., 2002), and forests rapidly regenerate after logging (Dickinson, Whigham, and Hermann, 2000; Fredericksen and

Licona, 2000b; Fredericksen and Mostacedo, 2000) reducing indicators visible through optical remote sensing (Stone and Lefebvre, 1998).

In Bolivia, selective logging is an important cause of degradation in the country's lowland Amazon region (Cordero 2003). Previous timber extraction in Bolivia depleted forests of mahogany (*Swietenia macrophylla*), oak (*Amburana cearensis*), cedar (*Cedrela sp*.), morado (*Macherium sp*.), tarara (*Centrolobium sp*.), and tajibo (*Tabebuia sp.*) (CORDECRUZ, 1994). Although recent changes in the Bolivian Forestry Law provide an exemplary framework for good forest management (1996; Griffith, 1999), clandestine and poorly regulated logging activities continue, and the extent and intensity of ongoing selective logging in the Bolivian Amazon has not been quantified (Cordero, 2003).

This study was designed to examine the potential applicability of remote sensing technology to the detection of selective logging in the Bolivian Amazon. In it I employ intensive spatial and temporal field measurements of structural changes associated with selective logging and then used these measurements to test the sensitivity and examine the temporal and spatial thresholds of a commonly used remote sensing vegetation index and an advanced linear spectral unmixing method. The unmixing method has previously been used for detection of selective logging in a limited number of locations in the Brazilian Amazon, where both standing and harvested volumes are substantially larger than at the study area I examined in Bolivia (Asner et al., 2002; Asner et al., 2004; Asner, Keller, and Silvas, 2004). The results of the analysis I present here can inform future efforts at monitoring the areal extent and spatial distribution of selective logging using remotely-sensed data.

2.2 Site Description

The study was conducted in the Agroindustria Forestal La Chonta Ltda. timber concession (15° 47’ S, 62° 55’ W) which encompasses 100,000 ha in the Guarayos forest preserve in the Department of Santa Cruz, Bolivia (Figure 2-1). The topography is slightly undulating and the vegetation is classified as Subtropical Humid Forest according to the Holdridge Life Zone System (Holdridge, 1971) and has an average biomass of 73 to 190 Mg/ha (Dauber, Teran, and Guzman, 2000). The elevation is 400 to 600 m above sea level, otherwise referred to as the Bolivian lowlands. Common canopy trees in the area, such as *Hura crepitans, Ficus boliviana,* and *Pseudolmedia laevis*, are typical of humid forests within Bolivia (Jackson, Fredericksen, and Malcolm, 2002). The average annual temperature is 15.3 °C and the mean annual precipitation is 1,560 mm, though 77% of the annual precipitation falls between November and April (Appendix B). During the dry season temperatures often drop to 5 to 10 °C due to Antarctic fronts (Gil, 1998). The soils are primarily moderately fertile inceptisols, though large areas of black anthrosols can be found throughout the concession (Calla, 2003; Paz, 2003). The region is vulnerable to wildfires (CAF, BOLFOR, and Geosystems, 2000), and 30% of the concession burned in 1995 (Gould et al., 2002).

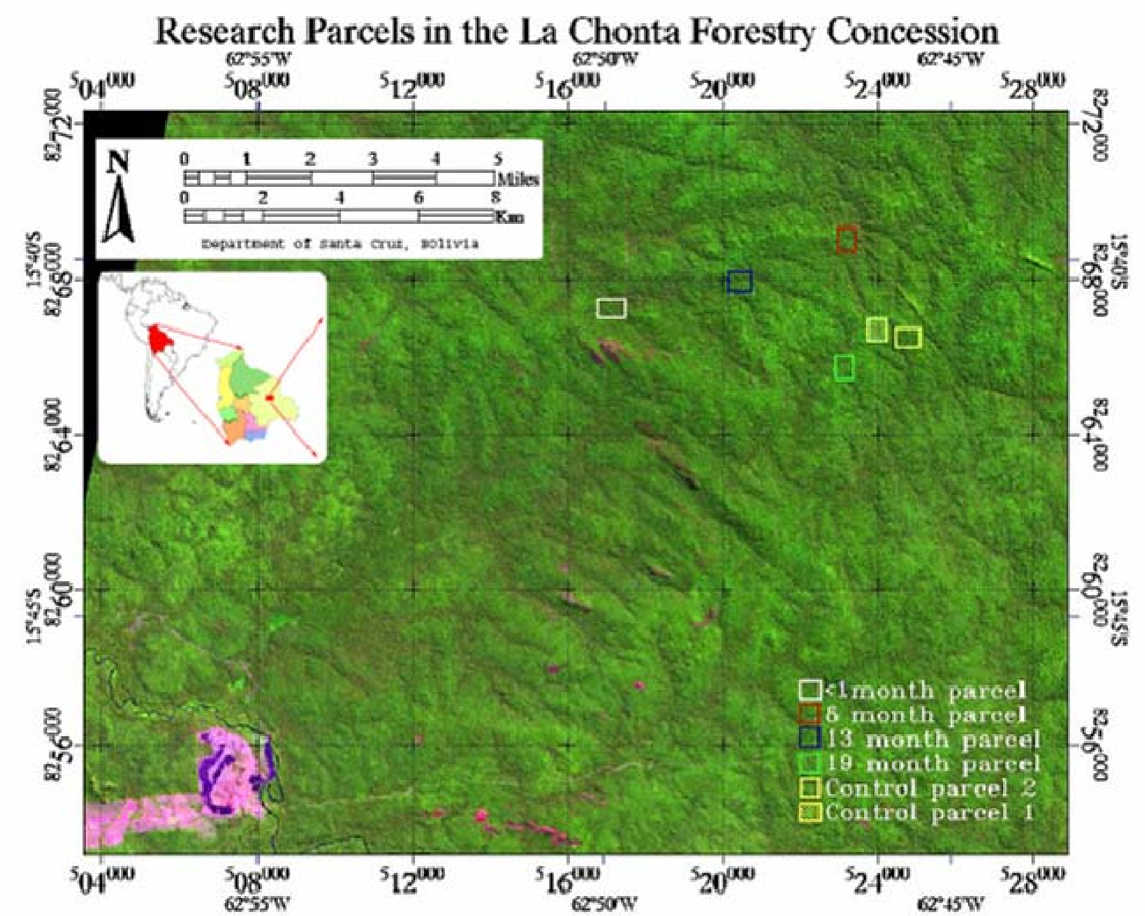

Figure 2-1. Location of research parcels in the La Chonta forestry concession, Department of Santa Cruz, Bolivia. The parcel boundaries are overlaid on a RGB composite image of ASTER bands 2, 3, and 1, respectively, from an image acquired on 30 June 2004.

There are approximately 100 tree species with individuals >20 cm diameter at breast height (DBH) within La Chonta (Gil, 1997; Gil, 1998). The mean tree density is 88 trees/ha (Alvira, 2002). Eighteen timber species are currently harvested, including *Ficus. sp*., *Pseudolmedia laevis*, *Hura crepitans, Ceiba pentandra,* and *Spondias mombin* (BOLFOR, 2000). Average canopy height is 21±1 m (unpublished data) within a non-logged control parcel.

The concession was previously high-graded for mahogany (*Swietenia macrophylla*) (Gil, 1998), but over 60% of the area is considered to be suitable for sustained-yield timber harvesting (Gil, 1997). The current annual cut is 2400 ha producing a wood volume of approximately 51,000 m^3 (Jackson, Fredericksen, and Malcolm, 2002). Average harvest intensity is 4.35 trees/ha (or 12.3 m^3/ha of wood) (Jackson, Fredericksen, and Malcolm, 2002). The cutting cycle, as set by forestry law #1700 introduced in 1996, is 30 years (1996; Fredericksen, 2000), though several years are granted to complete extraction of a given annual block.

La Chonta was certified by the Forest Stewardship Council (FSC) in early 1990 and abides by certification standards, including implementation of reduced impact logging (RIL) techniques (Johns, Barreto, and Uhl, 1996; Uhl, Barreto, and Verissimo, 1997; Nittler and Nash, 1999; Sist, 2000; Pereira et al., 2002)

- Inventory and mapping of trees to be harvested
- Planning of roads, log decks, and skid trails
- Vine cutting prior to harvest when necessary
- Directional felling, and
- Planning of extraction.

Harvesting is based on a 50 cm minimum DBH cutting limit, with the exception of *Hura crepitans* and *Ficus glabrata* that have a minimum DBH of 70 cm (Jackson, Fredericksen, and Malcolm, 2002). Twenty percent of harvestable trees are left as seed trees. One year prior to harvesting, crop trees are selected, marked, and mapped, and some of the lianas in their crowns are cut (Alvira, 2002; Krueger, 2003). Prior to harvest, skid trails are built every 150 m intervals perpendicular to the main access road (Jackson, Fredericksen, and Malcolm, 2002). Directional felling of harvested trees minimizes ecological damage and improves ease of yarding (Krueger, 2003). Caterpillar 518C skidders equipped with rubber tires and winches with 15 m of steel cable are used to drag the logs to roadside log decks (Krueger, 2003), where they are loaded on trucks for transport to the concession's sawmill.

2.3 Methods

Four logged parcels, ranging from 27 to 31 ha and two non-logged 27 hectare control parcels were used in this study. Two of the logged parcels, and both the control parcels, were previously established, measured, and mapped by the Instituto Boliviano de Investigaciones Forestals (IBIF). All four logged parcels were harvested using RIL harvesting techniques, with harvest intensities varying from 1 to 2 trees per ha (Table 2-1). Each parcel was logged at a different time, either <1, 6, 13 or 19 months prior to the collection of field data in July, 2003.

Table 2-1. Characteristics of the selectively-logged parcels used in this study

Parcel	Parcel area (ha)	Total trees harvested	Harvest Intensity (trees/ha)
<1 month post-harvest	29.7	56	1.8
6 months post-harvest	27.0	27	1.0
13 months post-harvest	32.0	64	2.0
19 months post-harvest	28.0	29	1.0

Within the constraints of the current study, it was not possible to measure replicate parcels for each stage of this selective logging chronosequence. As a result, in a formal sense, I am unable to extrapolate from the results I report below to all selectively-logged parcels in the region (Hurlbert, 1984). However, in this study, individual felling gaps and skid trail segments, rather than the parcels, are used as the units of analysis. The statistical tests I employ here are inferential and are used to provide an objective indication of whether significant differences between individual felling gaps, for example, were related to their location within a given parcel, and/or due to other factors, such as felling gap size class (Oksanen, 2001). Where parcel is a significant effect, I infer that the effect is largely a result of the differences in time post-harvest. I argue that this inference is justified because of the absence of plausible alternatives to explain such systematic between-parcel differences in individual felling gaps and skid trail segments.

2.3.1 Field Spatial Analyses

Parcel boundaries, skid trails, and felling gaps were geo-located for the < 1 and 6 months post-harvest parcels using a global positioning system (GPS) unit (maintaining precision <10 m and with a minimum of 5 satellites visible) and entered into a geographic information system (GIS) (ArcGIS; ESRI, Redlands, California, USA).

Skid trail and stump locations within the 13 and 19 months post-harvest parcels (450 m by 600 m) were mapped by IBIF. The maps were then geo-rectified using a minimum of 15 field GPS measurements per parcel. The root mean square error for the geo-located parcels was consistently < 5 m.

The area of each felling gap was entered into the GIS using field measured azimuth of fall (adjusted for declination) from the stump and field length and width measurements. The length of the gap was measured as the longest axis. The width (minor) axis of the gap was measured perpendicular to the length (major) axis at the 50% gap length point, and operationally the gap was defined as an oval with these two axes. Although most felling gaps have more varied shapes, this assumption was sufficiently accurate for the questions addressed within this study and convenient for integration with a GIS. These oval polygons were geo-referenced to the previously geo-located stump locations. Gap edges were defined by 10 m tall vegetation surrounding the ground area disturbed by the fallen tree or yarding process.

The definition of gap used in this study differs from ecological measurements of gaps (Brokaw, 1982; Uhl, 1988), which consider only areas with open canopy to be part of the gap. Because remote sensors are sensitive to ground disturbances occurring below forest canopies (Asner et al., 2004) I chose to define gaps with reference to the disturbed ground area, and separately estimate canopy openness within that area. The nature of the definition of gap used here means that the data I report should not be compared to measurements of gaps that follow the ecological convention (Brokaw, 1982; Uhl, 1988).

Skid trail width was defined as the distance between the outer edges of the most widely separated wheel ruts, and the mean width of 172 measurements was used to buffer the geo-referenced skid trail centerlines to calculate per-parcel skid trail area. Skid trail area was calculated for a total of 10 parcels, including six additional parcels that had been mapped previously by IBIF. Relationships between the area of skid trail and harvest intensity were investigated using a Michaelis-Menten non-linear regression in JMP© statistical software. The Michaelis-Menten non-linear regression ($y = ((\theta1 * x) / (\theta2 + x))$) was chosen to model the relationship as a previous study (Panfil and Gullison, 1998) showed that the total area of skid trails had a positive quadratic relationship with increasing harvest intensity.

2.3.2 Field Measurements and Analyses

Within the logged parcels, field measurements were made in felling gaps and skid trails. Felling gaps were classified as: large (> 800 m^2), medium (400 to 800 m^2), or small (< 400 m^2), and were divided in half to form trunk and crown zones of equal size. All field measurements were made separately within the two zones. Skid trails were sampled in 100 m transects along straight sections of the trails. A separate set of measurements was made in each 10 m segment of the 100 m transects. Additionally, a 50 m X 50 m grid layout was used to establish measurement points within a 450m X 600 m unlogged control forest.

Field measurements included cover estimates from 5 m above the ground surface for: photosynthetic vegetation (PV); non-photosynthetic vegetation (NPV), which includes trunks, branches and senesced leaves; exposed soil; and a separate estimate of lianas with green foliage (green foliage of lianas is also included in the PV estimation). Canopy openness was estimated using a scale of 0 to 1 defined as the proportion of a standard upward facing hemispherical mirror at 1.5 m height that has a clear view of the sky (no canopy obstruction). Previous studies have shown that a canopy densiometer has comparable accuracy to digital or film hemispherical photography (Englund, O'Brien, and Clark, 2000).Within the logged parcels, additional measurements included the maximum height of regeneration in felling gaps and skid trails, the height of residual non-photosynthetic vegetation in felling gaps (excluding the stump), and skid trail width.

Photosynthetic and non-photosynthetic vegetation, exposed soil, and liana cover were estimated for the entire trunk and crown zones of the felling gaps, and every 10 m along the skid trails, within a 2-m band perpendicular to the direction of the trail. At the grid points in the unlogged control forest, these cover estimates were made within a 2 m diameter circle placed 1 m to the edge of the path that connected the grid points. In the felling gaps, canopy openness readings were taken in the middle of each zone along the length axis. For skid trails these readings were taken from the middle of the 2-m bands described for the cover estimates.

Felling gaps that included more than one felled tree (defined as overlaid gaps and constituting < 5% of the total gap area) were identified in the GIS and removed prior to statistical analysis to avoid confounding relationships between field measurements taken in the trunk and crown felling gap zones. To analyze field data collected within the individual tree felling gaps, a mixed 3-way analysis of variance (ANOVA-SAS©, 2003) was used to test the main effects of parcel, size class (large, medium, and small), and gap zone (trunk vs. crown), and their interactions on canopy openness, vegetation height, PV, NPV, exposed soil, and NPV height in the individual tree felling gaps. For field data collected within the skid trail segments, one-way ANOVA was used to test for the effect of parcel on canopy openness, vegetation height, trail width, PV, NPV, and exposed soil. For both the felling gap and skid trail data, Tukey's and Dunnett's post-hoc tests were performed to identify significant, pair-wise differences between the four logged parcels, and between the individual logged parcels and the unlogged control forest parcel, respectively.

2.3.3 Remote Sensing Measurements and Analyses

Fourteen ASTER (Advanced airborne thermal emission radiometer) satellite images were obtained of the study area during the summer of 2003. Of these images four were found to be sufficiently cloud-and error-free for use in this study. These images were acquired on 13 May 2003, 30 June 2003, 16 July 2003 and 17 August 2003. In addition to these images a pre-harvest image had been previously acquired on 11 August 2001. These images were obtained in universal transverse mercator (UTM), world geodetic system (WGS) 1984 datum, zone 20 south projection and preprocessed by NASA to L2B surface reflectance. The preprocessing compensated for differences in sun angle / image geometry and atmospheric differences between the images. ASTER surface reflectance data have been validated to provide surface reflectance within 1% for actual surface reflectance < 15% and within 7% of actual surface reflectance > 15% (Abrams and Hook, 2001). Field validation of ASTER imagery, however, indicates that the absolute radiometric correction are, in general, better than 4% (Thome et al., 1998; Yamaguchi et al., 2001). These corrections are performed using radiative transfer calculations with atmospheric aerosol content from outside sources, such as the MODIS satellite or climatology data (Abrams and Hook, 2001).

The visible-infrared (15 m pixels) images were re-sized to 30 m using aggregate pixel mean values and co-registered to the short wave infrared (30 m pixels) image, then layer stacked using nearest neighbor to produce 9-band images. Band 9 was removed prior to imaging processing due to problems with atmospheric water vapor.

The 30 June 2003 image was chosen as the base image as it had the least cloud interference. The remaining images were geo-referenced to the base image using a minimum of 80 image-to-image control points dispersed throughout the image. The RMS errors for each geo-referencing were < 15 m (or half a pixel). All images were then layer stacked using the nearest neighbor re-sampling to get absolute pixel overlay. The stacked multi-date image was then geo-referenced to 95 field GPS ground reference points (UTM, WGS 84, Zone 20 S) which were acquired during the summer of 2004. The RMS error was < 15 m in the final warp model. The image was warped using a 1st order polynomial model with nearest neighbor re-sampling.

Finally the image overlays were visually assessed by flickering between the May, July and both August images against the 30 June 2003 base image. Systematic off-sets were observed with the 16 July 2003 image and were corrected through direct adjustment to the image map reference coordinates. The 4 post-harvest and 1 pre-harvest control images of the parcels enable a multi-temporal assessment of the sensitivity of the remote sensing methodology to selective logging at < 1-4, 6-9, 13-16 and 19-22 months post harvest.

A probabilistic spectral mixture model was used to decompose the ASTER image per-pixel surface reflectances into sub-pixel estimates of photosynthetic vegetation, non-photosynthetic vegetation, and exposed soil. Errors in the linear mixing assumption of the endmembers were shown in the per-pixel RMS error fraction. Development of this model was based on an automated probabilistic linear spectral unmixing procedure developed originally for woodland and shrubland ecosystems (Asner and Lobell, 2000a, b) and recently used for analysis of selective logging impacts in the Brazilian Amazon (Asner et al., 2004).

I used a general database of photosynthetic and non-photosynthetic vegetation and soil spectra that had been collected over logged and unlogged sites in South America (G. Asner, Personal Communication) which were deconvulved to ASTER bandwidths using published ASTER band response coefficients. Endmember bundles of several hundred mean spectra were used in the unmixing procedure. The use of endmember bundles, rather than single endmembers, is a technique to incorporate naturally occurring endmember spectral variability into the unmixing model (Bateson, Asner, and Wessman, 2000). A separate shade endmember was not included, as shade levels of 0 to 30% were incorporated into the photosynthetic vegetation endmember bundle to account for topographic and intra- and inter-crown shadowing which are prevalent within satellite imagery (Asner and Warner, 2003).

The 4 post-harvest images were corrected for pre-existing differences in topography and forest structure among the study parcels by subtracting the NDVI and fractional values of the pre-harvest image from each of the post-harvest images. The variability between images associated with seasonality and atmospheric differences were removed by normalizing each logged parcel with the control parcel from the same image date.

A digital elevation model (DEM) was obtained by request from NASA's Earth Observing System (EOS). The DEM was produced through stereoscopic comparison of nadir and side angle data from the 11 August 2001 pre-harvest control ASTER image, and has been validated to have <= 10 m relative accuracy (vertical) and < 50 m horizontal error (Abrams and Hook, 2001). The geo-location of the DEM was done through visually adjusting the DEM (through alterations to the map info reference coordinates) until shadows in a DEM based shaded relief model (based on the 2001 image from which it was created) matched up with the shadows in an RGB (bands 2, 3, and 1, respectively) composite of the 11 August 2001 ASTER image. Lambertian shaded relief images (on scale of 0–1 total reflectance) were modeled based on the sun elevation and azimuth.

Separate 2-way repeated measures ANOVA s were used for each remote sensing variable (per-pixel NDVI, and PV, NPV and soil fractions) to test the main effects of parcel and image date and their interactions for large, medium, and small felling gaps, and for skid trails. Dunnett's post-hoc tests were performed to identify significant differences between the large, medium, and small felling gap, and skid trail pixels and pixels located in the unlogged control parcel. Within the logged parcels, residual forest pixels (defined as those > 10 m from a felling gap or a skid trail) were used to illustrate the size of the disturbance effects relative to between-parcel effects when comparing felling gap and control parcel reflectance. The August 11 2003 image data of the 6 months post-harvest parcel was not used because the parcel had been re-entered for further extraction during that month. Separate linear regressions were run between NDVI, PV, NPV, and the soil fraction pixels within the control parcels for the four summer 2003 ASTER images (*n* = 530) and the Lambertian shaded relief values for those same pixels to estimate the influence of topographic shade.

The July 16 2003 image was acquired closest to the date of field data collection, so I used this image to examine the strength of relationships between the field measurements within the felling gaps and the remote sensing responses of those same felling gaps using Pearson bivariate correlation analysis within the < 1 month and the 6 months post-harvest parcels.

2.4 Results

2.4.1 Field Spatial Analyses

Higher harvest intensities within the logged parcels correlated with higher area in felling gaps. Felling gaps accounted for most of the disturbed area in the logged parcels, ranging from 4 to 11% of the total parcel area, while skid trails only accounted for a maximum of 5 % (Table 2-2). The spatial distribution of felling gaps and skid trails is illustrated in Figure 2-2. Gap size ranged from of 59 m^2 to 2200 m^2, and gaps > 800 m^2 were uncommon (Table 2-3).

Table 2-2. Percent parcel area disturbed by tree fall gaps and skid trails

Parcel	Parcel area in ha	Harvest intensity (trees/ha)	% of parcel in felling gaps	% of gap area in overlaid gaps	% of parcel in skid trails
<1 month post-harvest	30	1.9	8.7	3.4	4.0
6 months post-harvest	27	1.0	6.9	3.1	2.4
13 months post-harvest	32	2.0	10.5	6.7	5.1
19 months post-harvest	28	1.0	4.2	2.9	3.8

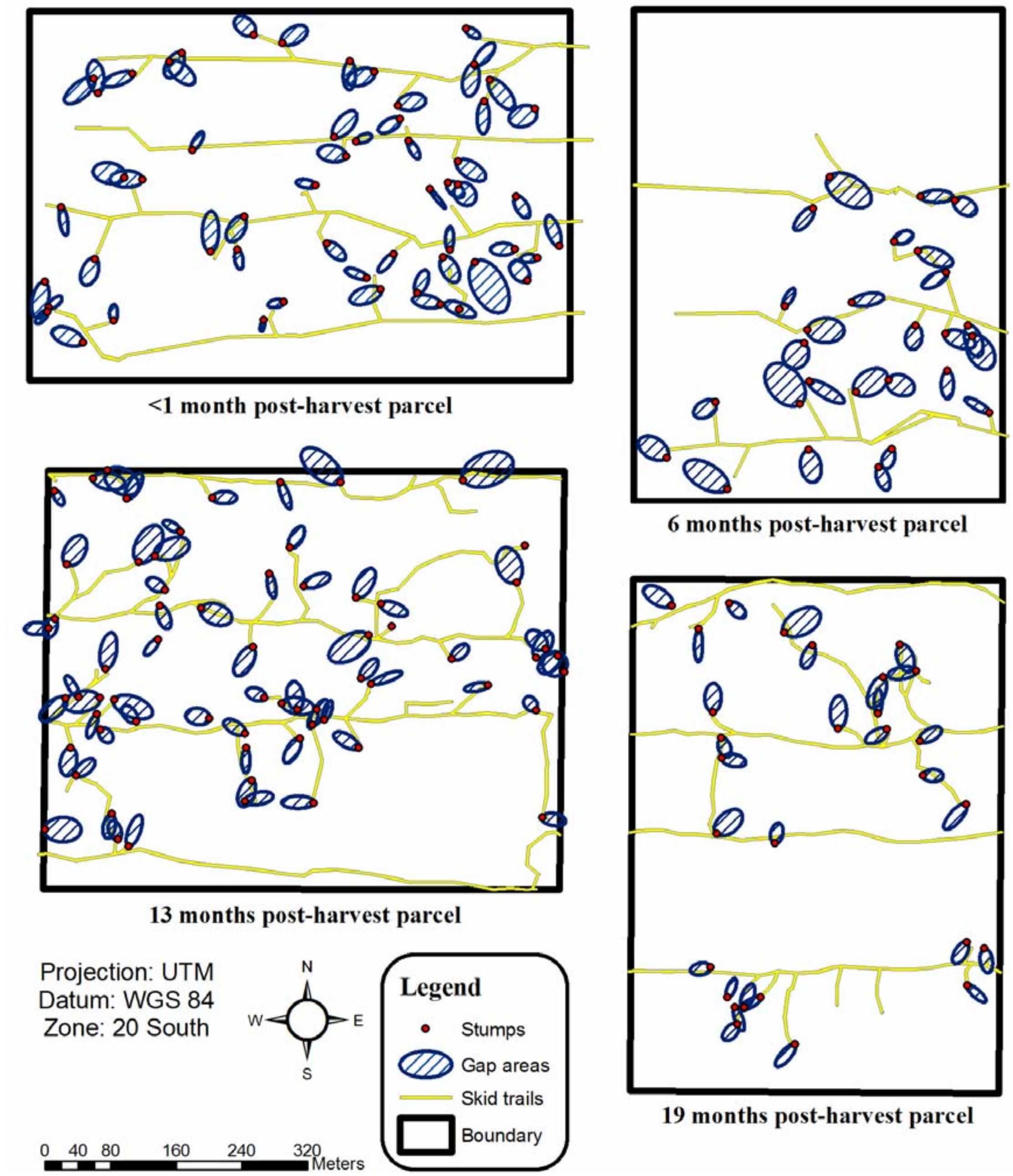

Figure 2-2. Locations of tree fall gaps and skid trails are shown for the logged study parcels. Maps of the locations of felled trees in the 13- and 19-month post harvest parcels were provided by IBIF, and were used as base maps for those parcels.

Table 2-3. Sample size of large, medium, and small felling gaps within the logged parcels (Appendix C)

Gap size	Parcel			
	<1 month post-harvest	6 months post-harvest	13 months post-harvest	19 months post-harvest
Small	26 (29)	5 (5)	24 (30)	15 (19)
Medium	27 (38)	13 (15)	14 (26)	5 (9)
Large	3 (3)	8 (9)	6 (9)	1 (1)

In parenthesis is the sample size before removing overlaid gaps

The addition of data from eight other IBIF research parcels shows a clear quadratic relationship between harvest intensity and the percent of a parcel covered by skid trail working surfaces (Figure 2-3, root mean square error for the fit Michaelis-Menten model was 0.53. Estimates of θ1 and θ2 were 7.40 and 1.22, respectively).

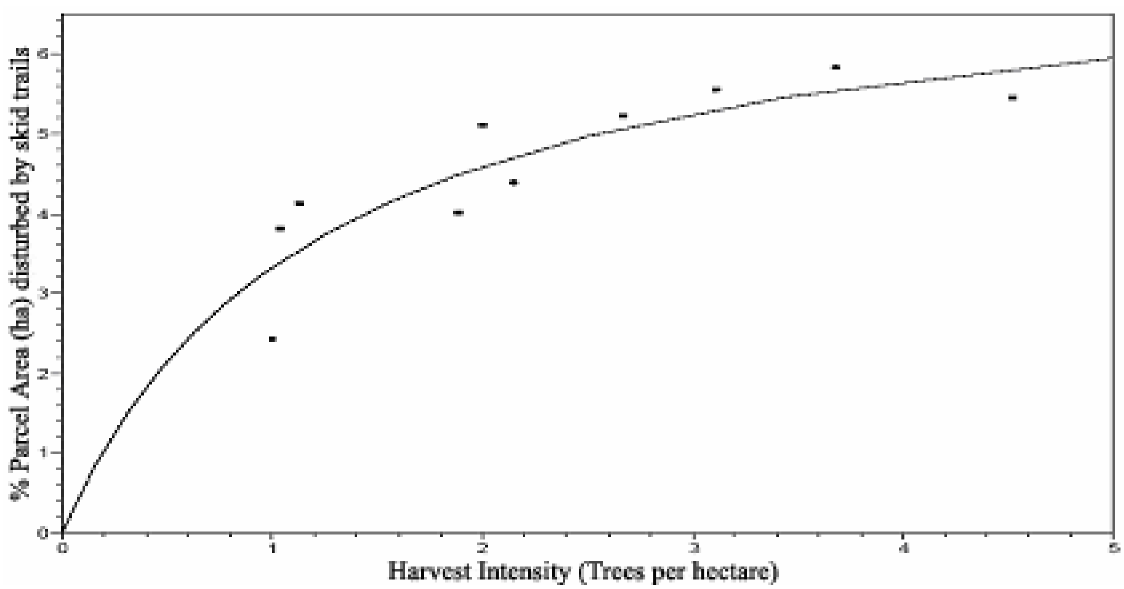

Figure 2-3. Michaelis Menten nonlinear model fit over harvest intensity versus % parcel area affected by skid trails. Data from Table 2-2 and Appendix D.

2.4.2 Field Measurements

2.4.2.1 Post-harvest recovery of forest structure in felling gaps

Results of the 3-way ANOVA testing the main effects of parcel, gap size, and gap zone, and their interactions, on canopy openness, liana coverage, vegetation height, photosynthetic (PV) and non-photosynthetic vegetation (NPV), exposed soil, and non-photosynthetic vegetation (NPV) height are reported in Table 2-4. There were no significant 3-way interactions. Mean values of those variables for the four logged parcels and the control forest parcel are provided in Table 2-5. Table 2-6 lists mean values for the field measurements by felling gap size and Table 2-7 provides mean values of field variables for trunk and gap zones.

Table 2-4. The F and P values for the main effects of parcel, gap size, and gap zone, and their interactions for mixed 3-way ANOVAs of variables measured in felling gaps

Factors	Parcel	Gap size	Gap zone	Parcel * gap size	Parcel * gap zone	Gap size * gap zone
Canopy Openness	14.8***	8.6**	7.0**	1.5	0.9	4.2*
Liana coverage (%)	5.4**	0.6	31.6***	0.6	18.8***	2.3
Vegetation height (m)	11.0***	3.4*	0.3	1.8	0.5	0.5
Photosynthetic vegetation (PV) coverage (%)	17.3***	0.3	13.1**	3.2**	0.1	0.2
Non-photosynthetic vegetation (NPV) coverage (%)	7.3**	0.0	44.1***	0.8	2.8*	0.7
Soil coverage (%)	5.2**	0.7	43.0***	1.1	21.9***	2.4
NPV height (m)	6.5***	0.9	170.0***	0.7	8.8***	5.6***

Asterisks represent significance of main effects and interactions (* = P <0.05, ** = p <0.01 and *** = P <0.001).

Canopy openness was significantly affected by parcel, size class, and gap zone, and there was a size class * gap zone interaction. Canopy openness within felling gaps decreased significantly with time post harvest and was significantly greater for all logged parcels than for the control forest. Canopy openness within felling gaps also increased with increasing gap size, and trunk zones had a significantly less open canopy than in crown zones. The size class * gap zone interaction reflects that canopy openness was greater in the crown zone than in trunk zone in large and medium gaps but not in small gaps (Figure 2-4).

Table 2-5. Mean values of field measurement variables within felling gaps for <1-, 6-, 13-, and 19-months post-harvest parcels. Unlogged control forest values are provided for comparison.

Factors	Parcel mean (±standard error)				
	<1 month post-harvest	6 months post-harvest	13 months post-harvest	19 months post-harvest	Control forest
	n = 56	*n* = 26	*n* = 44	*n* = 21	*n* = 130
Canopy Openness (%)	52.6 (6.2)***a	48.7 (3.3)***a	26.4 (2.7)***bc	18.1 (5.7)***c	3.7 (0.5)
Liana Coverage (%)	12.8 (5.4)***ac	8.0 (3.6)***a	24.4 (2.8)c	27.1 (5.8)c	21.7 (2.4)
Vegetation Height (m)	0.6 (0.4)***a	1.7 (0.3)***b	2.9 (0.2)***c	3.0 (0.5)***c	21.1 (1.0)
Photosynthetic Vegetation Coverage (%)	31.4 (5.4)***a	58.9 (3.6)***b	70.8 (2.8)c	79.5 (5.8)c	71.2 (1.7)
Non-Photosynthetic Vegetation Coverage (%)	49.6 (5.3)***a	36.6 (3.6)*b	26.1 (2.7)c	19.3 (5.7)c	28.2 (1.6)
Exposed Soil Coverage (%)	13.6 (2.6)***a	3.2 (1.7)b	3.1 (1.3)b	1.3 (2.8)b	0.6 (0.3)
NPV height (m)	2.6 (0.3) a	2.6 (0.2) a	1.8 (0.2) b	1.1 (0.4) b	na

Asterisks represent significant differences between treatment parcel felling gap and control forest values (* = P <0.05, ** = P <0.01, *** = P <0.001). Different letters represent significant differences between felling gap values in the different treatment parcels (Tukey's test, P < 0.05).

Table 2-6. Mean values (±standard error) of field measurement variables for all large, medium, and small felling gaps.

Factors	Gap size and control (±standard error)		
	Large	Medium	Small
	n = 18	*n* = 59	*n* = 70
Canopy Openness (%)	46.8 (6.2)***b	36.8 (2.5)***b	25.5 (2.3)***a
Liana Coverage (%)	22.5 (5.9) a	15.5 (2.4)***a	16.3 (2.5) a
Vegetation Height (m)	2.4 (0.5)***ab	2.3 (0.2)***b	1.6 (0.2)***a
Photosynthetic Vegetation Coverage (%)	59.2 (5.9) a	59.3 (2.4)***a	61.8 (2.5)***a
Non-Photosynthetic Vegetation Coverage (%)	32.3 (5.8) a	33.0 (2.4)***a	33.4 (2.4)*a
Soil Coverage (%)	6.1 (2.8) a	5.8 (1.2)***a	4.0 (1.2)***a
NPV height (m)	2.3 (0.4) a	2.0 (0.2) a	1.8 (0.1) a

Asterisks represent significant differences between treatment parcel felling gap and control forest values (* = P <0.05, ** = P <0.01, *** = P <0.001). Different letters represent significant differences between felling gap values in the different treatment parcels (Tukey's test, P < 0.05).

Table 2-7. Mean values (±standard error) of measured variables for all trunk and canopy felling gap zones.

Factors	Gap zone (±standard error)	
	Trunk (n = 147)	Canopy (n = 147)
Canopy Openness (%)	33.5 (2.7)***a	39.3 (2.5)***b
Liana Coverage (%)	10.4 (2.7)**a	25.7 (2.7)**b
Vegetation Height (m)	2.0 (0.2)***a	2.1 (0.2)***a
Photosynthetic Vegetation Coverage (%)	64.7 (2.6) a	55.6 (2.6)*b
Non-Photosynthetic Vegetation Coverage (%)	24.1 (2.6)**a	41.8 (2.6)*b
Soil Coverage (%)	10.0 (1.3)***a	0.6 (1.3) b
NPV height (m)	0.8 (0.1) a	3.3 (0.2) b

Asterisks represent significant differences between treatment parcel felling gap and control forest values (* = P <0.05, ** = P <0.01, *** = P <0.001). Different letters represent significant differences between felling gap values in the different treatment parcels (Tukey's test, P < 0.05).

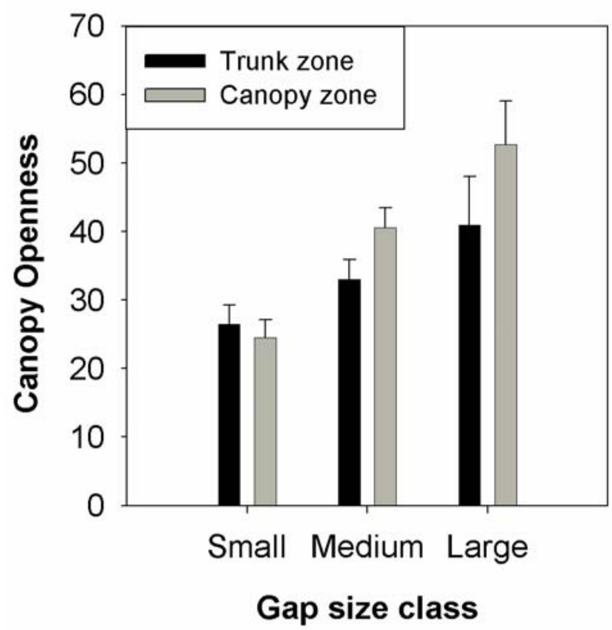

Figure 2-4. Canopy openness of all felling gaps as affected by the interaction between gap size and gap zone. Error bars represent standard error of the mean.

Liana coverage was affected by parcel and gap zone effects, as well as the parcel *gap zone interaction. Liana coverage dropped initially from the < 1 month post-harvest gaps to the 6 months old gaps, after which it increased dramatically. The < 1- and 6-months post-harvest parcels were significantly lower than the control forest mean but the

13- and 19-month post-harvest parcels were not (Table 2-5). Crown zones had significantly greater liana coverage than trunk zones (Table 2-7). The parcel * gap zone interaction reflects that the gap zone differences are not strongly apparent until 13 months after logging when canopy zone liana % becomes much greater than that in the trunk zone (Figure 2-5a).

The height of regenerating vegetation was greater in larger gaps, and in parcels that had more time to regrow following logging (Table 2-5, 2-6). Similarly, the coverage of PV was significantly affected by parcel and gap zone, as well as the parcel * size class interaction. PV increased with time post-harvest and in the13- and 19-months post-harvest plots, PV in the gaps was not significantly different from in the control forest (Table 2-5). The crown zone had significantly less PV than the trunk zone (Table 2-7). The interaction of parcel * size class showed that small gaps had significantly higher PV only in the < 1-month post-harvest parcel (Figure 2-6).

NPV was significantly affected by the main effects of parcel and gap zone, and the interaction of parcel * gap zone. NPV decreased with time post-harvest and was indistinguishable from the control forest in the 13- and 19-month post harvest gaps. The crown zone had significantly more NPV than the trunk zone (Table 2-7). The parcel * gap zone interaction revealed consistently higher levels of NPV% in crown zones (versus trunk zones) that diminished with parcel (Figure 2-5b).

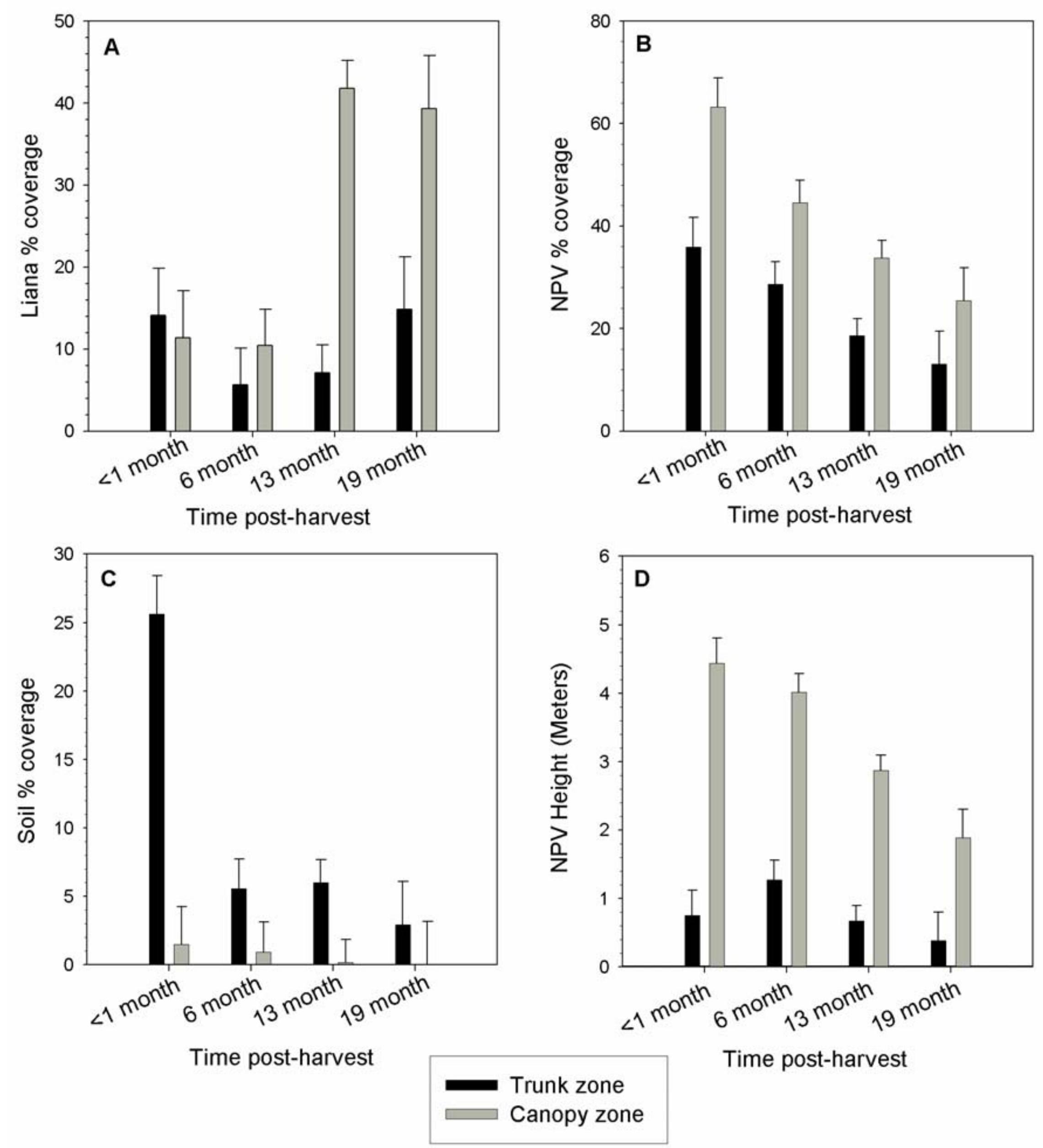

Figure 2-5. The field factors of A) Liana, B) NPV, C) soil coverage, and D) NPV height as affected by the interaction between parcel and gap zone. Error bars represent standard error of the mean. See Table 2-3 for sample sizes.

Soil exposure was also significantly affected by the main effects of parcel and gap zone, and the interaction of parcel * gap zone. Soil exposure decreased with time post-harvest and only the < 1-month post-harvest gaps had significantly more exposed soil than the control forest. Although there was a trend towards increasing soil exposure with gap size it was not statistically significant. Soil exposure was almost twenty times greater in the trunk zone than in the crown zone. The parcel * gap zone interaction reflected that the differences between gap zones diminished with increasing months post-harvest (Figure 2-5c).

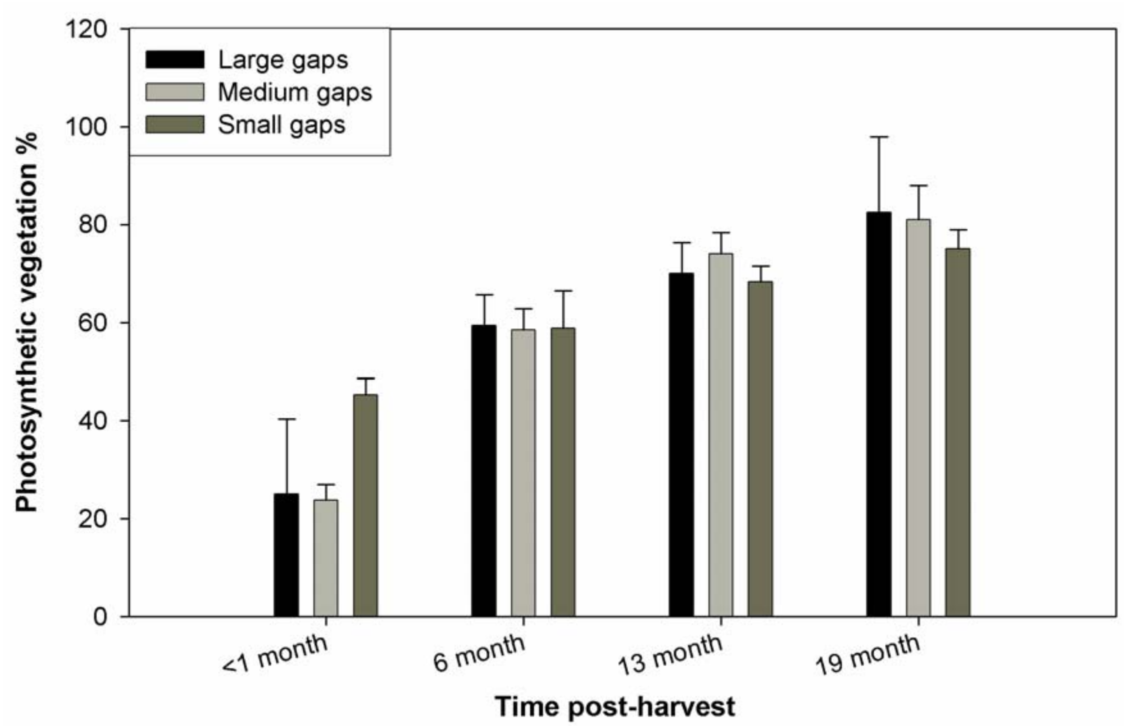

Figure 2-6. Photosynthetic vegetation coverage as affected by the interaction between parcel and gap size. Error bars represent standard error of the mean. See Table 2-3 for sample sizes.

NPV height was significantly affected by the main effects of parcel and gap zone, as well as both parcel * gap zone, and size class * parcel interactions. NPV height decreased with increasing months post-harvest and was higher in the crown portion of the gap. The parcel * gap zone interaction is a result of decreasing NPV height in the canopy zone with parcel but NPV height remaining the same in the trunk zone (Figure2-5d). The gap size * gap zone interaction was a result of smaller gaps having decreased differences in NPV height between the canopy and trunk zones (data not shown).

2.4.2.2 Skid trails

Canopy openness, vegetation height, PV, NPV, and soil exposure were significantly affected by parcel ($P < 0.05$). Skid trail PV increased with time post-harvest whereas skid trail soil exposure decreased; patterns were less consistent for the other variables (Table 2-8).

Table 2-8. Mean (±standard error) for field factors within skid trails <1, 6, 13 and 19 months post-harvest.

	n	Canopy openness	*n*	Veg. height (m)	*n*	Width (m)	PV %	NPV %	Soil %
<1 months post-harvest	63	17.3 (16.4)a***	41	0.0 (.1)a***	31	3.4 (0.4)a	5.8 (16.3)a***	33.6 (22.8)a	59.5 (26.1)a***
6 months post-harvest	45	10.1 (9.5)a**	45	0.7 (.3)a***	10	3.3 (0.3)a	18.5 (14.3)b***	47.5 (14.8)b**	32.0 (20.3)b***
13 months post-harvest	15	5.8 (3.8)b	15	0.3 (.3)a***	na	3.4 (0.4)a	na	na	na
19 months post-harvest	59	14.0 (14.9)a***	59	1.75 (1.2)a***	31	3.9 (0.4)a	51.5 (16.2)c***	40.8 (17.3)b**	8.7 (14.6)c***

Asterisks represent significant differences between treatment and control parcels (* = P <0.05, ** = P <0.01, *** = P <0.001).

2.4.3 Remote Sensing

Both NDVI and the soil fraction were significantly negatively correlated with increasing Lambertian shade levels ($P < 0.001$) while the NPV fraction was significantly positively correlated with increasing shade levels ($P < 0.001$). The PV fraction, however, was not correlated with shade intensity. Seasonality also affected NDVI, as well as the sub-pixel fractions (PV, NPV, soil), as illustrated in Figure 2-7. NDVI and PV fractional values within the control parcels declined steadily from May (early in the dry season) to mid-August (nearing the end of the dry season). Neither the NPV or soil fractions had strong correlations with seasonality.

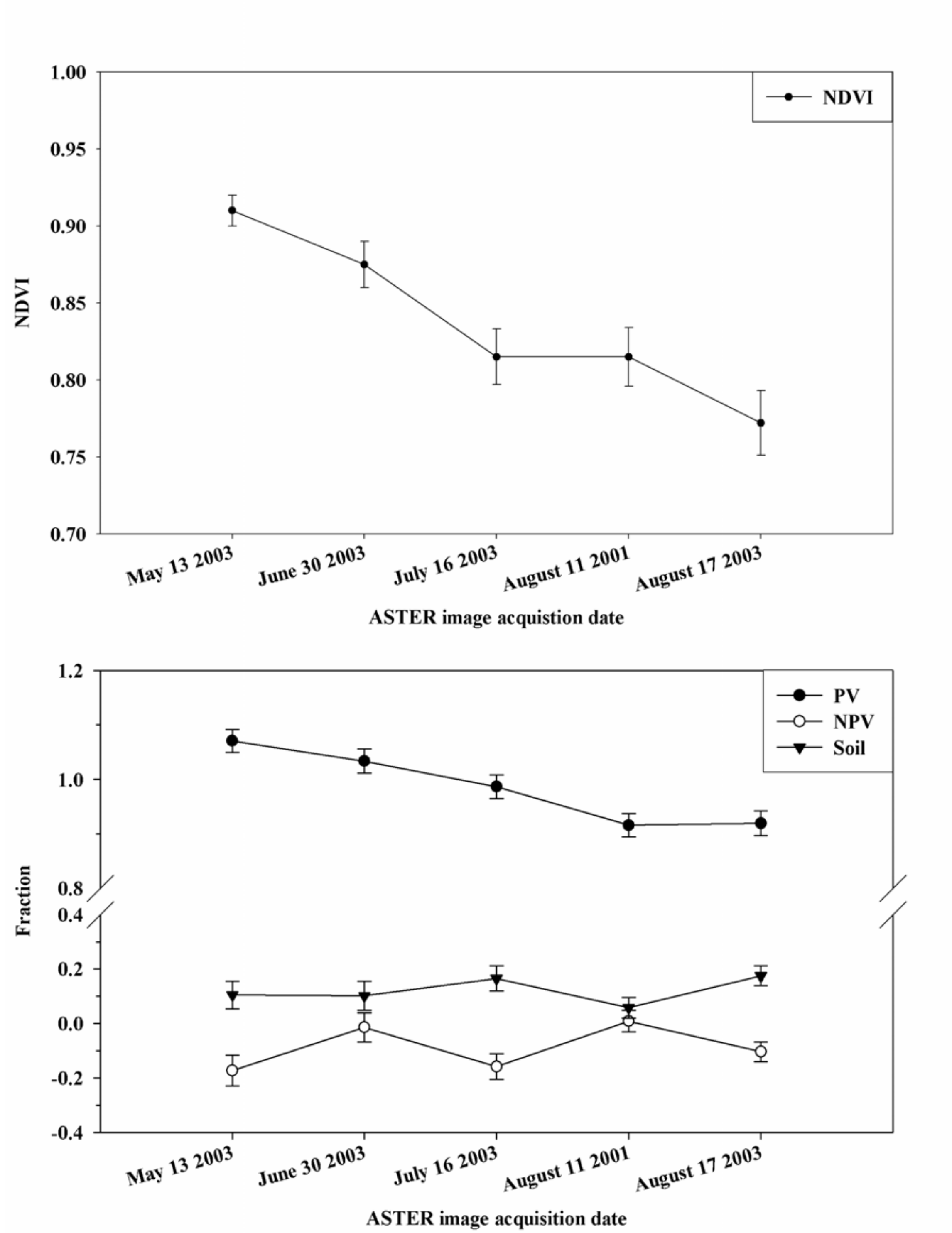

Figure 2-7. Control parcel mean values for NDVI and PV, NPV, and soil fractions versus image acquisition date. The dry season intensifies from May through August.

2.4.3.1 Post-harvest recovery of spectral characteristics of felling gaps

Felling gaps > 800 m^2. Figure 2-8 illustrates the evolution of spectral characteristics post-harvest for pixels in large felling gaps (Appendix E). Two-way repeated measures ANOVA revealed significant main effects of parcel for NDVI, PV, and NPV, and image date for PV and soil. The interaction effect was significant for NDVI and PV (Appendix E). NDVI was significantly lower than unlogged control pixels for up to 3 months after logging ($P < 0.001$), then higher at 6-8 months ($P < 0.001$) and at 16, and 20-22 months post-logging ($P < 0.05$). PV was lower for 2 and 3 months post-harvest ($P < 0.001$) and higher at 22 months post-logging ($P < 0.05$). NPV was higher 2 months post-logging ($P < 0.05$). The soil response had the highest variance.

Felling gaps 400-800 m^2. Figure 2-9 illustrates the evolution of spectral characteristics post-harvest for pixels in medium felling gaps (Appendix E). Two-way repeated measures ANOVA revealed significant main effects of parcel for NDVI, PV, and NPV, and image date for NDVI, PV and soil. The interaction effect was significant for all the variables. NDVI was significantly lower than for unlogged pixels for up to 3 months after logging ($P < 0.001$), then higher at 15-16 months post-logging ($P < 0.01$). PV was lower for 1, 2 and 3 months post-logging ($P < 0.01$). NPV was higher 1-3 and 8 months post-logging ($P < 0.05$). Again the soil response had the highest variance.

Felling gaps < 400 m^2. Figure 2-10 illustrates post-harvest spectral changes in small felling gaps (Appendix E). Two-way repeated measures ANOVA revealed significant main effects of parcel for NDVI, PV, and NPV, and image date for NDVI, PV and soil. The interaction effect was significant for all the variables. NDVI was significantly lower than for unlogged pixels only at 3 months post-logging ($P < 0.001$), but higher at 15 and 16 months post-logging ($P < 0.05$). PV was lower for 1, 2 and 3 months post-logging ($P < 0.01$). NPV was higher 1 and 2 months post-logging ($P < 0.05$).

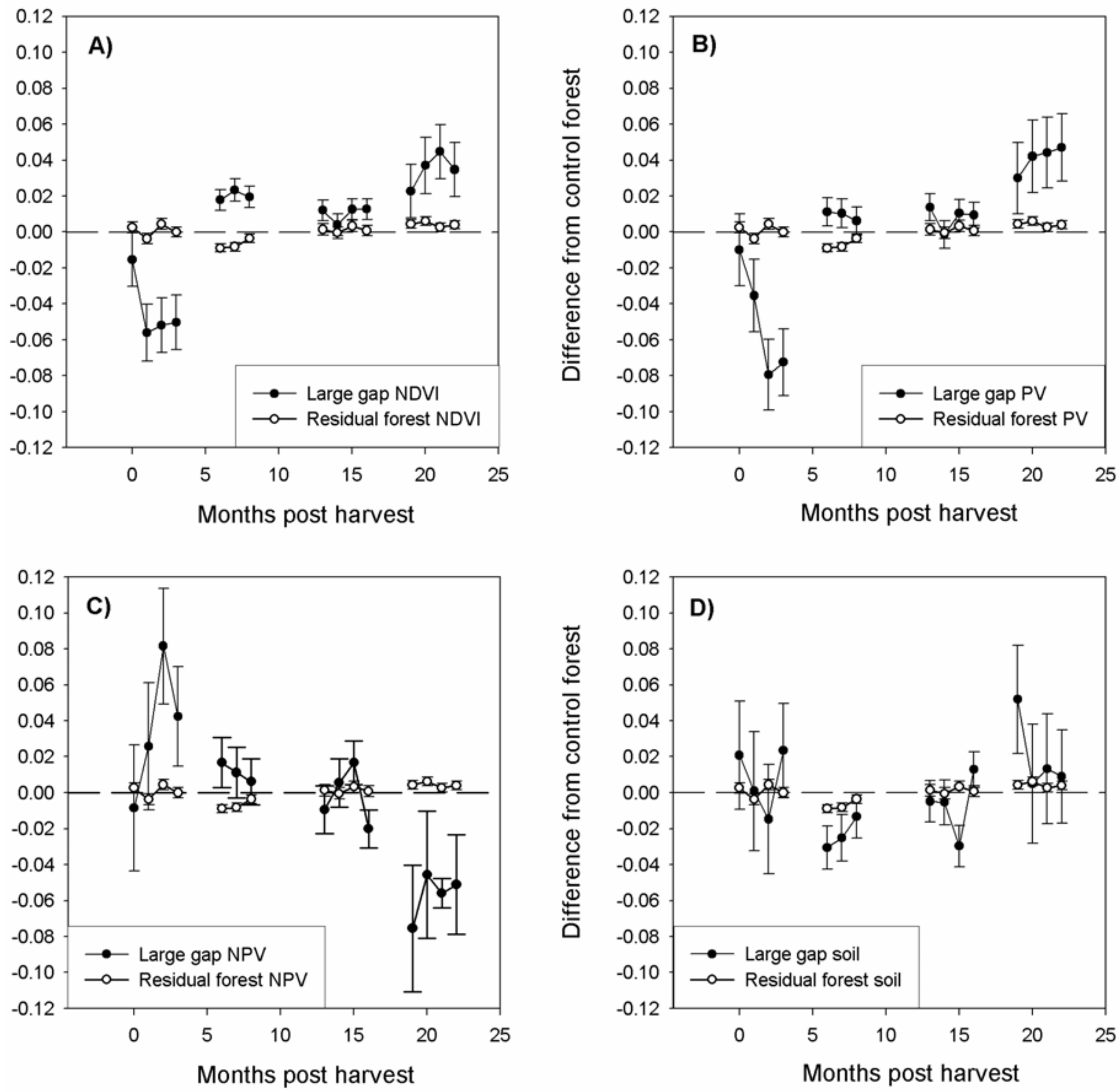

Figure 2-8. Difference between spectral characteristics of large felling gap and unlogged control parcel pixels for A) NDVI, B) PV, C) NPV and D) Soil. Error bars are standard errors for the large felling gap pixels; standard errors for the control pixels were < 0.001 on the y-axis. The differences between the treatment parcel's residual forest and unlogged control pixels are shown to distinguish the disturbance effect from any potential effect of between-parcel differences.

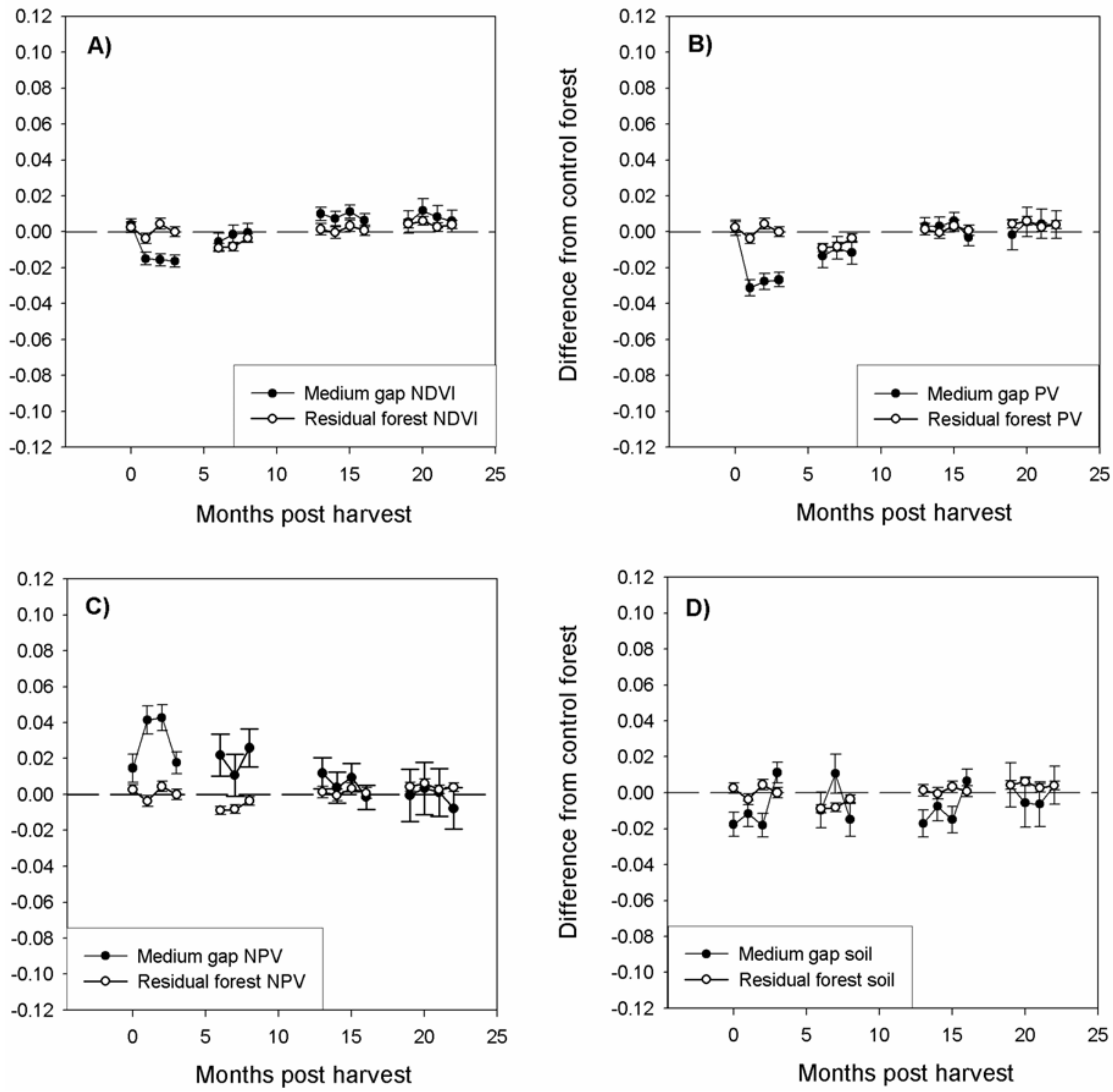

Figure 2-9. Difference between spectral characteristics of medium felling gap and unlogged control parcel pixels for A) NDVI, B) PV, C) NPV and D) Soil. Error bars are standard errors for the large felling gap pixels; standard errors for the control pixels were < 0.001 on the y-axis. The differences between the treatment parcel's residual forest and unlogged control pixels are shown to distinguish the disturbance effect from any potential effect of between-parcel differences.

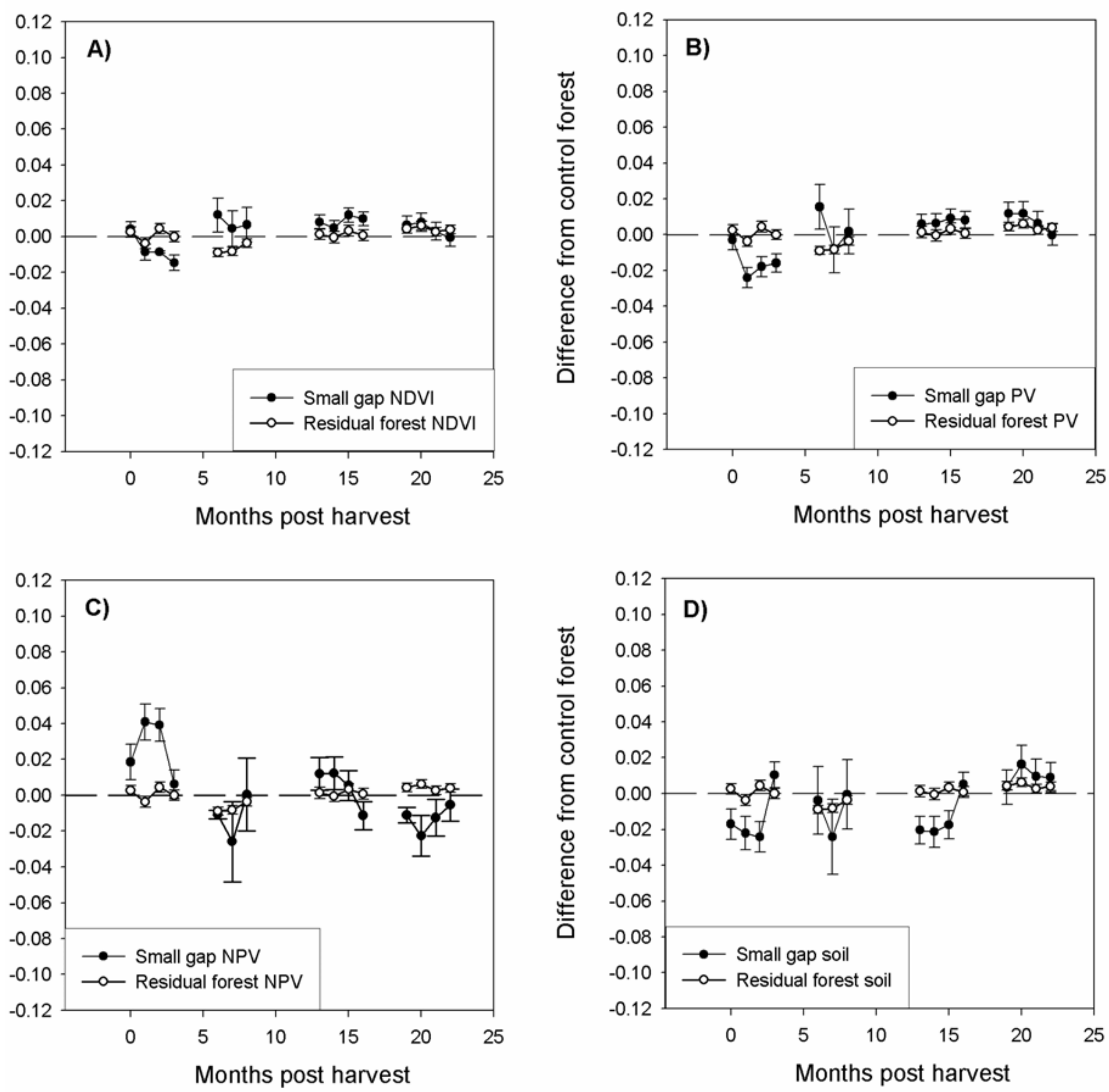

Figure 2-10. Difference between spectral characteristics of small felling gap and unlogged control parcel pixels for A) NDVI, B) PV, C) NPV and D) Soil. Error bars are standard errors for the large felling gap pixels; standard errors for the control pixels were < 0.001 on the y-axis. The differences between the treatment parcel's residual forest and unlogged control pixels are shown to distinguish the disturbance effect from any potential effect of between-parcel differences.

2.4.4 Linking Field and Remotely-Sensed Measurements

Pearson bivariate correlations between field and remote sensing measurements of all felling gaps in the < 1 and 6 months post-harvest parcels are presented in Tables 2-12 and 2-13, respectively. The significant positive correlations between NDVI and PV show they respond similarly to forest disturbances for both the < 1 and 6 months post-harvest parcels, and both are inversely correlated with NPV. Soil reflectance was also inversely correlated with NPV. Gap area was inversely correlated with NDVI and PV in the < 1-month post-harvest parcel but only with NDVI in the 6-month post-harvest parcel. Canopy openness in the crown zone was also inversely correlated with NDVI and PV in the < 1-month post-harvest parcel. In the 6-month post-harvest parcel, crown zone PV coverage was inversely correlated with NPV reflectance, which was positively correlated with NPV coverage. PV coverage in the trunk zone of the < 1 month post-harvest parcel felling gaps was correlated with NDVI and PV reflectance, whereas NPV coverage was inversely correlated with NDVI. NPV coverage in the trunk zone of the 6 month post-harvest parcel was positively correlated with NPV and negatively correlated with soil reflectance.

Table 2-12. Pearson bivariate correlations between field and remote sensing measurements of felling gaps in the < 1 month post-harvest parcel.

	NDVI	**PV**	**NPV**	**Soil**
NDVI	1			
PV	0.736***	1		
NPV	-0.450***	-0.612***	1	
Soil	ns	ns	-0.835**	1
Gap area (m^2)	-.322**	-0.344**	ns	ns
Gap canopy zone				
Canopy openness	-0.382***	-0.311**	ns	ns
Vegetation height (m)	ns	ns	ns	ns
PV % coverage	ns	ns	ns	ns
NPV % coverage	ns	ns	ns	ns
Soil % coverage	ns	ns	ns	ns
Gap trunk zone				
Canopy openness	ns	ns	ns	ns
Vegetation height (m)	ns	ns	ns	ns
PV % coverage	0.316**	0.265*	ns	ns
NPV % coverage	-0.248*	ns	ns	ns
Soil % coverage	ns	ns	ns	ns

Asterisks represent significant correlations (* = $P < 0.05$, ** = $P < 0.01$, *** = $P < 0.001$).

Table 2-13. Pearson bivariate correlations between field and remote sensing measurements of felling gaps in the 6 months post-harvest parcel.

	NDVI	**PV**	**NPV**	**Soil**
NDVI	1			
PV	0.779***	1		
NPV	-0.526**	-0.589***	1	
Soil	ns	ns	-0.748***	1
Gap area (m^2)	.338*	ns	ns	ns
Gap canopy zone				
Canopy openness	ns	ns	ns	ns
Vegetation height (m)	ns	ns	ns	ns
PV % coverage	ns	ns	-0.428**	ns
NPV % coverage	ns	ns	0.444**	ns
Soil % coverage	ns	ns	ns	ns
Gap trunk zone				
Canopy openness	ns	ns	ns	ns
Vegetation height (m)	ns	ns	ns	ns
PV % coverage	ns	ns	ns	ns
NPV % coverage	ns	ns	0.459**	-0.371*
Soil % coverage	ns	ns	ns	ns

Asterisks represent significant correlations (* = $P < 0.05$, ** = $P < 0.01$, *** = $P < 0.001$).

2.5 Discussion

Development of effective remote sensing based programs to monitor selective logging requires an understanding of the spatial and temporal thresholds that constrain the applicability of remote sensing to the detection of selective logging. Although this study was conducted in the context of low harvest intensities the dynamics of recovery of structural and spectral characteristics following selective logging should be applicable to improving understanding of the signatures of selective logging (e.g. felling gaps and skid trails) throughout the tropics.

I found that the NDVI and PV, NPV, and soil fractions were useful for identifying large and medium size tree fall gaps for between 3 and 6 months post-harvest. The PV fraction had the greatest response within felling gaps and, unlike NDVI, PV was not affected by topographic shade. The NPV and soil fractions were both highly correlated with topographic shade and were thus less useful for monitoring forest disturbances, especially in areas with more pronounced relief.

Canopy openness defines the ability of remote sensors to view ground disturbances indicative of logging activities and, in general, as felling gaps age from < 1 to 19 months, canopy openness declines from 50 to 60% to less than 20%. Simultaneously, rapid vegetation growth, reaching nearly 2 to 5 m by 19 months covers over the originally exposed soil (primarily in the trunk zone), and NPV (primarily in the canopy zone) causing the relative percentages of PV, NPV and soil to change from 30, 50 and 10, respectively, immediately following harvest to 80, 20, and 0, respectively, after 19 months. Rapid liana growth, primarily in the crown zone, covers nearly 30 percent of the entire gap zone in an often dense mat of verdant lianas by 19 months post-harvest. This rapid reduction in overall canopy openness means that felling gaps become indistinguishable from the surrounding forest after around 6 months post-harvest. The process occurs faster for smaller gaps as they begin with less persistent residual NPV and are characterized by less initial canopy damage.

Soil exposure within felling gaps, and therefore the utility of the soil fraction for identifying forest disturbances from selective logging, was limited primarily to the trunk zone. Though exposed soil in open areas is easily discerned from space, the gap trunk zone has little canopy damage, as compared with the crown zone, and by 6 months post-harvest canopy openness within the trunk zone is < 5%, due to canopy and vegetation regeneration. Although skid trails comprised 30 to 60% of the disturbed area, had the highest exposed soil levels, and had the slowest rates of vegetation recovery, they were not identifiable with remote sensing because they had little impact on canopy openness.

Working in the Brazilian Amazon, (Asner et al., 2002) showed that single band and textural analysis techniques were not sensitive to canopy damages from selective logging that were < 50% of complete canopy coverage. The analytical techniques assessed in this study show a considerable improvement in sensitivity to lower levels of canopy damage. Asner et al. (2004), using AutoMCU© derived per-pixel PV, NPV, and soil fractions of Landsat imagery, showed sensitivity to skid trails and felling gaps which diminished greatly from 0.5 to 1.5 year post-harvest, due to rapid regeneration of low-stature pioneer species. Remotely measured canopy openness values (derived from the PV fraction) of 12, 11, and 11 percent for felling gap pixels and 28, 11, and 12% for skid trail pixels were measured 0.5, 1.5, and 3.5 years post-harvest, respectively. Different from my results, Asner et al. (2004) found that felling gap and skid trail PV fraction remained consistently higher than in non-logged control forest. This may be a result of the higher harvest intensities in their study, leading to more prolonged canopy damage than was found in La Chonta.

Few studies have linked remote sensing data directly to selective logging disturbances through the collection of extensive field data. The results of this study help to better understand the utility of currently available remote sensing technologies for monitoring selective logging, as well as identifying limitations that future remote sensors and image analysis technologies can address. Future efforts will seek to delineate logged areas based on the differences in reflectance that are apparent in felling gaps for several months, and on their spatial distribution.

APPENDIX A
GROUND, STAND, AND CANOPY DAMAGE AFTER SELECTIVE LOGGING

Table A-1. Section 1 of ground, stand and canopy level forest damage after selective logging ordered according to level of harvest intensity (trees/ha)

	Johns et al. (1996)	Nicholson et al. (1958)	Pinard et al. (2000)	Johns et al. (1996)	Verissimo et al. (1992)	Webb, E.L. (1997)	Asner et al.(2002)	Crome et al. (1992)	Crome et al. (1992)
Harvest Management	Planned	na	RIL	Unplanned	na	Controlled	CL[11]	QSLS[9]	QSLS[9]
Forest Type or Location	Evergreen lowland rainforest, Paragominas, Brazil	Tropical rainforest,North Borneo	Gunung Rara, Sabah	Evergreen lowland rainforest, Paragominas, Brazil	Evergreen, Lowland Rainforest, Paragominas, Brazil	Lowland Swamp Forest, Northeast Costa Rica	Moist Tropical forest, Paragominas, Brazil	Upland Rainforest, North Queensland	Upland Rainforest, North Queensland
Harvest Intensity (trees ha-1)	4.5	4.7	5.3	5.6	6	6.3	6.4	6.6	7.6
Area Disturbed	17%	14%	17.4%	22%	13.7%[7]	4%	11.2%[2]	4.26%	4.8%
Residual Stand Damage – trees killed or damaged	7.2[3]	29.8[3]	30%[4]	4.9[3]	27[3&6]	17.6%[4]	na	18.1%[12]	20.4%[12]

[1]Areas needed to establish logging roads and log landing zones. [2]Road, deck and skid areas combined. [3]Per individual tree harvested. [4]Percentage of residual stand damaged or killed. [5]Including the area directly under roads, gaps and corridor of secondary damage next to roads. [6]Greater or equal to 10 cm diameter breast height (DBH). [7]Includes areas of scraped ground surface. [8]Canopy openings due to tree felling only. [9]Queensland selective logging system (QSLS). [10]Reduced impact logging (RIL). [11]Conventional logging (CL). [12]Including trees killed only. [13]Reduced from 80% to 45% following selective logging.

Table A-2.Section 2 of ground, stand and canopy level forest damage following selective logging ordered according to level of harvest intensity (trees/ha)

	Gullison & Hardner. (1993)	Whitman et al. (1997)	White, L (1994)	Uhl and Viera (1989)	Uhl et al. (1991)	Asner et al. (2002)	Van Der Hout, P (2000)	Uhl et al. (1989)	Jackson et al. (2002)
Harvest Management	na	na	Mechanised selective logging	na	Highly Selective	RIL[10]	RIL	Mechanized selective logging	Planned diameter-limit
Forest Type or Location	Chimanes, Bolivia	Tropical Forest, Northern Belize	Lowland rainforest, Lope Reserve, Gabon	Paragominas, Brazil	Tailandia, Eastern Amazonia, Brazil	Moist Tropical Forest, Paragominas, Brazil	Greenheart forest, Guyana	Interfluvial forest, Paragominas, Brazil	Tropical Humid Forest, Bolivia
Harvest Intensity (trees ha-1)	0.12	0.5	2	1.8	2	3.0	4	4 - 8	4.35
Area Disturbed	4.39%[5]	12.9%	28.3%	na	5.83%[1]	4.8%[2]	5%	8%	45.8%
Residual Stand Damage – trees killed or damaged	na	4.8%[4]	10.8%[4]	na	29[3]	na	16[6]	26% [4]	44[3]
Gap opening/canopy loss	0.47%	2%	10%	46.3%	8.1%	na	8.5%	50%[13]	25%[8]
Gap Fraction	na	na	na	na	na	3.4%	na	na	na

[1]Areas needed to establish logging roads and log landing zones. [2]Road, deck and skid areas combined. [3]Per individual tree harvested. [4]Percentage of residual stand damaged or killed. [5]Including the area directly under roads, gaps and corridor of secondary damage next to roads. [6]Greater or equal to 10 cm diameter breast height (DBH). [7]Includes areas of scraped ground surface. [8]Canopy openings due to tree felling only. [9]Queensland selective logging system (QSLS). [10]Reduced impact logging (RIL). [11]Conventional logging (CL). [12]Including trees killed only. [13]Reduced from 80% to 45% following selective logging.

Table A-3. Section 3 of ground, stand and canopy level forest damage after selective logging ordered according to level of harvest intensity (trees/ha)

	Van Der Hout, P (2000)	Pinard et al. (2000)	Pinard et al. (2000)	Cannon et al. (1994)	Abdulhadi et al. (1981)	Pinard et al. (2000)	Pinard et al. (2000)	Van Der Hout, P (2000)	Van Der Hout, P (2000)
Harvest Management	RIL[10]	RIL	RIL	Mechanized selective logging	na	CL[11]	CL[11]	CL[11]	RIL[10]
Forest Type or Location	Greenheart forest, Guyana	Dipterocarp forest, Kalabakan, Sabah	Dipterocarp forest, Ulu Segama, Sabah	Dipterocarp forest, West Kalimantan, Indonesia.	Lowland Dipterocarp Forest, East Kalimantan.	Dipterocarp forest, Kalabakan, Sabah	Dipterocarp forest, Kalabakan, Sabah	Greenheart forest, Guyana	Greenheart forest, Guyana
Harvest Intensity (trees ha-1)	8	8.4	8.8	8.5 - 10.6	11	11.2	13.6	16	16
Area Disturbed	8%	19%	13.6%	6 to 18%	30%	18.2%	33.2%	21%	9%
Residual Stand Damage – trees killed or damaged	13[6]	15%[4]	30%[4]	na	na	40%[4]	60%[4]	10[6]	9[6]
Gap opening/canopy loss	15.7%	na	na	45%	na	na	na	24.5%	30.1%

[1]Areas needed to establish logging roads and log landing zones. [2]Road, deck and skid areas combined. [3]Per individual tree harvested. [4]Percentage of residual stand damaged or killed. [5]Including the area directly under roads, gaps and corridor of secondary damage next to roads. [6]Greater or equal to 10 cm diameter breast height (DBH). [7]Includes areas of scraped ground surface. [8]Canopy openings due to tree felling only. [9]Queensland selective logging system (QSLS). [10]Reduced impact logging (RIL). [11]Conventional logging (CL). [12]Including trees killed only. [13]Reduced from 80% to 45% following selective logging.

APPENDIX B
MEAN MONTHLY PRECIPITATION IN LA CHONTA

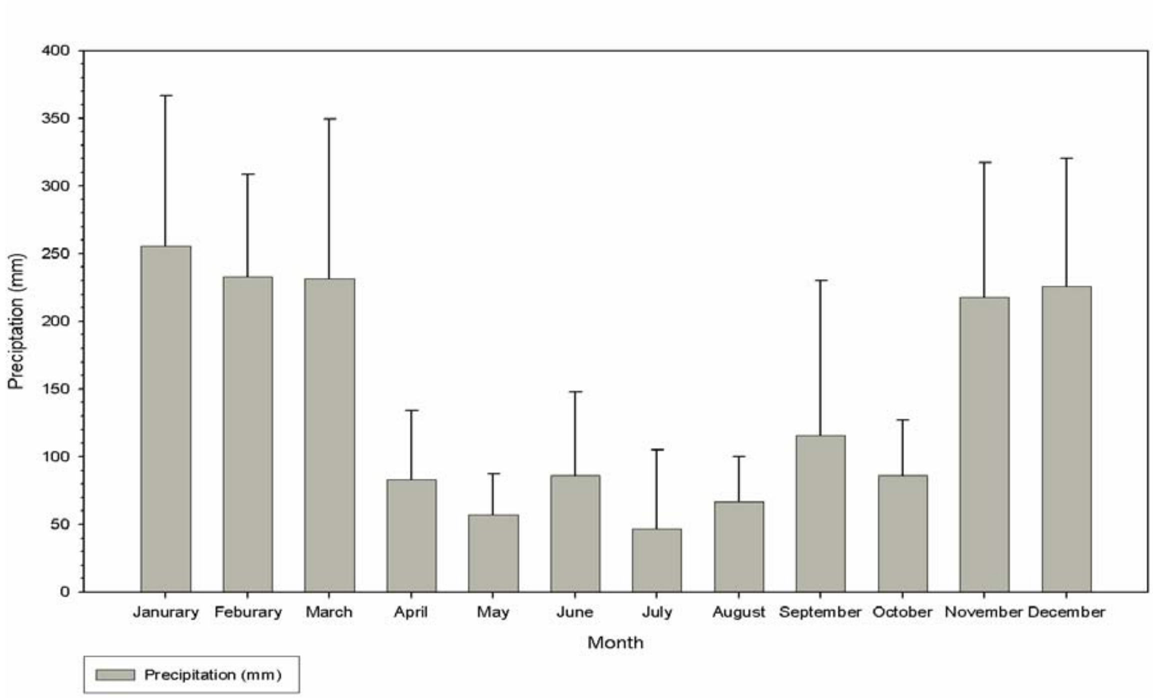

Figure B-1. Mean monthly precipitation (mm) measured in La Chonta from 1993–2001. The pronounced dry season starting in April and lasting through October is visible. Error bars represent standard errors around the mean.

APPENDIX C
DISTRIBUTION OF FELLING GAP AREA SIZES WITHIN THE STUDY PARCELS

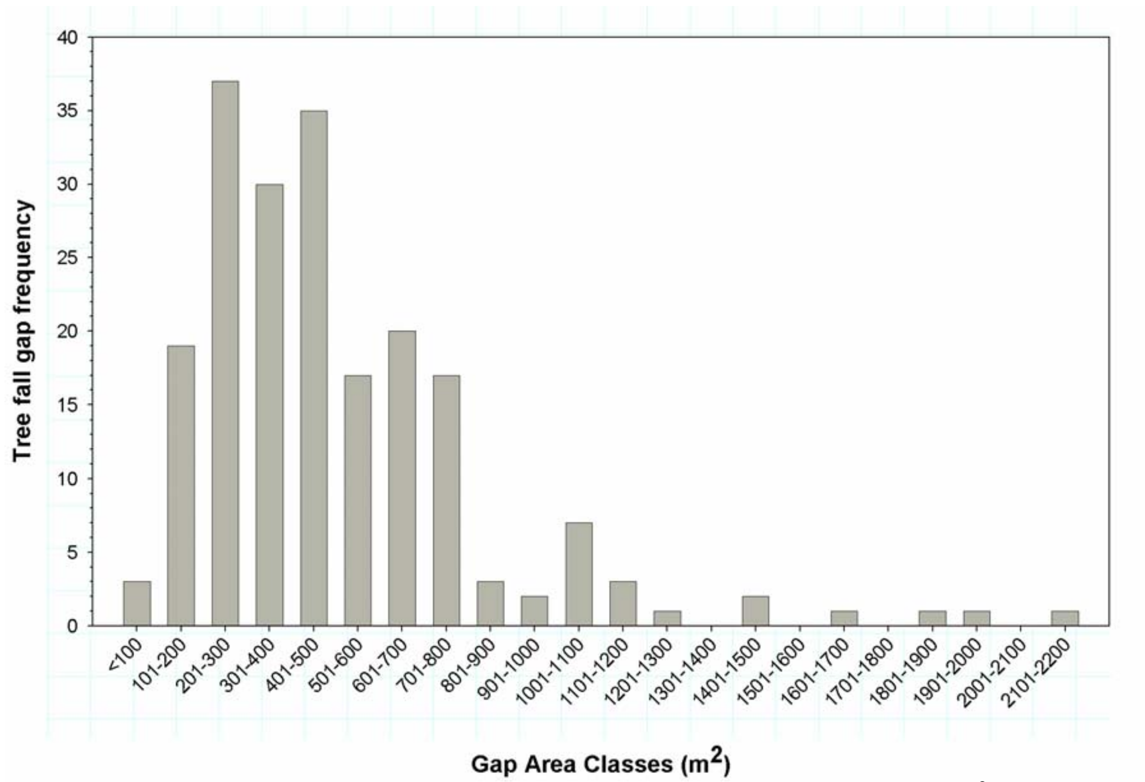

Figure C-1. Gaps size classes for this study were small felling gaps < 400 m^2, medium felling gaps 400 m^2 to 800 m^2, and large felling gaps > 800 m^2.

APPENDIX D
SKID TRAIL AREAS AND HARVEST INTENSITIES FOR ALL BOLFOR LONG TERM SILVICULTURAL RESEARCH PLOTS

Table D-1. Skid trail areas and harvest intensities for all BOLFOR long term silvicultural research plots

Parcel	Skid trail area (ha)	Parcel area (ha)	# trees harvested	Harvest intensity*	% parcel area in skid trails
6 months post-harvest	0.652	27	27	1	2.41
19 months post-harvest	1.062	27.98	29	1.036	3.80
B1-M	1.12	27.23	31	1.13	4.11
< 1 month post-harvest	1.186	29.7	56	1.885	3.99
13 months post-harvest	1.63	32	64	2	5.09
B3-M	1.26	28.81	62	2.15	4.37
B2-M	1.52	29.19	78	2.67	5.21
B1-I	1.51	27.27	85	3.11	5.54
B3-I	1.83	31.47	116	3.68	5.82
B2-I	1.48	27.23	123	4.52	5.44

* Mean trees/ha harvested

APPENDIX E
SIGNIFICANCE AND F VALUES OF 2-WAY REPEATED MEASURES ANOVAS OF REMOTE SENSING VARIABLES OF FELLING GAP PIXELS

Table E-1. Significance and F values of 2-way repeated measures ANOVAs of remote sensing variables of felling gap pixels

Effects	NDVI	PV	NPV	Soil
Felling Gaps > 800 m^2				
Parcel	12.08***	6.85***	2.83*	NA
Image Date	NA	2.79*	NA	44.59***
Parcel*Image Date	3.31***	3.22***	NA	NA
Felling Gaps 400 to 800 m^2				
Parcel	9.18***	15.98***	9.62***	NA
Image Date	2.98*	4.08**	NA	197.93***
Parcel*Image Date	6.15***	7.67***	2.31**	3.08***
Felling Gaps < 400 m^2				
Parcel	4.73***	6.76***	5.63***	3.69**
Image Date	3.44*	3.61*	NA	123.72***
Parcel*Image Date	3.02*	2.17*	2.34**	2.59**

Asterisks represent significant effects and interactions (* = $P < 0.05$, ** = $P < 0.01$, *** = $P < 0.001$).

Table E-2. Mean differences and P Values for two-way repeated measures ANOVA post-hoc comparisons (Dunnett's Test) of NDVI, PV, NPV and soil fractions in large (> 800 m^2) felling gaps versus unlogged control parcel pixels.

Parcel	Months post-harvest	NDVI	PV	NPV	Soil
< 1 month post-harvest	< 1	ns	ns	ns	ns
	1	-0.057***	ns	ns	ns
	2	-0.052***	-0.079***	0.082*	ns
	3	-0.050***	-0.072***	ns	ns
6 months post-harvest[a]	6	0.018***	ns	ns	0.058*
	7	0.023***	ns	ns	ns
	8	0.020***	ns	ns	ns
13 months post-harvest	13	ns	ns	ns	ns
	14	ns	ns	ns	-0.029*
	15	ns	ns	ns	ns
	16	0.013*	ns	ns	ns
19 months post-harvest	19	ns	ns	ns	ns
	20	0.037*	ns	ns	ns
	21	0.045***	ns	ns	ns
	22	0.035*	0.047*	ns	ns

Asterisks represent significant differences between treatment and control parcels (* = $P < 0.05$, ** = $P < 0.01$, *** = $P < 0.001$).

[a] No August remote sensing data of the 6 months post-harvest parcel was available as a portion of the parcel was re-logged during the last month of the study.

Table E-3. Mean differences and P Values for two-way repeated measures ANOVA post-hoc comparisons (Dunnett's Test) of NDVI, PV, NPV and soil fractions in medium (400 to 800 m^2) felling gaps versus unlogged control parcel pixels.

Parcel	Months post-harvest	NDVI	PV	NPV	Soil
< 1 month post-harvest	< 1	ns	ns	ns	0.071*
	1	-0.016***	-0.031***	0.041***	ns
	2	-0.015***	-0.028**	0.042***	-0.018*
	3	-0.016***	-0.027***	0.017*	ns
6 months post-harvest[a]	6	ns	ns	ns	ns
	7	ns	ns	ns	ns
	8	ns	ns	0.026*	ns
13 months post-harvest	13	0.010***	ns	ns	ns
	14	Ns	ns	ns	ns
	15	0.012**	ns	ns	ns
	16	ns	ns	ns	ns
19 months post-harvest	19	ns	ns	ns	ns
	20	ns	ns	ns	ns
	21	ns	ns	ns	ns
	22	ns	ns	ns	ns

Asterisks represent significant differences between treatment and control parcels (* = $P < 0.05$, ** = $P < 0.01$, *** = $P < 0.001$).

[a] No August remote sensing data of the 6 months post-harvest parcel was available as a portion of the parcel was re-logged during the last month of the study.

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BIOGRAPHICAL SKETCH

Eben Broadbent, as a young child, lived with his family in Japan and traveled throughout Eastern Asia. At the age of 12, he moved with his mother and sister to a solar-powered house, deep in the mountains of Vermont. He earned his Bachelor of Science degree from the University of Vermont with a major in botany, specializing in tropical areas, and with a minor in English. During this time, he worked in Costa Rica as an assistant teacher for a tropical ecology program based in Monteverde; and interned with botanists working for the Missouri Botanical Garden, looking for rare plant species within the Bosque Eterno de Los Ninos Rainforest Preserve. His undergraduate thesis studied niche partitioning among congeneric epiphytes within the Monteverde area cloud forests.

After graduation, he returned to Costa Rica to conduct research on forest regeneration and butterfly diversity after natural and anthropogenic forest disturbances in the Parque Nacional Corcovado. Returning to the US, he began working with the environmental nonprofit firm of Hudsonia Ltd. mapping areas of biodiversity concern within Dutchess County, NY, for use by local towns in creating ecologically sensitive development plans.

In 2001 he began an internship with BOLFOR, Proyecto de Manejo Forestal Sostenible de Bolivia, in Santa Cruz, Bolivia, identifying tree species within long term silvicultural research plots in the La Chonta forestry concession. For this thesis (part of his Master of Science degree in forestry) he returned to the La Chonta concession.

He is now working as a remote sensing and GIS technician for the Carnegie Institution of Washington at Stanford University. He is currently working on a project to identify selectively logged areas, deforestation, and new roads across the Brazilian Amazon. He is planning on beginning his doctoral studies in 2005, with the intention of studying the effects of land-use change on feedbacks among selective logging, wildfire, and climate change, for different aged deforestation frontiers in the Brazilian Amazon.