

Estimation of Tropical Forest Structural Characteristics using Large-footprint Lidar

Running Title: Estimation of Tropical Forest Structure using Lidar

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ABSTRACT

Quantification of forest structure is important for developing a better understanding of how forest ecosystems function. Additionally, estimation of forest structural attributes such as aboveground biomass is an important step in identifying the amount of carbon in terrestrial vegetation pools and is central to global carbon cycle studies. Although current remote sensing techniques recover such tropical forest structure poorly, new large-footprint lidar instruments show great promise. As part of a pre-launch validation plan for the Vegetation Canopy Lidar (VCL) mission, the Laser Vegetation Imaging Sensor (LVIS), a large-footprint airborne scanning lidar, was flown over the La Selva Biological Station, a tropical wet forest site in Costa Rica. The primary objective of this study was to test the ability of large-footprint lidar instruments to recover forest structural characteristics across a spectrum of land cover types from pasture to secondary and primary tropical forests. LVIS metrics were able to predict field-derived quadratic mean stem diameter, basal area and aboveground biomass with R^2 values of up to 0.93, 0.72 and 0.93 respectively. These relationships were significant and non-asymptotic through the entire range of conditions sampled at the La Selva. Our results confirm the ability of large-footprint lidar instruments to estimate important structural attributes, including biomass in dense tropical forests, and when taken along with similar results from studies in temperate forests, strongly validate the VCL mission framework.

1 INTRODUCTION

2
3 Tropical forests are among the most structurally complex and carbon-rich
4 ecosystems in the world. This complexity is related both to the size-frequency
5 distribution of woody stems (Clark and Clark, 2000; Denslow and Hartshorn,
6 1994) and to the three dimensional arrangement of canopy elements (e.g.,
7 leaves, branches, trunks) from the top of the canopy to the ground (Richards,
8 1996). Variation in tropical forest structure is influenced by underlying
9 environmental conditions (Clark and Clark, 2000; Clark et al., 1998; Laurance et
10 al., 1999), and in turn creates microclimatic (e.g., light, temperature, humidity)
11 gradients (Parker, 1995). These fine-scale gradients modify biological processes
12 such as competition and growth (Clark et al., 1996; Nicotra et al., 1999;
13 Oberbauer et al., 1993; Rich et al., 1993) which further modifies organization of
14 forest structural components.

15 Quantification of forest canopy structure provides information about the
16 primary surfaces of energy and matter exchange between the atmosphere and
17 one of the largest reserves of terrestrial aboveground carbon (Dixon et al., 1994;
18 Perry, 1994). Knowledge of the total carbon content in tropical vegetation
19 provides a critical initial condition for studies at multiple scales which examine
20 carbon flux caused by natural (e.g., landscape-level respiration of woody plants)
21 and anthropogenic (e.g., deforestation and afforestation) processes. However, the
22 accurate estimation of structural characteristics (e.g., aboveground biomass or
23 total amount of carbon within living tissues) of tropical forest vegetation remains
24 a major obstacle (Dubayah et al., 1997).

25 Most studies use forest aboveground biomass (AGBM), which is
26 approximately 50 percent carbon, as a surrogate for total aboveground carbon.
27 Because biomass can only be directly measured through destructive sampling, it
28 is usually estimated through a relationship with other measurable properties.
29 Field studies typically use allometric relationships between total biomass and the
30 height or bole diameter of trees. Although field biomass estimation methods are

1 useful for local scale studies, remote sensing techniques are necessary for the
2 recovery of biomass over broader spatial scales.

3 Most remote sensing studies illustrate the empirical correlation between
4 forest biomass and the intensity of EM energy (or the ratio of energy at different
5 wavelengths) that is received by the instrument. Unfortunately, many types of
6 remote sensing instruments suffer from the same problem: they are sensitive to
7 changes in biomass in relatively young and/or homogeneous forests, but in older
8 or heterogeneous forests the signal becomes less predictable with respect to
9 changes in biomass.

10 Several studies have shown that passive optical instruments are
11 insensitive to changes in tropical forest structural characteristics such as AGBM
12 beyond secondary forests of 10-15 years (Curran et al., 1997; Foody and Curran,
13 1994; Moran et al., 1994; Sader et al., 1989; Steininger, 1996). Metrics from
14 synthetic aperture radar (SAR) such as backscatter also tend to saturate in
15 dense forest conditions (Imhoff, 1995; Kasischke et al., 1997; Waring et al.,
16 1995; though see Smith and Ulander 2000 and Fransson et al. 2000) and have
17 been shown to be insensitive to changes in AGBM for secondary tropical forests
18 with AGBM levels >60 Mg/ha (Luckman et al., 1997).

19 New large-footprint lidar instruments (Blair et al., 1994; Blair et al., 1999)
20 may be able to overcome the saturation problems of other remote sensing
21 instruments. These instruments estimate canopy height as well as other
22 parameters related to the vertical arrangement of canopy elements from the top
23 of the canopy to the ground by directly measuring vertical structure (Blair et al.,
24 1999; Lefsky et al., 1999b; Weishampel et al., 1996). However, this technology
25 has not been applied to tropical forests. The objective of this study was to test
26 the ability of a new airborne large-footprint mapping laser altimeter instrument to
27 accurately estimate tropical forest structural characteristics such as aboveground
28 biomass and basal area in a dense, wet tropical forest. Related large-footprint
29 laser altimetry technology will soon be incorporated in the spaceborne
30 Vegetation Canopy Lidar (VCL) mission (Dubayah et al., 1997; Dubayah et al.,
31 2000).

1 In this paper we first provide a brief background on lidar remote sensing,
2 including previous lidar studies of forest structure, and highlighting some
3 differences between existing systems. Next we describe our study site and the
4 new lidar instrument used in this study. Finally we present the results from this
5 lidar instrument and discuss these results in relation to previous remote sensing
6 efforts to estimate tropical forest structure.

7 8 **Lidar Remote Sensing**

9
10 Lidar (**light detection and ranging**) is an active remote sensing technique
11 using laser light. Lidar systems measure the roundtrip time for a pulse of laser
12 energy (usually with a near-infrared wavelength for vegetation studies) to travel
13 between the sensor and the target. This incident pulse of energy interacts with
14 canopy (e.g., leaves, branches) and ground surfaces, and is reflected back to the
15 instrument. The travel time of the pulse, from initiation until it returns to sensor, is
16 measured and provides a distance or range from the instrument to the object
17 (hence the common use of the term "laser altimetry" which is now generally
18 synonymous with lidar).

19 Current lidar systems for terrestrial applications differ in: (1) whether they
20 record the range to the first return, last return, multiple returns or fully digitize the
21 return signal; (2) footprint size (from a few centimeters to tens of meters); and,
22 (3) sampling rate/scanning pattern. Most commercial airborne lidar systems are
23 low-flying, small-footprint (5-30 cm diameter), high pulse rate systems (1,000-
24 10,000 Hz). In addition, most commercial lidar systems record the range to the
25 highest, and/or lowest, reflecting surface within the footprint, and are not fully
26 imaging, using instead many laser returns in close proximity to each other to
27 recreate a surface.

28 Small-footprint lidar sensors may not be optimal for mapping forest
29 structure for several reasons. First, small diameter beams frequently miss the
30 tops of trees (see Nelson, 1997). Secondly, because of their small beam size,
31 mapping large areas requires extensive flying. Finally, with systems that only

record first and/or last returns, it is difficult to determine if a particular shot has penetrated the canopy all the way to ground. In areas of high canopy only one in several thousand returns may be from the ground (Blair and Hofton, 1999). If this topography cannot be recovered, accurate height determination is impossible because canopy height is measured relative to the ground.

Large-footprint lidar systems (Blair et al., 1994; Blair et al., 1999) have several advantages that help avoid these problems. First, by increasing the footprint size to the approximate crown diameter of a canopy-forming tree (~10-25 m), laser energy consistently reaches the ground even in dense forests (Weishampel et al. 1996). Second, the larger footprint size also avoids the biases of small-footprint systems that frequently miss the tops of trees. Third, large-footprint systems fly at higher altitudes and enable a wide image swath, which reduces the expense of mapping large areas on the ground (Blair et al., 1999). Finally, large-footprint lidar systems also digitize the entire return signal (or "waveform"), thus providing data on the vertical distribution of intercepted surfaces (i.e., canopy and ground elements) from the top of the canopy to the ground.

The conceptual basis for a large-footprint lidar return is illustrated in figure 1. The time history of the reflected energy is fully digitized, and is converted to units of distance (accounting for the speed of light through the atmosphere). The first energy return above a threshold is used to derive the distance to the canopy top, and the midpoint of the last energy return is used to find the range to ground, the subtraction of which yields laser-derived canopy height. The return waveform gives a record of the vertical distribution of nadir-intercepted surfaces (i.e. leaves and branches). At any particular height, the amplitude of the return waveform measures the strength of the return. Thus, for surfaces with similar reflectances and geometry within a footprint (and under similar atmospheric conditions), a larger amplitude indicates more canopy material and a smaller amplitude less. The waveform provides only an apparent canopy profile (leaves and branches) because of attenuation of the beam through the canopy, and must be adjusted to approximate the true canopy profile (Lefsky et al., 1999b; Ni et al., in review).

Previous Lidar Studies of Forest Structure

Measurements from small-footprint laser altimeter instruments have been useful in estimating tree heights (e.g., Magnussen and Boudewyn, 1998; Naesset, 1997a; Nelson et al., 1988; Nilsson, 1996), percent canopy cover (Weltz et al., 1994), timber volume (Naesset, 1997b) and in some cases forest aboveground biomass (AGBM) (Nelson et al., 1988). However, these fine-resolution sensors typically yield consistent ground returns only in relatively open forest canopies (Weishampel et al., 1996), thus making AGBM estimation difficult in dense tropical forests. Previous attempts to estimate tropical forest AGBM using small-footprint laser altimeters have also been complicated by the incompatibility of data sets, for example the lack of coincident field- and laser-derived data (Nelson, 1997; Nelson et al., 1997; Nelson et al., 1998).

Large-footprint lidar measurements, incorporating information contained in the laser return waveform, have been used to derive canopy height and structure in a variety of canopy closure conditions (e.g., Means et al. 1999 and Lefsky et al. 1999b). Because these large-footprint lidar instruments consistently measure subcanopy topography, even under conditions of high canopy closure, they have been shown to recover forest canopy structure that is statistically indistinguishable from field measurements (Lefsky, 1997), and are able to accurately capture spatial patterns of canopy heights (Drake and Weishampel, 2000). These instruments have also accurately estimated AGBM in both Douglas fir/western hemlock (Lefsky et al., 1999a; Means et al., 1999) and temperate mixed-deciduous forests (Lefsky et al., 1999b). In both cases, data from the lidar instruments were incorporated into regression models to derive plot-level forest structural (e.g., AGBM) estimates. These relationships were found to be significant even through dense structural conditions. For example, Means *et al.* (1999) predicted total plot AGBM with R^2 values of up to 0.96 using lidar-based AGBM estimation models through biomass levels of 1300 Mg/ha, far exceeding the normal saturation point of radar (≈ 150 Mg/ha from Dobson et al. 1992;

Waring et al., 1995; Imhoff 1995; Ranson et al. 1997). These results suggest that data from the upcoming (2001) spaceborne VCL (Dubayah et al., 1997) mission will greatly improve global biomass estimates.

METHODS

La Selva Biological Station

The La Selva Biological Station (Figure 2; also see Clark, 1990; McDade et al. 1994; Matlock Jr. and Hartshorn, 1999) is located near the Sarapiquí River in northeast Costa Rica. Over its 46 year history, La Selva has become one of the most heavily studied tropical field stations in the world (McDade et al. 1994). This 1536 ha area is comprised of a mixture of lowland primary and secondary tropical wet forest (sensu Holdridge et al., 1971), abandoned pasture, current and abandoned plantations, and agroforestry plots. The elevation range at La Selva is approximately 35-135 m above sea level, with a north to south gradient resulting in higher elevations and steeper slopes to the south where it borders on the 47,000 ha Braulio Carrillo National Park. The soils at La Selva are primarily a mixture of inceptisols (particularly in alluvial terraces in the north), and residual ultisols to the south (Clark et al., 1998).

The primary forest estimated AGBM and basal area values at La Selva are low in comparison with other primary tropical rainforests (Brown et al., 1995; Brown, 1997; Laurance et al., 1999; Saldarriaga et al., 1988). This may be due to differences between tropical moist forests (where the majority of studies are conducted) and tropical wet forest such as La Selva (see Clark and Clark, 2000 for a more detailed discussion). Nevertheless the variety of land cover types, and the wealth of ancillary data (e.g., soil, topography, forest structural data) available, makes La Selva an ideal study site for this study.

Field Data

Forest structural data (Table 1) were collected across a successional spectrum ranging from abandoned pasture to primary wet tropical forests (Figure 2.). Primary tropical forest data were collected in 18, 0.5-ha plots that are part of an ongoing landscape-scale carbon storage and flux study (Clark and Clark, 2000). The plots were stratified over three edaphic conditions: relatively fertile flat inceptisols on old alluvial terraces (A plots); relatively infertile ultisols areas on ridgetops (L plots); and ultisol areas on steep slopes (P plots). All 18 plots were geolocated without knowledge of existing forest structure. This approach eliminates placement biases that can lead to large inaccuracies when AGBM values are extrapolated over a landscape-scale (Brown et al., 1995; Clark and Clark, 2000).

Secondary forest data were collected in three different areas that were approximately 14, 22 (Chazdon, 1996; Guariguata et al., 1997; Nicotra et al., 1999) and 31 (Pierce 1992) years old respectively as of March 1998. The 14 and 22 year old secondary forest plots are each approximately 0.5 ha. Within the 31 year old secondary forest area, 6 circular plots of 12.5 m radius were geolocated so as to approximately coincide with LVIS footprints.

In each primary forest plot, all stem diameters greater than 10 cm were measured in a marked location on each tree, either at breast height (1.37m) or, when necessary, above buttressing (Clark and Clark, 2000). In the 31 year old secondary forest plots, all stem diameters greater than 10 cm at breast height were measured. In the 14 and 22 year old secondary forest plots all stem diameters greater than 5 cm at breast height were recorded. These measurements were taken both as a part of a March 1998 VCL calibration/validation campaign, and as a part of the separate long-term studies.

Stem diameters were used to calculate quadratic mean stem diameter (QMSD, Equation 1) basal area and aboveground biomass using an equation for tropical wet forests (Brown, 1997). Quadratic mean stem diameters were calculated to compensate for the different (i.e. 5 cm vs. 10 cm) minimum diameter thresholds that were used in the existing studies. In addition, published

aboveground biomass values from agroforestry plots at La Selva (Menalled et al., 1998) and for tropical pastures (Olson et al., 1983) were used in this study.

Equation 1. $QMSD = [(\sum D^2) / n]^{1/2}$ where **D** is stem diameter and **n** is the number of stem diameters in the area

Lidar Data

The airborne instrument used in this study is the Laser Vegetation Imaging Sensor (LVIS, Blair *et al.*, 1999). LVIS is a medium-altitude imaging laser altimeter, designed and developed at NASA's Goddard Space Flight Center. Variable-sized footprints and a randomly positionable laser beam and 7 degree telescope field of view allow LVIS to operate in a variety of modes. Footprint diameters can be varied from 1 to 70 m, and footprint spacing can be varied both along and across track. The return signal, or waveform, is digitally recorded and converted to units of distance (by accounting for the speed of light through the atmosphere). In this study the vertical resolution was approximately 30 cm, as determined by the digitization rate. Ancillary information such as the pointing direction and position of the laser at the time of each pulse (provided using an inertial navigation system and GPS unit) are also recorded. The combination of these data post-flight enables the geolocation of the laser footprint on the ground within a global reference frame (usually to better than 1 m horizontal accuracy) (Hofton et al., 2000 a).

In March 1998 LVIS was flown in a NASA C-130 airplane to map the La Selva Biological Station and surrounding regions of NE Costa Rica. LVIS was in VCL emulator mode and operated at an altitude of 8 km above the ground to produce eighty, 25 m diameter footprints separated by ~25 m along- and ~9 m across-track (See Figure 1). Unlike previous laser altimeter instruments which record narrow transects of data, LVIS is able to map entire landscapes with relatively few flights. Only LVIS footprints that were coincident with field study plots (see below for details) were selected.

Four metrics were derived from the waveforms (see Figure 3). Lidar canopy height (LHT) was calculated by identifying 1) the location within the waveform when the signal initially increases above a mean noise level/threshold (the canopy top) and 2) the center of the last Gaussian pulse (the ground return), and then calculating the distance between these locations. Second, the height of median energy (HOME) was calculated by finding the median of the entire signal (i.e., above the mean noise level) from the waveform, including energy returned from both canopy and ground surfaces. The location of the median energy is then referenced to the center of the last Gaussian pulse to derive a height. The HOME metric is therefore predicted to be sensitive to changes in both the vertical arrangement of canopy elements and the degree of canopy openness (including tree density). Third, the height/median ratio (HTRT) is simply the HOME divided by canopy height. The HTRT provides an index of how the location of HOME may change relative to the canopy top height (LHT) through succession. Finally, a simple ground-return ratio (GRND) was calculated by taking the total intensity (i.e., the number of digitizer counts) contained in all 30 cm vertical bins contained in the last Gaussian peak (Hofton et al., 2000 b) divided by the sum of the intensity of all other canopy vertical bins of the waveform (see Figure 3). Thus, GRND provides an approximation of the degree of canopy closure (note that the canopy closure can be directly derived from the waveform under suitable canopy assumptions, as found in Means et al. 1999). These four metrics were then incorporated into a stepwise regression procedure to predict field measured basal area and QMSD and field estimated AGBM.

Analysis

The analysis involving ground and laser altimeter derived data was performed at both the level of individual LVIS footprints (25 m diameter circle) and at the level of the average plot size (0.5 ha) for areas with coincident LVIS and field data (Figure 4a and b). For each field plot, only LVIS footprints that are located entirely within the plot (i.e., footprint center over 12.5 m from plot edge)

were selected to avoid the affects of outside canopy structure that was not measured on the ground (Figure 4).

In all plots where stem maps were available (18 primary plots and the six 31 year old secondary forest plots), footprint-level analysis was performed. All stems located within each LVIS footprint were selected and used to calculate forest structural characteristics (see below). In addition, a plot-level analysis was performed using all stems and LVIS footprints that fell entirely within each field plot (or in the case of pasture, using shots falling within an area of pasture)(Figure 4). Field and lidar data from the six footprint-sized plots, were combined into two (0.15 ha) plot-scale subsets.

The diameters of all stems within the respective footprints or plots were used to calculate stem basal area. These stem diameters were also used to estimate aboveground biomass using the tropical wet allometric equation of Brown (1997):

Equation 2. $\mathbf{AGBM_s} = 21.297 - 6.953(\mathbf{D}) + 0.740(\mathbf{D}^2)$

where **D** is stem diameter in cm, and **AGBM_s** is the estimated oven-dried AGBM for the stem

Basal area and estimated AGBM were then summed within the footprint or plot and were converted to standard units of area, m²/ha and Mg/ha respectively. Additionally, the quadratic mean diameter (Equation 1.) within each footprint or plot was also calculated.

At the footprint-level, the lidar metrics were derived from individual waveforms. Plot-level values were calculated as the means of metrics for all footprints within the plot. For example, plot-level LHT was calculated for each plot by taking the mean of LHT values for all footprints within the plot (Figure 4).

Metrics derived from LVIS waveforms (Figure 3) were then used to estimate the field-derived forest structural summaries at both the footprint and plot levels using stepwise multiple linear regression. During this process transformations of dependent and independent variables (including square,

square root and logarithmic) were also explored. Those models that were found most predictive were then cross-validated (Cressie, 1991) to define a generalization error. Finally, these models were applied to all of the LVIS data over La Selva to produce landscape-level maps of forest structural characteristics.

RESULTS

The assortment of plots from different land cover types that are incorporated in this study span the range of forest structural characteristics for the La Selva landscape. Additionally because the 18 primary forest plots are evenly stratified over the main upland edaphic and topographic conditions at La Selva (Clark and Clark, 2000), the primary forest data are an unbiased, representative sample of the structural conditions found in this primary tropical wet forest.

In general all of the forest structural characteristics increase through the range of land cover types that were sampled (Table 1). There is a trend of increasing estimated AGBM and QMSD from pasture through secondary forest and into primary tropical forests. The exception to this trend is for the average QMSD value for the six 31 year old secondary forest sites, which is larger than the average QMSD of the primary forest sites. This exception is likely the result of large remnant trees (i.e., those not cut-down when the area was originally deforested), which are found within the 31 year old forest area (D.B. Clark, pers. obs.) and strongly influence the QMSD values

Overall, the lidar metrics from these areas (Table 2) are sensitive to changes in forest structure in the different land cover types included in this study. The height metrics (i.e., LHT, HOME and HTRT) are the most sensitive, and increase with increasing forest age, basal area and biomass. Ground return ratio is generally insensitive to changes in forest structure beyond a secondary forest age of approximately 14 years.

At the footprint-level (0.05 ha) metrics from LVIS are able to significantly estimate all three forest structural attributes throughout the range of conditions at La Selva, though in most cases logarithmic transformations of dependent variables was necessary. The HOME metric is the best single predictor of both QMSD (Table 3, equation 1) and AGBM (Table 3, equation 5), and explains 59% and 53% of the variation in these attributes respectively. The ground-return ratio metric was the best single-term predictor of basal area (Table 3, equation 3), and explained 27% of the variation.

For all three structural characteristics, multiple-term equations (Table 3, equations 2, 4 and 6) explain much higher levels of variation (R^2) than the single-term equations. The level of variation of basal area that is explained by both single and multiple-term equations is over 40% lower than the levels for AGBM and QMSD.

At the plot level (~0.5 ha) all of the relationships between forest structural summaries and lidar metrics are much stronger than at the footprint level. For all single-term equations the levels of variation in forest structural summaries explained (R^2 values) are over 35% higher at the plot level than at the footprint level, and range from 0.72 to 0.92. Again, the R^2 values for AGBM and QMSD are higher than for basal area.

The metric that is the best single-term predictor of both plot-level QMSD (Table 4, equation 1) and AGBM (Table 4, equation 4) is HOME, as is the case at the footprint level (Table 4). The HOME metric explains 89% of the variation in estimated AGBM and 92% of the variation in QMSD with no transformation of the dependent or independent variables. The best single-term predictor of plot-level basal area is HTRT ($R^2=0.72$), instead of GRND, which is the best predictor of basal area at the footprint level.

Multiple-term equations (Table 4, equations 2 and 5) only marginally improve the relationship for both QMSD ($R^2= 0.93$ vs 0.92) and estimated AGBM ($R^2=0.93$ vs. 0.89). For basal area, the single-term equation (Table 4, equation 3) was selected through all combinations and transformations in the stepwise multiple regression procedure.

To further examine the nature of the single-term relationships, they are graphically represented in scatter plots (Figures 5-7). In all three cases the metrics significantly estimate forest structural summaries without reaching an asymptote throughout the entire range of conditions at La Selva. In addition, the cross-validated generalization error (RMSE) for all three single-term relationships (Table 4) is low. As a result these relationships were applied to LVIS data over the entire La Selva landscape to produce images of estimated QMSD (Figure 8), basal area (Figure 9) and AGBM (Figure 10) with a resolution equal to the plot level used in this study (~0.5 ha). In addition, the footprint-level (~0.05 ha) equation for AGBM (Table 3, equation 5) was applied to a subset of the LVIS data within a primary forest area to produce a high-resolution image of estimated AGBM variability (Figure 10, inset).

DISCUSSION

Field and Lidar summaries

The trends in forest structural summaries (Table 1) are primarily in agreement with results from other studies for La Selva. As has been reported in other studies at La Selva (e.g., Guariguata et al., 1997) basal area does not significantly differ between older (i.e. ~22 yr) secondary and old-growth forests. The large remnant stems in the 31 year old secondary forest area result in the exception to the trend of increasing QMSD size through secondary forests and into primary forest plots, as mentioned above. Estimated AGBM is not as sensitive to remnant stems in secondary forest areas, and increases through the range of successional conditions sampled at La Selva.

Lidar-derived metrics are quite sensitive to changes in forest structure, particularly LHT, HOME and HTRT (Table 2). The canopy height metric (LHT) from the 14 year old secondary forest plot is higher than expected, which could be the result of two factors. First, large remnant stems, which can account for as much as 15% of the total basal area in secondary forests at La Selva

(Guariguata et al., 1997), coupled with the sensitivity of LVIS canopy height to the maximum detectable canopy surface may explain why these values are higher than expected. Second, precise plot boundary coordinates were not available for the 14 year old secondary plot, so the LVIS shots may not be entirely coincident with the actual plot location.

Footprint-level relationships

The relationships between lidar metrics and field-derived forest structural summaries at the footprint scale (~0.05 ha), though not as strong as the plot-level relationships (Tables 3 and 4), are significant. The multiple-term equations (Table 3, equations 2, and 6) selected through a stepwise multiple regression procedure explain 77% of the variation in QMSD and 73% of the variation in estimated AGBM across the range of conditions sampled in this dense tropical landscape. Still the footprint scale R^2 values are less than 65% of the plot-level single-term equations and less than 80% of the plot-level multi-term regression equations (Tables 3 and 4).

The footprint-level relationships could be negatively affected by two factors. First, the level of variability in forest structure at the scale of an LVIS footprint (0.05 ha) is much higher than at the plot level (~0.5 ha). The level of variation in forest structural characteristics (as determined by calculating the coefficient of variation or CV) is 2-3 times higher at the footprint scale as the plot level (Table 5). This agrees with other studies that have reported that a plot size of approximately 0.35-0.5 ha is necessary for sampling tropical forest estimated aboveground biomass and other structural characteristics (Brown et al., 1995; Clark and Clark, 2000).

A second factor that contributes to the weaker relationship between forest structural attributes and lidar metrics at the footprint-level is geolocation of LVIS observations and stems in each forest area. Although LVIS shots may be geolocated to within 1-2 meters (Blair and Hofton, 1999; Hofton et al., 2000 a), the location of stems within primary and the 31 year old secondary forest plots

were referenced to a plot corner using a compass and nylon measuring tapes. As a result stem locations may be off by 5-10 m in random (i.e., approximately unbiased) directions. Thus, stems that were included in particular LVIS footprints for this analysis may be as many as 12 m (LVIS shot geolocation uncertainty + stem geolocation uncertainty) outside of the footprint area, and stems that are up to 12 m outside of the footprint area and were not included may have truly been within the footprint.

Plot-level relationships

The relationships between lidar metrics and forest structural characteristics at the plot level are strong (Table 4). Metrics from LVIS are able to explain very high levels of variation (R^2 up to 0.93) in tropical forest aboveground biomass, basal area and quadratic mean stem diameter. These relationships are non-asymptotic (Figures 5-7) through the entire range of conditions sampled at La Selva, and permit estimates of AGBM to approximately the same level of accuracy as related large-footprint lidar studies in temperate coniferous forests (Lefsky et al., 1999a; Means et al., 1999).

The slightly weaker relationship between basal area and lidar metrics is caused by the lack of significant differences in basal area between secondary and primary forest areas that has been reported in field studies at La Selva (Guariguata et al., 1997). Although the frequency distribution of basal area (i.e., number of stems in different size classes) does change, the overall total basal area at La Selva is not significantly different beyond a secondary forest age of approximately 16 years since abandonment (Guariguata et al., 1997). As a result, lidar metrics such as LHT, HOME and HTRT which continue to increase with increasing forest age (Table 1) may not be as predictive of changes in total basal area compared to changes in estimated AGBM and QMSD. This may explain why ground return ratio (which is also insensitive to changes beyond a young secondary forest) was the best single-term predictor of basal area at the footprint-level (Table 3).

1 The height of median energy (HOME) is perhaps the metric with the
2 strongest potential for estimating tropical forest structural characteristics. It is the
3 best single-term predictor of both footprint- and plot-level QMSD and AGBM
4 (Tables 3 and 4). The canopy height (LHT) metric is strongly influenced by the
5 highest detectable canopy surface within a footprint. The HOME metric, however,
6 may be more sensitive to both the vertical arrangement and density of canopy
7 elements. In areas with densely packed canopy materials less lidar energy will
8 reach the ground, thereby increasing HOME. Conversely in more open or
9 disturbed areas (e.g., a treefall gap), more lidar energy will reach the ground,
10 thus reducing HOME. Because primary tropical forests represent a spectrum
11 from newly-created treefall gaps to mature patches with high canopy closure
12 (Lieberman et al., 1989), the sensitivity of HOME to these changes make it an
13 excellent predictor of forest structural attributes such as biomass.

14 The generalization error (RMSE) of 22.54 Mg/ha for the aboveground
15 biomass (Table 4, equation 4) level is 13.75% of the mean (160.5 Mg/ha) plot-
16 level AGBM for all primary forest areas sampled at La Selva. This value is also
17 comparable to a recent study in temperate coniferous forests where RMSE levels
18 (131 Mg/ha) were approximately 14% of the mean (965 Mg/ha) primary
19 coniferous forest AGBM level (Means et al., 1999). Additionally this value (the
20 generalization error divided by the mean primary forest AGBM level) is
21 approximately equal to the coefficient of variation of field-estimated AGBM at La
22 Selva (Table 5) and is approximately equal to the level of error from field
23 measurements (Brown et al., 1995).

24 The images of forest structural characteristics (Figures 8-10) over the
25 entire La Selva landscape allow for an unprecedented examination of the
26 relationship between forest structural characteristics and environmental (e.g.,
27 edaphic and topographic) conditions. Field based efforts (Clark and Clark, 2000)
28 have shown that although the AGBM summaries from primary forest plots in
29 areas with different soil and topographic conditions do not significantly differ, the
30 way in which this AGBM is distributed (i.e., the distribution of stem sizes) does

1 vary. In future work we hope to fully explore the variability in AGBM arrangement
2 over the entire La Selva landscape.

3 The landscape-scale images of tropical forest structural characteristics (8-
4 10) reveal several trends. First, through comparisons with a map of La Selva land
5 cover (Figure 2) secondary and primary forest areas are clearly distinct in terms
6 of estimated AGBM (Figure 10) and QMSD (Figure 8), but not in terms of basal
7 area (Figure 9), as expected from field studies (Guariguata et al., 1997).

8 Secondly, an area of primary forest in western La Selva that was selectively
9 logged (i.e., commercial stems >70 cm diameter were removed) in the late 1970s
10 is also distinct from the undisturbed primary forest in eastern La Selva (with
11 approximately the same edaphic and topographic conditions). Third, high
12 estimated AGBM (Figure 10), basal area (Figure 9) and QMSD (Figure 8) values
13 are clustered around stream valleys throughout the La Selva landscape,
14 consistent with field data (Clark and Clark, 2000).

15 Previous remote sensing studies using passive optical and SAR
16 instruments have had great difficulty in estimating tropical forest structural
17 characteristics such as AGBM. Metrics from passive optical instruments such as
18 Landsat are highly sensitive to leaf area index, or LAI (Hall et al., 1995; Running
19 et al., 1986) but in the tropics LAI and leaf biomass levels may become
20 asymptotic in secondary forests less than 10 years old (Brown and Lugo, 1990;
21 Foody et al., 1996). This may explain why passive optical instruments are
22 insensitive to changes in AGBM beyond secondary forests of 10-15 years (Sader
23 et al., 1989; Steininger, 1996). Similarly, SAR backscatter tends to saturate in
24 dense forest conditions (Imhoff, 1995; Kasischke et al., 1997; Waring et al.,
25 1995) and has been shown to be insensitive to changes in AGBM for secondary
26 tropical forests with AGBM levels >60 Mg/ha (Luckman et al., 1997).

27 Consequently, the ability of a large-footprint lidar to accurately predict tropical
28 forest structural characteristics across a dense, structurally complex, dense
29 tropical forest landscape is extraordinary.

30 31 **CONCLUSIONS**

Metrics derived from a large-footprint lidar instrument were significantly correlated with tropical forest structural characteristics at both footprint and plot levels across the entire range of conditions in a structurally complex tropical wet forest. Although the majority of the field-measured forest structural data are from the high-end of the biomass and basal area spectrum at La Selva, the instrument nonetheless successfully measured the structural heterogeneity within this dense primary forest at both footprint (0.05 ha) and plot (~0.5 ha) levels.

At the level of individual LVIS footprints (0.05 ha) the relationship between lidar metrics and forest structural characteristics is weakened by problems of geolocation (stems and LVIS footprints) and the level of variation in forest structure at that scale. Nevertheless, even with these factors the relationships between lidar metrics and tropical forest structural attributes are strong through the entire range of conditions sampled.

At the plot level (0.5 ha) these factors are negligible and the relationship among plot-level forest structural summaries and lidar metrics are extremely strong. The levels of variation explained by metrics from the LVIS instrument at this scale are significantly higher than for any other remote sensing instrument for tropical forests areas to our knowledge. The level of generalization error of the relationships between lidar metrics and QMSD and estimated AGBM is approximately the same as from previous studies in more open temperate forests. As a result, when these relationships are applied to LVIS data over the entire landscape at La Selva, it is possible to examine the relationship between forest structural characteristics and environmental conditions (e.g., topography) and past land use (e.g., selective logging).

Although several of the forest structural characteristics used in this study from La Selva are lower than many moist tropical rainforests (Brown et al., 1995; Brown, 1997; Laurance et al., 1999; Saldarriaga et al., 1988) this is not the case for all forest characteristics at La Selva. For example, the heights of emergent (>50 m) and average canopy-forming trees (~33 m) at La Selva are

1 approximately equivalent to those found in other neotropical rainforests
2 (Richards, 1996).

3 Perhaps more important from a lidar remote sensing point of view is the
4 light availability at ground level. The degree of canopy closure in primary and
5 secondary forest areas at La Selva is approximately 98-99% at 1m above ground
6 level (Fetcher et al., 1994; Nicotra et al., 1999). This is among the highest
7 canopy closure values found in tropical and extra-tropical forests (Baldocchi and
8 Collineau, 1994). Thus, although large-footprint lidar has proven effective for
9 estimation of forest structure in temperate forests with higher AGBM levels than
10 La Selva, the ability of this technology to recover forest structural characteristics
11 in a dense tropical forest with 3-4 times higher canopy closure than most
12 temperate forests (Baldocchi and Collineau, 1994) is critical. This ability is
13 particularly important at a global scale because tropical forests are estimated to
14 contain approximately 40% of the carbon in the terrestrial vegetation pool (Dixon
15 et al., 1994). The combination of the previous efforts in temperate forests along
16 with this study in tropical forests strongly confirm that next-generation lidar
17 technology, as found on the Vegetation Canopy Lidar (VCL) mission, will greatly
18 improve global estimates of aboveground biomass and other forest structure.

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Table 1. Forest structural summaries for all field data used in this study by land cover types sampled at La Selva Biological Station

Land Cover Type	Approximate Age (year)	Number of Sites	Plot Size (ha)	Quadratic Mean Stem Diameter* (cm)	Basal Area (m ² ha ⁻¹)	Mean Estimated AGBM (Mg ha ⁻¹)	Related Study/ Data Source
Primary Forest	Old-growth	18	0.5	20.76	23.6	160.5	Clark and Clark (in press)
Secondary Forest	31	6	0.05**	22.24***	26.71	147.7	VCL****
	22	1	0.25	12.85	22.05	129.4	Nicotra et al. 1999
	14	1	0.25	10.46	14.28	78.5	Nicotra et al. 1999
Agroforestry	7	6	0.12	9.03	14.48	34.3	Menalled et al. 1998 (literature values)
Pasture	<5	2	0.05**	N/A	N/A	8	Olson, 1983 (literature values)

* See equation 1.

** Size of a LVIS footprint

*** Stem diameters not measured above buttressing, median stem diameter= 18.70

**** Data collected as part of 1998 pre-launch VCL field campaign at La Selva

Table 2. Summaries for all lidar data used in this study by land cover types sampled at La Selva Biological Station

Land Cover Type	Approximate Age (year)	Lidar Height (m) [LHT]	Height of Median Energy (m) [HOME]	HOME/LHT Ratio [HTRT]	Ground Ratio [GRDRT]
Primary Forest	Old-growth	31.33	20.14	0.64	0.014
Secondary Forest	31	25.48	16.65	0.65	0.016
	22	17.68	11.32	0.63	0.013
	14	23.67	9.21	0.38	0.023
Agroforestry	7	9.47	1.68	0.17	0.067
Pasture*	<5	5.09	0.54	0.11	0.740

*-Data from two LVIS shots from abandoned pasture sites at La Selva were compared to tropical pasture AGBM data from Olson (1983)

Table 3. Regression equations and values for footprint-level (0.05 ha) forest structural characteristics

Forest Structural Characteristic	Equation	R ² *	RMSE
Quadratic Stem Diameter (cm)	(1) QMSD = 10.39+0.72*HOME	0.59	3.84 cm
	(2) Log(QMSD) = 1.14+0.05*LHT-0.05*HOME-0.72*GRND+2.43*HTRT	0.77	3.74 cm
Basal Area (m ²)	(3) Sqrt(BArea) = 5.11-6.28*GRND	0.27	7.88 m ² /ha
	(4) Sqrt(Barea) = 3.24 +0.04*LHT-4.12*GRND+1.15*HTRT	0.39	7.16 m ² /ha
Estimated Aboveground Biomass (Mg/ha)	(5) Log(AGBM) = 3.58+ 0.07* HOME	0.53	63.17 Mg/ha
	(6) Log(AGBM) = 2.06+0.07*LHT-0.08*HOME-1.05*GRND+3.51*HTRT	0.73	60.02 Mg/ha

*All values significant (p<0.01)

Table 4. Regression equations and values for plot-level (0.25-0.5 ha) forest structural characteristics

Forest Structural Characteristic	Equation	R ² *	RMSE**
Quadratic Mean Stem Diameter	(1) QMSD = 8.19+0.81*HOME	0.92	2.09 cm
	(2) QMSD =5.97+0.15*LHT+1.05*HOME-0.01*[LHT*HOME]	0.93	2.00 cm
Basal Area	(3) Barea = 11.09+20.10*HTRT	0.72	3.00 m ²
Estimated Aboveground Biomass	(4) AGBM = 26.28+ 6.77*HOME	0.89	22.54 Mg/ha
	(5) AGBM = 15.64+9.54*HOME-0.01*HOME ³	0.93	18.39 Mg/ha

* All values significant (p<0.01)

** Numbers are cross-validated

Table 5. Coefficients of variation in forest structural characteristics at the footprint-level (0.05 ha) and at the plot-level (0.5 ha, old-growth and 0.3 ha for 6 combined 31 year old secondary forest plots).

Forest Structural Characteristic	Footprint-level CV*	Plot-level CV*
Quadratic Mean Stem Diameter	22.54	9.60
Basal Area	33.56	11.94
Estimated Aboveground Biomass	43.41	14.01

*These values were calculated using only primary and 31 year old secondary forest

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Figure 1. Conceptual basis of lidar remote sensing. Incident gaussian-distributed pulses of laser energy from airborne or spaceborne instruments reflect off various portions of the canopy, resulting in a return waveform where the amplitude of the pulse is a function of the area of reflecting surfaces (leaves and branches) at that height. The entire waveform gives the vertical distribution of surfaces intercepted by the incident beam. Some of the incident light penetrates all the way through the canopy to produce the last large-amplitude Gaussian-shaped spike in the waveform known as the ground return. Lidar systems do not measure canopy height, but rather a target range determined by measuring the travel time of the pulse (accounting for the speed of light through the atmosphere). Canopy height is determined by subtracting the range to the ground from that to the first detectable return or some threshold above that return. The Laser Vegetation Imaging Sensor (LVIS), a large-footprint airborne scanning lidar instrument that was used in this study, is illustrated in the top portion of the figure.

Figure 2. La Selva Biological Station is located near the Sarapiquí River in northeast Costa Rica. This 1536 ha area is a mixture of primary and secondary wet tropical tropical rainforest, pasture, plantations, and agroforestry plots.

Figure 3. Metrics derived from lidar waveforms. See text for discussion. These metrics are then used to estimate forest structural characteristics such as aboveground biomass at both the footprint and stand levels.

Figure 4. (A) Footprint-level (0.05 ha) analysis involved all stems that were located within LVIS footprints. **(B)** Plot-level analysis involved all stems that were located within a plot, and all LVIS shots that fell entirely within the same plot (i.e., 12.5 m from the plot edge). In this case the clear LVIS shots would be included, but the gray shot would not be included. At both the footprint and plot level, the stems that fell within the designated areas were used to calculate forest structural characteristics such as basal area and aboveground biomass. The

relationship between these field values were then compared to metrics from individual footprints (A) or means of metrics for all footprints within the plot (b).

Figure 5. Plot-level quadratic stem diameter predicted from the LVIS height of median energy (HOME, Figure 4) metric. The regression line is equation 1 in Table 4.

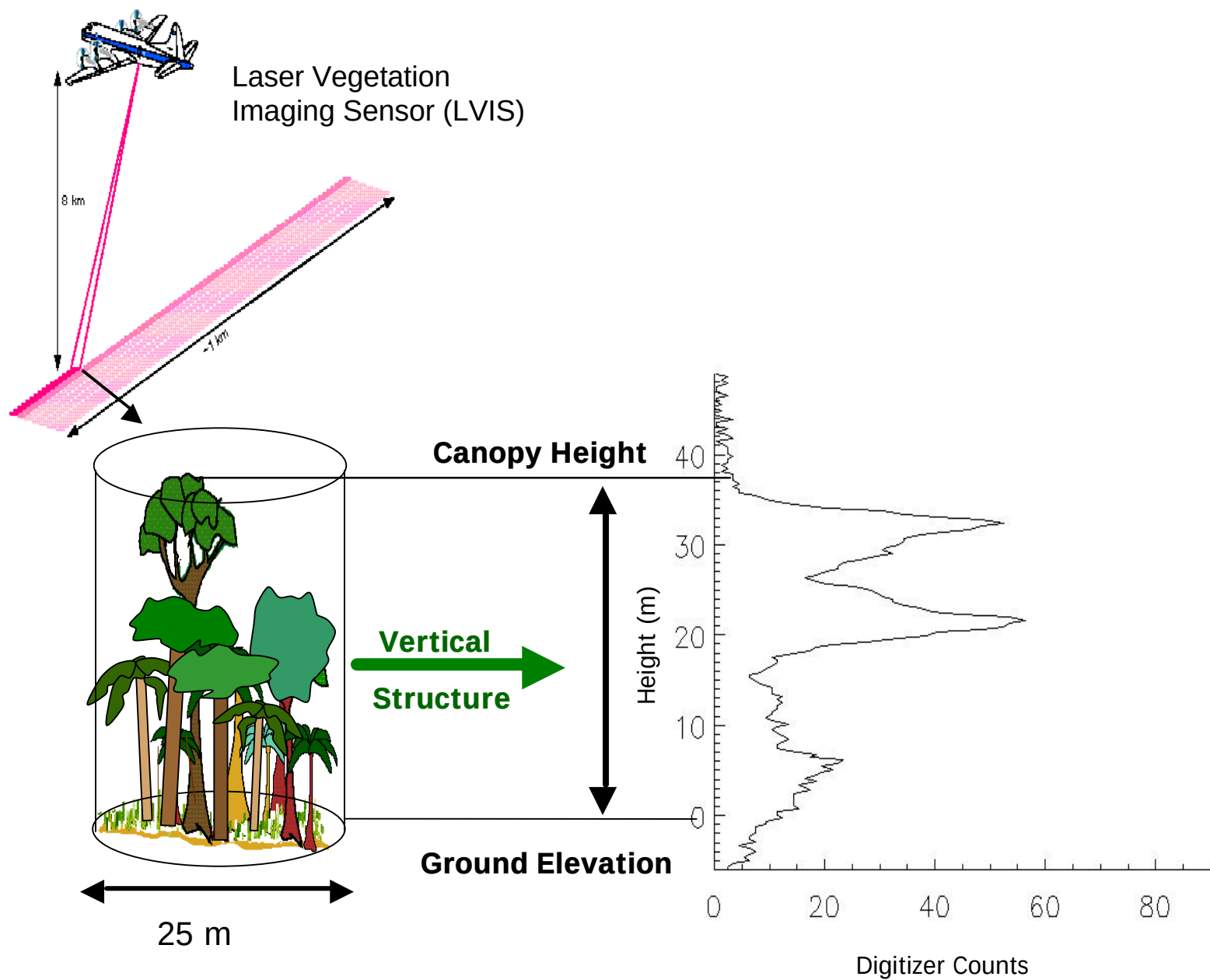
Figure 6. Plot-level basal area predicted from the LVIS height ratio (HTRT) metric (Figure 4). The regression line is equation 3 in Table 4.

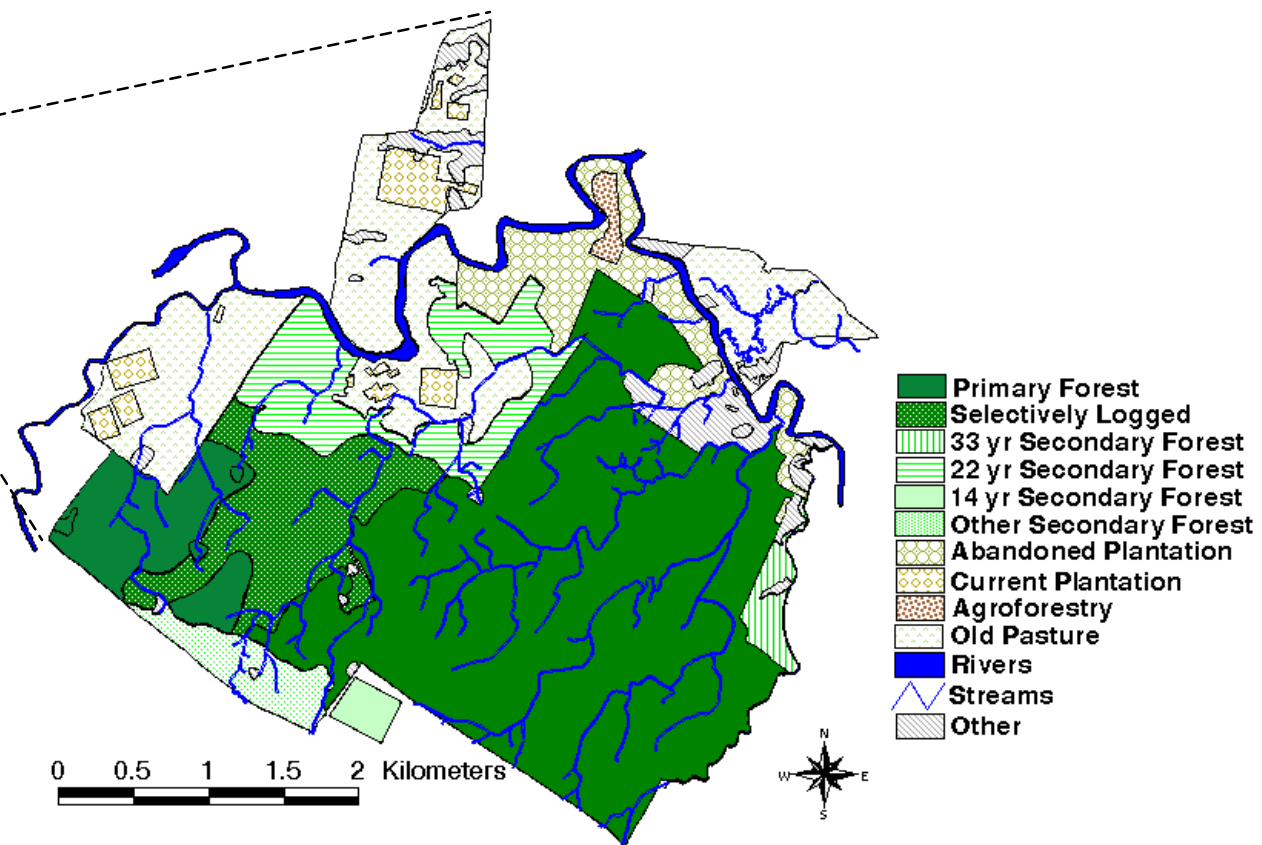
Figure 7. Plot-level aboveground biomass (AGBM) predicted from the LVIS height of median energy (HOME, Figure 4) metric. The regression line is equation 4 in Table 4.

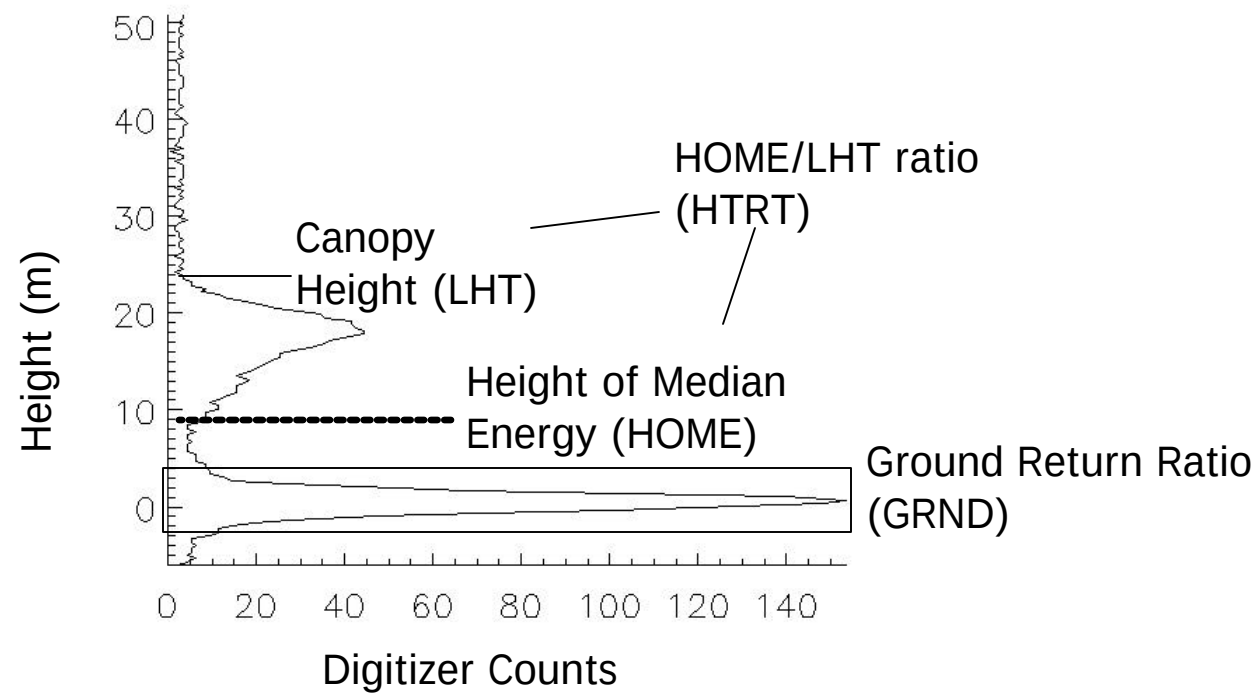
Figure 8. Image of quadratic mean stem diameter (QMSD) predicted from LVIS data over La Selva Biological Station using equation 1 in Table 4. Note the areas of lower QMSD in western portions of La Selva that were selectively logged in the late 1970s, and the clustering of high QMSD values near streams.

Figure 9. Image of basal area predicted from LVIS data over La Selva Biological Station using equation 3 in Table 4. Note the differences in basal area between younger secondary forest areas and primary forests (see land cover data in Figure 2).

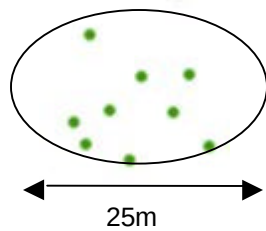
Figure 10. Image of aboveground biomass (AGBM) predicted from LVIS data over La Selva Biological Station using equation 4 in Table 4. Note the areas of lower AGBM in western portions of La Selva that were selectively logged in the late 1970s. In the right inset, AGBM predicted using the footprint level (~0.05 ha) equation (Table 3, equation 5) clearly reveals the clustering of high AGBM values near streams.



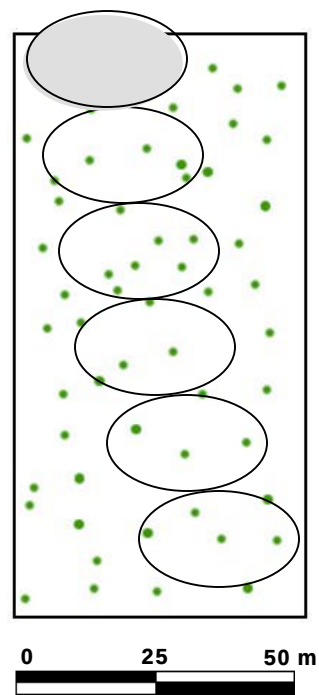


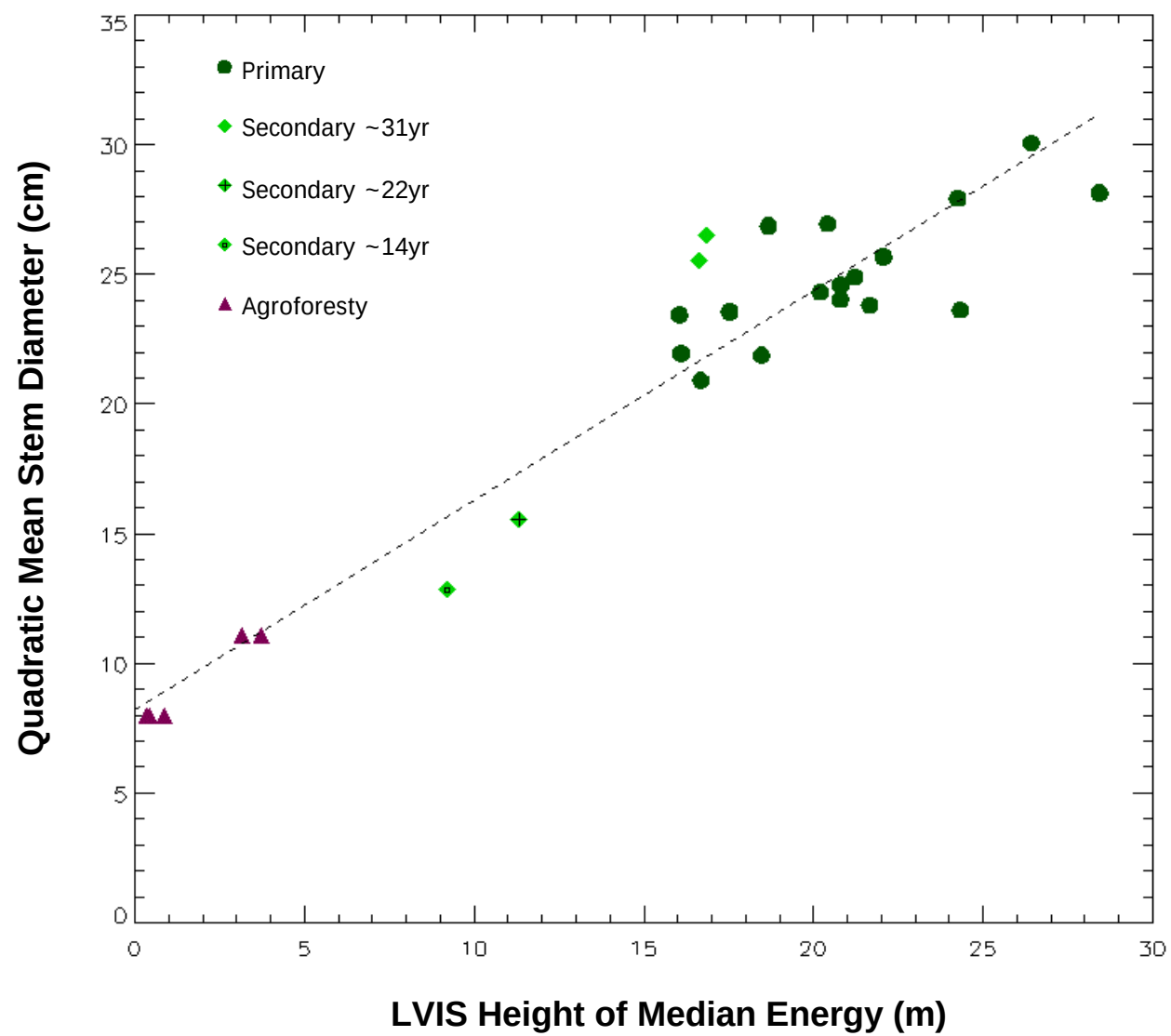


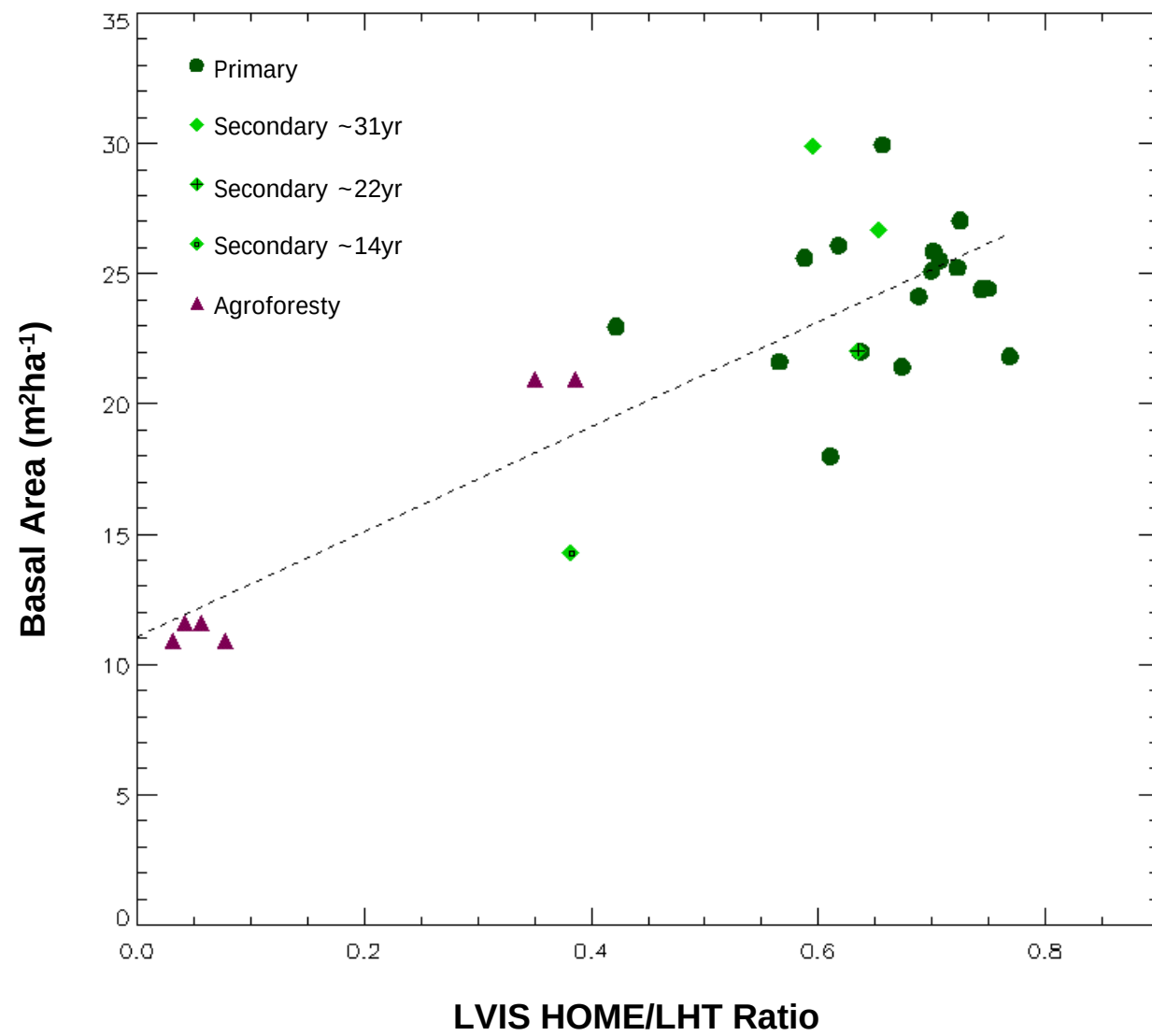
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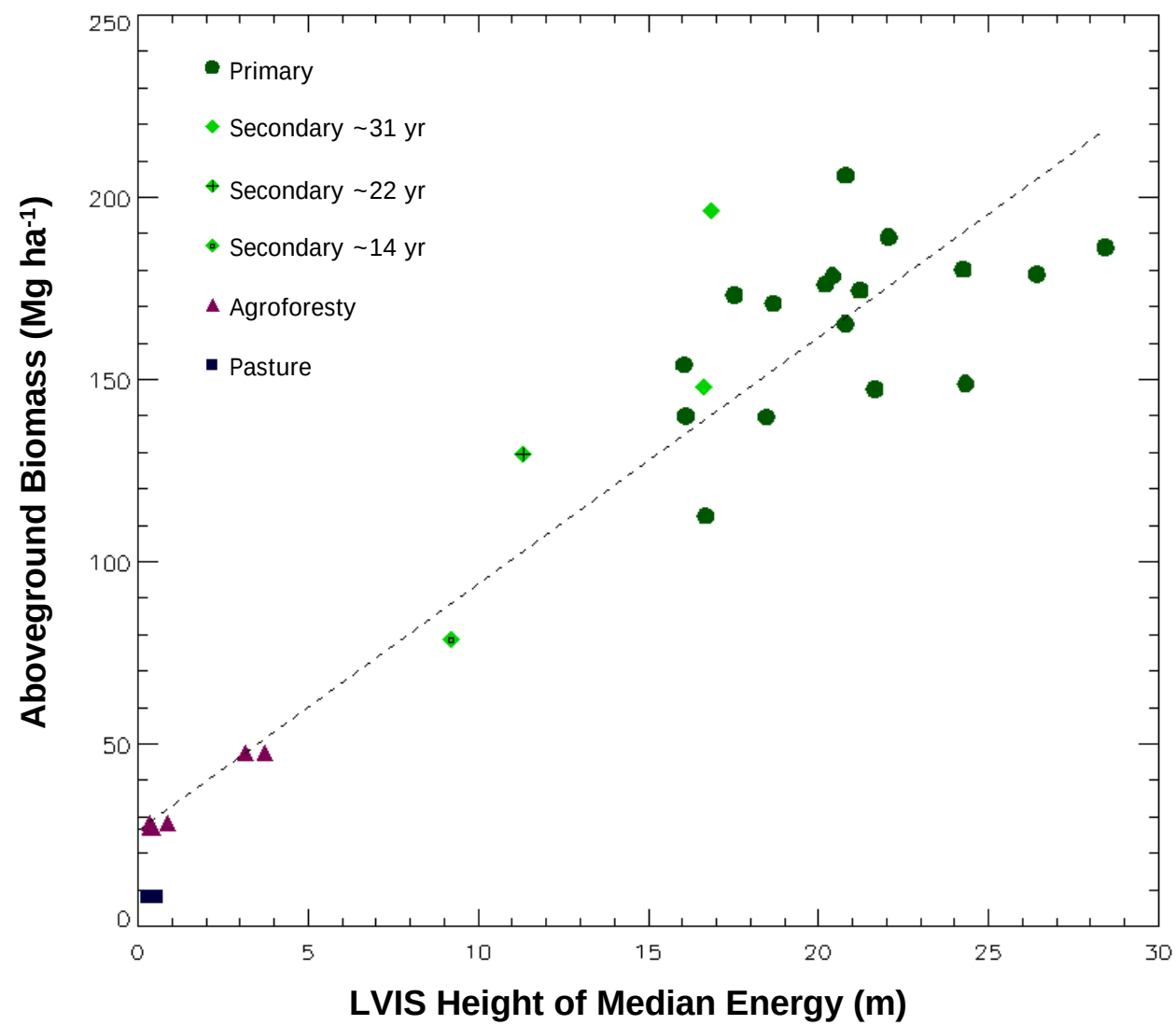


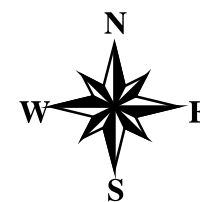
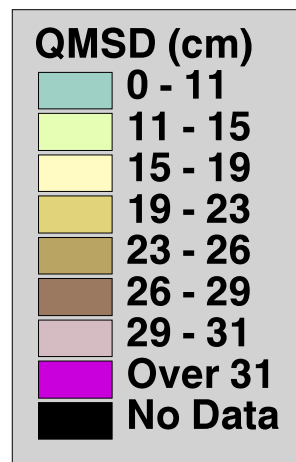
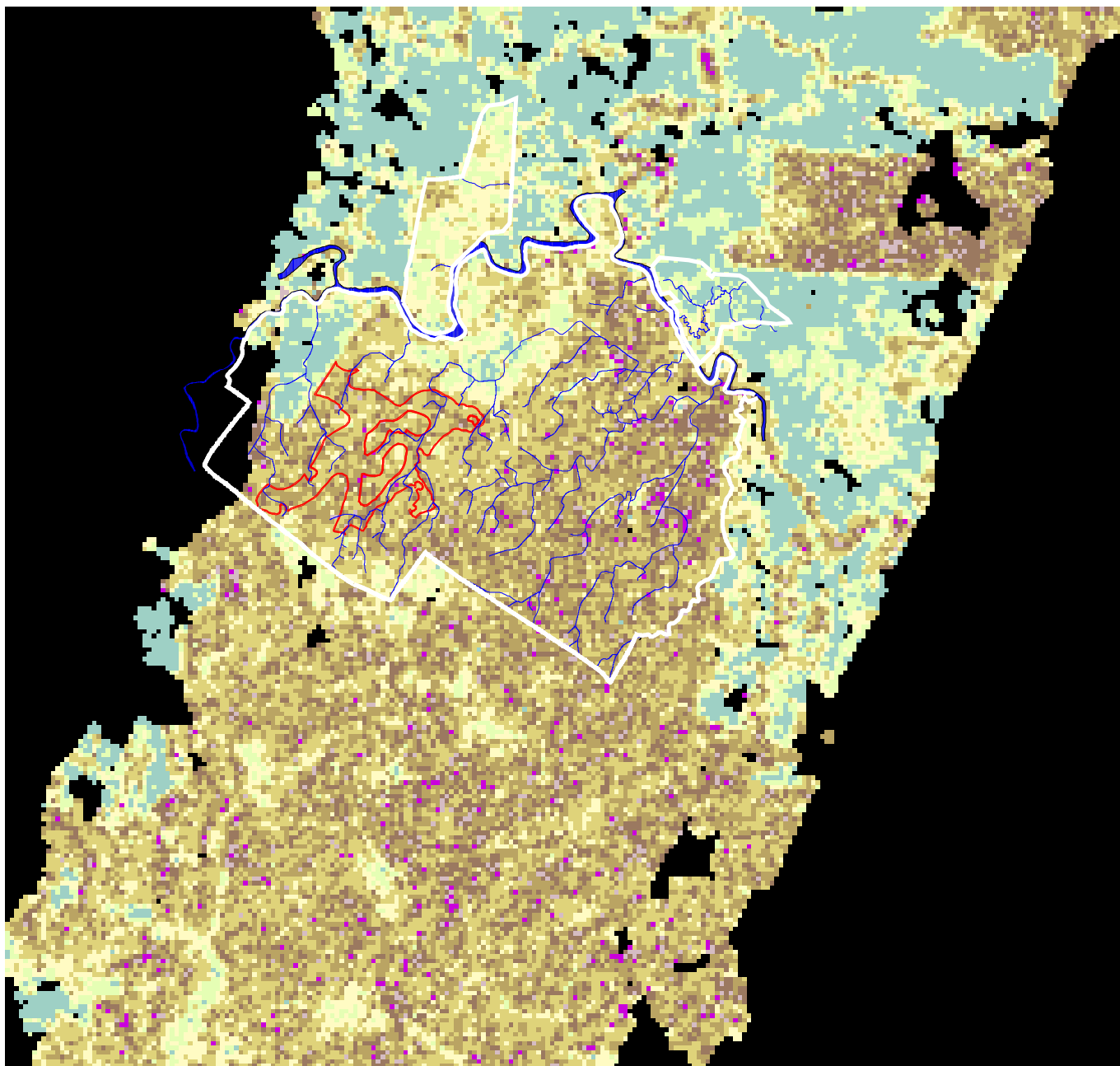
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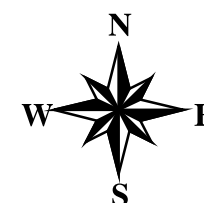
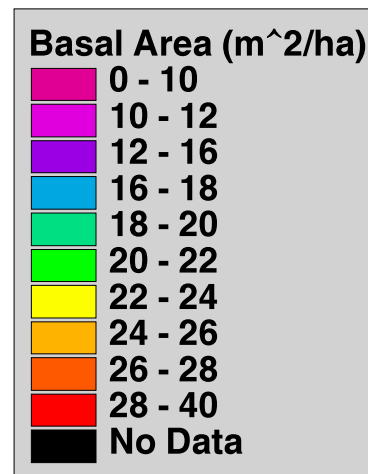
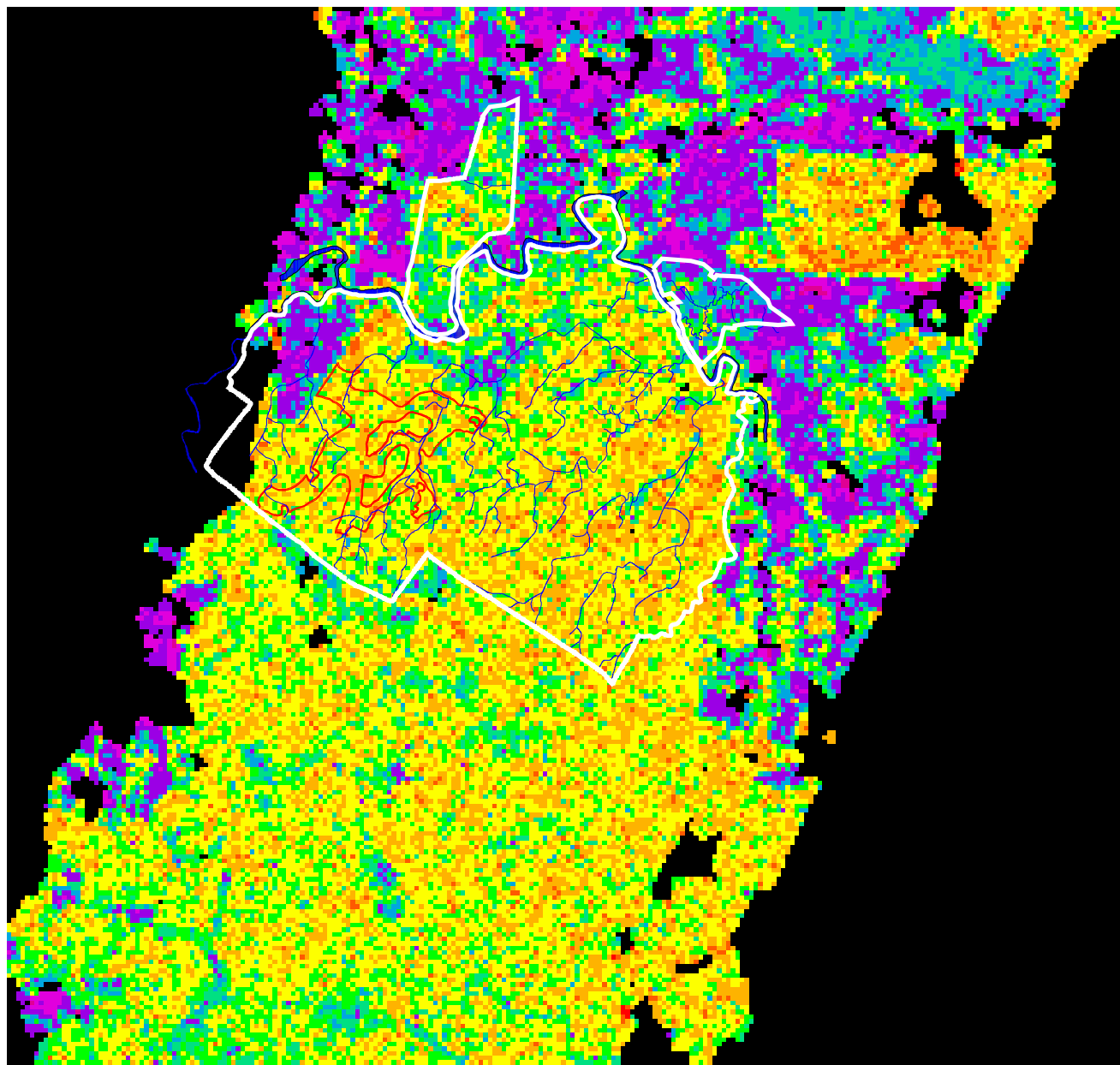






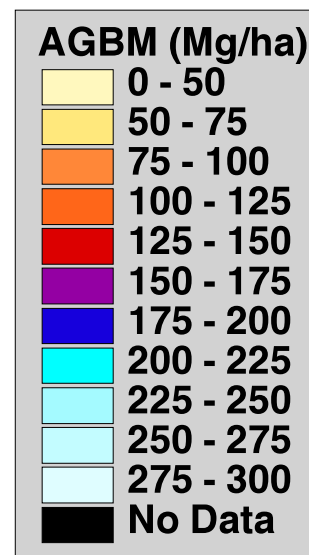
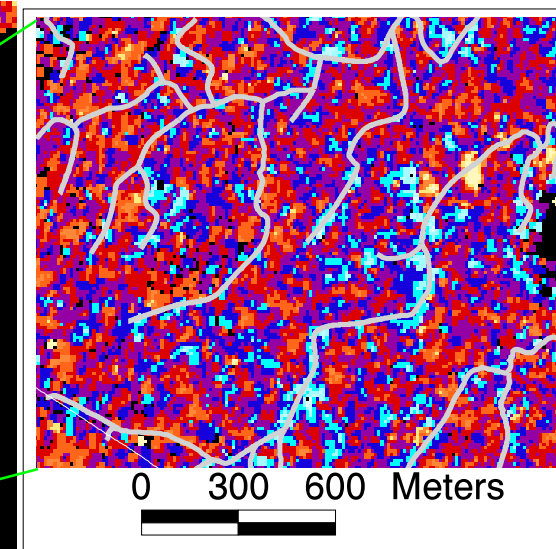
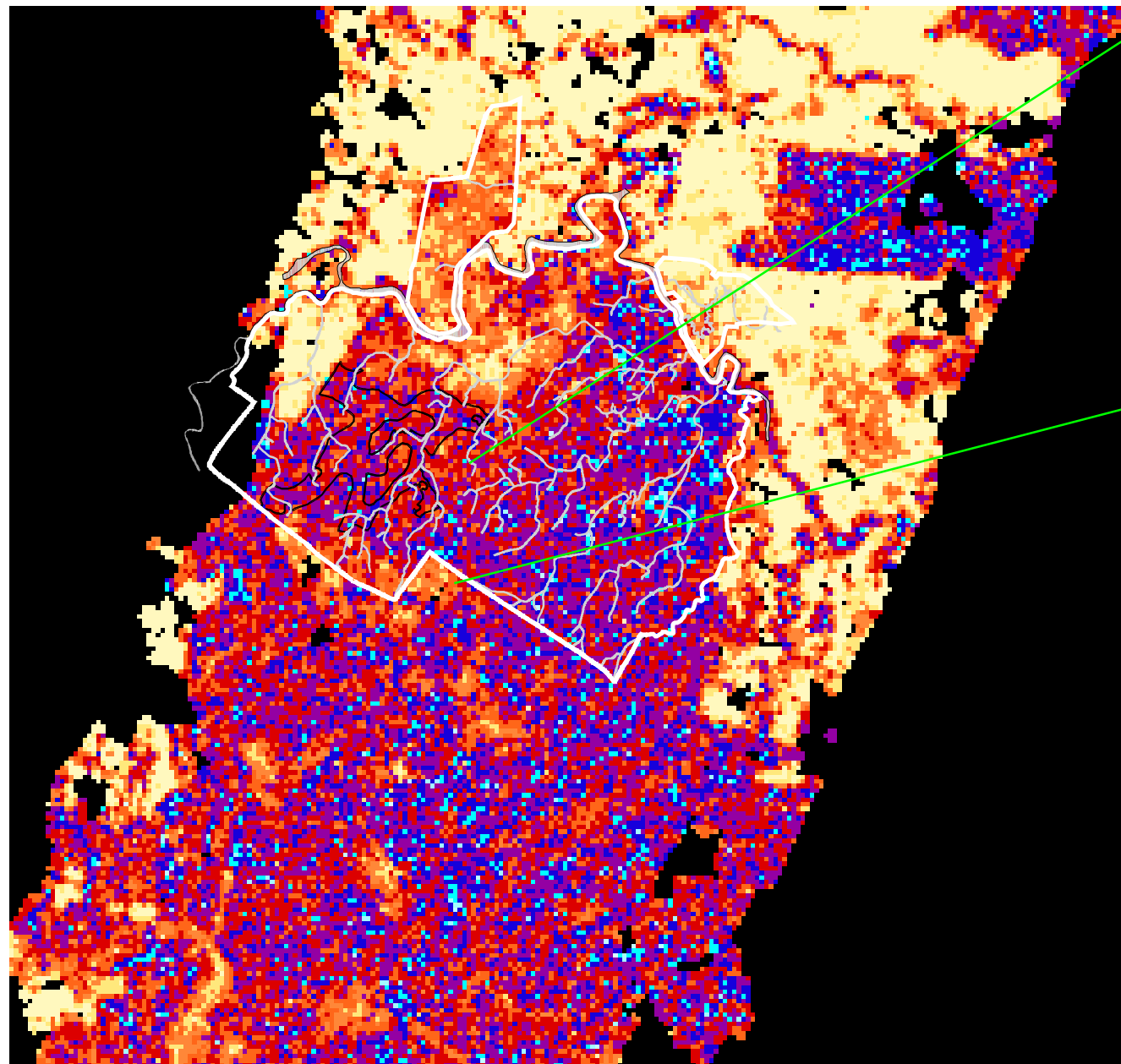
0 3 6 Kilometers





0 3 6 Kilometers





0 3 6 Kilometers

