Estimation of tropical forest height and biomass dynamics using lidar remote sensing at La Selva, Costa Rica

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[1]   In this paper we present the results of an experiment to measure forest structure and biomass dynamics over the tropical forests of La Selva Biological Station in Costa Rica using a medium resolution lidar. Our main objective was to observe changes in forest canopy height, related height metrics, and biomass, and from these map sources and sinks of carbon across the landscape. The Laser Vegetation Imaging Sensor (LVIS) measured canopy structure over La Selva in 1998 and again in 2005. Changes in waveform metrics were related to field-derived changes in estimated aboveground biomass from a series of old growth and secondary forest plots. Pairwise comparisons of nearly coincident lidar footprints between years showed canopy top height changes that coincided with expected changes based on land cover types. Old growth forests had a net loss in height of −0.33 m, while secondary forests had net gain of 2.08 m. Multiple linear regression was used to relate lidar metrics with biomass changes for combined old growth and secondary forest plots, giving an r^2 of 0.65 and an RSE of 10.5 Mg/ha, but both parametric and bootstrapped confidence intervals were wide, suggesting weaker model performance. The plot level relationships were then used to map biomass changes across La Selva using LVIS at a 1 ha scale. The spatial patterns of biomass changes matched expected patterns given the distribution of land cover types at La Selva, with secondary forests showing a gain of 25 Mg/ha and old growth forests showing little change (2 Mg/ha). Prediction intervals were calculated to assess uncertainty for each 1 ha cell to ascertain whether the data and methods used could confidently estimate the sign (source or sink) of the biomass changes. The resulting map showed most of the old growth areas as neutral (no net biomass change), with widely scattered and isolated sources and sinks. Secondary forests in contrast were mostly sinks or neutral, but were never sources. By quantifying both the magnitude of biomass changes and the sensitivity of lidar to detect them, this work will help inform the formulation of future space missions focused on biomass dynamics, such as NASA's Deformation Ecosystem Structure and Dynamics of Ice mission.

1.   Introduction

[2]   Forests are the focus of intense research in global environmental change. The effects on carbon of natural and anthropogenic forest structural changes and dynamics are of particular interest. A major source of error in estimates of land surface carbon and other biogeochemical fluxes arises from uncertainty in prescribing initial forest carbon stocks, and subsequent changes to these from growth, degradation and deforestation [*Brown*, 1997; *Houghton et al.*, 2001; *Clark*, 2004; *Houghton and Goetz*, 2008]. Furthermore, attempts to understand and predict how tropical forests will respond to continued global changes in climate will require refined and spatially explicit estimates of biomass and other forest structure changes [*Clark*, 2004].

[3]   New remote sensing technologies have the potential to provide these estimates by quantifying stocks, sources, and sinks of land surface carbon [*Houghton and Goetz*, 2008]. Among these technologies is lidar remote sensing. Studies using airborne and spaceborne lidar have validated its ability

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to retrieve many aspects of forest structure important for carbon and ecosystem studies, including canopy height, leaf distribution, and aboveground biomass stocks [*Lefsky et al.*, 2002; *Drake et al.*, 2002a; *Clark et al.*, 2004; *Naesset and Gobakken*, 2005]. Three NASA missions have used lidar as a central aspect of an observing strategy for forest structure. The first was the Vegetation Canopy Lidar (VCL) which was never launched [*Dubayah et al.*, 1997]. The second is the ICESAT (Ice, Cloud, and land Elevation Satellite) mission [*Lefsky et al.*, 2005] currently in orbit. The third is the planned DESDynI (Deformation, Ecosystem Structure, and Dynamics of Ice) mission [*Donnellan et al.*, 2008]. DESDynI will combine a multibeam lidar with polarimetric and interferometric SAR capability to measure forest structure, biomass, and their dynamics. One of the motivations of our research is to explore the efficacy of lidar for capturing forest structural changes to help inform planning of the DESDynI mission.

[4] A major application of forest structure data from DESDynI and other sources is for carbon flux modeling. Forests are typically a heterogeneous mixture of stands of different successional age and both ecosystem structure and carbon fluxes vary strongly with successional status. This heterogeneity is typically manifested through variability in canopy height. Observations of these heights by lidar provide large clues to the successional state of the vegetation. The assumption is that taller trees are older and shorter trees are younger. Using lidar-derived heights under this assumption in ecosystem modeling greatly constrains model estimates of aboveground biomass and associated carbon flux between the vegetation and the atmosphere [*Hurtt et al.*, 2004; *Thomas et al.*, 2008].

[5] However, knowledge of canopy height alone is not always sufficient to ascertain successional status and therefore the sign (source or sink) and magnitude of carbon fluxes for particular areas, even when initial carbon stocks are correctly determined. This is because stands may be short not because they are young, but rather because they are limited by edaphic and climatic conditions [*Clark and Clark*, 2000]. Modeled fluxes will then vary greatly depending on the prescribed successional state. One way to overcome these obstacles is to directly measure canopy changes by acquiring two or more sets of canopy structure observations separated in time [*Kellner et al.*, 2009]. Successional status may be inferred, rates of regrowth and mortality directly observed, and biomass accumulation and loss more directly modeled. Given the difficulties of measuring canopy dynamics in the field, there is considerable uncertainty about rates of regrowth and mortality in tropical forests. Furthermore, the efficacy of waveform lidar, such as used from spaceborne missions, to determine such changes across a tropical land use gradient has not been demonstrated.

[6] In this paper we present the results of an experiment to measure canopy structure dynamics over the tropical forests of La Selva Biological Station in Costa Rica between the years 1998 and 2005 using a medium resolution (25 m footprint) lidar. Our main objective was to observe changes in forest canopy height, related height metrics, and estimated aboveground biomass (hereafter "biomass"), and from these map sources and sinks of carbon across the landscape. This research further provides an assessment of the capability of medium resolution, waveform lidar to determine canopy

changes over subdecadal time spans. By quantifying both the magnitude of the changes, as well as the sensitivity of lidar to detect them, this work will help inform the formulation of future space missions focused on biomass dynamics, such as DESDynI.

2. Lidar Remote Sensing at La Selva

[7] La Selva Biological Station is located in northeast Costa Rica. The area is renowned for the depth, variety, and history of its biological data sets, and is among the most studied field sites in the humid tropics. The topography of the area is varied but low lying (<150 m) and receives 4 m of rain on average per year (see *McDade et al.* [1994] for full overview of La Selva). The Station proper is a mix of old growth and secondary lowland Tropical Wet Forest [*Hartshorn and Hammel*, 1994], along with remnant plantations and various agroforestry treatments. As part of a long-term study called the Carbono Project [*Clark and Clark*, 2000], all stems ≥10 cm diameter (at 1.3 m height or above basal irregularities like buttresses) in a network of 180.5 ha old growth plots are censused annually for growth, mortality and recruitment. Plot-level basal area and allometrically estimated aboveground biomass (EAGB) are calculated yearly [*Clark and Clark*, 2000]. We used EAGB data from the September–October 1997 and September–October 2004 Carbono censuses to compare with lidar data acquired in 1998 and 2005. Additionally, information including stand age, basal area, EAGB, and tree density were collected for all stems >5 cm diameter in two, 1 ha secondary forest plots at La Selva during the study period [*Chazdon et al.*, 2007]. Stem diameter is used to calculate EAGB using *Brown*'s [1997] equation for tropical wet forests. These field data are summarized in Table 1 and Figure 1.

[8] Lidar data were acquired over the La Selva region by the Laser Vegetation Imaging Sensor (LVIS) [*Blair et al.*, 1999]. LVIS is a medium altitude, waveform digitizing lidar. Footprint size can be varied, but it is usually flown in a medium resolution format with diameters from 10 to 30 m. The return signal is digitized to correspond to a vertical resolution of 30 cm that provides a vertical record of intercepted canopy surfaces. From each waveform, canopy height, canopy vertical metrics, and subcanopy topography may be directly derived, relative to the WGS-84 ellipsoid (see *Hofton and Blair* [2002] and *Hofton et al.* [2002, 2006a] for more details). Waveforms are geolocated generally to within 2 m or better [*Blair and Hofton*, 1999].

[9] LVIS was flown over La Selva in March 1998 at an altitude of 8 km. Nominal footprint diameters were 25 m, with 80 footprints scanned across track (separated by 25 m), and 9 m separation (overlapping) along track [*Hofton et al.*, 2002]. La Selva was then reflown by LVIS in March 2005 at an altitude of 10 km. The swath width in 2005 was 2 km, using 25 m footprints with 20 m spacing along track and across track. The initial 1998 flight was a part of a calibration and validation campaign for the VCL mission.

[10] Although LVIS is an imaging lidar, the images are made up individual footprints. For various reasons, such as cloud cover, flight path irregularities, pointing and noise, among others, portions of the landscape may not be completely mapped. In addition, because footprints overlap and there are often overlapping flight lines, some portions may

Table 1. Estimated Aboveground Biomass Data From La Selva[a]

ID	Biomass (Mg/ha) 1998	Biomass (Mg/ha) 2005	Biomass Change (Mg/ha), 2005–1998	Number of Lidar Observations 1998	Number of Lidar Observations 2005
a1	176.11	181.06	4.95	35	65
a2	135.32	150.26	14.94	35	16
a3	166.87	157.59	−9.28	23	34
a4	178.20	186.26	8.06	25	33
a5	180.79	197.81	17.02	26	27
a6	161.71	177.27	15.56	11	51
l1	134.66	120.91	−13.75	20	38
l2	135.84	119.63	−16.22	25	32
l3	180.37	163.70	−16.67	13	46
l4	133.45	118.99	−14.46	20	50
l5	157.96	151.61	−6.35	17	63
l6	160.34	169.28	8.94	21	63
lep*	144.67	175.62	30.95	62	40
lsur*	90.73	142.08	51.34	20	38
p1	105.53	123.52	17.99	26	26
p2	137.94	137.71	−0.22	17	20
p3	162.15	163.43	1.28	23	49
p4	172.23	182.12	9.89	9	45
p5	194.95	192.94	−2.00	29	54
p6	160.61	143.47	−17.14	19	40

[a]Lidar observations refer to the number of lidar footprints that fell within a plot in a particular year. Plots labeled "a" are on flat inceptisols, "l" plots are on flat ultisols, and "p" plots are on steep ultisol slopes. Plots lep* and lsur* are 1.0 ha secondary forest plots. All others are 0.5 ha old growth plots of the Carbono project.

be mapped several times during the same campaign. Thus a given area on the ground may have varying numbers of spatially irregular lidar observations (given in Table 1) either between plots or between years.

[11] Although canopy height is a primary measurement, other waveform metrics are calculated. Among these are the relative height (RH) metrics associated with energy quantiles (25%, 50%, and 75%). For example, the RH50 metric or HOME (height of median energy) is the height above the
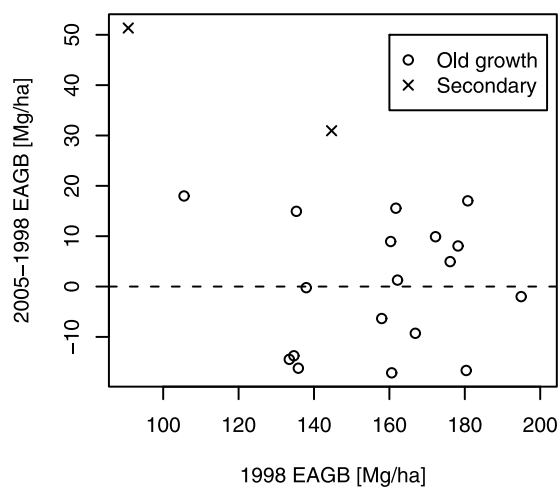

Figure 1. Changes in EAGB for 18 old growth Carbono plots and two secondary forest plots. Over the 7 year period, changes in EAGB for the Carbono plots were mostly balanced between those that gained and those that lost biomass (sinks and sources, respectively), whereas the two secondary plots were strong sinks.

ground elevation at which 50% of the returned energy in the waveform (including the ground portion of the return) is above and 50% below. We calculate these metrics because they have been shown to be useful predictors of biomass and of canopy vertical structure [*Drake et al.*, 2002a, 2002b, 2003; *Duong et al.*, 2008].

[12] Some of the essential features of the waveform are shown in Figure 2. The entire "extent" of the waveform is first positioned in absolute elevation space relative to an ellipsoid (such as WGS-84). The extent goes from the first return above a noise threshold (the "leading edge") to the last return above the noise threshold (the "trailing edge"). The ground return is that portion of the waveform that originates from reflectance off the ground underneath the canopy and is found by starting at the trailing edge and subsequently finding an inflection point or peak where the slope of the waveform changes from positive to negative. The strength of this return is dependent on several factors, but most importantly on canopy cover, ground reflectance and slope. The elevation of the ground return is specified as the center of the ground return portion. The location of the ground, in elevation space, must always be above the trailing edge.

[13] The ground return ordinarily is strong and there is usually little doubt about its elevation. However, for weak returns there is often an element of interpretation. This occurs for two reasons. The first is that weak returns seldom show sharp central peaks, so that automated algorithms either interpret other peaks as ground or have difficulty deciding
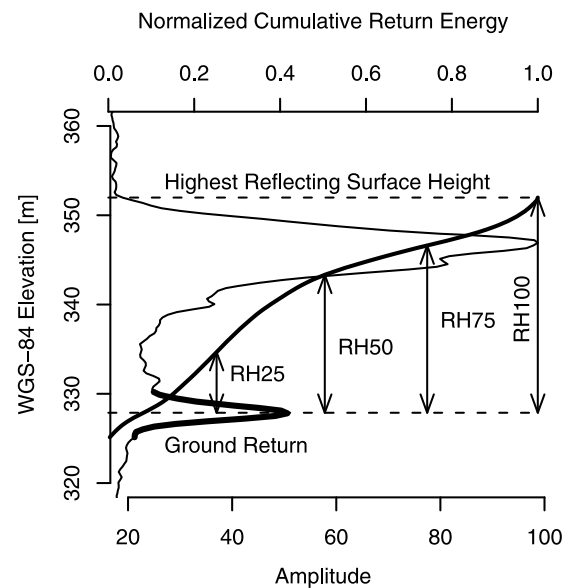

Figure 2. Components of a return lidar waveform. The endpoints of the waveform extent are positioned in elevation space relative to the WGS-84 ellipsoid. The RH metrics are the quantiles of the cumulative return (the monotonically increasing curve) starting at the trailing edge, but expressed as a height above the interpreted ground return. RH100 corresponds to height above the ground of the highest reflecting surface that triggers a return above the noise level. Because of canopy penetration, this height may be below the actual tallest leaves in the canopy. The ground portion of the return is shown as bold.
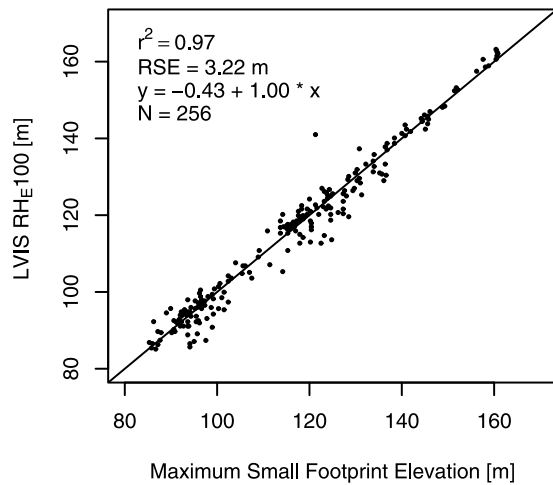
Figure 3. Comparison of discrete return small footprint lidar canopy elevations with LVIS over La Selva [*Peterson*, 2000]. There is a small (0.43 m) bias between the two data sets that may be the result of canopy penetration by LVIS or seasonality. LVIS data were acquired during the dry season when some deciduousness occurs, while the small footprint data were acquired in the wet season.

exactly where the center of an extended bump is in elevation space. The second reason is that the last detectable return may be in the canopy because insufficient numbers of photons penetrated to the ground, as can happen in canopies with very high cover. In this case, even though the waveform extent from leading to trailing edge is correctly located in elevation space to within tens of centimeters, the canopy will be misinterpreted as ground.

[14] The canopy return is that portion of the waveform that originates from the canopy components themselves. The top of the canopy return is found by starting at the leading edge of the return until a signal greater then some noise threshold is found. Maximum canopy height above the ground (RH100) is found by subtracting the elevation of the leading edge of the waveform from the determined ground elevation. This maximum height is more properly viewed as the "highest reflecting surface height" because it is dependent on sufficient canopy material (about 0.5 m^2 in the case of LVIS) to enable a reflectance above the noise threshold.

[15] Canopy height metrics are energy based, and other than RH100, are not generally validated because they are viewed as fundamental measurements (e.g., like measures of radiance for passive optical sensors), simply measuring the height where that amount of energy has been accumulated. These heights are all given relative to the ground, so that if the ground is found incorrectly, the RH metrics will have corresponding errors.

[16] Areas of dense canopy with high canopy cover as found in La Selva may sometimes present a challenge for lidar. LVIS was designed to be sensitive enough to detect a ground pulse in canopy cover of up to 99% and comparisons with small-footprint systems have shown this to be true [*Hofton et al.*, 2002]. However, certain environmental conditions such as slope or low-lying canopy material such as shrubs can weaken already weak ground returns to the point where automated ground finding algorithms misidentify the

ground and assign an elevation that is either too high or too low. As will be shown, some lidar data at La Selva show signals of ground finding errors, evidenced by an apparent change in the ground elevation between acquisition years.

[17] One approach when considering canopy height change is to compare the change in the ranges (distances) to the top of canopy from the sensor, which are readily converted to elevations above the ellipsoid. We call this range-based canopy top elevation RH_E100 where the subscript now denotes the height is relative to the ellipsoid. Thus a change in height may be found by subtracting two RH_E100 measurements. The other RH metrics may also be defined in elevation terms relative to their height above the ellipsoid as well. Even though the RH_E metrics are integrals (except for RH_E100), their starting point is always defined relative to the trailing edge, not the ground (i.e., the integration does not start from the center of the ground peak, but below it as shown in Figure 2). Their elevation will be correct even if the ground is found incorrectly in the waveform as long as the last detectable return originates from the ground portion and not the canopy. If on the other hand, there is insufficient energy reaching the ground, the trailing edge will originate in the canopy and this canopy return will be misinterpreted as ground, even though the waveform is correctly located in elevation space. This would result in and both the RH and RH_E metrics (except for RH_E100) having some degree of error. RH_E100 will never have errors caused by ground finding and should thus be a better predictor of canopy change. The other RH_E metrics should also be better than their RH counterparts as it is more common to have errors that arise from misidentification of the location of the ground in a weak return than it is to have no return from the ground at all.

[18] Additional possible sources of error in determining the RH_E metrics mainly are related to geolocation and range inaccuracies. These would be expected to produce precision errors of a few tens of centimeters for canopy range retrievals [*Hofton et al.*, 2002, 2006b], i.e., repeated measurements of the canopy at the same location are precise to this level. The accuracy (as opposed to the precision) of the range retrieval is based primarily on the amount of leaf material near the top of the canopy (a result of canopy shape and architecture) and the background noise level. The background noise level includes both system-level noise, as well as the noise from the solar background (the amount of reflected solar irradiance in the near-infrared in the sensor field of view).

[19] The range measurements from LVIS were validated at La Selva in 1999 using a discrete return small-footprint system [*Peterson*, 2000]. The maximum canopy elevation within each LVIS footprint obtained from the small footprint system was compared to RH_E100 (Figure 3). The agreement was excellent ($r^2 = 0.97$, RMSE = 3.22 m) considering the differences in spatial scale and seasonality (dry versus wet season) that were involved. Our emphasis here is that regardless of whether the system is small or medium resolution, waveform or discrete return based, the fundamental measurement is range, and this is determined both precisely and accurately from airborne systems.

3. Methods

[20] Three types of analyses were performed using the 1998 and 2005 data sets. In all cases, because of potential
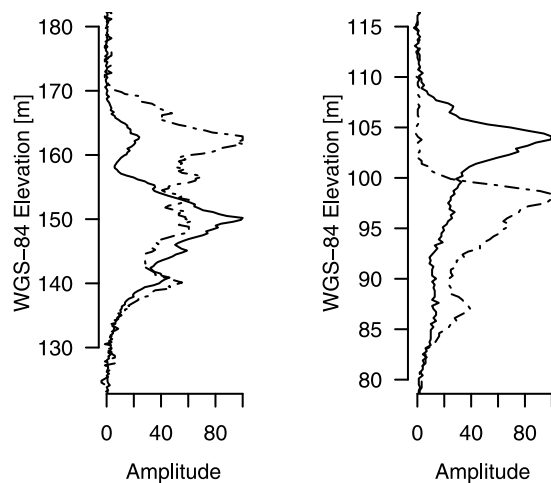
Figure 4. Two LVIS waveforms from La Selva are shown for 1998 (dashed line) and 2005 (solid line). The waveforms show the vertical distribution of leaves and branches from the top of canopy to the ground where the amplitude is proportional to the amount of canopy material at that height. (left) An apparent loss of upper canopy with subsequent regrowth of the lower canopy or lateral in-growth into the gap from the surrounding canopy. (right) An example of apparent growth. Note that if the regrowth or lateral filling is rapid it may be difficult to detect such losses through changes in overstory canopy height. However, the great advantage of waveform lidar is that it provides a vertical record of changes throughout the canopy.

ground finding errors, the RH_E metrics were used. First, footprint-to-footprint changes were assessed by comparing differences in RH_E100 for lidar footprints with centers that were within 2 m of each other (the maximum likely geolocation error [*Hofton et al.*, 2002]). Figure 4 shows an example of two sets of coincident waveforms, one illustrating apparent growth and the other apparent loss. Because there is a Gaussian drop in sensitivity (energy) in the waveform from the center outward, comparisons are best done between waveforms that are illuminating approximately the same location. There were no field estimates of height available for 2005 to use as direct validation of observed changes in height. *Peterson* [2000] validated LVIS heights using field-measured heights as well as the previously discussed small-footprint discrete return lidar data and found good agreement in both. *Kellner et al.* [2009] validated a later small-footprint acquisition (from 2006) using field-based measures of canopy for trees ≤15 m and found good agreement as well.

[21] Second, footprint level changes were compared to field-based calculations of changes in EAGB in the Carbono and secondary plots. The RH_E metrics derived from LVIS footprints that fell within the plots were averaged for each year and associated with changes in biomass using linear regression. Most of the plots were heavily oversampled in each year (see Table 1) by the lidar instrument because of overlapping flight lines. For example, some 0.5 ha plots had over 60 LVIS footprints, for a combined area of some 6 times greater than the plot area. None of the waveforms are identical because they image slightly different areas (that is the foot-

prints are never exactly coincident). Therefore, all footprints fully contained within a plot were used to obtain the average. One secondary forest plot (ID = "lep" in Table 1), a 1 ha plot, was not imaged uniformly in 2005 leading to unrepresentative measures of mean RH_E change metrics.

[22] Last, landscape-level canopy height changes and EAGB changes were mapped. A 1 ha grid was placed over La Selva and changes in RH_E metrics were calculated for each grid cell. This grid size corresponds to modeling grids used for carbon estimation at La Selva using the Ecosystem Demography model [*Hurtt et al.*, 2004]. It further avoids the problem of needing coincident footprints to estimate change. Additionally, RH_E height changes were stratified by land cover class, including old growth, secondary, and plantation (Organization of Tropical Studies, unpublished data, 2000). Changes in EAGB were mapped across the entire landscape using the relationship developed at the plot level and the 1 ha RH_E metrics.

4. Results

4.1. Footprint to Footprint Comparisons

[23] Lidar footprints with centers within 2 m of each other were selected for analysis. This resulted in a comparison of 5595 footprint pairs. For each of these, RH_E metrics and their changes were found between years. The relationships among select RH and RH_E metrics, and apparent elevation changes are shown in Figure 5. Note that the RH metrics are negatively correlated with elevation changes. An apparent gain in elevation would lead to an apparent loss of height. Conversely, RH_E100 shows no correlation with elevation changes because ground finding is avoided. The other metrics, such as RH_E50, should show a similar improvement; however, as discussed, ground-finding errors caused by misidentifying canopy as ground may not be entirely eliminated. Figure 6 shows histograms of changes for all of La Selva and Table 2 summarizes these changes by land cover class. Average canopy top height change between years was 0.57 m ± 4.64 (SD = standard deviation). Old growth forests showed a change of −0.33 m ± 4.09 (SD). In contrast, secondary forests had a positive change of 2.08 m ± 3.71 (SD). Plantations underwent the greatest average change in canopy top height of 6.22 m, an expected result as these are fast growing areas. Interestingly, selective logged forests showed a slight positive change (0.34 m). All land cover types showed positive changes for all RH_E metrics, except for old growth forests and an essentially zero term for RH_E75 for selectively logged forests. Only RH_E25 showed a positive change for old growth forest. As upper canopy is lost, this increase may be indicative of the lower, formerly suppressed canopy growing.

[24] The distributions shown in Figure 6 for metrics other than RH_E100 show a mild negative skewness, while RH_E100 is positively skewed, relative to a normal distribution. This seems reasonable given that the large amount of secondary forests at La Selva should have positive canopy top height changes. The distributions of changes additionally become increasingly leptokurtic from RH_E25 to RH_E100.

[25] The number of RH_E100 pairs that had changes greater than 5 m was 19.9%, with about 60% (12.1% of total pair comparisons) of these showing positive changes and about 40% (7.9% of comparisons) showing negative changes.
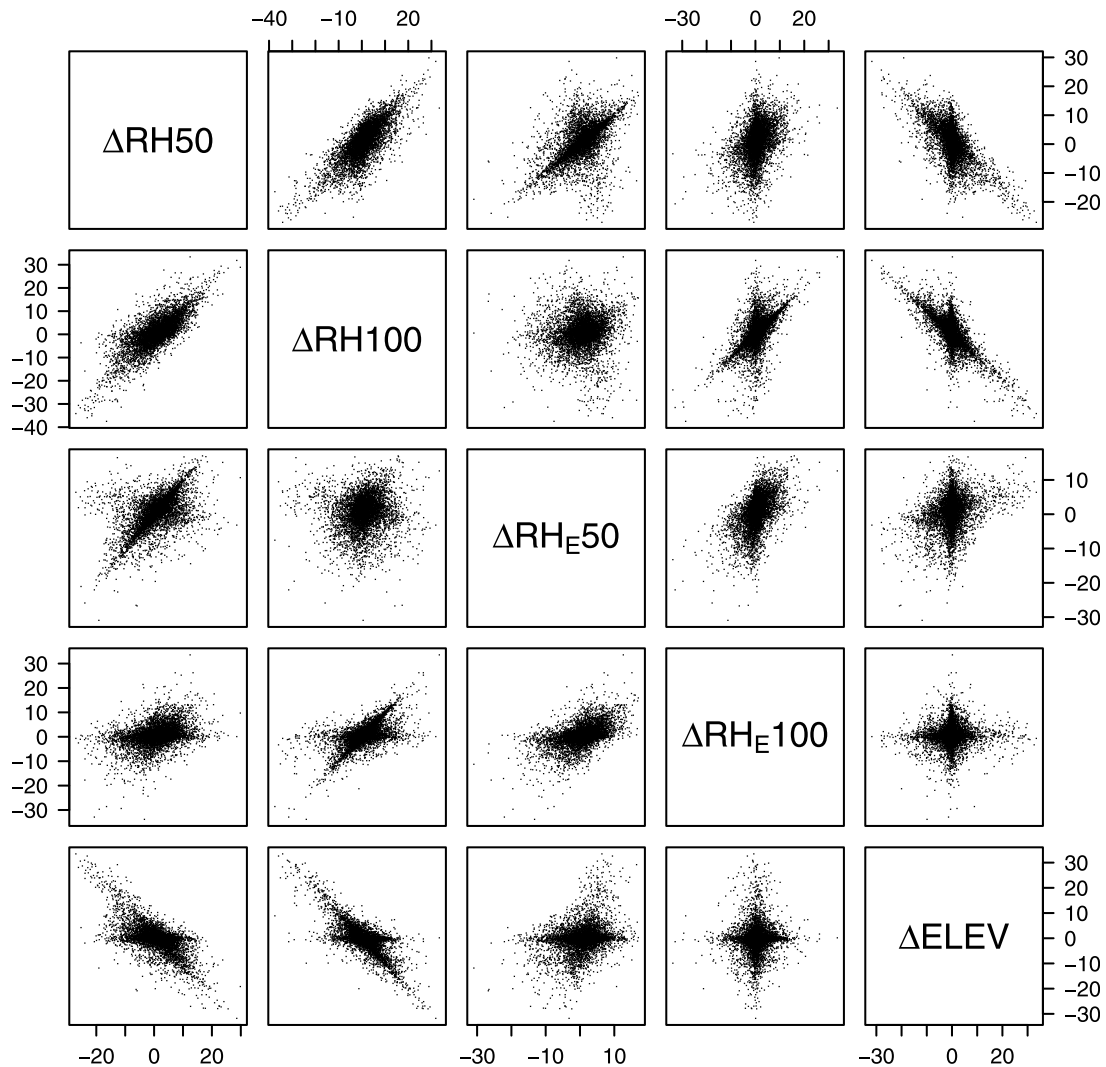
Figure 5. Pairwise comparison of changes in select RH and RH_E metrics, and apparent elevation changes caused by differences in ground finding between years. Note that the RH metrics are negatively correlated with apparent changes in ground elevation. RH_E100 is determined without the use of ground finding, and should be uncorrelated with elevation errors. The units on all axes are in meters.

The spatial distribution and magnitude of changes in canopy top height as found using RH_E100 is shown in Figure 7. As can be seen, some secondary forest areas grew over 10 m, consistent with known growth rates of for young forests at La Selva.

[26] *Kellner et al.* [2009] performed an analysis of canopy height and gap transitions over old growth forests in the eastern half of La Selva proper using discrete return lidar data separated by 8.5 years. Using the average height of all intercepted canopy elements in 5 m cells, they found a mean change of height for the same approximate period of -0.32 ± 6.80 (SD), a result almost identical to ours found using RH_E100. They also report that 39% of the old growth landscape at La Selva had changes that exceeded 5 m, and these were evenly balanced between height gains and losses. We see a similar pattern of balanced changes in old growth forests in our pairwise comparisons of maximum canopy heights (Figure 7). However, for La Selva as a whole we found that about half as much of the landscape had such large changes (19%), with positive changes outweighing negative changes (for differences greater than 5 m). We expect more positive changes because our analysis includes secondary forests and plantations. We also expect to find fewer cases of large canopy changes because the scale of our analysis is coarser (5 m versus 25 m).

[27] A height transition matrix was constructed using RH_E100 to examine the probability of height changes from one class to another over the 7 year period between LVIS flights (see *Kellner et al.* [2009] for discussion of a matrix constructed from the small-footprint data above). The columns in this matrix (Table 3) give the probability of a height transition from a 1998 height class to a 2005 height class using the footprint pair data. Values along the diagonal of this matrix give the probability that no net change occurred (that is, the 1998 and 2005 RH_E100 heights remained in the same height class). Reading across rows gives the likelihood that
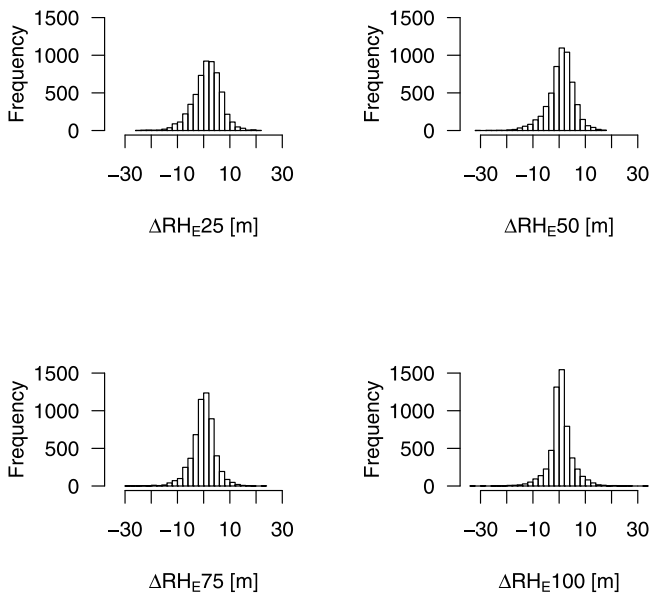
Figure 6. Histograms of RH$_E$ metrics for all of La Selva. See Table 2 for statistics as a function of major land cover types.

an observed height in 2005 originated from the height class in that column from 1998. In general, the diagonal shows an increasing trend: the larger the canopy height in 1998, the more likely it was to remain in that class. For shorter canopy heights (<30 m) transition probabilities are strongly weighted toward positive height gains. For the shortest canopies in 1998, observed canopy top height changes could be 20 m or more reflecting the large growth changes young secondary forests can exhibit. For 1998 heights in presumably older forests in the 30–40 m class, transition probabilities are relatively equally weighted between changes to higher and lower height classes. These areas appear to be in a type of balance on the whole, where transitions to higher height classes through growth are about as likely as transitions to lower height classes through disturbance and mortality. As we reach the limits of canopy height at La Selva, transitions must necessarily be more likely into lower height classes.

[28] Our data suggest that footprints from the shortest height class can transition to a much higher class (see the first column of Table 3). However, this does not require that the canopy grows vertically but can also happen as a gap fills in laterally from the sides and above. Conversely, we do not see cases in the smallest height class in 2005 that were transitions from height classes greater than >20 m (see the first row of Table 3). This does not mean that there was no

large tree mortality but rather that such mortality did not produce a gap that extended through the canopy at the scale of LVIS and persist to 2005.

[29] *Kellner et al.* [2009] reported a median gap area of 25 m^2 in the old growth forest. Gaps of this size are far smaller than the area of an LVIS footprint (~500 m^2) and would be difficult to detect as changes in RH$_E$100, and thus may explain why we do not see such transitions.

[30] There were a large number of footprint pairs that had significant height loss (>5 m). Approximately 9% of the footprints in the old growth forest had such losses. Published rates of mortality for very large trees (DBH ≥ 70 cm) for this area are about 1% per year [*Clark and Clark*, 1996]. Thus, over a 7 year time span we would expect about 7% of the footprint pairs to show a large (>5 m) height loss caused by mortality. Our number of 9% for old growth forests is reasonably close to this. We do not expect all such height losses can be explained only through mortality events, nor do we require that when a mortality of a tree does occur, that there is a collapse of the entire canopy to ground level within the 25 m footprint observed by LVIS. In addition, trees smaller than those at the DBH cutoff limit will undergo mortality but will affect RH$_E$100 only if they are canopy-forming components. This is because RH$_E$100 detects a maximum height. Loses reported in the transition table always refer to loses in the canopy top, and not, by definition, in the understory. The loss of understory trees would not appear as a lowering of canopy top height, but would affect the other energy quantiles, such as RH$_E$50. There is also the issue of the timing of the mortality event. If it occurs early in the observation period, even if a gap were formed, it is likely that through canopy growth or lateral filling, significant canopy materials would be found at height, limiting the change detection.

4.2. Plot-Level Biomass Dynamics

[31] We related changes in EAGB in the old growth and secondary plots to changes in the RH$_E$ metrics. Because there are only two secondary plots, our results are heavily weighted toward old growth plots. We used a Bayesian model averaging approach to pick the best set of predictors among the four RH$_E$ metrics and selected RH$_E$50 and RH$_E$100. The relationship was $\Delta EAGB = 4.58 + 3.17 * \Delta RH_E50 + 6.37 * \Delta RH_E100$, with a standard error (RSE) of 10.54 Mg/ha, an adjusted r^2 of 0.65 (p value < 0.002). The intercept term was not significant (p = 0.08), but the remaining terms were significant (p < 0.01). Figure 8 shows predicted $\Delta EAGB$ versus allometric $\Delta EAGB$. The parametric 95% confidence interval for r^2 was (0.50–0.86). This interval may be optimistic given the few data points and colinearity of RH$_E$50 and RH$_E$100. We subsequently performed a bootstrap with 1000 iterations. The 95% confidence

Table 2. RH$_E$ Metric Change Statistics From 1998 to 2005 for Nearly Coincident Footprint Pairs by Land Cover Type

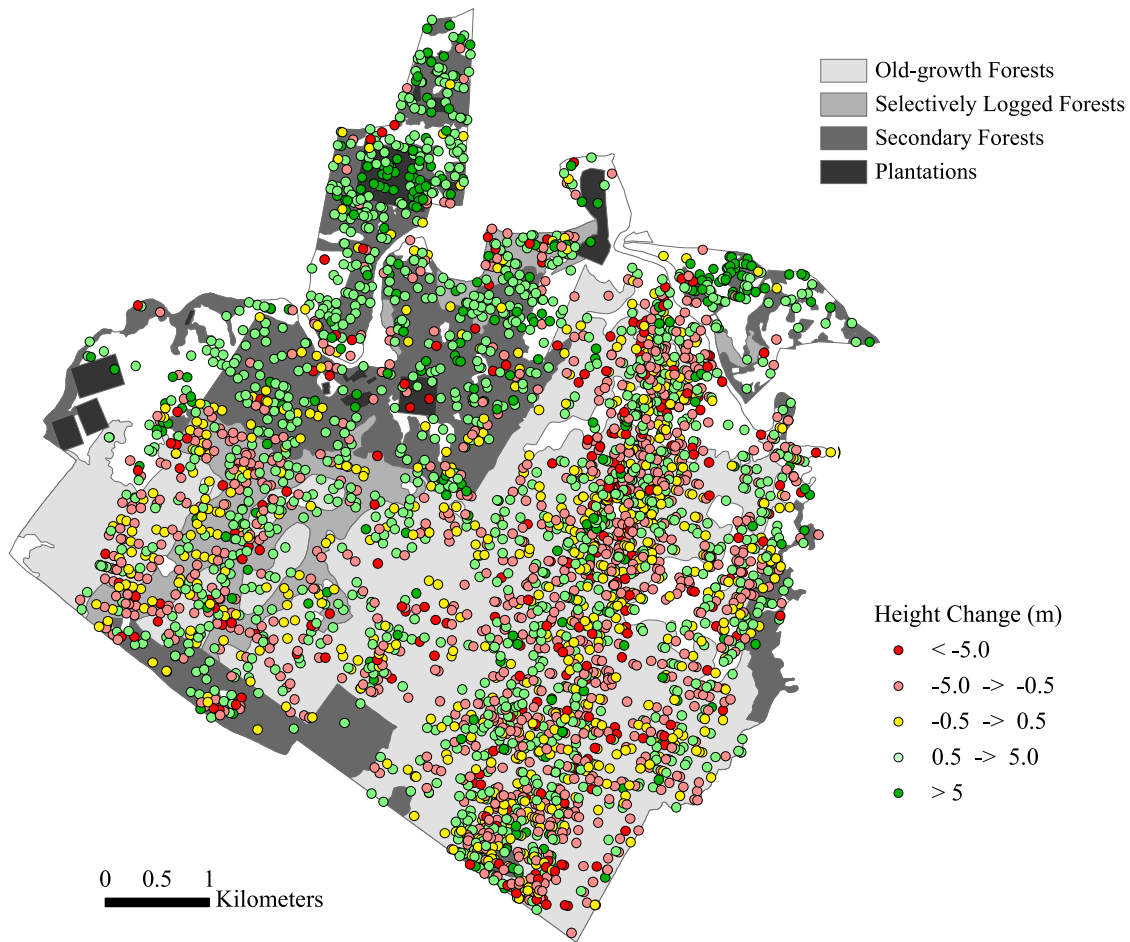|	RH$_E$100		RH$_E$75		RH$_E$50		RH$_E$25		
Land Cover	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
Plantations	6.22	5.07	5.27	5.1	4.85	5.14	3.47	3.98	238
Secondary forest	2.08	3.71	1.67	3.66	2.44	3.94	2.69	4.24	855
Selectively logged forest	0.34	4.37	−0.03	4.25	0.99	4.53	1.49	4.9	466
Primary forest	−0.33	4.1	−0.98	4.1	−0.08	5.03	0.86	5.65	3069
All La Selva	0.57	4.64	−0.12	4.54	0.63	5.09	1.24	5.3	4628

Figure 7. The distribution of footprint-to-footprint canopy top elevation (RH$_E$100) changes from 1998 to 2005 for nearly coincident waveform centers. The largest growth changes are seen in the secondary and plantation areas (top left). In contrast, the old growth forests show a mix of loss and growth. Only footprints with centers within 1 m of each other are shown in this plot for clarity (statistical analysis discussed in the text included all footprints within 2 m).

intervals obtained using an adjusted bootstrap percentile method were (0.22–0.80) for r^2 and (9.70–13.47 Mg/ha) for the RSE. As can been in Figure 8, the model did not predict changes in secondary forest plots well and may lack sensitivity to small changes in biomass.

[32] The model was able to correctly predict the sign of the biomass change (source or sink) in 16 out of 20 cases (80%) (see Figure 8). However, when the mean regression 95% confidence intervals are used to determine the sign (i.e., does the interval encompass zero?) 10 of the plots (all with

Table 3. Matrix of Height Transitions From 1998 to 2005[a]

2005 Height	1998 Height										N
	<5	5–10	10–15	15–20	20–25	25–30	30–35	35–40	40–45	>45	
<5	**0.19**	0.04	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	19
5–10	0.25	**0.16**	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	38
10–15	0.25	0.35	**0.17**	0.02	0.02	0.00	0.00	0.00	0.00	0.00	80
15–20	0.12	0.23	0.35	**0.30**	0.06	0.01	0.00	0.00	0.00	0.01	226
20–25	0.12	0.17	0.31	0.42	**0.43**	0.10	0.02	0.02	0.01	0.00	622
25–30	0.00	0.02	0.07	0.21	0.39	**0.59**	0.15	0.05	0.02	0.01	1251
30–35	0.00	0.02	0.00	0.02	0.09	0.25	**0.60**	0.22	0.08	0.02	1531
35–40	0.06	0.00	0.00	0.01	0.01	0.04	0.19	**0.56**	0.24	0.11	1128
40–45	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.13	**0.57**	0.20	516
>45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	**0.65**	184
n	16	92	150	325	600	1081	1505	1161	494	171	5595

[a]Columns give the probability a footprint of that particular canopy height class transitioned to a new, future class in 2005 given by the row. Diagonals give the probability that there was no net change in canopy height. Reading across rows gives the probability that the footprint in that height class originated in the column height class in the past. Diagonal of the matrix is shown in bold.
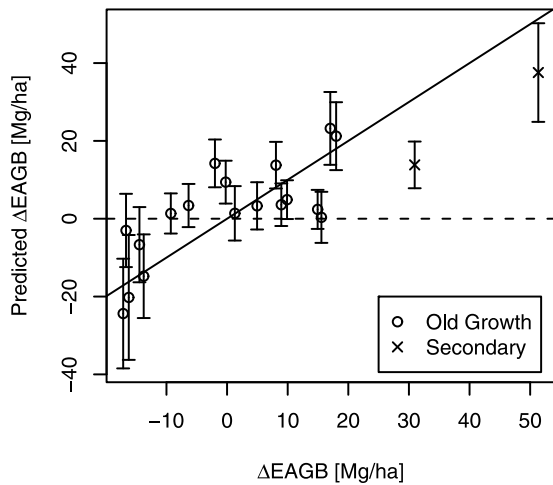
Figure 8. Changes in EAGB (2005–1998) as predicted from lidar metrics. Bars are the 95% confidence interval of the regression shown along with the 1:1 line. The regression-adjusted r^2 was 0.65, with a standard error (RSE) of 10.54 Mg/ha.

low biomass changes) had predicted changes that were statistically indistinguishable from zero.

[33] When the two secondary plots were removed from the analysis the relationship was $\Delta EAGB = 2.23 + 2.3*\Delta RH_E50 + 4.9*RH_E100$, with a standard error of 8.86 Mg/ha, and an adjusted r^2 of 0.50 (p < 0.001). Again, the intercept term was not significant (p = 0.33), but the other terms were (p = 0.04 and p = 0.02, respectively). The parametric 95% confidence interval for r^2 was (0.33–0.80), and bootstrap intervals were (−0.01–0.69) for r^2 and (7.47–12.17 Mg/ha) for the RSE. The wide bootstrap confidence intervals suggest that in the absence of more plot data from which to build a relationship, there may not be enough variation in the old growth plots by themselves over the time period to enable more robust estimates.

4.3. Landscape-Level Patterns

[34] Previous carbon modeling work has taken place at a 1 ha grid spacing [*Hurtt et al.*, 2004] using maximum canopy heights derived from lidar; it is therefore of considerable interest to map landscape-level changes at this resolution. In addition, this enables an estimate of change using all footprints, not just those that are within 2 m. A 1 ha map of the change in canopy height (2005–1998) was derived using RH_E100 (Figure 9). Secondary forests showed increases in height with some areas exceeding 5 m, consistent with known
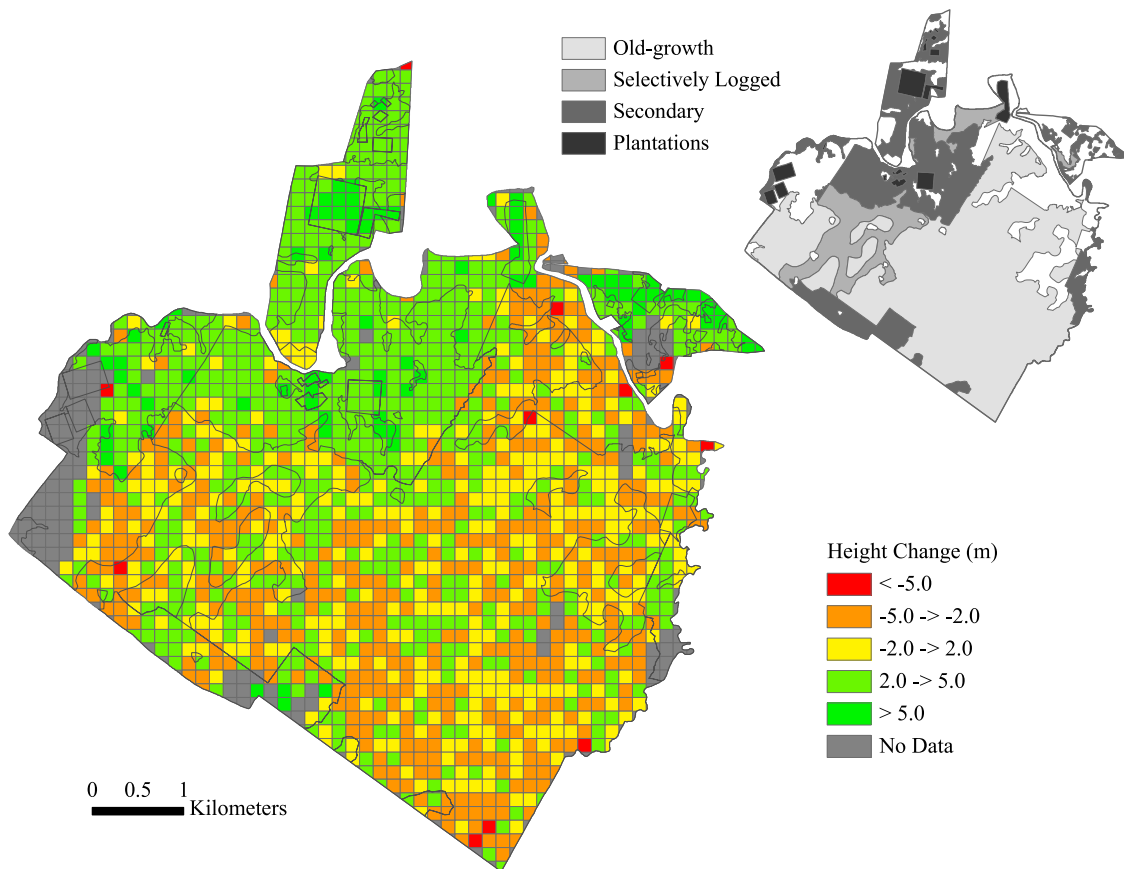

Figure 9. Change in canopy top height (RH_E100) for La Selva (2005–1998). Old growth areas (see inset) are a mixture of height gains and losses, while secondary forests areas show consistent growth.
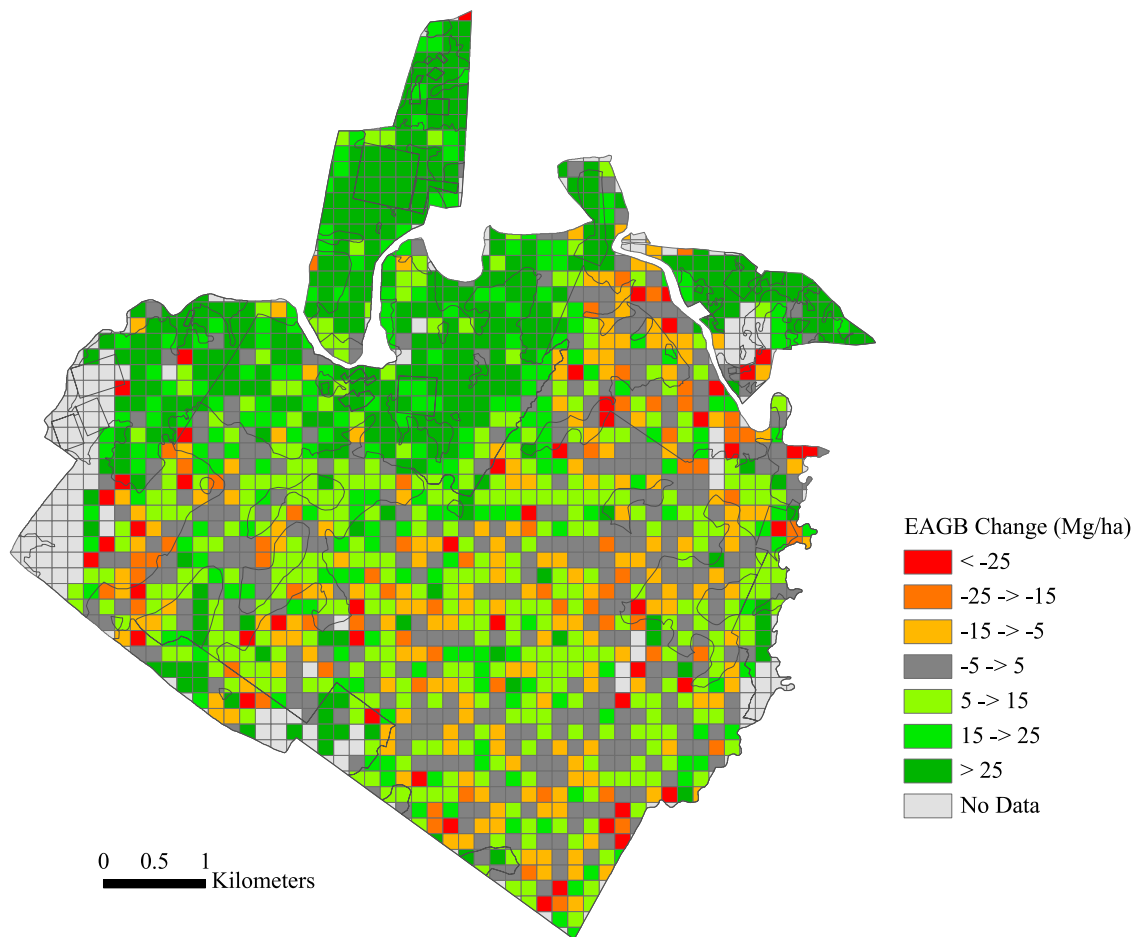
Figure 10. Changes in EAGB from 2005 to 1998 at 1 ha scale. Each cell is a prediction from a regression equation created by relating plot-level biomass changes to changes in RH_E50 and RH_E100. This equation was then used with 1 ha averages of the RH_E metrics to map EAGB change across the landscape. Note that the secondary forests show uniformly positive changes in biomass, while old growth forests appear as mixture of positive, negative, and neutral changes (see Figure 9).

rates of growth for younger forests at La Selva. In contrast old growth forests were a mix of both height gain and loss.

[35] The regression equation derived for combined secondary and old growth plot data was used to map ΔEAGB into 1 ha cells across the landscape (Figure 10). Average change in biomass for secondary forests was 25.2 Mg/ha ± 15.0 (SD). Old growth forests had an average biomass change of 1.9 Mg/ha ± 12.5 (SD).

[36] The map in Figure 10 is spatially consistent with known land use history: secondary forests appear as relatively uniform sinks of carbon and old growth forests appear as a heterogeneous mixture of sources, sinks, and neutral areas. Recall, however, that there is uncertainty in our model equation and that we have extrapolated far beyond our initial plot data, which included only two examples of secondary forests and no plantations or other land cover types. For these reasons, there is uncertainty in this map. One way to quantify this uncertainty in a manner relevant to carbon flux applications is to examine the signs of the biomass change across the landscape, that is to map areas that are likely sources, those that are sinks, and those where we cannot tell. We calculated the 95% prediction interval (which is much wider than the

95% regression confidence interval) for each cell and mapped these as source, sink, and neutral areas (Figure 11). The secondary forests appear again uniformly as sinks or neutral areas. In contrast, the old growth areas are classified as mostly neutral, with widely scattered source and sink areas at the 1 ha scale. Thus, even with the limitations of the data used to create the relationship between changes in EAGB and the RH_E metrics, a map of source and sinks areas may be produced that mirrors the expected distribution of these across the known land use gradient at La Selva.

5. Discussion

[37] The goal of our study was to explore the efficacy of using changes in lidar metrics over time to map changes in height, biomass and interior canopy structure, as reflected by RH_E metrics, over time. We can summarize our major results as follows:

[38] 1. Pairwise comparisons of nearly coincident lidar footprints between years showed canopy top height changes that coincided with expected changes based on land cover
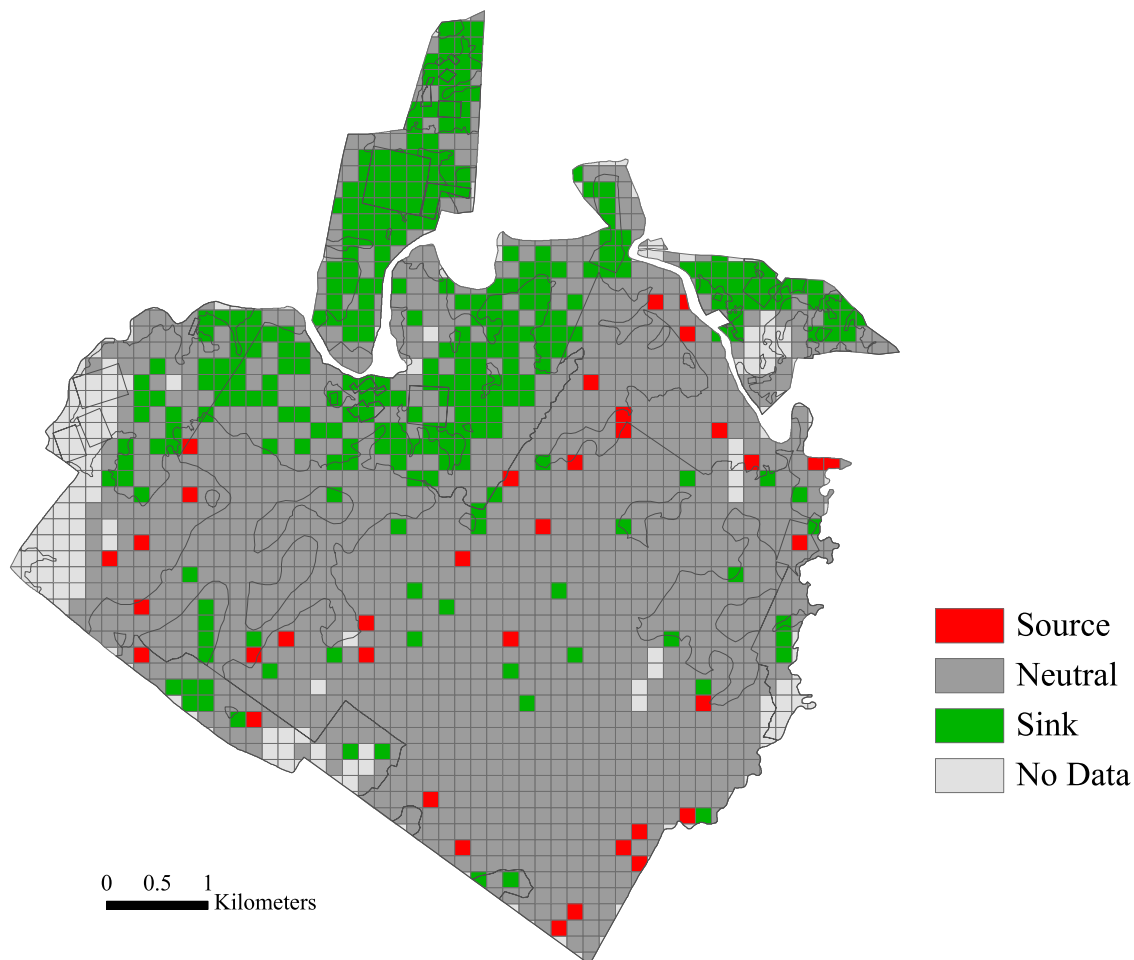
Figure 11. Map of sources, sinks, and neutral areas for La Selva. The 95% prediction interval was created for changes in EAGB. Those cells from Figure 10 whose intervals were positive were mapped as sinks; those that were negative were mapped as sources. If the interval spanned zero, the cell was mapped as neutral. Secondary forests again appear uniformly as sinks or neutral areas, whereas old growth areas now appear mostly neutral with scattered source and sinks areas at the 1 ha scale.

types: plantations > secondary forests > selectively logged forests > old growth forests

[39] 2. Canopies that were shorter in 1998 had greater probability of a transition to a taller canopy height class in 2005. Conversely, canopies that were taller in 1998 had transition probabilities that were increasingly weighted toward neutral changes in 2005.

[40] 3. About 20% of the pairwise comparisons showed height changes in excess of 5 m, with positive changes outweighing negative ones.

[41] 4. The lidar RH_E100 and RH_E50 metrics were linearly related to biomass changes for combined old growth and secondary forest plots, with an r^2 of 0.65 and an RSE of 10.5 Mg/ha, but both parametric and bootstrapped confidence intervals were wide, suggesting weaker model performance.

[42] 5. Landscape-level mapping at a 1 ha scale of canopy height changes matched expected spatial patterns for the distribution of land cover types at La Selva. Mean changes were 0.57 m for all La Selva, and −0.33 m and 2.08 m for old growth and secondary forests, respectively.

[43] 6. Landscape-level mapping at 1 ha scale of biomass changes matched expected spatial patterns for the distribution of land cover types at La Selva. Mean changes were about 25 Mg/ha for secondary forests and about 2 Mg/ha for old growth forests.

[44] 7. When prediction intervals were calculated to classify 1 ha areas as biomass source and sinks, the resulting map showed most of the old growth areas as neutral (statistically indistinguishable from zero), with widely scattered and isolated sources and sinks. Secondary forests in contrast were mostly sinks or neutral, but never sources.

[45] To understand these results and place them in a context for future analysis, both airborne and spaceborne, requires discussion of several issues relating to the limitations, errors and ultimate efficacy of the data and methods presented. We begin by first noting that the experiment at La Selva was arguably under some of the most difficult conditions that will be experienced. First, as will be discussed, there were no large-scale changes in structure and biomass because there were no recent anthropogenic or

natural disturbances. As a result there were no data on large negative biomass changes, such as would occur through deforestation. Second, the majority of secondary forests were at least 15 years into their recovery in 1998, so that the change in signal between years was not large on the positive side for canopy structure and biomass at the landscape scale. Our study also was limited by having only two secondary plots for building a model relationship. Thus, we were left with changes that were mostly related to isolated losses and incremental gains at the plot level.

[46] One confounding aspect of our analysis was the changes in apparent ground elevation experienced between years. Our approach was to use the range measurements for canopy top height changes instead of using heights found relative to the ground. Other change studies with LVIS have not shown these apparent elevation differences in closed canopy deciduous forests in the northeast United States and conifer forests in the western United States [*O'Dell*, 2006]. Some ground finding errors are always present in lidar data, but these are generally rare enough that they do not limit the usefulness of lidar, even in tropical forests.

[47] We hypothesized that the elevation errors seen occurred in areas of high canopy cover or steep slopes. Both will weaken ground returns and hinder the accurate retrieval of ground elevation. Slope will also be a factor if the footprint comparisons have centers that are far apart (as these will have truly different elevations, not just apparent elevation changes). There are a significant number of slopes that exceed 10° at La Selva, however we found no statistically significant relationship between slope and apparent elevation error. A similar study in the rugged terrain of the Sierra Nevada of California found no relationship between errors in LVIS heights versus field-measured heights and slope as well [*Hyde et al.*, 2005]. We also found no relationship between apparent elevation changes and canopy cover. The difficulty is that canopy cover, as derived from lidar, is explicitly linked with finding the ground correctly (so that the relative energies in the canopy portion of the return and the ground portion of the return may be found). Those areas that would have the highest canopy cover, and thus the highest elevation errors, would also be the same ones where canopy cover was most in error as well, complicating attempts to infer causation directly from the lidar data. Thus, we are unsure of the relative importance of each of the above factors for the appearance of ground finding errors in our data sets. We do know that there is a complex interaction between sensor sensitivity, both spatially and vertically within footprints, canopy shape, canopy structure and topography that will require more research to resolve for relevance to change studies.

[48] The issue of validation of lidar-derived height changes is a difficult one. We did not have field-validated changes in height for both years. As discussed, the 1998 heights were validated by *Peterson* [2000] who found accuracies that were comparable to other lidar studies [e.g., see *Means et al.*, 1999; *Hyde et al.*, 2005; *Anderson et al.*, 2006] that have generally shown height retrieval accuracies in the 3–5 m range, but much of the reported error may be attributable to the difficulties in accurately determining height from the ground (a daunting task in closed canopy forests). Small-footprint data may be used as a type of validation for canopy height and more directly, for canopy top elevation (height above

ellipsoid) as shown in Figure 3. The use of small-footprint lidar for validation assumes that these data are correct or otherwise validated. Again, such validation may not be simple, especially when multiple platforms acquire observations separated in time, as biases and errors may creep into the process at several points. The great advantage of space-based missions, such as DESDynI, is that they provide stable measurement platforms that allow for more direct intercomparison of data sets within a common observational framework.

[49] What do our results tell us about the magnitude of canopy height changes required for detection as a function of the spatial scale of observation? Validations of height might suggest 3–5 m as these brackets commonly reported accuracies from field studies. However, these may be too conservative because of the difficulties of field validation.

[50] Measuring changes in the range to canopy top (RH_E100) may be more accurate than measuring heights (as done in field studies). For example, consider a 0.5 m^2 panel of leaf material (about the minimum detectable area for LVIS), oriented horizontally. LVIS would measure changes in the range to this panel with centimeter to tens of centimeters-level accuracy. This repeatability of successive height measurements is essentially random measurement error and what we would characterize as instrument error.

[51] If canopies were composed of architectures like these, decimeter accuracies for changes in height using RH_E100 would be achievable. However, canopy architectures and the environments they occur in are variable and lead to height errors that are not easily categorized as "instrument error." Slopes accentuate pointing errors that lead to errors in the horizontal locations of the range measurements, and thus in turn to errors in the absolute vertical elevations of returns used to find differences in elevation. The systematic errors in pointing are generally accounted for and are included in the instrument error. Random errors in pointing do occur as well, however. Slopes may produce additional errors that may be viewed as some combination of both systematic and random. Consider a 25 m footprint with an even height stand on a slope. The instrument will systematically measure the range to trees that occur at the edge of the upslope portion of the footprint. As long as trees grow uniformly in the entire footprint over time, a difference of ranges remove this effect. If trees do not grow uniformly, or if the stand has an uneven height structure within the footprint, then errors in range difference will occur.

[52] Canopy architecture and its changes over time are another source of error. Pointing errors are less important for flat canopies than they are for steep-sided canopies, such as conifer forests. This could then translate into errors in range retrieval as a function of forest type. Changes in canopy architecture over time can also be important. For example, if a canopy becomes more closed over time so that there is less penetration of the beam into the canopy, the change in range may be inferred as growth, when actually none occurred.

[53] Attributing these types of errors, whether from slope or canopy conditions into instrument or environmental, and into random or systematic, is difficult because of the interactions that occur between sensor and the landscape, but is the subject of continued study. However, the distinction between random and systematic errors is important because the former can be overcome by increased sampling, as will be discussed, but the latter leads to a bias that cannot.
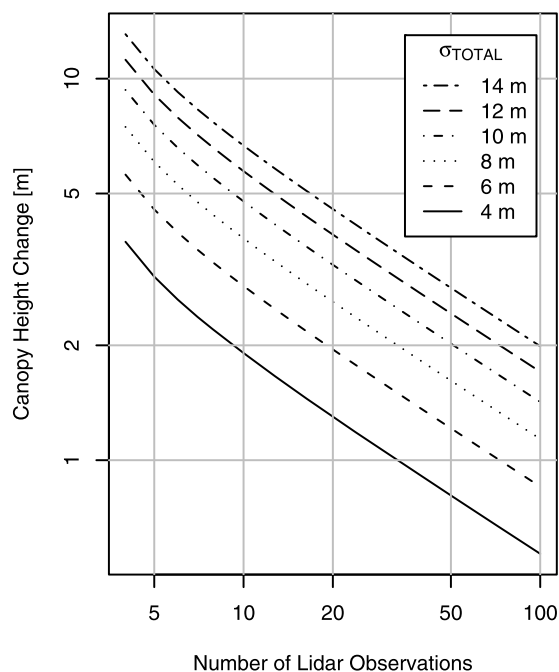
Figure 12. Number of lidar observations required to detect a given difference of mean canopy height within an area. Each line gives the total variability σ_{TOTAL} (within cell height variability and sensor error) varying from 4 to 14 m (from bottom line to top line). For example, with $\sigma_{TOTAL} = 4$ m, a change in mean of ±1 m would require about 30 observations. Note the logarithmic scale on the x and y axes.

[54] Thus, characterizing the magnitude of the changes required for detection is complex. For footprint-to-footprint comparisons, the most conservative answer is to assume that (1) field-based estimates of height errors are correct, and (2) the errors are not random between years, so that the errors do not cancel when calculating a change. In this worse case, an estimate of the expected error would be $\sigma = \sqrt{(s_1^2 + s_2^2)}$, where s_1 and s_2 are the overall validation errors from each year. So within year errors of 3–5 m would yield RMS errors of about 4–7 m. However, this is overly conservative, especially for mission design, as it conflates errors in field measurements, sensor errors and their interaction with canopy and environmental conditions. A more reasonable estimate for within year errors is likely around 1–2 m, which would yield RMS errors of about 1.5–3 m. This suggests that changes might need to exceed this range to be detectable by an individual footprint-to-footprint comparison between years.

[55] As we increase to the 1 ha scale and beyond, sampling issues arise and our errors will also now be a function of how many observations are available. We have more observations in a cell from which to calculate a cell mean for a particular year than we do footprints between years that are coincident. We can thus calculate a difference of means between years using all the observations that fall within a cell. To determine if there is a difference in the mean canopy height requires that we have an estimate of the height variance at that scale, an estimate of sensor error, and sufficient numbers of observations. We have a variance contributed by the natural variability of the landscape and that induced by

sensor measurement error. An estimate of the variance in a particular year is $\sigma_{TOTAL}^2 = (s_{sensor}^2 + s_{height}^2)$, where s_{sensor} is our estimated sensor measurement error and s_{height} is the height variability within a cell. The second term, s_{height}, may also include the interaction of sensor pointing variability with the spatial variability of canopy height (a variation in pointing on a homogenous canopy will exhibit no height variance, whereas the same variation on spatially varying canopy will produce an additional height variance component). Alternately, this type of interaction could be book kept as an additional error term in the equation given above. The average RH_E100 (canopy top) variability at La Selva varied as a function of cell size and location, with a mean value of about 6 m at the 1 ha scale and was constant between years. If we assume an average sensor error of about 2 m (in the middle of our 1.5–3 m range above), the total variability is $\sigma_{TOTAL} = 6.3$ m. This number expresses the combined uncertainty of the measurement process and the sampling process.

[56] The height requirement for DESDynI observations within cells of varying size is that the estimate of the mean must be within 1 m about 68% of the time (i.e., ±1 standard deviation and referred to as a "one meter, one sigma" requirement). The error associated with a difference of means, assuming the same number of observations and the same total variability in each year for simplicity, can be expressed as $d = \pm t_\alpha * \sqrt{(2\sigma_{TOTAL}^2/n)}$, where d is the error or detectable difference, t_α is the t statistic for a given significance level, and n is the number of observations in a given year.

[57] We can vary the magnitude of σ_{TOTAL} to approximate the required sample size (number of lidar observations) to detect a specific height change d under the same assumptions as given above. Figure 12 shows the relationship for σ_{TOTAL} ranges from 4–14 m, and with $t \approx 1$ (as in the DESDynI requirement). As can be seen the number of observations required to get relatively small errors (and thus small detectable changes) is large. If we assume we have an 8 m variability and 16 observations, say in a 1 ha cell, the error would be ±2.93 m. For the greater than 5000 observations of footprint pairs we have for La Selva our estimate of the difference of means for the entire landscape between years should be accurate to within ±0.13 m. If sensor error can be shown to be closer to 1 m, then these accuracies would increase and the number of observations required would decrease. Likewise, fewer observations would be required for more even-aged stands that have smaller spatial variability. Note that systematic errors or biases are not necessarily removed by increased sampling. A more complete analysis of errors would include an n and σ_{TOTAL} that vary in each observation year, as well as a desired level of β or "Type II" error, in addition to the α level, to determine a priori the required numbers of observations to detect a change of a given level. Such an analysis would also include modeling the effects of using nonpoint (areal lidar footprint) sampling on spatially autocorrelated fields of height structure, but is beyond our scope here.

[58] Assigning an error to the other RH_E change metrics is not easily done using field observations. Our approach is to assume these have small errors when expressed in elevation space. As discussed earlier, the waveform as defined by its vertical extent is a fundamental measurement that gives the record of intercepted surfaces. Errors appear when the
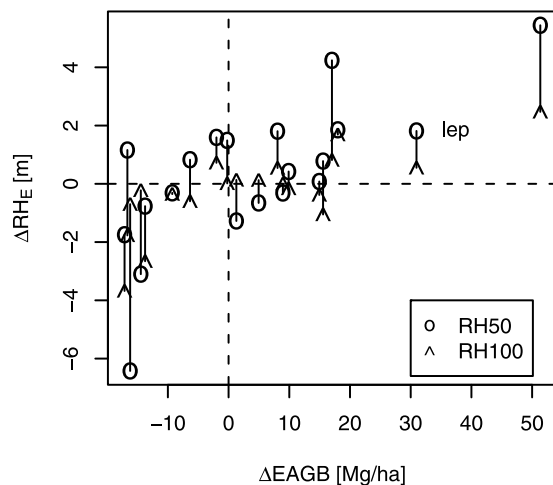
Figure 13. Relationship between changes in RH_E100 and RH_E50 heights and EAGB for the Carbono and secondary forest plots. The vertical line gives the distance between the changes in RH_E100 and RH_E50, and the symbols give the change for that particular metric. The signs of the changes are generally the same: when both metrics are positive, biomass change is positive, and vice versa. Note that often the change in RH_E50 was larger than that for RH_E100. Additionally note the small changes (less than 2 m) in the metrics for many of the plots. The secondary plot "lep" was incompletely sampled and has metric changes that are not representative.

waveform is interpreted, and such interpretation is minimal if the waveform is kept in elevation space. In practice, however, most users would prefer RH metrics interpreted as a height above the ground, and thus any errors in ground finding may again appear. There has been little evaluation of the effects of geolocation errors, topography, off-nadir pointing, and canopy penetration on these metrics, either for RH or RH_E. If the use of these metrics for change analysis continues, studies should be done that attempt to define their accuracy relative to vertical canopy structures.

[59] We developed two linear regression equations to predict biomass change. Their form was consistent, with the coefficient for ΔRH_E100 about twice that for ΔRH_E50. The intercept term was rather large, but statistically not significant. The equations, as models of the relationships between canopy structure variables and biomass are physically reasonable. As canopies grow and accumulate biomass we expect both variables to positively increase. The opposite is also true: as biomass decreases, both of these metrics will decrease. However, it is possible, as our model suggests, to have alternate signs for these variables, and depending on their magnitude, achieve either a positive, negative or neutral change in biomass. To a first approximation, changes in canopy top height must be related to changes in biomass; it is more likely that large changes in this height will lead to changes in biomass than it is these height changes will occur but that biomass stays the same. This would happen if positive or negative changes in RH_E50 take place that are approximately twice that of the RH_E100, but have opposite signs. If the changes in RH_E50 are large enough relative to RH_E100, they will drive the biomass toward the direction of that

change. How these changes occurred at La Selva is given essentially in Figure 10, which maps our regression equation using the actual cooccurrences of ΔRH_E50 and ΔRH_E100. At the 1 ha scale, positive/positive changes (both ΔRH_E100 and ΔRH_E50 are positive, respectively) occurred 50% of the time; negative/negative changes occurred 28% of the time; negative/positive and positive/negative changes occurred at a frequency of 12% and 10%, respectively. This suggests that it is far more likely for changes in both metrics to occur in the same direction (78% of time). It further suggests that for the landscape of La Selva, the most likely changes in structure were positive for both metrics. This is a reasonable result given the area of secondary forests and plantations. We find similar results at the footprint scale as well: 68% of the changes were in the same direction with 43% positive-positive. Figure 13 shows the relationship of these metrics to biomass changes for the 20 plots used in our study.

[60] The small number of total plots and limited number of secondary plots hindered the development of our combined old growth/secondary regression equation. Our equation did not predict the secondary changes well. One secondary plot, "lep" (see Table 1), had low values for both ΔRH_E100 and ΔRH_E50 (0.58 m and 1.7 m) even though the change in biomass was large (31 Mg/ha). The reason for this, discussed earlier, was that the plot was not sampled uniformly each year. In 2005 only about 1 half of the plot had usable lidar returns, and this half was composed of taller trees that did not grow as much as the half that was not sampled again. The result was little change in metrics as compared to the other secondary plot and even some old growth plots.

[61] Judging from Figures 8 and 13, small changes in biomass were difficult to model at the plot scale. This was reinforced by the weaker regression relationship found using only old growth plots. This may be because such changes at the scale of 0.5 to 1 ha plots may occur from many small changes in canopy structure, each of which is hard to detect. A forest far along in its successional trajectory may accumulate biomass slowly, with occasional mortality events. As can be seen from the height transition matrix (Table 2), 25 m footprints detect these changes at the footprint level across La Selva (for 5 m height classes, many transitions away from the previous height class occurred), but average changes to these metrics at the plot scale may be difficult to establish accurately unless the changes are large. The metrics for many plots used in this study had relatively small (0–2 m) changes over the 7 year period. For the 0.5 ha Carbono plots it seems unlikely that average changes less than 2 m in RH_E100 are detectable by LVIS based on our error analysis.

[62] The regression equations themselves had RSE values (around 10 Mg/ha) that were significant fractions or exceeded in some cases the magnitude of the changes being modeled, with the exception of the secondary plots. Because of these large errors, we explored whether the lidar data could at least be used to map source and sink areas with confidence. Our results suggest that maps of source/sink areas inferred from lidar growth changes are possible at the 1 ha scale. Using the 95% prediction interval to find cells with biomass changes significantly different from zero gave spatially meaningful results that matched known land use types. Again, the changes observed at the plot level were not large at La Selva because of the lack of recent disturbance and recovery. If the old growth forest biomass change rates at La Selva are rep-
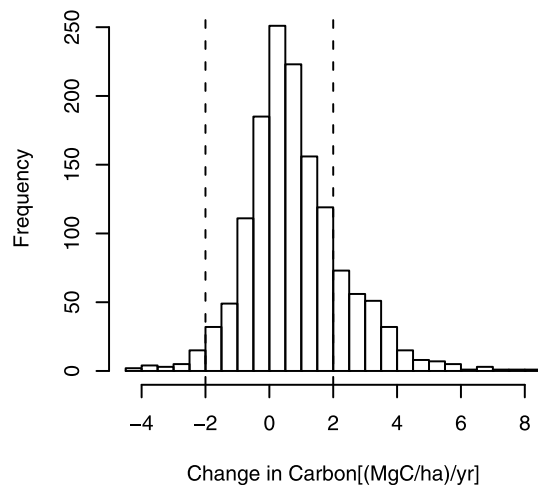
Figure 14. Estimated rates of change in aboveground carbon for 1 ha cells. The dashed vertical lines give the lower change requirement for DESDynI (2 MgC/ha/yr).

resentative of the tropics as a whole, it may be difficult to go beyond source/sink designation and quantitatively assess accumulation and loss over these forests if they are undergoing no changes other than normal mortality and growth at the 1 ha scale. If footprint based biomass equations can be developed with suitable accuracy (as in the work of *Drake et al.* [2002a]), footprint-scale changes may be easier to assess. As the scale gets even smaller (as in the work of *Kellner et al.* [2009]), changes should be even more evident.

[63] Our results as compared with those of *Kellner et al.* [2009] show differences, such as the percentages of areas undergoing positive versus negative changes. These may be attributed to the nonidentical domains of analysis, with our study including land cover types other than old growth. Others may have to do with the differences in spatial scale of the lidar footprints and subsequent aggregation scales. For example, we found higher probabilities of canopy observations remaining in the same height class between years (i.e., the diagonal of Table 3 has higher probabilities). One reason for this may be that canopy changes at the 5 m scale, in particular gaps, are either too small or otherwise average out at 25 m scales, and thus are harder to detect. Interestingly, we found identical changes in canopy height ($\Delta RH_E 100$) for old growth forests (-0.33 m) as *Kellner et al.* [2009] who report -0.32 m, even though different definitions of height were used. *Kellner et al.* [2009] calculated the average height above ground of all lidar returns within 5 m cells for each year and subtracted these. For canopies that are somewhat open, using an average height derived from small footprint lidar will result in a mean height that is below the top of the canopy as returns will go back to the sensor from the entire depth of canopy. With larger footprint systems, there will also be some penetration into the canopy until enough signal is generated to get above the noise level. That these two different types of measurements using different definitions of height observed an identical change is not intuitive. We doubt, though it is possible, that such close agreement is by chance. One explanation may lie with the canopy structure of the old growth forests at La Selva. These forests are quite closed and much of the leaf material is concentrated near the top of the

canopy [*Clark et al.*, 2008]. Thus a small-footprint system utilizing a last-return technology would have many of its returns from the outer canopy surface. We also note that LVIS was biased low (-0.43 m, see Figure 3) relative to small-footprint maximum returns within LVIS footprints, suggesting that some canopy penetration may have occurred with LVIS (however, this difference may also have been caused by dry season leaf drop during the LVIS acquisition). It may be then, that for these closed forests, average small-footprint height and LVIS canopy top heights are similar enough, that when averaged over thousands (in the case of LVIS) and hundreds of thousands of observations (in the case of *Kellner et al.* [2009]), the same average change is measured. This theory potentially could be tested by following the method of *Blair and Hofton* [1999] that creates "pseudowaveforms" from small footprint data. Pseudowaveforms could be created for each year and changes in these compared to changes observed by LVIS.

[64] The magnitude of changes in biomass mapped spatially at fine scales provides important information for future space missions, such as DESDynI, whose central goals include observing changes in biomass. We have limited knowledge of the spatial and temporal variability of such changes across the globe. Efforts using airborne lidar such as presented here can help provide this information. In addition, these types of results serve as benchmarks for establishing and predicting mission performance. Science considerations have established a DESDynI accuracy requirement for biomass changes of ± 2–10 MgC/ha/y (or 20%, whichever is larger) annually at 500 m to 1000 m resolution. The largest of these changes, and most important, will be from deforestation events and the subsequent rapid regrowth that occurs within a nominal 5 year mission length. However, the changes associated with small-scale disturbance, such as mortality events, and later stages of regrowth may be more difficult to detect. At La Selva there have been no recent large-scale disturbances (and the magnitude of changes present there reflect this). For example, in 2000, only about 95 ha of secondary forest out of the 1600 ha of La Selva were in the age class of 1–12 years. The remaining 250 ha of secondary forest were in the age class of 13–34 years, well into their recovery period. Therefore, only a small portion of La Selva observed in 1998 by LVIS was recently (<5 years) disturbed. Only eight of the 18 Carbono plots exceeded the rate of 2 Mg/ha/yr according to field-based estimates (Table 1), and only one exceeded 2.5 Mg/ha/yr. Assuming 50% of the change of biomass is carbon, none of the plots had rates that would be detected by DESDynI.

[65] We can get an approximate sense of the rate of change across the landscape by using the predictions shown in Figure 10. About 20% of the 1 ha cells had rates that exceeded 2 MgC/ha/yr (Figure 14). This is an uncertain estimate however, because of the errors in the regression equation used to estimate change. If we use a 95% prediction interval again, we can be certain that only 30 cells had ranges that exceeded the DESDynI requirement, and of these only one was negative. This does not mean that such changes did not occur, only that we cannot confidently predict these rates with the data used in this study. Nonetheless, the combination of our model results along with the actual changes measured in the field suggests rates of change below what DESDynI will measure, except for secondary forests and other rapidly

changing land cover types. However, the very fact that such areas would appear neutral under DESDynI observations would identify these forests as likely old growth areas, and when taken together with the larger changes associated with disturbance and regrowth, should enable a greatly improved accounting of the flux of carbon between the land surface and the atmosphere.

[66] Another aspect of our study with relevance to DES-DynI is that more variability was observed when footprint level changes are estimated (Table 3 and Figure 7) as opposed to averages over plots. DESDynI will have billions of "crossovers," places on the Earth where orbital paths cross and footprints overlap. The planned geolocation accuracy is 10 m, on average. Even though many of these footprint pairs will be much closer together than 10 m, we may not have a posteriori knowledge of the distance between specific footprint pairs to better than this distance. Nonetheless, these will provide valuable information on mortality rates and height dynamics. As we look at slightly larger areas around the crossover points, geolocation errors become less important, and the increased numbers of observations will enable more accurate determination of change within these.

[67] Last, some consideration must be given to the difficulties of field validation. We have already discussed issues related to validation of lidar remote sensing. A much larger problem exists with the validation of biomass. In tropical regions all such field estimates are done via generalized allometric equations that are derived from a remarkably limited number of trees. This problem is well known but widespread: no study that aims to predict tropical biomass can avoid it. The precision of biomass estimates at La Selva is high, so that year-to-year changes should be well characterized. But there remains the possibility that lidar captures structure that is well related to biomass and biomass changes, but that the dbh-based allometries are in error, and therefore lidar model failures to accurately predict changes actually may be failures to match another model's estimates that in itself has errors of the same magnitude.

[68] A solution to this problem is better allometry. Field-based estimates of biomass will be essential to relate global observations of structure from DESDynI to biomass and improved allometry is key. Additionally, a global network of plot data is required. This is especially true for biomass dynamics. There are very few sets of permanent plots similar to the Carbono project globally, yet even this unmatched data set was not ideal because the range of biomass changes was narrow, and consequently limited our analysis. Even if biomass changes are found by year-to-year differences of biomass in DESDynI, these will require actual measurements of change for validation and error analysis. In the coming years, if methodologies such as presented here can be improved and extended, then limited field data can be used with airborne lidar data to make spatially extensive maps of change in different biomes that can then be used to both calibrate and validate measurements from DESDynI.

6. Conclusion

[69] Our results at La Selva reveal a landscape under constant change as a result of growth, mortality, recruitment, and recovery from disturbance. When the effects of anthropogenic changes are superimposed, along with climatic and edaphic factors, determining the true successional status of a landscape required for accurate estimation of carbon stocks, fluxes and other ecosystem functions is a daunting challenge. Our basic premise in initiating this research was that inference of successional state and measurement of net terrestrial carbon flux between the land surface and the atmosphere may be approached by directly observing changes in canopy structure over time. This would enable the spatial mapping and quantification of the magnitudes of carbon source and sink areas. However, because spatially explicit maps of canopy and biomass dynamics over tropical forests at fine scales are rare, the ability of lidar and other remote sensing technologies to capture this variability over relatively short time spans and within their measurement accuracies was unknown. The work presented here suggests that lidar remote sensing is a viable method for quantifying short-term tropical forest dynamics. While changes in old growth biomass may be hard to detect at the plot scale over these time spans because they are small, larger changes associated with disturbance and recovery should be measureable. Even over slowly evolving old growth forests, footprint-level changes in canopy structure associated with small-scale disturbance, mortality and regrowth are observable. The ability of lidar to capture transitions across the entire spectrum of canopy structure and height is unprecedented and will provide a valuable new tool for deepening our understanding of how forest structures respond through time to changes in land use and climate.

[70] Our results also suggest that the mission concept of DESDynI, combining both lidar and radar to observe source and sink dynamics from space should be effective in measuring the larger changes in biomass for which it is designed: those that occur from deforestation and subsequent regrowth. The combination of the spatially complete coverage of radar and the tens of billions of detailed lidar profiles expected from the DESDynI should revolutionize our understanding of forest dynamics and its effect on carbon cycling and habitat structure.

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